DEVELOPMENT OF AN ANN BASED PLANT CONTROLLER FOR BIOMASS DOWNDRAFT PACK BED GASIFIER

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ABSTRACT

Energy crisis and emerging negative impacts on environment are the leading factors of industries to increase the share of sustainable resources in the energy production. Biomass based solutions have become as an alternative for fossil fuels due to its availability and sustainability. There are several energy conversion method to utilized biomass, among them. gasification is the one of main energy conversion method. However, biomass gasification has shortcomings due to the barriers like unpredictable variability of biomass properties, process complexity, and controllability of the process.

There are several types of gasification types. Downdraft back bed biomass gasifire is the most suitable one for small power application (10-1000kW) and it is beneficial over the other types because of less complexity of construction and low carbon footprint.

Aim of this study is to develop an artificial neural network based on plant controller for biomass gasifier. Biomass gasification process model was developed using feedforward neural network model (FFNN) and neural network based nonlinear autoregressive model with external output (NNARX). According to results, NNARX showed the best performance for prediction of process output.

The effectiveness of the neural network based internal model controller (IMC) was successfully tested for gasification plant. Two experiments were carried out using 12kg of coconut shells. One experiment plant was run with proposed neural network internal model controller (NNIMC) while second experiment was done without NNIMC and blower was operated at constant reference RPM.

Developed NNIMC was tested using 15kW pack bed imbert type downdraft biomass gasifire and controller algorithms. Performance of introduced IMC was analysed using 72 minutes of continuous plant operation. The analysis revealed that 12% of gasification efficiency can be improved while increased the performance in terms of stability by the introduced of NNIMC.

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LIST OF ABBREVIATIONS

Abbreviation	Description
AI	: Artificial Intelligent
ANN	: Artificial Neural Network
CFB	: Circulating Fluidized Bed
DC	: Direct Current
ER	: Equivalence Ratio
FBNN	: Feedback Neural Networks
FFNN	: FeedForward Neural Networks
HMFNN	: Hybrid Multilayer FeedForward Neural Networks
IC	: Internal Combustion
IMC	: Internal Model Controller
NN	: Neural Network
NNARX	: Neural Network based nonlinear Autoregressive model with external output
NNIMC	: Neural Network Internal Model Controller
RNN	: Recurrent Neural Networks

1.0. INTRODUCTION

1.1. Background

Sri Lankan industrial energy demand is being increased with the population growth and urbanization [1]. Therefore, the cost of electricity and fossil fuel, which are the primary energy sources of current Sri Lanka is also continuously going up. In this context, usage of renewable energy sources is becoming more popular, particularly, industrial sector is interested in biomass-based solutions to meet their thermal, electricity and other forms of energy demands due to low cost [4]. At the same time, biomass is the cheapest energy source available in Sri Lanka. And it also can save the foreign exchange and minimise the net carbon emission as a developing country.

Biomass is generally all materials that contain organic carbon, produced by plants due to photosynthesis. It was the oldest fuel for mankind. Although, the discovery of fossil fuel was a turning point of worldwide energy demand due to its easy applicability compared to biomass, it has been revealed that the growing energy demand would not be satisfied only by the currently available fossil fuel reserves. Therefore, researchers have started searching for alternative methods to convert energy by innovative and sustainable manner to address the growing demand [5].

Interest towards all renewable energy sources including biomass was renewed during 1970s as a result of crude oil crisis, but development of biomass technologies is yet impeded by high energy density of fossil fuel with the detection of new fossil fuel reserves. In 1980s, global warming and climate changes due to emission of CO_2 resulting from fossil fuel consumption were thoroughly concerned, and then documented as an objective of Kyoto protocol to reduce the CO_2 emissions due to human activities [6]. Renewable energy sources would have to provide considerable part of energy requirement in order to attain the Kyoto objective, therefore, in this century, biomass has become the most vital renewable energy source [4, 6]. At the same time, there are different types of biomass conversion methods into usable energy.

“Gasification” is one of the process of converting solid fuel, which was invented during World War II [1]. In this process, there is a thermochemical conversion of solid fuel into high calorific and useful gaseous fuel or chemical products [5], which can directly use for internal combustion engine and gas burners. However, this technology is still not much acquainted for small scale domestic power generation application. Because of complexity and operation difficulties of those processes such as maintaining continuous process output due to process uncertainties and process disturbances like fuel properties. Most of past researchers tried to overcome those problems by improving reactor geometry and fuel pre – processing. In this study, process stability and efficiency is going to be improved using artificial neural network based control technology, which is highly applicable for non-linear, uncertain process.

1.2. Significance of the Study

Biomass gasification is renewable and sustainable energy conversion method. This method is very much effective for developing countries that import fossil fuels. However, gasification has considerable operational problems arose due to process nonlinearity and uncertainty of fuel properties. Therefore, past researchers studied about gasification enhancing reactor geometry. But, there is very little literature on use of artificial neural networks (ANNs) and process control techniques for improving process efficiency and dynamics of biomass gassifire. Therefore, in this research, ANN with process control is used to enhance efficiency of biomass gasifire.

1.3. Aim

Aim was to develop an artificial neural network based plant controller for biomass pack bed downdraft gasifire with enhanced efficiency and stable plant output.

1.4. Objectives

Objectives were to develop

- a biomass down draft gasifier for small scale power application
- a gasification plant model
- a biomass gasification plant controller with enhanced plant efficiency.

2.0. LITERATURE REVIEW

2.1. Gasification

"Gasification" is one of the principal energy conversion process, which produces combustible gas from solid fuel (coal, peat) or biomass that can be consequently used for internal combustion engine or turbine engine to generate electricity and/or process heat requirement. The overall efficiency of electricity generation by gasification process is higher than direct combustion of biomass [5]. Typically biomass gasification includes steps as drying, pyrolysis, combustion and char reaction (gasification) as illustrated in Figure 2.1 [7].

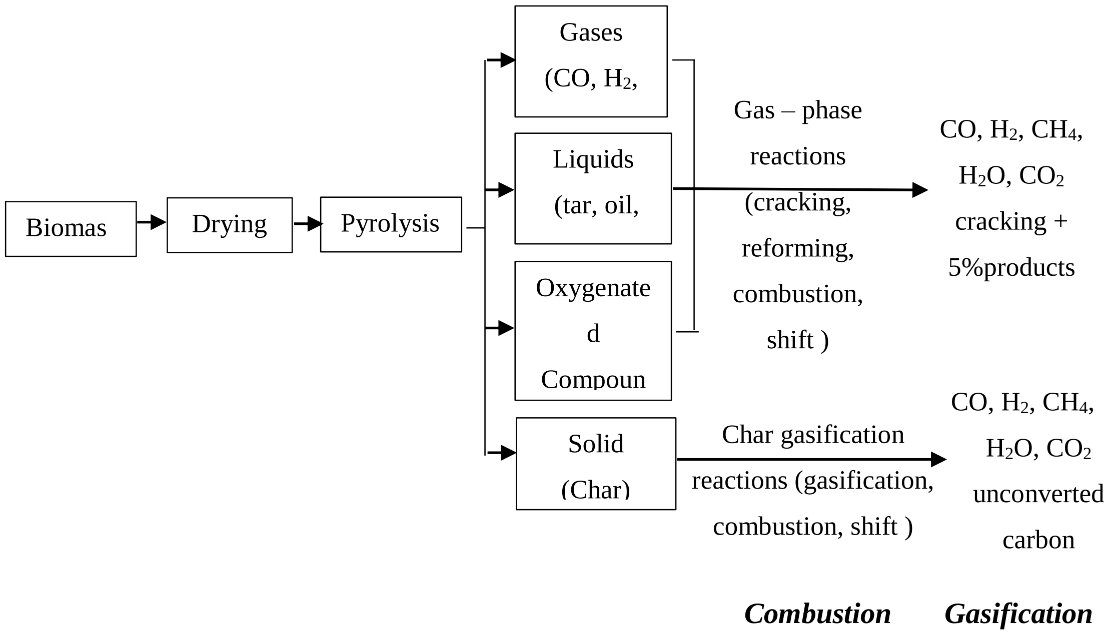


Figure 2. 1: Schematic Diagram of Gasification Process [6]

Drying zone is the zone where bounded water of biomass irreversibly removes at above 100℃ due to heat from high temperature zone (combustion zone). Moisture content of fresh wood and dry biomass is usually between 30% - 60% and 10-20% respectively.

In the stage of pyrolysis, large hydrocarbon molecules in biomass are broken down in to small hydrocarbons and char due to lack of oxygen at relatively low temperature as shown in Figure 2.1. Gasification pyrolysis occurs between 300℃ - 650℃, which is called as pyrolysis temperature. Quality of process out puts depends on heating rate and pyrolysis temperature.

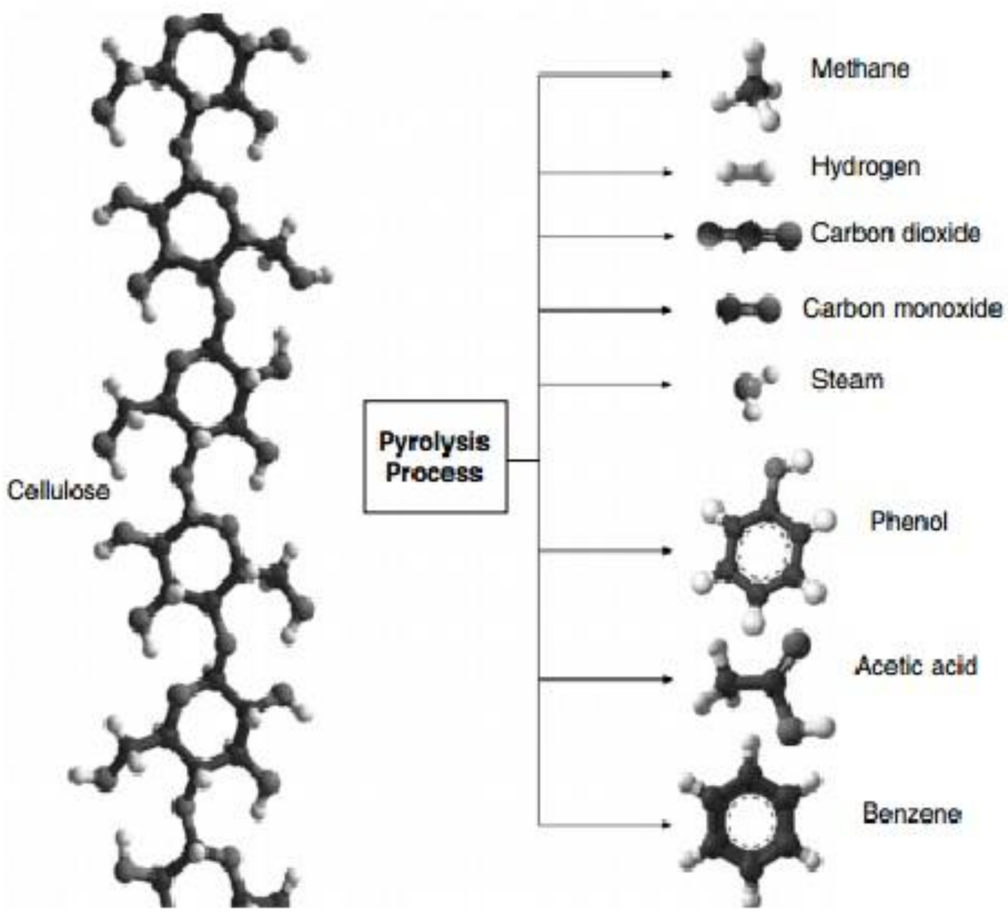


Figure 2. 2: Large Hydrocarbons Decomposition into Mall Hydrocarbons during Pyrolysis Process [7]

Equation 2.1 represents the generic reaction of biomass pyrolysis.

$$C_nH_mO_p \text{ (Biomass)} \xrightarrow{\text{Heat}} \Sigma_{liquid}(C_xH_yO_z) + \Sigma_{gas}(C_aH_bO_c) + H_2O + C \quad \ldots\ldots (2.1)$$

Figure 2.3 shows combustion of a biomass particle, where oxygen is richest. Therefore, particular quantity of gas and liquid which has been realised during pyrolysis contact with oxygen and burn out. Heavy hydrocarbons (tar) decompose to low weight hydrocarbons due to higher temperature, and some low weight hydrocarbons burn and produce CO_2, CO, H_2O and C (char).

Remained char reacts in gasification zone. Steam released from drying and combustion of hydrocarbons goes through red hot char and produces CH_4 and H_2 while CO_2 from combustion zone reacts with red hot char and create CO. Chemical reactions occur in gasification zone at 800°C-1000°C are as shown as below.

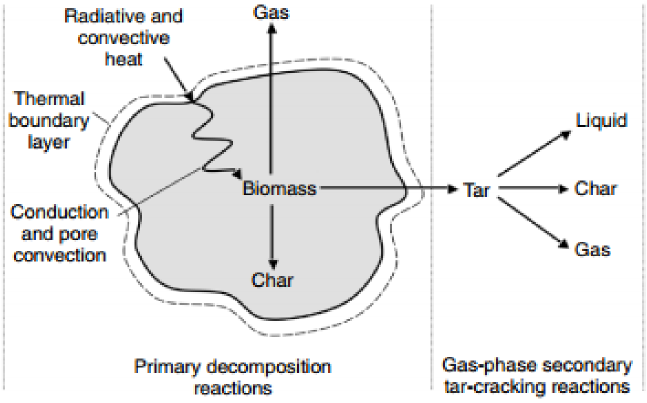


Figure 2. 3: Combustion of Biomass Particle

$2C + 2H_2O \longrightarrow CO_2 + CH_4$ (Gasification) ……………………..…... (2.2)

$C + H_2O \longrightarrow CO + H_2$ (Gasification) ………………………...... (2.3)

C + H2O $\longrightarrow CO_2 + H_2$ (Gas shift) ………………………….. (2.4)

$CO + 2H_2 \longrightarrow CO_3OH$ (Methanol) ………………………...... (2.5)

$C + CO_2 \longrightarrow 2CO$ (Boudouard) ………………………...... (2.6)

$CO + 3H_2 \longrightarrow H_2O + CH_4$ (Methanation) ………………………….. (2.7)

At higher temperature (1200°C-1400°C), gasification output consists of CO and H_2, which is called as bio syngas while at lower temperature (800°C-1000°C), gasification output varies to CO, H_2, CH_4 and C_xH_y [5]. Therefore, gasification temperature is one of the main process parameter that depends on fuel, gasification agent and rector type.

2.2. Types of Gasification Reactor and Construction

Gas – solid contacting mode and gasifying medium are the primary classification factors of gasifiers. Gasifiers are further categorised into three principal types based on gas –solid contacting mode as entrained flow, fixed or moving bed, and fluidized bed. Each type of those three subdivides into specific categories as shown in Figure [5, 7].

The type of gasifier should be selected based on the power generation range. To illustrate that for small scale power requirement (5kW-10MW) can be provided by fixed bed/moving bed gasifire, while medium scale power range fluidized bed are more appropriate for 5MW-100MW. Furthermore, entrained flow gasifire is used for large capacity units (>50MW).

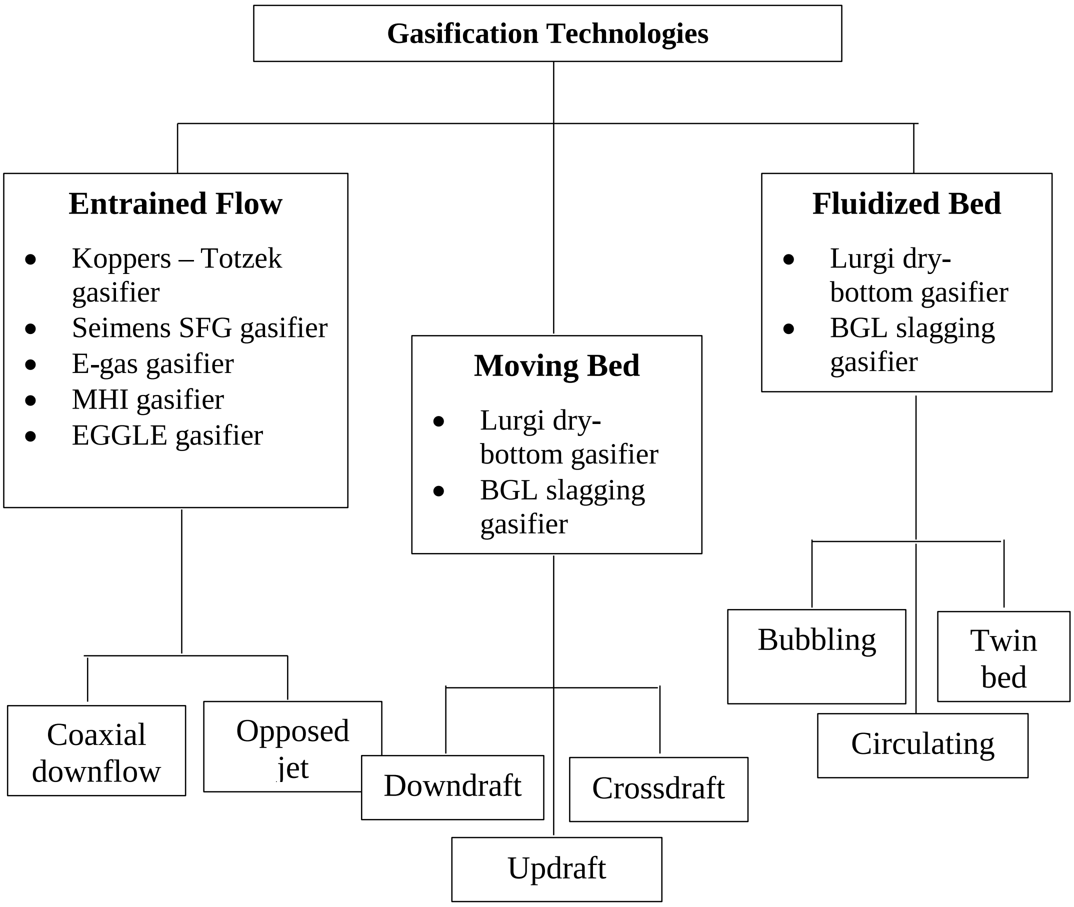


Figure 2. 4: Classification of Gasifier [7]

2.2.1. Fixed/moving bed gasifier

In fixed/moving bed gasifire, fuel particles keep stationary on grate, which is designed according to relative motion with fuel particle for ash removing and better contact between char and gases. There are three different reactors such as updraft, downdraft and cross draft in fixed/moving bed gasifire as illustrated in Figure 2.5.

One of main feature of fixed bed/moving bed gasifier is clearly separated zones as drying, pyrolysis, combustion and gasification (char burning). This type of reactor is not effective for large scale power requirement for the reason that poor heat and mass transfer across the cross section of reactor. However, construction of this type of gasifire is relatively not expensive and less complex.

