CHAPTER 2

OPEN LOOP EXPERIMENTAL INVESTIGATIONS

2.1 GENERAL

The open loop studies are required to study the non-linear characteristics of the process to identify the process parameters, to develop a mathematical model and also an ANN model of the air heating system (AHS). These models are used to design various closed loop control strategies. To fulfil this objective, an experimental set-up is necessary. The following paragraphs describe fabrication of the experimental set-up, details of the open loop studies carried out and development of the AHS models.

2.2 FABRICATION OF EXPERIMENTAL SET-UP

An experimental set-up of AHS is designed and fabricated to carry out the open loop studies. The important components of the experimental set-up includes air heating chamber, heater coil, temperature sensor, thermostat and an exhaust fan as shown in Figure 2.1. The air heating chamber consists of transparent flexi-glass chamber of 4mm thickness, built on a wooden base. All other components are mounted on the chamber. The heater has a nichrome wire of length 25cm, diameter 3.5cm wound on a cylindrical ceramic former. The coil is placed at the entry point of the chamber and is surrounded by a hollow galvanised-iron cylinder to prevent the heat directly affecting the flexi-glass chamber. The temperature sensor, PT100-RTD (platinum based) is mounted at the end of the chamber to sense the temperature of the exit air. When the
Figure 2.1 Experimental set-up of AHS for open loop studies
chamber temperature exceeds the higher limit, the power supply to the heater is cut off automatically with the help of a thermostat. The exhaust fan is used for ventilating the air in the chamber.

The output of the temperature sensor is fed to a smart temperature transmitter (Model No. 3244, Fisher Rose Mount make). It converts the signal from RTD into a standard 4-20mA signal proportional to the sensed temperature of the exit air. Before installation, the smart transmitter is calibrated using HART (Highway Accessible Remote Transducer) communicator for the range 0° C to 100° C. The specifications of smart temperature transmitter is given in Appendix 1.

The signal conditioning unit consists of (a) ADAM 4012 (A/D) input module, (b) ADAM 4021 (D/A) output module and (c) ADAM 4520 communication module. The ADAM modules are set of intelligent sensors containing built-in microcontrollers. They are remotely controlled through a simple set of commands issued in ASCII format and transmitted in RS-485 protocol. They provide signal conditioning, isolation, A/D and D/A conversion and communication. By merely issuing a command from the host computer, the analog input module can be made to accept several ranges of voltage input, thermocouple input or RTD input. The module configuration can be set remotely. The communication module namely ADAM 4520 converts RS-485 protocol to RS-232 protocol before being fed to the computer. The specifications of ADAM 4012, 4021 and 4520 are given in Appendices 2-4.

The relative humidity is measured by an RH-meter. The speed of the exhaust fan is sensed by a stroboscope. The velocity of exit air is measured with the help of an anemometer. The specifications of stroboscope and anemometer are presented in the Appendices 5 and 6 respectively. The schematic of the computer controlled air heating system is shown in Figure 2.2. The design specifications of the fabricated AHS are given in Table 2.1.

FT - Flow transmitter, MM - Moisture meter, TI - Temperature indicator, TT - Temperature transmitter, N - Speed indicator, PC - Process computer, TC - Thyristor controller.

Figure 2.2 Schematic of the computer controlled air heating system.
Table 2.1 Design Specifications of the Air Heating System

<table>
<thead>
<tr>
<th>Component</th>
<th>Specifications</th>
</tr>
</thead>
<tbody>
<tr>
<td>Size of air heating chamber</td>
<td>100 x 12.5 x 12.5 x 10⁻² m³</td>
</tr>
<tr>
<td>Heater</td>
<td>750 w, 230 v, 50 Hz</td>
</tr>
<tr>
<td>Temperature sensor</td>
<td>-200 °C to 800 °C</td>
</tr>
<tr>
<td>Temperature transmitter</td>
<td>0-100 °C</td>
</tr>
<tr>
<td>Exhaust fan</td>
<td>3000 RPM</td>
</tr>
<tr>
<td>Stroboscope</td>
<td>100 to 10,000 FPM</td>
</tr>
<tr>
<td>Anemometer</td>
<td>0.4 -30 ms⁻¹</td>
</tr>
</tbody>
</table>

