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Optimizing Heating Potential in Solid Biomass Fuels: A Machine Learning Perspective

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Abstract

Utilizing solid biomass fuels efficiently becoming more and more critical as the need for environmentally friendly energy sources rises. The current approaches to determining the heating effectiveness of biomass fuels frequently include costly, laborious, and lengthy laboratory tests. The present investigation tackles the urgent issue of maximizing solid biomass fuels' heating performance by carrying in Machine Learning (ML) as a viewpoint to improve and expedite the evaluation procedure. In this work, we propose a novel Harmony Search Optimized Extreme Gradient Boosting (HSO-XGB) method. To ensure better prediction accuracy, the XGB model's characteristics are adjusted using HSO, which was motivated by the technique of music creativity. The suggested approach is assessed against more techniques after trained with a Python application and confirmed with a biomass dataset. The results of the proposed method were better than the standard methods, particularly in terms of RMSE (1.47), MSE (1.97) and MAE (1.08).Through the provision of an inventive methodology for maximizing the estimation of heating capability in solid biomass fuels, this work advances the use of energy from biomass.

Keywords: Biomass fuel, heat, sustainable energy source, machine learning, HSO-XGB

Full length article **Corresponding Author*, e-mail: dhwani.bartwal24197@paruluniversity.ac.in

1. Introduction

Biomass is gaining more recognition as a feasible and environmentally friendly option in the search for renewable energy resources. Among the various types of biomass, solid fuels made from biomass have emerged, as an attractive option a renewable and carbon-neutral solution for meeting our growing energy needs [1]. The term solid biomass fuels encompasses a broad range of organic resources, including wood, crop wastes, and specific energy crops. These materials store energy from sunlight absorbed during their development. Recognizing and harnessing the natural heating capacity of these solid biomass fuels is crucial for achieving a less polluting and more economical energy future [2]. Recognizing the fundamental link between biomass and its carbon cycles is essential. Unlike fossil fuels, which release carbon that has been stored in the environment for an extended period, biomass fuels operate in a closed carbon cycle. Plants employ photosynthesis to convert atmospheric carbon dioxide into nutrients during their growth [3]. When these crops are utilized for energy, carbon dioxide is emitted and returned to the environment, completing the cycle. The balance between solid biomass fuels and carbon emissions renders, in a carbon-neutral energy source, providing a practical approach to mitigating the impacts of global warming [4]. Wood, the most easily identifiable type of solid biomass, has been used for heating and cooking since ancient times. Burning this substance releases stored energy in the form of heat, making a crucial element in human history. However, the contemporary exploration of solid biomass fuels goes beyond the traditional use of burning wood. Agricultural leftovers like crop stalks and husks have become integral components of the biomass ecosystem [5]. Additionally, cultivated energy crops such as switch grass and miscanthus have been intentionally grown for energy generation, highlighting the versatility and broad range of solid biomass as a fuel option [6]. The thermal capability of solid fuels made from biomass is closely linked to their composition, which exhibits significant variation among various raw materials. Wood primarily consists of glucomannan, beta-glucan, and lignocelluloses. The combustion of these elements releases Heat energy, with the number of calories removed varying depending on factors such as moisture content and wood type [7]. Understanding these subtle differences is crucial for optimizing the combustion process and maximizing energy output. Technological advancements, such as gasification and pyrolysis, have increased the efficiency of solid biomass consumption, resulting in cleaner and more manageable energy extraction [8]. As society faces the pressing need to transition away from fossil fuels, biomass-based solid fuels offer a compelling solution that can bridge the gap between current energy demands and a sustainable future. Utilizing biomass for heating provides alternative and addresses concerns related to waste management and reforestation. This is achieved through the utilization of residual biomass derived from farming operations [9]. The composition of solid fuels made from biomass can display significant variations, even fuels categorized under the same umbrella. The chemical composition, moisture content, and calorific value of biomass are influenced by factors such as species, age and processing methods. The diverse array of characteristics in solid biomass poses a challenge in establishing standardized values for heating potential [10]. The moisture content of solid fuels made from biomass influences their heating capacity. Higher levels of moisture reduce the calorific content but also impact the efficiency of combustion. The moisture level of biomass is influenced by factors such as climate, storage conditions and the specific type of biomass. Consequently, providing applicable data without accounting for these variables is challenging. Furthermore, the presence of contaminants, including ashes and pollutants, can impact the combustion process and reduce the heating capacity of solid biomass fuels. The type and quantity of ash produced during combustion depend on the specific origin of the biomass. Consequently, this ash may lead to complications such as deposition and fouling in combustion systems [11]. The aim of this study is to increase energy output and reduce environmental impact by implementing Harmony Search optimized Extreme gradient boosting (HSO-XGB)to enhance the efficiency and effectiveness of heat generation from solid biomass sources.