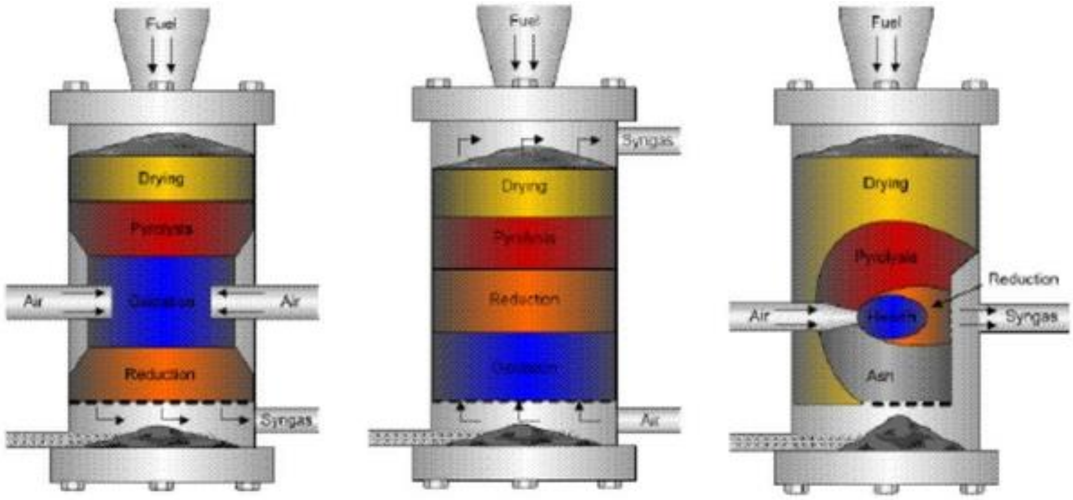


Figure 2. 5: Different Constructions of Fixed Bed / Moving Bed Gasifier (Left to right: Downdraft, Updraft, and Cross Draft)

2.2.1.1. Updraft gasifire

Updraft gasifire is also called as counter current gasifire, which is the oldest and simplest of all of designs. Fuel feeds at the top of gasifire while gasification agent feeds at the bottom of reactor. Then, the gasification agent passes through hot char, combustion zone, pyrolysis zone and drying zone respectively. Produced gas removes at the top of the updraft reactor. Updraft gasifire is appropriate for biomass having higher ash amount (up to 25%) and higher moisture content (up to 60%) [7]. Higher tar production is the main drawback of this gasifire since it causes a significant damage for downstream equipment in plant such as, internal combustion engines and gas burners. All the micro scale cooking gasifier are updraft gasifiers, and dry ash gasifire and slagging gasifier are examples for commercially available large scale applications.

2.2.1.2. Cross draft gasifier

Cross draft gasifire is another simple gasification design. Unlike co-current or counter current gasifire, air (gasification agent) enters from side direction of reactor (right hand side drawing in Figure 2.5) and produced gas removes from opposite side direction of wall, which air enters. However, fuel entry from upper part of the gasifire is alike other fixed bed/moving bed gasifire. Cross draft has the most light power capacity, where output gas directly connects to the internal combustion engine after gas is cleaned [7, 9]. Low respond time for load change and low tar generation are the main advantages of this type, thus, it is required a simple gas cleaning system. Cross draft gasifire is not suitable for fuel contents higher ash amount, but it can handle fuels having higher moisture.

2.2.1.3. Downdraft gasifier

Downdraft gasifier is a co-current reactor where air enters to gasifier at a certain height below the top. Product gas flows downward as implies from the name and leaves through a bed of hot ash as shown in Figure 2.6. Since it passes through high-temperature zone of hot ash, tar in the product gas finds favourable conditions for cracking. Therefore, downdraft gasifier has the lowest tar production rate (0.015-3g/nm^3) among all those types [7, 9, and 11]. It is the main reason of downdraft gasifire for well performance as internal combustion engine. The engine suction draws air through the bed of fuel, and gas is produced at the end. Furthermore, ignition and required time for reactor to get active temperature for downdraft gasifire is shorter than updraft type.

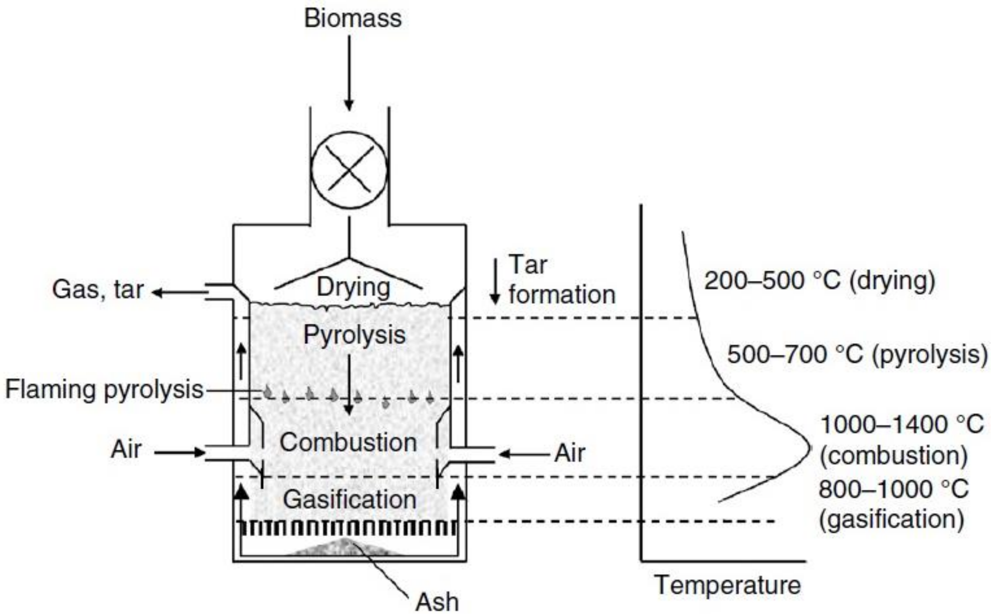


Figure 2. 6: Schematic of Downdraft Gasifier and Temperature Gradient with Height [7]

According to geometrical shape, there are two types of downdraft gasifire; Downdraft Imbert gasifier and Stratified Downdraft gasifire as illustrated in Figure 2.7.

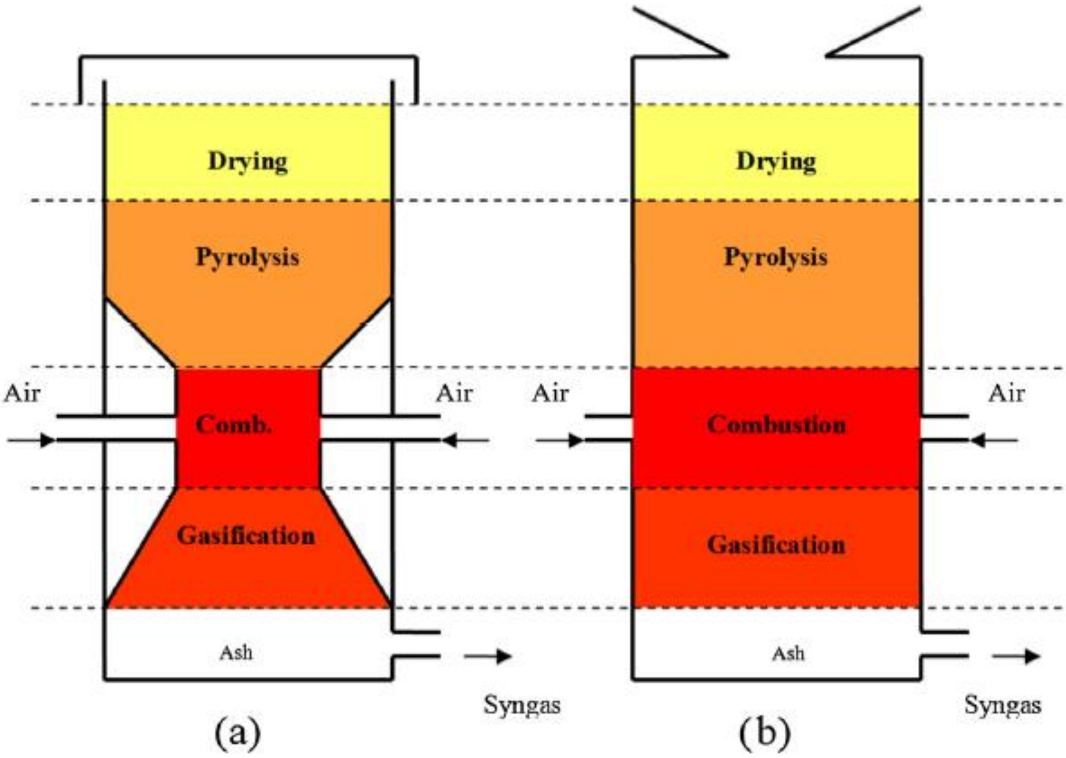


Figure 2. 7: (a) Imbert Downdraft Gasifier, (b) Stratified Downdraft Gasifier [10]

2.2.1.4. Stratified gasifier

Stratified gasifier is also called as open top, or throat less, where the top is exposed to the atmosphere, and there is no narrowing in gasifier vessel because walls are vertical as shown in Figure 2.7(b). Conical groove type fuel flow is avoided in this construction. Therefore, it is better for low shrinkage fuel (light weight and finer). Moreover, best performance is in pelletized fuel rather than fine light biomass, however, additional cost is added for fuel pelletizing. As well as, moisture content of fuel must not exceed 25%. Similarly, another negative point is that large amount of residual as ash and dust in the product gas. And lower gasification temperature is resulted due to higher temperature at exit.

Georges Imbert invented the original design of throated or constricted gasifier in 1920s, which is popularly known as an Imbert gasifier [7] which is displayed in Figure 2.7(a). It has a cross-sectional area that is reduced at the throat and expanded afterwards.

Here, fuel is fed at the top, and then descended along the cylindrical section that serves as storage. At the height of about one-third of way up from the bottom, air is injected just above the constriction through nozzles. Air pyrolysis the biomass and all of those pyrolysis gas is forced to pass through the narrow passage, because oxidation (combustion zone) facilitates at the narrowest part of the throat. There, pyrolysis products are burnt. A uniform temperature distribution, char gasification and cracking of the most of tar are appeared because the entire mass of pyrolysis product moves through this hot and narrow zone, over the cross-section. However, throated downdraft gasifiers are not advantageous when scale-up to larger sizes because they do not allow for uniform distribution of flow and temperature in the constricted area.

2.2.2. Fluidized –bed gasifier

Fluidized - bed is prepared using granular solids, known as bed materials where those materials are kept in fluidized state (semi-suspended condition) by the passage of gasifying medium through them at appropriate velocities. Excellent mixing and temperature uniformity are the key features of the fluidized-bed gasifiers. However, this type of gasifier is relatively insensitive to fuel's quality because of this excellent gas–solid mixing and the large thermal inertia of the bed (Basu, 2006). Hence, risk of fuel agglomeration is reduced significantly by the temperature uniformity. The fluidized-bed design is specially evidenced that it is beneficial for biomass gasification. Tar production rate of this type of gasifier is usually around 10 g/nm^3, which lies between downdraft (~1 g/nm^3) and updraft (~50 g/nm^3) gasifiers.

2.3. Gasification Modelling and Control

Marketable fuel or products are created by gasification with the means of low value feedstock. This conversion process is considerably more complex than combustion, and influenced by a number of factors, including amount of oxidant, feedstock composition, gasifier temperature, reactor geometry and mode of gas–solid contact.

Modelling is very effective in order to optimize the operation of an existing gasifier and explore operational limits instead of sizing of reactor. A model can identify the sensitivity of gasifier performance according to the variations of different operating and design parameters [12]. Furthermore, there are different modelling approach, such as thermodynamic equilibrium, kinetic, computational fluid dynamics and artificial neural network.

2.3.1. Equilibrium modelling

The maximum yield that can be accomplished a desired product in a reacting system can be calculated using a thermodynamic equilibrium model. Equilibrium of thermochemical system is determined based on the equilibrium constant or minimization of Gibbs free energy [8, 12]. Furthermore, there are two equilibrium models such as Stoichiometric and Non stoichiometric depending on above two techniques. Stoichiometric approach requires a detailed specification of all the chemical reactions and species involved in the model while non-stoichiometric method is relied on Gibbs free energy minimization. Moreover, in non-stoichiometric method, it needs not to consider each and every individual chemical reactions in gasifire, but global chemical reaction which represents the input and output only.

Thermal chemical equilibrium is practically not possible in gasifire reactor [12] because gasification is a dynamic process. The main advantage of the equilibrium model is that its independence from gasification geometry. Different authors had been developed gasification equilibrium models both in non-stoichiometric and stoichiometric models for downdraft gasifire [20, 21]. The main purpose of equilibrium modelling is to predict the performance of gasifier in design stage. However, high computation time is required due to several complex nonlinear thermochemical equations and equilibrium describes only the stationary gasification process, thus, equilibrium model is not appropriate for online plant control. Similarly, equilibrium models do not estimate the difference between required time to reach equilibrium and residence time, and assume that all reactions reach chemical equilibrium. But, gasification process involves heterogeneous char reactions that occur slowly.

2.3.2. Kinetic model

Development of kinetic models to evaluate and imitate the gasifier behaviour is caused by the inadequacy of equilibrium model to correlate the reactor design parameter with the final product gas composition. Reaction rate, residence time, reactor hydrodynamics (superficial velocity, diffusion rate) and length of reactor are the kinetic model parameters, therefore, a wide range of dimensions are provided by kinetic model to investigate the behaviour of a gasifier via simulation. Further, they are more accurate but intensive in computations. It is difficult to formulate the exact reaction pathways and simulate for quite extensive process of biomass gasification.

Majority of models model for reduction reaction and often separate sub-models for pyrolysis, oxidation and reduction. Simplifying the model by separating the overall process into sub- models of pyrolysis, oxidation and reduction zones provides a better understanding of downdraft gasifier behaviour [12]. Ozgun Yucel 2016 [22] has developed a kinetic model for downdraft and predicted the reactor performance for different throat angles. However, due to nonlinearity and complexity of the model, gasifire kinetic model is also difficult to use for online plant control.

2.3.3. Artificial neural network modelling

When developing a mathematical model (equilibrium or kinetic modelling), many idealized assumptions have to be considered due to complexity of the gasifier system. Artificial neural networks (ANNs) is a useful tool especially, when the primary aim is to optimize the process parameters and output of a complex system. ANNs are extensively used in the field of pattern recognition, signal processing, function approximation and process simulation. However, they have not been used in the field of biomass gasification modelling, therefore none or very limited literature could be found on it.

Hybrid multilayer feedforward neural networks (HMFNN) were improved by Guo et al. (2001) [23] to forecast the plant output of fluidised bed gasifire and they had only considered temperatures of gas and bed as model inputs. Furthermore, Puig- Arnavat et al. (2013) [25] developed an ANN model for fluidised bed gasifire. That model consisted of input output layer; one hidden layer; and composition of the biomass in terms of C, H, and O, equivalence ratio, gasification temperature, ash and moisture content as model inputs. Predicted output were percentage values of CO, CO_2, H_2 and CH4 in produced gas as illustrated in Figure 2.8.

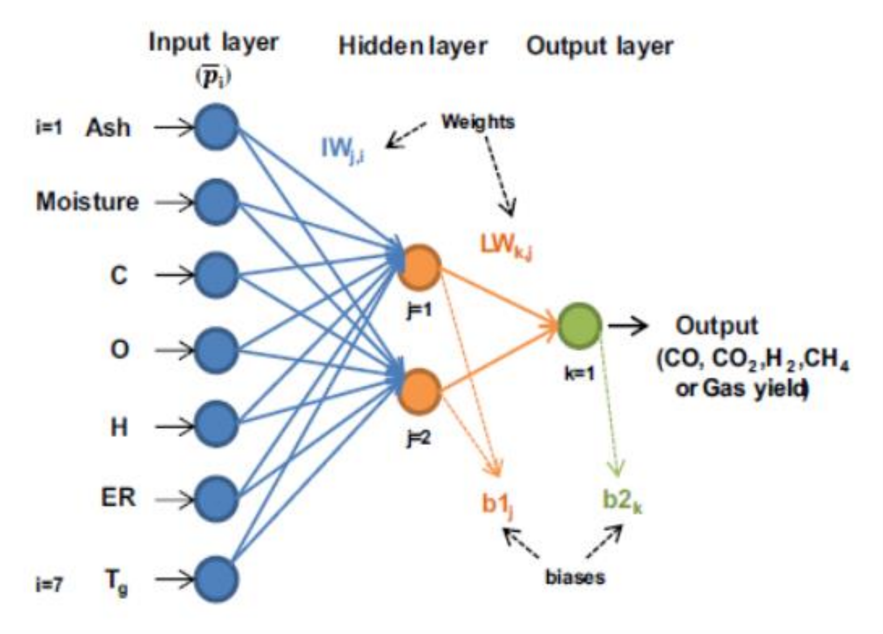


Figure 2. 8: ANN Model Structure to Predict Produced Gas Composition of CFB Gasifier [25]

A summary of different biomass gasification models are presented in Table 2.1. Equilibrium and kinetic models are useful in prediction of gasifier performance under number of different stationary operating conditions therefore, they are often used for preliminary design and optimisation purposes. According to [26], many equilibrium models have been verified just on several particular operating points or with data derived due to lack of extensive measurements. Less number of artificial intelligence systems based on biomass gasification models have been reported because ANN model does not create intensive measurement.

ANN is a universal function approximator that can approximate any continuous function to an arbitrary precision even without a prior knowledge on structure of the function that is approximated [24]. Furthermore, ANN models have proven their potential of forecasting the process parameters in energy related processes such as in biodiesel production process [27] and applied for different thermochemical reactor applications such as flotation column, packed distillation column [28,29]. For that, ANN models use a non-physical modelling approach which correlates input and output data to form a process prediction.

Table 2. 1: Summary of Gasification Modelling

Process Modelling Approach	Advantages	Disadvantages
Kinetic Model	• More realistic process description • Extensive information regarding process operation • Good for gasification design and improvement purposes	• All possible process reactions are not considered as different model reaction coefficients and kinetics constants • Dependable on the gasifier design • Impractical for online process control
Equilibrium Model	• Independent from gasifier type and design or specific range of operating conditions • Useful in prediction of gasifier performance under various different operational parameters • Easy to implement • Fast convergence	• Describe only stationary gasification process • Do not offer insight in gasification process
Stoichiometric Model	• Applicable for describing complex reactions in general	• Only some reactions are taken into consideration • Reaction mechanisms must be clearly defined • Equilibrium constants are highly dependable on • specific range of process parameters
Non-stoichiometric Model	• Simplicity of input data	• Describe gasification process only in general
Artificial Neural Network Model	• Do not need extensive knowledge regarding process • Applicable for online process control	• Depends on large quantity of experimental data • Many idealised assumptions • Knowledge regarding process is needed

3.0. METHODOLOGY

3.1. Downdraft Gasifire Designing and Implementation

3.1.1. Gasifire sizing

Design of an Imbert type downdraft gasifire is based on the specific gasification rate, that is also called as hearth load G_h. It is defined as the amount of produce gas to be obtained per unit cross-sectional area of the throat, which is the smallest area of cross-section in the reactor. It is generally expressed in terms of Nm^3/hcm^2, where N indicates the calculated volume of gas at normal pressure and temperature. Furthermore, it is reported that the gasifier can be operated with G_h in the range of 0.1-0.9 Nm^3/hcm^2 [7, 14].

Figure 3.1 shows key dimensions of the main design of a downdraft Imbert type gasifire. As the first step, volumetric gas production rate was determined. Then, Imbert diameter was calculated.

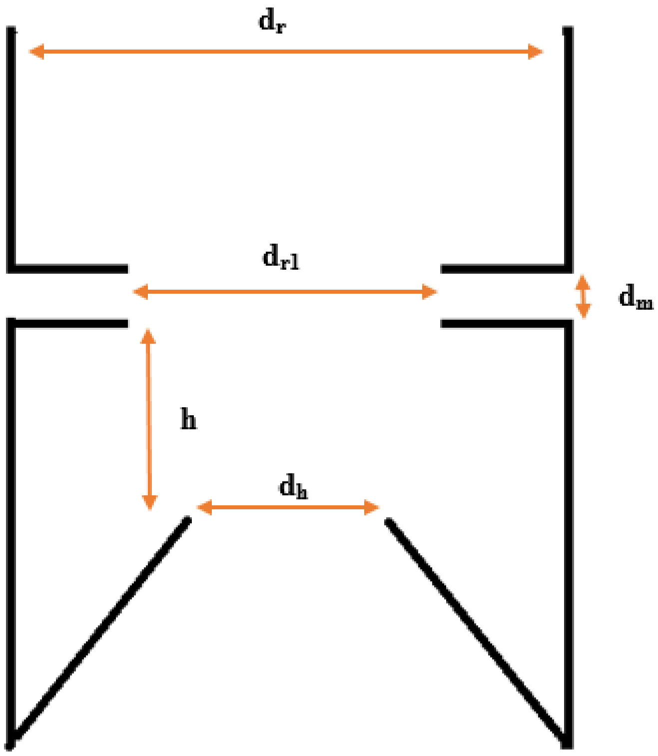


Figure 3. 1: Design Parameter for Imbert- Type Gasifier

In this research, gasifire plant was designed for engine shaft output of 3-5kW. Typical efficiency of internal combustion (IC) engine was approximately 20%. Therefore, predicted plant output power was 15-25kW. Average heating valve of biomass downdraft gasifire is 4.6 - 6.00 MJ/m^3 [13].

