Off-season Supply Forecasting in Thai Longan Supply Chain with Artificial Neural Network

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ABSTRACT

This paper presented the application of artificial neural networks (ANNs) in forecasting amount of off season longan. With their ability to discover patterns in nonlinear and chaotic systems, ANNs offer the ability to predict off season longan supply more accurately than any current techniques. Three layers back-propagation neural network was constructed with 40 nodes input or influent factors and 1 node output or amount of longan. Empirical data sets were feed into the networks for the training step. Finally, tested data sets were used to verify the capability of ANNs model.

Key words: ANNs, Forecasting, Longan, Back-propagation

INTRODUCTION

During the past few years, several novel paradigms for solving forecasting problems have emerged. One paradigm, the neural networks are algorithms with certain characteristics and restrictions the facilitate parallelism in an ultimate hardware implementation, or which possess biological compatibility (Efendigil and Kahraman, 2009). To be overly, succinct, computation proceeds through a system of processing elements linked by weighted connections. These processing elements compute from local information stored and storage is restricted to the information on connections. According to their topological structure of connectivity, artificial neural networks can be categorized into feed forward neural networks and recurrent neural networks (Saini, 2008). In the feed forward neural networks, states of neural are activated from external inputs to outputs in a unidirectional fashion. In the recurrent neural networks, on the other hand, state feedback is allowed and dynamic behaviors are exhibited. A popular approach of using neural networks for forecasting is back-propagation neural networks which motivation is universal approximation (Fahimifard et al., 2009).

From report of the supply chain of fresh longan in Thailand, Sopadang et al. (2008) reported that two of main reasons to over supply crisis are off-season planting for the lucrative profit without collaborative planting with the other agriculturalists in the neighborhood area and they also cultivated the off-season longan based on their potential and experience by trial-error without the supply forecasting. When the off-season longan cultivation came, they also reap their product in the same time without the harvest priority in the area because they also start to cultivate in the same period. Providing that they have some tool to foresee their orchard potential to plant the off-season longan based on five main aspects as follows

1) General profile of agriculturalists to off-season longan comprised of their gender, cultivation's experience, educational level

2) General profile of longan orchard including density of garden, longan type, height of longan trees, diameter of the longan canopy and longan cultivation period.

3) Technical longan cultivation information about the care of longan for instance, shape pruning after harvest, the frequency of longan orchard treatment, early recovery period after harvest before pouring fluid catalytic productivity, the continuity of the catalytic productivity fluid, irrigation system to orchard, volume of potassium chlorate and other chemicals usage in the treatment of leaf,

flower, the other chemicals used to eliminate diseases and insects and how to add substance.

4) Longan orchard environment information such as garden's soil characteristics, the sunlight, temperature, humidity, rainfall on soil nutrients, moisture in the soil, diseases and insect pests of longan.

5) Productivity information for example, harvest date, the average harvest yield per day, ratio of good grade longan, the percentage of blooming flower, inflorescence characteristics of longan and longan color.

According to many influenced factors to longan productivity, it seems hard to off-season longan orchard's cultivation planning in terms of number of their promising profitable longan in each year. This is enabling to conform as the interesting research question and the novel framework to solution this topic. To carry it out is the ultimate aim of this research.

METHODOLOGY

Our research began by constructing the neural network model which so called feed forward training neural network. The advantage of the usage of feed forward neural networks for prediction is that they are able to learn from examples only and that after their learning is finished, they are able to catch hidden and strongly non-linear dependencies, even when there is a significant noise in the training set. Feed forward neural network will be formulated by training process. Unfortunately, we did not obtain an enough training data sets. Subsequently, we introduced monte carlo simulation technique for generating data sets. By applied statistical process, distribution functions of promising parameters were constructed.

Feed forward neural network model

If we consider the human brain to be the ultimate neural network, then ideally we would like to build a device which imitates the brain's functions. However, because of limits in our technology, we must settle for a much simpler design. The obvious approach is to design a small electronic device which has a transfer function similar to a biological neuron, and then connect each neuron to many other neurons, using RLC networks to imitate the dendrites, axons, and synapses. This type of electronic model is still rather complex to implement, and we may have difficulty teaching the network to do anything useful. Further constraints are needed to make the design more manageable. First, we change the connectivity between the neurons so that they are in distinct layers, such that each neuron in one layer is connected to every neuron in the next layer. Further, we define that signals flow only in one direction across the network, and we simplify the neuron and synapse design to behave as analog comparators being driven by the other neurons through simple resistors. We now have a feed-forward neural network model that may actually be practical to build and use.

