Forecasting Fish Stock Recruitment and Planning Optimal harvesting strategies by Using Neural Network

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Abstract—**Recruitment prediction is a key element for management decisions in many fisheries. A new approach using neural network is developed as a tool to produce a formula for forecasting fish stock recruitment. In order to deal with the local minimum problem in training neural network with back-propagation algorithm and to enhance forecasting precision, neural network's weights are adjusted by optimization algorithm. It is demonstrated that a well trained artificial neural network reveals an extremely fast convergence and a high degree of accuracy in the prediction of fish stock recruitment.**

Index Terms—**neural network, prediction of fish stock recruitment, optimal harvesting strategy, management decision**

I. Introduction

Marine ecosystems are notoriously difficult to study. Trophic relationships are multidimensional, relevant biophysical factors vary widely in their spatial and temporal scales of influence, and process linkages are complex and highly non-linear showed that the problem is further compounded by inaccuracies in measuring environmental variability, as well as the biotic response. Consequently, applied ecological investigations attempting to relate oceanic physics, atmospheric physics, and marine biology to variations in fish stock-recruitment are difficult to carry out. Nonetheless, the collective impacts of regime shifts, large multi-decadalscale forcings of marine ecosystems (such as those attributed to the NAO), and natural and man-made influences on variability in fish populations and future states of ecosystems are widely recognized as important areas of study [1]. To set accurate preseason fishing quotas, it is important to be able to forecast the biomass of young fish (recruits) that will join the fishable stock for the first time before the fishing season opens. Experience has proven that the level of recruitment is difficult to forecast for most fish stocks because the survival of juvenile fish is affected by a number of variables. For example, the biomass of 3-year-old recruits to the west coast of Vancouver Island (WCVI), British Columbia, Pacific herring (Clupea pallasi) stock over the last 60 years has fluctuated over a 350-fold range in response to interannual and decadal time scale variations in the spawning biomass (of parents) and in the state of the environment, which in turn affects the Pacific herring food supply and mortality rate [2]. A long-term ecosystem research program has identified that the key variables determining Pacific herring recruitment are the lagged biomass of adult spawners, the summer biomass of Pacific hake (Merluccius productus), which is a significant predator, and two lagged environmental factors (annual sea surface temperature (SST) and salinity). The annual SST is believed to be a general indicator of mortality and the state of the food supply. In many cases, it is difficult to clarify and model the mechanism controlling recruitment by using conventional mathematical and statistical methods because the survival process is nonlinearly related to several factors [3].

Understanding and predicting biological productivity is considered a key question by lake fisheries scientists. Several ecologists and fisheries managers have tried to determine the abundance of living stocks or the specific biodiversity in aquatic ecosystems using some of their characteristics, i.e. surface of the river drainage basin, surface area of lakes, flood plain areas, morphoedaphic index, depth, coastal lines, primary production, etc [4]. In developing countries, the economical importance of fish and as a food source makes this topic particularly relevant. Diverse multivariate techniques have been used to investigate how the various richness of fish is related to the environment, including several methods of ordination and canonical analysis, and univariate and multivariate linear, curvilin-ear, and logistic regressions. However, for quantitative analysis and more particularly for the development of predictive models of fish abundance, multiple linear regression and discriminate analysis have remained, the most frequently used techniques. These conventional techniques (based notably on multiple

