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A survey of Artificial Neural Network-based Prediction Models for Thermal Properties of Biomass

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Abstract

The global community has supported the need for sustainable and renewable energy due to environmental concerns from the greenhouse gas emission. Biomass stands as one of the most abundant and predictable sources of renewable energy. Therefore, to explore the maximum potential of biomass, a detailed understanding of its embedded potential is needed. However, most experimental procedures require equipment that is highly sophisticated and expensive. The advancement of knowledge in artificial intelligence and blockchain technology is unlocking new potential prediction accuracy for biomass thermal properties. Artificial Neural Network (ANN) is proving to be a vital tool that can enhance the research development in biomass energy prediction. This review highlights the stages in ANN modeling and the application of ANN in Biomass thermal value prediction. It identifies the research gaps in the current status of research on ANN as related to biomass and the direction for further study.

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Keywords: ANN; biomass; heating value; elemental composition; transfer functions; prediction models.

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1. Introduction

As it stands, one cannot imagine a life without energy consumption in one form or another. The manufacturing industry is the most energy intensive sector as most of the related activities are heavily dependent on the energy availability [2, 3]. Therefore, exploring renewable energy option will directly impact on the performance of manufacturing industries since most of the industrial waste can be converted to energy [4]. Most countries across the globe have to combat the concerns around climate change, which is a major consequence of fossil fuel consumption amidst the diminishing oil supplies. The report from BP energy [5] shows that global oil consumption is 86.6 million barrels per day as at 2008, and it stands at 96.6 million (BPD) in 2016. This increasing trend can be observed in global oil consumption as shown by Fig. 1.

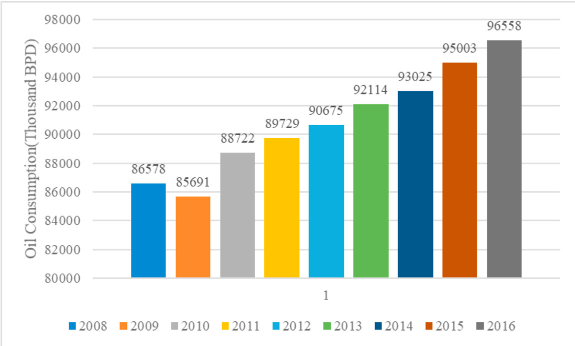

Figure 1: Global oil Consumption [1]

This report is consistent with the projection of World Energy Council [6] which forecasted that global consumption of oil would increase to 97.6 million (BPD) in 2020 and 112.2 million (BPD) by 2035 [6]. It is pertinent to note that the disparity in energy demand and shortage in supply would eventually lead to worldwide energy crises [7]. In 2016, about 10% of total U.S. energy consumption was from renewable energy sources, that is about 10.2 quadrillion British thermal units (Btu). In the same vein, around 55 % of U.S. renewable energy use is by the electric power sector for producing electricity, and around 15% of US electricity generation was from renewable energy sources [6].

There are five renewable energy resources, which have been identified and explored to a different extent [6]. These are Biomass in the form of Municipal solid waste, wood and wood waste, Landfill gas and biogas, Ethanol and Biodiesel; Hydropower; Geothermal; Wind; and Solar energy. Biomass stands as the most abundant and predictable source of renewable energy. In a year, the production of biomass is around eight times the summation of other types of renewable energy sources [8] and it is the only renewable resource, which can be converted directly to liquid fuel [9]. Biomass exploration has the potential to employ thousands of people along the entire value chain. The energy derived from biomass in different forms (liquid, solid, gaseous) can be used in all sectors of the society for production of electricity, transportation, heating and cooling, and industrial processes. Of the total 18 % renewable energy that was consumed in 2016, bioenergy contributed 14%; this underlines the increasing significance of biomass [3]. In 2012, about 2.6 billion people depended on traditional biomass to meet their energy needs [10].