2.3 OPEN LOOP STUDIES

Various experiments are carried out on the fabricated set-up to obtain the steady state and dynamic responses of AHS. The objective is to study the non-linearity present in the input and output behaviour and also in the various process parameters of the AHS. The effect of changes in the voltage input to the heater on the temperature of the exit air is recorded and plotted. The values of the operating parameters for conducting the open loop studies are presented in Table 2.2.

Step change in the inlet air temperature is obtained by changing the voltage input to the heater in steps. The dynamic response of the exit air temperature for step change in the heater voltage from 0-230 V are presented in Figures 2.3 (a) to (e). Similarly the effect of gradual positive step changes and both positive and negative step changes in the heater voltage on the exit air temperature is observed and plotted in Figures 2.4 and 2.5 respectively.
Figure 2.3(a) Dynamic response of exit air temperature for a step change in heater voltage from 0 to 50V.
Figure 2.3(b) Dynamic response of exit air temperature for a step change in heater voltage from 0 to 75 V.
Figure 2.3(c) Dynamic response of exit air temperature for a step change in heater voltage from 0 to 100 V.
Figure 2.3(d) Dynamic response of exit air temperature for a step change in heater voltage from 0 to 125V.
Figure 2.3(e) Dynamic response of exit air temperature for a step change in heater voltage from 0 to 150V.
Figure 2.3(f) Dynamic response of exit air temperature for a step change in heater voltage from 0 to 230V.
Figure 2.4. Dynamic response of exit air temperature for step changes (positive) in heater voltage (0 - 50 - 75 - 100 - 125 - 150 V)
Figure 2.5. Dynamic response of exit air temperature for step changes (Positive and negative) in heater voltage (0 - 50 - 100 - 150 - 100 - 50 - 0 V).
Table 2.2  Values of Operating Parameters for the Open Loop Studies

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Inlet air temperature</td>
<td>27 °C</td>
</tr>
<tr>
<td>Velocity of air</td>
<td>1.7- 4.7 ms⁻¹</td>
</tr>
<tr>
<td>Humidity of inlet air (% RH)</td>
<td>60</td>
</tr>
<tr>
<td>Voltage input to the heater</td>
<td>0-230 V</td>
</tr>
</tbody>
</table>

The step changes are also made in the superficial velocity of air from 0-4.7 ms⁻¹ by changing the speed of the exhaust fan. The effects of these changes on the exit air temperature are observed and presented in Figures 2.6 (a) to (d). The Figure 2.7 shows the dynamic response of the exit air temperature for gradual positive and negative changes in the air velocity. From these results, the process parameters of AHS are determined using reaction curve method. The variation of the process parameters namely; process gain, process lag (dead time) and time constant with the voltage input to heater are shown in Figures 2.8 to 2.10 respectively. Similarly the variation of the process parameters with the air velocity are presented in Figures 2.11 to 2.13 respectively. These results reflect the non-linearity present in the process parameters of AHS.

