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Review

Neural networks in fisheries research

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Dedicated to Dr. A.V. Raman, Professor of Marine Zoology, Andhra University, Visakhapatnam, India on his sixtieth birthday.

Abstract

Piscimetrics deals with software implementation of experimental design, second-generation artificial intelligence tools, viz. Neural Nets (NNs), genetic algorithms, Fuzzy Logic, Expert Systems, Wavelets and Image analysis in the field of fisheries. A brief sketch of NNs is followed by a review of their applications in forecasting, classification, distribution and fisheries management since 1978. Forecasting in fisheries covers distribution of eggs, recruitment, fish growth/age, biomass and fish catch. Other major areas are identification, abundance and food products, environmental factors and collapse of fishery industry. The data structures are given in tensorial notation. The need for the paradigm shift from classical to multi-level hybrid NNs is emphasized.

Keywords: Piscimetrics; Fisheries; Neural nets; Forecasting; Classification; Catch–effort; Artificial intelligence; Data structures

Contents

Abbreviations: ARIMA, auto regressive iterative moving average; BP, back propagation; DFA, discriminant function analysis; FFNN, feed forward neural network; GP, geometric programming; LDA, linear discriminant analysis; MA, moving average; MLP, multi-layer perceptron; MLR, multiple linear regression; NN, neural network; OODB, object oriented Database; PCA, principal component regression; PE, processing element; PLS, partial least squares; PR, pattern recognition; RBFNN, radial basis function NN; SG, sigmoid; SOM, self-organizing map; SVM, support vector machine; TF, transfer function.

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1. Introduction

Generalized modelling of microbiological, chemical and physical mechanisms is a Herculean task. It is also difficult to develop models for each biological species in spacio-temporal regions. The best approach is the empirical modelling with available data/processes in small tasks. One can improve the modelling methodology or can adopt the latest and robust ones proven in other disciplines.

The study of fisheries is multi-, inter-, and intra-disciplinary research comprising information, knowledge bits, theories and heuristics in zoology, hydrography, oceanography and information theory (Shannon and Weaver, 1949). Fishery hydrography deals with complex hydrographical patterns with abundance and dynamics of different phases in the life cycle of the fish. Although the incorporation of the information and knowledge of fishermen and fishery managers into scientific knowledge base is essential (Mackinson and Newlands, 1998), interpretation is difficult with traditional inference systems. However, fuzzy-logic expert system can give reliable advices even in the presence of noisy, imprecise, inexact, missing and interdependent data.

With two decades of experience in Chemometrics (Sambasiva Rao and Sambasiva Rao, 1998; Priyabrunda et al., 1997; Braibanti et al., 1997; Lingeswara Rao et al., 1994; Ravindra Babu et al., 1993; Ravindra Babu and Sambasiva Rao, 1992; Sambasiva Rao et al., 1984) and Envirometrics (Panakala Rao et al., 2000; Braibanti et al., 2000), we have initiated Piscimetrics, which deals with the application of second-generation intelligent tools in fisheries research. The tools include Neural Nets (NNs), Genetic Algorithms (GAs), Fuzzy Logic, wavelets, evolutionary programming and image analysis. A CDROM search of Aquatic Science Fisheries Abstracts (ASFA) has produced 97 and 103 titles (Table 1) during 1978–1999 and 2001–2006 for NN applications, which are reviewed here.

1.1. Neural networks

Data, information and knowledge processing involves estimation of parameters in mathematical space. Since data in fisheries, chemical and atmospheric research are indirect observations, projection of their results to biological measurement scale distinguishes adequate from over-ambitious and inadequate models. Uncertainty in data, vagueness of information, missing data points and imprecise goals add to the complexity. Thus, there is a need for a paradigm shift from classical model driven methods to artificial intelligence (AI) tools. To surmount the difficulties of deductive methods based on strong assumptions about continuity of parameter space and error structure, natural computations with weak assumptions were proposed in

Table 1
Literature search on application of NNs in fisheries research

Keyword	Number of hits	
Fish*	2,27,426	
Model		*50,728*
Neural*	1906	
Networks*		*5346*
Genetic*	2554	
Alg*		*45,133*
Fuzzy*	274	
Log*		*9337*
Maximum	29,531	
*Entro**		*360*

Fish* and (Neural* Network or Genetic* Alg* or Fuzzy* Log* or Max* Entro*) 97.

Neural Network	:	MLP (Multilayer perceptron)
	:	Feed Forward , Fully Connected
Data	:	Explanatory variable (X) Response (Y)
Architecture	:	I#-H1#-H2#-O
Activation function	:	I - Linear
		H# - [sigmoid ....]
		O - Linear
Training algorithm	:	[BP CG Marquardt ----]
Output	:	yTr
		TrE VE TeE

Chart 1.

the later part of the 20th Century. Neurophysiologists and cyberneticists introduced connectionist model to explain vision and tactile senses. The neurons in bundles organized in a very complex manner are instrumental for the functioning of a human brain. Mathematicians proposed perception model consisting of neurons, also called Processing Elements (PEs). That was the beginning of the era (McCulloch and Pitts, 1945) of artificial neural networks (ANNs), which gained momentum in mid-1980s.

ANN is a reality although artificial brains are in the realm of scientific fiction because understanding of human brain is so complex that it yet remains to be fully understood. It is worth mentioning that Artificial Intelligence algorithms can hardly replace an expert, but they are effective tools in the decision making process. Data processing with NNs is performed either by direct implementation on a chip or by a software. NN implementations in software are popular and have been successfully used in predicting stock market, forex, sun spots, onset of diabetes, distinguishing renal cell carcinoma from cyst, diagnosing acute myocardial infarction and classifying iris data.

NN is a data driven imbibing technology (Stern, 1996; Cheng and Titterington, 1994; Platei et al., 2000; Sugiyama and Ogawa, 2001; Leondes, 1998; Pham and Xing, 1995; Kay and Titterington, 1999; Raudys, 2001). It models multivariate and non-linear data even with discontinuous regions. It does not need transformation of data unlike the classical linearization techniques. NNs are broadly classified into self-organizing map (SOM) and multi-layer perceptron (MLP). Kohonen SOM is a low (2D or 3D) dimensional visual display technique for high dimensional data. It is a non-linear surrogate of principal component analysis (PCA). Recent advances in SOM endorse its utility in diverse disciplines overshadowing many other soft modelling procedures (Brosse et al., 2001a,b). SOM handles only response data in an unsupervised learning form and is a preferable pattern recognition (PR) technique to describe spatio-temporal variability in fisheries and oceanographic process. On the other hand, MLP (Chart 1) requires explanatory variables also and processes them in the supervised learning mode. The predictive capability, generalisibility and the higher performance of NNs over statistical multi-linear regression (MLR) models, time series analysis and non-linear methods are discussed in relation to fisheries data (Tan and Beklioglu, 2006; Oakes et al., 2005; Lloret, 2003; Lou, 2001a,b; Olden and Jackson, 2001).

1.1.1. Architecture

Neural network contains a sequence of layers. Each layer consists of a set of PEs. The first and the last are called input and output layers and the PEs correspond to the explanatory and response variables, respectively. The maximum number of intermediate layers is two. Since an end user is interested in input and output patterns and not in the intermediate processes, the latter are called hidden layers. Transformation of input to output is in the forward direction and it is referred as Feed Forward NN (FFNN).

The number of PEs in different hidden layers need not be same. With some exceptions, the usual number of PEs is less than 50% of the data points. The processes in the hidden layers are vital in understanding the complex patterns in the output layer. Full or random connections of PEs with different layers result in different NN models. The extent of connection between PEs in two layers is called a weight, which is analogous to synapse strength in biological neural nets. They are the parameters of NN; initially chosen from random numbers and are refined until convergence or maximum clock time set is over.

1.1.2. Transfer function

Transfer Function (TF) is a mathematical equation associated with the PE. The primitive TF is multiplication by unity, i.e. doing nothing. Typical TFs are polynomial (linear, quadratic, cubic, etc.), hyperbola (tanh, sigmoid), kernel (Gaussian) and wavelet. Depending upon the nature of the TF, different nets have been proposed. For example, Radial Basis Function (RBF) NN and probabilistic NN use radial and probability density functions, respectively. A PE, in a given hidden layer, receives information from PEs of the previous layer. The TF operates on the information and produces the result, which is passed on to the next layer.

Sigmoid (SG) is a popular TF. Its output range is 0 and +1 (Fig. 1a). One of its two parameters, translation factor (θ) shifts the entire profile in horizontal direction (Fig. 1b) and the other; scale factor (α) changes the steepness (Fig. 1c). The α renders SG profile to be a hard limiter (Fig. 1d) and a straight line (Fig. 2a and b). This is responsible for the ability of NN with SGTF to model linear and non-linear profiles. Wavelets as TFs have good zooming property, i.e. they explore fine details in non-linear multi-response surfaces. Other transfer functions suggested are the binary products of tanh, arctan and sigmoid.

1.1.3. Training

A vector in the data matrix is a pattern. Each pattern is given to the network and the output is compared with the response. Hence, it is a supervised learning. The error function is calculated after all the patterns are presented. The widely employed optimisation procedure (learning rule) in 1980s was back propagation (BP), which is a variation of steepest descent algorithm.

