A New Modified Back-propagation Algorithm for Forecasting Malaysian Housing Demand

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Abstract. Over the past decade, the growth of the housing construction in Malaysia has been increase dramatically and the level of urbanization process in Malaysia is considered to be important in planning for low-cost housing needs. Unfortunately, there is a clear miss-match between the supply and the demand of low cost housing in Malaysia. Due to the problems faced, there have been several attempts in predicting housing demands using the artificial-neural networks (ANN) technique particularly back-propagation (BP). However, the training process of BP can result in slow convergence or even network paralysis and can easily get stuck at local minima. This paper presents a new approach to improve the training efficiency of BP algorithms to forecast low-cost housing demand in one of the states in Peninsular Malaysia. The proposed algorithm (BPM/AG) adaptively modifies the gradient based search direction by introducing the value of gain parameter in the activation function. The results show that the proposed algorithm significantly improves the learning process with more than 31% faster in term of CPU time and number of epochs as compared to the traditional approach. The proposed algorithm can forecast low-cost housing demand very well with 6.62% of MAPE value.

Introduction

Housing is a basic social need and it is one of the main aspects of urban problems which directly linked to the economy. Every five years National Plan, Malaysia's government has focused on various housing programs to ensure that all Malaysian particularly the low income groups have access to adequate and affordable shelter and related facilities [1].

During the Ninth Plan period, the development of the housing sector continues to focus on the provision of adequate, affordable and quality houses for all Malaysians [1]. The housing category is divided into four main categories including low cost, low medium cost, medium cost and high cost housing. In Malaysia, low cost housing is defined at a ceiling price RM25, 000 per unit or less. Low cost housing can be sold to households with monthly income between RM500 to RM750 while low medium is defined at ceiling price RM25,001 to RM60,000 and can be sold to households with monthly income between RM750 to RM1,500 [2]. On the other hand, the construction cost alone ranges from as low of RM12, 000 per unit to a high of RM43, 000 with average cost RM23,000 per unit for terrace house [1]. Therefore, to ensure an adequate supply of low cost houses for the low income group, any mixed-development projects undertaken by private developers, continued to be guided by the 30% low cost housing policy requirement [1]. Construction each category of housing should build fairly especially in such area which located level of people with the different incomes. By develop low cost and low medium cost housing it can reduce housing growth illegally on government's land and also prevent the public creating other new squatters.

However, there is a clear miss-match between the supply and demand of low-cost housing in Malaysia [3]. At some place the supply of low-cost is over the demand and this lead to waste of over the supply, where the supply of low-cost house is not enough especially at urbanized area. Specific planning for low-cost housing is important to overcome such problems of miss-match between supply and demand.

Furthermore, the present policy of 30% of low-cost house in any housing project is not so practical, since the numbers of low cost houses to be built do not reflect the actual demand of low cost housing. Due to the increment of the demand for low cost houses is very significant and vital; there have been several attempts in predicting housing demands using computational methods [4]. Several relational factors are applied as the input to forecast the demand of housing. However, the lack of information had an effect on the output pattern.

Recently, some papers have found the potential applications of Artificial Neural Networks (ANN) particularly back propagation algorithm as a successful forecasting tools to forecast low-cost housing demand in Johor, one of the states in Peninsular Malaysia [5]. The back-propagation algorithm has been the most popular and most widely implemented algorithm for training these types of neural network [6]. When using the back-propagation algorithm to train a multilayer neural network, the designer is required to arbitrarily select parameter such as the network topology, initial weights and biases, a learning rate value, the activation function, and a value for the gain in the activation function. Improper selection of any of these parameters can result in slow convergence or even network paralysis where the training process comes to a virtual standstill and can easily get stuck at local minima [7].

In this research, a new algorithm will be applied to the current working back propagation algorithm in order to make a future prediction of the number of low-cost houses needed so there shall be no over construction of houses or else insufficient supply of houses to the public. This research suggests that a simple modification to the current working gradient based search direction used by almost all optimization method that has been summarized by Bishop [8] can substantially improve the training efficiency. The gradient based search direction is locally modified by a gain value used in the activation function of the corresponding node to improve the convergence rates respective of the optimization algorithm used.

