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Forecasting Sugar Cane Yield in the Eastern Area of Thailand with ANN Technique

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Abstract

The eastern area of Thailand effectively produced the highest sugar cane yield which was in accordance with the report of the Information Division of the Cane and Sugar Industry. Sugar cane yield also varies from year to year relying on various factors; for example, size of sugar cane cultivated area, quantity of sugar cane delivered to the chest, average sugar cane price, maximum and minimum temperature, overall rain fall, number of rainy days, maximum rainfall. Forecasting of sugar cane yield will consequently assist in determining both demand and supply for the sugar production. Forecasting sugar cane yield in the eastern area of Thailand, the artificial neural network (ANN) technique was then applied and created in both structures of the simple (MLP) and advanced (RBF) models. The study results found that the sugar cane yield in the eastern area of Thailand was capably well predicted with all models of ANN technique. Also, the best performance model of ANN technique is the simple ANN model, MLP 8-3-1, as considering from the minimum root mean square error. The ANN technique is quite a proficient strategy for forecasting sugar cane yield since it efficiently predicted the sugar cane yield in close vicinity to the real value no matter what the simple or advanced ANN models were applied. The Thai sanctioned government representative then may employ these useful findings as a supplementary guideline for planning and controlling the production of sugar cane yield in the eastern area of Thailand.

Key words: Sugar Cane Yield, ANN Technique, MLP, RBF.

INTRODUCTION

Sugar cane is the monocotyledon belonging to the family of grass well grown up in subtropical and tropical areas. Thailand can export sugar cane with a large income about two hundred thousand million baht in 2013 (KASETSART UNIVERSITY, 2014). Sugar cane is also productively cultivated in almost every parts of Thailand except the southern area because it's weather is unsuitable due to frequently rain throughout the year. Office of the Cane and Sugar Board, Ministry of industry separates the sugar cane cultivated areas into 4 sectors; northern, central, eastern and northeastern Thailand. The eastern area of Thailand is composed of sugar cane cultivated area covered in 6 provinces; Rayong, Sa Kaeo, Prachinburi, Chonburi, Chantaburi and Chachoengsao. Total sugar cane cultivated areas of the eastern concluded 501,300 rai (Thai unit, 1 rai=1,600 m^2) which was increasing from the yearly production of 2012/2013 in the amount of 17,844 rai or it could say sugar cane cultivated areas were decreasing 3.69%. The eastern area therefore capably produced the highest sugar cane yield in Thailand (INFORMATION DIVISION OF THE CANE AND SUGAR INDUSTRY, 2014).

Although Thai sugar cane and sugar industries have presently made great progress, sugar cane cultivators still confront a problem of high production costs owing to its yield per rai is lower than other competitors like Brazil and Australia. The annual quantity of Thai sugar cane is also not stable. That leads to sugar production cannot be accurately estimated because over 80% of sugar cane cultivated areas depend on rainfall (PROJECT OF ANNUAL CONFERENCE OF NATIONAL SUGAR AND CANE 2012, 2012). Moreover, many parameters have an impact on the sugar cane yield such as size of sugar cane cultivated area, quantity of sugar cane delivered to the chest, average sugar cane price, temperature or rainfall, etc. In accordance with mentioned

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reasons, finding strategy to forecast sugar cane yield is substantially essential for planning and policy making to direct the production of sugar cane in the eastern area of Thailand.

In agriculture, the traditionally simple statistical tool used for prediction objective is regression. The important nature of regression models focuses on linear relationship, so it requires to fulfill the regression assumptions and multiple collinearity between dependent and independent variables. Many of works; for example, BINBOL *et al.* (2006), CHIMNARONG (2009), XU et al. (2010), SAITHANU *et al.* (2017), usefully employed multiple regression models for forecasting sugar cane production. Nevertheless, data sometimes is nonlinear or consisted of extreme values so using regression models for prediction is inappropriate and inefficient (MOLAZEM *et al.*, 2002 and ZAEFIZADAH *et al.*, 2011). The artificial neural network (ANN) technique is hence proposed to solve problems of the complicated association and strong nonlinearity between different parameters and dependent variable. The ANN technique is one of the best strategies utilized for extracting information from questionable and nonlinear data (CASELLI *et al.*, 2009). The ANN models have then applied as a significant tool across many fields including prediction of crop production (PASWAN & BEGUM, 2013). The structure of ANN models called ANN architecture usually presented in 2 forms. A multi-layer perceptron (MLP) is firstly represented the simple ANN model. It considers estimated weights between inputs and the hidden layers with nonlinear activation function. The other is a radial basis function (RBF) stand for the advanced ANN model which the activation function can be any of various functions on the nonnegative numbers with a maximum at zero, approaching zero at infinity. Both simple and advanced of ANN techniques were competently performed in sugar cane prediction such as XU e*t al.* (2010), OBE & SHANGODOYIN (2010), BUKATE & SERESANGTAKUL (2013), etc. The purpose of present study then completely executes to forecast sugar cane yield in the eastern areas of Thailand with the simple and advanced models of ANN technique.

