Pak. J. Biotechnol. Vol. 15 (Special Issue ICRAME 17) Pp. 22-25 (2018) T. Sathish et al.,
www.pjbt.org PISSN: 1812-1837, EISSN 2312-7791

ANALYSIS AND MODELLING OF SUPPORT VECTOR MECHANISM FOR THE BIOMASS GASIFICATION PROCESS

T. Sathish*[1], M.D.Vijayakumar[2], P. Periyasamy[3]

*[1]*Managing Trustee, Vesta Educational and Charitable Trust, Pudukkottai, Tamil Nadu, India.*
[2]*Head / Department of Mechanical Engineering, Chennai Institute of Technology, Tamil Nadu, India.*
[3]*Head/ Professor, Dept. Mechanical Engg., St. Peter's University, Tamil Nadu, India*
E-mail: sathish.sailer@gmail.com

ABSTRACT

Biomass gasification process is one of the major process of producing combustible gases like Carbon monoxide (CO), Hydrogen (H2) and traces of Methane and non-useful products like tar and dust are used in hot air generators, dryers, boilers, ovens, industries and in many other applications. So in order to improve the accuracy and efficiency of biomass gasification a precise modelling technique based on artificial intelligence is proposed in this paper. Support Vector Mechanism (SVM) is the proposed method used to increase the efficiency of the biomass gasification and to predict the biomass gasification by back propagation algorithm.

Key words: Biomass gasification, Artificial Intelligence, Support Vector Mechanism

1. INTRODUCTION

Since now and the last century gasification process is well known method. Biomass is a promising sustainable energy source. It leads to a mixture containing hydrogen, water etc and small amount of methane and higher hydrocarbons (Florin and Harris, 2007). The biomass gasification technologies to produce hydrogen rich fuel gas present highly interesting possibilities for biomass utilization as the sustainable energy (Cao, et al., 2006). Transplant of commercial coal or oil-based gasification process to biomass utilization is an optimal choice to produce hydrogen rich fuel gas (Faaij, 2006). The biomass is the agricultural and forestry products, the increased use of biomass as an energy source would develop the economic condition of the rural areas especially in the developing countries. Moreover, the biomass-based technology would reduce the dependence on foreign petroleum (Demirbaş, 2003, Domac, et al, 2005). It is also known that for low carbon taxes ((below 50 to 100-USD/Toricredits) biomass is most cost-effective for heat production (Chong, 2014). Waste incineration was one of the technologies in the past which was used to reduce the volume and destroy harmful substances to prevent threats to human health. But waste incineration is almost always combined with energy recovery nowadays (Bosmans, 2013). Thus, Understanding the interaction between the chemical and physical mechanisms during gasification is of fundamental importance for the optimal design of biomass gasifiers.

2. Related Work

Pavlas, et al, (2010) have proposed a biomass gasification system for complex design interactions as many streams requiring heating and cooling in the energy recovery. Yunus, et al, (2010) have proposed a biomass gasification process in PETRONAS's ICON process. Colpan, et al, (2010) have proposed a biomass gasification system in which energy and exergy analysis was done. Inayat, et al, (2010) have introduced a method for hydrogen production from biomass steam gasification. Atri et al, (2010) have proposed the successful detachment of surfactants and organic materials, for example, suspended solids, fragrant substances and colors.. Dahot et al., (2011) have proposed to verify the various the effect of different concentrations of Sodium azide 0.5% and 1% on the seeds of Sorghum. The review has explored the research trends in the experimentation of biomass gasification process. However the derived models have not been proved for its precision and accuracy. All these drawbacks in the literature have motivated to do the research work in the current area.

