# Controlling and improving quality of the fertiliser production process using neural network models

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**Abstract:** Fertiliser production process is characterised by being a dynamic process which is not easy to be predicted and controlled due to uncertain, imprecise and vague parameters' relations. Although mathematical modelling techniques are very well developed, these types of dynamic processes are difficult to be modelled by those techniques and also the regression models are complex to be used for real time control and, usually, their errors are significant.

The main and most important quality characteristic in the fertiliser production process is the moisture content. This parameter affects the product shelf life, effectiveness and harmful internal reactions.

In this research, two different artificial neural network (ANN) approaches are developed to predict the moisture content of the produced fertiliser: the back-propagation multilayer perceptron (BPMLP) and the radial basic function (RBF) nets. The two models performed satisfactory in predicting the moisture content with low error percent. Predicting the moisture content, the quality of the produced fertiliser can be enhanced either by reheating, adding chemicals, or both.

**Keywords:** fertiliser industry; MLP neural network; RBF neural network; process control; quality improvement.

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## 1 Introduction

Fertiliser production is a chemical mixing process of several components under heating such that certain elements will be contained in the produced mixture with prespecified percentages. Moisture content in the resulted product is an important quality characteristic that should be predicted and controlled because of its negative effects on the product's shelf life and effectiveness. It is fortunate that the moisture content, when it is known to be beyond acceptable limits, can be recovered by reheating (drying) the output product for a time period that depends on that moisture level. Accordingly, it is important to have a prediction system that estimates the moisture level in the produced fertiliser such that a corrective action (either reheating, adding chemicals, or both) can be taken to sustain the product quality, and this is the aim of this research.

Unfortunately, because of many affecting parameters, the fertiliser production process is not simple to be mathematically modelled; or the suitable math-models [like those by Duy and Tanner (2005), Li et al. (2007), Zuppa (2003), or Suykens and Vandewalle (1999)] could be too complex to be used in real-time control. The answer to this problem is to utilise the artificial neural network (ANN) in predicting the moisture content. ANN is capable of approximating continuous non-linear functions and they have been applied to non-linear process modelling (Fabri and Kadirkamanathan, 1996). The major task of an ANN is to learn the model of the environment in which it is embedded and maintained consistently with the real-world problems, so as to achieve the specific goals of the application of interest. The observations so obtained provide the pool of information to train the neural network (NN).

The methodology adopted in this research includes the following steps. First, the production process in 'Technogreen Group' Company of Fertilisers, Borg ElArab, Egypt, was described and analysed to determine, or identify, the process's controllable parameters that affect the resulted moisture content. Data are then collected which included values of the process parameters and the corresponding output moisture content (the main quality parameter). Next, the NN models are developed (trained and verified) and their performance is evaluated. Quality improvement actions are then potentially taken to get rid of the excess undesirable moisture by reheating for suitable time period.

Although this research methodology is applied here to the fertiliser production process, it can be also applied to control similar dynamic, non-linear, complex processes by predicting their quality characteristics based on the values of the input parameters, and then controlling them. Among those applications are food industries (Jeng, 2003), ceramic industries (Taylan and Haydar, 2004), maintenance (Wu and Tws, 2004) and material science (Rashed and Mahmoud, 2002).