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regressions) are capable of solving many problems, but show sometimes serious shortcomings. This difficulty is that relationships between variables in sciences of the environment are often non-linear whereas methods are based on linear principles. Non-linear transformations of variables (logarithmic, power or exponential functions) allow to significantly improve results, even if it is still insufficient. However, the neural network, with the error back-propagation procedure, is at the origin of an interesting methodology which could be used in the same field as regression analysis particularly with the non-linear relations [5]. Ecological applications of multivariate statistics have expanded tremendously during the last two decades. Among these methods, the principal component analysis (PCA) is now used routinely by ecologists. It is known as able to simplify large data sets with reasonable loss of information and to assess inter-correlation among variables of interest [6]. However, the information given by PCA techniques suffers from some drawbacks in that the relationships between variables in environmental sciences are often non-linear, while the methods used are based on linear principles. Transformation of non-linear variables by logarithmic, power or exponential functions can appreciably improve the results, but have often failed to fit the data. In the same way, ecologically relevant, but unusual observations, are frequently deleted from the data sets to reduce data heterogeneity. Although these deletions satisfy statistical assumptions, they are likely to bias the ecological interpretation of the results. To overcome these difficulties, the artificial neural networks which are known to be efficient in dealing with heterogeneous data sets should constitute a relevant alternative tool to traditional statistical methods [7].

II. A Neural Network Model for Forecasting Fish Stock 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. 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, sand eel Ammodytes personatus in Eastern part of seto Island sea, Northern Benguella, Sardine Sardinops, sagax in South Atlantic 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 . 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 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 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 [8]. Artificial neural networks are computer algorithms that simulate the activity of neurons and information processing in the human brain. In general, a neural network is an interconnected network of simple processing layers where typically the first layer (input layer) makes independent computations and passes the results to a hidden layer. This layer may in turn make an independent computation and pass the results to another hidden layer. This signal process may continue to produce more hidden layers depending on the complexities of the problem. Finally, the last layer (output layer) determines the output from the network. Each processing layer makes the computation based on the weighted sum of its inputs. This signal processing between layers enables neural networks to model complex linear and nonlinear systems. Unlike the more commonly used regression models, neural networks do not require a particular functional relationship or distribution assumptions about the data. This makes neural network modeling a powerful tool for exploring complex, nonlinear biological problems like recruitment forecasting [9].

The main factors affecting fish stock recruitment consist of spawning biomass (SB in million tones,x1) , mean annual sea surface temperature (SST in °C, x2), and North Atlantic Oscillation index (NAO, normalized sea level pressure anomaly, x3) [1]. An artificial neural network model is a system with inputs and outputs based on biological nerves. The system can be composed of many computational elements that operate in parallel and are arranged in patterns similar to biological neural nets. A neural network is typically characterized by its computational elements, its network topology and the learning algorithm used.

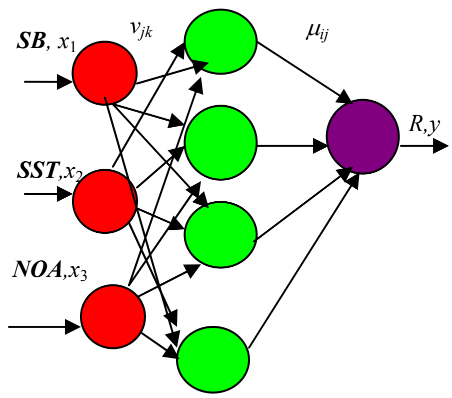

Fig. 1 A schematic of neural network model

The architecture of BP networks, depicted in Figure 1, includes an input layer, one or more hidden layers, and an output layer. The nodes in each layer are connected to each node in the adjacent layer. Notably, Hecht-Nielsen proved that one hidden layer of neurons suffices to model any solution surface of practical interest. Hence, a network with only one hidden layer is considered in this study. There are three nodes in input layer. The input of each node is SB, SST, and NAO, respectively. There is only one node in output layer, which denotes forecasting fish recruitment. Before an ANN can be used, it must be trained from an existing training set of pairs of input-output elements. The training of a supervised neural network using a BP learning algorithm normally involves three stages. The first stage is the data feed forward. The computed output of the i-th node in output layer is defined as follows [10]

$$y_i = f(\sum_{j=1}^{N_h}(\mu_{ij} f(\sum_{k=1}^{N_i} v_{jk} x_k + \theta_j) + \lambda_i)). \quad (1)$$

