Response Surface Method Application in Gasifier System Identification for Biomass Power Plants

A. Oonsivilai[1*], J. Satonsaowapak[1], T. Ratniyomchai[2],

T. Kulworawanichpong[2], P. Pao-La-Or[2], and B. Marungsri[1].

[1] Alternative and Sustainable Energy, Smart Materials and Intelligent System Research Unit,
[1, 2] School of Electrical Engineering
Institute of Engineering, Suranaree University of Technology
111 University Avenue, Muang District, Nakhon Ratchasima, 30000
THAILAND
*Corresponding author: anant@sut.ac.th

Abstract: - The use of renewable energy sources becomes more necessary and interestingly, wider application of renewable energy devices at domestic, commercial and industrial levels is not only resulted in greater awareness but also significantly installed capacities. In addition, biomass principally is in the form of woods and more than that used in form of energy by humans for a long time. Gasification is a process of conversion of solid carbonaceous fuel into combustible gas by partial combustion. Many gasifier models have various operating conditions thus the parameters were kept in each model are different. This study applied the experimental data which have three inputs that are biomass consumption, air flow rate and ash discharge rate and one output is gas flow rate. For this paper, response surface methods was used to identify the gasifier system equation that suitable for this experimental data in this paper and the method were used to identify gasifier system model were multiple linear regression, quadratic model and cubic model. In the result, cubic model was better way from three methods to get the answer.

Key-Words: - Gasifier System, Identification, Response Surface Method

1 Introduction

The use of renewable and sustainable energy resources will play a major role in many aspects of electricity generation. In particular, due to environment issues and ever increasing energy demands, the world is forced to look for alternative energy sources. Also, it is anticipated that shortage of hydrocarbon fuel will be inevitable. In terms of population growth, it has been estimated that by the year 2060, the world population will be in excess of 12 billions. Currently, over 80% of the crude oil reserves are under the control of only eight countries. Therefore, a number of strategies, such as special tariff and subsidy agreements, have been established in many countries in order to stimulate the research and utilization of alternative energy sources [5].

Biomass is organic material, which has stored solar energy from sunlight in the form of chemical in the plants through the process called photosynthesis. Biomass fuels include agricultural wastes, crop residues, wood, and woody wastes etc. Unless like fossil fuels biomass does not add carbon dioxide to the atmosphere as it absorbs the same amount of carbon while growing. It is the cheapest, eco-friendly, renewable source of energy [4].

Power generation from biomass has emerged as a very interesting complement to conventional sources of energy because of its contribution to the reduction of the green house effect [1]. Biomass is recognized to be one of the major potential sources for energy production. There has been an increasing interest for thermochemical conversion of biomass and urban wastes for upgrading the energy in terms of more easily handled fuels, namely gases, liquids, and charcoal in the past of decade. It is a renewable source of energy and has many advantages from an ecological point of view [2]. Biomass fuels are characterized by high and variable moisture content, low ash content, low density, and fibrous structure [3].

Biomass gasification is a technology that transforms solid biomass into syngas. It is important and efficient energy conversion technology along with interventions to enhance the sustainable supply of biomass fuels can transform the energy supply situation in rural areas [2].

Gasifier system is an important part to produce fuel gas. This paper studied the experimental data which have three inputs that are biomass consumption, air flow rate and ash discharge rate and one output is gas flow rate. This is the energy conversion technologies which is suitable for small-scale.

The response surface method has been widely used in practical engineering design optimization problems [6]. This method originates from science disciplines in which physical experiments are performed to explore the unknown relations between a set of variables and the system output, and these unknown relations are modeled as polynomials using the least square method. These straightforward polynomial models allow the objective and constraints of the optimization to be evaluated quickly to obtain better search points for more accurate surrogate models and eventually converge to the global optimum [7].

This paper is divided into five sections. Section 2 presents gasification system. Section 3 presents response surface method. Section 4 shows results. Finally, conclusions are presented in section 5.

2 Biomass Gasification

Biomass gasification is a Technology that transforms solid biomass into syngas (hydrogen and carbon monoxide mixtures produced from carbonaceous fuel). Biomass fuels are characterized by high and variable moisture content, low ash content, low density and fibrous structure. In comparison with other fuels, they are regarded as of low quality despite low ash content and very low sulfur content [1]. Biomass gasification system consists of 2 main parts. They are gasifier and gas cleaning system. For the first part, this paper used downdraft gasifiers which are simple and robust. The gas exiting the reactor flowed through a cyclone and scrubbers just to remove a dust and the tars. Next, the clean gas passed through several heat exchangers to condense water vapor. After that, the gas was conditioned to be used in the internal combustion engine [1]. Figure 1 show the biomass gasification system which consists of gasifier, gas cleaning system and engine-generator.