Nomenclature

BPD	Barrel per day
Btu	British thermal Units

The experimental procedure for ultimate analysis and heating value requires equipment that is highly sophisticated, expensive and requires a stable electricity supply except that proximate analysis can be easily carried out and needs only a furnace. Also, production of bioenergy from biomass involves several interrelated process variables, in view of this a robust model, which can sufficiently and accurately capture the input parameter for output need to be developed. The advancement of knowledge in artificial intelligence and blockchain technology is unlocking new potential prediction accuracy for renewable energy system and biomass cannot be ignored. The efficient and effective prediction of heating value and elemental composition of biomass call for a versatile model which can accurately predict the process output from the input parameters.

In this regard, Artificial Neural Network is proving to be a crucial tool, which can enhance the research development in biomass energy prediction. They are used for virtual experimentations and can potentially enhance bioprocess research and development. ANN has been employed in various processes such as weather forecasting, food science, sensorial test, forensic science, medicine, automobile, electrical and electronic engineering [11]. Also, ANN has been applied in several manufacturing processes such as risk assessment, process monitoring, and control, production management, equipment life assessment, and so on [2, 3, 12-14]. However, the use of ANN in the prediction of thermal properties of biomass and elemental composition is still at its developmental stage.

Therefore, this review highlights the stages of ANN modelling, and classification of ANN. It also discusses the most recent findings and application of ANN in biomass elemental composition and heating value prediction. It identified the research gaps in the existing prediction models and the current status of research on ANN as related to biomass and chatted the direction for further study.

2. Biomass energy and ANN

ANNs are applied in the prediction of various processes [15-19]. ANNs have been applied successfully in various fields of mathematics, engineering, medicine, economics, neurology, and many others. Also, in the field of biomass energy, AI has been applied as outlined by Kalogirou [20]. Among so many other advantages, they can handle noisy [21] and incomplete data that are the characteristic of most renewable energy data. They can correlate the hidden data in a large pile, which may significantly influence the model, and also handle a vast array of data been flexible in adjusting to change in parameters. Once ANN has learnt the pattern, they can perform complex tasks such as a prediction, modeling, identification, optimization, forecasting, and control. Several researchers have addressed the problem of overfitting and underfitting which are associated with random selection of hidden nodes [22, 23], but such has not been implemented in the most biomass models. Most of the models which are developed for biomass prediction are based on trial and error.

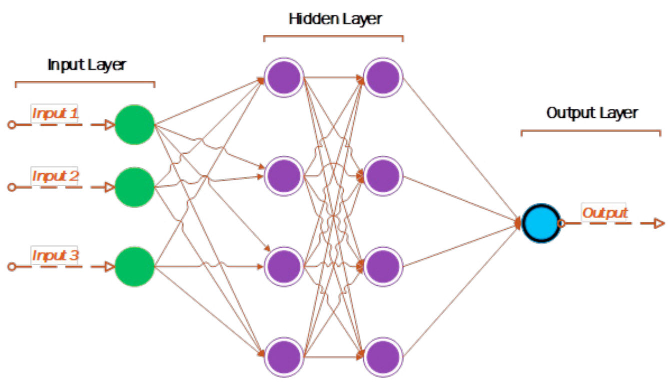

Figure 2: Schematic diagram of Multilayer ANN

ANN can be defined as a complex network, which is made up of interconnected elementary processing units called neurons [24]. ANN can be defined by three factors viz; Structure, Learning algorithm, and activation functions. Fig. 2. shows a schematic of 3-4-4-1 multilayer ANN. Neurons of the hidden layers are organized into a complex stratum which is associated with the input and output parameters [25, 26]. An inbound connection has a dual value associated with it, an input value and a weight. The output of the unit is a function of the added value. ANNs are trained with data sets to learn the pattern. Once trained, new patterns may be presented to them for prediction or classification [25]. The configuration of connections between neurons determines the network architecture and is related to the problem to be solved whether it is a non-linear regression, classification or optimization.

