A Quality Control-Based In-process Artificial Neural Network Surface Roughness Prediction System

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Abstract

In-process surface roughness (Ra) prediction systems for CNC machining incorporate quality control inspection while machining instead of performing inspection post-production. Such systems generally consist of a sensing technology and a decision making model. Data preprocessing is established as a necessary but often overlooked step in data analysis. Using acoustic emission (AE) signals as a sensing technology and artificial neural network (ANN) as a decision making model, the researchers were able to build and compare two ANN models using input variables feed rate, frequency, and peak volume— an original unfiltered ANN and a quality control-based filtered ANN which uses an individual quality control chart as a data preprocess. Based on a milling process dataset, results show that the QCbased ANN model makes better, more accurate Ra predictions, with a mean square error (MSE) of 0.0214, compared to the original unfiltered ANN, with an MSE of 0.0189. These results prove the success of the QC-based in-process ANN Ra prediction system.

Keywords: CNC machining, surface roughness prediction, AE signals, artificial neural network, data preprocessing

1 Introduction

CNC machining has been in use by many modern manufacturing companies such as those in the aerospace and automobile industry which typically use CNC machining for end milling operations, helping to improve product quality, while increasing productivity. However, CNC machining does not guarantee total defect elimination. The machining operations that the CNC is capable of are subject to various factors that influence the outcome and thus the quality of the products (Huang et al., 2015).

Quality control inspection is used to ensure that defective products do not reach the market. The problem with inspection, on the other hand, is that it takes too much time and labor to execute. Although it ensures quality, it sacrifices productivity in the process, thus increasing cost as well (Huang, 2002).

Previous researches have aimed to solve this problem by proposing in-process monitoring systems (Chen & Huang, 2003; Delio et al., 1992; García Plaza et al., 2017; Lai et al., 2016; Yen et al., 2013) that ensure product quality in real time at the least possible cost. The goal is to incorporate quality control within the machining instead of performing quality control after the defects have occurred.

It has been established that surface roughness (Ra) can be used as an index of product quality as well as tool conditions. Surface roughness serves as an index for tool wear as well, thus making in-process monitoring of surface roughness serve more purpose than that of tool condition monitoring alone (Huang, 2002).

In-process monitoring systems primarily require two components; namely the sensing technology and the decisionmaking model (Huang et al., 2015).

Studies (Lee et al., 2006) generally suggested the application of AE signals for ultra-precision scale monitoring such as in surface roughness and subsurface damage monitoring. Precision manufacturing processes entails the need for precision monitoring (Lee et al., 2006). AE signals' advantage over other sensing technologies is its capability to respond effectively to high-frequency range from submicrometer-level of machining precision (Duro et al., 2016). Ra, among other indices, require a certain signal-to-noise (S/N) ratio and sensitivity to be acquired as a signal. Other sensing technologies will not be able to meet this prerequisite, making AE signals the best option over other conventional sensing technologies (Lee et al., 2006).

A previous work (Roy, 2006) developed a simulation system that can both predict the surface roughness and at the same time optimize cutting condition, as applied in diamond turning. The study combined two soft-computing tools: fuzzy logic and genetic algorithm. Other previous studies (Huang, 2016; Kwon et al., 2002) combined the principles of artificial neural networks (ANN) and fuzzy logic. Other works (Nalbant et al., 2007) compared the prediction performance of ANN with multiple regression analysis. These studies have shown that ANN is more superior in this aspect.

A prior research (Kotsiantis et al., 2006) conducted a study given the knowledge that Machine Learning algorithms are capable of successfully processing the data inputted into their systems. However, at times, the problems lie within the datasets. Datasets can sometimes be too saturated and redundant. Datasets also, more often than not, contain data that deviate from the rest among the set (referred to as outliers). These render the datasets unreliable. The solution proposed for this problem is data preprocessing.

This study utilized an individual quality control chart to remove data deviations that lie beyond the 3-sigma limits, rather than the use of other data outlier removal techniques. Quality control is used as a data pre-process technique instead of using it after production as a remedial stage.

