CHAPTER 7

RESULTS AND DISCUSSION

7.1 RESULTS AND DISCUSSION OF BIOMASS GASIFIER SYSTEM (135Kg/hr)

Experimental analyses were conducted on downdraft biomass gasifier system with capacity (135kg/hr). The gas composition (CO, CO₂, H₂, N₂, CH₄, C₂H₂, C₂H₄ and C₂H₆) was analyzed using gas chromatography by taking samples for every hour. The lower heating value of the producer gas was calculated using empirical methods. This lower heating value helps in determining the quality of the gas.

7.1.1 Lower Heating Value Analysis

The selection of optimum operating region of the biomass gasifier has been done based on experimental with lower heating values (LHV) of the gas. The LHV must be desirably around 4– 4.5 MJ/Nm³ for wood. In Figure 7.1 the relationship between LHV and CO/CO₂ ratio has been plotted and it was found that the LHV was maximum when the CO/CO₂ ratio ranges between 1-1.5. From the graph plotted for LHV versus temperature in Figure 7.2, it was inferred that the LHV was maximum when the temperature ranges between 700 -1000°C. Hence it was essential to design and develop a controller that has maintained the CO/CO₂ ratio and temperature in the inferred optimum ranges to obtained higher efficiency.
7.1.2 Static Model Analysis

A static model of the biomass gasifier process (135kg/hr) was obtained by empirical method. The model was tested for different set of input data and the results were compared with the results of actual system. The
comparison graph plotted in Figure 7.3 validates the developed model for CO/CO$_2$ ratio versus airflow rate ($F_A$) and Figure 7.4 validates the developed model for temperature versus airflow rate ($F_A$). From the results it was concluded that the model resembles the actual process approximately.

**Figure 7.3 CO/CO$_2$ ratio versus airflow rate**

**Figure 7.4 Temperature versus airflow rate**
Additional experiments were carried out to show the influence of the air flow rate on the biomass consumption. The Figure 7.5 shows the comparison between values predicted by the sub model and the values obtained from actual plant for biomass consumption versus airflow rate. Hence it was observed that the sub model values are closely related to experimental data.

The equivalence ratio was calculated and a sub model of biomass gasifier was developed, using these data. The cold gas efficiency, which can be defined as the ratio of chemical energy in gas to the chemical energy in fuel, is related to the equivalence ratio. The Figure 7.6 shows equivalence ratio versus airflow rate graph. It was observed from graph that the values predicted by model almost equal the actual plant data.

Figure 7.5 Biomass consumption versus air flow rate
7.1.3 **Fuzzy Model Analysis**

A fuzzy model of the biomass gasifier process (135kg/hr) was obtained by empirical method. This model was tested for different set of input data and the results were compared with the results of actual system. The comparison graph plotted in Figure 7.7 validates the developed model for CO/CO$_2$ ratio versus airflow rate ($F_A$) and Figure 7.8 validates the developed model for temperature versus airflow rate ($F_A$). From the results it was concluded that the model resembles the actual process.
7.1.4  Fuzzy Implementation Analysis (135kg/hr)

The fuzzy controller has been developed for downdraft biomass gasifier system with capacity (135kg/hr). Fuzzy inference system was implemented in a microcontroller and the controller outputs were fed to gasifier model simulated in LabVIEW. From the response shown in Figure 7.9 it was observed that temperature was controlled at setpoint 850°C with fuzzy controller.
The CO/CO\textsubscript{2} ratio was also perfectly controlled by controller within the optimum 1.5 ranges. From the response shown in Figure 7.10 fuzzy controller gives better performance in terms of negligible over shoot and under shoot. The CO/CO\textsubscript{2} ratio control was developed using fuzzy inference system and the designed fuzzy controller could control the ratio to its desired value 1.5.
7.2 RESULTS AND DISCUSSION OF BIOMASS GASIFIER SYSTEM (6Kg/hr)

Experimental analyses were conducted on downdraft biomass gasifier system with capacity (6kg/hr) and dynamic model was obtained using process reaction curve method. The obtained model was first order with dead time. Using this model various controllers have been developed and also verified by simulation.