From the summary of the studies on prediction models for the heating value of various biomass-based materials using proximate analysis components [27], most of the modelling studies up till the year 2000 are majorly based on linear regression method. However, the relationship between some proximate analysis components of biomass and their High Heating Value, HHV is nonlinear. Therefore, the prediction of linear regression-based models may be insufficient, especially when they are tested by different samples [28]. In the articles which reviewed both linear and nonlinear regression approaches to HHV analyses, the nonlinear-based models gave better prediction results [29-31]. Also, Ghugare et al. [28] proposed a novel artificial intelligence formalism for developing biomass HHV prediction models.

3. Paradigms of machine learning

Data scientist employ different kinds of learning algorithms to discover the pattern in a big data to gain insight [32]. The primary learning paradigms include (1) supervised learning, (2) unsupervised learning and (3) reinforcement learning. Supervised learning finds the pattern from the input and output that are already provided, but for unsupervised learning, the neural network would find the pattern on its own. Meanwhile, for reinforced learning, the machine is not provided with any input or output except for the methods, which the machine can use to quantify its pattern. Reinforcement learning allows the ANN agents to determine the ideal behaviour within a specific environment automatically. Thus, the ANN learns its behavior based on the feedback from the environment.

3.1. Types of noises

The vectors in the training data may be corrupted due to internal or external factors These error sources in data mining can be categorized into two: (a) attribute noise, and (b) class noise [33]. Attribute noise is due to the errors introduced to the values. These include; erroneous attribute values, missing attribute values, incomplete attributes. Also, the sources of the class noise are; different examples, misclassifications. According to Zhu and Wu [33], elimination of instances in a dataset, which contains class noise, has the likelihood of enhancing classification accuracy. Although attribute noise is less harmful when compared with class noise, it could still bring severe problems to learning algorithms. Cleaning attribute noise from a training vector will likely enhance the classification accuracy in details irrespective of the noise condition of the data. The noises, which are often found in biomass data, can be reduced (if not eliminated) by proper selection of training algorithm.

3.2. Activation functions and their peculiarities

The activation function is applied in the conversion of the activation level of a neuron into an output signal. The activation function is one of the essential parameters in a Neural Network. The following have been previously applied in the modelling of biomass heating value; Linear, sigmoid, sigmoid symmetry, Gaussian symmetry [17, 19, 34-38]. This list is by no means exhaustive as there are many others, which have not been used.

3.3. Classification of ANN

There are various types of ANN with some distinguishing characteristics. Table 1 shows the classification and the examples of their application in biomass thermal property prediction.

Table 1: The classification of Artificial Neural Networks

Network Classification	Characteristics	Example
Support vector Machine	It is a classifier. It can support both regression and classification and can handle multiple continuous variables.	[15, 18]
Kohonen	Multilayered, non-recurrent, unsupervised	
Hopfield	Non-multilayered, recurrent, supervised	
Radial Basis function(RBF)	Applicable to the problems of supervised learning	[39]
Adaptive Neuro	Universal approximation when there is	[27][22]

Fuzzy Inference systems (ANFIS)	no rule restriction. It combines ANN and fuzzy logic.Higher capability to adapt to the learning environment.	
Generalized Regression Networks	Variation of RBF used for function approximation	[40]
Boltzmann machine	Multilayered, recurrent, supervised or unsupervised It makes a stochastic decision about whether to be on or off	Not used
Feedforward back propagation	Supervised, multilayer, non recurrent	[16, 31, 34, 40, 41]

4. Stages in ANN modeling

At different stages of ANN modelling, researchers are often confronted with several questions such as; Data collection and variable selection, noises, incomplete dataset, small dataset, how to divide the dataset for learning, testing, and validation, selection of activation and data transformation functions, weight initialization, choice of training algorithm, learning criteria and the number of hidden layers.

1) Preliminary development of models
2) Actual Model Development
3) Post modelling and Data Analysis.