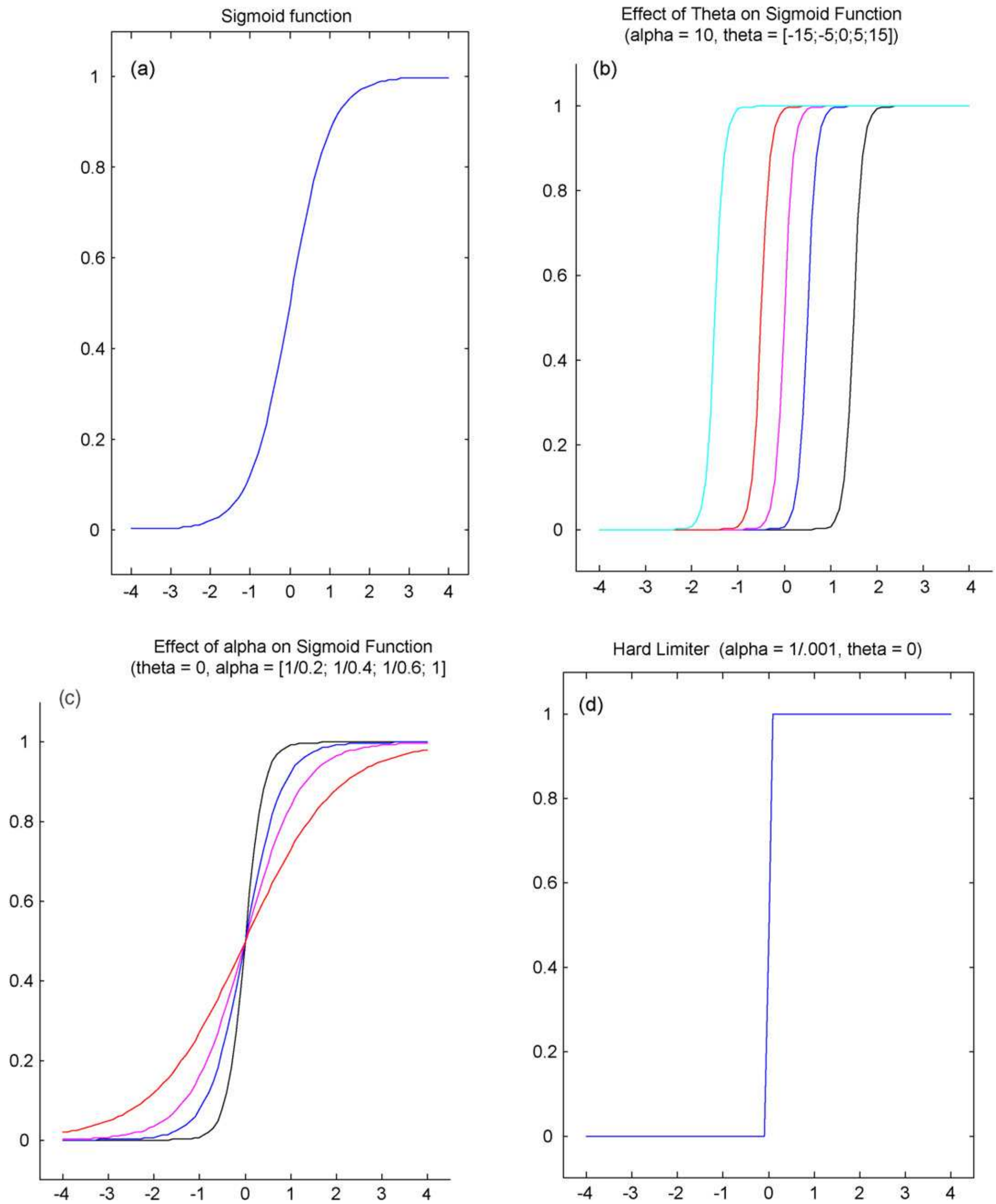


Fig. 1. Profiles of sigmoid transfer functions (non-linear).

Recently Marquardt, Conjugate Gradient, Simulated Annealing Algorithms, Genetic Algorithm, etc. have been incorporated in NN software.

1.1.4. Illustration

The pattern of a NN (input–hidden–output layers) is depicted in Fig. 3. The response is modeled as a linear combination of sigmoid functions. Non-linearity in input to output (I/O) mapping increases with the second hidden layer. The data set is randomly divided into training, verification and test sets. The best architecture is chosen by changing the number of hidden layers (1 or 2), hidden neurons in each layer (1–50% of the number of data points), transfer function and learning algorithm. A quick heuristic is to propose the best set of models with a minimum training error (err.Tr), verification error (err.Vr) and test error (err.Te). Advanced residuals in the measurement scale and influential statistics have also been handled in some packages by an intelligent module. There are more than eighty commercial packages with unlimited capabilities and a few typical ones are given in Table 2. An object oriented database (OODB) for components of NN, viz. TF, learning rule, training algorithm, object function, pre- and post-processing, etc. has been developed in this laboratory under MATLAB environment (The MathWorks Inc., 2000). Its unique feature is that the algorithms are developed as MATLAB functions. The data structures of dependent and explanatory variables are presented in Table 3. The modelling and predictive algorithms depend upon number of response (Y) and explanatory/causative (X) variables. The num-

Table 2
Features of NN packages

Package	Type of network	Algorithm	Salient features
Direct executing simulation in real time (DESIRE)/NEUNET		Fuzzy logic	Dynamic-system simulation (6000 differential equations, 20,000 difference equations, 13 integration rules) for control, aerospace, chemical engineering, physiological modeling, ecology
Matlab: Neural Network Toolbox	Perceptron RBF Hopfield LVQ Competitive NN Kohonen Elman Hebb	BP Levenberg–Marquard	MATLAB Signal processing Nonlinear control Financial modeling
NeuralWorks	ART 1 Kohonen Modular NN General Regression Fuzzy ART Probabilistic NN LVQ Boltzmann BSB SPR	BP	NeuralWorks Explorer Developers package NeuralWorks Professional
NeuroShell	Ward nets Recurrent Kohonen Probabilistic NN General regression	BP	DuPont in making safety glass Texaco in process control in oil refineries
STATISTICA: Neural Networks	Kohonen PNN GRNN	BP Levenberg–Marquardt conjugate gradient Quick propagation Delta–Bar–Delta Linear SVD *k*-Means *k*-Nearest neighbour isotropic deviation	Genetic input selection, automatic network designer
Trajan	Kohonen	Levenburg–Marquardt Conjugate gradient BP Quick propagation Delta–Bar–Delta SVD *k*-Means, *k*-nearest Weighed weight regularisation	PCA Neuro-genetic input selection, automatic network design
SNNS	RBF MLP Competitive NN Associative memory Jordan Elman Kohonen SOM Elman ART1, ART2 ART MAP Time Delay NN	BP Quick propagation Resilient Prop Backpercolation Counter propagation Dynamic LVQ Dynamic decay adjustment for RBF Simulated annealing Scaled conjugate gradient TACOMA (Task decomposition Correlation Measures and local Attention)	http://www-ra.informatik.uni-tuebingen.de/snns/

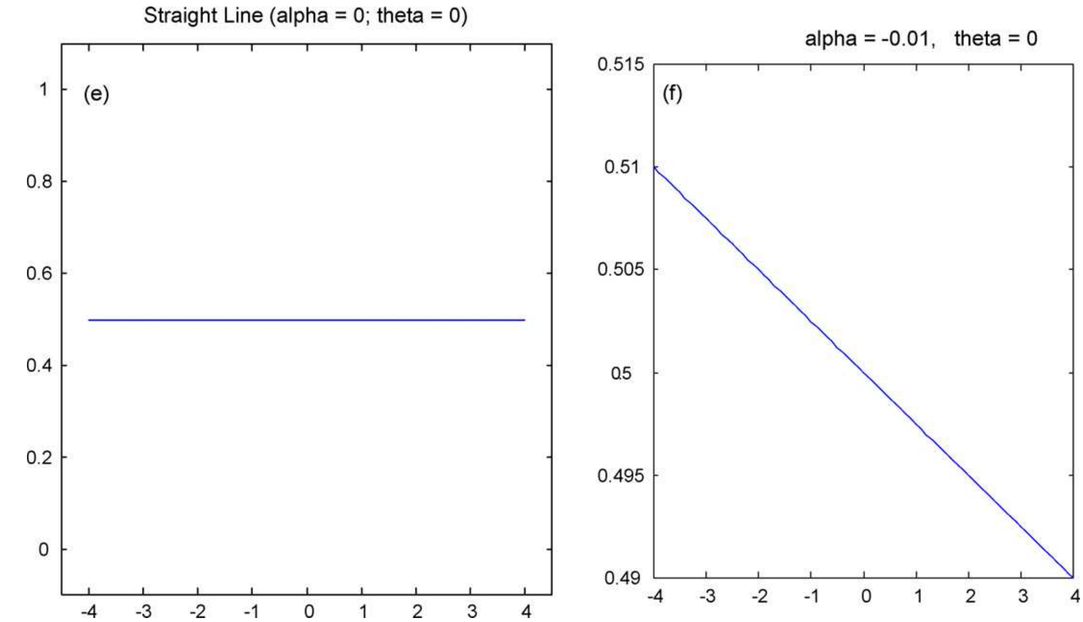


Fig. 2. Profiles of sigmoid transfer functions (linear).

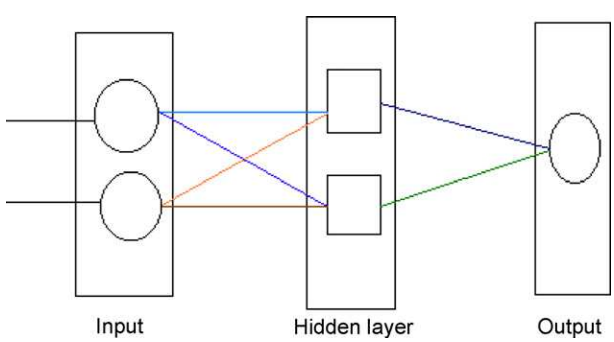


Fig. 3. Architecture of multi-layer perceptron NN (MLP-NN).

ber of dimensions is also denoted as ‘way’ or order of tensor in modelling nomenclature. Considering the catch–effort models with and without environmental variables, one-way–one-way to two-way–two-way data structures are possible. When a variety of fish species at different sites over a time, the response matrix is a three-way matrix or second order tensor. Similarly, the corresponding effort is a two-way or three-way tensor of numbers. A three-way data can be considered as two matrices arranged as flakes in a tube.