Where μ_{ij} is the connective weight between nodes in the hidden layer and those in the output layer; v_{jk} is the connective weight between nodes in the input layer and those in the hidden layer; θ_j or λ_i is bias term that represents the threshold of the transfer function f, and x_k is the input of the kth node in the input layer. Term N_i, N_h, and N_o are the number of nodes in input, hidden and output layers, respectively. The transfer function f is selected as Sigmoid function [11]

$$f(\cdot) = 1/[1+\exp(-\cdot)]. \quad (2)$$

The second stage is error back-propagation through the network. During training, a system error function is used to monitor the performance of the network. This function is often defined as follows

$$E(w) = \sum_{p=1}^{P}(\sum_{i=1}^{N_o}(y_i^p - o_i^p)^2). \quad (3)$$

Where y_i^p and o_i^p denote the practical and desired value of output node i for training pattern p, P is the number of sample. Training methods based on back-propagation offer a means of solving this nonlinear optimization problem based on adjusting the network parameters by a constant amount in the direction of steepest descent, with some variations depending on the flavor of BP being used. The optimization algorithm used to train network makes use of the Levenberg-Marquardt approximation. This algorithm is more powerful than the common used gradient descent methods, because the Levenberg-Marquardt approximation makes training more accurate and faster near minima on the error surface [12].

$$w(k+1) = w(k) - H^{-1}(k)g(k). \quad (4)$$

Where w(k) is the vector of network parameters(net weights and element biases) for iteration k, matrix H^{-1}(k) represents the inverse of the Hessian matrix. The vector g(k) represents the gradient of objective function. The Hessian matrix can be closely approximated by

$$H \approx J^T J. \quad (5)$$

Where J is the Jacobian matrix, and the gradient of the objective function can be computed as

$$g = \frac{\partial E}{\partial w} = J^T e. \quad (6)$$

Where e is an error vector, and it can be calculated as follows

$$e = y - o. \quad (7)$$

The iterative formulas of adjusting weights can be rewritten as follows

$$w(k+1) = w(k) - [J^T(k)J(k)]^{-1} J^T(k)e(k). \quad (8)$$

One problem with the iterative update of weights is that it requires the inversion of Hessian matrix H which may be ill conditioned or even singular. This problem can be resolved by the regularization procedure as follows

$$H \approx J^T J + \mu I. \quad (9)$$

Where μ is a constant, I is a unity matrix. The weight adjustment using Levenberg-Marquardt algorithm is expressed as follows

$$\begin{aligned} w(k+1) &= w(k) - \\ &[J^T(k)J(k) + \mu I]^{-1} J^T(k)e(k). \end{aligned} \quad (10)$$

The Levenberg-Marquardt algorithm approximates the normal gradient descent method, while if it is small, the expression transforms into the Gauss-Newton method. After each successful step the constant μ is decreased, forcing the adjusted weight matrix to transform as quickly as possible to the Gauss-Newton solution. When after a step the errors increase the constant μ is increased subsequently. The number of neurons in the hidden layer is determined by the following equation

$$N_h = 2 \times N_i + 1. \quad (11)$$

Where N_i and N_h are the amount of input, hidden neurons, respectively.

III. Case Study

Data for Norwegian spring-spawning herring, potentially the largest of the herring stocks in the northeast Atlantic, were taken from information presented in Toreson [13]. Time series for fish recruitment and affecting factors were plotted in Fig.2, 3, 4 and 5. Some of data series were used as training neural network; and others were taken to validate the effectiveness of proposed forecasting procedure based on neural network. Fig. 6 depicts the comparison of forecasting and practical fish recruitment.