It is inferred from the results of the above figures that the interaction between the input/output variables yield the non-linear behaviour of the process parameters. This gives rise to irregular performance of the dryer. A perturbation in the heater voltage/air velocity, changes the process gain in an unpredictable manner. Thus, it is felt that, there is a need to design controllers which can adapt the non-linearity of the process. Also, the controller need to possess learning, self organising and decision making capability. The ANN and Fuzzy logic based intelligent control techniques exhibit the above characters. Hence, these intelligent control strategies are implemented on the present process (presented in the subsequent chapters).
Figure 2.6(a) Dynamic response of exit air temperature for a step change in air velocity from 0 - 1.7 m/s
Figure 2.6(b) Dynamic response of exit air temperature for a step change in air velocity 0–2.8m/s.
Figure 2.6(c) Dynamic response of exit air temperature for a step change in air velocity from 0 - 3.6 m/s.
Figure 2.6(d) Dynamic response of exit air temperature for a step change in air velocity from 0–4.7 m/s.
Figure 2.7 Dynamic response of exit air temperature for step changes (positive and negative) in air velocity (0 - 2.1 - 4.7 - 2.1 m/s).
Figure 2.8 Variation of process gain with heater voltage.
Figure 2.9 Variation of time constant with heater voltage.
Figure 2.10 Variation of process lag with heater voltage.
Figure 2.11 Variation of process gain with air velocity.
Figure 2.12 Variation of time constant with air velocity.
Figure 2.13 Variation of process lag with air velocity.
2.4. DEVELOPMENT OF MATHEMATICAL MODEL

A theoretical model for the AHS is developed incorporating the energy balance in the air heating chamber using convective method of heat transfer mechanism (Roache 1976). Accordingly, the AHS can be represented mathematically as given by the equation (2.1).

\[
\frac{\partial T}{\partial t} + U \frac{\partial T}{\partial x} + V \frac{\partial T}{\partial y} = \alpha' \left( \frac{\partial^2 T}{\partial x^2} + \frac{\partial^2 T}{\partial y^2} \right)
\]  

(2.1)

By dimensionless treatment, the equation (2.1) becomes,

\[
\frac{\partial \tilde{T}}{\partial \tilde{t}} + u \frac{\partial \tilde{T}}{\partial \tilde{x}} + v \frac{\partial \tilde{T}}{\partial \tilde{y}} = \alpha' \left( \frac{\partial^2 \tilde{T}}{\partial \tilde{x}^2} + \frac{\partial^2 \tilde{T}}{\partial \tilde{y}^2} \right)
\]  

(2.2)

where

\[
x = \frac{x}{H} \quad \text{(2.3)}
\]

\[
y = \frac{y}{H} \quad \text{(2.4)}
\]

\[
u = \frac{U}{(\alpha' / H)} \quad \text{(2.5)}
\]

\[
u = \frac{V}{(\alpha' / H)} \quad \text{(2.6)}
\]

\[
T = (T_{\infty} - T_1) / (qH / k) \quad \text{(2.7)}
\]

\[
t = \frac{t}{(H^2 / \alpha')} \quad \text{(2.8)}
\]

The boundary conditions are taken as specified below:

(i) When \( t = 0 \), \( T = 27^\circ \text{C} \)

(ii) At \( x = 0 \), \( \frac{\partial T}{\partial x} = -q/k \)

The following assumptions are made in this study:

(i) The velocity of air in \( y \)-direction (\( v \)) is assumed as zero.

(ii) Outer wall of the chamber is insulated.
(iii) There is no temperature variation of exit air along y-direction
(iv) The value of q at 230 v is 800 wm$^{-2}$ (Gupta et al 1995)

With the above assumptions, the equation (2.2) can be rewritten as

$$\frac{\partial T}{\partial t} + u \frac{\partial T}{\partial x} = \alpha^1 \left( \frac{\partial^2 T}{\partial x^2} \right)$$  \hspace{1cm} (2.9)

where

$\alpha^1$ is the thermal diffusivity given by $1.8 \times 10^{-5}$ m$^2$ s$^{-1}$ (Perry 1988)

$k$ is the thermal conductivity given by 69 w m$^{-1}$ K$^{-1}$

The dynamic model equation (2.9) representing the exit air temperature along the x-direction (as a function of distance from the heat source and time) is solved numerically (Smith 1985).