2. Life cycle of fish

2.1. Recruitment

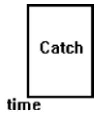
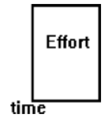
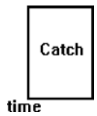
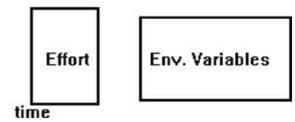
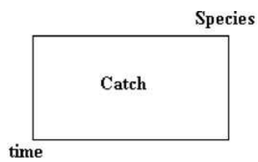
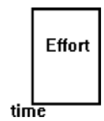
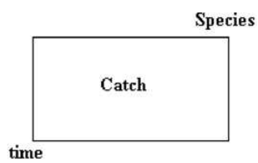
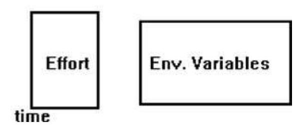
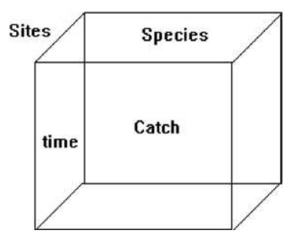
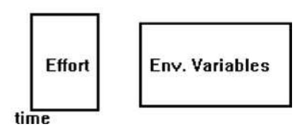
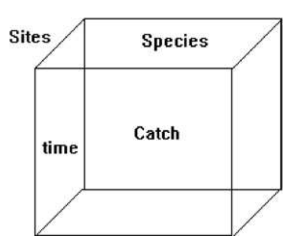
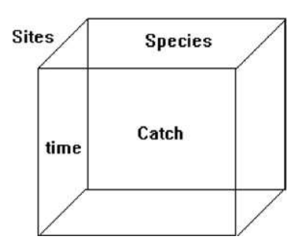
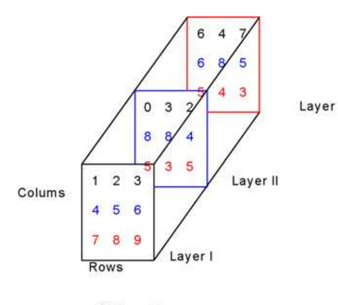
The factors and phenomenon affecting recruitment in marine fish are complex and not yet fully explored. Thus, mechanistic models or model driven statistical techniques poorly result in prediction or utterly fail (Megrey et al., 2005). Data driven paradigm with implicit evolving nature is the best alternative. NNs, inspired by the functioning of human brain are in a state of maturity with excellent mapping and predictive characteristics for both supervised and unsupervised two-way data structures.

The recruitment of Norwegian spring-spawning herring (*Clupea harengus*) in Norway (Engelhard and Heino, 2002), sand eel *Ammodytes personatus* in Eastern part of seto Island sea, *Northern Benguella*, *Sardine Sardinops*, *sagax* in South Atlantic (Megrey et al., 2005) were modelled with NNs. Hardman-Mount ford et al. modelled recruitment success of *Northern Benguela*, *Sardine sardinops*, *sagax* in South Atlantic ocean employing a seven year time series data (Hardman-Mountford et al., 2003) An adequate model for the recruitment of sand eel *A. personatus* in eastern part of Seto Island Sea in the month of February was developed (Kusakabe et al., 1997) with a three-layer FFNN trained with BP algorithm. The influential input variables of the model are reflected in the magnitude of the weights. Inferences based on the NN indicated that recruitment was higher when the water temperature was low in preceding September. SOM could identify characteristic patterns based on sea level difference, which are related to SST. The Pacific *halibut* stock data (Chen et al., 2006) were analysed for fish recruitment by models with different basis assumptions and the results are compared. In the models Pacific Decadal Oscillation (PDO) index, environmental variable was employed along with autoregressive component. Fuzzy-logic model out performed the traditional Ricker stock recruitment model. MLP-NNs are tested with several performance criteria. Typical literature reports are summarized in Table 4.

2.2. Fish growth

The age and growth parameters of fish play an important role in marine ecology and stock assessments. The predicted values of post-larval stages of Japanese *sardine* were in good agreement with the observed values (Komatsu et al., 1994a,b). A close examination of the weights of the NN model indicated that the distance between Kuroshio axis and Cape Iroh-zaki was an influential variable. These

Table 3
Data structures

X	*Y*	*Y*	*X*	Dependent variables	Independent variables
One way	One way			Y_1	X_1
One way	Two way		NENV 	Y_1	$[X_1, X_2, \ldots, X_c]$
One way	One way			$[Y_1, Y_2, \ldots, Y_c]$	X_1
Two way	Two way		NENV 	$[Y_1, Y_2, \ldots, Y_c]$	$[X_1, X_2, \ldots, X_c]$
Three way	Two way		NENV 		$[X_1, X_2, \ldots, X_c]$
Two way	Two way				

authors studied the effect of the length of the time series on forecasting.

2.3. Age of fish

Hitherto, manual methods were in practice for the age of the fish. The automation with statistical learning and AI2 tools will relieve not only the drudgery, but also reduce subjective errors. Robertson and Morison (1999) used NNs to reduce subjective error, to increase confidence and with the ultimate goal of automating the process. They classified the age of three temperate species and compared the results with those by human expert. The results were comparable for two types of species while for the third error rates in NN were larger. It was explained based on the more complex otolith structure of *Macruronus novaezelandiae*. Fablet and Le Josse (2005) (analysed 320 images of plaice otolith in the age group of 1–6 with support vector machines (SVMs) and NNs. The prediction of age compared to that by an expert agrees to the extent of 88%. Engelhard and Heino (2004) and Engelhard et al. (2003) modelled the age at maturation of individual *Norwegian spring-spawning herring* of the year classes (1930 and 1992) with discriminant and NN

Table 4
Recruitment and age of fish

	Explanatory variable	Species	Location	Comment	Ref.
Recruitment	• Water temperature • Salinity • Strength of west wind • Spawning data • Catch	Sand eel *Ammodytes personatus*	Eastern part of Seto Inland Sea		Engelhard and Heino (2002)
Recruitment	• SST • Spawning biomass • North Atlantic oscillation	Norwegian spring-spawning herring (*Clupea harengus*)	Norway	• MLR • NL-Regression • GAM • NN	Megrey et al. (2005)
Recruitment	• Time (7 year period)	Northern Benguela Sardine Sardingops Sagax	South Atlantic	SOM	Kusakabe et al. (1997)

Response	Explanatory variable	Species	Comment	Ref.
Age of fish	Pixel brightness Values along transects across images of sectioned otoliths	• Sparidae • *Acontho pagrus butcheri* • Pagrus auratus	Forecast by human expert and NN are compared	Robertson and Morison (1999)
Age of fish		• Merlucciidae • *Macruronus novaezelandiae*	High error rate for NN NN better than DA	Potter et al. (1993)
Age at maturation	3 years 4 years 9 years	• Norwegspring-spawning herring		Engelhard et al. (2003)

	DA %	NN %
Pre error	5.2	2.9
Coreect classification	5.2	66.6

methods. During the time of the collapse of the fishery, the age at 50% maturity was considerably reduced and length at 50% maturity increased both before and after collapse. It indicates that stock abundance influences the maturity changes. Engelhard et al. (2003) and Engelhard and Heino (2004) predicted the age at maturation of Norwegian Spring-spawning herring with NN and discriminant function analysis (DFA). From NN models and behavioural experiments, Phelps et al. (2001) reported that female *tungara* frogs prefer choice of a mate based on stimuli resembling a recent ancestor.

3. Fish identification

3.1. Detection

A comparative study of DFA and FFNN (BP) was made (Mastorillo et al., 1997) for the detection of three species of small body fish making use of ten environmental variables at 464 sampling points by electro fishing in the Ariege river (France). NNs predicted better compared to DFA (Table 5). Olden (2003) developed an NN model to predict the entire fish species membership of a community in 286 lakes. The multi-response NN correctly classified 22 out of 27 species in 91% of the lakes irrespective of the functional differences among the species. Tomas et al. (2005) found the natal origin of *Allis shad* from isotopic measurements of Co, Fe, Sr and Rb with inductively coupled plasma mass spectrometry (ICP–MS) for the fish samples of south west France in the two river systems Dordogne and Garonne. ANN excelled linear discriminant analysis (LDA) in correct classification. Table 6

incorporates the summary of studies of fisheries detection.