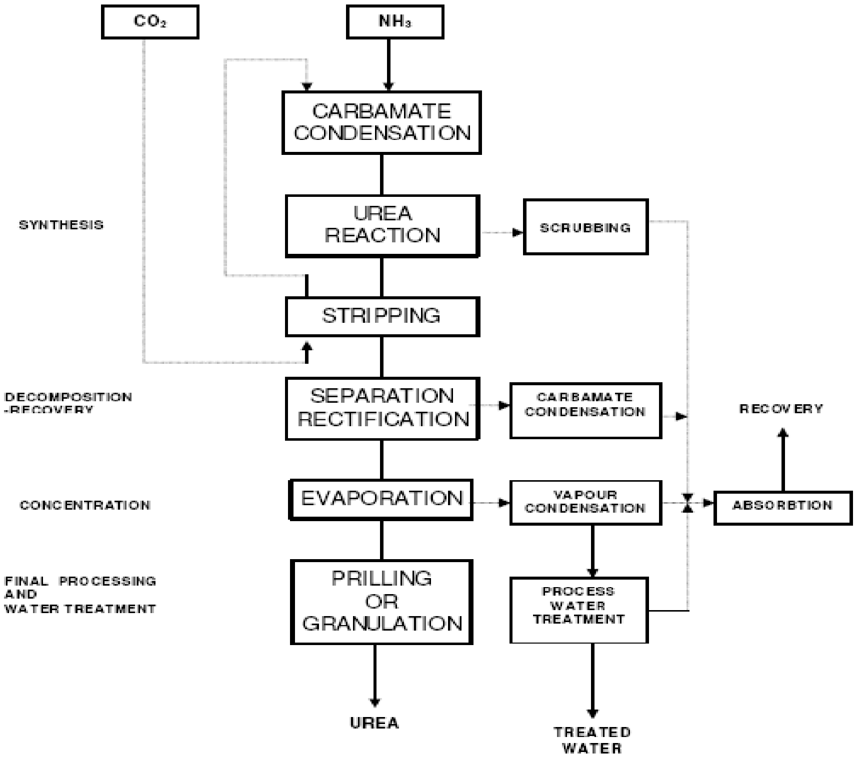
## 2 Process description and analysis

Figure 1 describes the process flow of fertiliser production process. The raw materials are prewashed, drayed and mixed to be prepared for chemical reactions inside the furnace. The design of commercial processes involves major considerations:

- to separate the urea from other constituents
- to recover excess NH3
- decompose the carbamate for recycle.

The produced fertiliser usually contains vapour as a result of the chemical reaction and non-sufficient extraction of that vapour lefts undesirable moisture which lowers the quality of the fertiliser. Extracting vapour (or reducing moisture) depends on many parameters and this is the main concern of this research.

**Figure 1** The processes involved in fertiliser production process




Many operational variables associated with fertiliser production process and the drying operation can alter the characteristics of the output products. After thorough analysis of the manufacturing process with the quality control staff of Technogreen Group Company, the affecting parameters on the process characteristics are suggested and recommended; and the required data are collected. It was found that there are five parameters that can be considered significantly affecting the product quality. The parameters affecting the moisture content are:

1 the inlet temperature

2 the outlet temperature

3 the feeding rate

4 the pressure of the production system

5 the amount of added chemicals.

These concluded parameters are compatible with those of other researches who are interested in fertiliser quality like Hshuan et al. (2001), Hshuan (2008) and Song (2004).

For a fixed moisture content and dryer design, the outlet temperature (parameter 2) must be kept within a narrow range to allow for the flow requirements and packing. The increase in the outlet temperature decreases moisture content at constant air-flow and heat input conditions. The increase in the inlet temperature (parameter 1), which is the first parameter that affects the moisture content of fertiliser, increases the evaporative capacity at constant air rate (Hshuan, 2008; Hogetsu 2005). Increased inlet temperature often causes a reduction in bulk density, as evaporation rate is faster than product drying, so it causes a more porous or fragmented structure.

The feed rate (parameter 3) is another affecting parameter (sometimes called in-system time). An increase in feeding rate will result in producing coarser product at fixed operating conditions. Increasing the feed rate (lower in-system time) affects evaporation characteristics and usually causes higher moisture content (Agrium, 2004; Mark and Wysor, 2005; Van and Tijskens, 2005).

The pressure of the production system (parameter 4) gives control over the feeding rate and, in turn, on the moisture content. Increase of system pressure affects positively the flow rate of the product which increases the evaporation rate under normal air flow (Agrium, 2004; Rod and Craswell, 1997).

Finally, as an attempt from the process controllers, some chemicals are added to absorb the excess moisture and getting rid of unwanted elements (Hshuan et al., 2001; Agrium, 2004). The amount of these chemicals is restricted by narrow ranges because of their side effects on the specifications and effectiveness of the produced fertiliser (Mark and Wysor, 2005; Rod and Craswell, 1997; Hogetsu, 2005; Ibis World, 2009).