Required plant output per hour for 25kW = 25x1000x360

= 90 MJ/h

Required volume of produced gas per hour $= \dfrac{\text{(Required plant output per hour)}}{\text{(Produced gas calorific energy)}}$

$= 90MJh^{-1}/4.6MJm^{3}$

$= 19.56m^3/h$

Specific gasification rate $= \dfrac{\text{(Volumetric gas production rate)}}{\text{(Hearth cross section area)}}$

Maximum specific gasification rate for downdraft biomass gasifire was $0.9Nm^3/h$ [14], therefore, hearth diameter (d_h) was calculated as below;

$0.9Nm^3/h\ (G_h) = 19.56m^3h^{-1}$/Hearth cross section area

Hearth cross sectional area $= 21.39cm^2$

Therefore, hearth cross section diameter (d_h) = 52.2mm

Likewise, all dimensions of main design were selected according to Table 1, based on the calculated hearth cross section diameter (d_h) of 52.2mm. Therefore, selected hearth cross section diameter (d_h) from Table 3.1 is 60mm. According to Table 3.1, selected values are 268mm, 150mm, 80mm, and 7.5mm for d_r, $d_{r'}$, h, and d_m respectively.

Number of nozzles should be an odd number to avoid hitting jet from one nozzle with the jet of opposite side and ensure a dead space in between. And the total nozzle area is typically 4 to 7% of the throat area [7]. Therefore, in this design, 5 number of air inlet nozzles were used.

Table 3. 1: Sizes of Imbert –Type Gasifier

d_r/d_h (–)	d_h (mm)	d_r (mm)	$d_{r'}$ (mm)	h (mm)	H (mm)	R (mm)	A (no.)	d_m (mm)	Range of Gas Output (Nm^3/h)	Maximum Wood Consumption (kg/h)	Air Blast Velocity (m/s)
268/60	60	268	150	80	256	100	5	7.5	4–30	14	22.4
300/100	100	300	208	100	275	115	5	10.5	10–77	36	29.4
400/130	130	400	258	110	370	155	7	10.5	17–120	57	32.6
400/150	135	400	258	120	370	155	7	12	21–150	71	32.6
400/175	175	400	308	130	370	155	7	13.5	26–190	90	31.4
400/200	200	400	318	145	370	153	7	16	33–230	110	31.2

Variables not defined in the figure are defined as follows:

d_m = inner diameter of the tuyere
A = number of tuyeres

Source [7, 15]

3.1.2. Gasifire design and implementation

There are various approaches for handling inlet and out gas. It is essential to maintain a higher temperature inside of the reactor for proper gasification and minimisation of tar in produced gas [16, 17, and 18]. In Figure 3.2, there are three different produce gas outlets and reactor contractions.

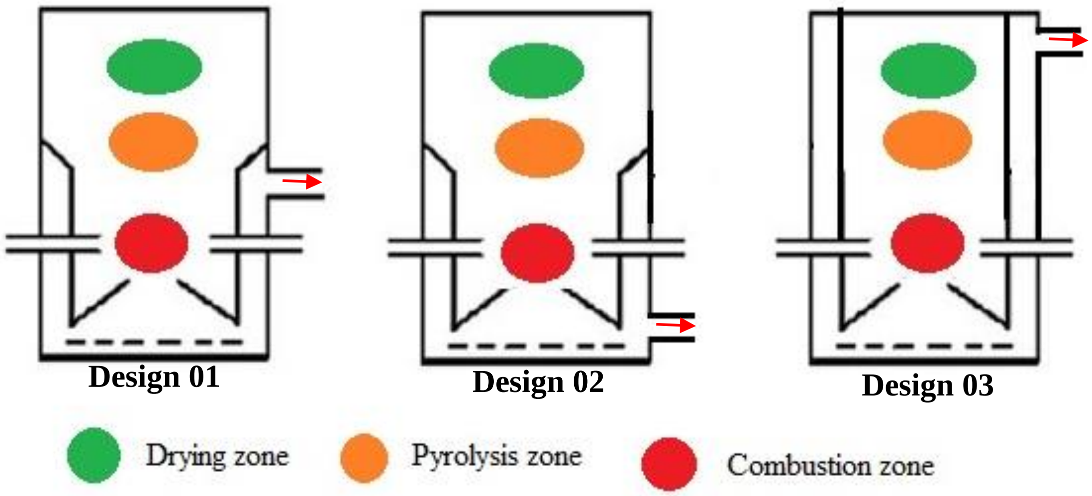


Figure 3. 2: Different Locations of Produce Gas Outlet

Table 3.2 summarises properties of different gas output concepts of above three reactor designs shown in Figure 3.2.

Table 3. 2: Properties of Different Produce Gas Outlets

Design No.	Output gas temperature	Output gas quality	Heat recovery of reactor	Energy for biomass drying
01	High	Medium ash and dust	High	Low
02	High	High ash and dust	Low	Low
03	Low	Low ash and dust	High	High

When temperature of output gas is high, subsequently, it results a low thermal efficiency and requires an external cooling process because high output temperature produced gas is not appropriate for internal combustion engine applications. In addition to that, higher content of ash and dust in produced gas increases a gain for gas cleaning. In Design 03 shown in Figure 3.2 has a properly insulated reactor, which increases the heat absorption for biomass drying, thereby, temperature of produced gas becomes low whereas thermal efficiency is high.

Figure 3.3 illustrates different orientations for air (gasification agent) inlet. In first three, air is reached to combustion zone at lower temperature which causes for reduction of temperature at combustion zone. Low temperature of the reactor leads to high tar and poor gasification. But, according to fourth orientation, input air is preheated by produced gas flow and radiation heat come from the reactor. As well as this can reduce output temperature of produced gas. Thus, finalised conceptual design of gasifier based on those facts is shown in Figure 3.4.

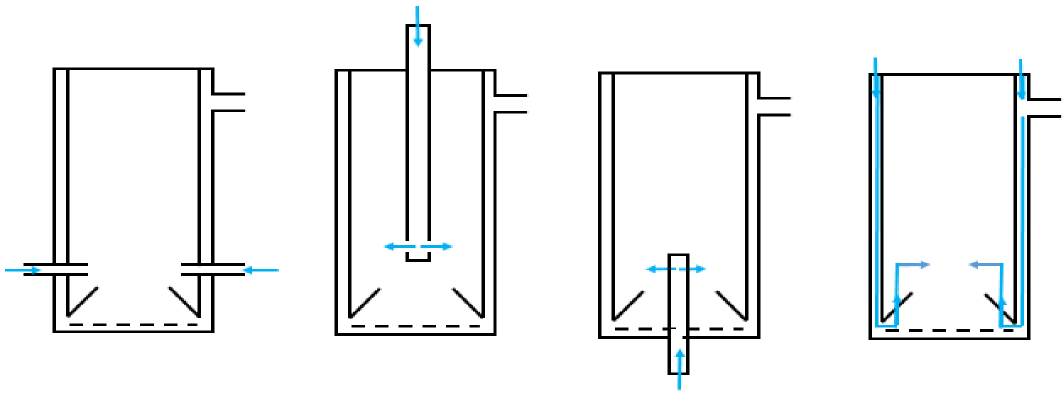


Figure 3. 3: Different Air Inlet Concepts

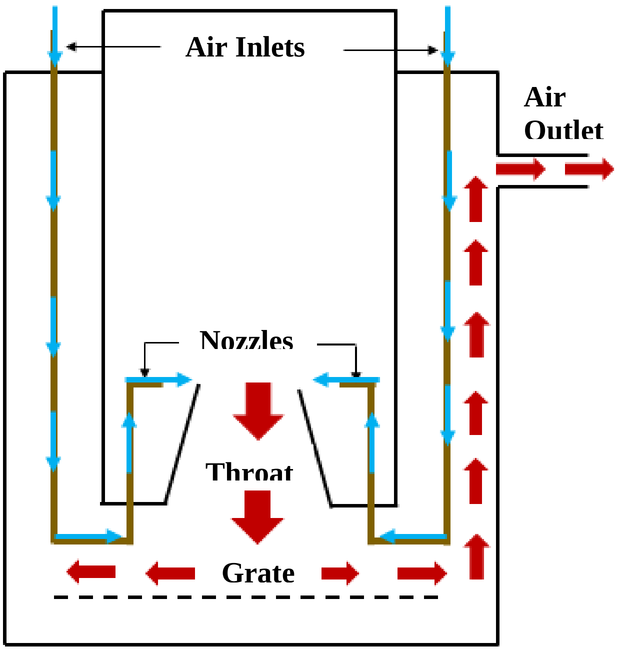


Figure 3. 4: Finalized Conceptual Design of Gasifire

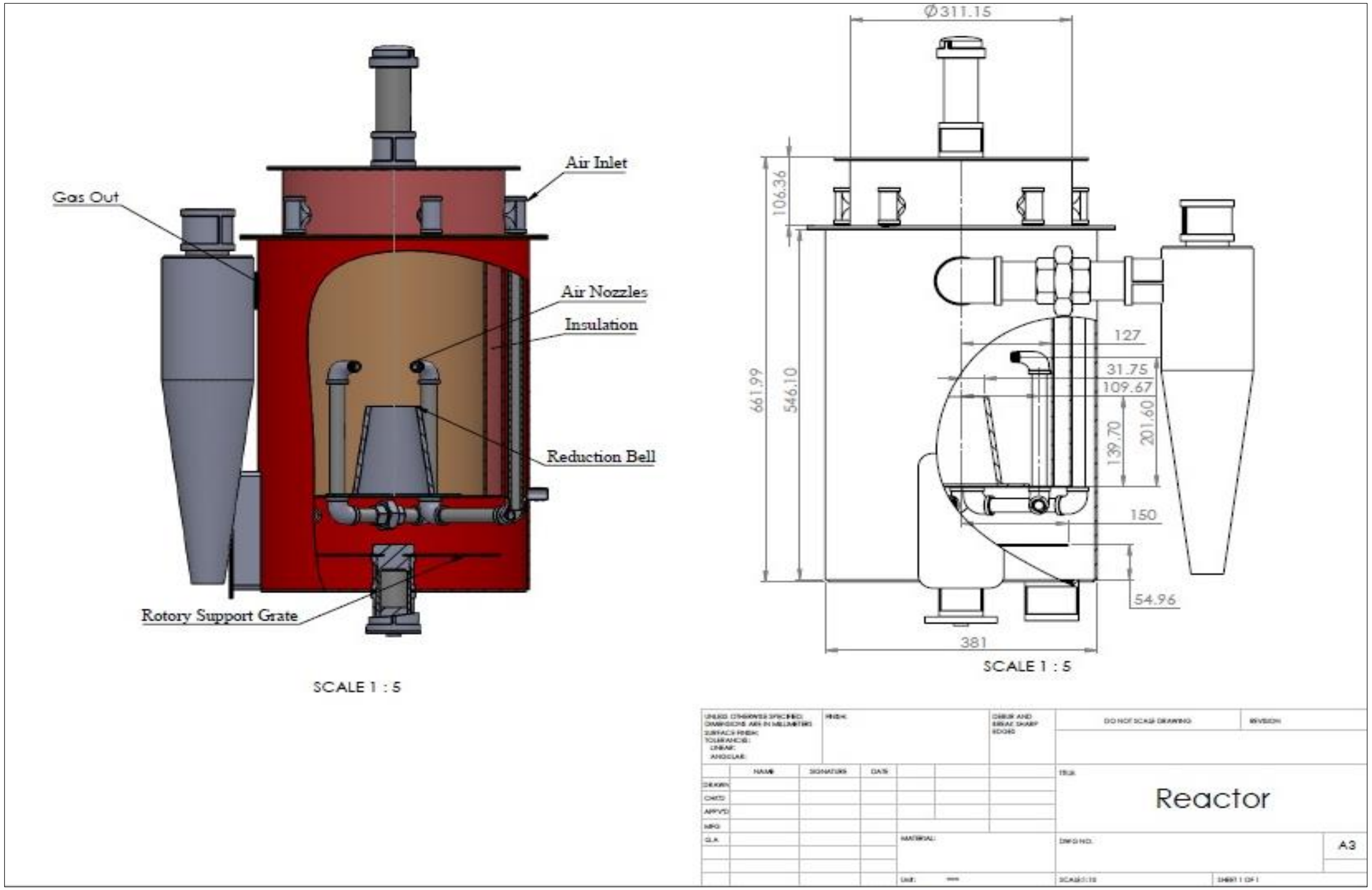


Figure 3. 5: Imbert Type Downdraft Gasifier

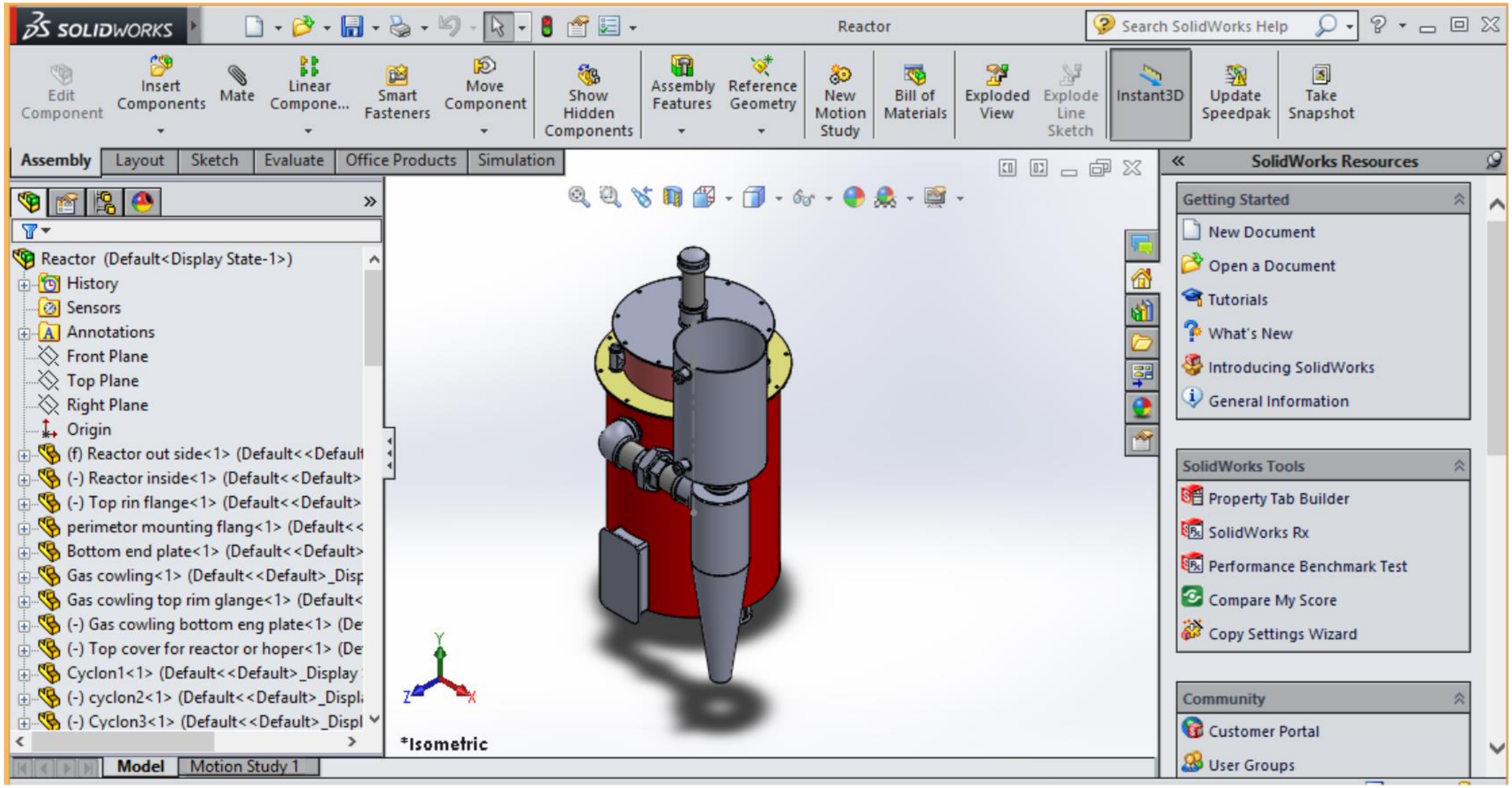


Figure 3. 6: Solidwork Design Platform of Gasifire

3.2. Gasification Plant Design

Plant arrangement and its equipment depend on energy application and gasifire type. If produced gas is applied for an internal combustion engine, the plant must have a gas cooling unit and higher filtering system. However, in this study, direct combustion was applied as shown in Figure 3.7, because cost of plant construction for IC engine is more expensive than direct combustion application.

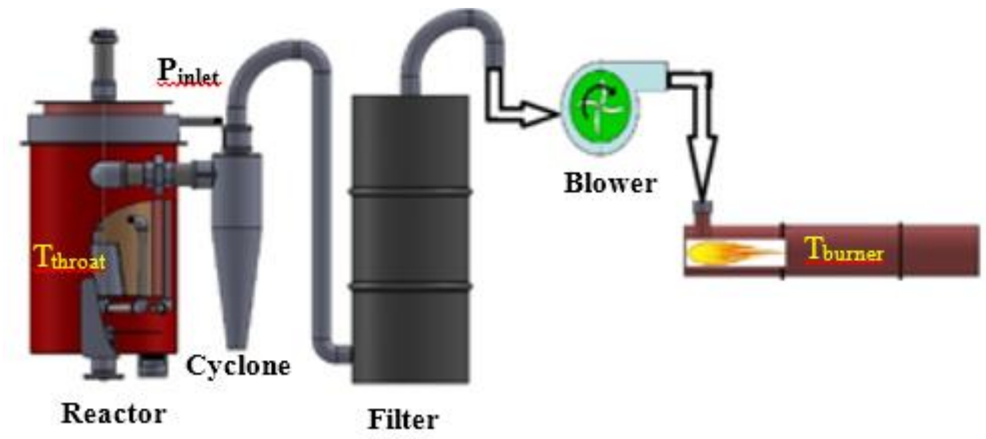


Figure 3. 7: Schematic Diagram of Gasification Plant for Direct Combustion

3.2.1. Design of cyclone

Cyclones are simple and inexpensive dust and droplet separators which are fixed to the very next produced gas outlet of reactor. Hot gas cyclone separators are well suited to remove solid particles larger than 10 μm as a pre-filters. Cyclone separator of this research was developed relying on proportions shown in Appendix 1 and engineering drawing of cyclone construction displays in Appendix 2.

3.2.2. Gas moving system

It is important to provide a suitable method to gas for pulling or pushing through the gasifier where air supply rate is the key parameter. Further, equivalence ratio (ER) which is defined in Equation 3.1, depends on air supply rate [17, 30, and 31]. Gasification efficiency is high at low ER value. Therefore, performance is better in terms of pulling than pushing the gas through gasifire. Operation range of downdraft gasifire is 0 – 20 inch H_2O according to [7]. Therefore, 8 inch H_2O 0.5 hp centrifugal blower was selected as shown in Figure 3.8.

$$\text{Equivalence ratio (ER)} = \frac{\text{Actual fuel / air}}{\text{Stoichiometric fuel / air}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(3.1)}$$

Figure 3. 8: 8 inch H2O 0.5hp Centrifugal Blower

3.2.3. Swirl burner

The ignition propagation rate of produced gas is low [7, 8] thus, it takes some considerable time for ignite. In swirl type burner, gas circulation time is more than direct burner hence it is better to biomass gasification produced gas. Swirl burner during operation is displayed in Figure 3.9.

Figure 3. 9: Image of Swirl Burner

3.2.4. Instrumentation

Experimental set-up of biomass gasification plant is shown in Figure 3.10. NI USB6211 analog input output model which was used for data acquisition and K type thermocouples were used to measure the temperature. Table 3.3 and 3.4 present all specification about instrumentation equipment (sensors, actuators, controllers and signal amplifiers).