3.2. Identification of fish-type

Different schools of fish – sardine, anchovy and horse mackerels – can be identified using a towed dual beam 120 kHz transducer data. MLP-FFNNs were used with the input param-

Table 5
Comparison of the performance of NN and DFA

Species	Percent classification	
	NN	DFA
Stone load	82.1	62.5
Gudgeon	87.7	66.6
Minnow	90.1	78

Table 6
Detection, classification, distribution, discrimination, clustering and discrimination of fish

Response	Explanatory variable	Species	Location	Comment	Ref.
(a) Detection					
Presence or absence of small body fish	• Fish • Ten environmental variables	• Minnow (*Phoxinus phoxinus*) • Gudgeon (*Gobio gobio*) • Stone Loach (*Barbatula barbatula*)	Ariege River (France)	NN superior to DFA 464 samples	Mastrorillo et al. (1997)
Presence or absence	8 empirical input parameters	18 different species	Seine basin		Boet and Fush (1995), Haralabous and Georgakarakos (1996)
Presence or absence	• Latitude • Elevation • Catchment area • Average air temperature • Vegetation type • Land use catchment geography	14 species	Wellington Region New Zealand	- GIS data - Multi-response ANN	Joy and Death (2004)
Migration	• Physical - Temperature, salinity, flow, height, etc. • Biodata - Prey, predator, life cycle	Demersal fish	Southern sea of Korean Peninsula	- NN - Lorenz Chaos theory	Kim (2003)
(b) Classification					
Classification of fish to their native estuary		• Juvenile (young) cynoscion regalis	East coast of USA • Doboy sound (Georgia) • Pamlico Sound (NC) • Shesapeake Bay (Virginia) • Delaware Bay (Delaware) • Peconic Bay (New York)	NN 94 KNN 96 LDA failed QDA failed	Thorrold et al. (1998)
Classification of parasite species	• *Aphanurus stossichii* • *Bacciger israelensis* • *Hemiurus communis* • *Microcotyle erythrini* • *Lecithocladium excisum*	• Bogue (Boops boops)	Off Atlantic coast of Spain (year 2001)		Power et al. (2005)
Eel size (4) classes	• Width of ditch section • Silt depth • Density of emergent plants	European eel *Anguilla anguilla*	France	Small eels are wide spread than larger ones	Laffaille et al. (2003, 2004)
	• Environmental variables • Depth • Distance from the bank • Vegetation cover • Slope of the bank	Eurasian perch *Perca fluviatilis*	Large lake (Lake Pareloup, France)	Abundance in an area between shallow and open water	Brosse and Lek (2002)

Table 6 (*Continued*)

Response	Species	Methods	Ref
Six wind regimes	Benguela 01-08-1989 to 29-11-2000	NN wavelet	Risien et al. (2002)

α	Max power	Peak (day)
10 to 15	Winter	6 to 16
15.5 to 18.5		
19.0 to 23.5		
24.0 to 28.5	Summer	35 to 40
29.0 to 32.5		
33.0 to 35.0		

Clusters	Related to	Explanatory variable	Species	Location	Model	Comment	Ref.
(c) Clustering							
1,2	Month	• Site	Littoral fish	Lake Constance (South Germany)	SOM	Temporal patterns of species succession-partitioning of habitat	Reyjol et al. (2005)
	Time of the day	• Year • Month • Time of the day					
3	Month, site						
4	All factors						
3	Fish clusters	• Altitude • Distance from source • Surface area of drainage basin		Adour-Garonne Basin	SOM MLP > discriminant analysis		Park et al. (2006)
		• Catch for 48 years • Environmental and economic forcing	30 species	South Korea	SOM		Hyun et al. (2005)
Fish clusters	y: Microsatellites character	• Chinese sturgeon • Acipenser sinensis	Yangtze river (China)	SOM			Zhao et al. (2005)

No	Time period
1	1954 to 1961
2	1962 to 1973
3	1974 to 1983
4	1983 to 1996
5	1997to 2001

Response	Explanatory variable	Species	Location	Comment	Ref.
(d) Distribution					
Distribution prediction	• GIC derived characteristics • Stream segments	38 fish species	Great plain river basin USA	LDA NN Classification trees	Oakes et al. (2005)
Distribution—horizontal	• Temperature range • Prey • Abundance	Capelin	Barents Sea	NN Adopted random walk	Huse (2001)
Distribution—micro-habitat scale	• Environmental variables	Pisces	• France • New Zealand streams	NN MVA $r^2 = 0.61–0.92$	Brosse et al. (2001a,b)

Table 6 (*Continued*)

Response	Explanatory variable	Species	Location	Comment	Ref.
Distribution—special (#)		American lobster (*Homarus americanus*)	Spring, summer and fall of 2001	Bayesian NN	Crivello et al. (2005)
			Late summer of 2001 and 2002		
(e) Discrimination					
Native farm-reared		Chinook Salmon *Oncorhynchus tashawytscha*	Vancouver Island-West coast		Withler et al. (1993)
New shell Old shell	Hardness			NL PNN One year prediction	Hicks and Johnson (1999)
North American European	• River age • Fork length • Scale circuli counts - Two variables	• Salmon *Salmo salar*		NN Architecture: 33-17-2 LDA	Potter et al. (1991)
Diversity macroinvertebrates	• Environmental variables	• Aquatic insects pisces	Netherlands	ANN + ANOVA $r^2 = 0.61–0.92$	McKenna and James (2005)

Response	Species	Comment	Ref.
(f) Miscellaneous			
Echogram 1992–1993	• Sardines • Anchovies • Horse mackerels	ANN (BP)	Haralabous and Georgakarakos (1996)
Acoustic Back scatter	• Mackerel • Horse mackerel Saithe • Haddock • Cod	ANN 95% success LDA	Simmonds et al. (1995)
Sonar	• American lobster • *Homarus americanus*	2 years ahead forecast MLP: 80% NN: 90% Detection: 98% fuzzy – ES	Saila (1997)

Response	Explanatory variable	Species	Location	Comment	Ref.
Acoustic data	• Prior information from acoustic expert	• Juvenile to adult Pollock (*Theragra chalcogramma*)	Bering Sea	Bayesian special composition estimation	Hammond et al. (2001)
ICP–MS 15 isotopes	• Natal origin to juvenile shad	• Allis shad (*Alosa alosa*)	Dordogne-Garonne (South West France)	LDA	Tomas et al. (2005)
				NN	

eters derived from hydro-acoustic data of 1992 and 1993. The classification power of NN was tested with the data not used in developing the model. NNs are useful when the parametric assumptions are not satisfied or the characteristics of the schools are overlapping. The application of different types of NNs to detect and identify (Ramani and Patrick, 1992) fish schools was studied from laboratory acoustic data. A three-layer FFNN could predict 80% of the targets, which were not included in the models. The first NN modelled the trends in the raw data and the second pre-processed the peak detection. Parallel NNs were significantly better than single NN and correct identification reached above 90%. Success rates were over 98% when the objective was the detection of the fish but not identification. NN model (Brion et al., 2005) successfully predicted the presence and absence of adenovirus (ADV), norwalk-like virus (NLV), and enterovirus (EV) in shellfish from different countries in Europe (Spain, Sweden, Greece and UK). This binary classification is highly successful with more than 95% performance rate, while *M*-logistic regression gives a maximum of 75% performance. The presence and absence of red mullet and *anglerfish* was easier, while that of hake was difficult even with NNs (Maravelias et al., 2003).

3.3. Classification

The activities in fisheries require a database of presence/absence, detection/identification, distribution, classification/discrimination of each fish species in different geographic locations. These tasks were accomplished in early part of 20th Century with the knowledge of fisherman, biological/taxonomical tools and classical statistical techniques, viz. Linear Discriminant Analysis (LDA), Discriminant Factor Analysis (DFA), Dendograms and Pattern Recognition (PR). The recent advances in hydro-acoustic instrumentation, pattern recognition tools and NNs improved the prediction.

The classification of *Juvenile cynoscion regalis* in different states of east coast of USA (Hanson et al., 2004), *bogue* (Boops boops) off Atlantic coast of Spain (Georgakarakos et al., 2006), *juvenile gag otoliths* along Florida coast was studied with NNs and image analysis. The shell conditions of *Dungeness crab cancer magister* from four Kodiak bays were classified (Niculescu et al., 2004) to distinguish the new shell from the others with a success rate of 90% by Probabilistic NN. The monthly shell hardness (Y) was measured by a durometer over a year (x) and classical non-linear model was attempted.

$$y = -\frac{82.2}{1 + \exp((x - 2.7)/-1.5)}$$

The NN technique with high predictability alleviated the subjectivity in existing shell hardness methods and improved managerial decisions. Morimoto et al. (2003) considered the radius of the segment between the centre of eye and the origin of *pectoral fin* as a landmark in their attempt in classification, identification of fish species with NNs. With the increasing number of the landmarks in fish head, compared to earlier investigations, the results are not perturbed with distortion of the image. The chemical concentration of *juvenile gag* otoliths in four nursery areas along the Florida west coast during 1992–1995 and 1996 are used to classify (Hanson et al., 2004) *juvenile gag*, *myctero perca*, *microlepis* habitats with an error rate less than 10% employing neural networks. Among discriminant function analysis and NNs, the latter outperformed in classification, predicting presence or absence of a number of fish species (Maravelias et al., 2003). The details of classification, distribution, discrimination and clustering are incorporated in Table 6.

3.4. Distribution

The complex responses of the distribution of fish in different locations are a result of natural adoptive trade off between searching for food and avoiding predators. It is hardly possible to invoke models from first principles of fisheries science (Laffaille et al., 2003, 2004; Brosse and Lek, 2002; Huse, 2001). NN models which are data driven with no a priori knowledge of the micro-processes is one of the best choices. The other natural computational techniques like immune algorithms, ant algorithm and genetic based evolutionary procedures enhance the performance of such complex tasks.

The distribution of European eel (*Anguilla anguilla*) in France (Laffaille et al., 2003, 2004), Eurasian perch *Perca fluviatilis* in large lake of France (Brosse and Lek, 2002), American lobster (*Homarus americanus*) (Crivello et al., 2005), thirty eight fish species in great plain river basin in USA (Oakes et al., 2005), pisces in France/New Zealand streams (Brosse et al., 2001a,b), capelin in Barents Sea (Huse, 2001), 14 types of fresh water fish and crustaceans in New Zealand (Joy and Death, 2004) was investigated employing NN models. NN model of the vertical distribution of (Wieland and Jarre-Teichmann, 1997) Baltic cod eggs in Bornholm Basin data of a decade explained 82% of variance. One-year ahead prediction was successful. The error in the prediction of egg development time was less than 1%. An outlier in the data set was an artefact of exceptional hydrographic situation and NN model predicted a high residual for this observation. It indicates the robustness of NN models to outliers, which result due to transcription errors, physico-chemical phenomena and biological/hydrographic avalanches.