The above brief analysis of the fertiliser production process explains that the relationship between the moisture content and the input controllable parameters are highly non-linear and the parameters' interactions are not easy to be mathematically modelled. These non-linear relations can be better modelled using non-linear empirical modelling techniques. NNs are capable of approximating continuous non-linear functions, and have been applied to non-linear process modelling (Stanislav et al., 2008). A major task for a NN is to learn a model sufficiently consistent with the real world so as to achieve the specific goals of the application of interest. In any event, the observations so obtained provide the pool of information from which the examples used to train the NN are drawn.

In this work, two different types of ANN models are designed to predict the process performance and to represent the knowledge about the fertiliser production process. The first model is the back-propagation multilayer perceptron (BPMLP) and the second one is the radial basic function (RBF) network. These two models are usually recommended to model non-linear complex systems; and also they are suitable to be used for online applications because of their fast response (Azadeh and Faiz, 2007). The two models are characterised by their power of interpolation in multidimensional space (Stanislav et al., 2008) and that suits the fertiliser process characteristics. In the next section, these two models will be presented in detail to explain their design parameters that will be determined experimentally in Section 4.

## 3 The NN models

An ANN, often just called a 'neural network' (NN), is a mathematical model or computational model based on biological NNs. It consists of an interconnected group of artificial neurons and processes information using a connectionist approach to computation. In most cases, an ANN is an adaptive system that changes its weights based on external or internal information that flows through the network during the learning phase. In more practical terms, NNs are non-linear statistical data modelling tools. They can be used to model complex relationships between inputs and outputs or to find patterns in data. Generally speaking, ANNs are computing systems made up of a number of simple highly interconnected signals or information processing units that are called artificial neurons.

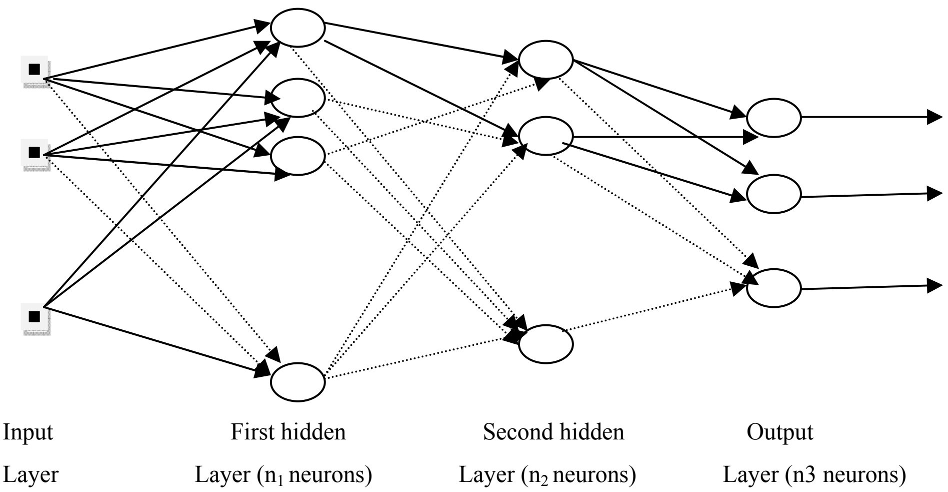
In this research, two different models of NN are used to model the fertiliser production process. The first approach is the BPMLP algorithm. This model is a feed forward network in which neurons are arranged in a feed forward manner (Zbeda and Nathan, 2005). The second approach is the RBF network. This model is selected because it transforms the information from input space to output space non-linearly (Adriano et al., 2005); and that suits the characteristics of the process under study.

The reason for using more than one model in this work is to prove that the ANN is suitable for the problem under study; beside, of course, to realise the better model in terms of the error percentage results. The two models will be discussed, in detail, to figure out their design parameters that will be selected for the case under study. The collected data will be used later to determine the suitable values of these design parameters.

### *3.1 The first model: the BPMLP*

The used network' architecture is shown in Figure 2. It consists of $n_o$ input neurons (input layer) followed by two hidden layers that contain $n_1$ and $n_2$ neurons; and finally an output layer with $n_3$ artificial neurons.

