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An ANN Model to Estimate the Impact of Tea Process Parameters on Tea Quality*

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Present study deals with the development of an artificial neural network (ANN)-based technique for tea quality quantification by monitoring fermentation and drying condition of the tea processing stages. An RS485 network-based instrumentation system has been developed and implemented for data collection for these two stages. Three calibrated sensor nodes are installed in the fermentation room due to its larger floor area to collect temperature and relative humidity (RH). Dryer inlet temperature is recorded using a calibrated thermocouple-based sensor node. From seven input parameters and target quality data obtained from tea taster, the ANN model has been developed to find the correlation between the process condition and the tea quality. From the correlation study, more than 90% classification rate is obtained from the model. The model is also validated with some independent data showing more than 60% correlation. Error in terms of root mean square error (RMSE) is about 0.17. This model will be helpful for improvement of tea quality.

Keywords: Artificial neural network; tea fermentation; tea drying; relative humidity; temperature.

1. Introduction

Assam is the single largest tea-growing region in the world. The reasons behind this are: low altitude, rich loamy soil conditions, ample rainfall and a

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unique climate. Because of the special and unique environmental condition, the tea production is satisfactory in this region.[a] However, in the factory, different process parameters like temperature, RH, moisture content are monitored and controlled by manual means and sometimes even by guesswork leading to fall in quality.[1]

Tea is produced from the plant *Camellia Sinensis*. There are different varieties of tea: green tea (unfermented), black tea (fully fermented), Oolong tea (partially fermented), etc. and out of these, black tea is the most common beverage. After tea leaves are plucked from the tea plants, a number of processing stages, viz., withering, pre-conditioning, cut–tear–curl (CTC) operation, fermentation and drying, etc. are involved in producing finished black tea.[2,3]

Tea quality quantification is a subjective matter due to the presence of numerous compounds and their contribution in the final product. There are several process conditions that can affect the tea quality. Temperature and RH are two among those important parameters in the fermentation room where tea color and flavor are changed. Dryer inlet temperature also plays a crucial role in the final tea quality.[2–4] Some pioneering work had been done by Bhattacharya *et al.* where electronic nose-based technique is used to monitor the fermentation process of black tea and correlated these data with the results of colorimetric tests and human expert evaluation.[5] In another study by Bhattacharya *et al.*, it is reported that the optimum fermentation time can be detected by electronic nose-based technique where electronic nose readings accurately matched with the colorimetric as well as human panel data.[3] Bhattacharya *et al.* also correlated the electronic nose data and electronic tongue data with the tea taster's marks to classify black tea quality.[4,6] In those studies, different neural network topologies like back propagation multilayer perceptron (BP-MLP), radial basis function (RBF), probabilistic neural network (PNN) are used. Along with this topology learning vector quantization (LVQ) is used by Dutta *et al.*[7] in their study to standardize tea quality using electronic nose data.

In this paper, an artificial neural network (ANN) based technique has been developed for quantification of tea by using the process parameters of tea processing with special emphasis on fermentation and drying. The main objectives are:

- To develop an ANN model to observe the correlation between the process parameters and the tea quality.
- Validate the model with some independent data.
- To predict the optimum process condition.

This will be very helpful for the tea factory to control the process parameters to get the best quality tea.

[a] Tea statistics, http://assamgovt.nic.in/business/business_entrprise.asp.

2. Data Collection and Preparation

2.1. *Development of the network based instrument: A data collection technique*

To collect the tea process parameters network-based instrumentation is developed as shown in Fig. 1. A total of six sensor nodes are required to monitor the process parameters of the fermentation room, dryer and the ambient condition. Sensor node 1 is placed in the monitoring room where ambient temperature and RH are monitored. Sensor nodes 2–4 are installed in the fermentation room to monitor temperature and RH. Sensor nodes 5 and 6 are installed in the dryer inlet and outlet to monitor dryer temperature.