The remaining of the paper is organized as follows: Section two illustrates the proposed algorithm in gradient descent optimization process. In Section three, the robustness of proposed algorithm is shown by comparing convergence rates and the accuracy of the proposed algorithm on forecasting low-cost housing demand in Johor. The paper is concluded in the final section along with short discussion on further research.

The Proposed Algorithm

In this section, a novel approach for improving the training efficiency of back propagation neural network algorithms (BPM/AG) is proposed.Based on several researchers hypothesis about the existence of a relationship between gain of the activation function and the weights [9] or between the gain and learning rate [10], [11]. This research proposed an algorithm that modifies the initial search direction by changing the gain value adaptively for each node. Gain update expressions as well as weight and bias update expressions for output and hidden nodes have also been proposed. These expressions have been derived using same principles as used in deriving weight updating expressions.

The following iterative algorithm has been proposed for changing the gradient based search direction using a gain value.

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Initialize the initial weight vector with random values and the vector of gain values with unit values.
Repeat the following Steps 1 and 2 on an epoch-by-epoch basis until the given error minimization
criteria are satisfied.

Step 1 By introducing gain value into activation function; calculate the gradient of error with respect
to weights by using Equation (3), and gradient of error with respect to the gain parameter by using
Equation (5)

Step 2 Use the gradient weight vector and gradient of gain vector calculated in Step 1 to calculate
the new weight vector and vector of new gain values for use in the next epoch.
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The derivation expression for modifying gain values for each epoch in most of gradient based optimization methods use the following gradient descent rule:

$$\Delta w_{ij}^{(n)} = -\eta^{(n)} \frac{\partial E}{\partial w_{ij}^{(n)}} \tag{1}$$

Where $\eta^{(n)}$ is the learning rate value at step n and the gradient based search direction at step n is $d^{(n)} = -\frac{\partial E}{\partial w_{ij}^{(n)}} = g^{(n)}$.

In the proposed algorithm the gradient based search direction is modified by including the variation of gain value to yield

$$d^{(n)} = -\frac{\partial E}{\partial w_{ij}^{(n)}}(c_j^{(n)}) = g^{(n)}(c_j^{(n)}) \tag{2}$$

The derivation of the procedure for calculating the gain value is based on the gradient descent algorithm where the error function is differentiated with respect to the weight value w_{ij}^s. The chain rule yields,

$$\frac{\partial E}{\partial w_{ij}^s} = \frac{\partial E}{\partial net^{s+1}} . \frac{\partial net^{s+1}}{\partial o_j^s} . \frac{\partial o_j^s}{\partial net_j^s} . \frac{\partial net_j^s}{\partial w_{ij}^s}$$

$$= [-\delta_1^{s+1} \dots - \delta_n^{s+1}] . \begin{bmatrix} w_{1j}^{s+1} \\ \vdots \\ w_{nj}^{s+1} \end{bmatrix} . f'(c_j^s net_j^s) c_j^s . o_j^{s-1} \tag{3}$$

where $\delta_j^s = -\frac{\partial E}{\partial net_j^s}$. In particular, the first three factors of Equation (5) indicate that the following equation holds:

$$\delta_1^s = (\sum_k \delta_k^{s+1} w_{k,j}^{s+1}) f'(c_j^s net_j^s) c_j^s \tag{4}$$

It should be noted that, the iterative formula as described in Equation (4) to calculate δ_1^s is the same as used in the standard back propagation algorithms [6] except for the appearance of the gain value in the expression. The learning rule for calculating weight values as given in Equation (1) is derived by combining (3) and (4).