Through this paper, the authors have determined what characteristics of AE signals influence surface roughness, built an original unfiltered neural network model, built a quality control-based filtered neural network model, and verified and compared the results between the two artificial neural network models.

A quality control-based in-process neural network surface roughness prediction system was developed to strengthen the research field in the topic of in-process surface roughness prediction through the use of artificial neural networks and in the field of data preprocessing.

2 Methods

2.1 Sources of Data

In this study, the researchers used AE signals as a sensing technology, and ANN as a decision-making model. The data used in this study were originally acquired by Yu-Xuan Jiang Xie in his own study and the researchers acquired some of its useful data to further the previous studies on the development of an in-process surface roughness prediction system.

The experimental set-up consists of a CNC machine, with the machining tool above the workpiece material. The microphone that picks up the AE signals was placed beside the material. The AE signals the microphone acquired were converted by the Data Acquisition (DAQ) instrument into the computer software. The Ra values were obtained using a surface profilometer with a contact stylus.

Originally, some values included in the acquired raw dataset are machining parameters such as speed, feed rate (shown as "feed") and depth of cut (shown as "depth"), AE signals such as frequency and peak volume at each their highest and average values. The initial raw dataset acquired is divided into three trials; each consisting of 80 data for a total of 240 data, as obtained through a milling process using a CNC machine. In this study, speed and depth of cut are constant at 1600 RPM and 2 mm, respectively. Since these values are constant, they can be disregarded as parts of the Input dataset. Only the feed rate is retained in the Input dataset, and from here on will be referred to as FEED.

2.2 Procedure

The researchers recognized the need to resolve the inefficiency and decrease of productivity of the machine during offline inspection and the possible consequence of inaccuracy of the model if there are deviations in the data. Through this study, a quality control-based in-process neural network system was developed for the prediction of surface roughness. The main objective of this study is to compare two neural network models: an original neural network without the proposed preprocess and a proposed neural network with an individual control chart preprocess. The goal is to verify the accuracy of the proposed neural network and to determine if there exists a significant difference compared with the original neural network. Figure 1 presents the conceptual framework of the study. From this figure, the researchers developed the two models: the original artificial neural network (original ANN) model and the quality control-based artificial neural network (QC-based ANN) model.

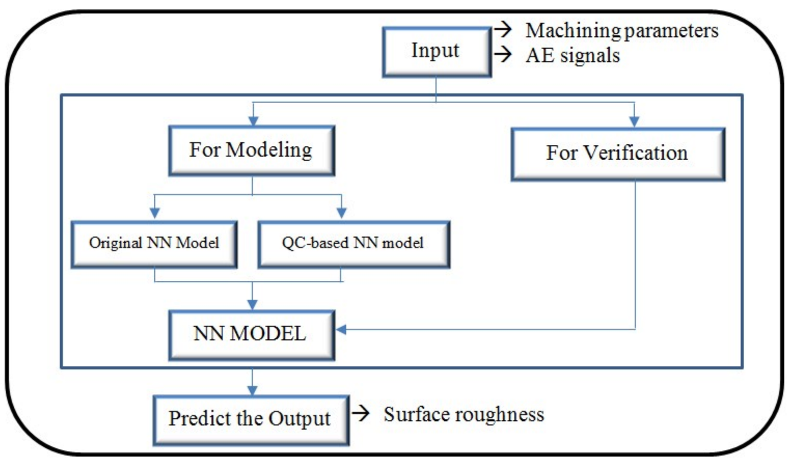

Figure 1. Conceptual framework of a quality control-based in-process artificial neural network surface roughness prediction system

The Input dataset was processed through simulating the networks to get the predicted Ra values for both the modelling and verification data. These predicted Ra values were compared with the actual Ra values for both subsets.

The first phase of the study is to determine what characteristics of AE signals influence Ra. Through review of related literature, possible factors and characteristics of AE signals were identified and compared. The raw dataset contains the initial data obtained through a milling process using a CNC machine, specifically, the machining parameters, AE signals and the corresponding Ra. The researchers considered frequency and peak volume as AE signals in this study through review of related literatures. Frequency is defined as the number of complete oscillations per second of energy (as sound or electromagnetic radiation) in the form of waves. Peak volume is the maximum volume of noise that occurred during the milling process.