**Figure 2** Multilayer perceptron (MLP) network architecture




The MLP is supposed to perform a specific non-linear mapping which can be expressed in terms of a given set of learning examples. Learning of MLP consists in the adaptation of all synaptic weights in such a way that the discrepancies between the actual output signals and the desired signals (the errors), averaged over all learning examples, are as small as possible. The standard back propagation algorithm uses the steepest descent algorithm to minimise the mean squared error function (Zbeda and Nathan, 2005). The error function for the pth example is defined as follows:

$$\text{Ep} = \frac{1}{2}\sum\nolimits_{j=1}^{n3}\left(d_{jp} - y_{jp}\right)^2 = \frac{1}{2}\sum\nolimits_{j=1}^{n3} e_{jp}^2 \quad (1)$$

where $e^2_{jp}$, $d_{jp}$ and $y_{jp}$ are the instantaneous squared error, desired output signal and the actual output signal for the pth learning example respectively. The global error function can be summed over all learning examples and can be given as follows:

$$E_{total} = \sum\nolimits_p E_p = \frac{1}{2}\sum\nolimits_p \quad \sum\nolimits_j e_{jp}^2 \quad (2)$$

In this work, the online algorithm to update the weights is used, where by, for each learning example presented as an input, all weights are updated before the next learning example is presented. In this algorithm, all the synaptic weights $w_{ij}$ are changed by an amount of $\Delta w_{ij}$ where:

$$\Delta w_{ij} = -\eta \frac{\partial E_p}{\partial w_{ij}} \qquad \eta > 0 \quad (3)$$

In the above equation, $\eta$ is a learning constant parameter. The formula for updating the weights can be stated as follows:

$$\Delta w_{ij} = -\eta \delta_j o_i \quad (4)$$

where $\delta_j$ is the local gradient of the hidden neuron j and $o_i$ is the function signal at the output of neuron i. This function signal $o_i$ at the output of neuron i is obtained by passing the weighted sum of inputs to neuron i from a non-linear activation function. The activation function chosen in this work is a unipolar sigmoid function which can be defined as follows:

$$o_i = \psi(\mu_i) = \frac{1}{1 + exp\,(-\gamma_i \mu_i)} \quad (5)$$

where $\gamma_i > 0$ is a constant value.

In equation (5), $\mu_i$ is the weighted sum of the inputs to the neuron i; and for the first hidden layer it can be defined as:

$$\mu_i = \sum\nolimits_{j=1}^{n_o} w_{ij} x_j + \theta_i \quad (6)$$

where $\theta_i$ is a bias value and $x_j$ is the jth component of the input pattern. The local error of the internal hidden layer is determined on the basis of the local errors at the upper layer. Starting with the highest output layer $\delta_j^{out}$ which is a vector of the local gradient at the output layer of the jth neuron using the equation given as:

$$\delta_j^{out} = \left(d_{jp} - y_{jp}\right)\frac{\partial \psi_j^{out}}{\partial \mu_j^{out}} \quad (7)$$

where $\psi_j^{out}$ is the unipolar sigmoid function at the output layer. Smoothing the weight changes by over relaxation can be used to improve the back-propagation learning. This can be defined as:

$$\Delta w_{ij}(k) = \eta \delta_j o_i + \alpha \Delta w_{ij}(k-1) \quad (8)$$

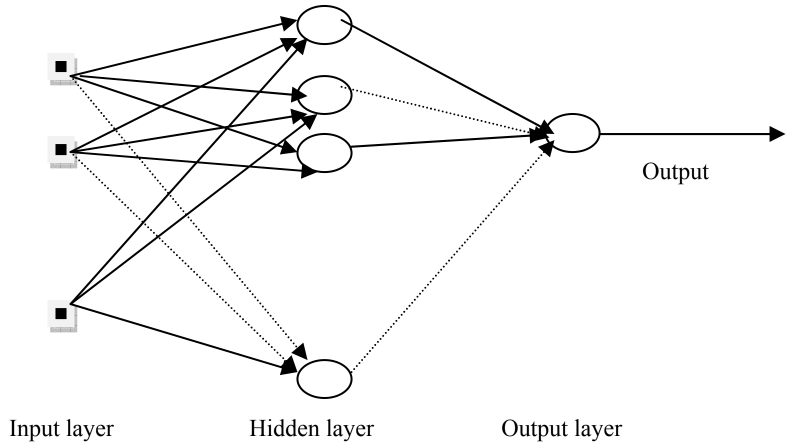
where $0 \le \alpha < 1$

The second term in equation (8) is called the momentum term that makes the current kth search direction an experimentally weighted average of the past $(k-1)^{th}$ directions. This term damps the effect of the learning parameter, $\eta$, that may cause parasitic oscillations which prevent the algorithm from converging to the desired solution (Zbeda and Nathan, 2005). Thus, it enables the improvement of the convergence rate and the steady state performance of the back-propagation multilayer learning algorithm.

