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Application of artificial neural network into the freshwater fish caught in Turkey

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Abstract
Artificial neural networks (ANNs) are computational intelligence techniques, which are used in many applications, such as forecast. The aim of this study was to evaluate artificial neural networks created for freshwater fish caught in Turkey between the years of 2003 to 2012. As a decision system, ANNs are an important tool for forecast in fisheries. A feedforward neural network was selected, with two layers, sigmoid functions, and adaption learning function for the training of the ANNs. The results of the application of created neural networks for fishery products of forecast based on test cases validated by MAPE. Estimates of 2015, data was found to be 15147.6 tons. Freshwater fish caught in Turkey is forecasted in the next years. This result shows us that, in the coming year's aquaculture and freshwater products are alarming. However, fish catch data are not regularly collected because of lack of fish catch information collected by officials.

Keywords: Artificial Neural Networks, Feedforward algorithm, Freshwater products, Turkey

1. Introduction

In developing world, the fisheries sector provides the basis for the livelihoods and nutrition of millions of people, and constitutes a significant source of foreign exchange for many developing economies. Despite its considerable contributions to development, however, it is often not seen as a priority sector by policy makers or donor agencies, and activities such as aquaculture are frequently seen as relatively low-priority for the allocation of scarce resources such as water. This lack of attention to the sector is particularly problematic given that capture fisheries are currently being fished at capacity, and that further increases in production will have to come from expansion of aquaculture. There is, therefore, an important role for developing country governments to play, both in managing capture fisheries to prevent further stock depletion, and in regulating the development of aquaculture to ensure that it is both environmentally sustainable and pro-poor. Under such conditions, fisheries and aquaculture can realise their potential as an important and growing source of economic development in rural areas [1].

Fisheries management is a governmental system of management rules based on defined objectives and a mix of management mean to implement the rules, which are put in place by a system of monitoring control and surveillance. Modern fisheries management is most often based on biological arguments where the idea is to protect the biological resource in order to exploit the resource in a sustainable manner. In case of fishery statistics, there are several collection programs for fishery data, involving the Department of Statistics, the Ministry of Environment Protection and National Resources, and the Department of Fisheries of the Ministry of Agriculture. Data collection of fisheries-related data was not coordinated among the different government units in the past. Data collection for estimating fishing effort did not use sampling techniques. Basic variables such as production by species and prices were obtained directly from the landings of licensed fishing units and/or from market research [2].

ANNs models are based on the same learning processes as the animal brain, which gathers information from the environment (input data) and gives an answer (output data) after using learned training algorithms. Much work has been performed in predicting future data with artificial neural networks (ANNs) as they exhibited better results than the traditional methods from the literature [3-8]. Previous findings indicate that neural network models are significantly better than traditional statistical and human judgment methods when forecasting monthly and quarterly data [9].

Fish are renowned for their extreme plasticity in individual growth [10]. One aspect of this plasticity is the dependence of growth on population density, which is well documented in wild populations [11] and in extensive aquaculture [12]. Growth, one of the most essential traits for animals, is defined as an increase in tissues and organs of the animals per unit time and effected by genetic and environmental factors [13].
In recent years, ANNs have become a popular and useful tool for modelling environmental systems. For example, they have already have been successfully used to simulate the export of nutrients from river basin [14], to forecast salinity [12] and ozone levels [15], the functional characteristics of ecosystems [16].
ANNs have been widely used for both prediction and classification tasks in many fields of knowledge. However, few studies are available on animal science. Very little research has been conducted to model animal growth using ANNs. Yee *et al.* [17] compared the modelling of a data set of rats with traditional regression and neural networks. They found that both methods produced models that adequately the body weight [18].
The fact that the ANNs provides a better model was highlighted by better predictions for lower values, the normality of the residuals and their independence from the predicted variable. Several authors have reported greater performances of ANNs compared to linear regressions [19]. ANNs have another advantage in that the ANN modeling approach is fast and flexible [20].
The aim of this study was to evaluate artificial neural networks created for the sea, aquaculture and freshwater products between the years of 2003 to 2012 (annual data). The results of the application of created neural networks for fishery products of forecast based on test cases validated by mean absolute percentage error (MAPE). In this study, the ANN has demonstrated a new and alternative approach for its application in predicting the product of fishes.