The Study [12] explored the possibilities of wood as a local source of energy. To assess the potential of energy production from these substances from biomass were essential to determine their “higher heating values (HHV)”. “Artificial Neural Network (ANN)” strategy was utilized to forecast the HHV of wood bioenergy.3-ANN algorithms were created utilizing the record input. The ANN models exhibited superior accuracy in predicting the HHV of biomass contrasted to the correlation-based methods. The paper [13] examined the method for identifying the ideal quantity of input factors by utilizing “Linear Regression (LR) and the multivariate adaptive regression splines (MARS)”to construct an ANN framework for forecasting the HHV of specific bio resource samples. The study clearly demonstrated that employing ANN was a convincing approach for predicting the HHV of biomass. The provided technique proved to help by calculating the HHV of a wide range of solid materials. The research [14] examined the connections and suggested the development of algorithms for efficient prediction of biomass HHV based on other analytical data. Novel techniques, such as the LR and “Stochastic Gradient Descent (SGD)”, were employed in a ML framework to predict the HHV of bio resource. The experimental findings agreed with the displayed outcomes of the model. Values that were closer to parity suggested a higher level of precision. The article [15] presented a novel hybrid strategy that utilized Support Vector Machines (SVMs) along with the simulated annealing (SA) optimizing method. The algorithm was designed to forecast the HHV of biomass based on operational input variables that were established directly throughout the decomposition process. Furthermore, the experimental information was analyzed using a MARS method and a Random Forest (RF) technique for comparison. The findings demonstrated a significant enhancement in predicting capability when employing the SVM–SA approach, as opposed to use only an SVM regressor. The paper [16] developed a simulation model capable of identifying HHV in a bio resource decomposition procedure at an early stage. The paper proposed a new hybrid method that combined an SVM with “particle swarm optimization (PSO)” strategy. The approach was utilized to estimate the HHV of bio resource based on operational input variables that were established directly during the decomposition procedure. The outcomes demonstrated that the combined PSO-SVM regression technique significantly enhanced the capacity for distillation that could be achieved with the SVM-based regressor. The study [17] investigated the development of regression models for forecasting a three-phase distribution of products and bio-oil HHV using gradient boost, RF, SVM, and multilayer perceptron methods. The characteristics of the input were evaluated and contrasted based on the complete properties of the raw material and the circumstances of pyrolysis. The RF approach was highly appropriate for predicting the yields of three-phase products and the HHV of bio-oil. The research [18] presented the development of a predictive model for the HHV and nitrogen content (NC) values in roasted biomass. The model combined the SVM framework with the RBF Core function and the Sparrow Search Algorithm (SSA) improvement. The model took into consideration the feedstock attributes and decomposition circumstances. Finally, SSA optimization proved to be a highly effective technique for enhancing the predictive capability of the SVM model. The study [19] developed a soft computing model to forecast the HHV of biomass utilizing the technique of proximate analysis. The soft computing system employed in the current research was the “Adaptive Neuro-Fuzzy Inference System (ANFIS)". The ANFIS methodology had been hired to forecast the HHV of biomass using carbon fixation, volatility issue and ash as input variables. Higher forecast accuracy indicated a significant impact of the input data on the HHV. The paper [20] examined a substantial dataset of 1140 samples of data using a combination method of grading and value predictions to estimate the HHV. Three ensemble ML techniques, specifically Bagging, "Multiclass classifier (MCC), and Classification-via-regression (CVR)" were utilized when combined with RF, "multilayer perceptron (MLP)"frameworks to forecast HHV. The combined method of RF and MLP models demonstrated the best correlation factor and smallest Root Mean Squared Error (RMSE) values, highlighting the possibilities as a predictive biomass growth model HHV. The aim of this study is to increase energy output and reduce environmental impact by implementing Harmony Search optimized Extreme gradient boosting (HSO-XGB) to enhance the efficiency and effectiveness of heat generation from solid biomass sources. This study sections were as follows: Part 2, Methodology; Part 3, Result; and Part 4, Conclusion

2. Materials and Methods

In this paper, we gathered a biomass dataset to identify patterns and correlations in various biological mass measurements. The HSO-XGB approach is introduced as a novel and potentially more efficient method to enhance the efficiency and effectiveness of heat generation from solid biomass sources.