### *3.2 The second model: the RBF network*

RBFs are powerful techniques for interpolation in multidimensional space (Stanislav et al., 2008). RBF is a function which has built into a distance criterion with respect to a centre. RBF have been applied in the area of NNs where they may be used as a replacement for the sigmoidal hidden layer transfer characteristic in multi-layer perceptrons. RBF networks have two layers of processing: In the first, input is mapped onto each RBF in the 'hidden' layer. The RBF chosen is usually a Gaussian. In regression problems, the output layer is then a linear combination of hidden layer values representing mean predicted output. The interpretation of this output layer value is the same as a regression model in statistics where there is a difference between the predicted and actual value. In classification problems, the output layer is typically a sigmoid function of a linear combination of hidden layer values, representing a posterior probability. Performance in both cases is often improved by shrinkage techniques, known as ridge regression in classical statistics and known to correspond to a prior belief in small parameter values (and therefore smooth output functions) in a Bayesian framework (Adriano et al., 2005; Haykin, 2004).

**Figure 3** RBF network




RBF networks have the advantage of not suffering from local minima in the same way as multi-layer perceptrons. This is because the only parameters that are adjusted in the learning process are the linear mapping from hidden layer to output layer. Linearity ensures that the error surface is quadratic and therefore has a single easily found minimum 23 and 25. RBF networks have the disadvantage of requiring good coverage of the input space by radial basis functions. RBF centres are determined with reference to the distribution of the input data, but without reference to the prediction task. As a result, representational resources may be wasted on areas of the input space that are irrelevant to the learning task. A common solution is to associate each data point with its own centre, although this can make the linear system to be solved in the final layer rather large, and requires shrinkage techniques to avoid overfitting (Adriano et al., 2005).

The second model that used in this work utilises these features mentioned above in the prediction process. The developed network is presented in Figure 3. It consists of an input layer, one hidden layer and an output layer.

The transformation from input space to output space is non-linear and the transformation from hidden unit space to output space is linear (Haykin, 2004). The set of basis functions $\{\varphi_i(x) \mid i = 1, 2, \ldots, M\}$ is defined as follows:

$$\phi_i(x) = G\left(\|x - t_i\|\right) = \exp\left(-\|x - t_i\|\right), \qquad i = 1, 2, \ldots, M \tag{9}$$

where $\{t_i \mid i = 1, 2,.., M\}$ is the set of $M$ centres to be determined and x is the one of the training (input) data in a set $\{x_i \mid i = 1, 2,.., M\}$ of size $N$. Typically, the number of basis functions is less than the number of data points (i.e., $M \leq N$). The aim is to find the suitable $w$ values in order to minimise the Euclidean norm $\|d - Gw\|^2$, where $d = [d_1, d_2,\ldots.d_N]^T$.

$$G = \begin{bmatrix} G\left(\|x_1 - t_1\|\right) & G\left(\|x_2 - t_2\|\right) & \cdots & G\left(\|x_1 - t_M\|\right) \\ G\left(\|x_2 - t_1\|\right) & G\left(\|x_2 - t_1\|\right) & \ddots & G\left(\|x_2 - t_M\|\right) \\ G\left(\|x_N - t_1\|\right) & G\left(\|x_N - t_2\|\right) & \cdots & G\left(\|x_N - t_M\|\right) \end{bmatrix} \tag{10}$$

$$\text{and } w = [w_1, w_2, \quad \ldots., w_M]^{\mathrm{T}}$$

The vector $d$ is an N-dimensional desired response vector, the matrix $G$ is an $NxM$ matrix of Green's functions and the vector $w$ is an $M$ $x$ 1 weight vector for the linear transformation from hidden unit space to output space. The minimum norm solution to the over-determined least squares data fitting problem can be given as follows:

$$w = (G^T G)^{-1} G^T d \tag{11}$$

The set of centres $\{t_i \mid i = 1, 2,.., M\}$ can be selected randomly from the set of data points, and can be selected using the clustering techniques to find the suitable centres or can be selected using gradient descent algorithm (Wu and Tws, 2004) In this study, we used random selection and also K – means clustering algorithm (Adriano et al., 2005) to find the set of centres for the radial basis functions.