MATERIALS AND METHODS

The annual data for forecasting sugar cane yield in the eastern area of Thailand was gathered and collected corresponding to 8 variables during 2002 to 2014 from following 3 sources.

1. Office of the Cane and Sugar Board, Ministry of industry provided 3 variables; the sugar cane yield rai (Y: rai), size of sugar cane cultivated area (X_1: rai) and quantity of sugar cane delivered to the chest (X_2: ton) (OFFICE OF THE CANE AND SUGAR BOARD, 2011).
2. Office of Agricultural Economics, Ministry of Agriculture and Cooperatives reported average sugar cane price (X_3: baht/ton) (OFFICE OF AGRICULTURAL ECONOMICS, 2015).
3. National Statistical Office from Thai Meteorological Department equipped the five remaining variables; maximum temperature (X_4: $^{\circ}C$), minimum temperature (X_5: $^{\circ}C$), overall rain fall (X_6: mm.), number of rainy days (X_7) and maximum rainfall (X_8: mm.) (NATIONAL STATISTICS ORGANIZATION OF THAILAND, 2014).

Data analysis of a procedure for forecasting sugar cane yield in the eastern area of Thailand with the ANN technique was performed as follows.

1. Separating a whole data into 2 sets. Training data set contained 70% of whole data was employed for training the ANN models. The remaining of whole data called validation data set was used for validating suitability of ANN models.
2. Creating both of ANN models, simple and advanced, with 3 layers. The architecture of all models was designed as 8 input nodes in the input layers correlated to the number of independent variables (X_1-X_8), 3 or 5 hidden nodes in the only one hidden layer on the recommendation of CYBENKO (1989), HORNIK (1989) and GUO (1992) and merely single output node in the output layer expressed as the sugar cane yield (Y). The hyperbolic tangent and exponential functions were a representative of activation functions for MLP models while the RBF models were trained with Gaussian and identity functions at the hidden and output nodes, respectively.
3. Evaluating and comparing a performance of ANN models with the root mean square error (RMSE) defined as $RMSE = \sqrt{\frac{\sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)^2}{n}}$, where Y_i and $\hat{Y}_i$ be respectively the *i*th observation and predicted value of sugar cane yield in the eastern area of Thailand and n be the total observations in training or validation data set.

RESULTS

The four ANN models were then illustrated as Figure 1 (MLP 8-3-1 and RBF 8-3-1) and Figure 2 (MLP 8-5-1 and RBF 8-5-1).

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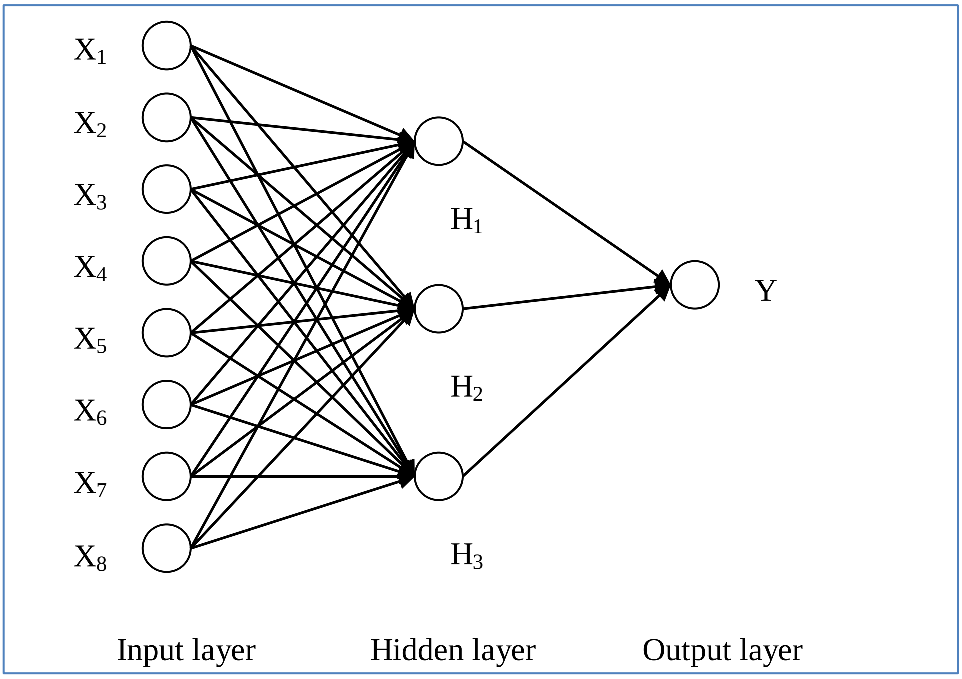