2.1 Gasifier

Biomass gasification converts solid biomass into more convenient gaseous form. This process is made possible in a device called gasifier. The gasifier was a cylindrical reactor which had the moving bed of biomass rested on a perforated eccentric rotating grate which was at the bottom of

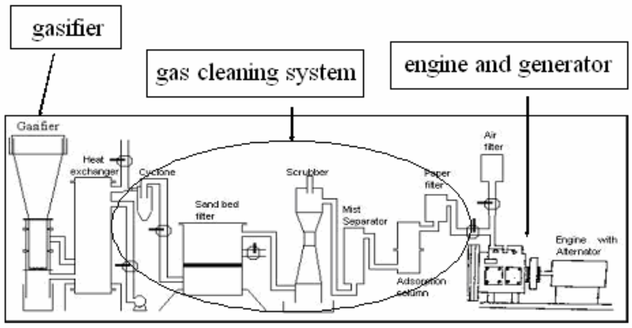

Fig.1 shows biomass gasification system.

the gasifier. The ash fell through the perforated grate to be collected in a lower chamber. The biomass feeding at the top of gasifier after that biomass was burnt in process zones. Finally, the gasifier received producer gas [4].This is the energy conversion technologies which is suitable for small-scale. Figure 2 shows process zone for downdraft gasifiers

2.1.1 Process zone

Four distinct process take place in a gasifier as the fuel makes its way to gasification. They are:

a) Drying zone
b) Pyrolysis zone
c) Combustion zone
d) Reduction zone

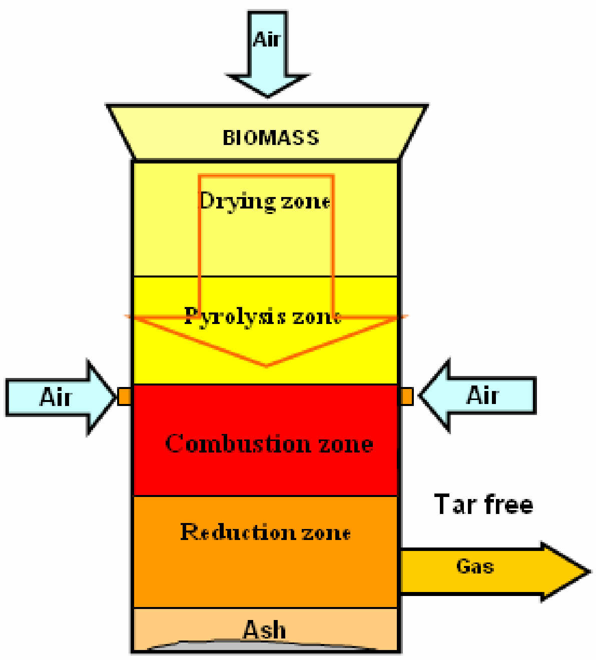

Fig.2 shows process zone for downdraft gasifiers.

2.1.2 Reaction chemistry

The following major reactions take place in combustion and reduction zone [12]

Combustion zone

The combustible substance of a solid fuel is usually composed of elements carbon, hydrogen and oxygen. In complete combustion carbon dioxide is obtained from carbon in fuel and water is obtained from the hydrogen, usually as steam. The combustion reaction is exothermic and yields a theoretical oxidation temperature of 1450 ^{o}C. The main reactions are:

$$\mathrm{C+O=CO_2 \quad (+393\,MJ/kg\,mole)} \tag{1}$$

$$\mathrm{2H_2+O_2=2H_2O \quad (-242\,MJ/kg\,mole)} \tag{2}$$

Reaction zone

The products of partial combustion (water, carbon dioxide and uncombusted partially cracked pyrolysis products) now pass through a red-hot charcoal bed where the following reduction reactions take place.

$$\mathrm{C+CO_2=2CO \quad (-164.9\,MJ/kg\,mole)} \tag{3}$$

$$\mathrm{C+H_2O=CO+H_2 \quad (-122.6\,MJ/kg\,mole)} \tag{4}$$

$$\mathrm{CO+H_2O=CO_2+H_2 \quad (+42\,MJ/kg\,mole)} \tag{5}$$

$$\mathrm{C+2H_2=CH_4 \quad (+75\,MJ/kg\,mole)} \tag{6}$$

$$\mathrm{CO_2+H_2=CO+H_2O \quad (-42.3\,MJ/kg\,mole)} \tag{7}$$

Reactions (3) and (4) are main reduction reactions and being endothermic have the capability of reducing gas temperature. Consequently the temperatures in the reduction zone are normally 800-1000 ^{o}C. Lower the reduction zone temperature (~700-800 ^{o}C), lower is the calorific value of gas.

Pyrolysis zone

Up to the temperature of 200 ^{o}C only water is driven off. At temperature of 200 to 280 ^{o}C carbon dioxide, acetic acid and water are given off. The real pyrolysis, which takes place between 280 to 500 ^{o}C, produces large quantities of tar and gases containing carbon dioxide. Besides light tars, some methyl alcohol is also formed. At temperature of 500 to 700 ^{o}C the gas production is small and contains hydrogen. In downdraft gasifier the tar have to go through combustion and reduction zone and are partially broken down. Since majority of fuels like wood and biomass residue do have large quantities of tar, downdraft gasifier is preferred over others.

Drying zone

The main process is of drying of wood. Wood entering the gasifier has moisture content 10-30%. Various experiments on different gasifiers in different conditions have shown that on an average the condensate formed is 6-10% of the weight of gasified wood. Some organic acids also come out during the drying process. These acids give rise to corrosion of gasifiers.

