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ESTIMATION OF SHRIMP FARMING PRODUCTION IN BANYUWANGI, EAST JAVA USING GRADIENT DESCENT MOMENTUM METHOD

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ABSTRACT

Estimation of shrimp farming production in district area have been developed to successful in consistently predicting the performance of the farmers. The complex set of problem processes within shrimp farming have made the development of analytical models to be a significant challenge. Advanced simulation tools are needed to become more accurately model shrimp farming production systems. As an alternative approach, we have begun development of shrimp farming production modeling based on Gradient Descent Momentum which uses Matlab 7.6.0(R2008b). A neural network based learning system method has been proposed for estimation of shrimp farming production. Gradient Descent Momentum based technique is used for learning shrimp farming production. Thus a precision model of Gradient Descent Momentum has been evaluated. The precise of the Gradient Descent Momentum model has error less than 0.301 percent.

Keywords: estimation, gradient descent momentum, learning, neural network.

INTRODUCTION

The potential of fisheries resources in Banyuwangi not yet have a crucial role to GDRB of the agricultural sector. The average of role of fisheries sub sector accounted for only 7.34% of the overall agricultural sector. It's certainly a very small value compared with the wealth owned fishery resource potential (Central Bank of Indonesian Republic, 2008). Banyuwangi with 175.8 km beach area and 178.8 km sea area are fisheries and marine resource large enough potential. The potential of fishery resource is very large for the local economy and public welfare. However, the management of this potential has not been optimally developed. Technology has not been much used in the management and development of its main resource potential of shrimp farming. Economically, a high resource potential is not yet provide support for GDRB. It is possible that data errors will have an impact on policy making in the development of fisheries resource potential further. In order to determine the policy is necessary to do some activities that support, among others: a survey mapping the potential of fishery resources, problems and obstacles encountered in the development of fisheries and estimation of fishery farming.

The estimation of modeling is a key point of development successfully (Kaloko, 2011). Modelling estimation using RBF method provides accuracy 0.99977. The estimation modeling using BPN method has errors of 0.00045 percent (Kaloko, 2011).

The modeling estimation of shrimp farming should be developed to get the policy model right. In this paper we propose a new estimation model with a neural network using Gradient Descent Momentum method.

METHOD

Mathematical Laboratory (Matlab) version R2008b (developed by MathWorks, Natick, Massachusetts) was employed to perform the simulation procedures and development of mathematical computing. All computational simulations were performed on a Window machine with Intel Dual Core 2GHz as the processors and 1 GB of RAM.

This function uses the basic gradient descent algorithm. Gradient Descent Momentum has a constant momentum value between 0 until 1. Weights will be corrected, with the changes as shown in equation:

$$\Delta w_{jk} = \alpha\varphi 2_{jk} \; ; \qquad \Delta b2_k = \alpha\beta 2_k$$

$$\Delta v_{ij} = \alpha\varphi 1_{ij} \; ; \qquad \Delta b1_j = \alpha\beta 1_j$$

where: w ; weight b; bias v; weight correction.

This parameters related to learngd, namely learning rate. The greater value of learning rate will have implications on the magnitude of the learning step. If the learning rate is set too large, then the algorithm will become unstable. Conversely, if the learning rate is set too small, then the algorithm will converge in a very long period of time.

This function is similar to learngdm, which is done in an incremental fashion. Parameter to be set for this learning is a function of training, become traingdm. The parameters that must be set for this training and iteration termination criteria, the same as the training algorithm traingd. One more parameter that needs to be set is the momentum with the instruction: net.trainParam.mc=Momentum.

OVERVIEW OF GRADIENT DESCENT MOMENTUM

The ANN is an inductive, or database model for the simulation of input/output mappings. The ANN can be used in numerous frameworks to simulate many types of system behavior including physical, financial, and, as will be shown here, production systems. ANNs require training data to learn patterns of input/output behavior and, once trained, can be used to simulate system behavior within that training space. They do this by interpolating specified inputs among the training inputs to yield outputs that are interpolations of training outputs. The reason for using ANNs to simulate system behavior is they provide accurate approximations of system behavior and are typically much more computationally efficient than phenomenological models. This efficiency is very important in simulations where multiple response or prediction computation are required. Some examples of computationally intensive applications are: (1) optimization of system performance, (2) system identification, (3) system design, and (4) Monte Carlo analysis of probabilistic system response.

The ANN architecture used as a model of shrimp farming production is shown in Figure 1.

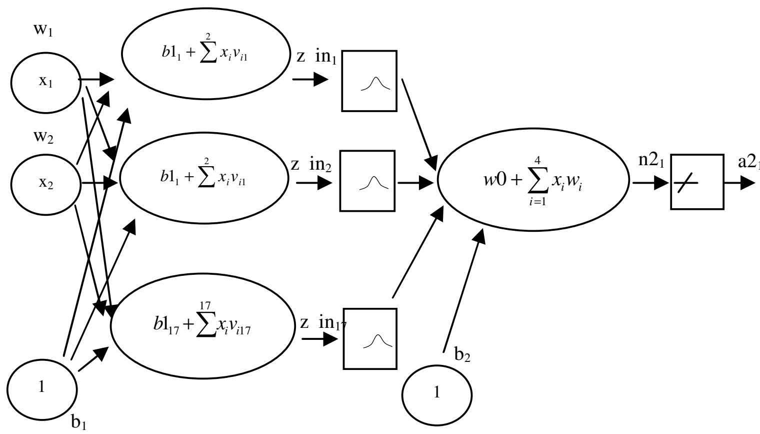

Figure. 1. ANN architecture used to model of shrimp farming production (number of input variable 2, amount of data 17, single target).