3. Support Vector Mechanism in in Biomass Gasification

Biomass usually refers to animal wastes and plant materials which are used as fuel. Gasification means the partial combustion of the biomass takes place at a temperature of 1000^{o}C. The combustion products from incomplete combustion of biomass generally contain combustible gases like Carbon monoxide (CO), Hydrogen (H2) and traces of Methane and non useful products like tar and dust. These are totally referred to as producer gas. Here we are going to predict the next day percentage of each gas and also by using back propagation algorithm we are going to increase the performance of the biomass gasification process by reducing the tar and dust.The SVM has considered as a machine learning algorithm for the classification of two-class problems. The training of support vector machines with the positive and negative types of data is known as one-against-all or one-against-rest. The two-class type SVM is combined for creating a multi-class support vector machine. The classification by this algorithm is represented as in the equation (*Cao, et al, 2006*).

$$F(\theta) = \operatorname{sgn}\left[\left(\sum_{j=1}^{n} \gamma_j x_j \tau(\theta, \theta_j) + b\right)\right] \qquad (1)$$

In (1) γ_j is the Lagrange Multiplier, θ_j *and* x_j are the dimensional vectors of the two associated classes and $\tau(\theta, \theta_j)$ is the Kernel function. The numerical difficulties of this method are eliminated using Kernel function.

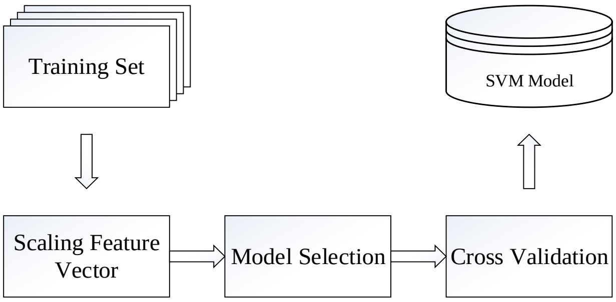

Figure 1: Flowchart for SVM

4. Results and Discussion

The proposed technique for biomass gasification process based on artificial Intelligence using SVM is implemented in the working platform of MATLAB (version 2016a). The testing on Gasifier system was carried out at a capacity of 5.0-5.5 KVA and the following parameters were tested for the experimental implementation. The experimental values obtained are given in the table 1 to table 4. The samples of cut wood and charcoal pieces from the ash pit (bottom of the gasifier), were analyzed for the following parameters. ASTM international standard test methods for proximate analysis were adapted for the analysis.

Table 1: The average values of proximate analysis

Sample	Description	Day 1	Day 2	Day 3	Average
Fuel –Wood	Total solids –TS (%)	93.02	92.88	93.13	93.01
	Volatile Matter – VM (% of T.S)	81.98	82.55	82.68	82.40
	Ash (% of T.S)	1.23	0.98	1.47	1.2266
	Fixed Carbon (% of T.S)	16.79	16.50	15.85	16.38
	Calorific value (MJ/Kg)	19.93	t9,35	20.06	19.78
Charcoal	Total solids –TS (%)	96.98	97.23	96.31	96.84
	Volatile Matter – VM (% of T.S)	19.96	19.23	19.84	19.67
	Ash (% of T.S)	2.09	2.13	2.00	2.0733
	Fixed Carbon (% of T.S)	77.95	78.64	78.16	78.25
	Calorific value (MJ/Kg)	35.06	31.0l	34.68	33.5833

In order to estimate quality of gas in terms of Tar & Particulate content, experiments were carried out. As per the guide lines of European Commission for each day single set (both raw and clean gas samples) of experiments were performed and results are summarized as below.

Table 2: Tar and Dust Content in Producer Gas

Day	Tar (mg/m^3)		Dust mg/m^3	
	Raw	Clean	Raw	clean
1	449	85	427	159
2	542	172	727	191
3	509	165	604	190
Average	500	142	586	180

The frequency was kept in the range of 50 ± 2Hz most of the time indicating stable system operation by adjusting the engine control system. Further with the help of flue gas analyzer engine exhaust was monitored for its CO and other pollutant emissions.