Distribution of cod (*Gadus morhua*) in the Baltic Sea during the period 1978–1993 was modelled with NNs using hydrological and fish survey data (Fuchs, 1996; Alkan et al., 2004). The visual mapping of spatial–hydrographical patterns and total biomass for the distribution of cod in 3D Baltic Sea topology is instrumental in understanding the interactions between environment and fishes. Joy and Death (2004) predicted the distribution of 14 types of fresh water fish and crustaceans in New Zealand. The study was aimed at understanding how the human activities and climatic changes affect fish communities. This results in pinpointing the geological sites requiring protection, hotspots of biodiversity and for growing of endangered/rare species. Brosse et al. (2001a,b) reported the distribution of dominant and scarce fresh water fish in littoral zone of large French lake using SOM. It is reported that SOM is a dependable visual display of multidimensional data of complex ecological information in lower dimensions compared to traditional PCA mapping. The distribution of capelin in Barents Sea (Huse, 2001), four classes based on the European eel (Laffaille et al., 2003, 2004) and Eurasian perch *P. fluviatilis* (Brosse and Lek, 2002) in France are studied with environmental variables and geographic patterns. The prediction with NN excels compared to linear regression or nonlinear additive models. Kim (2003) used NNs and Lorenz chaos theory to model migration of demersal fish in southern sea of Korean Peninsula. The complexity of environmental changes and behaviour of the fish species renders the explicit model for the migration impossible. Hence, knowledge bases with predictive equations from first principles are not realizable. Thus, data driven NN is employed with success.

3.5. Discrimination

The discrimination between native and farm-reared Chinook salmon in Vancouver Island in West coast (Alkan et al., 2004), new shell and old shell (Niculescu et al., 2004), North American and European Salmon (Ojeda et al., 2004), Antarctic Krill with *Euphausiid salp* was studied with MLP-, RBF-NNs, image and LDA analysis. Morimoto et al. (2001) employed 21 parameters, calculated from the landmarks along with those for partial region and the centre of the eye. The method is successful to discriminate 11 types of species. Taira et al. (2004) adopted NNs to discriminate the fish species based on image data of the fish from manual and automatic procedures. The image of the fish obtained with a camera is processed with image techniques. The landmarks and distances between them are the input features to an NN with a high success rate. Multi-frequency acoustic data (Woodd-Walker et al., 2003) and swarm morphology parameters in NNs resulted in better discrimination between Antarctic krill with *E. salp* aggregations and other zooplankton compared to classical techniques.

Taira et al. (2005) discriminated fish species with imaging processing data reducing the number of input features from 19 to 4 using NN models. Simmonds et al. (1995) identified mackeral, horse mackeral, saithe, haddock and two sizes of cod from acoustic back scattering coefficients in the range of 27–54 kHz. Replicate data were measured with 4–12 h intervals. NN and classical discriminant analysis achieved more than 95% success. The discrimination between farm-reared (commercial) and native Chinook salmon (*Oncorhychus tashawytscha*) was attempted (Withler et al., 1993) by NN and discriminant analysis using DNA patterns. Two sets of samples from a commercial farm and five on the west coast of Vancouver Island were modelled. The fish populations in Big Qualicum River and two farms were differentiated from all the five native west coast ones. The success rate reached 97% for the native and 83% for the west coast. The continent of origin of Atlantic Salmon (*Salmo salar*) caught at west Greenland was inferred (Potter et al., 1991) from scale characters. Using 33 input variables from river age, fork length and two-scale circuli counts, two output neurons discriminate between North American and European origin. NN with 17 hidden neurons predicted better (85.8%) than the earlier discriminant analysis (80.3%).

3.6. Clustering

The clustering of littoral fish in Lake Constance (South Germany) (Reyjol et al., 2005), juvenile to adult pollock in Bering Sea (Hammond et al., 2001), fish in Adour Garonne Basin (Park et al., 2006), Chinese sturgeon in China was studied with SOM- and MLP-NNs. A binary data set of fish occurrences in southwest France was trained with SOM followed by *k*-means algorithm to distinguish through major headwater, montane and plain clusters of sites. Zhao et al. (2005) made a cluster analysis based on microsatellite characteristics with SOM for Chinese sturgeon. The SOM analysis of environmental variables, viz. elevation, stream order, distance from source, catchment area, slope, stream width and richness of fish species in 474 sites showed the co existence of gudgeon and minnow in Piedmont streams and their coexistence along with stone loach in headwater streams (Cereghino et al., 2005a,b). These studies enhance the effectiveness of conservation of fish populations.

4. Fish stock

Abundance of fish (Perspar and Vvlema, 1998) depends on dynamics of eggs, distribution, recruitment, various stages of growth, biomass availability, death including predator consumption, closure of fishery, unorganised fishing and catastrophic events. Automatic counting of fish populations in fish tanks was studied by a three layer FFNN. This AI pattern recognition method outperformed both pixel counting and energy estimation procedures. NNs are acclaimed for 94% success even for scenes in different orientations and overlaps.

A time series of trawl survey of American lobster abundance (Saila, 1997) was modeled with NNs for a 2-year ahead forecast. In the second phase, these results were combined with temperature data to develop a fuzzy rule based expert system to project final abundance. Fuzzy logic deals with even complex processes, when the interactions among the micro-components are unknown. Investigation with simulation proved that the model is robust and gives accurate estimates compared to traditional methods. Zhou (2003) found SLP-NNs excel moving average (MA) for the escapement of oregon coastal fall Chinook salmon *otshawytscha* in Siletz and Nehalem Rivers. This study is crucial for the forecasts of abundance and ocean escapement of Pacific salmon *oncorhyncus* spp. using the time series data for the period 1986–2000.

4.1. Collapse of fisheries

The collapse as well as the abundance of a type of fish is due to natural and human intervention. Sometimes, natural calamities and avalanches all together change the pattern and thus predictive modelling for a disaster and for restoring the normal situation is desirable. Yet, it is a complex task with low success rates. In western Long Island Sound (LIS), there was a complete collapse of American lobster (*H. americanus*) in 1999. A survey of egg bearing female lobsters collected from three sites within LIS and Hudson Canyon were studied. Tissue samples were also collected from female lobsters in spring, summer and fall of 2001 and lobster larvae were collected in the late summer of 2001 and 2002 from five sites within LIS (Crivello et al., 2005). Bayesian NNs were used to find the female lobster based on differences in microsatellite allele frequencies based on the relative contributions in different areas. Reestablishment of their commercial fishery was successful.

The collapse of Norwegian spring-spawning herring (*C. harengus*) in 1960 was attributed to over fishing. The stock was however recovered (Hardman-Mountford et al., 2003) by 1980s. A reaction norm approach was developed by the same group to distinguish genetic from phenotypic aspects of maturation of commercial fisheries. It is to probe into the key factors for sudden decrease in fish stock and to implement remedial measures during disaster.

4.2. Fisheries management

Fishing, recreation and production of biodiversity are key factors in management of fisheries in addition to economics and meeting the demand (Maravelias et al., 2003). The health and productivity depends on diversity of fish population. The impact of environmental variables generates valuable information for managerial decision in fishery industry (McKenna and James, 2005). Various tasks in fisheries research are recruitment, age at maturation, age of the fish, migration, escapement, natural death, decline of population due to predators and distribution. The detection/classification/discrimination of fish based on species, region and spacio-temporal abundance/distribution are crucial in fishing (catch/CPUE) activity. The nutritious value of food products by different food processing procedures and the extent of toxic materials is a matter of prime concern. The impact of toxic chemicals, environment and deceased species, cyanophyta/biomass and NH_3 on the growth and health of fish species is of concern to fishery managers.

The design of fishing vessel, its characteristics in rough sea, the knowledge of experienced fishermen and knowledge/intelligence bits derived from artificial fishermat (animat) in simulated world offer complimentary information. MODELKEY (Models for assessing and forecasting the impact of environmental key pollutants on fresh water and marine ecosystems and biodiversity) is a mega European software project to develop tools for river systems. It comprises methods for cause–effect relationships between insufficient ecological status and environmental pollution as explanatory variables. It will be interlinked with laboratory and field data. The system is useful for early warning messages, whenever catastrophic levels are reached. Decision supporting systems, predictive component effect models and NNs are used in this strategy with the participation of 14 European countries. Taking into consideration of exposure, effects on biofilms, invertebrate and fish communities, correlation of chemical analysis in water/sediment/biota, simulations of data in vitro/in vivo are a subset of the activities (Brack, 2005).

SOM was used to map the highest and lowest risk of invasion in different areas for freshwater fish population in France. It is instrumental to plan the future management projects (Cereghino et al., 2005a,b). In spite of good fisheries management practices (GFMP), there are sudden decline of fish stocks-instances (Laffaille et al., 2004; Engelhard and Heino, 2004). Shrewd inspection and intensive modelling of the historical time series along with ground truth factors restored the stocks. The predictive modelling ensures avoiding recurrence of the disaster and instrumental for prospective planning of sustained commercial/recreation fisheries.

Fish populations have complex and non-linear response and reactions to biotic inter-reactions and environmental changes (Olden and Jackson, 2001). Thus, fish–habitat models are not amicable from first principles. The management of fisheries in this decade requires data driven and evolutionary approaches with robust characteristics unlike the yester years' statistical methods. The catch for a single species over a period is a column vector of size time $\times$ 1. In tensorial notation it is one-way data or first order tensor. Effort and environmental variables form a data matrix (second order tensor or two-way data) of size time $\times$ (NENV + 1), where NENV is the number of environmental variables (Table 3).

Catch data for a multi-species fishery at a single site and in different sites form two-way and three-way data sets, respectively. The size of explanatory data also grows to three-way. Then the modelling is for three-way response as a function of three-way independent variables. The complexity grows not only with the increase of dimensionality but also with non-linearity, discontinuity, correlation among the variables/parameters, etc. The theoretical models in vogue in fisheries are based on steady state assumptions, equilibrium and other biological processes. They are linear or non-linear in variables/parameters.