The second phase is to build the original ANN Model. In this phase, there are two parts, first is the data grouping process for the ANN model and second is the ANN modelling. The first part was the data grouping for ANN model where the Input dataset was arbitrarily subdivided into two subsets: modelling data and verification data. The second part was the building of the original ANN model.

The Input dataset now contains all the useful data for the commencement of the study. The Input data has undergone min-max normalization to adjust values from 0 to 1; by normalization, the entire probabilistic distribution of data will be aligned.

To develop an ANN model, the researchers divided the Input dataset into two subsets, the modelling data and the verification data. Also, training the neural network requires the assignment of data for INPUT, OUTPUT and TARGET. INPUT, OUTPUT and TARGET data will all come from the modelling data and verification data. The input factors are the machining parameters and the significant AE signals. The input factors of the modelling data were assigned as the INPUT, the input factors of the verification data were assigned as the OUTPUT, and the Ra of the modelling data is the TARGET.

The second part of the second phase is the modelling of the original ANN. The review of related literature supports why artificial neural network is the best decision-making model to use. In this study, the researchers developed two models, the first original model was not preprocessed using an individual quality control chart, discussed as follows.

Generally, neural networks have corresponding weights and biases after training. The researchers used an experimental design with i factors and j levels in neural network training in determining which combination yields the lowest possible mean square error, MSE. Where i factors are the functions and j levels are the specifications. In this study, the determination of the total number of neural network training combinations, x, can be expressed as:

$$x = k \times l \times m \times t \tag{1}$$

where k is total number of training functions, l is total number of learning functions, m is total number of transfer functions and t is the number of repetitions that all combinations will be repeated.

The number functions and number of repetitions vary according to preference of the researchers. Through altering the training parameters, the researchers will be able to identify which network has the lowest average mean square error (MSE). This network will be simulated and its predicted Ra values will be compared with that of the QC-based neural network.

The first part of the third phase was the preprocessing of the data. The Input data was pre-processed, an individual quality control chart was used to remove data deviations that lie beyond the 3-sigma limits. Quality control was used as a data pre-process technique instead of using it after production as a remedial stage. The remaining data of the Input data after preprocessing was used as a new preprocessed set of data (from here on referred to as “preprocessed Input data”) which was assigned as the Input data of the QC-based ANN model.

The second part of the third phase was the developing of the QC-based ANN model. The same process and procedure with the original ANN model was used to process the QC-based ANN model. The same INPUT, OUTPUT, and TARGET assignments were made accordingly. The only difference is that, in QC-based ANN model, the preprocessed Input dataset was used. The researchers still used the same set of training parameter combinations used in the original ANN training. The network with the training parameter combination which yields the lowest MSE was simulated and its Ra prediction values was compared with that the original ANN model.

The fourth phase was the comparison of the two ANN models. Ra predictions simulated for both the modelling and verification data were compared, MSE was used as an index of comparison between the two networks. The MSE was computed to measure the average of the squares of the errors or deviations. MSE could be expressed as:

$$MSE = \frac{\sum e_i}{n} \tag{2}$$

where e_i is the mean square error of i^{th} individual data and n = total no. of data. MSE of the individual data, e_i could be expressed as:

$$e_i = (Ra_i - Ra_p)^2 \quad (3)$$

where in this study, Ra is the actual surface roughness and Ra_p is the predicted surface roughness.

The closer the value of mean square error to zero, the better the prediction of the model. In order to verify the significance of the result and verify the best neural network model, a hypothesis test was conducted for both the modelling data and verification data.