Table 3: Percentage of gas components in engine exhaust

Day	Percentage of gas components in engine exhaust			
	CO (%)	CO_2 (%)	O_2 (%)	NOx (ppm)
1	0.2	15.3	2.89	86
2	0.23	15.4	2.24	215
3	0.21	14.4	3.99	125
Average	0.21	15.0333	3.04	142

Producer gas samples were taken at regular intervals for measuring its composition using Gas Chromatography (GC). GC results were obtained using TCD (Thermal Conductivity Detector) and using chromos orb 102 & Mol. Sieve-l3x columns in series.

Table 4: Volumetric composition of producer gas and Calorific Value

Day	Percentage of Producer gas constituents (%)						Total	Calorific Value
	CO_2	H_2	O_2	N_2	CH_4	CO	(%)	Kcal/m^3
1	15.16	11.98	1.12	48.95	0.85	21.39	100	1026.11
2	13.24	12.30	2.87	49.07	0.99	21.53	100	1053
3	17.13	10.68	1.63	49.08	0.88	20.50	100	968.37
Average	15.1766	11.65	1.8733	49.03	0.9066	21.14	100	1015.8266

The proposed neural network is trained separately for the fuel-wood and charcoal. The Total solids, Volatile Matter, Ash, Fixed Carbon and Calorific value are considered as the input for the neural network. The percentages of gas constituents like CO2, H2, O2, N2, CH4, CO etc. are considered as the output for the artificial neural networks. Thus these above given values are considered as the dataset for training and testing the SVM. In our proposed work we have used the cross validation method for training and testing the dataset. Hence each and every data considered for training as well as testing. Comparison of the experimental results with those calculated via SVM for all gas species in engine exhaust are shown in Figures 1 to 15. First some data is used to train the network and then another set of data is used to test the network. Given below are those figures which compare the model result and experimental results of 3 woods namely babul wood, neem wood and mango wood for the respective temperature, equivalence ratio and the power generated value. From these figures we can analyze the performance of SVM.

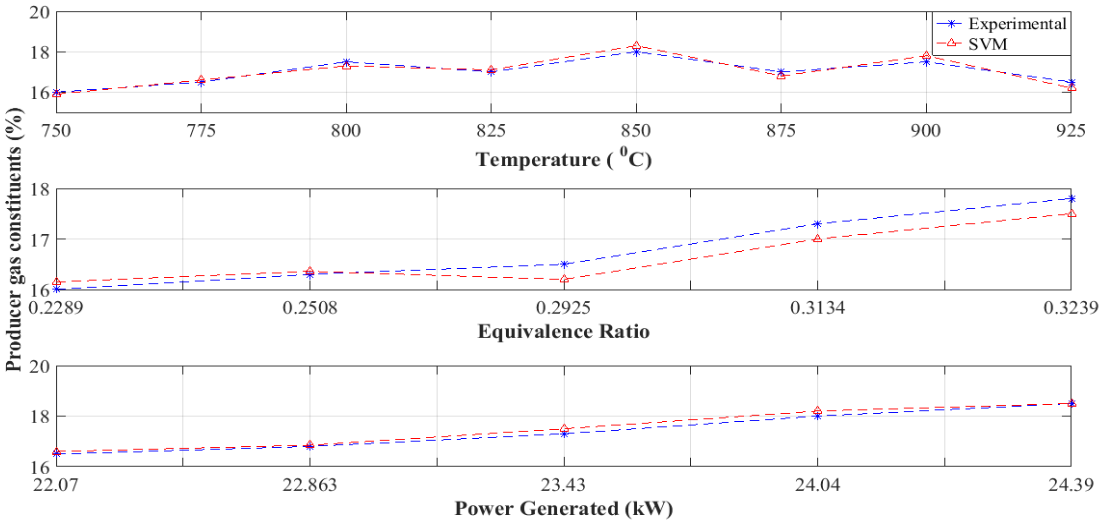

Figure 2: Prediction Performance Comparison

Recently it is seen that the Green House Gas (GH-G) emission reduces the carbon-trading through Clean Development Mechanism (CDM), which have increased prominence for the climate cha-nge. Biomass gasification technology helps for conservation of environment from global warm-ing and pollution and also encourage energy plan-tation thus resulting in a green environment. It is concluded that our proposed method is helpful to minimize the error. Therefore, proposed method and the neural network training by back propaga-tion algorithm method is very useful in predicting the percentage of gas content and helpful for the biomass gasification process and so for human needs. Model will be more precise when compa-red to the other conceptual model.