Table 3. 3: Specification of Sensors

Requirement	Measurement	Sensor type	Remarks
Temperature measurement	300℃ -1300℃	K type thermocouple	▪ -200 to 1400℃ linear amusement range ▪ Low cost
Air flow rate measurement (Q)	0 -100m^3/h	Differential pressure sensor	▪ Measures the pressure different between orifice plate ▪ $Q \propto \sqrt{\Delta P}$

Table 3. 4: Specification of Other Equipment

Requirement	Other Equipment	Remark
Data acquisition	NI USB 6211	▪ 16 analog input ▪ 2 analog output ▪ -10V to 10V and -200mC to 200mV input output range ▪ 4.8μV sensitivity ▪ USB interface
Amplified and signal condition of thermocouple output voltage	Quarter channel analog thermocouple amplifier	▪ Compatible for K type thermocouple ▪ Supply voltage 5-32v ▪ 0-10v out put ▪ +/-3℃ initial accuracy
Rotary grate motor speed control		▪ 10-90V input ▪ 0-15A current out ▪ Max power 1000W ▪ 0-5V control signal
Control blower speed	Variable frequency controller	▪ Frequency range 0-400Hz ▪ Max power 0.75 kw ▪ 230V 50Hz signal phase input ▪ Three phase output

Figure 3. 10: Experimental Set-up of Downdraft Gasfier

3.3. AI Development

In 1940s, neural networks developed to understand the complexity of the nervous system for cognitive scientists. Progress of neural networks was steady hence, they were implemented in many areas of science, mainly inspiration in numerical structures of ANNs for learning the process of human brain was remarkable. Diversity of problems in fields of system identification, forecasting, pattern recognition, classification, process control was solved using this alternative mathematical tool [32, 33, 34, and 35] and consolidation of theoretical background and development of underlying learning and optimization algorithms of ANN were caused as a mathematical tool due to its emerging interest. For an example, modelling in simulating of chemical process was one of interested research area. Mathematical difficulties and inaccuracies were found in implementation of mechanistic models that depends on fundamental material and energy balances as well as empirical correlations. Neuron-based modelling is a confident substitution for such situations due to the favourable features entailed in their use such as simplicity, fault and noise tolerance, plasticity property (retention of predicting efficiency even after the removal or damage of some of its neurons), black box modelling methodology, capability to adapt to process changes according to Shahaf and Marom, (2001).

3.3.1. Artificial neural network topology

Figure 3.10 shows single-input neuron. There, scalar input ***p*** is multiplied by scalar weight of *w* to form '***wp***', which is sent to Σ. The other input, 1, is multiplied by ***a*** bias ***b*** and then passed to Σ . ***n*** is the output of Σ , often refers as the net input, which goes into a transfer function *f* that produces scalar neuron output ***a*** (also called as "activation function"). Equation 3.2 shows the calculation of neuron output.

$a = f\,(wp + b)$……………………………………………………..………. (3.2)

where,

w and ***b*** are adjustable scalar parameters of the neuron

Designer usually selects the transfer function and then the parameters ***w*** and ***b*** will be adjusted by some learning rule so that the neuron input/output relationship meets some specific goal.

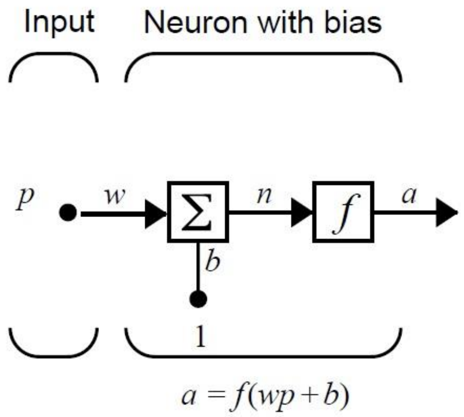


Figure 3. 11: Single Input Neuron

Neural Network consists of many transfer functions and appropriate transfer functions are selected according to network type, training method and application. Most common are hard-limit, linear and log-sigmoid transfer functions.

Sigmoid type transfer function is widely used for back propagation networks but in part because it is differentiable. Leaner type transfer functions are used as linear approximators and hard limit type transfer function is used in "Perceptron," to create neurons that make classification decisions [35, 36].

Generally, a neuron has more than one input. Figure 3.12 displays a neuron with *R* inputs where individual inputs are $p_1, p_2,...,p_R$ and $w_{1,1},w_{1,2},... ,w_{1,R}$ are weights of corresponding elements that form weight matrix W. In order to include more detail and reduce the complexity of network, abbreviated notation is introduced. As shown in Figure 3.12 (b), solid vertical bar represents input vector **P** and its dimensions are displayed as *R* x1, indicating that the input is a single vector of *R* elements. These inputs go to the weight matrix W, which has R columns but only one row in this single neuron case. Constant 1 enters to neuron as an input and is multiplied by a scalar bias *b*. The net input to the transfer function *f* is *n*, which is the sum of bias *b* and product W_p. Output of neuron is *a* scalar in this case. If there had more than one neuron, the network output would be a vector.

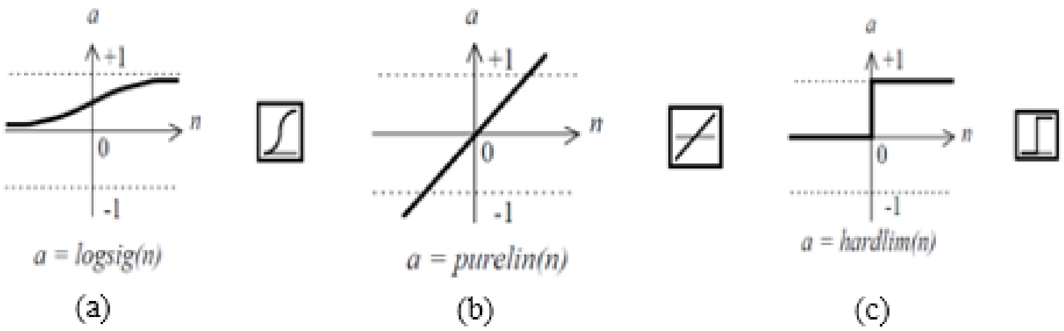


Figure 3. 12: (a) Log – sigmoid Function, (b) Leaner Function, (c) Hard – limit Transfer Function [35]

A network with several layers are shown in Figure 3.12 where each layer has its own weight matrix, bias vector, net input vector and output vector as W, *b*, *n* and *a* respectively. Introducing some additional notation to distinguish between these layers are essential, therefore, superscripts are used to identify the layers, particularly, appending the number of the layer as a superscript to the names for each of these variables. For an example, weight matrix for the first layer is written as W^1, and the weight matrix for the second layer is written as W^2. This notation is used in the three layer network shown in Figure 3.13.

According to Figure 3.12, there are R inputs, S^1 neurons in the first layer, S^2 neurons in the second layer, etc. and different layers can have different numbers of neurons. The outputs of layers one and two are the inputs for layers two and three. Thus, layer

2 can be viewed as a one-layer network with R = S^1 inputs, S = S^2 neurons, and any weight matrix of S1 x S^2 is W^2. The input to layer 2 is a^1, and the output is a^2.

A layer whose output is the network output is called an output layer while other layers are called hidden layers. In Figure 3.13, output layer is layer 3 and two hidden layers are layer 1 and 2.

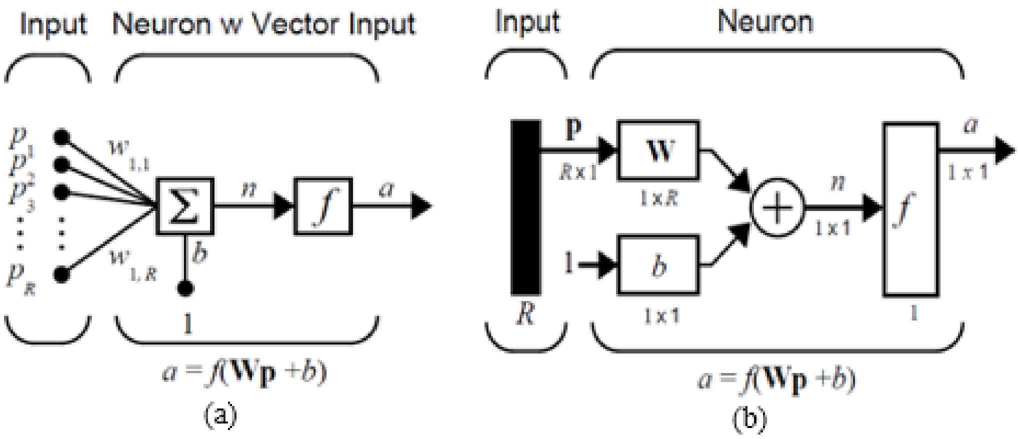


Figure 3. 13: (a) Multiple Input Neuron, (b) Abbreviated Notation

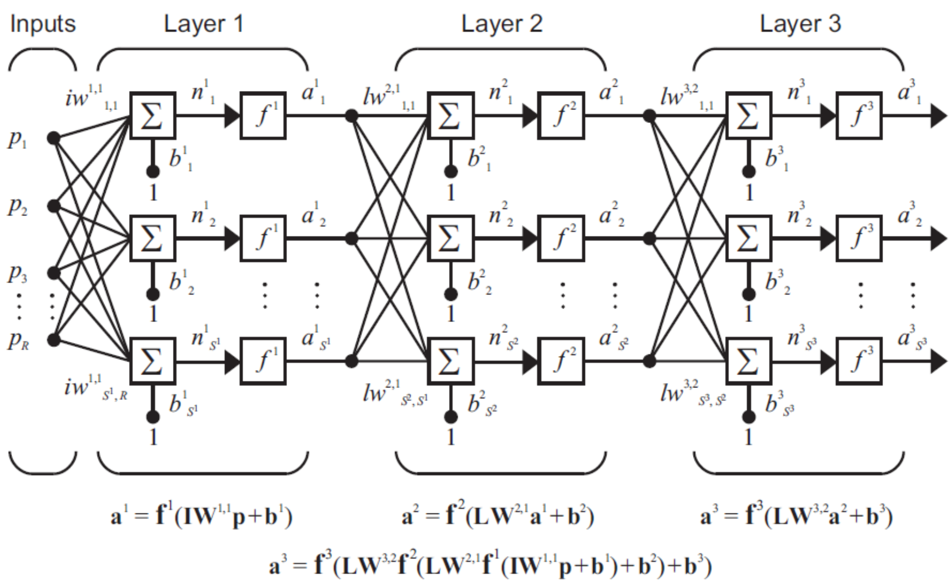


Figure 3. 14: Multiple Layer Neural Network Architecture

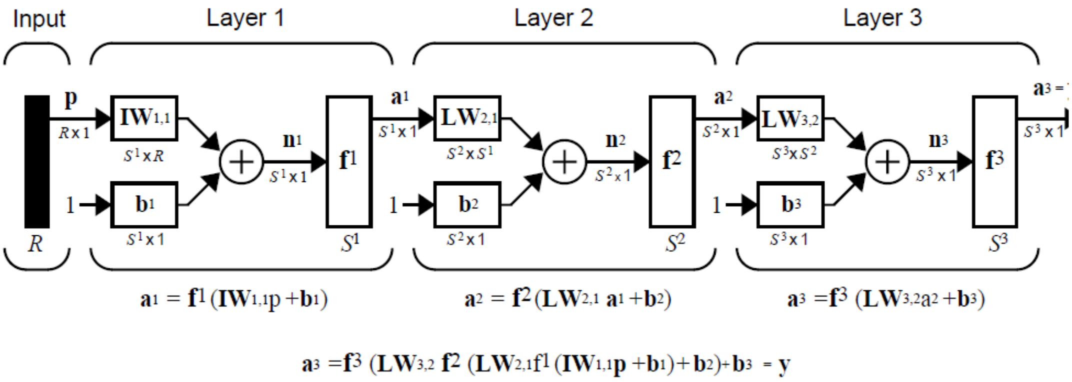


Figure 3. 15: Abbreviated Notation of Multiple Layer Neural Network Architecture

3.3.2. Feedforward neural network

ANNs can be categorized as single and multi-layer feedforward neural networks (FFNN), feedback neural networks (FBNN), recurrent neural NETWORKS (RNN), self-organized networks in terms of topology. Moreover, they can be classified in terms of application, connection type and learning methods. FFNN is the most common type of networks in the field of modeling and prediction as shown in Figure 3.16, which is composed of one input layer, one output layer and a minimum of one hidden layer. As implies as its name the way in which the output of the FFNN is calculated from its input layer-by-layer throughout the network. In this case, cycles are not formed in connections between network neurons. Building block is a simple structure called neuron regardless the complexity of network that performs a weighted sum of its inputs and calculates an output using certain predefined activation functions. Activation functions for hidden units are needed to introduce nonlinearity into the network. Most common choices for the activation Sigmoidal functions are logistic, tanh, and Gaussian function. Linear transfer function is used to output layer because if last layer of a multilayer network has sigmoid neurons, then the outputs of the network are limited to a small range. If linear output neurons are used, the network outputs can take on any value.

Number of neurons and the way in which neurons are interconnected, are used to define the neural system architecture. The network is fed with a set of input–output pairs and trained to reproduce outputs. The training is done by adjusting the neurons weights using an optimization algorithm to minimize the quadratic error between observed data and computed outputs. A good reference on the FFNN and their applications is given by Fine (1999) [36].

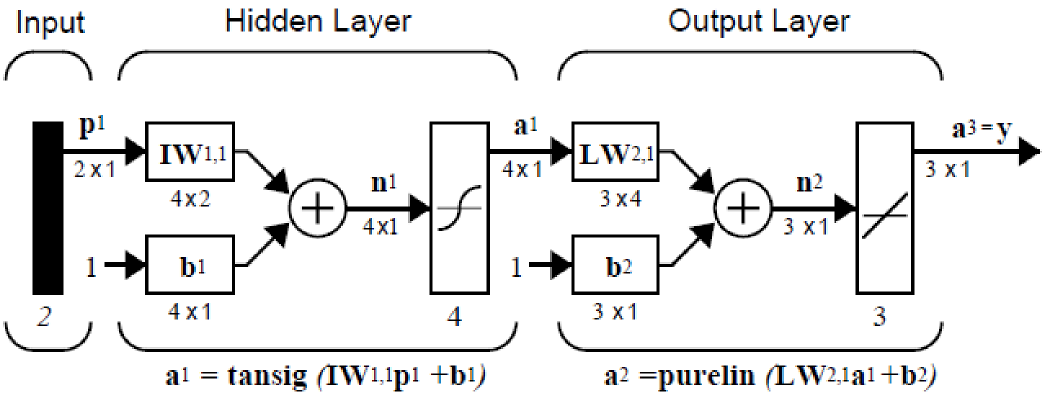


Figure 3. 16: Multi-Layer Feedforward Networks

In order to improve the numerical condition for the optimization problem and for better behaviour of the training process, input-target training data are usually pre-treated as explained. Training, validation and testing subsets are the usual three subsets that data are normally divided. Training subset data are used to accomplish the network learning and fit the network weights by minimizing an appropriate error function. Back propagation is the training technique generally used for this purpose which refers to the method for computing the gradient of the case-wise error function with respect to the weights for a feedforward network. Independent evaluation of error function using the validation subset data was carried out to compare the performance of the networks. To measure the generalization of network, testing subset data are used (i.e. how accurately the network predicts targets for inputs that are not in the training set) this is sometimes referred to as holdout validation.

3.3.3. Dynamic network

Dynamic and static are the broad categories of neural networks. There are no feedback elements for static (feedforward) networks and no delays; the output is calculated directly from the input through feedforward connections. “Back propagation” is also used same as FFNN for training of static networks. In dynamic networks, the output depends not only on the current input to the network, but also on the current or previous inputs, outputs, or states of the network. Moreover, they can also be divided into two categories: those that have only feedforward connections, and those that have feedback, or recurrent, connections.

3.4. Gasification Plant Control System

First step of developing control system for gasification plant is identifying input, controlled, manipulated variables and plant parameter which capable to describe plant performance. Plant input variables for biomass gasifire are calorific value of fuel, inlet air flow rate and plant output power that depends on calorific value and flow rate of output gas.

Table 3. 5: Process Variables and Parameters

Manipulated variables	Control variables	Disturbance	Plant parameters
Input air flow rate	Flue gas temperature	Properties of fuel	Reactor temperature
Rotary grate RPM	Flue gas flow rate		

Biomass gasification process is a time delaying process according to process dynamic since changing on upper stream input variable takes a considerable time to respond at downstream. Also most of the process input and output variables cannot measure directly like calorific value of product gas and input biomass. Therefore, internal model controller (IMC) architecture was selected for development of controller of bio mass gasification. Furthermore, artificial neural network can be used for internal model control [33, 34]. In this structure, a system forward and inverse model are used directly as elements within the feedback loop. IMC has been thoroughly examined and shown to yield transparently to robustness and stability analysis [34].

Figure 3.17 shows a controller architecture of the internal model control. P, C and M are nonlinear plant, nonlinear controller and nonlinear plant model respectively. F is first order liner filter. The important characteristics of IMC are summarised with the following properties [34].

Property P1: Assume that plant and controller are input-output stable and that the model is a perfect representation of the plant. Then the closed-loop system is input-output stable.

Property P2: Assume that inverse of operator describing the plant model exists, that this inverse is used as the controller, and that the closed-loop system is input-output stable with this controller. Then the control will be perfect, i.e.$y = y^s$.

Property P3: Assume that the inverse of the steady state model operator exists, that the steady state controller operator is equal to this, and that the closed-loop system is input-output stable with this controller. Then offset free control is attained for asymptotically constant inputs.

All system variables and parameters are shown in Table 3.6 which used to develop forward plant model. Considered process parameters were same as an input of the model and biomass gasifire control structure displayed in Figure 3.18.

Difference between plant output and model output is the feedback signal (y_f) as in Equation 3.3 and set value is y^s and error (e) is the difference between set value (y^s) and feedback (y_f) in Equation 3.4 .Infinity gain is required to be a perfect controller but it is impossible in real situation and will lead sensitivity problem under model uncertainty therefore filter (F) was introduced for controller input. F is a linear filter. M is the forward model of the plant and C (controller) is the inverse model of the plant.