RESULT AND DISCUSSION

The Gradient Descent Momentum coefficient initialize of shrimp farming production is required with error term ΔE. The network feedforward training conducted in order to make the adjustment weights, so that at the end of the training to be gained weights is good. In the training process, weights adjusted iteratively to minimize the network performance function. Performance function that is often used for backpropagation is the mean square error (MSE), this function will take the average squared error that occurred between the network output and target. Most of the training algorithm for networks using a gradient of performance function to determine how to adjust the weights in order to minimize the performance. This gradient is determined by using a technique called backpropagation name. Basically, algorithm of backpropagation training will move the weights with a negative gradient direction. Basic principles of simple backpropagation algorithm is to improve the weights of the network with the direction that makes the performance function to be falling rapidly. In incremental mode, the gradient calculation and repairs performed at each operating weight of the input data. This function will use the network object, a collection of input data as input and target training, and will produce well-trained network objects, network output, errors that occur weights final as the output value.

Table 1. The growth of shrimp farming production in Banyuwangi (Bank Indonesia, 2011).

Year	*Production[kg]*	*Output model [kg]*	*Error (%)*
1991	6842929	6675650	2.44
1992	5417428	5524560	-0.46
1993	4349300	4357372	-0.18
1994	2835195	2995386	-0.00000035
1995	3014500	2863523	5.00
1996	3125625	3240780	-3.68
1997	2980130	2770080	7.04
1998	2396395	2473271	-3.21
1999	2415565	2453443	-1.56
2000	3081610	2997810	2.71
2001	3174058	3090303	2.68
2002	3238850	3242015	-0.09
2003	3562735	3577311	-0.40
2004	3205689	3412079	-6.02
2005	3600950	3357283	0.67
2006	4100700	3356664	0.18
2007	4285543	3356656	2.16

Initial plot is shown in Figure 2, a number of data are carried out for validation of proposed method. In each initial data learning is given the perturbation to test the effectiveness of algorithm. The fourteenth until the seventeenth data is used as checking data. The plot after four data checks learning cycles is shown Figure 3. The network output and target for the data were analyzed with linear regression. The linear regression for the target and network output in this model is shown in Figure 4. The equation for best fit in this model is:

$$Y = 1T + 2.5e^{-12}$$

where Y: output network, T:target.

The correlation coefficient of this model is 1, shows good results for the target and network output.

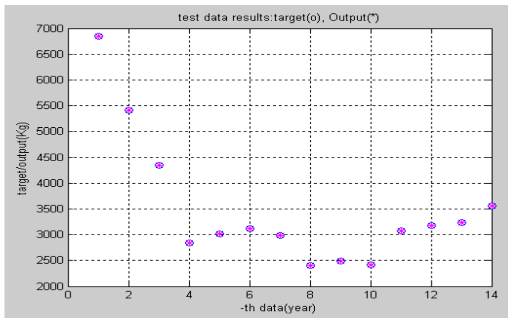

Figure 2. ANN comparison to actual data

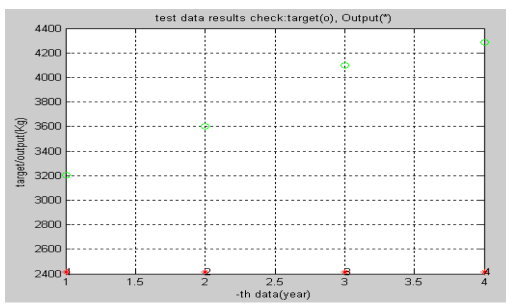

Figure 3. The ANN checking data

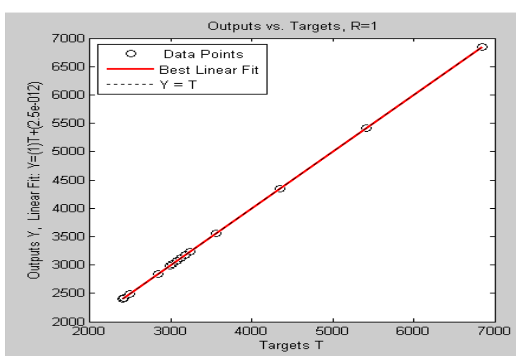

Figure 4. The linear regression for the target and network output

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REFERENCES

Kaloko et al., (2011). Estimation of Capacity of Lead Acid Battery using RBF Model, *International Review on Modelling and Simulations (I.RE.MO.S.) Vol 4 No.3, pp. 1184-1189*.

Kaloko et al., (2011). Mapping of Electrochemistry and Neural Network Model Applied in State of Charge Estimation for Lead Acid Battery Used in ElectricVehicle. *Indonesian Journal of Chemistry*, Vol. 11 No.2,pp. 140-147.

Bank Indonesia (2011). Penelitian Potensi Pengembangan Industri Perikanan di Wilayah Eks Karesidenan Besuki.

Kusumadewi, S (2004). *Artificial Intelligence.* Yogyakarta: Graha Ilmu.

Kusumadewi, S (2004). *Membangun Jaringan syaraf Tiruan.*Yogyakarta: Graha Ilmu.