2.1. Dataset

A total of 522 data points were utilized in this research to forecast the HHV of biomass. The range of the volatile matter level spans between 1.28% to 89.3%, while the constant carbon level ranges from 0.45% to 87.6%. The amount of ash content, in its dehydration state, ranges from 0% to 74.51%. Additionally, the range of HHV ranges from 5.41 to 33.04 mega joules per kilogram. The 522 samples were split into a training set consisting of 359 samples and a testing set consisting of 163 samples. [21].

2.2. Enhanced Solid Biomass Fuel Heating Potential Optimization

In this section, we integrate XGB with "Harmony Search optimization (HSO)" to improve the Heating Capacity of Solid Biomass Fuels (HPSBF). HSO enhances a range of solutions, encouraging the identification of the best combinations for biomass features with inspiration from harmonic music. In the meantime, the robust ML method XGB improves prediction accuracy by boosting weak learners.

2.2.1. Harmony Search optimization

HSO is utilized to enhance the identification of HPSBF. The HSO system modifies variables such as moisture level, weight, and structure to identify the effective combination that optimizes the efficiency of heating. The computational method is highly beneficial for optimizing parameters related to biomass fuels, making a significant contribution to the generation of sustainable and adequate energy. The process of musical improvising inspires the HSO method. In this process, a musician creates a song that adheres to a specific harmony. Furthermore, it is utilized to address a multitude of optimization problems in areas such as finance, engineering, and other related fields. The HS algorithm mimics a collective of musicians that create unique tunes through improvisation and adaptation of their playing style, attracting from their past encounters and the melodic harmony. The algorithm attempts to find the optimal solution by fine-tuning the balance between the issue's variables. The HS technique is highly efficient in resolving intricate optimization problems, particularly in scenarios where the problem domain is continuous and characterized by a large number of dimensions. The HSO algorithm has been applied in diverse fields, including optimization of designs, image processing and processing of signals. Various enhancements and expansions of the HS algorithm have been suggested to enhance its efficiency and versatility. The initial set of members of the HS method is mutually independent in each dimension and is confined in the permissible range. The algorithm generates a solitary new member during each cycle. Next, the generation of every dimension of the unique point is carried out by applying the memory consideration rule and a pitch adjustment factor by doing randomized reinitializations in the allowed range of dimensions, utilizing the answers in the Harmony Memory (HM). The individual in the group with the highest value of the cost function is contrasted with the most recent generation of solutions. If the latest solution has less expense, the individual in the population is substituted. This procedure continues until one of the terminating criteria is met. Specify the cost function $(f(x))$ it must be minimized to accomplish the aim of the algorithm. To start, adjust the settings as indicated below.

$$HM = \begin{bmatrix} W_1^1 & W_2^1 & \dots & W_i^1 \\ W_1^2 & W_2^2 & \dots & W_i^2 \\ W_1^3 & W_2^3 & \dots & W_i^3 \\ \vdots & \vdots & \dots & \vdots \\ W_1^{HMS} & W_2^{HMS} & \dots & W_i^{HMS} \end{bmatrix} \quad (1)$$

In the given formula, the population's number refers to the HS memory, whereas the total amount of dimensions of the variable is denoted by(i). Each dimension of every population member can be randomly assigned a value with the specified range. The default settings for the HS consideration rate (HMCR) and Pitch Adjustment Rate (PAR) are commonly assigned as 0.995 and 0.1, respectively. Produce an initial point $(W^{new} = W_1^{new}, W_2^{new}, w_3^{new}, \dots, W_i^{new})$ by executing the subsequent steps: Every n dimension randomly selects a corresponding member dimension using the HMCR method. The amount of the new point is selected randomly from the permissible range.

$$W_j^{new} = \begin{cases} W^{new}(j) \in \{W_i^1, w_i^2, W_i^3, .., W_i^{HMS}\} if rand(0,1) \\ \le HMCR \\ W^{new}(j) is random if it isn't \end{cases} \quad (2)$$

$$W_j^{new} = W^{new}(j) + RAND(-1,1) \times bw, if rand(0,1) \le PAR \quad (3)$$

$$where\ bw = 0.04 \quad (4)$$

If the computed harmonic vectors W^{new}exhibit a low cost, substitute the lowest performing member of the population with it. Validate the termination conditions, and if they are met and proceed with step three, determine the optimal point.