2. Materials and Methods

2.1. Artificial Neural Networks

ANNs are computational systems that simulate biological neural networks, which can also be defined as a specific type of parallel processing system, based on distributional or connectionist methods [21]. ANNs is used to predict the future is one of the key areas. ANNs data, the power relations between the unknown and unnoticed can reveal. ANNs is not linear. Linear models can understand the important details and can be beneficial if they could explain. The structure of a network of this type is characterized by a number of interconnected elements (neurons) that learn by modifying themselves. As in nature, the function of the network is determined by the connections between the elements [22].
Hann and Steurer [23] find that ANNs outperform the linear models when weekly data are used and if monthly data are used, ANNs and linear methods yield similar results. ANNs, between input and output variables without the need for any prior knowledge and any assumptions, nonlinear modelling cans provide [24].
Data pre-processing refers to analyzing and transforming the input and output variables to minimize noise, highlight important relationships, detect trends, and flatten the distribution of the variable to assist the neural network in learning the relevant patterns. Since neural networks are pattern matchers, the representation of the data is critical in designing a successful network. The input and output data variables for which the data was collected are rarely fed into the network in raw form [24].
Network, input data and the input-output relationship between the learning of the network is provided, so the network's training is taking place. This method is generally called supervised learning preferred is a method [25]. Supervised learning method trained with network structure (Back propagation Networks), will be used in the solution of existing problems.
Artificial neuron is a basic building block of every artificial neural network. Its design and functionalities are derived from observation of a biological neuron that is basic building block of biological neural networks which includes the brain, spinal cord and peripheral ganglia. Similarities in design and functionalities can be seen in Figure 1. Where the left side of a figure represents a biological neuron with its soma, dendrites and axon and where the right side of a figure represents an artificial neuron with its inputs, weights, transfer function, bias and outputs.

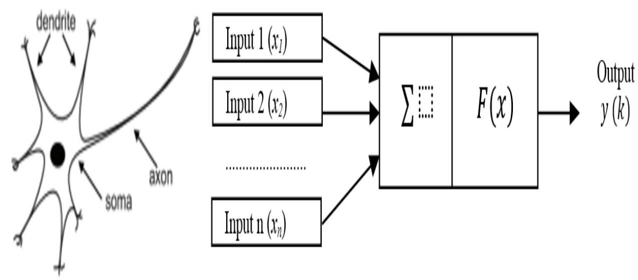

Fig 1: Biological and artificial neuron network design.

In case of biological neuron information comes into the neuron via dendrite, soma processes the information and passes it on via axon. In case of artificial neuron the information comes into the body of an artificial neuron via inputs that are weighted (each input can be individually multiplied with a weight). The body of an artificial neuron then sums the weighted inputs, bias and "processes" the sum with a transfer function. At the end an artificial neuron passes the processed information via output(s). Benefit of artificial neuron model [26] simplicity can be seen in its mathematical description below:

$$y(k) = F(\sum_{i=0}^{m} w_i(k).\, x_i(k)\ ) \qquad (1)$$

Where:
$w_i(k)$ is weight value in discrete time k where i goes from 0 to m,
$x_i(k)$ is input value in discrete time k where i goes from 0 to m,
F is a transfer function,
$y_i(k)$ is output value in discrete time k.
As seen from a model of an artificial neuron and its equation (1) the major unknown variable of our model is its transfer function. Transfer function defines the properties of artificial neuron and can be any mathematical function.

2.2. Backpropagation Neural Networks and Feedforward Neural Networks

Backpropagation Neural Networks (BNNs) consist of a collection of inputs and processing units knows as either neurons, neurodes or nodes. The neurons in each layer are fully interconnected by connection strengths called weights which, along with the network architecture, store the knowledge of a train network. In addition to the processing neurons, there is a bias neuron connected to each processing unit in the hidden and output layers. The bias neuron has a value of positive one and serves a similar purpose as the intercept in regression models. The neurons and bias terms are arranged into layer; an input layer, one or more hidden layers, and an output layer. The number of hidden layers and neurons within each layer can vary depending on the size and nature of the data set [24].

Backpropagation algorithm, the first time Werbos [27] and then Rumelhart *et al.* [28] have been proposed. In 1986, Rumelhart *et al.* [28] to explore the backpropagation algorithm again, and widespread use has led to the recognition algorithm. Backpropagation algorithm is the most used as a supervised learning algorithm. Feedforward Neural Networks are used in a variety of problems especially in forecasting because of their inherent capability of arbitrary input–output mapping.

A single hidden layer feedforward neural network is observed in Figure 2. N in the input layer, hidden layer and output layer of m neurons are p. The weight of each layer to the arrangement of connections between neurons of the network will be trained.

Weight arranging process, the minimization of the error function is provided. The training of an ANNs corresponds to minimizing the associated measure of error represented by the predefined error function [7]. Equation (2) shows the total error squared error function.

$$E = \frac{1}{2}\sum_{k=1}^{m}(y_k - t_k)^2 \qquad (2)$$

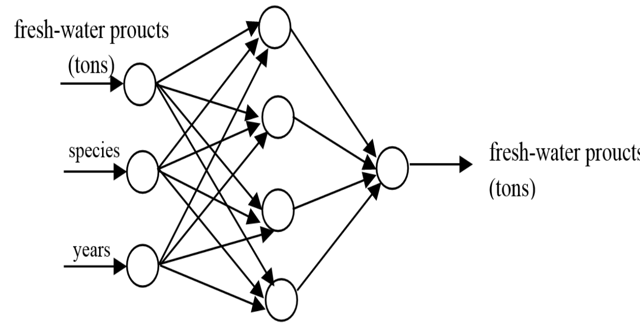

Fig 2: An ANN consisted of an input layer with 3 nodes, hidden layer, and an output layer with 1 node to be predicted.