2.3 Statistical Analyses

In the raw dataset, there are two characteristics of each AE signals acquired, the researchers determined which characteristic of AE signals more significantly influences the Ra, which was done through Pearson correlation. The researchers used Slovin's formula to determine the sample size to be used in the pearson correlation. Slovin's formula can be expressed as:

$$n = \frac{N}{1+Ne^2} \quad (4)$$

where n is the sample size, N is the total number of data and e is the margin of error.
From the acquired data, the researchers used Pearson's correlation coefficient, r, developed by Karl Pearson, which has a value between +1 and -1, where the values closer to +1 indicate a more positive linear correlation and values closer to -1 indicate a more negative linear correlation, while a value of 0 indicates no linear correlation. The Pearson's correlation coefficient can be expressed as:

$$p = \frac{\sum XY - \frac{(\sum X)(\sum Y)}{n}}{\sqrt{((\sum x^2 - \frac{(\sum X^2}{n})(\sum Y^2 - \frac{(\sum Y^2}{N})}} \quad (5)$$

where N is the total number of data. X is the independent variable, Y is the dependent variable, $\sum$ X and $\sum$ Y is the sum of the independent and dependent variables, respectively, $\sum$ XY is the sum of the products of the independent and dependent variables, $\sum X^2$ and $\sum Y^2$ is the sum of the squares of the X and Y variables, respectively. In this study, the independent variables (X) are the AE signals and the dependent variable (Y) is the Ra. According to literature, the machining parameters are correlated with Ra, and therefore, need not be subjected to these computations.

Prior to conducting a hypothesis test to verify the significance of the result between the two neural network models, a normality test was done. The normality test determines whether the data follows a normal distribution and computes the likeliness of any random variable in the dataset to be normally distributed. The researchers used Anderson-Darling Method to test the normality of data and a significance level, denoted as α, of 0.05 because it has been proven to work well as a value for α. The data does not follow a normal distribution if P-value $\leq \alpha$, otherwise, if the P-value $\geq \alpha$, then the data follows a normal distribution.

3 Results

In the raw dataset, there are two characteristics of AE signals, specifically, the average and the highest AE signals (frequency and peak volume). To identify which characteristic of frequency and peak volume have more significant influence on the Ra, the researchers used Pearson correlation to determine the respective correlation coefficients of each characteristic of the two AE signals with Ra. The sample size to be used in correlation was determined using Slovin's formula as expressed in eqn. 4 which resulted in a sample size of 67, considering that there are 80 data per trial in three trials. 0.05 was used as the margin of error.

Results show that the average frequency and highest peak volume are the characteristics that bear correlation with Ra. Average frequency and highest peak volume are referred to as FREQ and PEAK respectively for the following parts of the study.

After these steps, the Input dataset is finalized. This Input dataset are the same dataset of the previously presented data, it is still divided into three trials; each consisting of 80 data for a total of 240 and this Input data contains the values of FEED, FREQ, PEAK and its corresponding Ra. The speed and depth are disregarded in the Input dataset since these values are constant. To recall, the Input dataset consists of one machining parameter (FEED), two significant AE signals (FREQ and PEAK), and the corresponding Ra. The FEED, FREQ and the PEAK are referred to as the input factors of the Input dataset. The Input dataset was then translated into values between 0 to 1 using minmax normalization.

To develop the original ANN model, the researchers divided the Input dataset into two subsets, the modelling data and the verification data. Also, training the neural networks requires the assignment of data for INPUT, OUTPUT, and TARGET. INPUT, OUTPUT, and TARGET data will all come from the modelling data and verification data.

The input factors are the machining parameters and the significant AE signals. In this study, the FEED is the machining parameter, and FREQ and PEAK are the input factors from the Input dataset. The input factors of the modelling data were assigned as the INPUT, the input factors of the verification data were assigned as the OUTPUT, and the Ra of the modelling data were assigned as the TARGET.

The researchers used an experimental design with i factors and j levels in neural network training in determining which combination yields the lowest possible MSE. Where i factors are the functions and j levels are the specifications. Training functions, learning functions and transfer functions are some of the training parameters in ANN training. The number of functions and number of trials vary according to the preference of the researchers. In this study, the researchers assigned variables k, l and m as the training functions, learning functions and transfer functions, respectively and t as the number of trials that all combinations will be repeated.

Following the experimental design as expressed in eqn. 1, Table 1, table 2 and table 3 shows the acronyms, algorithms, and the descriptions of the complete list of training, learning and transfer functions, respectively, in Matlab's NN toolbox and table 4 shows the neural network training parameter design of experiment; the training functions (k), learning functions (l), transfer functions (m) and number of repetitions (t) used in the experiment.