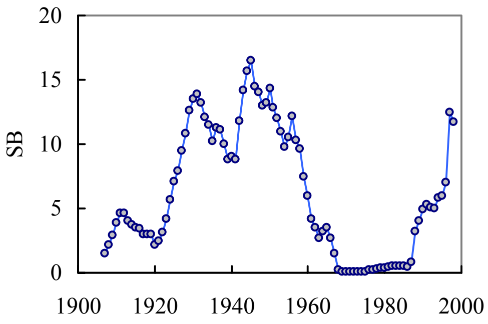

Fig. 2 Time series plot for spawning biomass (SB in million tones)

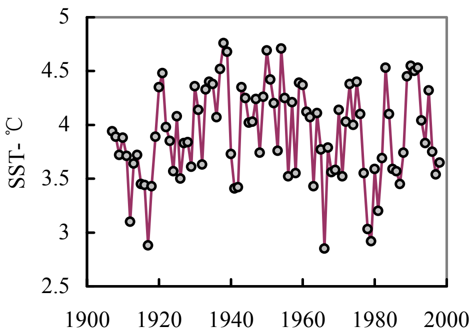

Fig. 3 Time series plot for mean annual sea surface temperature (SST in °C)

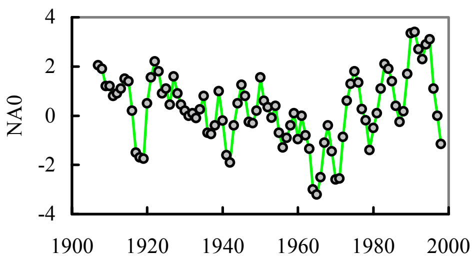

Fig. 4 Time series plot for North Atlantic Oscillation index (NAO)

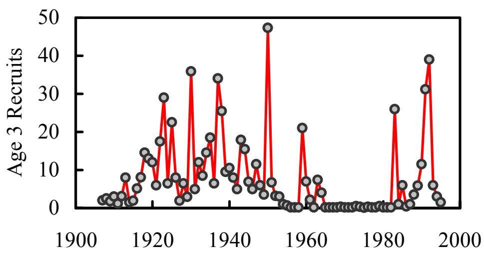

Fig. 5 Time series plot for age-3 recruitment (R in billions)

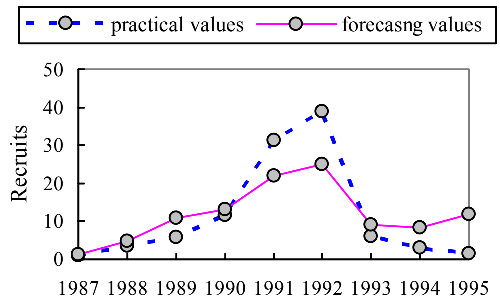

Fig. 6 Comparison of forecasting and practical fish recruitment (R in billions)

IV. Optimal Harvesting Strategies for Fisheries Managements

Bio-economic fisheries models, depicting the economic and biological conditions of the fishery, are widely used for the identification of Pareto improvement fisheries policies. The models that have been constructed for this purpose differ in size, detail and technical sophistication. Virtually all, however, model the fishery as a technical relationship between the use of fishery inputs and the resulting biological and economic outcomes. In order to model growth of biological systems numerous models have been introduced. These variously address population dynamics, either modelled discretely or, for large populations, mostly continuously. Others model actual physical growth of some property of interest for an organism or organisms. The rate of change of fish stock *dx/dt* is determined by natural reproductive dynamics and harvesting [14]

$$\dot{x} = f(x,t) - h(e,x,t). \qquad (12)$$

Where $f(x,t)$ is the natural growth rate of fish stock which is dependent on the current size of the population x. The quantity harvested per unit of time is represented by $h(e,x,t)$. The net growth rate dx/dt is obtained by subtracting the rate of harvest $h(e,x,t)$ from the rate of natural growth $f(x,t)$. Functional relationships commonly used to represent the natural growth rate of fish stock is the logistic model [15].

