Global Journal of Pure and Applied Mathematics.
ISSN 0973-1768 Volume 11, Number 4 (2015), pp. 2191-2194

http://www.ripublication.com

Development Of Neural Network Models For Forecasting Rice Yield In The Northern Thailand

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Abstract

This work was objective to exemplify the development of neural network models for forecasting rice yield in the northern Thailand. Multi-Layer Perceptron (MLP) and Ordinary Radial Basis Function (ORBF) neural network architecture were designed and then trained by using of several meteorological variables as the input nodes with different activation functions at the computing nodes. Root mean square error (RMSE) of the validation data set of each network models were finally calculated and compared for measuring model performance. The result of this work indicated the MLP7-5-1 provided the best performance with the smallest RMSE of validation data set. In addition, the potential neural network models in forecasting rice yield were also additionally guided for development.

Keywords: Rice yield, Neural network model, MLP, ORBF

Mathematics Subject Classification: 62-07, 62G35

INTRODUCTION

Rice is life-sustaining to more than half of the world population. Rice is also the most staple crop for Thailand. Thailand exported rice from around 6.2 million ton in 1995 to 8.9 million ton in 2010 and grew at about 4% per year in 2005-2010 [1]. The northern field of Thailand is almost one-third of the land area which is about 20% of the total rice land in the country. Thai rice production is produced from 2 periods. One is called in-season rice cultivated in rainy season. The other is known as off-season rice which is able to harvest throughout the year. Rice production is affected by various crucial factors such as water or rainfall [2], sunshine hour or solar radiation and even temperature [3], [4]. The multiple linear regression (MLR) model is usually the simple statistical analysis tool used for forecasting rice yield presented in [3], [5]. Neural network method has been recently purposed in agriculture for predictive purpose. Then, many researchers widely applied neural network model to forecast rice yield at present; for example, [4], [5], [7], [8], [9], including Thai papers like [6], [10]. Therefore, the aim of this work was to develop neural network models for obtaining the potential model in forecasting rice yield in the northern Thailand which was contained 13 provinces; Chiang Rai, Phayao, Lampang, Lamphun, Chiang Mai, Mae Hong Son, Tak, Kamphaengphet, Sukhothai, Nan, Phrae, Phitsanulok and Phetchabun.

MATERIALS AND METHODS

The annual data in the northern Thailand composed of 156 observations of rice yield (Y: ton) and 7 predictor variables containing of 6 predictor variables; total rainfall (X_1: mm.), number of rainy days (X_2), daily maximum rain (X_3: mm.), extreme maximum temperature (X_4: °c), extreme minimum temperature (X_5: °c), mean of relative humidity (X_6: %), and the last remaining predictor variable; type of rice (X_7; X_7=1 explained for in-season rice otherwise X_7=0 defined off-season rice), were gathered during 2008-2013 by Office of Agricultural Economics, Ministry of Agriculture and Cooperatives [11] and National Statistical office [12] supported from Thai Meteorological Department.

Data analysis initiated with separating whole data into 2 sets. The training data set was firstly utilized for training the neural network model. It equally contained each of 54 observations for both types of rice. The validation data set was the rest of data operated for verifying suitability of model. Neural network technique was then developed by training different diverse architectures. Once both of the MLP and ORBF networks were designed with 7 input nodes equal to the number of predictor variables, 3 or 5 hidden nodes in a hidden layer in agreement of [13], [14], [15] and only one output node represented the rice yield. The MLP network were trained with hyperbolic tangent and logistic activation functions at the hidden nodes as well as the exponential and identity activation functions at the output nodes. The ORBF networks were applied with only Gaussian activation function at the hidden node which was compatible with the exponential and identity activation functions at the output node.

Finally, the performance of all network models was measured with the Root Mean Square Error computed as $RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)^2}$, where Y_i be the ith observation of rice yield, $\hat{Y}_i$ be the ith predicted value of rice yield obtained from the network model and n be the total observations in the validation data set.

RESULTS

A comparison of the performance of all network models was verified by considering the RMSE of the validation data set of each model as shown in Table 1.

The best performance network model was MLP7-5-1 with hyperbolic tangent activation function at the hidden nodes and identity activation function at the output nodes. Contrarily, the worst one was ORBF7-3-1 with Gaussian activation function at the hidden nodes and identity activation function at the output nodes.

Table 1: RMSE of validation data set of each network model

Architecture of Neural Network	Activation Function at		RMSE of Validation
	Hidden Node	Target Node	
MLP7-3-1	Hyperbolic Tangent	Exponential	2.515366
MLP7-3-1	Logistic	Exponential	2.502805
MLP7-3-1	Hyperbolic Tangent	Identity	2.632840
MLP7-3-1	Logistic	Identity	2.694124
MLP7-5-1	Hyperbolic Tangent	Exponential	2.449470
MLP7-5-1	Logistic	Exponential	2.568154
MLP7-5-1	**Hyperbolic Tangent**	**Identity**	**2.268837**
MLP7-5-1	Logistic	Identity	2.615406
ORBF7-3-1	Gaussian	Exponential	2.802068
ORBF7-3-1	Gaussian	Identity	3.041892
ORBF7-5-1	Gaussian	Exponential	2.875939
ORBF7-5-1	Gaussian	Identity	2.807648

DISCUSSION

Generally, all MLP networks gave smaller RMSE of validation data set than RBF networks. It indicated that training network model with the simple architecture provided better performance than the advanced one. In addition, the network model with having more hidden nodes (5 nodes) displayed smaller RMSE value than the fewer one (3 nodes). Further study would work on improving network model performance for forecasting rice yield by adjusting network parameters like number of hidden nodes or hidden layers or even other activation functions at computing nodes, etc.

ACKNOWLEDGEMENT

The authors wish to thank to the Office of Agricultural Economics and National Statistical office, for kindly supporting all data.

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