2.2. *Specifications of the sensors*

2.2.1. *Sensing the temperature*

Thermocouple: A K-type thermocouple is used to measure the temperature of the dryer.[8]

LM 35: It is an IC temperature sensor which gives 10 mV/°C output with ±1.5°C accuracy.[b]

2.2.2. *Sensing the RH*

For sensing RH, low power RH to voltage converter is used. It is basically a LASER trimmed, thermoset polymer capacitive type sensing element with on-chip integrated

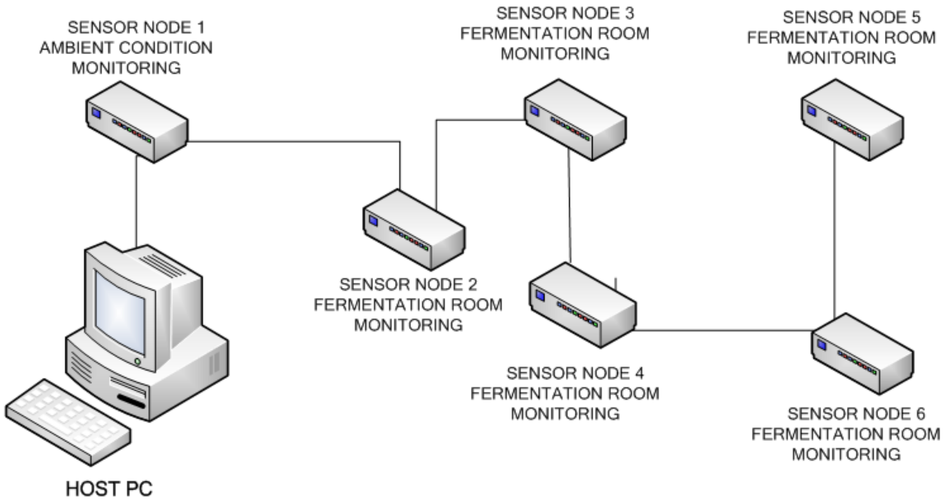

Fig. 1. Block diagram of the process parameter monitoring system of tea factory.

[b] Datasheet of LM 35, www.ti.com/lit/ds/symlink/lm35.pdf.

signal conditioning. The accuracy of the sensor is ±3.5% at 25°C with 5 V DC supply.[9,10,c]

2.3. Sensor nodes development for fermentation room and dryer

2.3.1. *Fermentation room monitoring sensor nodes*

An RH to voltage converter (HIH 4000)[c] and temperature to voltage converter type sensors (LM 35)[b] are used to develop the RH and temperature monitoring sensor node for fermentation room. The output voltage of the sensor is read by the 10-bit built in ADC of the PIC microcontroller.[d] In case of RH measurement, ambient temperature effect is nullified by temperature compensation as described in Refs. 9 and footnote c. These values are sent to PC via RS485 communication. All these corrections and communications are done by the application algorithm embedded in the microcontroller. The transceiver for RS 485 communication in both the cases are MAX 485.[e] The system is calibrated[9,10] using four standard saturated binary salt solutions. Calibration curve with equation of linear regression and residual versus fitted curve for RH measurement are shown in Figs. 2 and 3, respectively. The accuracy of the system found from the recorded data is ±1% RH in the range of 50–100% RH and ±0.5°C at 30°C.

2.3.2. *Dryer temperature monitoring sensor nodes*

For dryer temperature monitoring, a K-type thermocouple-based measurement system is developed. The signal conditioning for thermocouple is achieved by AD595[f]

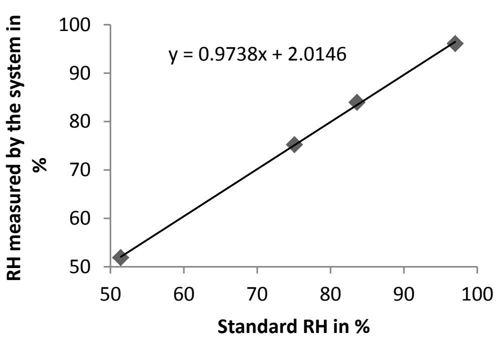

Fig. 2. Calibration curve of RH measurement.

[c] Datasheet of HIH4000, http://sensing.honeywell.com/index.cfm/ci_id/1/document/1/re_id/0.
[d] Datasheet of PIC18F452, http://ww1.microchip.com/downloads/en/DeviceDoc/39564c.pdf.
[e] Datasheet of MAX 485, http://datasheets.maximintegrated.com/en/ds/MAX1487-MAX491.pdf.
[f] Datasheet of AD595, http://www.analog.com/static/imported-files/data_sheets/AD594_595.pdf.