This paper interested in four parameters that were three inputs and one output. Three inputs were biomass consumption, ash discharge rate and air flow rate. The output is gas flow rate.

3 Response Surface Method

Response surface method is a statistical and mathematical method that gives an effective practical means for design optimization. When response y, which should be taken into consideration for design, is determined as a function of multiple design variables x_i, the behavior in response surface method is expressed by the approximation as a polynomial $y = f\left(x_i\right)$ on the basis of conservation data [8],[10]. The response surface method postulates a model of term:

$$y = f\left(x_1, x_2, ..., x_k\right) + \varepsilon \tag{8}$$

Where the form of the true response function y is unknown or very complicated, $f\left(x_1, x_2, ..., x_k\right)$ is a known polynomial function of$\left(x_1, x_2, ..., x_k\right)$, and ε is a term that represents random error. It is assumed to be normally distributed with mean zero and variance.

Because the form of y is unknown, it must be approximated by a known polynomials function $f\left(x_1, x_2, ..., x_k\right)$. The more suitable approximation for y, the accuracy is higher. In general, the first-order polynomials are [9, 11]

$$y = b_0 + \sum_{i=1}^{k} b_i x_i + \varepsilon \tag{9}$$

The first-order model is likely to be appropriate when the experimenter is interested in approximating the true response surface over a relatively small region of the input variable space in a location where there is little curvature in f.

For a quadratic response function with k variables by a regression model, it is expressed by (10)

$$y = b_0 + \sum_{i=1}^{k} b_i x_i + \sum_{i=1}^{k} b_{ii} x_i^2 + \sum_{i=1}^{k} \sum_{j=i+1}^{k} b_{ij} x_i x_j + \varepsilon \quad (10)$$

And, a cubic response function with k variables by a regression model, it is expressed by (11)

$$y = b_0 + \sum_{i=1}^{k} b_i x_i + \sum_{i=1}^{k} b_{ii} x_i^2 + \sum_{i=1}^{k} \sum_{j=i+1}^{k} b_{ij} x_i x_j + \sum_{i=1}^{k} \sum_{j=1}^{k} \sum_{l=1}^{k} b_{ijl} x_i x_j x_l + \varepsilon \quad (11)$$

For this paper, the response function with $k = 3$ variables, the first-order polynomials is

$$y = b_0 + b_1 x_1 + b_2 x_2 + b_3 x_3 + \varepsilon \quad (12)$$

the quadratic response function is

$$y = b_0 + b_1 x_1 + b_2 x_2 + b_3 x_3 + b_{12} x_1 x_2 + b_{13} x_1 x_3 + b_{23} x_2 x_3 + b_{11} x_1^2 + b_{22} x_2^2 + b_{33} x_3^2 + \varepsilon \quad (13)$$

the cubic response function is

$$y = \text{quadratic model} + b_{123} x_1 x_2 x_3 + b_{112} x_1^2 x_2 + b_{113} x_1^2 x_3 + b_{122} x_1 x_2^2 + b_{133} x_1 x_3^2 + b_{223} x_2^2 x_3 + b_{233} x_2 x_3^2 + b_{111} x_1^3 + b_{222} x_2^3 + b_{333} x_3^3 + \varepsilon \quad (14)$$

where

x_1 is biomass consumption (kg/h)

x_2 is ash discharge rate (kg/h)

x_3 is air flow rate (kg/h)

y is gas flow rate (kg/h)

Then, n sets of observation data in correspondence with design variables can be expressed by matrix representation in (15) and (16)

$$\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix} = \begin{bmatrix} 1 & x_{11} & x_{12} & \vdots & x_{1k} \\ 1 & x_{21} & x_{22} & \vdots & x_{2k} \\ 1 & \vdots & \vdots & \ddots & \vdots \\ 1 & x_{n1} & x_{n2} & \vdots & x_{nk} \end{bmatrix} \begin{bmatrix} b_0 \\ b_1 \\ \vdots \\ b_n \end{bmatrix} + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_n \end{bmatrix} \quad (15)$$

$$y = Xb + \varepsilon \quad (16)$$

Coefficient vector b is obtained by the following equation using the condition where the square of error is minimized:

$$b = \left(X^T X \right)^{-1} X^T Y \quad (17)$$

where X the design matrix of sample data points is, X^T is its transpose, Y is a column vector containing the values of the response at each sample point.

By obtaining coefficient vector b from (17), the response surface is prepared [8].

4 Results and Discussion

The method described in the previous section was applied to estimate the coefficient of model. Fig.3-5 show values comparison of response surface method with observed data in different equation model. Fig. 3 presents comparison of linear equation with observed data. Fig.4 presents comparison of quadratic equation with observed data. Fig. 5 presents comparison of cubic equation with observed data. From these answer, the error value can calculate by using values from experiment compared with values from response surface method as shows in Fig. 6-8. Fig. 6 presents gas flow rate error with linear equation. Fig. 7 presents gas flow rate error with quadratic equation. Fig. 8 presents gas flow rate error with cubic equation. Table 1 shows the experimental data test for solving response surface method which was kept at biomass power plant in Suranaree University of Technology. Table 2 presents the gas flow rate which approximated by using response surface method (linear equation, quadratic equation and cubic equation). Table 3 presents error values from different method. These errors were used to consider the response surface method which should be to be represented the gasifier system that had three outputs which were biomass consumption, ash discharge rate and air flow rate and one output is gas flow rate. From three equations, the cubic equation is most suitable than others equation for this experimental data. In the future, the method which better than three methods may be used to solve and present replace such as artificial intelligent (fuzzy, neuron network, etc.) which can used with complicated system and widely use in engineering fields [13-34].