4.3. Forecast

During the last 5 years, not only in fisheries literature, but also even in chemical sciences, prediction is accepted as an essential component of mathematical as well as conceptual modelling (Hansen et al., 2001). The spatio-temporal variation of fish communities is of utmost interest in fresh water systems. The effects of reoligotrophication process, plasticity to the fish nycthemeral preferences are also a matter of concern. The prediction of catch, CPUE and abundance of critical data sets are briefed in Table 7.

4.3.1. Abundance

Forecasting of fish abundance is commercially important, instrumental in avoiding decline of the number of species and promoting sustainable growth. The abundance of a single or multiple fish species is interrelated with bio-/oceanographic-factors as well as human intervention. The cause–effect (MLR, NN), time series (MA, NN) and unsupervised (SOM) models are employed in this task. The calculation of abundance of salmon O. in Siletz and Nehalem Rivers (Zhou, 2003), salmonid in Canada (McKenna and James, 2005), annual loliginid in north Aegean Sea (Georgakarakos et al., 2006), brown trout, European minnow, Eurasian perch *P. fluviatilis* of lake pareloup in France (Brosse and Lek, 2002) and stone laoch in France (Cereghino et al., 2005a,b) with NNs excelled traditional statistical methods in performance and prediction. The effect of environmental conditions on pelagic fish abundance in South Africa for the period 1982–1999 (Shillington, 2002) was studied in a collaborative project consisting of three African and five European countries. SOM analysis was the highlight of the scheme and in probing into the fluctuations in the distribution of fish stock.

The forecasting of catches of multiple species (Hwang and Aoki, 1997) in the set net of Seisho region of Sagami Bay, Japan was attempted by three-layer FFNN with BP algorithm. The explanatory variables are average temperature anomalies (around set nets, at the surface and 50 m depth), Kuroshio path type and distance of Kuroshio current from the Cape Irou-Zaki and Nojima-Zaki. The response is 3 months average of CPUE of three species and total catch of species. The study indicated that predictions using the same season data were more successful than using preceding season data. The prediction of CPUE of jack mackerel (*Trachurus japonicus*) in Sagami Bay of central Japan (Hwang et al., 1996) was based on the preceding month data and temperature. The FFNN with two input variables (sea surface temperature and temperature at 50-m depth) was used. The training method was in the supervised mode employing BP. The predictive knowledge of catch of young sardine (*Sardinops melanostictus*) off Joban-Bosa (Japan) (Aoki and Komatsu, 1992) in winter was modelled by NNs (Table 8). The input data matrix consisted of five variables, viz., egg abundance, catch of larvae, Kuroshio path, Oyashio intrusion and oceanographic pattern in Kashima-Nada Sea. The NNs were pro-

Table 7
Forecasting of fish

Response	Explanatory variable	Species	Location	Comment	Ref.
Catch	Hydrographic conditions	Japanese Sardine	Segami Bay		Komatsu et al. (1994a,b)
Catch	• Egg abundance • Catch of Larvae • Kuroshio path • Oyashio intrusion • Oceanographic pattern	Young Sardine	Joban Boso, Japan		Aoki and Komatsu (1992)
Catch	• Oceanographic - Geographic positions for the center of warm core rings off Kushiro and Sanriku - Nothward expansion of warm tongue in near and off shore Kuroshio - First and second branches of the Oyashio • Biological - Body length - Condition factor	Skipjack	Northeast coast of Japan	Tr: 1981–1995 Te: 1996–1997	Tameishi et al. (1998)
Catch	• Climactic - Southern oscillation index • Hydrographic - Patterns of Kuroshio and Oyashio currents - SST • Biological - Zooplankton densities	• Young Japanese Sardine	• Joban-Boso seas off pacific coast of central Japan		Aoki and Komatsu (1997)
CPUE		• Tuna purse-seine		Power curve between CPUE and abundance	Gaertner and Dreyfus-Leon (2004)
CPUE	• Six set nets • SST • Temp. at 50 m depth	• Jack Mackerel (*Trachurus japanicus*)	Segami Bay	Catch from preceding month Temp	Hwang et al. (1996)
CPUE	• Average temp anomalies • Around set nets • Surface • 50-m depth - Kuroshio path type - Distance of Kuroshio current from Cape Irou-zaki and Cape Nojima-zaki	• Jack Mackerel *Trachurus japanicus* • Japanese Sardine *Sardinops melanosticus* • Chub mackerel *Scombar japanicus*	Seisho in Sagami Bay		Hwang and Aoki (1997)

posed to be promising tools to describe the dynamics of fishing conditions and forecasting.

FFNN with BP was used (Svoboda and Fetcho, 1996) to develop stochastic model for the prediction of fish in Garonne River basin. The causative variables are distance from source and elevation. The correlation between the predicted and observed values from an independent test data set is 0.90 with 99.9% acceptability. It is claimed to be a powerful predictive tool compared to traditional modelling methods. Annual catch data for 15 years (Tameishi et al., 1998) was used to develop an NN model for one-step and two-step ahead forecasting of skipjack (*Katsuwonus pelamis*) off northeast coast of Japan in Pacific Ocean. The factors responsible for the variation of catch were discussed based on the trained network. The six input factors are mainly of two categories—oceanographic and biological. A systematic study of catch–effort data of Shellfish in north Andhra coast of Bay of Bengal has been performed using theoretical models and NNs. It was found that NNs have better explainability and high predictability compared to non-linear methods (Sudarsan et al., 1999).

4.3.2. Fish catch

Response variable is expressed as catch per unit effort (CPUE), log(CPUE), or any other function of catch. Effort is

Table 8
Abundance of fish

<table>
<tr><th>Response</th><th>Explanatory variable</th><th>Species</th><th>Location</th><th>Comment</th><th>Ref.</th></tr>
<tr><td>Abundance</td><td>• Distance from bank
• %Boulders
• %Pebbles
• Gravel
• Sand
• Mud
• Depth
• Velocity</td><td>• Minnow</td><td></td><td>NSAM: 372 randomly chosen from 465 electro-fished point samples</td><td>Mastorillo et al. (1997)</td></tr>
<tr><td>Abundance</td><td>• Distance from source
• Elevation</td><td></td><td>Garonne River Basin</td><td></td><td>Mastrorillo et al. (1997–1999/12)</td></tr>
<tr><td>Abundance</td><td>• Distance from the bank
• Water depth
• Water velocity
• %Different substratum
• Fractions (boulders large and small)
• Pebbles (large and small)
• Gravels
• Sand mud
• Bedrock
• Flooded vegetation cover
• Blockage
Presence/absence</td><td>• Brown trout (Salmo trutta L.)
• European minnow (Phoxinus phoxinus L.)
• Stone loach (Barbatula barbatula L.)</td><td>Garonne River Basin</td><td>NN<table><tr><th></th><th>MSE</th><th>PI(%)</th></tr><tr><td>Tr</td><td>0.4 to 1.93</td><td>60</td></tr><tr><td>te</td><td>0.53 to 8.53</td><td>51 to 80</td></tr></table></td><td>Reyjol et al. (2001)</td></tr>
<tr><td>Abundance</td><td>• Inflow
• Water Temperature
• Phosphorous
• Total nitrogen</td><td>Dahuofang Reservior (China)</td><td>1980–1989 Tr
1990–1999 Te (average error 1%)</td><td></td><td>Wu et al. (2001)</td></tr>
<tr><td>Abundance</td><td></td><td>Dominant and scarce species</td><td>Littoral zone (Large French lake)</td><td>SOM > PCA</td><td>Brosse et al. (2001a,b)</td></tr>
<tr><td>Abundance</td><td>• Time (1986–2000)</td><td>Oregon coastal fall
Chinook Salmon O. tshawytscha</td><td>Siletz and Nehalem rivers</td><td><table><tr><th></th><th>Siletz</th><th>Nehaleum</th></tr><tr><td>NN</td><td>24.1</td><td>27.7</td></tr><tr><td>MA</td><td>31.7</td><td>34.8</td></tr></table></td><td>Zhou (2003)</td></tr>
<tr><td>Abundance
(1982–1999)</td><td>• SST
• Vertical chlorophyll
• Sea level
• QuikSCAT winds</td><td>Pelagic fisheries
Benguela
Angola</td><td></td><td>SOM</td><td>Shillington (2002)</td></tr>
</table>

Table 8 (*Continued*)

Response	Explanatory variable	Species	Location	Comment	Ref.
Abundance of Perch	• Eight habitat descriptors	Eurasian perch *Perca fluviatilis*	Lake Pareloup, France	r^2: NN 0.78; MLR 0.20; GAM 0.33	Brosse and Lek (2002)
Abundance	• 17 input variables	Salmonid	Eastern basin Lake Ontario (Canada)	NN ≫ [MLR, LD]	McKenna and James (2005)
Abundance landing	• Temperature	• Annual loliginid	Northern Aegean Sea (1984–1999)	$r^2 = 0.96$	Georgakarakos et al. (2006)
	• SST	• Ommastrephid		NN ARIMA Bayesian	

GAM: Generalized additive model.

standardised considering several intrinsic factors. Fish catch is modelled from catch versus effort data, catch versus environmental variables, and CPUE versus time. CPUE is a good measure of the scenario in a year, but need not necessarily reflect (Hinton and Maunder, 2004) the real abundance of fish stock. However, predictive modelling of catch or function of it with effort leads to propose indices for relative abundance (Kashimori et al., 2001). The other facet is to find the deficiencies in the currently available data, success/failure of modelling algorithms for different tasks in fisheries and future designs in collection of data with changing targets in fisheries management. The data from fisheries operating independently (individuals) and those with information sharing (code group) is a crucial factor in explaining peaks and troughs in CPUE versus effort profiles (Gaertner and Dreyfus-Leon, 2004). A 50 years catch database of FAO was analysed with *k*-means clustering and NNs. Here, local rather than remote synchrony patterns, which coincide with simulated time series based on random walk method were observed.