Table 2: Reported heating value prediction based on ANN

Author	Input variables	Output variables	Type of ANN	ANN Architecture	R^2	Activation functions	Comments
[42]	Fatty acid feedstock	HV	Levenberg-Marquardt backpropagation	5-2-4	0.997	Linear and sigmoid symmetry	Trial and error
[43]	%C, %H, %O, %N, %S on the dry basis	HHV	Levenberg-Marquardt backpropagation	5-4-1	0.9231	Linear and sigmoid symmetry	No clear description of how the number of the hidden layers was determined.
[36]	FC, VM, MC, A	HHV	Levenberg–Marquardt	3-7-1	0.9852	Sigmoid symmetric	No clear definition of how the hidden layer arrived
[44]	FC, VM, MC, A	HHV	Levenberg–Marquardt	1-23-1-1 1-21-1-1 1-25-1-1	0.9591	Hyperbolic ta ngent sigmoid and linear	Trial and error method was used for the determination of hidden layer.
[17][17]	Heating rate, blending ratio and temperature,	TG mass loss	Levenberg–Marquardt-Back propagation	3-5-15-1-1	0.9995	Not stated	The hidden layers, neurons in the hidden layers, and activation functions were selected by trial and error

[38]	FC, VM, Ash	Gross Heating Value	Leven-Marquardt backpropagation	3-3-19-1	0.9959	Not stated	The number of hidden layers, number of neurons in the hidden layers, training epochs, and activation functions were selected by trial and error
[39]	C, H_2O, O, H, N, S, Ash	HHV	Radial basis function combined with Levenberg Marquardt		0.997	Radial basis function	Ability to generalize, Noise tolerance
[27]	FC, VM, Ash	GHV	Leven-Marquardt backpropagation	3-12-1	0.9478	Sigmoid	Neurons in the hidden layer were determined by trial and error method
[19]	FC, VM, Ash	HHV	Hybrid	2-2-1	GP=0.878 SC=0.884 FCM=0.857	Grid partitioning (GP) Subtractive clustering (SC) Fuzzy c-mean (FCM) clustering	R^2 lower when compared with other methods that are discussed
[44]	FC, Ash, MC	HHV	Linear	3-3-1 3-20-1	0.963 and 0.962	Sigmoid and Sigmoid symmetry	Trial and error method was used to select the hidden layer, thought author underline some other methods which can be applied
[44]	FC, Ash, MC	HHV	Hybrid		0.9639	NA	

4.1 The outlook for further research

From the literature review as shown in Table 1 and 2, the division of dataset for learning and testing of ANN models developed for the prediction of thermal properties was based on trial and error, or at most random selection without any underlining principle. It must be noted that the division of the dataset has a significant influence on the accuracy and performance of the ANN model. Therefore, further research should explore the existing dataset division methods for their suitability and impact on the performance of the prediction model for heating value and elemental composition.

The training algorithm is an important design variable, which has to be applied during the training phase. Levenberg-Marquardt has been mostly applied in the prediction of heating value with a few application of other tested algorithms, so other training algorithms should be explored bearing in mind the need to handle noises and outliers that are often associated with some types of biomass data. A comparative study of different training algorithm should be carried out in order to determine their generalisation capability.

The selection of the number of nodes and hidden layer is mostly based on the rule of thumb for the prediction of biomass properties. In order to select the optimum nodes at the hidden layer, the standard method could be formulated or applied. The choice of hidden layers and hidden nodes is paramount because it influences the complexity of the model, its predictive capability and training time. On the general note, most of the model reported did not give detailed information that could assist in the replication of the model. The research effort should be geared toward a detailed understanding of the hidden layer since this plays a prominent role in the performance of the model.

In overall, there is a need for further research which could eventually lead to the formulation of universal correlations which can accurately predict the properties of biomass from different sources. The aspects of model development such as data division, network architecture and the model development for small data size would progress the thermal property prediction for biomass.

5. Conclusion

The ANN has simplified prediction of the thermal property of biomass with many promises in term of higher prediction accuracy when compared to the previous methods. This review has explored recent prediction model for the prediction of thermal properties of biomass. The models were based on the data from various sources. The data, which were used for the development of these models, were mostly based on the ultimate, proximate and thermogravimetric analysis. Comprehensive implementation of ANN will eventually lead to the design of robust proprietary software that can be used for real time prediction of the thermal property of biomass.

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