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Forecasting Sugar Cane Yield In The Northeast Of Thailand With MLP Models

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Abstract

The intention of this work was to forecast sugar cane yield in the northeast of Thailand by developing the Multi-Layer Perceptron (MLP) models. The MLP models were created and trained by using various explanatory variables as the input nodes with different activation functions at the computing nodes. The performance of each MLP model was then measured with the root mean square error (RMSE) of validation data set. The result of this work displayed the MLP8-3-1 trained with Hyperbolic Tangent activation function at the hidden nodes and Exponential activation function at the output nodes performed the best performance with the smallest RMSE (10.46268).

Keywords: Sugar cane yield, MLP models

Mathematics Subject Classification: 62-07, 62G35

INTRODUCTION

The northeast of Thailand is tropical and subtropical area so it is suitable for cultivating sugar cane. Also, the northeast region is the largest producer of sugar cane in Thailand. Production of sugar cane is based on many variables specifically the meteorological variables like the rainfall, temperature, humidity or even the cultivated area, sugar cane variety [1], [2], [3], [4]. It is necessary, therefore, to find an analysis tool for forecasting sugar cane yield in the northeast of Thailand. The Multi-Layer Perceptron or MLP technique is one of the versatile mathematical models widely applied in prediction problem. Such of works, [3], [5], presented application of neural network for forecasting sugar cane production. This work was then objective to create and develop MLP models relating on various explanatory variables for forecasting sugar cane yield in the northeast of Thailand contained 15 provinces; Nakhon

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MATERIALS AND METHODS

The annual data in the northeast of Thailand consisted of 175 observations of sugar cane yield (Y: rai or 1,600 square metres) and 8 explanatory variables; cultivated area (X_1: rai), sugar cane quantity sent to factories (X_2: ton), average price of sugar cane (X_3: baht/ton), maximum temperature (X_4: $^{\circ}$c), minimum temperature (X_5: $^{\circ}$c), total rainfall (X_6: mm.), number of rainy days (X_7) and maximum rainfall (X_8: mm.), were measured during 2002-2013 by Office of The Cane and Sugar Board, Ministry of Industry [4], Office of Agricultural Economics, Ministry of Agriculture and Cooperatives [6] and National Statistical office supported from Thai Meteorological Department [7].

The first step for data analysis was dividing whole data into 2 sets. The training data set was used for training the MLP models. It comprised of 75% of whole data. The validation data set was the remaining of whole data utilized for validating suitability of MLP model. The MLP networks were created with 8 input nodes equal to the number of explanatory variables, 3 or 5 hidden nodes in a hidden layer following suggestion of [8], [9], [10] and only one output node represented the sugar cane yield. The MLP networks 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 performance of each MLP model was finally 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 sugar cane yield, $\hat{Y}_i$ be the ith predicted value of sugar cane yield obtained from each MLP model and n be the total observations in the validation data set.

RESULTS

A comparison of the performance of each MLP model was considered by the RMSE of validation data set as displayed in Table 1.

Table 1: RMSE of validation data set for each MLP model

Architecture of MLP	Activation Function at		RMSE of Validation
	Hidden Node	Output Node	
MLP8-3-1	**Hyperbolic Tangent**	**Exponential**	**10.46268**
MLP8-3-1	Logistic	Exponential	10.68753
MLP8-3-1	Hyperbolic Tangent	Identity	11.88099
MLP8-3-1	Logistic	Identity	12.50270
MLP8-5-1	Hyperbolic Tangent	Exponential	11.23929
MLP8-5-1	Logistic	Exponential	13.78151
MLP8-5-1	Hyperbolic Tangent	Identity	11.60382
MLP8-5-1	Logistic	Identity	12.84951

The best performance model was MLP8-3-1 with Hyperbolic Tangent activation function at the hidden nodes and Exponential activation function at the output nodes. Contrarily, the worst one was MLP8-5-1 with Logistic activation function at the hidden nodes and Exponential activation function at the output nodes.

DISCUSSION

Regard of the same architecture of MLP, training MLP model with 3 hidden nodes generally obtained smaller RMSE except only one case which was applied with the hyperbolic tangent activation function at hidden nodes and identity activation function at output nodes. That implied, it was enough for training MLP network with a few hidden nodes could obtain a good performance for forecasting sugar cane yield in the northeast of Thailand.

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REFERENCES

[1] Chimnarong, V., 2009, The relationship between climatic parameters and sugarcane yields: the case study of Mitr Phukieo Sugarcane Plantations," Thesis, Master of Environmental Science, Khon Kaen University.

[2] Kapetch, P., & Pannangpetch, K., 2012, "The Effects of Climate Change on Sugarcane Production in Northeast of Thailand: A case Study in Kalasin Province," Khon Kaen Agr. J. 40 Supplment 3: 83-91 (201823).

[3] Bukate, O., & Seresangtakul, P., 2013, "Sugarcane Production Forecasting Model of the Northeastern by Artificial Neural Network," KKU Sci. J. 41(1) 213-225.

[4] Office of The Cane and Sugar Board, 2011, "Report of sugarcane cultivated area in Thailand," Retrieved 29 March, 2015 from web site: http://www.ocsb.go.th/th/cms/detail.php?ID=923&SystemModuleKey=journal

[5] Xu, Y. C., Shen, S. Q., & Chen, Z., 2010, "Comparative Study of Sugarcane Average Unit Yield Prediction with Genetic BP Neural Network Algorithm," China: Department of Computer Science, Guangdong Polytechnic Institute Guangzhou, College of Engineering, South China Agricultural University.

[6] Office of Agricultural Economics, 2015, "Commercial price of sugarcane," Retrieved March 30, 2015 from web site: http://www.oae.go.th/main.php?filename=index

[7] National Statistics Organization of Thailand, 2014, "Rainfalls and Temperatures Statistics at Meteorological Department," Retrieve April 10, 2015 from web site: http://service.nso.go.th/nso/web/statseries/statseries27.html

[8] Cybenko, G., 1989, "Approximation by superpositions of a sigmoidal function," Mathematics of Control, Signals, and Systerms, 2(4), 303-314.

[9] Hornik, K., Stinchcombe, M., & White, H., 1989, "Multilayer feedforward networks are universal approximators," Neural Networks, 2(5), 359-366.

[10] Guo, Y., & Dooley, K. J., 1992, "Identification of Change Structure in Statistical rocess Control," The International Journal of Production Research, 30(7), 1655-1669.