Referring to Figure 1a and 1b, the network functions as follows: Each neuron receives a signal from the neurons in the previous layer, and each of those signals is multiplied by a separate weight value. The weighted inputs are summed, and passed through a limiting function which scales the output to a fixed range of values. The output of the limiter is then broadcast to all of the neurons in the next layer. So, to use the network to solve a problem, we apply the input values to the inputs of the first layer, allow the signals to propagate through the network, and read the output values.

For the universal approximation, back propagation (BP) is the most broadly adopted learning algorithm (Carbonneau et el., 2008). The output layer gives a response depending on training history of the network. The trained network should be able to acceptably predict outputs for unseen input conditions. The BP algorithm can be expressed as follows:

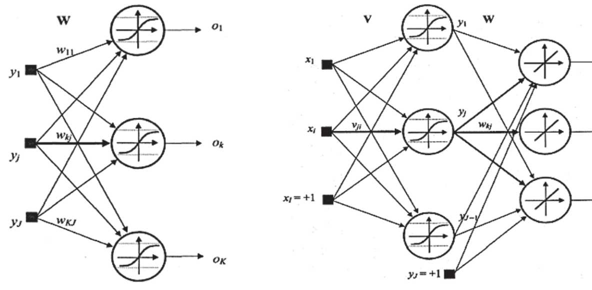

Figure 1. Neural network architecture.

Given $x_j^{[s]}$: the current output state of the j^{th} neuron in layer (s), $w_{ij}^{[s]}$: weight on connection joining i^{th} neuron in layer (s-1) to j^{th} neuron in layer (s) , $I_j^{[s]}$: weighted summation of inputs to the j^{th} neuron in layer (s), l_{coef} : learning coefficient.

1) Feed i to the input layer of the network through the output layer to attain an output vector o. At this stage, summed inputs i_j and output x_j of each neuron will also be calculated.

2) For each neuron in output layer, calculate the scales local error $e_k^{(o)}$ and delta weight

$$e_k^{(o)} = \left(d_k - o_k\right) \bullet f'(I_k) \tag{1}$$

$$delta\ of\ w_{ij}^{[s]} = l_{coef} \bullet e_j^{[s]} \bullet x_i^{[s-1]} + momentum\ (delta\ of\ w_{ij}^{[s]}) \tag{2}$$

3) For each layer, calculate the scaled local error $e_j^{[s]}$ and delta weight

$$e_j^{[s]} = x_j^{[s]}\ (1.0 - x_j^{[s]}) \bullet \sum_k (e_k^{[s+1]} \bullet delta\ of\ w_{kj}^{[s+1]}) \tag{3}$$

4) Add the delta weights to the previous weights to update all weights in the network.

The Quickprop algorithm, (Gutierrez et al., 2008) uses the conception of second order error derivative information instead of only the usual first order gradients. This is based on two hypothesizes. First, the error function ε is a parabolic function of any weight w_{ij}, and second the change in the slope of the error curve is independent of other concurrent weight changes. To compute the weight, the previous value of the gradient $\partial\varepsilon / \partial w_{ij}^{[s-1]}$ and the previous weight change $delta\ of\ w_{ij}^{[s-1]}$ are required. Then

$$delta\ of\ w_{ij}^{[s]} = \frac{\frac{\partial \varepsilon}{\partial w_{ij}^{[s]}}}{\frac{\partial \varepsilon}{\partial w_{ij}^{[s-1]}} - \frac{\partial \varepsilon}{\partial w_{ij}^{[s]}}}\ delta\ of\ w_{ij}^{[s-1]} = \alpha_{ij}^{[s]}\ delta\ of\ w_{ij}^{[s-1]} \tag{4}$$

Proposed neural network model

The architecture of proposed neural network model was presented in Figure 2. The network composed of 3 layers which are 40 nodes in input layer, 20 nodes in hidden layer and 1 node in output layer. According to 40 nodes input, it means we have 40 factors affected to the amount of longan supply. We can classify into 2 groups of effected 40 factors, certainty and uncertainty factors. By applying statistic process, we can obtain the distribution function of the uncertainty factors corresponding to time period as shown in Table 1.