4.4. Food products from fish

The freshness of fish, quality of cooked food and concentrations of chemicals (Huang et al., 2003) in the processed dishes are investigated with near infrared (NIR), chemical sensors (Hammond et al., 2002), and thermal conductivity measurements. NNs are found to be better models compared to partial least squares (PLS) in estimating salt and moisture contents in cold smoked Atlantic salmon (*S. salar*) or teijin. The sampling from different axial location on the fish or ventral portion has no effect on the error of moisture predictive models. The general porosity of calamari, squid and celery as well as apple, carrot, etc. is studied during air-drying in food processing (Hussain et al., 2002). The variables considered are temperature of drying, moisture content, initial porosity and product type.

The fish during degradation emits volatile gases and several physico-chemical and bio-chemical changes occur. The freshness of Atlantic salmon (*S. salar*), Haddock (*Melanogrammus aeglefinus*) and Atlantic cod (*G. morhua*) is modelled from semi conductive metal oxide sensors, pH and bacterial aerobic and anaerobic plate counts (Hammond et al., 2002). The semi metal oxide (SMO) results can replace classical and biochemical procedures (Hammond et al., 2002). RBF-NN model classifies the start of degradation of the fish up to 15 days based on SMO sensor array data. The classification of newly killed and processed cod was studied from the proton nuclear magnetic resonance (^{1}H NMR) data of compounds extracted with perchloric acid using probabilistic NN (Prob-NN) (Martinez et al., 2005). The heating procedures (boiling, frying) retain the bioactive compounds in the fillet, while freezing and thawing lose them. The first 20 principal components (PCs) of selected region of NMR spectrum are used as inputs for Prob-NN. Sohn et al. (2006) predicted the odour from the pond using the data from electronic nose and olfactometry measurements employing an NN model with high success. The predictions by the AI technique correlated with the rate of loading of the solids into the pond. However, continuous odour monitoring instrument is indispensable at effluent ponds at critical locations.

5. Factors affecting fish stock

5.1. Biomass

In a pilot study, acceptable results (Jarre-Teichmann et al., 1995) for 3-month ahead forecast were obtained for biomass of Peruvian anchoveta *Engraulis ringens*. The data consisted of monthly time series of oceanographic variables and predator abundance. Annual spawning biomass of Pacific sardine (*Sardinops sagax caeruleus*) was predicted successfully 1 year ahead (Cisneros-Mata et al., 1996) by analysing time series data of water temperature, cube of wind speed and spawning biomass of northern anchovy (*Engraulis mordax*) (Table 9). The prediction of monthly current neritic ecosystem was modelled with NNs. This method of prediction was successful up to 9 years ahead. NN and MLR models (Baran et al., 1996) were compared in the prediction of density and biomass from 11 different streams in central Pyrenean mountains. The correlation coefficients between estimated and desired values of models using 220 observations and 165 randomly chosen points were high for NN. Optimisation of aquatic fodder recipe was non-linear with many linear and non-linear constraints. Ji et al. (1996) introduced NNs and made use of expert system technology to overcome the inaccurate predictions by linear programming.

Table 9
Biomass forecast

Response	Explanatory variable	Species	Location	Comment	Ref.
(a)					
Biomass	Environmental variables	Peruvian anchoveta *Engraulis ringens*		Time series; Three months/more ahead prediction	Jarre-Teichmann et al. (1995)
Biomass	Streams in Central Pyrenean mountains	Brown trout *Salmo trutta*	Central Pyrenean mountains	Tr: 165; Te: 55	Baran et al. (1996)
Spawning biomass	• Water Temperature • Wind speed • Egg abundance • Larval abundance • Commercial catch	Pacific Sardine	California Current neritic ecosystem	One year ahead forecast	Cisneros-Mata et al. (1996)

	Correlation coefficient	
	NN	MLR
(b) Comparison of MLR and NN modeling for prediction of density and biomass		
Predictor		
Density	0.93	0.69
Biomass	0.92	0.54
Channel marphodynamic units (Tr)		
Density	0.81	0.37
Biomass	0.72	0.59

Wu et al. (2001) proposed NNs as predictive tools for phytoplankton dynamics in Dahuofang reservoir in China in preference to classical statistical tools. Silulwane et al. (2001) reported that large peaks of surface chlorophyll dominate in water with low temperature, while smaller peaks at higher temperatures in Angola-Benguela front in South Africa. The inferences are with extensive Gaussian parametric and SOM NNs employing sea surface temperature (SST), surface chlorophyll, mixed layer depth and euphotic depth. Muttil and Lee (2005) reported a real time NN modelling and prediction of algal blooms in Kat O station, Hong Kong that has an indirect ill effect not only on fisheries but also on human health. Genetic programming (GP) imbibes the auto regressive nature and non-linear effects due to complex environmental phenomena. Reyjol et al. (2001) developed a predictive NN model for the brown trout, European minnow and stone loach in natural and regulated flows of Garonne River. He considered 13 explanatory variables with a data set consisting of 1107 data points and the sensitivity of the NN response with the explanatory variables was investigated. The invasion of lakes by smallmouth bass was modelled with NNs for 3046 central Ontario lakes. Of them 788 lakes are highly vulnerable to bass occurrence (Van der Zanden et al., 2004). The presence of bass has influence on the occurrence as well as abundance of minnows and small body fish (Van der Zanden et al., 2004). The wind stress variability over Benguela upwelling system was studied from the response of Scatterometer smoothed for a 2-day period and half degree spatial resolution employing wavelet and NN analysis (Risien et al., 2002). A biomodel distribution with two peaks spread over 6–16 and 35–40 day period is reported. The prediction of the distinction between the hard and sand bottom is crucial in detecting sessile benthic organisms. This study is interesting as reef-dwelling fish species are attracted (Ojeda et al., 2004). The water quality, harmful Algal Blooms (HABs) and rainfall have indirect effect on aquatic ecosystems and thus on fisheries (Muttil and Lee, 2005). Sovan and Guegan (1999) reviewed the state of art of ecological modelling using NNs both in supervised and unsupervised mode. Nuno et al. (2005) used SOM for the warming up-cooling down tendency, SST, chlorophyll concentration, altimetric anomaly and presence of a thermal front to explore the inter relationship amongst the factors, from satellite data during 1998 and 1999 to predict the captures of Prionace Glauca, a type of shark.

5.2. Effect of contaminants

The effect of pollutants and contaminants at molecular, organ or species level of the fish and the consequent threat to the morbidity and mortality rate of humans consuming the fish is complex. There is no question of finality on this issue (Adams et al., 1996) as the knowledge of bio, physico-chemical, hydrological principles are under continuous refinement. Further, the opaqueness increases due to large differences in the time scales of the response and influence of ecological factors on the exposure to high doses.

The relationship between fish growth and extent of food and ecological variables was investigated (Adams et al., 1996) by BP-NN. The predictive ability of the model for the growth of the fish was not satisfactory under field conditions and contaminant exposure regimes. It substantiates indirect effects of the pollutants on the growth and complexity of the phenomenon. Statistical and biological experimental planning in selection of the variables and field data is a prerequisite. Nevertheless, this case study should not be considered as a failure of a model. It is only an artefact of inadequate, non-influential data and missing of influential subset. A summary of applications of NNs in fisheries research task-wise is given in Tables 6–8. Emphasis is on the task on hand with explanatory variables, species and location. The effect of SO_2 emission from power plants causing acid rain conditions is not only hazardous to human health but also results in loss of fish in acidic lakes in north eastern US and south eastern Canada (Grubert, 2003). NNs successfully predicted the seasonal changes in sulphate, hydrogen, nitrate and ammonium ion concentrations. The projected control measures by 2010 will reduce the acid rain conditions below the threshold values. Yang and Li (2002) studied the causes of death of the fish in polluted piscatorial waters with NN using BP training algorithm. The causative variables considered are extracted characteristics of the dead fish. Seawater quality is of paramount importance for eco-balance, morbidity, and mortality of fish and safety of marine food products. Lou (2001a,b) developed seawater quality assessment model using MLP training with BP. Ammonia causes stress in fish (Gutierrez-Estrada et al., 2004) and its prediction/control in fish rearing tanks minimises the stress status. The time series data for eel was modelled with NN employing BP and EDBD training algorithms. These models excelled autoregressive integrated moving average (ARIMA) in their performance.

5.3. Effect of weather and other factors on the lifecycle of fishes

The effect of phytoplankton dynamics in China (Wu et al., 2001), chlorophyll in Benguela front in South Africa (Silulwane et al., 2001), Cyanophyta in China (Wu et al., 2001), biomass/water levels (Jarre-Teichmann et al., 1995; Cisneros-Mata et al., 1996; Baran et al., 1996), harmful algal blooms (Muttil and Lee, 2005), Brown trout in Garonne River (Reyjol et al., 2001), smallmouth bass in central Ontario lakes (Van der Zanden et al., 2004), rainfall/wind stress (Muttil and Lee, 2005; Risien et al., 2002) over Benguela upwelling systems and hard/sand bottom have been modelled with high predictive capability using NNs. These factors have indirect influence in various phases of life cycle of fish. Forecasting water levels concentration of pollutants, biochemical levels, etc., in lakes, streams and rivers (Table 10) are crucial in fishery management, agriculture and planning wastewater discharge (Mercan and Kabdasli, 2003).

5.4. Effect of toxic compounds on fish

Laboratory studies (Niculescu et al., 2004; Huuskonen, 2003; Martin and Young, 2001) of toxicity of organic compounds to fathead minnow are modelled with NN and regression procedures (Table 11). This study helps in prescribing the limits in industrial effluents. The effects of diazinon, anti-cholinesterase insecticide on the smooth and shaky movement behaviour of medaka (*Oryzias latipes*) are modelled by MLP (6-8-1) with BP training algorithm (Kwak et al., 2002). The input measurements are speed, degree of backward movement, stop duration, turning rate, mean and maximum distance of movements in the direction of *y*-axis during 1-min time. NN models are useful for an indirect inference of the presence of toxic chemicals in water bodies polluted with toxic chemicals.