Error in function, y_k, which produces the output of the network, t_k, shows the desired output value. $\frac{1}{2}$ constant factor and is added to facilitate the derivative function. Back propagation algorithm name, to minimize errors in the output layer backward to the process of regulation of weight is from.

2.3. An application of the methods

In this study, MINITAB and MATLAB Neural Network Toolbox software's (version 2013) were used. An application was carried out as listed below.

2.4. Data and identification models

Neural Network Toolbox of MATLAB was used for the ANN calculations. Data were taken from Turkish Statistical Institute database. This study was to evaluate artificial neural networks created for the sea, aquaculture and freshwater products in Turkey between the years of 2003 to 2012. (Table 1). Data were divided into three equal parts: training, validation and test sets. The MATLAB functions were used for "training", "testing", and "validation". They were used randomly: 70% in training, 15% in testing, and 15% in the validation of the fish products.

Table 1: Quantity of caught freshwater products.

TYPE OF FISH	YEARS									
	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
Total	44698	45585	46115	44082	43321	41011	39187	40259	37096.8	36120.0
Chub	82	93	87	85	82	71	63	92	130.7	90.5
Trout	393	352	376	374	550	630	557	738	518.5	444.0
Bream	221	213	234	259	225	170	148	151	180.4	141.5
Sand smellt	1826	2107	5248	6677	6540	6630	6184	4438	6705.2	3608.5
Tarek	14215	14259	14103	11978	11623	11758	10685	11382	9167.7	9621.0
Tench	785	1 875	1 792	1 953	1 884	1 632	1 482	1 162	623.9	63.0
Catfish	507	487	480	478	486	339	310	341	361.8	299.0
Bighand goby	73	79	105	101	70	57	51	47	70.3	60.5
Mullet	738	820	830	948	927	1023	970	1512	1325.3	1138.0
Rudd	247	267	281	285	258	261	239	251	270.3	241.5
Frog	792	803	803	833	895	668	622	780	749.5	648.0
Pike perch	1751	1852	1768	1656	1586	1346	1234	1476	737.2	593.0
Snail	1850	1879	1873	1462	1397	1007	2227	1991	1410.0	1193.0
Common Carp	13820	13451	13718	12116	12286	11625	10964	12058	9998.1	9973.0
Transcaucasian barb	1 013	1 027	971	967	985	993	891	962	923.8	812.5
Wels	912	897	804	1245	1293	1275	1193	1178	946.1	816.0
Eel	158	165	176	162	179	171	158	182	28.3	38.0
Pike	237	253	249	279	242	213	197	228	238.2	215.0
Cray fish	2183	2317	809	797	816	783	734	1030	609.6	492.0
Gibel Carp *	-	-	-	-	-	-	-	-	-	5090.0
Diğer - Other	2852	2352	1367	1378	952	312	236	223	1988.7	457.0
* It was compiled starting from 2012.										
Source: Data on administrative register of Ministry of Food, Agriculture and Livestock.										

2.5. Performance criteria

In this study, the sum squared error (SSE) and mean absolute percentage error (MAPE) is used in two performance criteria. SSE was used as a criterion for determine training during the training of the network. In addition we can make comparisons involving more than one method since the MAPE of each tells us about the average relative size of their errors.

SSE and MAPE following equation show the formulation of criteria.

$$SSE = \sum_{i=1}^{n} e_i^2 \qquad (3)$$

$$MAPE = \frac{1}{n_i} \sum_{i=1}^{n} \left| \frac{e_i}{Y_i} \right| . 100 \qquad (4)$$

Where, Y_i is the actual observation value, e_i is the difference between the actual vale and prediction value, and n is the number of total observation.

3. Results and Discussion

3.1. Optimistic results of ANNs

ANNs designed for forecasting problem, according to the organizational structure, non-linear or non-linear autoregressive model, the regression model trainable and can produce results. ANNs established for existing problems, a non-linear regression model acts and model results were found.

Back Propagation Networks (BPN) design is conducted as follows: One of the input and output layer neurons is used. Single hidden layer is used, and this hidden layer neuron has four neurons. Hidden layer activation function is the hyperbolic tangent function. Output layer activation function is identifying function. Learning rate and momentum coefficient value of 0.5 were used. Learning methods are used as the Powell-Beale algorithm. Available in MATLAB Neural Network Toolbox with different learning methods solved the problem, but the Powell-Beale algorithm prefers to give better results has helped [4].