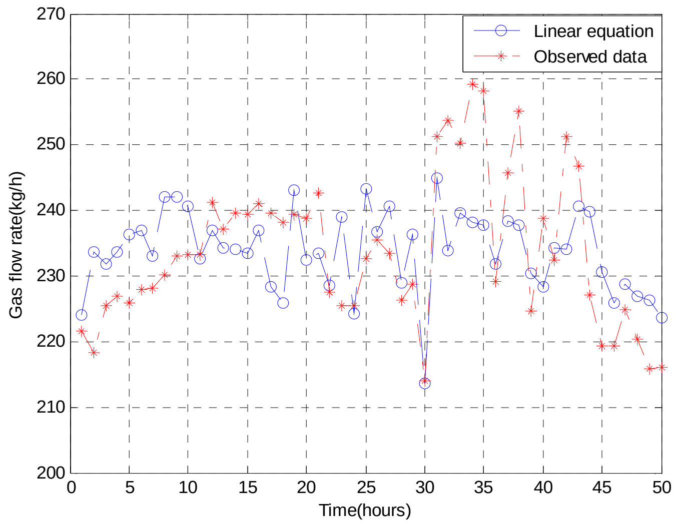

Fig. 3 comparison of linear equation with observed data

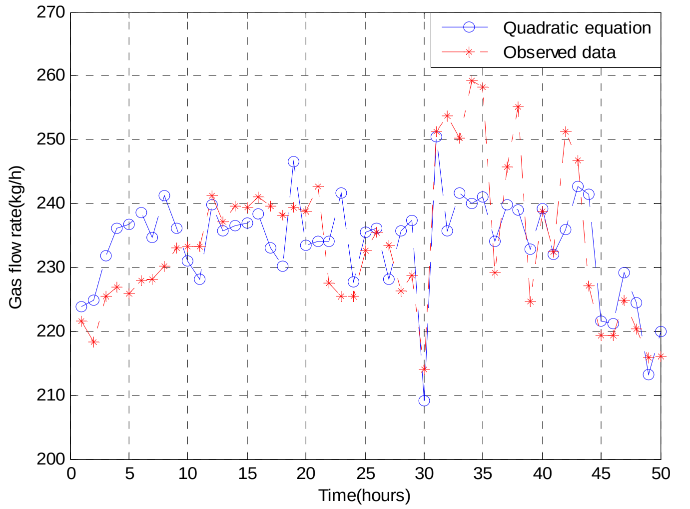

Fig. 4 comparison of quadratic equation with observed data

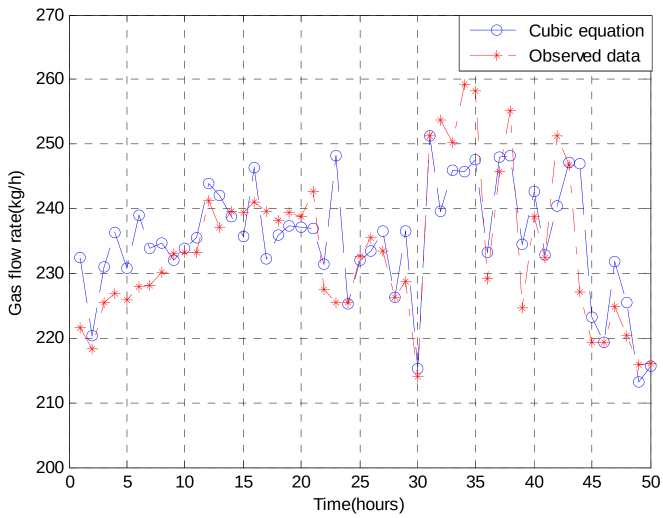

Fig. 5 comparison of cubic equation with observed data

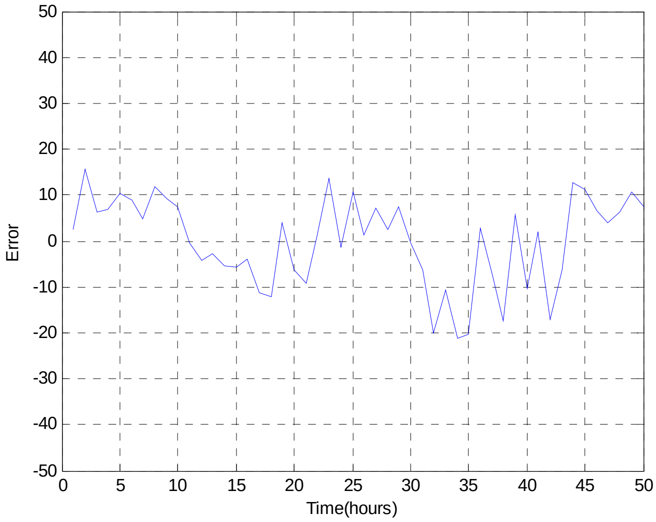

Fig. 6 Gas flow rate error with linear equation.