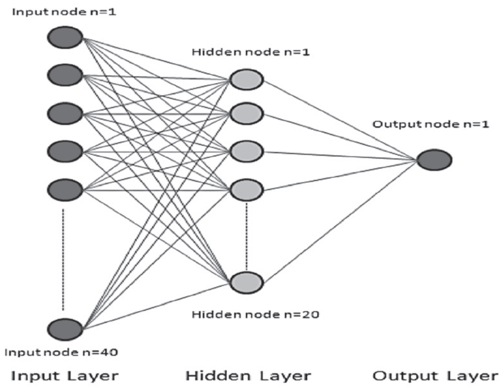

Figure 2. Architecture of the proposed neural network.

Table 1. Distribution function of uncertainty factors corresponding to time period.

Factors	Distribution function			
	April-June	July-Aug	Nov-Dec	Jun-March
Temperature	Tria (24.3, 28.9, 30)	Tria (24, 28.5, 29.8)	6.32 + 16.3 x Beta (2.33, 1.62)	Norm (26, 2.52)
Absolute humidity	67 +Gamm (4.68, 1.87)	18 + 72 x Beta (0.939, 1.17)	Norm (77, 2.78)	Norm (59.3, 8.31)
Wind velocity	0.09+Weib (0.345, 2.41)	Logn (0.176, 0.0961)	Beta (5.54, 5.18189)	1.33 x Beta (1.19, 2.51)
Rain fall	Expo (4.04)	Weib (0.109, 0.402)	Expo (0.111)	Expo (0.124)

We collected the data from three distingue groups of longan agricultures. Fifty seven data sets were obtained. However, these numbers of data sets are not sufficient for training the proposed neural network to forecast efficiently. From the collected data sets and factor distribution function in Table 1 by using monte carlo simulation, we can increase the number of data set to 1,710 data sets. Among 1,710 data sets, we separated into 3 purposed groups, 80% of data sets will be used for neural network training, 10% of data sets will be used for validation and other 10 % will be used for testing. Training process will pursue until the neuron network steady.

RESULTS AND DISCUSSION

At this stage of research, we conduct a number of numerical simulation data sets instead of dealing with the collected data sets. For the purpose of training neural network, Matlab program were developed, based on proposed neural network model. Based on Matlab program, Figure 3 was generated to present the relationship between training iterations (1 iterations = 1,368 data sets) and mean squared error. We can notice from the Figure 3 that at iteration 46 obtained the lowest mean squared error in training, validation and testing process.

It means that all parameters at iteration 46 such as connection weight and bias matched for the neural network to forecast longan supply efficiently.

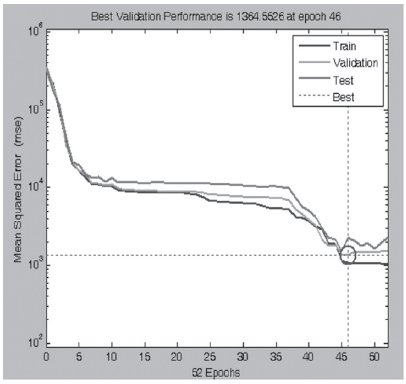

Figure 3. Relationship between number of iterations and sum square error.

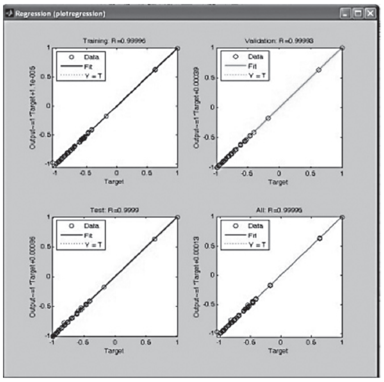

Figure 4. Statistic fitting data.

Figure 4 showed the statistic fitting data in training, validation and testing process. The experimental results presented that proposed neural network worked well in all processes; the forecasting values are nearly the target values. Thus, we could clearly conclude from the results that the proposed neural network is the other potential tool for supply forecasting.

CONCLUSION

This research presented the application of neural network approach in supply forecasting. We have described the approach of obtaining the data and also simulation approach to obtain more sufficient data for training process. Validation and testing have been conducted to confirm the potential of the neural network. However, in solving the forecasting problem by neural network energy function, many factors have influence on the efficiency of the algorithm. They include those numbers of input nodes and number of data sets feed in to the neural network while training process. Besides the efficiency of the algorithm, those will affect to the computation runtime even the training and forecasting process. Consequently, further research may be conducted by reducing the input node with maintain its forecasting accuracy. Additionally, fuzzy neural network will be the solution.

ACKNOWLEDGEMENT

This work was supported by the Higher Education Research Promotion and National Research University Project of Thailand, Office of the Higher Education Commission.

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