While training the network, two parts of the data as training set and validation set were used. The network run for 10 times, verify that the best results for network structure according to the validation set data. The best network structure was generalized by using the test set data.

For the training set, in each execution of the algorithm finds the mean squared error (SSE- Sum Squared Error) values, 0.003 - 0.004, respectively. Termination of the algorithm at each execution varies between cycle of 50 -75 (epoch). According to model, the values shown in Table 2 and Figure 3, Fishery Product using last 10 years data with artificial neural network model was generated and were made to forecast for the year 2015. Estimated freshwater products value for 2015 is 15147 ton.

Table 2: Predicted values for ANNs

	ACTUAL DATA			FORECAST			MAPE (%)		
	2010	2011	2012	2010	2011	2012	2010	2011	2012
Freshwater products (tons)	40259	37096.8	36120	40436	38187.1	35466.9	0.440	2.939	1.808
Average MAPE							1.728		

MAPE: Mean Absolute Percentage Error

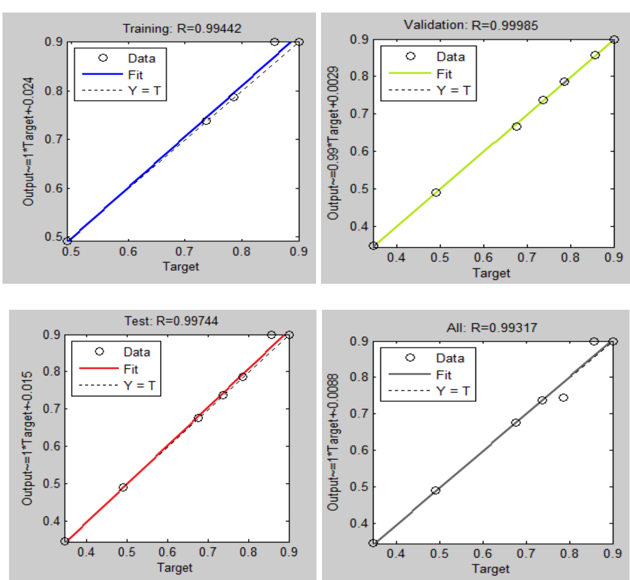

Fig 3: Regression results (training, validation, test and all) for ANNs

Turkey is also enhanced with rich inland waters and river systems with significant capture fishery and aquaculture potential. This favourable geographic position of Turkey brings a major advantage in having a large range of aquatic species and provides plenty of resources to carry out fisheries work [29].

Fisheries production statistics have been collected every year by Turkey Statistic Institute and Ministry of Food, Agriculture and Livestock. For data collection, Turkey is divided into five areas for sea products: East Black Sea, West Black Sea, Marmara, Aegean, Mediterranean, and seven areas for inland aquaculture fisheries: Black Sea, Marmara, Aegean, Mediterranean, Middle Anatolia, East Anatolia and South-East Anatolia [30].

A summary on the development and present status of licensing, regulating and monitoring procedures for finfish aquaculture in Turkey was published by Yucel-Gier *et al.* [31]. In recent years both freshwater and sea farming have an increasingly important role in the production of fishery products. On the other hand, marine aquaculture production develops faster than aquaculture [30].

It is clear that Turkey has an important production capacity both in terms of freshwater and sea water products. Data collection should be carried out through sampling operations in order to lack of landing data recording system. An inland capture fishery is less important in quantity than marine catch, and would thus justify only a limited investment in data collection. Aquaculture statistics are still fairly unknown. However, in 2004 and 2005, with support from the FAO Technical Cooperation Program, statistical activities are described in much more detail in technical notes on statistics and data collection and in reports of workshops organized by the Project [2].

ANNs techniques are permissible if less data to work with.

However ANNs techniques, the black box (black box) show property they can sometimes produce negative results [32]. Therefore, when used as a means of forecasting, the results with conventional methods used to aid in supporting ANNs methods. A network built according to the structure of the problem, will give good results. Therefore, the appropriate network structure by examining problems should be investigated.

This study was to evaluate artificial neural networks created for the sea, aquaculture and freshwater products in Turkey between 2003 to 2012. Fishery Product using last 10 years data with artificial neural network model was generated and were made to forecast for the year 2015. This result shows us that, in the coming years aquaculture and freshwater products are alarming. Everyone should take the necessary measures regarding the subject. Studies done on the basis of species be improved. Ministry of Food, Agriculture and Livestock must be more accurate data collection such as monthly. Turkey should be ready for such actions. Regular fish data collection is important. Such work should be tried in species on the type derived from inland regularly collected data on monthly.

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