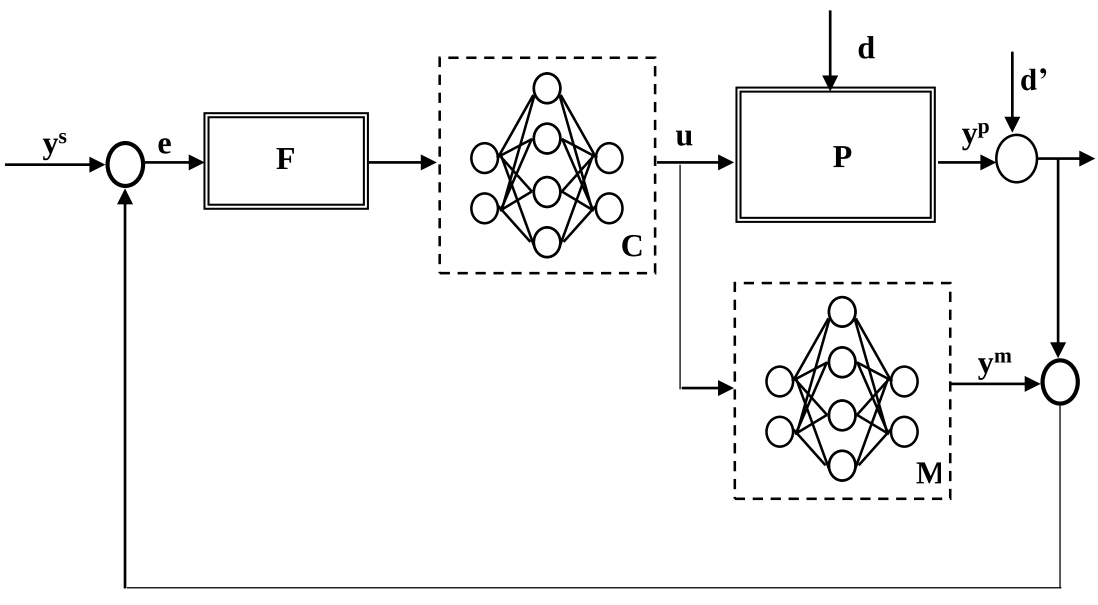


Figure 3. 17: Structure of Neural Network Based Internal Model Controller [34]

$Yf = Yp - Ym$..(3.3)

$E = ys - Yf\ wq$..(3.4)

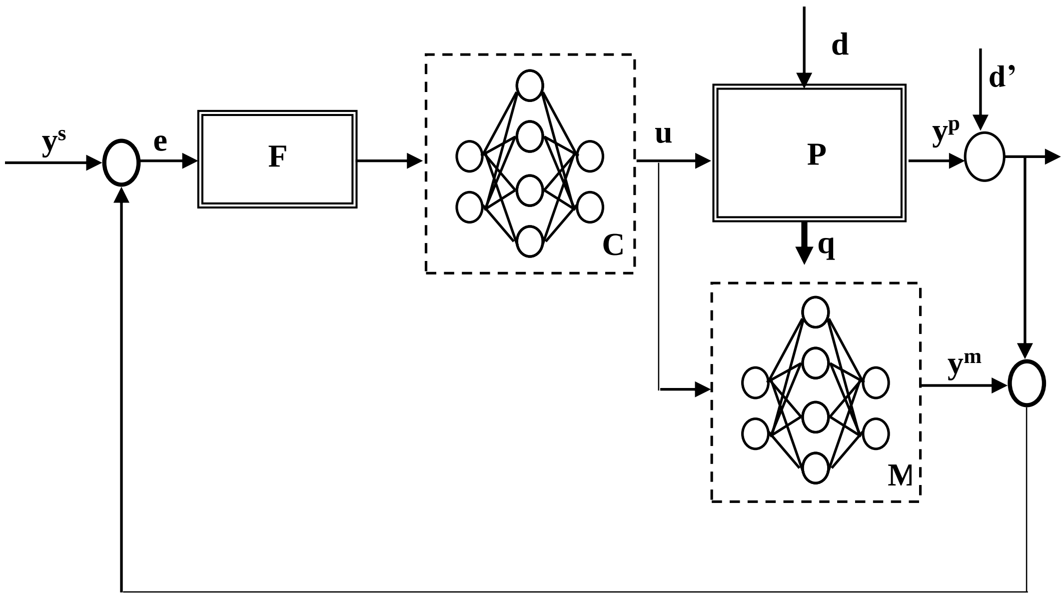


Figure 3. 18: Structure of Neural Network Based Internal Model Controller for Downdraft Gasifier [34]

Table 3.6 shows measurement and symbol of control and manipulated variables and process parameters of the down draft gasifier.

Table 3. 6: Control and Manipulated Variables, and Process Parameters

		Measurement	**Symbol**
Manipulated variables (u)	Inlet air flow rate	Output voltage of differential pressure sensors	P_{inlet}
	Rotary grate RPM	Pulse minute	G_{rpm}
Control variables (y)	(Flue gas temperature) x (Flue gas flow rate)$^{0.5}$	(Thermocouple voltage) x (V_{out} of differential pressure sensor)$^{0.5}$	T_{burner} x $(P_{burner})^{0.5}$
Process parameter (q)	Temperature at throat	Thermocouple voltage	T_{throat}
Disturbance (d)	Properties of fuel		

3.4.1. Plant identification

Development of internal model control is the first step of developing plant model. NN is the powerful tool for creation of system model for nonlinear dynamic system. Figure 3.19 shows the plant identification structure. Identifying plant when off line is the advantage in NNIMC.

In order to develop plant model, nonlinear autoregressive network with exogenous inputs (NARX) model is used while NN time series tool in Matlab is used for developing the plant model. NARX models are commonly used in the system of prediction area [35]. The nonlinear autoregressive network with exogenous inputs (NARX) is a recurrent dynamic network, with feedback connections enclosing several layers of network and based on the linear ARX model, which is commonly used in time-series modelling.

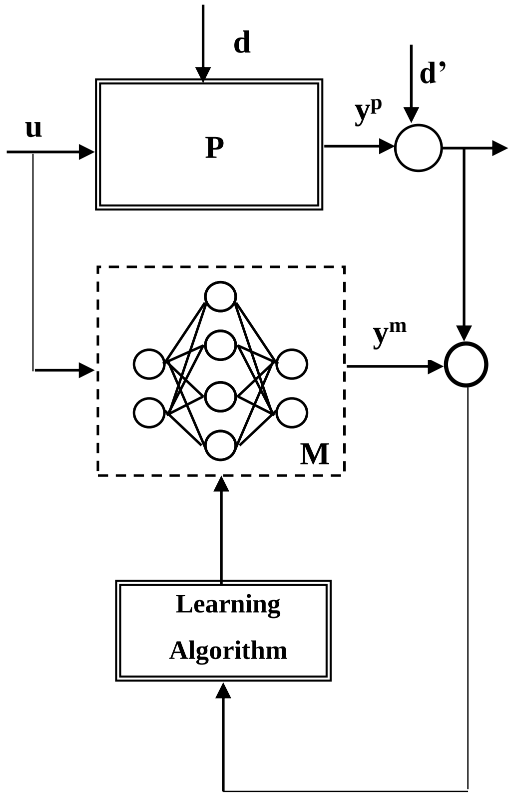


Figure 3. 19: Plant Identification Structure

Figure 3.20 illustrates the standard NARX network which consists of two-layer feedforward network, with a sigmoid transfer function in the hidden layer and a linear transfer function in the output layer.

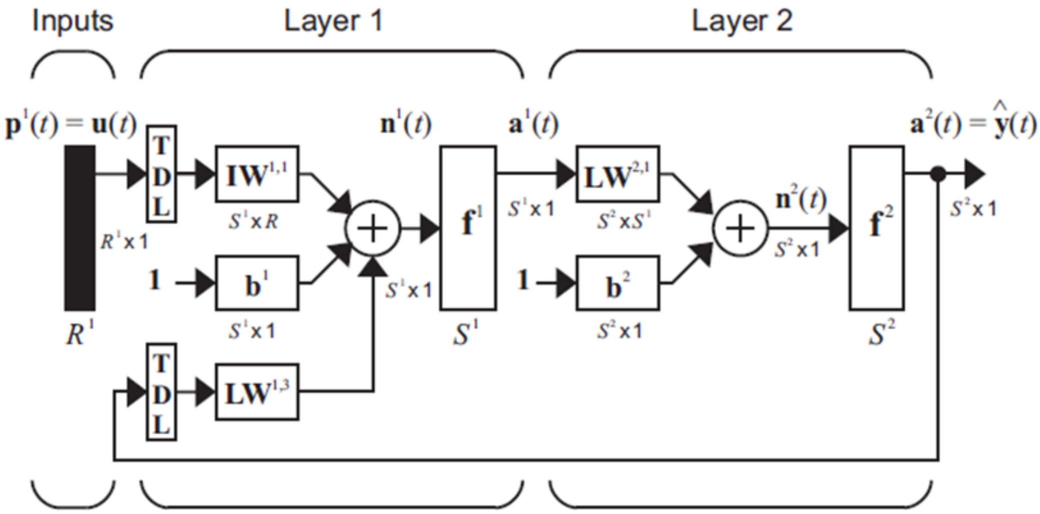


Figure 3. 20: Standard NARX Networks [35]

This network also uses tapped delay lines (d) to store previous values of the input, x (t) and output, y (t) sequences. First, load the training data and use tapped delay lines with two delays for both input and output, so training begins with the third data point. There are two inputs to the series-parallel network, the x (t) sequence and the y (t) sequence. Notice that the y (t) sequence is considered a feedback signal, which is an input that is also an output (target). The model can be shown as in Equation. 3.5.

$$y_t = f_{(t-1)}, y_{(t-2)}, \ldots\ldots, y_{(t-d)}, u_{(t-1)}, u_{(t-2)}, \ldots\ldots, u_{(y-d)} \ldots\ldots\ldots\ldots\ldots\ldots \quad (3.5)$$

It also has been reported that gradient descent learning can be more effective in NARX networks than in other recurrent architecture [38, 39].

To generate training data set for gasifire which runs 340 min., average value for each 5s of the input, output variable was record and process parameters were obtained at the data point of 4080 as a NN model training dataset as shown in Figure 3.21.

Using data in Figure 3.21, NN model for gasification plant was trained and network structure displayed in Figure 3.22 was achieved NARXNN, and Figure 3.23 displays response of output element 1 for time series 1, which was a training result of NN based biomass gasification model. Further, Figure 3.24 illustrates NN training performance as best fit at 70 epoch.

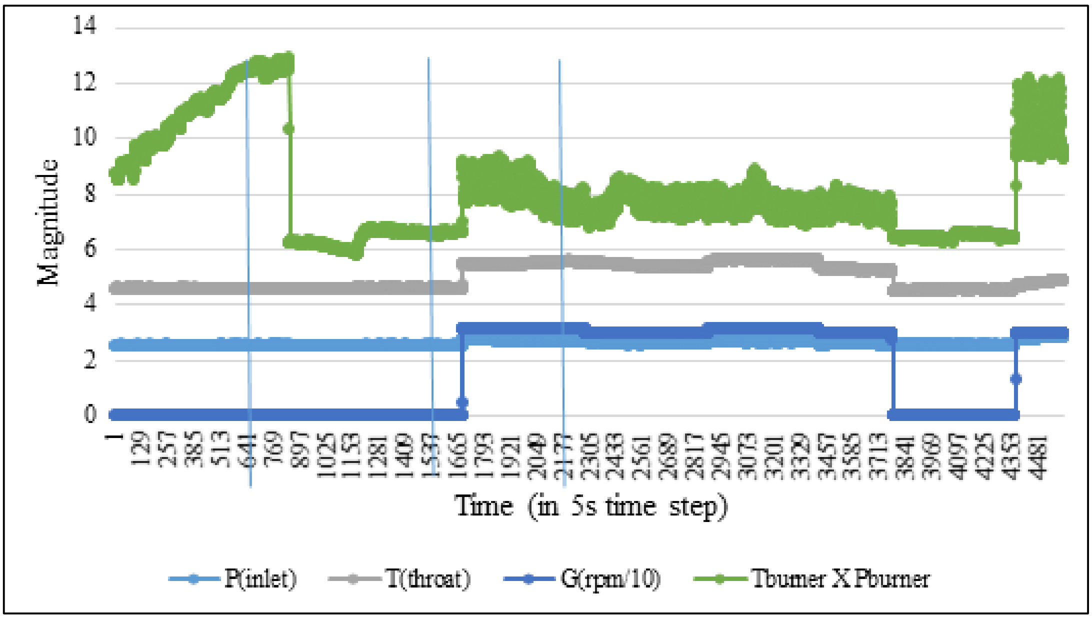


Figure 3. 21: Training Data Set for NN Model

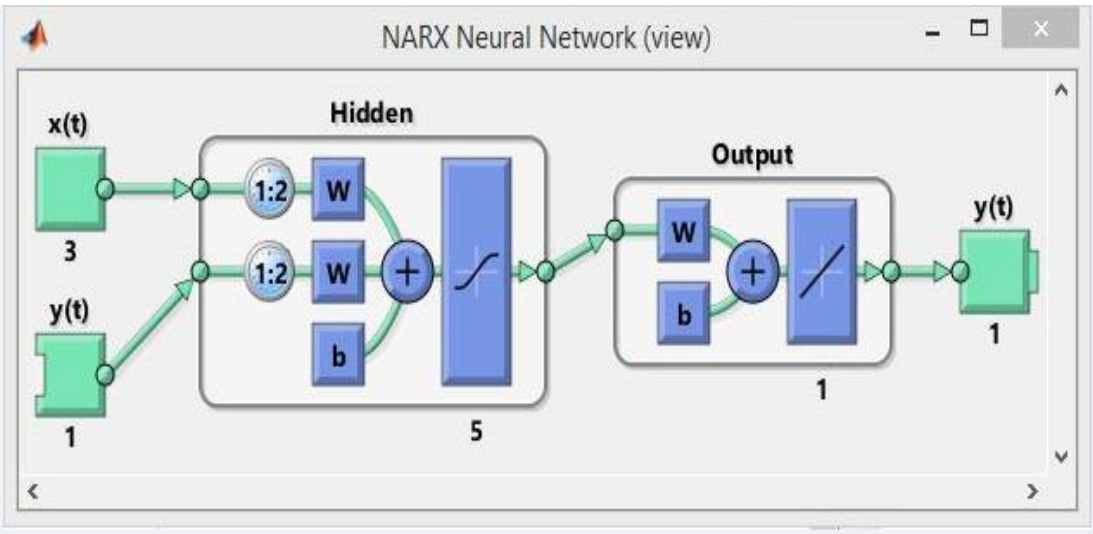


Figure 3. 22: View of NARX Neural Network

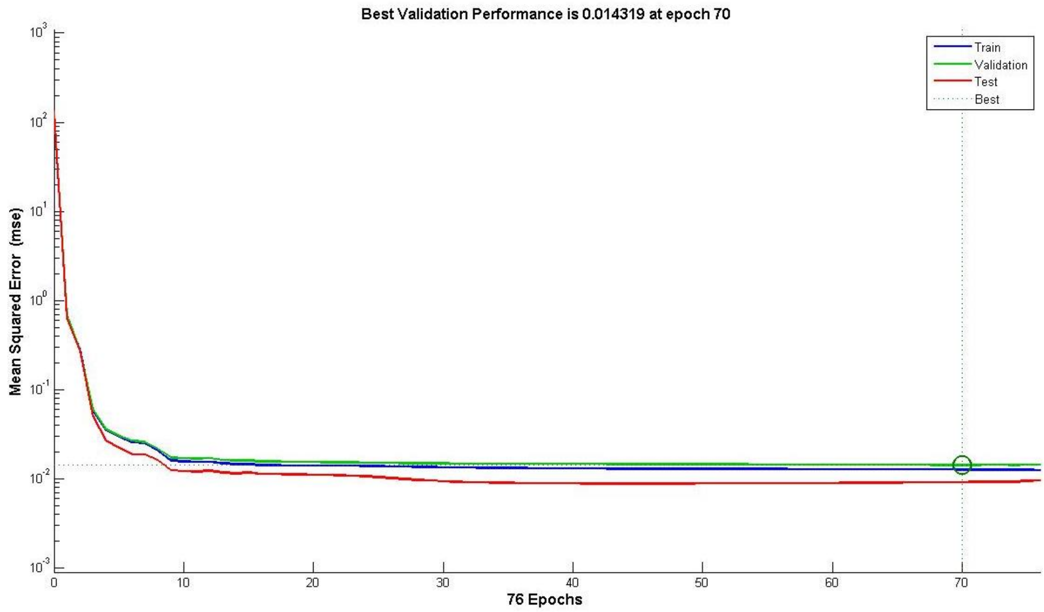


Figure 3. 23: Training Result of NN Based Biomass Gasification Model

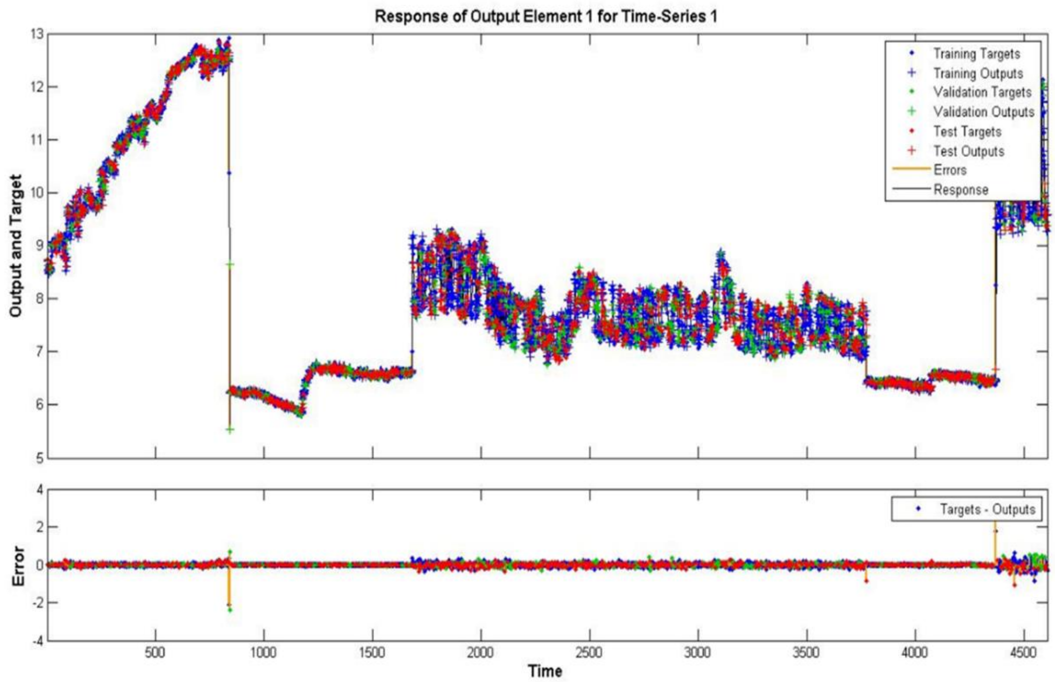


Figure 3. 24: NN Training Performance

3.4.2. NN based controller

If the model of plant is invertible, the inverse of plant can be approximated in a similar way to the plant. This model is then used as the controller as shown in Figure 3.25.

There are three tanning methods used to train the inverse model of plant. Those methods are shown in Figure 3.26 (a), (b), and (c) as direct inverse method, specialized inverse learning structure, and general learning architecture respectively.

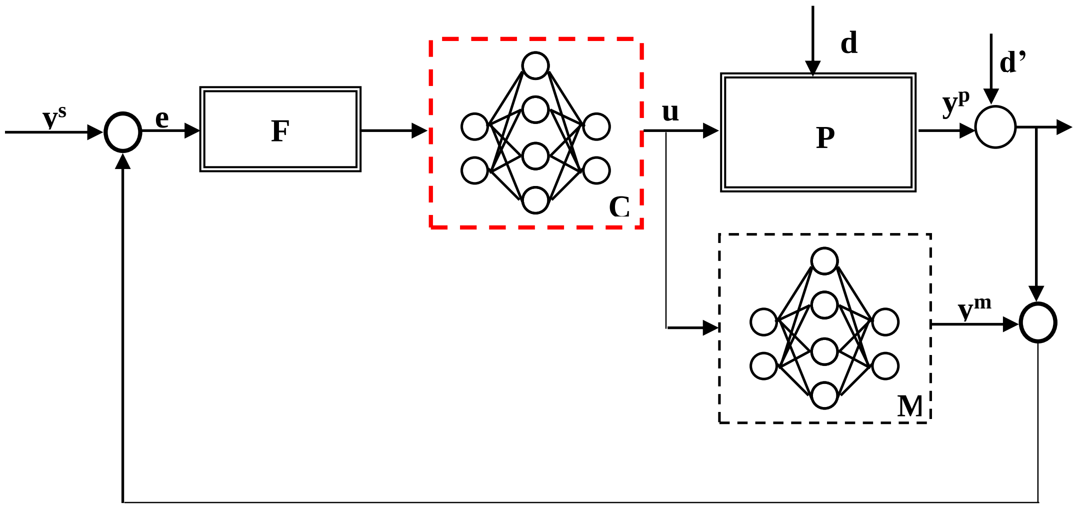


Figure 3. 25: Controller of Neural Network Based Internal Model Controller

Direct inverse method is an online training method which is used to real plant, however for development of proper inverse model, training network is required for a long data range and for it large data is needed. That implies online training is more expensive. In addition, controller which can get decided output from plant is essential. Therefore, plant model inverse was selected rather than the inverse of the real plant. Compared to remaining two training architectures, general learning architecture is the simplest one [35, 32]. This learning structure also contains a trained forward model of the system placed in parallel with the plant and error signal for the training algorithm in this case is the difference between the controller output signal and model input.