## 4 Experimental work and results

In this research, the author collected 520 set of data for input and output parameters from the fertiliser production process in Technogreen Company. The collected data was taken from the factory's quality control lab; where it was observed over a six-month time period. During this period, three different batches of raw material with different characteristics were used. Samples of output production were taken to the lab to be measured their characteristics; and records were filled by the staff. The sampling process is implemented taking into account the aspects by Thompson (2004). Each set of data includes five input parameters and an output parameter shows the moisture content percentage. The five input parameters and the output parameter are normalised using the formulas exhibited in Table 1. This normalisation helps overcoming the great differences between the values of the five input parameters (Taylan and Haydar, 2004; Haykin, 2004). The output parameter is also normalised to rescale it in the (0–1) range. However, in the calculation of training errors and testing errors, using equations (1) and (2), the predicted values are multiplied by ten and compared to the desired values. Among the collected 520 data set, 400 of them were randomly selected for training and the rest 120-set were used for testing.

**Table 1** The input and output parameters normalising formulas

| | *Parameter* | *Symbol* | *Normalising formula* |
|---|---|---|---|
| 1 | The inlet temperature °C | P1 | $P1_{norm} = (P1 - 200)/50$ |
| 2 | The outlet temperature °C | P2 | $P2_{norm} = (P2 - 80)/10$ |
| 3 | The feeding rate (k/sec) | P3 | $P3_{norm} = (P3 - 20)/10$ |
| 4 | The system pressure (bar) | P4 | $P4_{norm} = (P4 - 10)/10$ |
| 5 | The added chemicals | P5 | $P5_{norm} = (P5 - 50)/10$ |
| 6 | The moisture content | P6 | $P6_{norm} = P6/10$ |

## *4.1 Design and results of the MLP model*

As mentioned, while describing the model in Section 3, there are some system design parameters that should be selected. These parameters affect the effectiveness and convergence of the back propagation learning process. Three parameters are to be selected here, namely: the learning constant ($\eta$), the momentum parameter ($\alpha$) and the number of neurons in the two hidden layers $n_1$ and $n_2$. According to Zbeda and Nathan (2005), there is no single learning constant value suitable for different training cases and accordingly, $\eta$ is usually selected experimentally for different cases. A large value of $\eta$ could speed up the convergence but might result in overshooting while a smaller value of $\eta$ has a complementary effect. The momentum parameter $\alpha$ is mainly helping to speed up the convergence and to achieve an efficient and more reliable learning profile. The momentum parameter $\alpha$ is in the range of (0, 1) and usually set at 0.9 (Azadeh and Faiz, 2007). The third important parameter to be selected is the number of neurons $n_1$, $n_2$ in the two hidden layers. The exact analysis of this issue is not easy because of the complexity of the network. Hence, the parameters $n_1$, $n_2$ usually determined experimentally.

In order to select the design parameters, the author conducted some experimental work. MLP networks are established with different values of parameters, trained with the 400 training data sets, and evaluated their performance with the rest evaluating 120 data sets. Matlab 7.0 was utilised in establishing the networks. The total training error is used as an effectiveness measure for the network performance. Table 2 summarises the different parameters' values used in the experimental work.