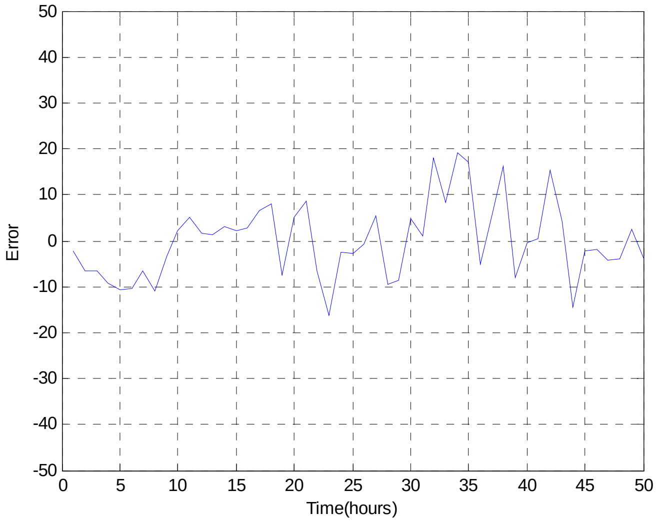

Fig. 7 Gas flow rate error with quadratic equation.

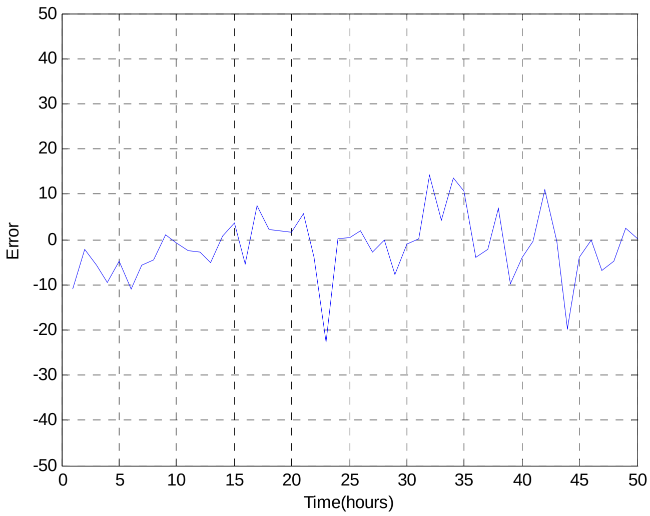

Fig. 8 Gas flow rate error with cubic equation.

Table 1: Experimental data test for solving response surface method

x_1	x_2	x_3	y
103.90	13.00	117.2899	221.5537
138.30	15.20	117.7695	218.2254
108.60	15.30	116.5175	225.4367
119.40	13.80	116.2114	226.8789
117.50	16.50	116.3934	225.9914
124.80	14.30	115.9330	227.9884
107.50	14.50	115.8788	228.2102
138.10	14.00	115.4149	230.2072
114.00	16.20	114.7040	232.9808
128.00	12.30	114.6112	233.2027
85.10	14.30	114.6112	233.2027
134.50	13.90	116.3644	241.3015
119.50	14.60	116.3415	237.0857
123.20	13.90	116.3644	239.6374
124.60	13.20	116.3644	239.3046
128.10	15.00	116.3644	240.9687
105.70	12.90	116.3644	239.6374
92.40	13.50	116.3644	238.1951
149.30	15.70	116.3644	239.3046
111.00	14.90	116.3644	238.7499
112.60	15.30	116.3644	242.6329
102.80	12.60	116.0728	227.4336
142.50	14.40	116.5175	225.4367
85.90	13.90	116.5175	225.4367
132.10	14.00	114.7895	232.6480
117.30	13.90	115.4245	235.4216
125.60	12.30	114.4316	233.5355
112.30	12.00	116.3283	226.3242
119.80	14.20	115.7427	228.7650
103.00	9.90	118.6889	214.1205
161.90	14.70	116.3644	251.2864
120.70	14.10	116.3644	253.7272
138.40	15.10	116.3644	250.1770
134.20	14.80	116.3644	259.2744
138.60	13.80	116.3644	258.1649
104.10	13.50	115.6583	229.0978
131.80	15.40	116.3644	245.7393
127.30	15.80	116.3644	255.1695
117.20	13.30	116.7175	224.6601
117.80	10.70	116.3644	238.7499
115.00	10.80	114.8220	232.4261
121.40	14.20	116.3644	251.2864
137.60	16.00	116.3644	246.8487
133.20	15.50	116.1584	227.1008
128.30	14.70	117.7502	219.3348
119.70	12.90	117.7502	219.3348
103.20	14.50	116.6633	224.8819
119.60	12.90	117.5429	220.4442
x_1	x_2	x_3	y
114.80	14.60	117.9394	215.7846
117.00	12.10	117.8948	216.0065