5. Conclusion

In this paper, a new algorithm is proposed to overcome the defaults occurs in the existing method. The proposed algorithm is the artificial neural network method using back propagation algorithm. Results presented in this paper shown that artificial neural network technique is more effective in predicting the gas content of biomass gasification process. It is clearly seen from the figures that the practical results and our proposed results are nearly similar to each other. Therefore, in conclusion we can clearly say that our propo-sed method is very useful in predicting the gas content in biomass gasification process. Also, the proposed method helps in increasing the effici-ency of the gas content in biomass gasification process. In future, our suggested method will be very helpful for the biomass gasification process. Therefore, biomass gasification process can be prepared very easily by artificial neural network method.

REFERENCE

Atri, M.R. and S.N. Ashrafizadeh, The importance of foams and antifoaming in bioprocesses. Pak. J. Biotechnol. 7(1-2):19-39 (2010).

Bosmans, A, I. Vanderreydt, D. Geysen and L. Helsen, The crucial role of Waste-to-Energy technologies in enhanced landfill mining: a technology review. J. Clean. Prod. 15(55):10-23 (2013).

Cao, Y., Y. Wang, J.T. Riley and W.P. Pan, A novel biomass air gasification process for producing tar-free higher heating value fuel gas. Fuel Pro. Tech. 87(4): 343-53 (2006).

Chong, K.H., P.L. Law, R.A. Henry, B. Rubiyah and F.S. Shanti, Performance Evaluation of a Horizontal Air Staged Inclined Biomass-to-Heat Energy Converter for Drying Paper Egg Trays. Int. J. Rene. Ener. Res. (IJRER) 4(1): 159-67(2014).

Colpan, C.O., F. Hamdullahpur, I. Dincer and Y. Yoo, Effect of gasification agent on the performance of solid oxide fuel cell and biomass gasification systems. Int J. Hyd. Ener. 35(10): 5001-9 (2010).

Dahot M.U., E. Rind and M. Rafiq, Physical and Biochemical Analysis of Sodium Azide treated Sorghum Bicolor (L.) Monech. Pak. J. Biotechnol. 8(2): 67-72 (2011).

Demirbaş, A., Sustainable cofiring of biomass with coal. J. Ener. Conv. and manag. 44(9): 1465-1479 (2003).

Domac, J., K. Richards and S. Risovic, Socio-economic drivers in implementing bioenergy projects. Biomass and Bioenergy 28(2): 97-106 (2005).

Faaij, A., Modern biomass conversion technologies. Mitigation and adaptation strategies for global change 11(2): 335-367 (2006).

Florin, N.H. and A.T. Harris, Hydrogen production from biomass coupled with carbon dioxide capture: the implications of thermodynamic equilibrium. Int. J. Hydr. Ener. 32 (17): 4119-4134 (2007).

Hofbauer, H. and R. Rauch, Stoichiometric water consumption of steam gasification by the FICFB-gasification process. Progr. Thermo. Bio. Conver. (2008).

Inayat, A., M.M. Ahmad, S. Yusup and M.I. Mutalib, Biomass steam gasification with in-situ CO2 capture for enriched hydrogen gas production: a reaction kinetics modelling approach. Energies 3(8): 1472-84 (2010).

Pavlas M., P. Stehlík, J. Oral, J. Klemeš, J.K. Kim and B. Firth, Heat integrated heat pumping for biomass gasification processing. Appl. Therm. Engg. 30(1): 30-5 (2010).

Yunus, M.K., M. M. Ahmad, A. Inayat and S. Yusup, Simulation of enhanced biomass gasification for hydrogen production using iCON. InProc, Worl. Acad. Sci. Engg and Tech. 62: 753-760 (2010).