Figure 1. MLP 8-3- 1and RBF 8-3-1

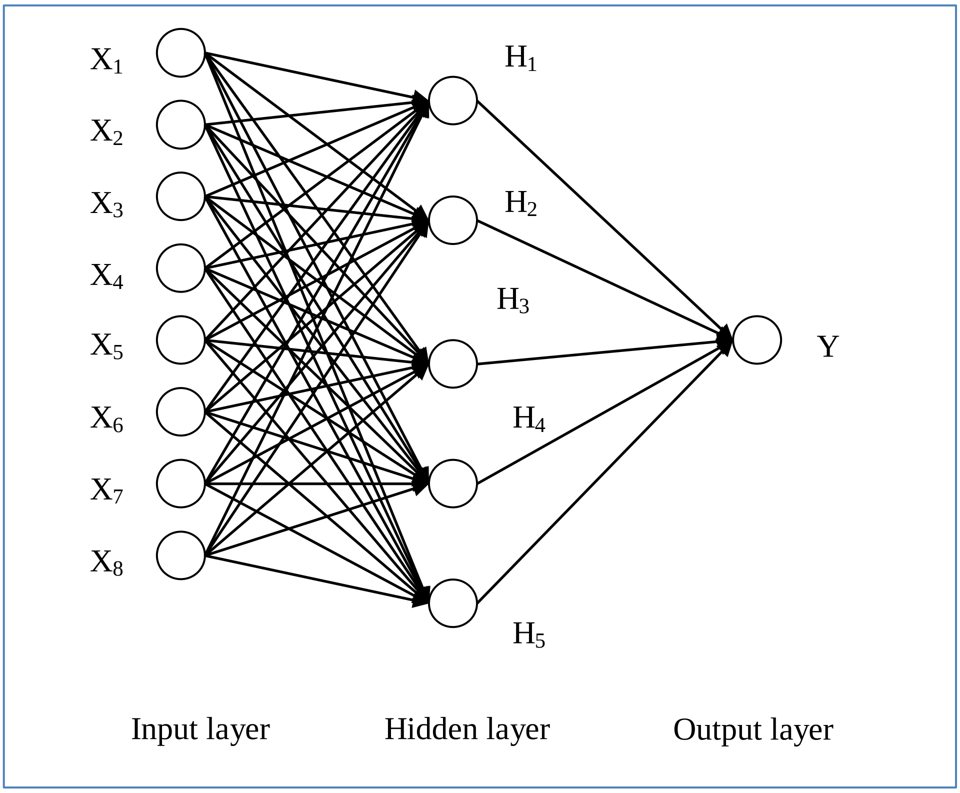

Figure 2. MLP 8-5- 1and RBF 8-5-1

To evaluate and compare a performance of these four ANN models, the values of RMSE were calculated in a following Table 1.

Table 1. The performance of ANN models

	Activation function of		RMSE of	
ANN model	**Hidden nodes**	**Output node**	**Training set**	**Validation set**
MLP 8–**1–3**	Hyperbolic Tangent	Exponential	0.455290	0.744068
MLP 8–1–5	Hyperbolic Tangent	Exponential	0.976472	0.961801
RBF 8–1–3	Gaussian	Identity	1.949770	0.995277
RBF 8–5–1	Gaussian	Identity	1.092490	0.945180

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Basing on the values of RMSE, the MLP 8-3-1 performed the best performance for forecasting sugar cane yield in the eastern area of Thailand since it showed both smallest RMSE values for training (0.455290) and validation data set (0.744068). Conversely, the worst one was RBF 8-3-1 exhibited the largest RMSE values for training and validation data set with 1.949770 and 0.995277, respectively.

CONCLUSION

The simple, MLP, and advanced, RBF, models were applied to forecast sugar cane yield in the eastern area of Thailand. Two architectures (8-3-1 and 8-5-1) for both models then diversely trained with 8 input nodes which were denoted to the eight influential independent variables, 3 or 5 hidden nodes and 1 output node stand for the sugar cane yield. Because of the smallest RMSE value of MLP 8-3-1, this model capably predicted the sugar cane yield in close vicinity to the real value. It indicates that training model with the simple model of ANN technique competently predict sugar cane yield in the eastern area more efficient than the advanced model. It also implies that the less hidden nodes in a hidden layer we used, the more accuracy in forecasting we obtained. Finally, it conducts to identifying the best model with ANN technique is count on selection of ANN architecture; like the number of hidden layers or nodes and the activation function of hidden nodes or output nodes, the methods of validated results, the measure utilized for comparison as well whether important difference exists in the results, etc.

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