Accordingly the equation (2.9) can be represented as follows:

$$\frac{\partial T}{\partial t} = \frac{T_{i,j+1} - T_{i,j}}{K^1}$$ \hspace{1cm} (2.10)

$$\frac{\partial T}{\partial x} = \frac{T_{i+1,j} - T_{i,j}}{h}$$ \hspace{1cm} (2.11)

$$\frac{\partial^2 T}{\partial x^2} = \frac{T_{i+1,j} - 2T_{i,j} + T_{i-1,j}}{h^2}$$ \hspace{1cm} (2.12)

where

$K^1$ is the sampling time

$h$ is the step size in terms of distance from the heat source.

Substituting the values of equations (2.10), (2.11) and (2.12) in equation (2.9) and simplifying we get,
The value of $T_{ij}$ can be written in terms of $T_{i+1,j}$ by using the boundary condition (ii). Thus, we have,

$$\frac{\partial T}{\partial x} = \frac{-q}{k} = 800 \frac{1}{69}$$

(2.14)

From the fundamentals, we have

$$\frac{\partial T}{\partial x} = \frac{T_{i+1,j} - T_{i,j}}{2h}$$

(2.15)

Thus from equations (2.14) and (2.15), we get

$$T_{i+1,j} = T_{i,j} + 2h \frac{800}{69}$$

(2.16)

From equations (2.13) and (2.16) we can determine the values of $T_{i,j+1}$ for different values of $i$ and $j$. The values of the exit air temperature thus obtained from the numerical solution technique at a distance of 0.35m from the heat source for a heater voltage of 230V are plotted against the sampling time. The dynamic response, thus obtained from the formulated model through simulation and that of the response obtained from the experimental open loop studies are shown in Figure 2.14.

The process model representing the exit air temperature of AHS should take care of the unmeasured disturbances and process non-linearity affecting the exit air temperature. The complexity involved in obtaining such a model of the AHS increases due to the presence of unmeasured disturbances and non-linearity
Figure 2.14. Dynamic response of exit air temperature for a step change in heater voltage. (Experimental & theoretical)
in the process parameters, forcing to make many assumptions. The inaccuracy in the modelling due to various assumptions results degraded performance of controllers. As the ANN technique has the capabilities of capturing the non-linearities of the process, an ANN model representing the AHS is developed. The subsequent sessions present the details of the ANN model developed for AHS.

2.5 FORMULATION OF ANN MODEL OF AHS

The advent of artificial neural network (ANN) technique has inspired researchers to develop better and more efficient models to synthesise MPC schemes. In the present work, the experimental input-output data obtained from the open loop studies are used to train the ANN. Once the training data is available, a suitable ANN architecture can be selected to carry out the training.

2.5.1 Selection of suitable ANN architecture

Among the various ANN models available, the feedforward model of multilayered perceptron (MLP) has been reported to yield encouraging results in various applications by many researchers. The Back Propagation Algorithm (BPA) is used in MLP. The ANN consists of a large number of simple processing elements (PE) called neurons. Each PE has many inputs and outputs. The output path of a PE is decided by the connection weights. Each connection has a corresponding weight and the signals on the input lines to the PE are modified by these weights. These weighted signals are summed up and is modified by an activation function which is then passed to the output path of the processing element. The output of ANN in the present model is given by equation (2.17).

\[ \text{OUT} = \frac{1}{1+e^{-A}} \]  

(2.17)
where

\[ A = \sum_{i=1}^{n} w_{i} x_{i} \]  

(2.18)

where

\[ n = \text{number of inputs to the neuron} \]

The feed forward nets with at least one hidden layer have the capability to approximate any desired non-linear mapping to an arbitrary degree of accuracy (Draeger et al 1995). The feed forward network topology with sigmoidal activation function was formulated based on the trials with different structures (varying the number of neurons in the hidden layer). The variation of recall error with number of hidden neurons is shown in Figure 2.15. The optimal structure of ANN, having the lowest error, thus obtained, is the model with 4 neurons in the hidden layer. Better accuracy of prediction is obtained by varying the iterations during training. Figure 2.16 shows the change of recall error with the number of iterations which reveals that the Integral Square Error (ISE) almost stabilizes with error of \( 7.5 \times 10^{-3} \) in 10,000 iterations. However, during training, the ISE is further reduced to \( 4.4 \times 10^{-3} \) by increasing the iterations to 1,38,400. The number of neurons in the input, hidden and output layers are 2, 4, and 1 respectively as shown in the Figure 2.17.