In this approach, the gradient of error with respect to the gain parameter can also be calculated by using the chain rule as previously described; it is easy to compute as

$$\frac{\partial E}{\partial c_j^s} = (\sum_k \delta_k^{s+1} w_{k,j}^{s+1}) f'(c_j^s net_j^s) net_j^s \tag{5}$$

Then the gradient descent rule for the gain value becomes,

$$\Delta c_j^s = \eta \delta_j^s \frac{net_j^s}{c_j^s} \tag{6}$$

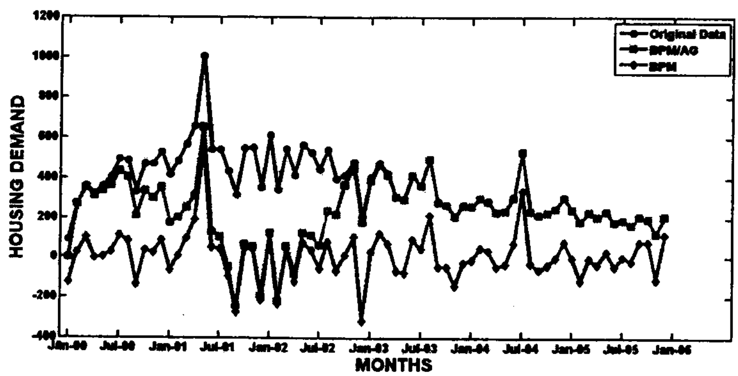
At the end of every epoch the new gain value is updated using a simple gradient based method as given by the following formula, By using the proposed algorithm namely as Back-propagation with Adaptive Gain Variation (BPM/AG), the gradient based search direction is calculated at each step by using Equation (2).

Results and Discussions

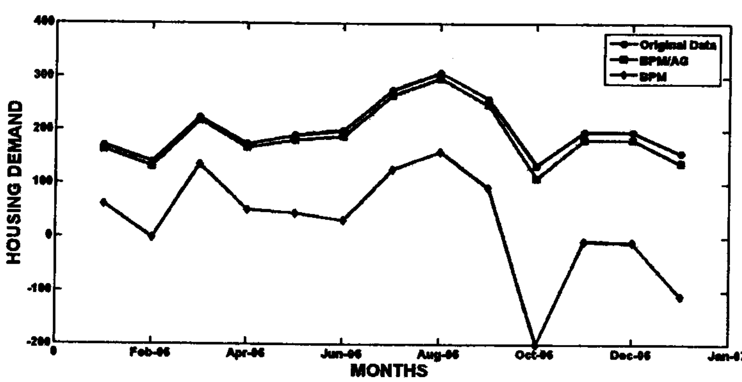
The performance criteria used to asses the result of the proposed method focuses on the effectiveness of models that gave the highest percentage of correct predictions for forecasting low-cost housing demand in Johor. PCA is used to derive new indicators; that is the significant indicators from the nine selected indicators. The indicators are: (1) population growth; (2) birth rate; (3) mortality baby rate; (4) inflation rate; (5) income rate; (6) housing stock; (7) GDP rate; (8) unemployment rate; and (9) poverty rate.

The simulations have been carried out on a Pentium IV with 3 GHz PC, 1 GB RAM and using MATLAB version 6.5.0 (R13). The following two algorithms were analyzed and simulated on the datasets.

1) The standard back propagation with momentum (BPM)
2) The proposed back propagation with momentum and Adaptive Gain (BPM/AG)



(a)



(b)

Fig.1: Results of forecasting the two algorithms on (a) training data; (b) testing data

Figure 1 demonstrates that the convergence speed of the proposed algorithm is high due to the modified gain values. The proposed algorithm required only 559 epochs to achieve the target error, whereas using the same set of initial weight and biases the standard back propagation algorithm with constant unit gain value required 1796 epochs to achieve the target error during training. The results show that there is a dramatic improvement in the learning speed of back-propagation algorithm by using the proposed method.

Summary

A novel approach for improving the training efficiency of back propagation algorithms has been proposed in this paper. The proposed algorithm uses the gain value to modify the initial search direction. The results clearly demonstrate that the proposed method (BPM/AG) is the most effective algorithm to predict low cost housing demand in Johor as compared to the standard algorithms. The proposed method (BPM/AG) need only 559 epochs whereas the standard method need 1796 epochs which is improved by 31.12% performance. The proposed algorithm can be helpful to the related agencies such as developer or any other relevant government agencies in making their development planning for low cost housing demand in urban area in Malaysia towards saving budget, time, man power and reducing the number of under or over construction of low-cost houses in Malaysia.

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