7.2.1 Conventional Controller Implementation Analysis

In this work a downdraft biomass gasifier system with capacity (6kg/hr) has been considered to develop, dynamic model and various controllers’ like PI, PID, Fuzzy logic controller and self tuning fuzzy controller. The model for the process was obtained with the real time data using process reaction curve method. The obtained and PID, PI controllers were designed for the same. The Ziegler Nichols method was employed to find out the gain values Kp, Ki and Kd. The Figure 7.11 shows a response of the process to PID controller. The response was initially oscillating and settles, at 100 seconds. The response of the process to PI controller is shown in Figure 7.12. From the response it was inferred that the process has faster settling time and reduced oscillations compared to PID. The urge to achieve faster settling time then PI controller has led to the development of fuzzy controller.
7.2.2 Fuzzy Controller Implementation Analysis

Biomass gasifier process is nonlinear, time variant and sensitive to disturbances, which is extremely complex and highly challenging to control. The dynamics of process offers great difficulty in controller design. The conventional industrial controllers such as Proportional integral (PI), Proportional integral Derivative (PID) controller have been designed for the
biomass gasifier process. When the process deviates from the steady state, the performance of linear controllers also tends to deviate. Thus the intelligent controller has been proposed to overcome the limitations of conventional controllers.

Figures 7.13, 7.14, 7.15 and 7.16 shows the responses of the plant with fuzzy logic controller for various set points 400°C, 600°C, 500°C, and 750°C respectively. From the response it was observed that fuzzy logic controller offers better performance in terms of settling time, overshoot and undershoot.

![Figure 7.13 Response of process to fuzzy controller (set point = 400)](image_url)

![Figure 7.14 Response of process to fuzzy controller (set point = 600)](image_url)
Figure 7.15 Response of process to fuzzy controller (set point = 500)

Figure 7.16 Response of process to fuzzy controller (set point = 750)

7.2.3 Self Tuning Fuzzy Controller Implementation Analysis

The reason to develop the self tuning fuzzy controller is to design the controller, which adapts to the changes of the process during the operation resulting in robust responses. For example, if the system response is slower than desired, the effect of the error on the system must be increased. Hence, the error scaling factor is increased. Similarly, if the overshoot or amplitude of oscillation is higher, the effect of the change of error on the controller should be bigger. Hence, the appropriate scaling factor is increased. The self-
tuning fuzzy logic controller was implemented with obtained dynamic model in LabVIEW. The response of the process to the self-tuning controller is shown in Figures 7.17, 7.18, 7.19 and 7.20 for various set points of 400°C, 750°C, 500°C, and 600°C respectively. The settling time was still faster for a self-tuning fuzzy controller compared to other controllers. The process reaches its desired value at about 25 seconds.

![Figure 7.17 Response to self tuning fuzzy controller (set point = 400)](image1)

![Figure 7.18 Response to self tuning fuzzy controller (set point = 750)](image2)
Figure 7.19 Response to self tuning fuzzy controller (set point = 500)

Figure 7.20 Response to self tuning fuzzy controller (set point = 600)
7.3 COMPARISON OF CONTROLLERS

The performances of the controllers are given in Table 7.1. From the results, the self tuning controller was found to be the better controller compared to conventional controllers like PI, PID and intelligent fuzzy controllers. The self tuning fuzzy controller offers faster settling time, without overshoot and undershoots and hence proves to be the versatile controller for gasifier process.

Table 7.1 Comparison of various controllers in temperature process

<table>
<thead>
<tr>
<th>Controller</th>
<th>Undershoot (%)</th>
<th>Overshoot (%)</th>
<th>Settling time (seconds)</th>
</tr>
</thead>
<tbody>
<tr>
<td>PID</td>
<td>12.5</td>
<td>50</td>
<td>100</td>
</tr>
<tr>
<td>PI</td>
<td>10</td>
<td>42</td>
<td>75</td>
</tr>
<tr>
<td>Fuzzy Logic Controller</td>
<td>Nil</td>
<td>Nil</td>
<td>50</td>
</tr>
<tr>
<td>Self Tuning FLC</td>
<td>Nil</td>
<td>Nil</td>
<td>25</td>
</tr>
</tbody>
</table>

7.4 ASH HANDLING SYSTEM WITH FLC

Ash removal from the gasifier unit requires utmost care because it affects the performance of the process. Ash handling system may be automated by regulating the pressure of the gasifier unit. A prototype was designed to regulate the pressure using microcontroller in laboratory set up. Fuzzy control was designed to regulate the pressure without overshoot. The pressure was regulated at various levels. The Figures 7.21, 7.22, and 7.23 shows the responses of the pressure process at various setpoints respectively. From the responses it was observed that the fuzzy controller regulate the pressure without overshoot. Hence the designed fuzzy controller can be suggested to be implemented for the actual process.
Figure 7.21 Response of pressure control loop with set point 1 Kg/Cm$^2$

Figure 7.22 Response of pressure control loop with set point 1.5 Kg/Cm$^2$

Figure 7.23 Response of pressure control loop with set point 2 Kg/Cm$^2$