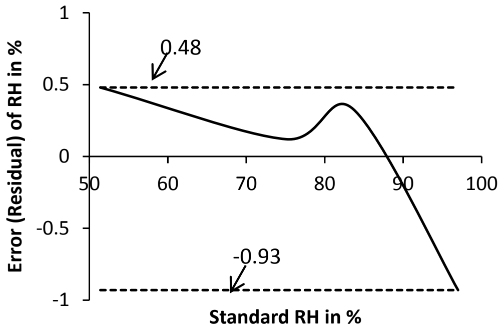

Fig. 3. Residual versus fitted curve for RH measurement.

which offers complete instrumentation amplifier and thermocouple cold junction compensator on a monolithic chip. It combines an ice point reference with a precalibrated amplifier to produce a high level (10 mV/°C) output directly from a thermocouple signal. The output of the AD 595 is connected with a 10-bit built in ADC of the PIC microcontroller.[b] The application algorithm embedded in the PIC microcontroller is used for data correction and communication through RS 485 network bus.[g] The system is calibrated using a temperature controlled bath as described in Ref. 8. Calibration curves with equation of linear regression and residual versus fitted curve for dryer temperature measurement sensor node are shown in Figs. 4 and 5, respectively. The accuracy found from the system is ±1°C in the range of 30–130°C.

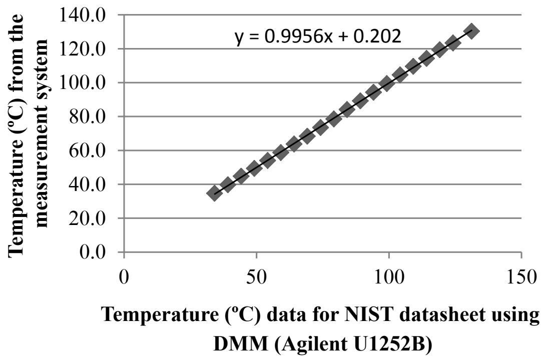

Fig. 4. Calibration curve of dryer temperature measurement sensor node.

[g]The RS 485 design guide, application report, http: www.ti.com.

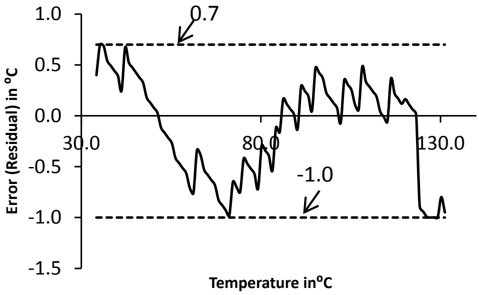

Fig. 5. Residual versus fitted curve for dryer temperature measurement sensor node.

2.4. *Firmware*

The firmware is developed in MPLAB IDE of Microchip Technology using PIC C language. The function of the firmware developed is as follows:

(i) Initialize ADC and serial port.
(ii) Wait for receiving address of the node.
(iii) If the address is matched, ADCs connected with the sensors are read.
(iv) Raw digital data is sent to PC.
(v) Go to step (ii) after completion of sending data.

2.5. *Data acquisition software*

The software required at PC to send and receive data serially using the protocol RS 485 is developed in LabVIEW. The primary responsibility of the software is as follows:

- Send the address of the sensor node through COM port.
- Receive raw digital data from the matched node.
- Separate the digital data with the help of signature attached with the data.
- Convert the data to RH and temperature with temperature compensation.
- Display the data.
- Store the data in HDD.
- Continue.

2.6. *Installation of the instrument*

The system described above has been designed, developed and successfully installed and operated in a tea factory near Mangaldoi, Assam, India after continuous testing for three months in the laboratory. The analysis is carried out for the period from 1st August 2013 to 30th November 2013.

Table 1. Sample data of tea quality as given by tea taster.

Sample	Date	Quality
Sample 1	18/08/2013	6
Sample 2	31/08/2013	7
Sample 3	17/09/2013	8

2.7. *Tea quality*

Quality of tea is collected from the tea taster on a scale of 0–10 depending on the dry leaf quality, infusion and liquor or cup characteristics of the tea sample.[4,6,h] Dry leaf quality is determined by several factors e.g., size of the tea grade, bloom of the dry leaf appearance, dry leaf color, dry leaf style, fiber content, etc. Infusion is an important attribute which is found from the wet residual tea leaf that is separated from the brewed tea liquor. It is a visual inspection where brightness and color of the infused tea is the key parameter. The most important parameter upon which the quality of tea is assessed is the liquor or cup characteristic of tea. It is assessed visually as well as by the taste. Tasting is done twice for the same cup, first without addition of milk and then with the addition of milk. Several parameters are taken into account to assess the cup characteristics, among these, briskness (astringency), strength, body (thickness of the liquor), brightness of the liquor, color with milk and flavor with milk are significant. Overall quality of the tea is assessed by taking all the above mentioned parameters in to account and it is expressed on a scale of 0–10.