**Table 2** Experimental design parameter values of the MLP network model

| *Learning constant (η)* | *0.1* | | | *0.15* | | | *0.2* | | *0.5* |
|---|---|---|---|---|---|---|---|---|---|
| No. of neurons $n_1 \times n_2$ | 5 × 3 | 5 × 5 | 5 × 7 | 7 × 3 | 7 × 5 | 7 × 7 | 9 × 3 | 9 × 5 | 9 × 7 |
| Momentum parameter (α) | | | | | 0.9 | | | | |

A fully factorial experimentation scheme is implemented where 36 experiments were conducted (4 learning constants × 9 values of $n_1$, $n_2$ × 1 momentum parameter value). Figure 4 exhibits the results of this experimental work where the total errors corresponding to different set of parameters are plotted. From Figure 4, one can conclude that the best combination of parameters to be selected are: $\eta = 0.15$, $n1 = 7$, $n2 = 5$, and $\alpha = 0.9$.

**Figure 4** Total error for different number of neurons at different learning constants (see online version for colours)

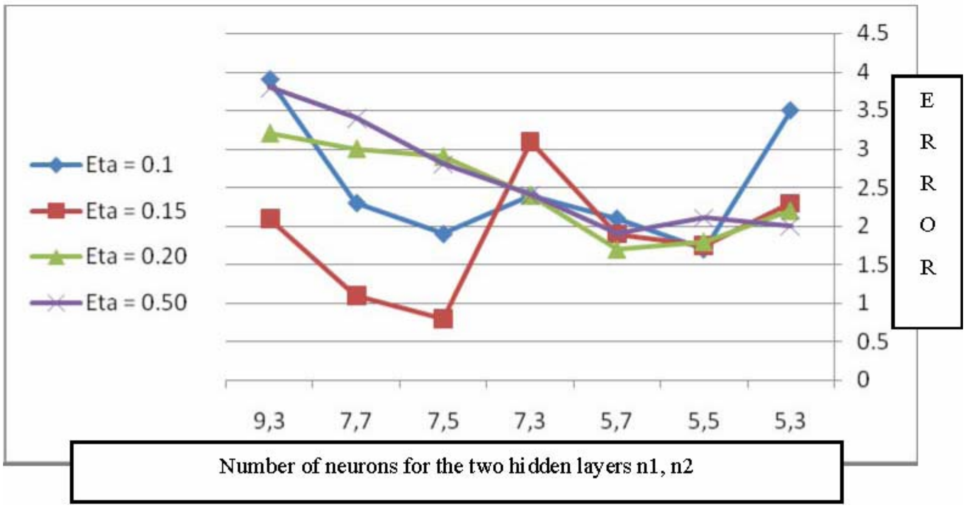
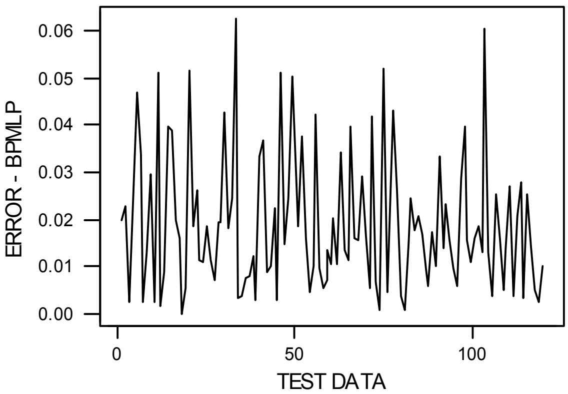