$$f(x) = rx(1-\frac{x}{K}). \qquad (13)$$

Where r is the intrinsic growth rate, K is the environmental carrying capacity, and x is the constant associated with the intrinsic growth rate. The rate of harvest $h(e,x,t)$ is assumed proportional to aggregate standardized fishing effort (e) and the biomass of the stock x; that is [16]

$$h(e,x,t) = \beta e(t) \times x(t). \qquad (14)$$

Where β is the catchability coefficient. Once average fishing power has been calculated, the standardized fishing effort is computed as [8]

$$e(t) = P\tau n. \tag{15}$$

Where e is the standardized fishing effort ; P represents average relative fishing power ; τ is the average fishing days at time t; and n denotes the number of vessels at time t. Fishing cost is evaluated by [17]

$$C(e,x,t) = ce(t). \tag{16}$$

Where $C(e,x,t)$ is the total cost function. (13) has solution

$$x(t) = \frac{Kx_0}{(K-x_0)\exp(-rt)+x_0}. \tag{17}$$

Let us start by briefly reviewing the essential structure of conventional bio-economic fisheries models. As discussed above, these models consist of two fundamental components: (i) a biomass growth function and (ii) an economic performance function. Their two basic components may be represented by the following four sets of equations:

$$\max \Pi = \int_0^\infty [p\times h - \mathrm{C}]\exp(-\alpha\times t)dt$$
$$= \int_0^\infty [p\times\beta\times e(t)\times x(t) - ce(t)]\exp(-\alpha\times t)dt. \tag{18}$$

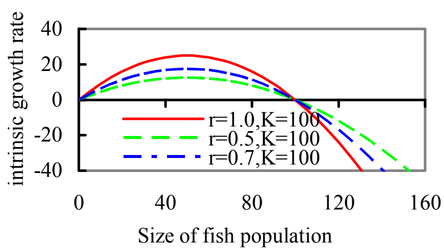

Fig. 7 Natural growth rate of fish stock versus the size of fish population

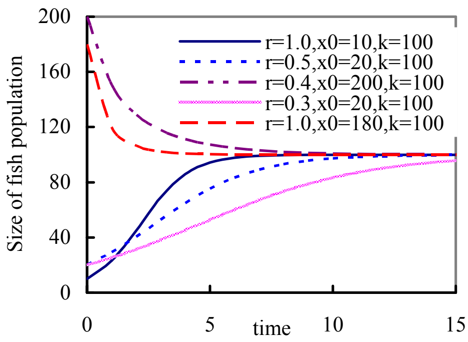

Fig. 8 Size of fish population versus time without catching

$$x(t>T) = x_{opt}. \tag{19}$$

$$h(e,x,t>T) = h_{opt}. \tag{20}$$

$$\dot{x} = f(x,t) - h(e,x,t). \tag{21}$$

In this formulation, Π is the ultimate performance measure of the fishery. P is output price of fisheries. T is starting catching time. x_{opt} is optimal size of fish population. h_{opt} is optimal rate of harvest. From (17), we can deduce the starting catching time

$$T = -\frac{\ln[(\frac{Kx_0}{x_{opt}} - x_0)/(K-x_0)]}{r}. \tag{22}$$

The optimal rate of harvest is expressed as follows:

$$h_{opt} = \beta\times e_{opt}\times x_{opt} = x_{opt}r(1-\frac{x_{opt}}{K}). \tag{23}$$

Let $\frac{dh_{opt}}{x_{opt}} = 0$, the optimal size of fish population and the optimal rate of harvest are solved

$$x_{opt} = \frac{K}{2}. \tag{24}$$

$$h_{opt} = \frac{rK}{4}. \tag{25}$$

The optimal fishing effort is deduced as follows

$$e_{opt} = r(1-\frac{x_{opt}}{K})/\beta = \frac{r}{2\beta}. \tag{26}$$

V. Sustainable Development Policies for Fisheries Management

There has been much comment in recent years on the nature of sustainable development and, in particular, on the internal contradictions implicit in this term.