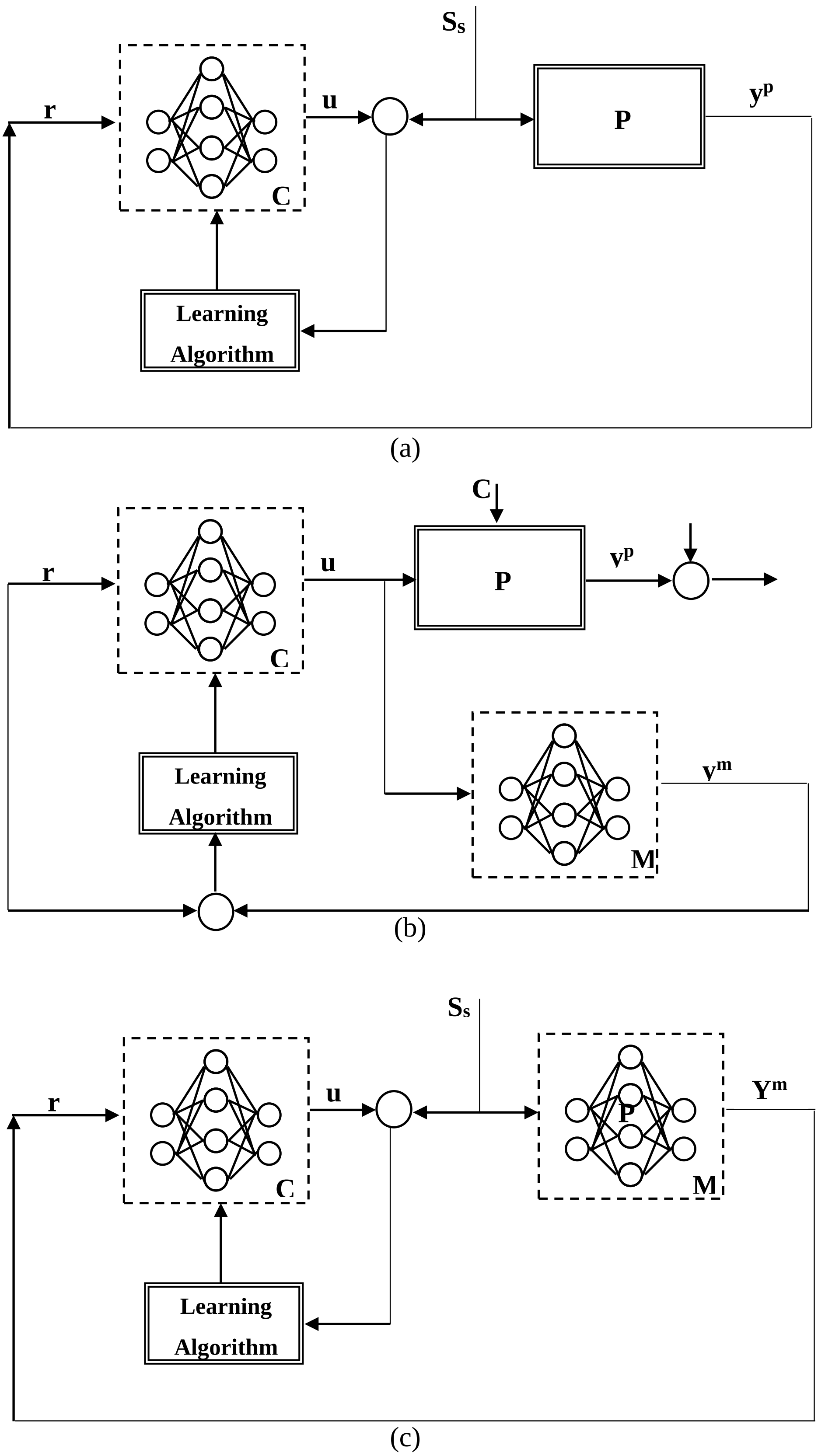


Figure 3. 26: (a) Direct Inverse Method, (b) Specialized Inverse Learning Method, (c) General Learning Architecture

4.0. RESULTS AND DISCUSSION

4.1. ANN Based Biomass Gasification Plant Model

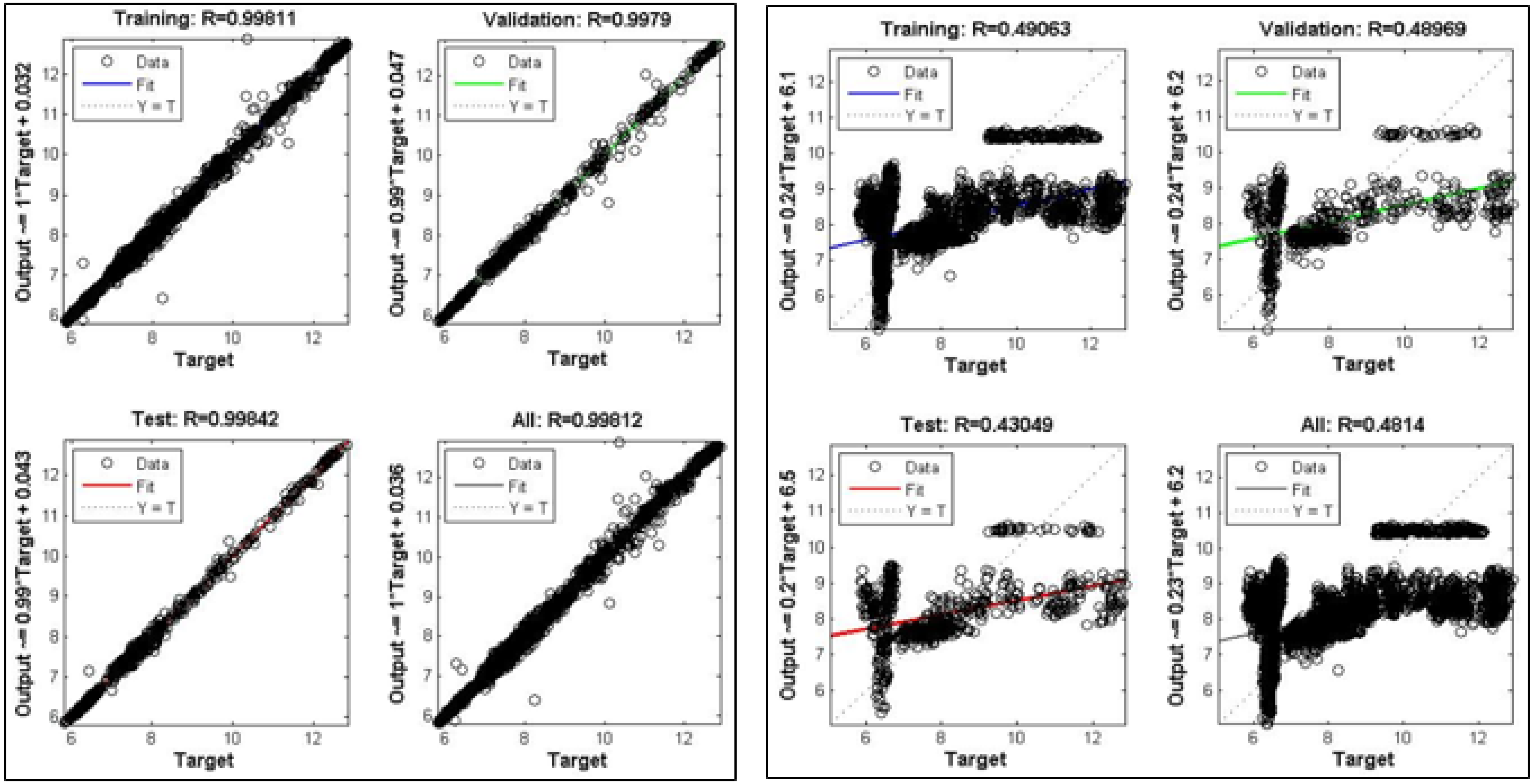
Neural network of three inputs, five neurons in hidden layer with one output was tested for both two layered feedforward neural network and NARX dynamic neural network. 4608 data points, which were collected during 384 min. from continuous plant operation were used for model training. Obtained regression of NARX dynamic NN model and feedforward NN are shown in Figure 4.1 (a) and (b) respectively. According to Figure 4.1(a), NARX dynamic neural network achieved the best fit curve along with the line of 45^0 to the horizontal, which was the well trained NN suitable for energy prediction ($T_{burner} \times P_{burner}$) of downdraft gasifier.

Table 4.1 and 4.2 present the obtained parameters ($IW_{j,i}$, $LW_{1,j}$, b_{1j}, b_2) of the best fit for five neurons in the hidden layer of developed ANN in the forward plant model. These parameters were used in the proposed model to predict the output values. In consequence, the proposed ANN model follows Equation 4.1.

$$y_m = \sum_{j=1}^{5}\left[LW_{1,j}\left(\left(\frac{1}{1+e^{-\sum_{i=1}^{8}\left(IW_{j,i}P_i+b_{1,j}\right)}}\right)+b_2\right)\right] \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (4.1)$$

Table 4. 1: Parameters of Input Layer (Input Weight Matrix)

IW	$\mathbf{P_{inlet(t)}}$	$\mathbf{T_{throat(t)}}$	$\mathbf{G_{rpm(t)}}$	$\mathbf{P_{inlet(t-1)}}$	$\mathbf{T_{throat(t-1)}}$	$\mathbf{G_{rpm(t-1)}}$	$\mathbf{T_{buner(t)} \times P_{burner(t)}}$	$\mathbf{T_{burner(t-1)} \times P_{burner(t-1)}}$
j \ i	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
1	0.2844	0.9999	0.3057	-0.1324	-1.0101	-0.6587	-2.2376	0.9075
2	-0.2744	-1.0746	2.8068	0.1666	1.1018	-2.4252	2.4329	-1.5875
3	0.3962	0.6605	-0.0390	-0.4304	-0.5886	0.0761	-0.6682	1.8631
4	0.2899	-0.3880	1.0961	0.9726	-0.8731	-0.2185	-0.3413	-0.5033
5	-0.5192	-1.1408	-1.8412	0.6862	-1.3676	-0.2501	-0.9953	-0.2662



(a)

(b)

Figure 4. 1: (a) Regression of NARX Neural Network Model, (b) Regression of Feedforward Neural Network

Table 4. 2: Table Output Weight Matrix and Base Values of Hidden Layer

j	**1**	**2**	**3**	**4**	**5**
LW	-0.5238	0.7194	0.4295	0.1229	0.3083
b_1	0.7461	0.6195	1.3412	-1.1761	-2.0366

Evaluation process based on the neural network weight matrix and Garson equation [25] were used to assess the relative importance of input variables. Garson proposed an equation based on the partitioning of connection weights. The numerator describes the sum of absolute products of weights for each input while the denominator represents the sum of all weights feeding into hidden unit, taking the absolute values. The proposed equation, adapted to the present ANN topology, which is presented in Equation 4.2: where I_i is the relative influence of the i^{th} input variable on the output variable. The relative importance of different input variables, for each ANN, was calculated using Equation 4.2, and is illustrated in Figure 4.1. As it can be observed, all variables have a strong effect on the outputs. It can be noted that inlet air flow rate (P_{inlet}) had less influenced on output relatively other inputs. Feedback of the output strongly affected on the prediction of future valve of plant. Because it may be that a wide range of air flow rate was not used for training the NN, though, air flow rate is the main control factor generally in combustion system. The effect of rotary grate had not been considered in most of researches related with the downdraft gasifire, however, Figure 4.2 shows its impact on plant output.

$$I_i = \frac{\sum_{j=1}^{5}\left[\left(\frac{|IW_{j,i}|}{\sum_{i=1}^{8}|IW_{j,i}|}\right)*|LW_{1,j}|\right]}{\sum_{i=1}^{8}\left\{\sum_{i=1}^{8}\left[\left(\frac{|IW_{j,i}|}{\sum_{i=1}^{8}|IW_{j,i}|}\right)*|LW_{1,j}|\right]\right\}} \quad \text{(4.2)}$$

Figure 4.3 and 4.4 show the testing results of biomass gasifire plant model for 10 min. and 46 min. operation respectively. The mean square error of prediction for both tests were 5.07876e^{-2} and 1.9317e^{-1} respectively.

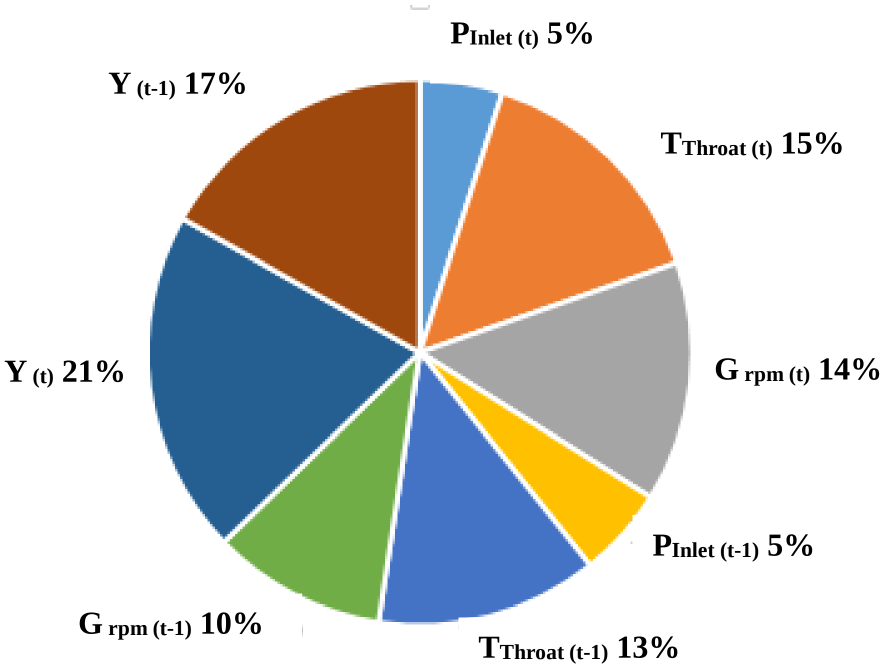


Figure 4. 2: Relative Influence of Inputs

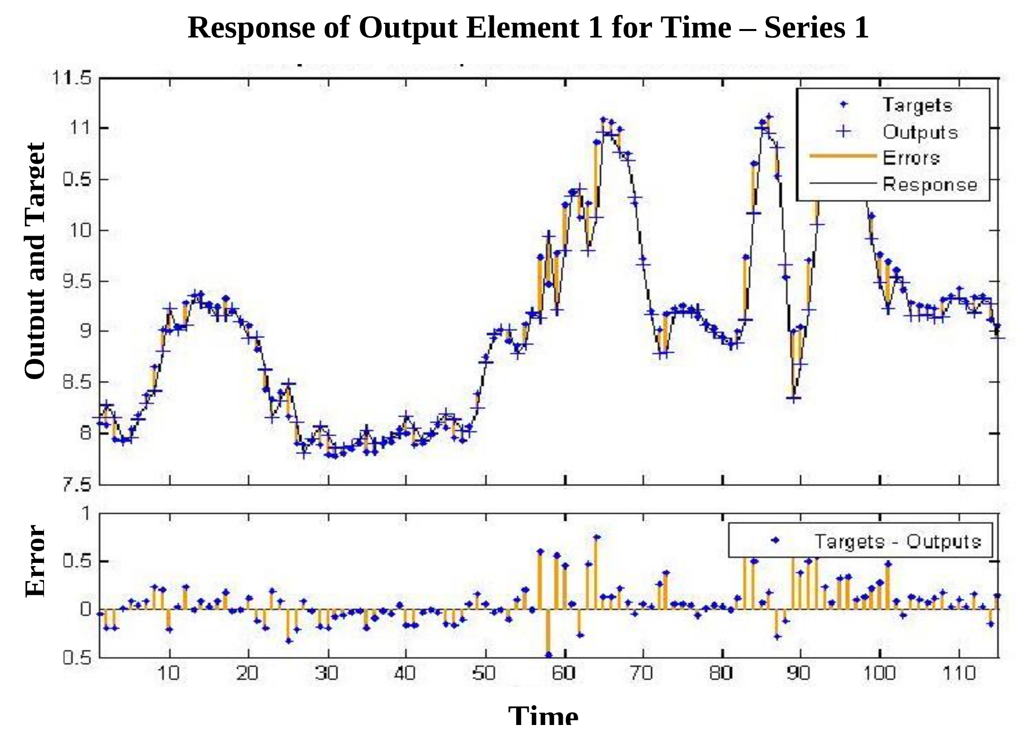


Figure 4.3: Prediction Output of 10min. Run

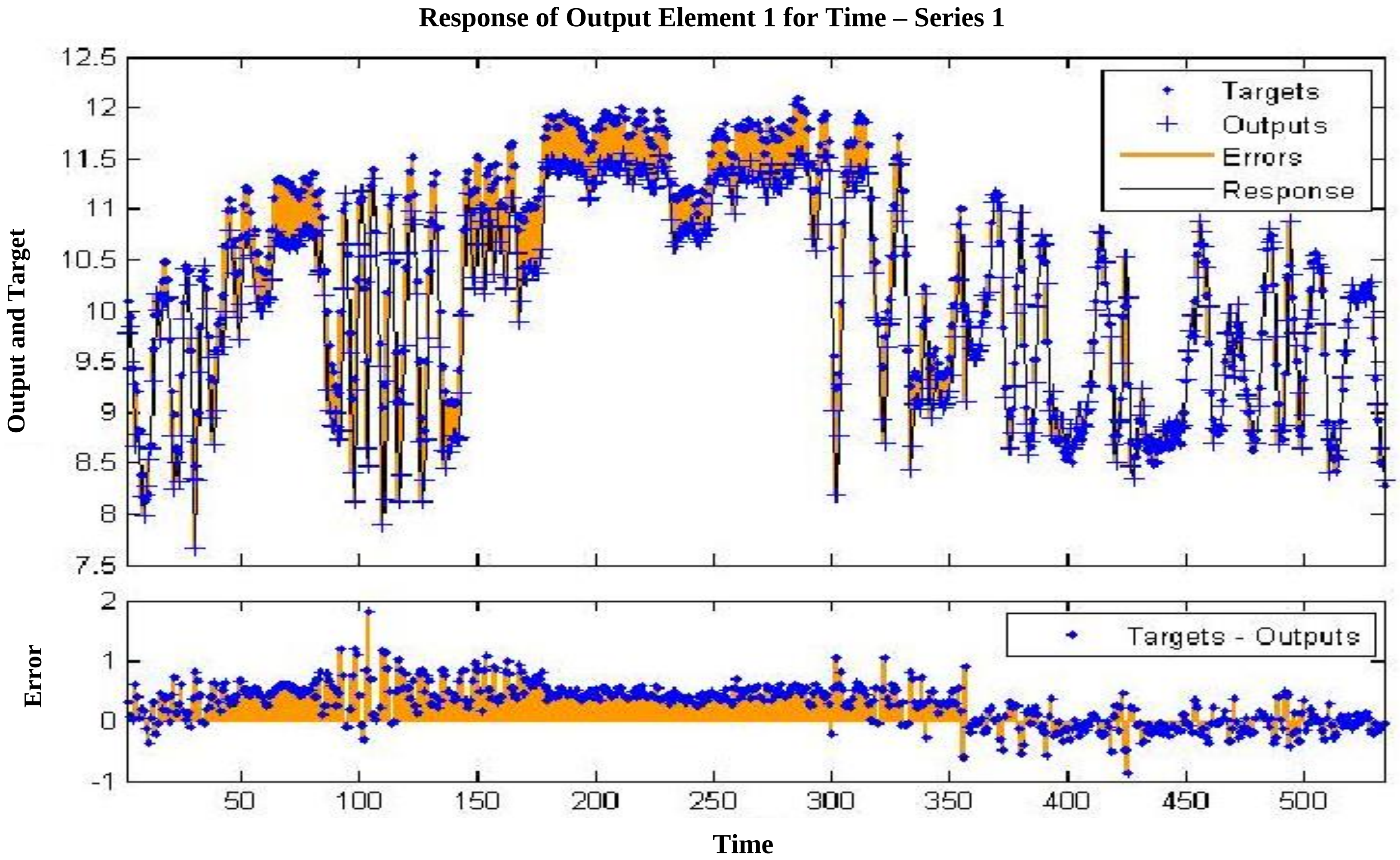


Figure 4. 4: Prediction Output of 46min. Run

4.2. Neural Network Based Plant Controller

Basically NN controller is the inverse model of the process. Plant inverse model, which generates control inputs of the plant was trained according to plant output feedback. NN controller of one input and 10 neurons in the hidden layer which generates an output is required blower RPM. Figure 45 illustrates the view of NARX neural network of plant inverse model while training performance of plant inverse model is shown in Figure 46.