Table 2: Comparison the answer from response surface method

y from data	y from linear	y from quadratic	y from cubic
221.5537	224.1418	223.7887	232.4226
218.2254	233.7366	224.9082	220.2762
225.4367	231.8209	231.9196	230.9956
226.8789	233.7054	236.1938	236.3622
225.9914	236.2436	236.7139	230.8330
227.9884	236.9332	238.4906	239.0053
228.2102	233.1437	234.7633	233.9202
230.2072	242.0234	241.1779	234.6349
232.9808	242.1413	236.2022	232.0724
233.2027	240.5492	230.9283	233.9752
233.2027	232.6885	228.1107	235.6134
241.3015	236.9482	239.7238	243.9408
237.0857	234.2981	235.7063	242.0908
239.6374	234.1392	236.4563	238.8243
239.3046	233.5059	237.0372	235.7444
240.9687	236.8993	238.2797	246.3773
239.6374	228.3870	233.0761	232.2378
238.1951	225.9219	230.2470	235.9443
239.3046	243.1506	246.6494	237.3718
238.7499	232.5083	233.5145	237.0982
242.6329	233.4667	234.1439	236.9103
227.4336	228.4863	234.0327	231.4417
225.4367	238.9864	241.7312	248.1160
225.4367	224.2154	227.7921	225.2218
232.6480	243.1929	235.5359	232.0899
235.4216	236.6717	236.1817	233.4258
233.5355	240.7168	228.2097	236.4518
226.3242	228.9197	235.6943	226.3865
228.7650	236.3598	237.3698	236.5295
214.1205	213.6197	209.1642	215.1954
251.2864	244.8810	250.3597	251.2532
253.7272	233.7981	235.7885	239.5268
250.1770	239.5999	241.7452	245.9601
259.2744	238.1353	240.0511	245.7369
258.1649	237.8272	241.0059	247.5644
229.0978	231.8348	234.1183	233.1635
245.7393	238.3798	239.8535	248.0519
255.1695	237.8219	238.9032	248.2492

224.6601	230.3041	232.8233	234.4443
238.7499	228.3109	239.2540	242.6230
232.4261	234.3179	231.9957	232.9261
251.2864	234.1123	235.9816	240.3618
246.8487	240.6627	242.7187	247.2194
y from data	y from linear	y from quadratic	y from cubic
227.1008	239.7445	241.5385	246.9711
219.3348	230.6319	221.5105	223.2733
219.3348	225.9708	221.1655	219.4175
224.8819	228.7367	229.2315	231.7332
220.4442	226.8280	224.4592	225.3833
215.7846	226.3308	213.1743	213.2890
216.0065	223.5628	219.8892	215.7291

Table 3: Comparison the error with different equation model on response surface method

Error from linear equation	Error from quadratic equation	Error from cubic equation
2.5881	2.235	10.8689
15.5112	6.6828	2.0508
6.3842	6.4829	5.5589
6.8265	9.3149	9.4833
10.2522	10.7225	4.8416
8.9448	10.5022	11.0169
4.9335	6.5531	5.71
11.8162	10.9707	4.4277
9.1605	3.2214	-0.9084
7.3465	-2.2744	0.7725
-0.5142	-5.092	2.4107
-4.3533	-1.5777	2.6393
-2.7876	-1.3794	5.0051
-5.4982	-3.1811	-0.8131
-5.7987	-2.2674	-3.5602
-4.0694	-2.689	5.4086
-11.2504	-6.5613	-7.3996
-12.2732	-7.9481	-2.2508
3.846	7.3448	-1.9328
-6.2416	-5.2354	-1.6517
-9.1662	-8.489	-5.7226
1.0527	6.5991	4.0081
13.5497	16.2945	22.6793
-1.2213	2.3554	-0.2149
10.5449	2.8879	-0.5581
1.2501	0.7601	-1.9958
7.1813	-5.3258	2.9163
2.5955	9.3701	0.0623
7.5948	8.6048	7.7645
Error from linear equation	Error from quadratic equation	Error from cubic equation
-0.5008	-4.9563	1.0749
-6.4054	-0.9267	-0.0332
-19.9291	-17.9387	-14.2004
-10.5771	-8.4318	-4.2169
-21.1391	-19.2233	-13.5375
-20.3377	-17.159	-10.6005
2.737	5.0205	4.0657
-7.3595	-5.8858	2.3126
-17.3476	-16.2663	-6.9203
5.644	8.1632	9.7842
-10.439	0.5041	3.8731
1.8918	-0.4304	0.5
-17.1741	-15.3048	-10.9246
-6.186	-4.13	0.3707
12.6437	14.4377	19.8703
11.2971	2.1757	3.9385
6.636	1.8307	0.0827
3.8548	4.3496	6.8513
6.3838	4.015	4.9391
10.5462	-2.6103	-2.4956
7.5563	3.8827	-0.2774

For this paper, the response function with the first-order polynomials from equation (12) is

$$y = 679.1520 + 0.2486x_1 + 1.4018x_2 - 4.2549x_3 \tag{18}$$

The quadratic response function from equation (13) is

$$\begin{aligned} y &= (-60830) + (-6.4469)x_1 + (98.189)x_2 \\ &+ (1049.6)x_3 + (0.019073)x_1x_2 + (0.051547)x_1x_3 \\ &+ (-0.94989)x_2x_3 + (0.0018346)x_1^2 + (0.3572)x_2^2 \\ &+ (-4.5033)x_3^2 \end{aligned}$$
(19)