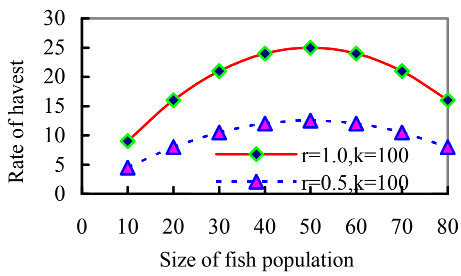

Fig. 9 Optimal rate of harvest versus the size of fish population

While it is generally accepted that sustainable use of natural resources means that their exploitation by one generation should not diminish their value for succeeding generations, application of this concept remains elusive and is the subject of much debate [9]. While we assume that sustainability is accepted as a desirable outcome of management of any renewable natural resource, there are cases where sustainability is not the expected outcome. When stocks have a low rate of natural increase, and so provide a low contribution to present value, but the owners have a high discount rate for their capital, the stock is likely to be exploited to extinction. In other words, if the rate of return on capital is greater than the value of the rate of natural production, for economically valuable stocks, extinction is a likely outcome.

Ocean fish stocks have traditionally been arranged as common property resources. This means that anyone, at least anyone belonging to a certain group (often a complete nation), is entitled to harvest from these resources. Thirty years ago, the common property arrangement was virtually universal. Today, at the beginning of the twenty-first century, it is still the most common arrangement of ocean fisheries. It has been known that common property resources are subject to fundamental economic problems of overexploitation and economic waste. The essence of the fundamental problem is captured by the diagram in Fig. 10. In fisheries, the common property problem manifests itself in: 1). Excessive fishing fleets and effort. 2). Too small fish stocks. 3). Little or no profitability and unnecessarily low personal incomes. 4). Unnecessarily low contribution of the fishing industry to the GDP. 5). A threat to the sustainability of the fishery. 6). A threat to the sustainability of human habitation.

Fig. 10 illustrates the revenue, biomass and cost curves of a typical fishery as a function of fishing effort. Fishing effort here may be regarded as the application of the fishing fleet to fishing. The revenue and biomass curves are sustainable in the sense that these are the revenues and biomass that would apply on average in the long run, if fishing effort was kept constant at the corresponding level.

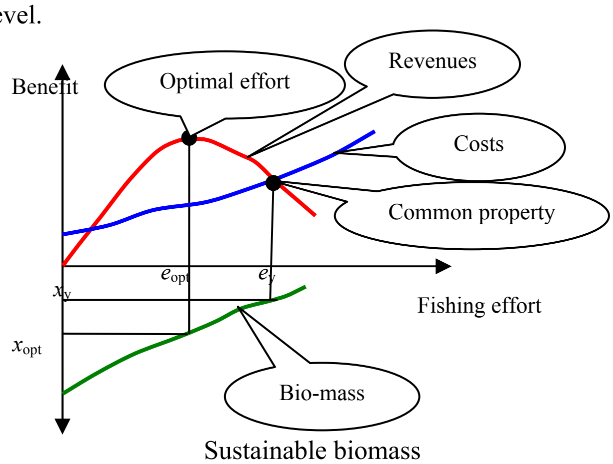

Fig. 10 Sustainable development model for fisheries management

Fig. 10 reveals that the profit maximizing level of the fishery occurs at fishing effort level e_{opt}. At this level of fishing effort, profits and consequently the contribution of the fisheries to GDP is maximized. Note that the profit maximizing fishing effort e_{opt} is less than the one corresponding to the maximum sustainable yield (MSY), e_{MSY}. Consequently, the profit maximizing sustainable stock level, x_{opt}, is comparatively high as can be read from the lower part of Fig. 10. The profit maximizing fisheries policy, consequently, is biologically conservative. Indeed the risk of a serious stock decline is generally very low under the profit maximizing sustainable fisheries policy. The rate of change of fish stock dx/dt is determined by natural reproductive dynamics and harvesting when fishing effort is not equal to optimal value

$$\dot{x} = xr(1-\frac{x}{K}) - \beta e(t) \times x(t). \tag{27}$$

The solution of Eq. (16) is deduced as follows

$$x(t) = \frac{Px_0}{x_0 + e^{(\beta e - r)t}(P - x_0)}. \tag{28}$$

$$P = (1-\frac{\beta e}{r})K. \tag{29}$$

What we are suggesting in terms of sustainability then, is that if we are talking about the recreational fishing experience rather than just catching fish, we do not need to assume that the same fish will be available in the same proportions/numbers in future, just that the same total experience will be available. This implies that you can substitute species, as they become less fashionable, or less available in response to human or natural pressures; but there is an obvious biological limit to the extent to which species can be substituted. In any case, if a fashionable species is dropping in numbers, it probably will be worth taking steps to arrest the decline. The shareholders in a company would expect the manager to take the most cost-efficient steps and provide the shortest interruption to their dividends. At present, marine fisheries rely almost wholly on wild stocks.