2.5.2 Training Algorithm

Obtaining the appropriate weights for the network is known as the training of an ANN. During the training cycle, the network is presented with a set of data pairs of the mapping desired. The objective of training is to adjust the weights so that application of a set of inputs produces the desired set of outputs. In the proposed work, the Back Propagation Algorithm (BPA) with momentum
Figure 2.15 Variation of recall error with number of neurons in hidden layer.

*Number of iterations = 10000*
Figure 2.16 Variation of recall error with number of iterations.
Figure 2.17 ANN architecture used for developing the ANN model of AHS.
factor and learning rate, is used. Initial weights are selected randomly between 0 and 1. Normalised input and target vectors obtained from open loop experimental studies are given to ANN. The output and the error are computed. The weights are adjusted till error gets minimised to an accuracy of third decimal for all the training sets. When the error for the entire set is acceptably low, the training is stopped. The weight up-dation (Wasserman, 1989) is performed using equations (2.19) to (2.24).

Weight up-dating equations for the weights between the output layer and the hidden layer:

\[ W_{pqk}(n+1) = W_{pqk}(n) + \Delta W_{pqk}(n+1) \]  \hspace{1cm} (2.19)

where

\[ \Delta W_{pqk}(n+1) = \eta \delta_{qk} \text{Out}_{pj} + \alpha [\Delta W_{pqk}(n) ] \]  \hspace{1cm} (2.20)

\[ \delta_{qk} = \text{Out}_{q}(1 - \text{Out}_{q}) \text{[target}_{q} - \text{Out}_{q}] \]  \hspace{1cm} (2.21)

Weight up-dating equations for the weights between the hidden layer and the input layer:

\[ W_{mpj}(n+1) = W_{mpj}(n) + \Delta W_{mpj}(n+1) \]  \hspace{1cm} (2.22)

where

\[ \Delta W_{mpj}(n+1) = \eta \delta_{pj} + \alpha \Delta W_{mpj}(n) \]  \hspace{1cm} (2.23)

\[ \delta_{pj} = W_{pqk} \text{Out}_{pj} (1 - \text{Out}_{pj}) \Sigma \delta_{qk} \]  \hspace{1cm} (2.24)

ANN parameters used in this work for developing ANN model of AHS are presented in Table 2.3. The ANN model thus formulated is tested with training data and test data. The prediction with training data and test data are shown in the
Figures 2.18 and 2.19 respectively. The ANN model, thus formulated, is used in designing the MPC schemes for AHS.

Table 2.3  ANN Parameters Used for Developing ANN Model of AHS

<table>
<thead>
<tr>
<th>ANN parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of input neurons</td>
<td>2</td>
</tr>
<tr>
<td>Number of hidden neurons</td>
<td>4</td>
</tr>
<tr>
<td>Number of output neurons</td>
<td>2</td>
</tr>
<tr>
<td>Initial bias at the hidden neurons</td>
<td>1</td>
</tr>
<tr>
<td>Learning rate</td>
<td>0.5</td>
</tr>
<tr>
<td>Momentum factor</td>
<td>0.5</td>
</tr>
<tr>
<td>Number of iterations</td>
<td>1, 38,400</td>
</tr>
</tbody>
</table>

2.6 SUMMARY

An experimental set-up of AHS is designed and fabricated to carry out the open loop studies. The experimental data, thus obtained, are used to

(i) study the non-linearities of the process parameters
(ii) develop a mathematical model
(iii) develop an ANN model and
(iv) identify the process parameters

These results are used subsequently to design and implement various conventional and intelligent control schemes for the air heating system.
Figure 2.18 Validation of ANN model with experimental data.
Figure 2.19 Validation of ANN model with test data.