Table 1. Descriptions of the training function

Training Functions		
Acronym	Algorithm	Description
BFG	TRAINBFG	BFGS quasi-Newton backpropagation
BR	TRAINBR	Bayesian regularization
CGB	TRAINCGB	Powell -Beale conjugate gradient backpropagation
CGF	TRAINCGF	Fletcher-Powell conjugate gradient backpropagation
CGP	TRAINCGP	Polak-Ribiere conjugate gradient backpropagation
GD	TRAINGD	Gradient descent backpropagation
GDM	TRAINGDM	Gradient descent with momentum backpropagation
GDA	TRAINGDA	Gradient descent with adaptive lr backpropagation
GDX	TRAINGDX	Gradient descent w/momentum & adaptive lr backpropagation
LM	TRAINLM	Levenberg-Marquardt backpropagation
OSS	TRAINOSS	One step secant backpropagation
R	TRAINR	Random order incremental training w/learning functions
RP	TRAINRP	Resilient backpropagation (Rprop)
SCG	TRAINSCG	Scaled conjugate gradient backpropagation

Table 2. Descriptions of the learning function

Learning Functions		
Acronym	Algorithm	Description
GD	LEARNGD	Gradient descent weight/bias learning function.
GDM	LEARNGDM	Grad. descent w/momentum weight/bias learning function.

Table 3. Descriptions of the transfer function

Transfer Functions	
Acronym	Description
LOGSIG	Log sigmoid transfer function
PURELIN	Hard limit transfer function
TANSIG	Hyperbolic tangent sigmoid transfer function

Table 4. Neural Network Training Parameter Design of Experiment

Factors i	Levels j
Training Functions (k)	BFG, BR, CGB, CGF, CGP, GD, GDM, GDA, GDX, LM, OSS, R, RP, SCG
Learning Functions (l)	GD, GDM
Transfer Functions (m)	LOGSIG, TANSIG, TANSIG
Repetition (t)	2

Using eqn. 1, the total number neural network training parameters are determined. There are k = 14 training functions, l = 2 learning functions, m =3 transfer functions and t= 2. These three functions were varied to make up the experimental design in training and determining which combination yields the lowest possible MSE. There are total of **168 combinations** of functions used.

$$x = 14\ x\ 2\ x\ 3\ x\ 2 = 168 \quad (6)$$

Considering that there are a total of 240 data used to develop the models, the data were grouped arbitrarily into: 200 modelling data and 40 verification data. Two models were developed in this study: one original ANN and one QC-based ANN. Note that the chosen 40 verification data are unchanged for both models, hence, for both models, the OUTPUT data were unchanged as well. Only the 200 modelling data were preprocessed for the QC-based ANN. Without filtering the data, all 168 combinations of training parameters were tested. Each combination yields different results including EPOCH, the number of iterations done within training, and the performance PERF. (MSE) in terms of MSE. ACCURACY is the difference between 1 and the performance, in percentage. The combination with the lowest PERF. (MSE) is chosen, which was found to be **0.0213** in the network with the LM training function, GD learning function, and TANSIG transfer function. This network from this point on will be called **LM-GD-TANSIGORIGINAL.** Network LM-GD-TANSIG-ORIGINAL is used to simulate the surface roughness predictions for the preprocessed data, for both the modelling and verification data. The predictions are to be compared to the predictions to be obtained in the preprocessed network.

Prior to developing the second model, the Quality Control-based ANN model (QC-based ANN model), the 200 modelling data were preprocessed. The researchers used an individual quality control chart to identify which Ra Input data lie beyond the 3-sigma limits or 3.00 standard deviations from center line, these are considered the deviations from the data set (outliers).

Figure 2 illustrates the individual quality control chart. There were 11 data points beyond the 3-sigma limits, at points: 11, 27, 29, 42, 68, 91, 99, 100, 104, 118, and 135 of the modelling data. These data points were removed and the remaining data were considered as the new preprocessed modelling data for the development of the QC-based ANN model.