**Figure 5** Errors resulting from validation of the MLP-NN model

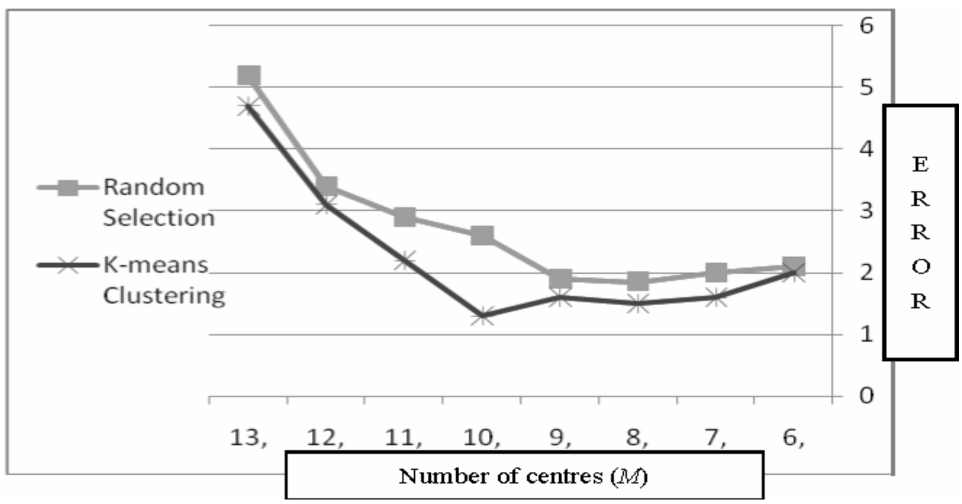


Using these selected values of parameters, the 120 test data are applied to the network selected; and the resulted testing errors (the difference between the desired outputs and the actual outputs) are obtained and plotted in Figure 5. From this figure, one can observe that almost all the predicted values of the test data are very close to the actual values. The sum of errors for the 120 data set is equal to 2.26 with an average error of less than 0.019 (1.9%).

## *4.2 The RBF model design and results*

The number of basic functions $M$ and the initial set of centres ($t_i \mid i = 1, 2,.., M$) are the main design parameters of this model. The selection of these parameters and their effects are investigated by conducting an experiment using different values of basic functions ($M$ = 6, 7,…., 13) and using two different selection methods, namely, random selection and K-mean clustering method. Matlab 7.0 was used to establish the nets and calculate the errors.

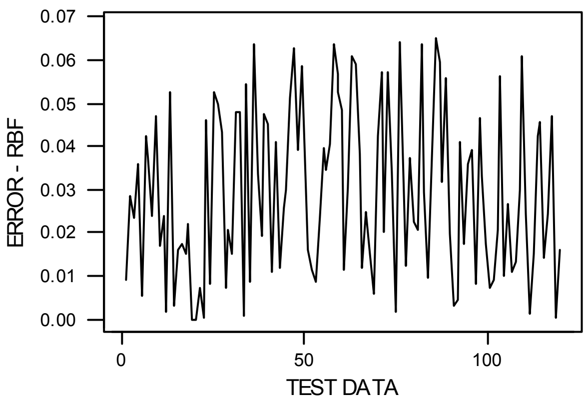
**Figure 6** Total error for different number of centres for RBF




The 400 training set of data are used to determine the errors of the predicted moisture content corresponding to different parameters' combination. The results of this experiment are exhibited in Figure 6.

From Figure 6, one can observe that the selection of $t_i$' s through the use of K-means clustering method outperforms the random selection in terms of the resulted prediction errors. Also, it can be concluded that nine to ten basic functions are enough to model the system under study. Hence, by selecting $M$ = 10 and using the K-means clustering algorithm for the centres selection, the weights of the BRF network are found using the 400 training data set. By using these weights, the prediction errors for the 120 evaluating data set are calculated, as done in the first model. Figure 7 exhibits these error values. The sum of these errors is found equal 3.54 with an average value of 0.029 or 2.9%.

**Figure 7** Errors resulting from validation of the RBF-NN model




The results exhibited in Figures 5 and 7 measure and validate the performance of the two net models. Generally, the two models gave satisfactory results considering prediction of the moisture content in the produced fertiliser; and accordingly, they can be considered as good solution for the problem under investigation. Analysing the results in Figures 5 and 7, one can conclude that the MLP model is dominant to the RBF model; and accordingly, the MLP model is recommended for the problem under study.

## 5 Conclusions

The quality of the fertiliser manufacturing process in Technogreen Group Company is analysed for control and enhancement. The moisture content percentage, the major quality characteristic, is found affected by five controllable factors that are non-linearly interrelated. Two models of NN are developed, using Matlab 7.0, to predict and control the moisture content, the MLP and the RBF models. 520 data sets are collected to design and validate the NN models. 400 data sets are used to train the NN models and the rest 120 sets are used to test the performance of the two models. The performance is characterised by the ability of the model to predict the moisture content and measured by the deviation of the predicted values from those corresponding actual values. It was found that the MLP model gives better results (an average error of 1.9%) than that of the RBF (2.9%). In general, the NN models give good results in predicting and controlling the fertiliser manufacturing process on line. Predicting the moisture content in the fertiliser produced, the quality of the product can be enhanced immediately either by reheating, adding chemicals, or both.

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