In this attempt, tea tasters have provided the quality index depending on the sample for each day collected from the tea factory where the system is installed. Tea tasters are associated with the tea factory and they usually do the tea tasting for the quality improvement of the tea garden of their interest. The quality varied from 6 to 8 in the provided tea samples for the period of 1st August 2013 to 30th November 2013. A sample of quality assessment data provided by tea taster is presented in Table 1.

3. Methodology

Figure 6 depicts the detailed methodology of the experiment. Data from the tea factory are collected and prepared for an ANN analysis. ANN is trained using those data and the model is validated with 600 independent data. The optimum condition is found out from the analysis. Output of the model is found out as tea quality indicator.

[h] Tea tasting, http://www.tocklai.net/activities/tea-manufacture/tea-tasting/.

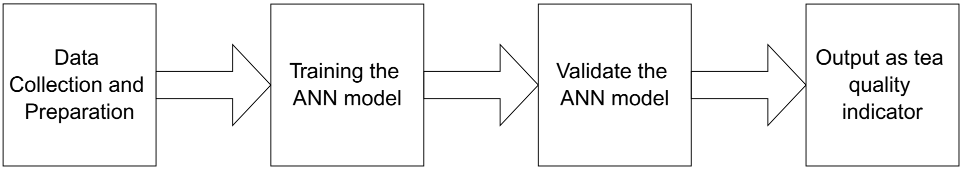

Fig. 6. Block diagram showing the detailed methodology.

4. Data Analysis

4.1. *Sample selection*

The MLP is trained using seven parameters (temperature and RH from three sensor nodes of fermentation room and firing temperature of dryer) recorded from tea factory as input data and quality index given by tea taster as output. Here, data from the sensor node 1 are not accounted because it is not installed in the tea processing area. Also, dryer outlet temperature is not taken for the analysis because it is dependent on inlet temperature. Tea process parameters are collected for 102 days for the period as given above and the complete data are taken into account. Total 49,125 data points are taken and out of these 39,300 data points are fed as training data and 9825 data points are taken as validation data i.e., whole data set are divided into two parts where 80% data are used as training data and 20% data are used for validation. A suitable algorithm is prepared to separate the training and validation data where out of each five data points first four data points are selected as training data and the fifth one is selected as validation data. The reason behind choosing the data in that manner is to ensure that the training as well as the validation data are chosen randomly and both of these two data sets include maximum variation of data. The data are normalized before training with ANN. Tea quality assessment is done every day by tea taster and these data are used as target for the corresponding input data.

4.2. *Training of ANN*

There are several topologies in neural network which can be implemented to standardize the tea quality. In this paper, back propagation multilayer perceptron (BP-MLP) is implemented. BP-MLP is composed of three layers, the input layer, the hidden layer and the output layer. It is formed by interconnected and interacting components called nodes. The number of the hidden layers and nodes of each layer may be varied. Nodes of each layer are connected by weights and thus forming a network which processes the inputs and compares its outputs against the desired output. The output error is found from the comparison and weights are updated with the output error according to the gradient descent rule. This process occurs several times for the same dataset during training in the network as weights are always updated.[11–13]

Each of the input is multiplied by the weight matrix and its output is multiplied by a transfer function at the hidden layer. In this case, sigmoid transfer function is used. It can be represented as follows:

$$F(s) = \frac{1}{1 + \exp(-s)} \,. \tag{1}$$

In BP-MLP, the network weights are updated and biased in the direction in which the performance function decreases more rapidly (the negative gradient). Weights are updated as:

$$w_{ik}^{t} = w_{ik}^{t-1} - \eta \frac{\partial E_k}{\partial w_{ik}} \,, \tag{2}$$

where, w_{ik}^{t} is the new updated weight at tth iteration, w_{ik}^{t-1} is the weight at $(t-1)$th iteration, E_k is the error at output node.[11]

Here, Levenberg–Marquardt algorithm is used for training purpose. It is advantageous because of its quick response as compared to most of the other training algorithms. Different networks are trained with different hidden layer sizes. There is no standard rule on the number of hidden layers, the number of nodes in the hidden layers, so on the basis of trial-and-error the optimum MLP is found. The optimum MLP neural network architecture is shown in Fig. 7. It consists of input layer with