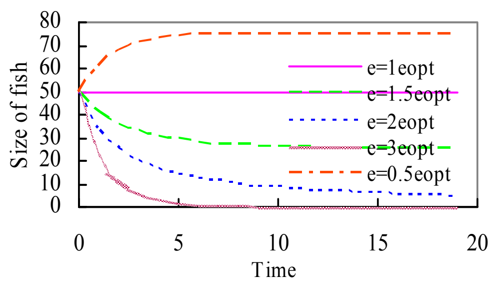

Fig. 11 Size of fish population versus time while excessive fishing(x0=50,K=100,r=1.0,β=0.1, eopt =5.0)

Unlike freshwater fisheries, there is little capacity at present for augmenting stocks from hatcheries. A properly priced stock would provide an impetus for developing more direct methods such as use of hatcheries to accelerate stock recovery, rather than removing fishing pressure and simply waiting for natural recovery of stocks. Prudent fisheries managers might make development of direct methods of restocking a priority [20].

A practical time-scale for sustainability for natural resource management broadly equates to 80–100 years. After that time, it would be difficult for people to imagine what society might be like. Even making predictions of what constitutes sustainability within that time period will be difficult because of natural changes beyond human control and changes to the way humans use natural resources. These issues become more focused when considering different forms of property rights, including those involving exploitation for commercial gain, as in fisheries. In this case, a minimum expectation is that those exploiting the resources would seek commercial returns on capital invested in acquiring access, and in harvesting and developing the resources. Open access and some forms of common property ownership result in overexploitation and collapse of resources, rather than in sustainable biological and social outcomes. This is not sufficient reason to argue that renewable natural resources should be maintained in government ownership and commercial exploitation prohibited. In reality, natural resources treated in this manner assume no value to the community, other than their intrinsic ecological and existence values. These resources are even more likely to be degraded or lost.

VI. CONCLUSIONS

Back propagation of the ANN was used to develop forecasting models of fish yield prediction using habitat features on a macrohabitat scale. This forecasting approach required an extensive database and care to obtain reliable models. The selection of input variables, their ecological significance and the use of a test data set to assess the model precision and accuracy are important elements of this type of approach. The advantage of ANN over MLR models is the ability of ANN to directly take into account any non-linear relationships between the dependent variables and each independent variable. Several authors have shown greater performances of ANN as compared to the MLR. The back-propagation procedure of the ANN gave very high correlation coefficients comparing to the more traditional models, especially for the training calculation. In the test set, correlation coefficients were lower than in training but still remained clearly significant. This difference between training and testing sets is more amplified when the data set is small, and when each sample is likely to have ‘unique information’; this is relevant to the model. This study demonstrates that neural network models can perform reasonably well in predicting the biomass of fish that will recruit to the fishery, given prior information on the state of several key factors during the first year of life of the year-class. Specifically, information on the biomass of their parents (i.e., spawners), the biomass of a key predator species (i.e., Pacific hake), and some important environmental variables that are believed to be proxy indicators of other predators and general feeding conditions is required. Comparison with a multiple regression and modified Ricker model demonstrated the superior ability of the neural network model to fit the underlying complex relationships between recruitment and the independent variables. The recruitment-environment problem is a difficult one, but it does not mean that we should stop exploring models and techniques to help understand the factors that control recruitment dynamics and their spatial and temporal scales of influence. Simple statistical approaches still have their place if used appropriately.

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