The cubic response function is from equation (14) is

$$
\begin{aligned}
y = &\left(8.2015\text{e+}006\right) + \left(\text{-}2796.2\right) x_1 + \left(\text{-}11704\right) x_2 \\
&+ \left(\text{-}2.0779\text{e+}005\right) x_3 + \left(5.2532\right) x_1 x_2 \\
&+ \left(47.321\right) x_1 x_3 + \left(200.53\right) x_2 x_3 + \left(\text{-}0.025587\right) x_1^2 \\
&+ \left(\text{-}11.763\right) x_2^2 + \left(1754.6\right) x_3^2 + \left(\text{-}0.035694\right) x_1 x_2 x_3 \\
&+ \left(\text{-}0.032769\right) x_1^2 x_2 + \left(0.0031139\right) x_1^2 x_3 \\
&+ \left(0.24306\right) x_1 x_2^2 + \left(\text{-}0.20375\right) x_1 x_3^2 + \left(0.22478\right) x_2^2 x_3 \\
&+ \left(\text{-}0.87786\right) x_2 x_3^2 + \left(0.00035003\right) x_1^3 + \left(\text{-}1.0499\right) x_2^3 \\
&+ \left(\text{-}4.9363\right) x_3^3
\end{aligned}
$$

5 Conclusion

Gasifier system is an important part to produce fuel gas. It is the good way to know the function which can use to predict the results. This study applied the experimental data which have three inputs that entry the system are biomass consumption, ash discharge rate and air flow rate and the output of system is gas flow rate which means fuel gas that used in the internal combustion engine. In the results, cubic equation is better than linear and quadratic equation. So the represent equation of gasifier system for this experimental data is shown in equation (20).

6 Acknowledgement

The experimental data was supported by Center of Excellence in Biomass Suranaree University of Technology. Funding in this research was supported by Suranaree University of Technology Research and Development Funds.

References:

[1] Sagues, C., Garcia-Bacaicoa, P. and Serrano, S., Automatic control of biomass gasifiers using fuzzy inference systems, *Bioresource Technology*, Vol.98, 2007, pp. 845-855.

[2] Sheth, P.N. and Babu, B.V., Effect of Moisture Content on Composition Profiles of Producer Gas in Downdraft Biomass Gasifier, *Proceedings of International Congress Chemistry and Environment (ICCE)*, 2005, pp. 356-360.

[3] Schuster, G., Loffler, G., Weigl, K. and Hofbauer, H., Biomass Steam Gasification-an Extensive Parametric Modeling Study, *Bioresource Technology*, 2001, pp. 71-79.

[4] Ashok, S. and Balamurugan, P., Biomass Gasifier Based Hybrid Energy System for Rural Ares, *IEEE Canada Electrical Power Conference*, 2007, pp. 371-375.

[5] Panote, W., Chun, C.F. and Chem, C.N., A Study on The Potential of Corn Cob Engine-Generator for Electricity Generation in Thailand, *Proceeding of IEEE TENCON'02*, 2002, pp. 1958-1961.

[6] Bo, P.W., Zhen, X.H. and Tommi, R., A Novel Response Surface Method for Design Optimization of Electronic Packages, 6^{th}. *Int. Conf. on Thermal, Mechanical and Multiphysics Simulation and Experiments in Micro-Electronics and Micro-Systems*, 2005, pp. 175-181.

[7] Ruoning, X. and Zuomin, D., Fuzzy Modeling in Response Surface Method for Complex Computer Model Based Design Optimization, *Mechatronic and Embedded Systems and Applications, Proceedings of the 2nd IEEE/ASME International Conference on*, 2006, pp. 1-6.

[8] Yingjun, C., Gaowei, X., Dapeng, Z., Wenjie, Z. and Le, L., Thermal Analysis for Indirect Liquid Cooled Multichip Module Using Computational Fluid Dynamic Simulation and Response Surface Methodology, *IEEE Transactions on Components and Packaging Technologies,* Vol.29, 2006, pp. 39-46.

[9] Ke, L., Haobo, Q., Liang, G. and Yifei, S., Comparison of Stochastic Response Surface Method and Response Surface Method for Structure Reliability Analysis, *IEEE Second International Conference on Intelligent Computation Technology and Automation*, 2009, pp. 172-175.

[10] Laurent, J., Jabbar, M.A. and Lui, Q., Design Optimization of Permanent Magnet Motors Using Response Surface Methodology and Genetic Algorithms, *IEEE Transaction on Magnatics*, Vol.41, 2005, pp. 3928-3930.

[11] Hsien-Chie, C., Wen-Hwa, C. and I-Chun, C., Integration of Simulation and Response Surface Methods for Thermal Design of Multichip Modules, *IEEE Transaction on Components and Packaging Technologies*, Vol.27, 2004, pp. 359-372.

[12] Anil, K.R., Biomass Gasification, *Alternative Energy in Agriculture*, Vol.II, 1986, pp. 83-102.