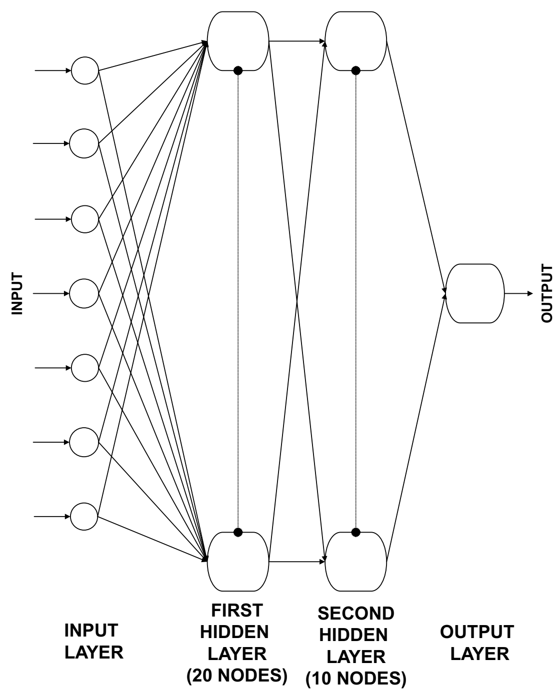

Fig. 7. MLP architecture.

Table 2. Result of ANN model.

Neural network topology	Architecture	Training/validation	% of correlation	RMSE
Multi layer perceptron	A feed forward back propagation neural network with SIGMOID transfer function	Training	93	0.16
		Validation	93	0.16

seven nodes, two hidden layers having 20 and 10 nodes, respectively and the output layer with one node with learning rate equal to 0.2.[11,13]

The results from the training of ANN to quantify the tea quality are presented in Table 3. It is observed that the result is same for training dataset as well as the validation dataset. RMSE for each dataset is also presented in Table 2. Overall, it is observed that the ANN is well trained with the training data set considered for the study.

5. Results and Discussions

5.1. *Validation with independent data*

To check the performance of the model developed we have tested its output with some independent data sets that are not the part of the training data set. The ANN model is validated with 600 independent data collected from tea factory. The corresponding tea quality is also collected from the tea taster to observe the optimum condition. The independent data is fed to the model and the output is compared with the corresponding tea quality. The correlation and the error analysis are given in Table 3.

5.2. *Technical contribution*

The developed ANN-based model is used to get optimum parameters for best quality tea. Thus, by controlling the process parameters in such fashion the best quality tea (in this case it is 8 out of 10) can be obtained. A trend of such condition is presented in Table 4 with its minimum and maximum values.

Here, minimum and maximum values (RH and temperature) represent the average of minimum and maximum values collected from the sensor nodes installed in the fermentation room of the factory.

Table 3. Result of validation of the ANN model with independent data.

Data	% of correlation	RMSE
Independent validation data	62	0.17

Table 4. A typical trend of optimum condition to get the best quality tea.

Minimum RH of fermentation room	Maximum RH of fermentation room	Minimum temperature of fermentation room	Maximum temperature of fermentation room	Minimum firing temperature	Maximum firing temperature
86%	93%	29°C	31°C	84°C	86°C

So, it is justified from the above study that there is an impact of process parameters on tea quality.

6. Summary and Conclusion

In this work, an ANN-based model is developed to quantify tea quality depending on the process parameters of tea production. Temperature and RH of the fermentation and dryer inlet temperature are taken into account for the purpose. These data are collected from the tea factory using the developed RS 485-based data logging system. The reason for choosing RS 485-based network is its sufficient reliability for the stated purpose and relatively low cost over wireless sensor network. Conventionally, data logging system with central monitoring facility is not incorporated in the tea factories of this region. On the other hand, this system is easy to install due to the small hardware setup. Due to these merits, the system can replace the conventional monitoring system for better recording of process parameters.

Tea quality index is taken from the tea taster in the range of 0–10. The collected sample has the tea quality in the range of 6–8. The process parameters are taken as input data and the quality indices are taken as output data. The optimum ANN model consists of input layer with seven nodes, two hidden layers having 20 and 10 nodes, respectively and the output layer with one node. Reasonably good correlation is found from the model as 93% correct correlation is found from the training and validation data. From the validation with independent data, it is justified that there is an impact of process parameters on tea quality and by controlling the process parameters with its optimum value found from the ANN model, the best quality tea can be obtained.

However, although the study shows a reasonably good result to find the optimum condition of fermentation and drying, it is worthwhile that the work should be extended with additional data with some more variations of quality to get an accurate model that can be used more precisely.

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