6. Communication and artificial fish

6.1. Communication and sensory systems in fish

Acoustic signals in animal communication, human speech and music are temporally structured in time domain. Thus, the pattern recognition and source apportionment in real time environment are complex. Compared to earlier signal extraction and simulation methods, NNs are found superior (Large and Crawford, 2002). Fish use simple sounds for communication. The activation of neurons in the auditory system (midbrain) of fish (Pollimyrus) was modelled with NNs. Kashimori et al. (2001) developed a neural network model for electro sensory system of fish. The components considered are electro receptors, afferent nerves, electrosensory lateral-line lobe (ELL) and torussemicircularis (TS). The encoding of amplitude and phase modulations of electric discharge in ELL and TS are also investigated.

6.2. Silicon fish models and fishing in artificial ocean

Giske et al. (2003) proposed a novel in-silicon model of fish and adopted a battery of sequential processes for the signals from environment. The in silicon fish moves vertically in the structured environment and subjected to predation and competition. It also responds to food, light and temperature. GA is employed to modify the response according to the internal needs. The response is processed through hedonic modelling. Generally, organism in nature responds either by rules of thumb (proximate) or those based on natural selection. These authors introduced hedonic tones, which are the factors to create feelings. These are responsible for behavioural (decision) patterns. The start of the process is simulation of signals from environment and the organism modifies depending upon the internal state. Strand et al. (2002) explored the feasibility of artificial evolution model to predict the behaviour fitness of planktivorous fish mueller's pearlside (mauro licus muelleri) in response to environmental changes and physiology of the organism. The factors, viz. habitat choice, energy allocation, spawning strategy and juvenile survival are considered in the model. An extensive simulation study (Gaertner and Dreyfus-Leon, 2004; Dreyfus-Leon and Kleiber, 2001) was made for fishing tuna schools introducing an artificial ocean (world) model and employing NNs for the movement of fishing vessels to a new location and local search. The results of SLP-NN with a single layer of hidden neurons using reinforced learning allowing acquisition of adopted behaviour and BP, training algorithm indicated that

Table 10
Forecasting water levels and fish density

Response	Explanatory variable	Location	Ref.
Classification of shallow lakes	• Phytoplankton • Zooplankton • Fish • Nutrient abundance • Information from satellite image	Pampean shallow lakes (Argentina)	Ferrati et al. (2005)

Objective		Explanatory variable	Location	Comment	Ref.
Forecasting water level		Water levels • Current day • *n*-Previous days	Beysehir Lake (Turkey)	1962–2001	Mercan and Kabdasli (2003)
Prediction (one day ahead)	Algal blooms	y: Chlorophyll fluorescence • Hydro-meteorological parameters • Water quality	Kat O station (Hong Kong)	ANN Geometric Programming	Muttil and Lee (2005)
Recognition	Hard bottom				Ojeda et al. (2004)
Prediction (daily)	Conc. of NH_3 in fish (eel) rearing tank	Concentration of previous days	Southern Spain	NN ≫ [ARIMA, MLR] Tr: BP, EDBD	Gutierrez-Estrada et al. (2004)
Causes	Death of fish in piscatorial water	Extracted characteristics of dead fish	China	NN (18-9-1) BP	Racca et al. (2004)

Response	Explanatory variable	Species	Location	Comment	Ref.
Density of fish spawning sites	Habitat characteristics	Brown trout		MR NN	Lek et al. (1996)
Density		Brown trout (*Salmo trutta*)			Baran et al., 1996
Path type of Kuroshio current distance between Kuroshio axis and Cape Iroh-Zaki	• Months precedent data of Kuroshio axis and major capes • Occurrence rates of Kuroshio path types • Deviation of SST				Komatsu et al. (1994a,b)
Behaviour	Temperature	Tuna	200 m of tropical seas	ANN + GA	Dagorn (1994)
Riverine fish density	Energy availability, Habitat heterogeneity			ANN 93%	Guegan et al. (1998)
Metabolic activity	Changes in salinity	Juvenile spotted sea bass Lateolabrax			Kim et al. (1998)
Spatial moments of fish	Levels of growth, Predation pressure			NN GA (for weights)	Huse and Giske (1998)
Rolling motion of small fishing vessels	Shapes of bodies			NN, AR	Amagai et al. (1997)

EDBD: Extended delta–bar–delta. NL: Non-linear Least Squares; PNN: Probabilistic Neural Network; LDA: Linear Discriminant Analysis.

purse-seine CPUE is not a good indicator of population trend. The sharing of information instead of search in isolation, fuzzy logic to account for the variation in individual fisherman's knowledge, folk knowledge/traditions along with risk prone/risk averse approach and sparkles of the genius will reap the benefits of structured scientific approach in understanding the nature.

The artificial (simulated) ocean (world) consists of a 200×200 square grid divided into *m*-toroidal locations (16×25) of 50×50 pixels (Gaertner and Dreyfus-Leon, 2004; Dreyfus-Leon and Kleiber, 2001). A prey is also considered in the model. All vessels start from the same port and after fishing for a fixed time interval (12 h), the NN tries for a decision either to remain in the same area or to move to a nearby, middle distant or far off area using characteristics of the area, fishing data, memory of recent decisions, previous successes in the same area, etc.

6.3. Rolling motion of fishing vessel

Designing the optimum structure of small fishing vessel in the rough sea requires a thorough knowledge in the trends of dynamic response of rolling motion. The waves and dynamics of the ship during fishing operation affect the rolling motion of a fishing vessel in a complex non-linear fashion. The safety being of prime concern in the design even in unforeseen rough environmental conditions, predictive modelling is essential during design phase. NNs being versatile in modelling, prediction and control, Alkan et al. (2004) studied the vertical centre of gravity height of transverse meta-centre above keel and verti-

Table 11
Toxicity of chemical compounds for fish

<table>
<tr><th>Fish</th><th>Response</th><th>Organic compounds</th><th>Explanatory variables</th><th>Models</th><th>Ref.</th></tr>
<tr><td>Fathead minnow (Pimephales promelas)</td><td>LC_{50} (96 h)</td><td>397: Tr</td><td></td><td>MLR; NN: $r^2 > 0.9$</td><td>Martin and Young (2001)</td></tr>
<tr><td>Fathead minnow</td><td>$\log(LC_{50})$</td><td>130: Tr
10: Te</td><td>14 atom type E-state indices</td><td><table><tr><td></td><td colspan="2">Training</td><td colspan="2">Testing</td></tr><tr><td></td><td>MLR</td><td>NN</td><td>MLR</td><td>NN</td></tr><tr><td>SD</td><td>0.36</td><td>0.31</td><td>0.41</td><td>0.30</td></tr></table></td><td>Huuskonen (2003)</td></tr>
<tr><td>Fathead minnow (Pimephales promelas)</td><td>LC_{50} (96 h)</td><td>800: Tr
86: T e</td><td>Fragment information</td><td>Prob NN (Gaussian kernel)</td><td>Niculescu et al. (2004)</td></tr>
</table>

LC: Lethal concentration, Tr: Training; Te: Testing.

cal centre of buoyancy to predict transverse meta centric height, one of the parameters responsible for the stability of the vessel. Kimura et al. (2004) proposed NNs to forecast the rolling motion of small fishing vessel under realistic fishing operation conditions. Dreyfus-Leon and Kleiber (2001) applied NN paradigm in fishing vessels concerned with yellowfin Tuna fishery in eastern Pacific Ocean. As the responses were non-linear, difficulties were faced in using differential equations based on the physical model. This is partly due to shape and large changes in the conditions of the vessel during fishing operations. Amagai et al. (1997) proposed that prediction of NNs was more reliable compared to that of auto Regression model.

7. Conclusions

- Prediction of abundance of fish is the key factor to maintain sustainable growth. The theoretical models from all processes are complex and thus empirical models are in vogue. Neural Networks, a data driven paradigm of second-generation artificial intelligence (AI-2) tools is the best and sought after approaches in this decade.
- The distribution of eggs, recruitment, age, growth of fish, biomass and fish catch are the explanatory factors in fisheries research. The successful predictive models for the recruitment of Sand eel, distribution of Baltic cod eggs, growth of Japanese Sardine, etc. are discussed.
- Apart from taxonomical methods statistical techniques like linear discriminate analysis (LDA) and quadratic discriminate analysis (QDA) was employed to detect identification and discrimination. Multi-layer perceptron (MLP) NNs, non-linear input/output mapping procedures are employed with a high success rate.
- The critical inspection of the available software packages for NN predictive models reveal that the choices of architecture, supporting tools, transfer function are key factors in comparing the end results.
- Catch–effort data, being three-way mode, demand multi-way metric methodology.
- The explanatory variables used in fish modelling are documented species and location wise.
- Piscimetrics, application of advanced modelling techniques in fisheries studies is the focus point for future years management of sustained fisheries technology.

8. Future scope

NNs of this decade like Modular, Fuzzy Adaptive Resonance Theory (Fuz.ART), Radial Basis Function (RBF), Probabilistic NN (PNN), Generalized Regression NN (GRNN) and Counter Propagation NN (CPNN) with advanced training algorithms (SAA, GA, BFGS) are far superior to the popular multi-layer FFNN with BP. A modeller needs to adopt the latest architecture, training algorithm and optimisation method from research reports. The ingenuity, man/machine interface and intelligent inference systems add a new dimension to the forecasting activity in exploring the variables, residuals and their trends. In the light of growing technology, it is worth reinvestigating the data with multiple nets.

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