[13] Oonsivilai, R. and Oonsivilai, A., Probabilistic Neural Network Classification for Model β-Glucan Suspensions, *Proceedings of the* 7^{th}

WSEAS Int. Conf. on Simulation, Modelling and Optimization, 2007, pp. 159-164.

[14] Oonsivilai, A. and El-Hawary, M.E., Wavelet Neural Network Based Short Term Load Forecasting of Electric Power System Commecial Load, *Proceedings of the 1999 IEEE Canadian Conference on Electrical and Computer Engineering*, Vol.3, 1999, pp. 1223-1228.

[15] Oonsivilai, A. and El-Hawary, M.E., A Self-organizing Fuzzy Power System Stabilizer, *Proceedings of the 1998 IEEE Canadian Conference on Electrical and Computer Engineering*, Vol.1, 1998, pp. 197-200.

[16] Oonsivilai, A. and El-Hawary, M.E., Power System Dynamic Load Modeling using Adaptive- Network- Based Fuzzy Inference System, *Proceedings of the 1999 IEEE Canadian Conference on Electrical and Computer Engineering*, Vol.3, 1999, pp. 1217-1222.

[17] Marungsri, B., Meeboon, N., and Oonsivilai, A., Dynamic Model Identification of Induction Motors using Intelligent Search Techniques with taking Core Loss into Account, *WSEAS TRANSACTIONS on POWER SYSTEMS*, Vol.1, 2006.

[18] Marungsri, B. and Oonsivilai, A., Fuzzy ArtMap technique for speech noise reduction, *WSEAS*, 2007.

[19] Oonsivilai, A. and Marungsri, B., Optimal PID Tuning for AGC system using Adaptive Tabu Search, *WSEAS. Sep 15-17, Beijing, China.*

[20] Oonsivilai, A. and Oonsivilai, R., Genetic Algorithm Approach to Twin-Screw Food Extrusion Process Frequency Domain Parameter Estimation, *Proceeding of the 7th WSEAS International Conference on Applied Computer and Applied Computational Science (ACACOS'08)*, 2008, pp. 645-650.

[21] Pao-La-Or. P., Kulworawanichpong, T. and Oonsivilai, A., Bi-objective intelligent optimization for frequency domain parameter identification of a synchronous generator, *WSEAS TRANSACTIONS on POWER SYSTEMS*, Vol.3, 2008.

[22] Oonsivilai, A. and Pao-La-Or. P., Application of adaptive tabu search for optimum PID controller tunning AVR system, *WSEAS TRANSACTIONS on POWER SYSTEMS*, Vol.3, 2008. pp. 495-506.

[23] Oonsivilai, A. and Marungsri, B., Application of artificial intelligent technique for partial discharges localization in oil insulating transformer, *WSEAS TRANSACTIONS on SYSTEMS.*, Vol. 8, 2008, pp. 920-929.

[24] Greyson, K.A. and Oonsivilai, A., Identification of critical measurements in power system network, *Proc. IEEE Power System & Conference and Exposition (PSCE),* 2009, pp. 1-6.

[25] Oonsivilai, A. and Oonsivilai, R., A genetic algorithm application in natural cheese products, *WSEAS TRANSACTIONS on SYSTEMS.*, Vol. 8, 2009, pp. 44-54.

[26] Greyson, K.A. and Oonsivilai, A., Alternative technique of classifying PMUs at optimal environment in power system, *WSEAS TRANSACTIONS on Power Systems,* Vol. 3, 2008, pp. 643-652.

[27] Oonsivilai, A. And Pao-La-Or. P., Optimum PID Controller tuning for AVR System using Adaptive Tabu Search, *12th WSEAS CSCC July 18-20*, 2008.

[28] Oonsivilai, A. and Marungsri, B., Optimal PID tuning for power system stabilizer using adaptive particle swarm optimization technique, *12th WSEAS CSCC July 18-20*, 2008.

[29] Oonsivilai, A. and Oonsivilai, R., Parameter Estimation of Frequency Response Twin-Screw Food Extrusion Process using Genetic Algorithm, *WSEAS TRANSACTIONS on SYSTEMS.*, Vol. 7, 2008.

[30] Xavier, P. and Andreu, C., Learning Fault Tolerance in Radial Basis Function Networks, *Proceedings of European Symposium on Artificial Neural Networks Bruges (Belgium),* 2001, pp. 341-346.

[31] Hafizah, H., Marzuki, K. and Rubiyah, Y., Nonlinear Function Approximation using Radial Basis Neural Networks, *Student Conference on Research and Development Proceedings,* 2002, pp. 326-329.

[32] Leonid, R. and Anthony, L., Choice of the Radial Basis Function Approximation in Neural Networks Used for Fuzzy System Implementation, *IEEE,* 2001, pp. 3032-3037.

[33] Bing, Y. and Xingshi, H., Traning Radial Basis Function Networks with Differential Evolution, *Proceeding of World Academy of Science, Engineering and Technology,* Vol.11, 2006, pp.157-160.

[34] Jea-Rong, T.,Pau-Choo, C. and Chein-I, C., A Sigmoidal Radial Basis Function Neural Network For Function Approximation, *IEEE*, 1996, pp.496-501.