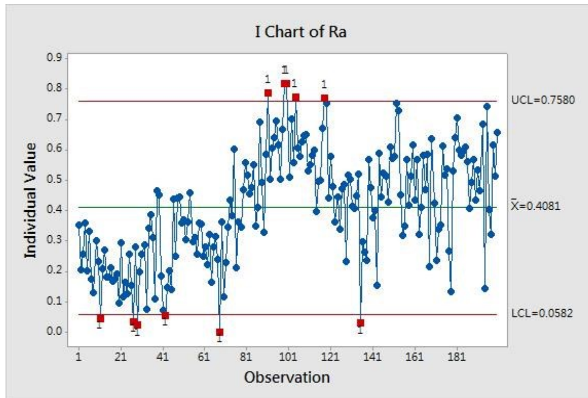

Figure 2. Individual Control Chart of Surface Roughness, Ra

The modelling data for the QC-based ANN model now consists of 189 data. The 40 verification data remain unchanged. The same INPUT, OUTPUT, and TARGET data assignments for the original ANN model were made for the QC-based ANN model.

After preprocessing, the 189 modelling data and 40 verification data are subjected to the same testing process of finding the ANN parameter combination with the least MSE. LM training function, GD learning function, and TANSIG training function yields the lowest MSE of **0.0147**. From this point on, this network is to be called **LM-GD-TANSIG-QC**.

Using network LM-GD-TANSIG-QC, surface roughness predictions are obtained for both modelling and verification data. These predictions are to be compared to the corresponding predictions obtained from the network LM-GDTANSIG-ORIGINAL.

LM-GD-TANSIG-QC network yields an MSE of 0.0147, which is 0.0066 less than that of LM-GD-TANSIGORIGINAL network with a value of 0.0213. This implies that the accuracy of the preprocessed network increased from around 97.97% to 98.53%.

To support the improvement from LM-GD-TANSIG-ORIGINAL to LM-GD-TANSIG-QC, the actual and predicted surface roughness values for both the modelling and verification data groups are compared. This is done by computing the MSE using eqn. 2 and 3.

The 200 original modelling data is tested against the 189 preprocessed modelling data using the two networks LM-GD-TANSIG-ORIGINAL and LM-GD-TANSIG-QC.

The MSE for both the 200 original modelling data and the 189 preprocessed modelling data are around 0.0214 and 0.0189 respectively. By observation, the MSE decreased by around 0.0024. However, this will not suffice to say that the difference is significant.

Actual and predicted Ra values of the two networks were compared using MSE for both modelling data and verification data. The MSE for both the 200 original modelling data and the 189 preprocessed modelling data are around 0.0214 and 0.0189 respectively. By observation, the MSE decreased by around 0.0024. However, this will not suffice to say that the difference is significant. It was observed that the verification data from the LM-GD-TANSIGQC network's MSE (0.0219) is less than that of the original (0.0239), with a difference of 0.0020.

To verify the existence of a significant difference between the MSE values, a hypothesis test is done for both modelling data and verification data. Normality test showed that the Ra values follow a normal distribution, which is a prerequisite to performing a hypothesis test. The following null and alternative hypotheses are as follows:

Modelling data

The null hypothesis (Ho) and alternative hypothesis (Ha) are stated as follows:
Ho: There is no significant difference between the two error means for the modelling data Ha:
There is a significant difference between the two error means for the modelling data

Verification data

The null hypothesis (Ho) and alternative hypothesis (Ha) are stated as follows:
Ho: There is no significant difference between the two error means for the verification data Ha:
There is a significant difference between the two error means for the verification data

The results of the hypothesis test, along with the summary of results are shown in Table 5. 200 modelling data were used in the original unfiltered ANN model, with 40 verification data. The QC-based filtered ANN model consists of 189 data after the data preprocess with the same 40 verification data.

Table 5. Summary of Models and Results

		n	Training Function	Learning Function	Transfer Function	ANN MSE	MSE	Hypothesis test p-value	with SD
Original unfiltered ANN model	Modelling data	200	LM	GD	TANSIG	0.0213	0.0214	0.022	YES
	Verification data	40					0.0239		
QC-based filtered ANN model	Modelling data	189	LM	GD	TANSIG	0.0147	0.0189	0.932	NO
	Verification data	40					0.0219		

For modelling data, since the p-value 0.022 is less than 0.05, therefore, Ho is rejected. There is a significant difference between the two error means. As for verification data, Since the p-value 0.934 is not less than 0.05, therefore, the researchers cannot outright reject the Ho. There is no significant difference between the two error means.