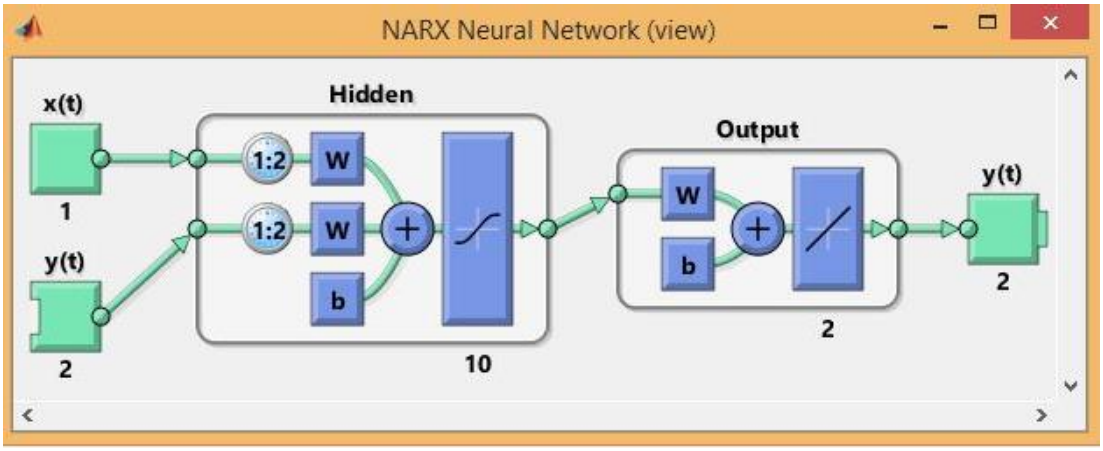


Figure 4. 5: View of NARX Neural Network of Plant Inverse Model (Controller)

Figure 4.7 shows the data set, which was used to train neural network controller. The blue colour line represents the blower RPM in Volt. It is feedback of the variable speed controller (Shenzhen EDS800 0.55kW). The orange line displays the amplified DC signal of flue gas temperature. They were measured to attain proper training dataset for gasifire to be operated at various blower speeds.

Developed neural network gasification plant model and neural network plant inverse model were used to create neural network internal model plant controller to control the biomass downdraft gasification plant. There, developed gasification model and plant inverse model were used as the internal model and control block respectively. Afterthat, designed controller using MATLAM was implemented on LabVIEW graphical inter face. The LabVIEW programme blog diagram is attached in Appendix 03.

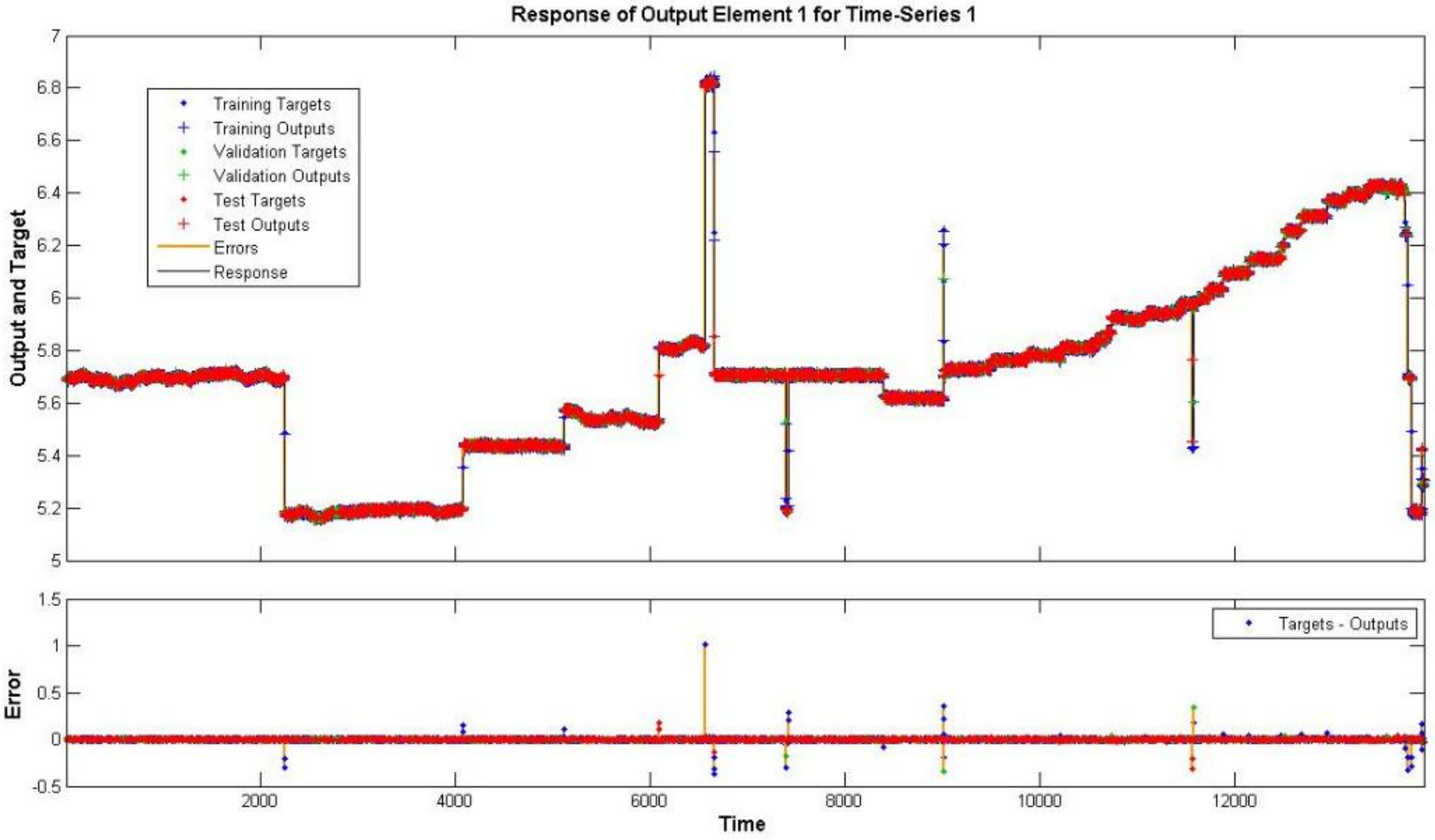


Figure 4. 6: NN Training Performance of Plant Inverse Model (Controller)

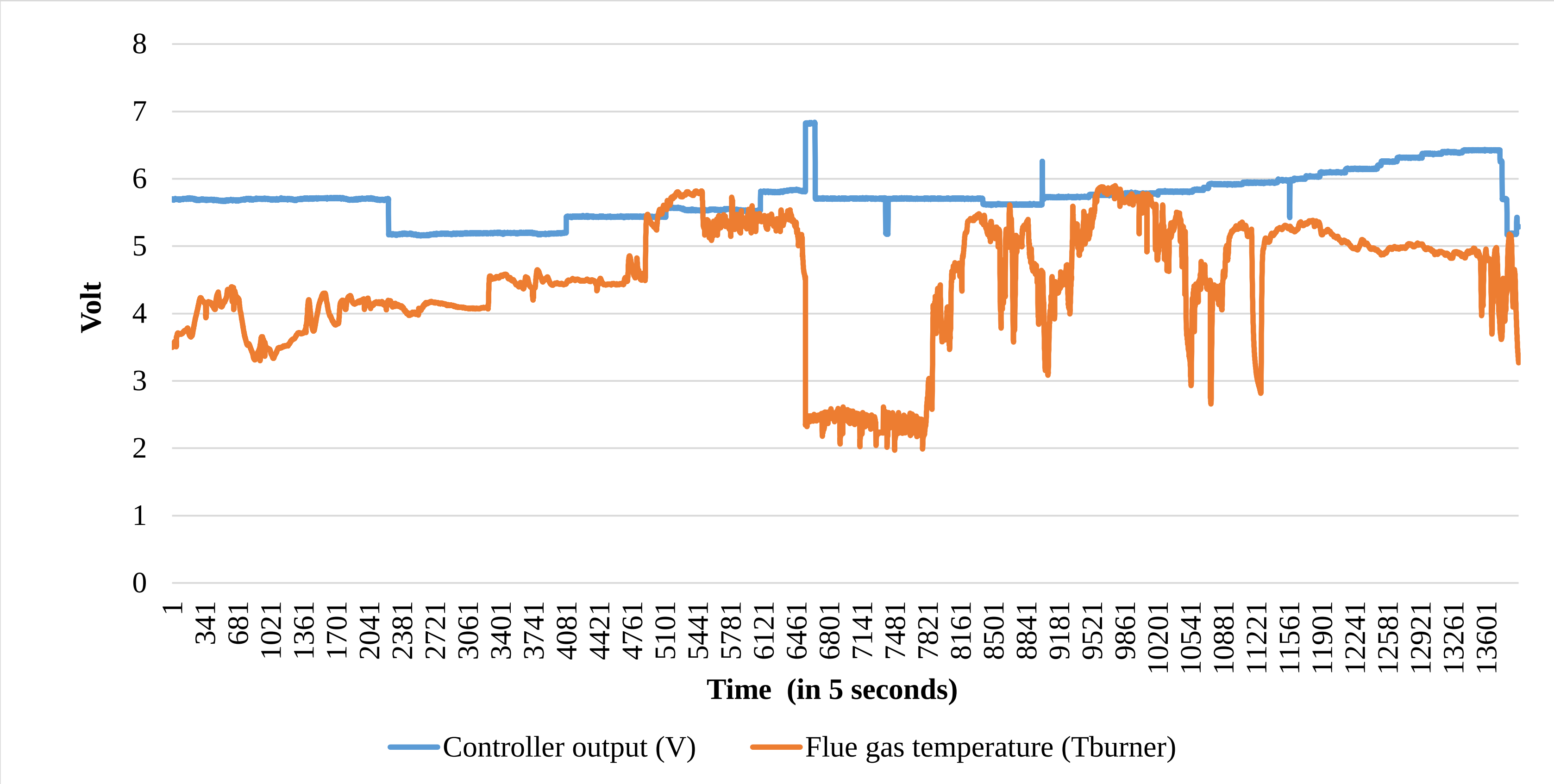


Figure 4.7: NN Training Data Set for Plant Inverse Model

Two experiments were arranged to investigate the performance of proposed IMC system for biomass downdraft gasifire. In first experiment, gasifire was operated with the proposed IMC system using 12kg of coconut shells. Set value was fixed during the operation as the ash colour line in the Figure 4.8. Step response was provided at t = 306, and t = 465 to controller within the range of set value from 960 K to 980K. According to the Figure 4.8, flue gas temperature follows the set value and it levells off all over the operation as indicated in orange line.

Secondly, gasifire was operated at constant blower speed of 3260 rpm for 12kg of coconut shells. Blue colour line represents the flue gas temperature at burner and it is not stable in second experiment. Also, ignition was disturbed and flame did not appear particularly at the lowest temperature points.

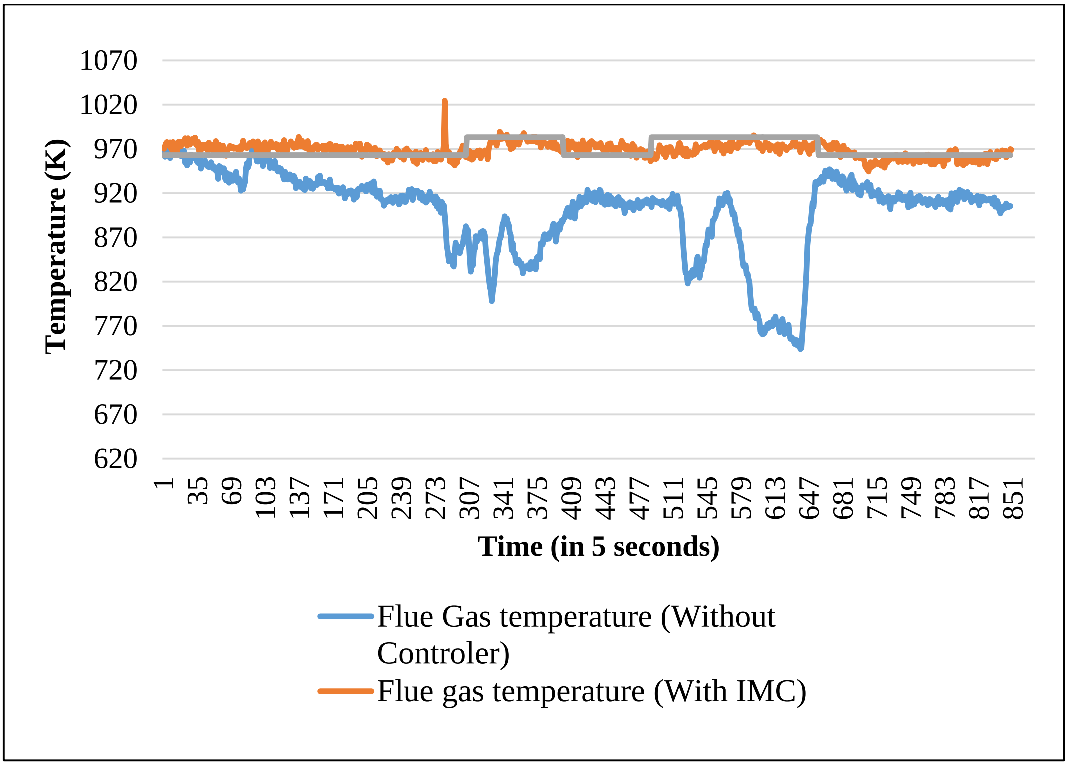


Figure 4. 8: The Graph of Flue Gas Temperature vs. Time

Figure 4.9 displays the variation of power output for both experiments. Flue gas flow rate was remained at a constant value of 0.029kg/s, therefore, variation of power output is proportionate to the flue gas temperature changes.

Total energy output without controller = 73878.75 kJ

Total energy output with IMC = 83201.58 kJ

Energy content for 12kg of coconut shells = 14644 kJ/kg x 12kg

= 175728kJ

Gasification efficiency (without controller) $= \frac{73878.5}{17572.00} \times 100\%$

= 42.04%

Gasification efficiency (plant operated by IMC) $= \frac{83201.58}{175728.00} \times 100\%$

= 47.34%

Efficiency improving over normal operation $= \frac{47.34-42.04}{42.04} \times 100$

= 12.60%

According to the calculated result, gasification efficiency of the downdraft gasifire operated under introduced IMC system and without IMC are 47.34% and 42.04% respectively. The overall improvement of efficiency is 12.60%.

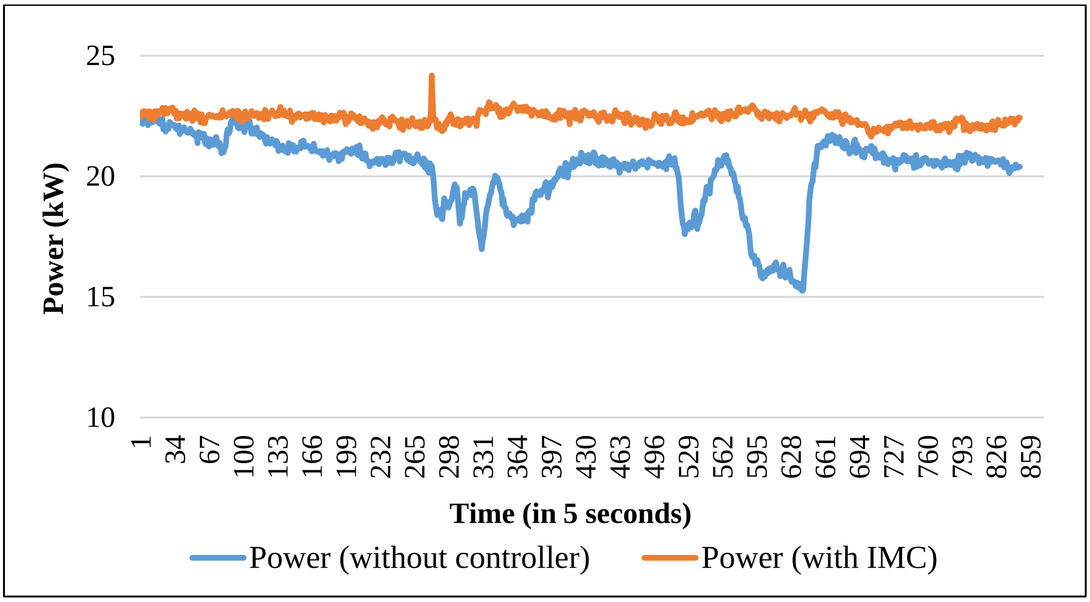


Figure 4. 9: The Graph of Power Output vs. Time

Figure 4.10 shows the fluctuation of the error during the operation with IMC system. The plant output gently reaches to set temperature, while error moves from (-10) to zero until t = 250 from the beginning. Also, moving average of the error remains at zero up to t = 313. The set point of burner flue gas temperature increases to 983K at t = 306 as in Figure 4.8 and at the same time, error presents a swift rise of positive 20K at around t = 313 as displayed in Figure 4.10. Rapid changes indicated by blue color line in Figure 4.10 at t = 313,391,495 and 560 are resulted due to variations of set temperature in burner.

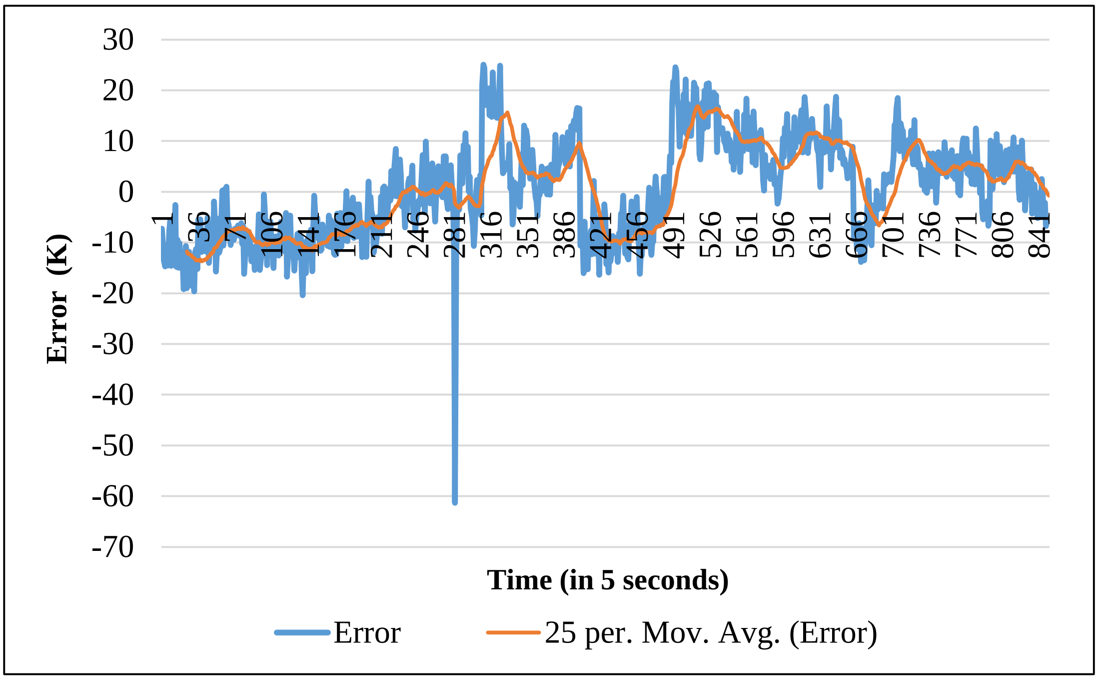


Figure 4. 10: The Graph of Error vs. Time

DC voltage signal is the output of neural network control, which illustrated in Figure 4.11. The orange colour line represents the moving average of blower RPM .There is a significant deviation near t = 306 and t = 676 as a result of fluctuation in set flue gas temperature. Initially, RPM decreases from 3265 to 3260 while variation of error at the beginning shifts from zero to (-10) as displayed in Figure 4.10. When flue gas temperature is high, blower RPM remains at a higher value. Also, while set value of flue gas temperature decreases, blower RPM slowly reaches to a lower value.

Figure 4.12 and 4.13 show temperatures at different locations; char and throat, when gasifier was operated with and without proposed internal model control. According to the temperature variations, introduced IMC system operates the gasifire at higher process temperatures. Higher gasification temperatures reflect a better oxidation, low tar production and higher calorific value of syngas [11].

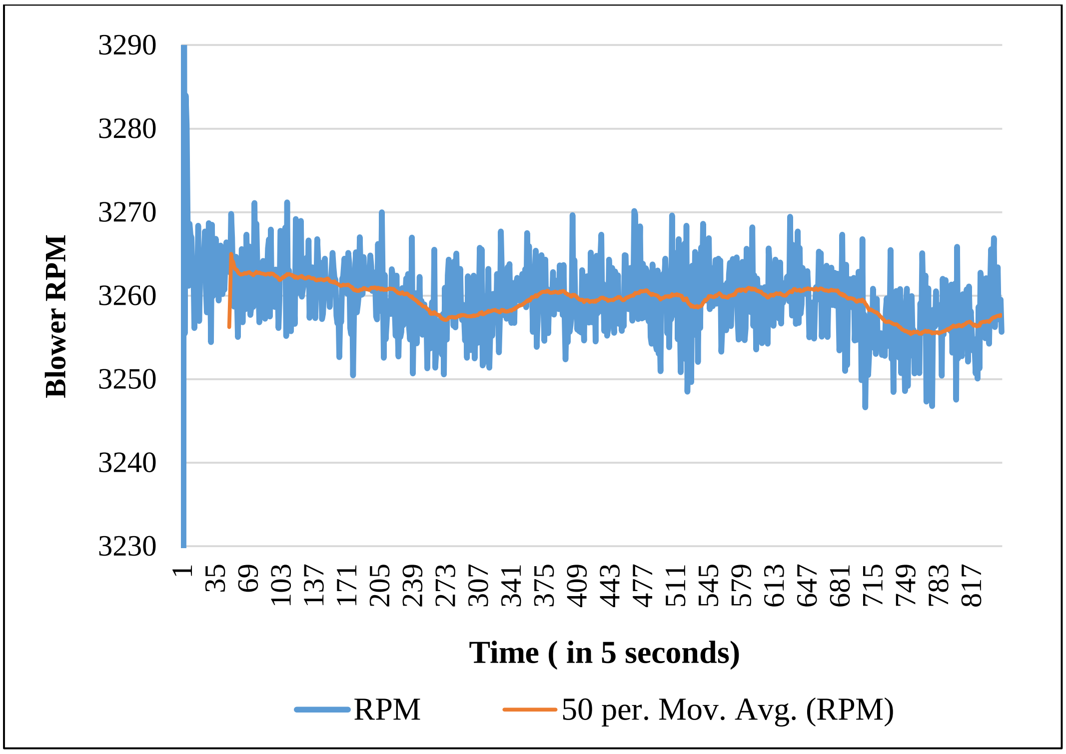


Figure 4. 11: The Graph of Blower RPM vs. Time

Higher gasification temperatures provide better CO, CH_4 and H_2 formation rate which lead to higher syngas heating value which is shown in Figure 4.8. When introduced IMC system operates gasifire, flue gas temperature of the burner is higher than without IMC. There are high temperature impulses indicated by orange colour line in Figure 4.12 at around t = 309 and 50. Those are resulted by the stuck char particles at throat. When the pressure difference increased by them across the throat, it causes a rapid high air flow and consequently flame at combustion area goes to char burning zone and throat.

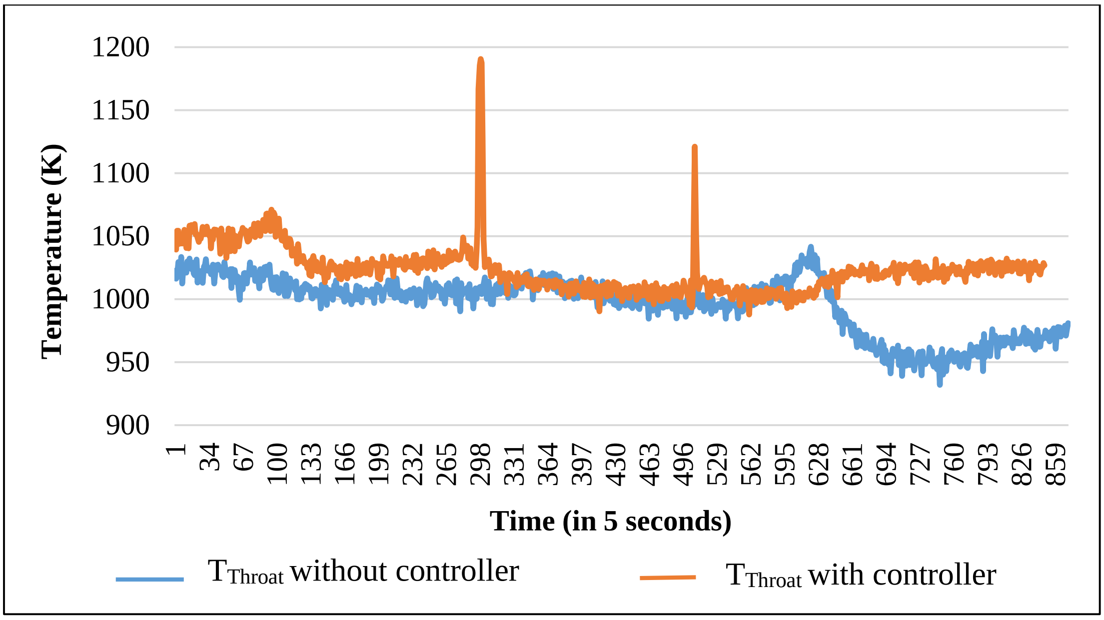


Figure 4. 12: Temperature Variations at Throat

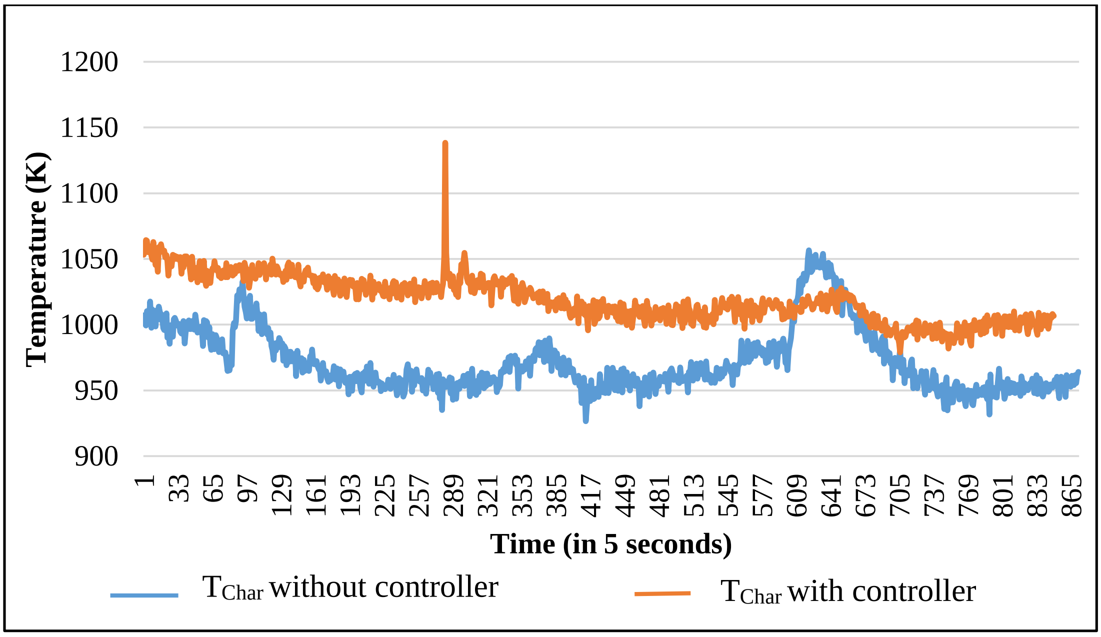


Figure 4. 13: Temperature Variations at Char

5.0. CONCLUSION

In this study, main objectives were to develop a biomass downdraft gasifire for small scale power application and process model to forecast process output, and thereby create a plat controller for enhancing the efficiency. Biomass downdraft gasifire was developed and modeled using artificial neural networks. Then, the model output was tested with actual process outputs. Based on the literature review and analysis of measured data, two different modelling approaches for prediction of process parameter have been developed which were depend on dynamic network architecture and feedforward NN architecture. According to model validation results, dynamic neural network was performed well than the feedforward neural network.

Relative influence of all parameters were calculated using Equation 4.2. The analyzed results show that the plant output, rotary grate rpm, temperature at throat and temperature of char have a significant influence on predicting future plant output. That was the reason for better performance of dynamic neural network in prediction than feedforward neural network. However, result of relative influence of air flow (P_{inlet}) is required to train for wide range of air flow in the network. Most of researchers had not considered about effect of rotary grate dynamics when developing process model. But, according to the results of this study, it is depicted that importance of evaluating rotary grate dynamics and its effects.

Internal model based control architecture was used for developing plant controller because of high process nonlinearity of biomass gasification process. Plant inverse model was also developed by using neural network. And developed biomass gasification plant model was then used as the internal model. The neural network technics can be easily combined with IMC control architecture. Furthermore, according to the results, neural network can be effectively used to model and control nonlinearity system.

Figure 4.8, 4.9 show that the syngas production stability is improved by IMC all over the plant operation. At the same time, IMC increases power output of the gasification. However, the plant output takes more time to reach to the set value because gasification is time delaying process.

During the development of plant model, it revealed the importance of grate shaking effect. However, the effect of grate shaking could not be considered for implementing the control because of a technical problem i.e., burnout of the grate shaking motor.

In this research, the neural network based IMC has been trained only for coconut shells. Therefore, this plant control may not applicable for other biomass types. As future directions, network should be developed for different biomass with different physical properties.

Moreover, gasification plant with internal combustion engine is one of very popular application. However, composition of gasification produced gas is not constant. This issue disturbs for smooth running of internal combustion engine because of the ignition preparation of gas component is different, for an example, ignition propagation of H_2 is high and ignition propagation of CO is very low than H_2. Therefore, advanced predictive controller will be an effective solution for smooth governor control.

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ANNEXES

Appendix 1

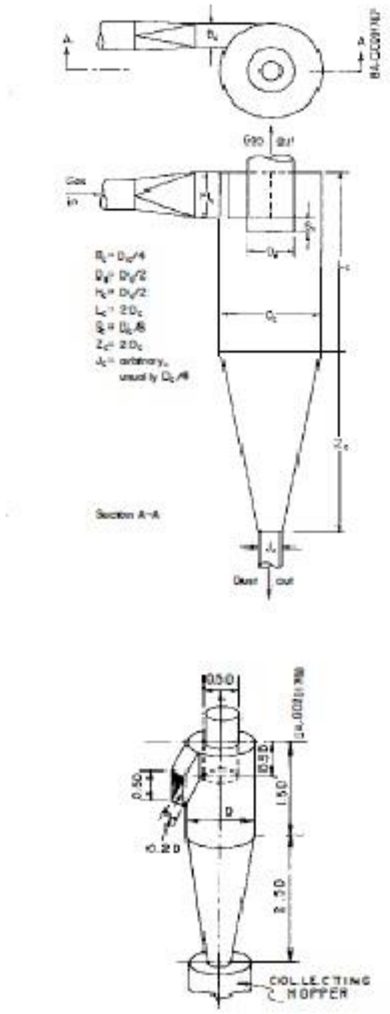

Figure 1.a: Proportions of a High Efficiency Cyclone [15]

Appendix 2

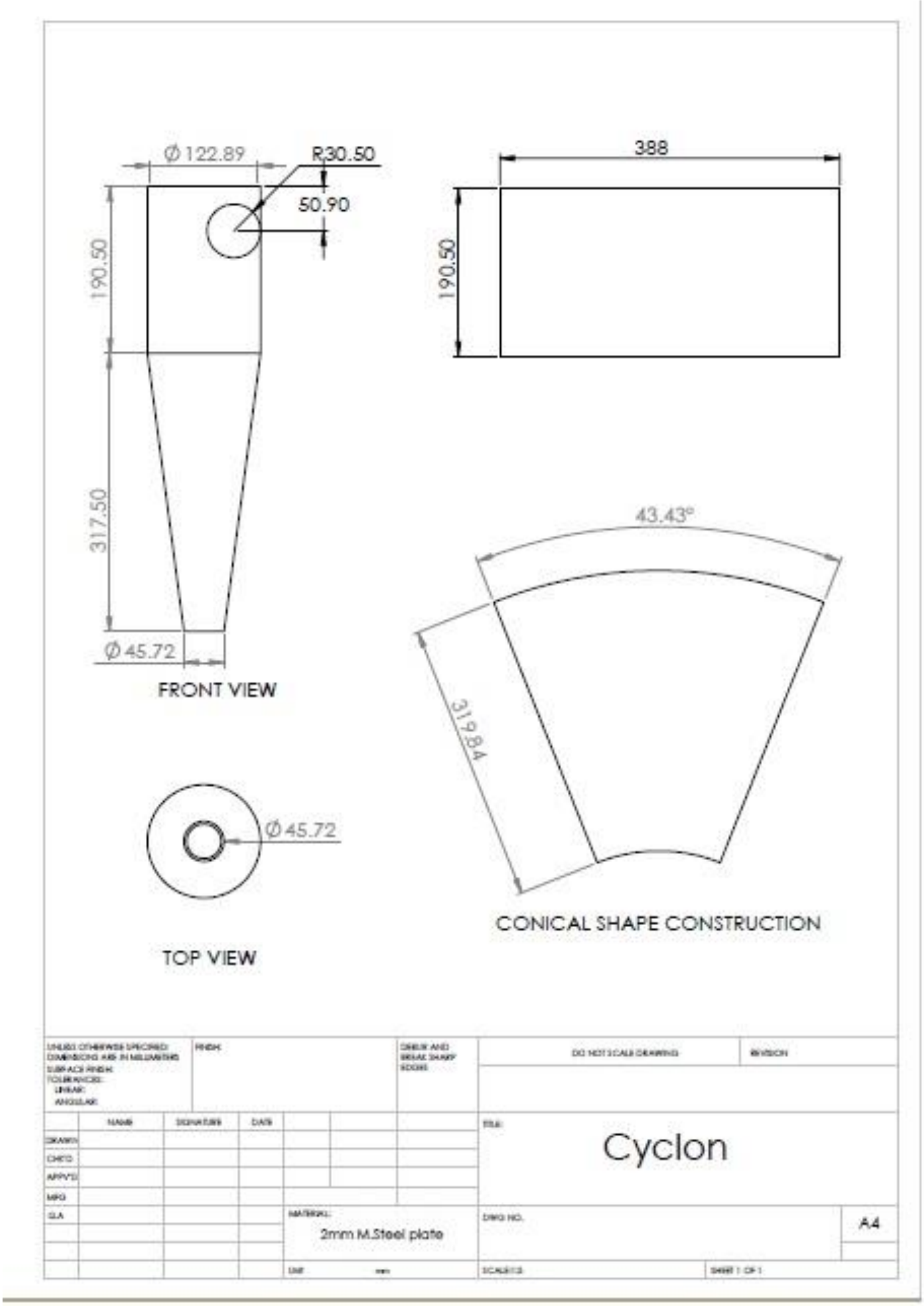

Figure 2.a: Engineering Drawing of Cyclone Construction

Appendix 3

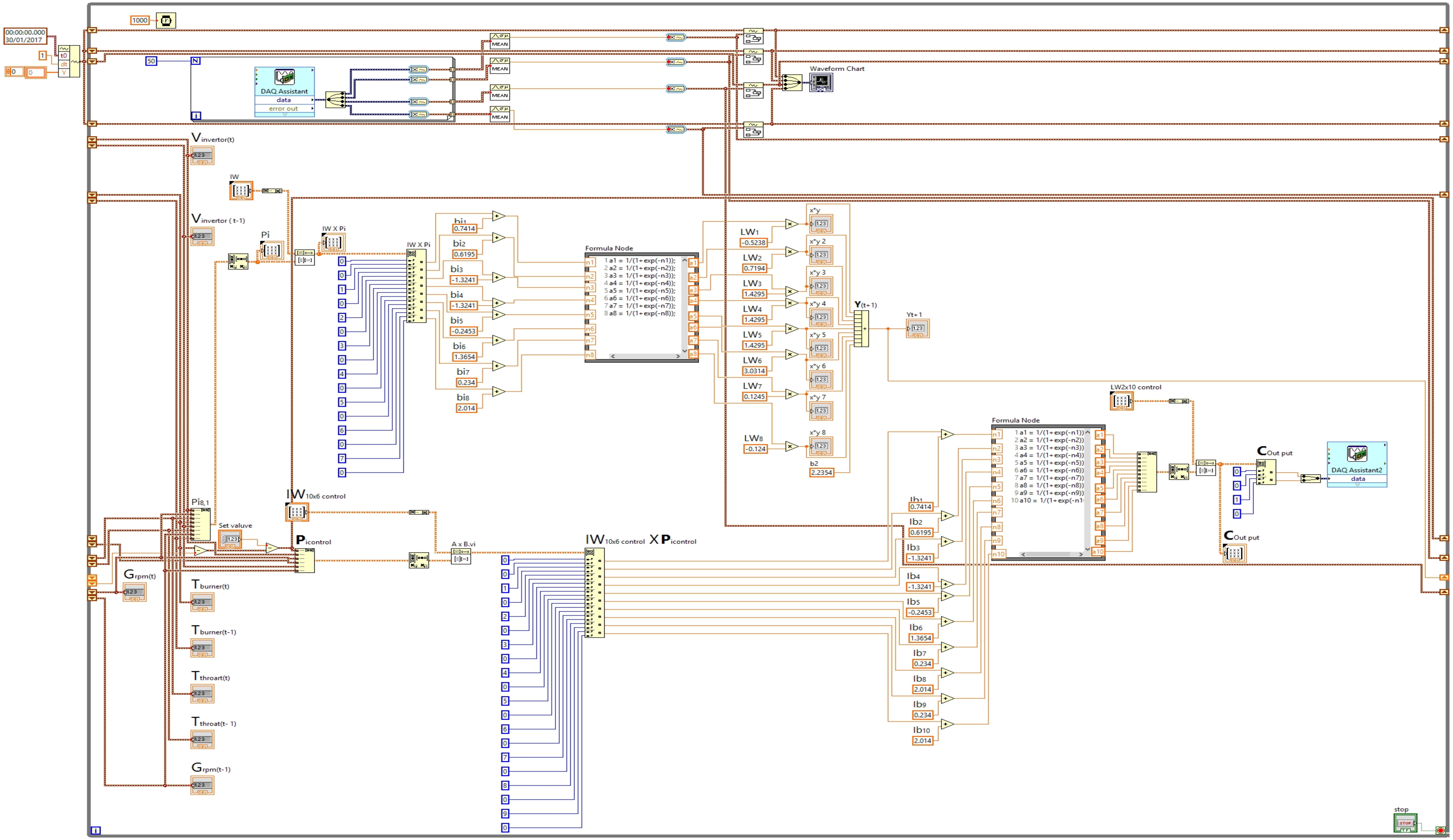

Figure 3.a: LABVIEW Block Diagram