4 Discussion

The dataset was arbitrarily subdivided into two subsets: modelling data and verification data. The input variables feed rate, frequency, and peak volume variables (named FEED, FREQ, and PEAK in this study) of the modelling data constitute the "INPUT" for the ANN models. These same input variables of the verification data make up the "OUTPUT" for the models. The corresponding Ra values of the modelling data is the ANN models' "TARGET" data.

Two ANN models were built. The first original model was not preprocessed using an individual quality control chart. Using 200 modelling data and 40 verification data, the researchers tested 168 ANN parameter combinations. The network with the lowest MSE of 0.0213 is the network with training function LM, learning function GD, and transfer function TANSIG. This network was referred to as LM-GD-TANSIG-ORIGINAL. The second model, the QC-based ANN model, was preprocessed using an individual control chart. 11 Ra values from the modelling data were found to exceed the 3-sigma limits. These are considered the outliers of the dataset and was therefore removed for the building of the second filtered model. After preprocessing, the modelling data comprised of 189 data. The same 40 verification data is used to build the second QC-based model. After testing all 168 ANN parameter combinations, the network with the training function LM, learning function GD, and transfer function TANSIG has the lowest MSE of 0.0147. This network is referred to as LM-GD-TANSIG-QC.

The networks with the lowest MSEs were chosen because these networks showed the best results among all 168 possible network combinations. Note that although the training function, learning function, and transfer function used were the same, LM-GD-TANSIG-ORIGINAL and LM-GD-TANSIG-QC are two separate networks.

Ra predictions were simulated for both the modelling and verification data of both LM-GD-TANSIG-ORIGINAL and LM-GD-TANSIG-QC. MSE was used as an index of comparison between the two networks.

The modelling data has an MSE of 0.0214 for the LM-GD-TANSIG-ORIGINAL network, and 0.01898 for the LM-GD-TANSIG-QC network. The improvement, by observation is a decrease in MSE of around 0.0024. The LM-GDTANSIG-ORIGINAL and LM-GD-TANSIG-FILTERED network has an MSE of 0.0239 and 0.0219 respectively for the verification data. There has been a decrease in MSE of around 0.0219.

Although in both modelling and verification the MSE for the filtered network decreased, a hypothesis t-test was done to determine if these differences are significant enough to be valid.

Considering that there are 40 data that comprise the verification data, this data size may be too small to draw an accurate conclusion. In the same sense, the modelling data is comprised of 200 and 189 data for the original ANN and QC-based ANN models respectively. This relatively larger dataset makes it more reliable to draw conclusions from. The existence of a significant difference between the two MSEs for the modelling data is enough to conclude the success of the proposed system; that is, that by comparison, the QC-based ANN model and its network LM-GDTANSIG-QC was able to yield more accurate Ra prediction values than the network LM-GD-TANSIG-ORIGINAL from the original ANN model.

5 Conclusion

Two ANN models were built and compared – one original model and one quality control-based model. The difference is that the latter made use of an individual quality control chart to filter out Ra data that lie beyond the 3-sigma limits. Both models consist of modelling data and verification data. Following the experimental design that determines how many training parameter combinations to use, 168 combinations were tried. Both models yielded the lowest MSE using LM as the training function, GD as the learning function, and TANSIG as the transfer function. Ra predictions were simulated and compared for both networks. In both occasions, the MSE values decreased, which means the quality control-based ANN model yields more accurate Ra predictions than the original one. To further validate, a hypothesis test was performed. Although no significant difference was found between the MSE values of the verification data, the modelling data showed significant results.

The success of the system may be attributed to the new behavior of the modelling data after the data preprocess done in building the QC-based ANN model. With new actual Ra values that do not go beyond the 3 sigma limits, the 189 Ra data lie closer to each other and were therefore more precise. After ANN simulation of the QC-based model, the simulated Ra values became more reliable in drawing predictions.

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