2.2.2. Extreme gradient boosting Algorithm

XGB algorithm improves accuracy in estimating biomass energy production. XGB effectively manages intricate interactions in biomass content by combining gradient boosting and decision trees, allowing the identification of critical parameters that impact heat capability. XGBoost is a method that expands upon the approach of gradient-boosted decision trees. The fundamental concept of boosting is to combine a sequence of weak prediction models into a solitary, robust learner. Ensemble approaches are incorporated one by one with the purpose of correcting the mistakes committed by the current learners. Gradient boosting improves the adaptability of the boosting technique by utilizing the gradient descent algorithm to eliminate errors in sequential models. A primary gradient boosting method is distinguished by its great precision in estimates, but inversely, this methodology is susceptible to overfitting. The XGBoost algorithm addresses this restriction by incorporating the regularization element into the aim of the function.

$$Obj^{(q)} = \sum_{j=1}^{m} K\left(z_j, \hat{z}_j^{(q)}\right) + \sum_{j=1}^{q} \Omega(\mathrm{h_q}) \tag{5}$$

z_j- True value
$\hat{z}_j^{(q)}$-The forecast in the q-th iteration,
$\mathrm{h_q}$-Indicating the configuration of a decision tree
$K\left(z_j, \hat{z}_j^{(q)}\right)$ −Error metric.
m −Quantity of training instances
$\Omega(\mathrm{h_q})$- Regularization parameter, as expressed in a formula:

$$\Omega(h_q) = \delta S + \frac{1}{2}\lambda \sum_{i=1}^{S} \omega_i^2 \tag{6}$$

Where:
S-Leaf count.
ω - Magnitude of leaf weights.
λ and δ represent coefficients, with default values initialized as $\lambda = 1, S = 0$.

2.3. Harmony Search Optimized Extreme Gradient Boosting Algorithm

The integration of the Hybrid Harmony Search (HS) Algorithm and Extreme Gradient Boosting (XGB) Algorithm presents a powerful method for optimizing the HPSBF. HSO navigates the range of possible solutions by utilizing its ability to search globally, while XGB improves predicted accuracy by learning through iterations. This collaborative combination provides a robust and precise optimization approach, taking into consideration many aspects influencing HPSBF. The hybrid model combines the advantages of both algorithms to create a complete solution for improving the combustibility of biomass. This ultimately leads to more efficient and sustainable use of energy in a constantly changing environment. The pseudo-code for HSO-XGB is presented in Algorithm 1.

Algorithm 1: HSO-XGB

Initialize parameters for Harmony Search optimization (HSO)
Initialize parameters for Extreme Gradient Boosting (XGB)
Initialize harmony memory with random solutions
For each iteration until convergence:
Perform Harmony Search optimization (HSO) to generate new candidate solutions
Evaluate the fitness of each candidate solution using a fitness function
Select the best solutions from harmony memory and candidate solutions
Update harmony memory with the selected solutions
Train an Extreme Gradient Boosting (XGB) model using the solutions chosen as training data
End for
Use the final Extreme Gradient Boosting (XGB) model for prediction

3. Results and Discussion

The recommended task is executed in python 3.7.0.It is required to be installed alongside to carry out the procedure. In this section, the performance evaluation of the proposed approach involves assessing in terms of "Root Mean Squared Error(RMSE),Mean Squared Error (MSE), and Mean Absolute Error (MAE)and conducting a comparative analysis with other existing methods, including decision tree (DT)[21] and Artificial Neural Network (ANN)[21]". RMSE as a crucial metric for evaluating the accuracy of predictive models in the optimization of HPSBF. When compared to existing methods such as DT and ANN, which have RMSE values of 2.09 and 1.56, respectively, the suggested HSO-XGB achieves an MSE value of 1.47. A lower RMSE indicates the high level accuracy of the proposed approach for forecasting the biomass heating value. (Fig1) and (table 1) depict the Comparative evaluation of RMSE. MSE as a crucial metric for evaluating the accuracy of predictive models applied to optimize the HPSBF. (Fig 2) and (table1) illustrate the comparison of MSE of Suggested Methods and the other existing methodologies. When compared to existing methods such as DT and ANN, which have MSE values of 4.36 and 2.43, respectively, the suggested HSO-XGB achieves an MSE value of 1.97. A lower MSE indicates the superior result of the proposed approach for predicting the biomass heating value. The MAE metric is employed to validate the accuracy of predictive models utilized in optimizing the HPSBF. The correctness of HHV predictions is measured as a percentage of complete occurrences. (Fig 3) and (table 1) depict the comparative evaluation of MAE in suggested and traditional methods. When compared to existing methods such as DT and ANN, which have MAE values of 1.48 and 1.21, respectively, the suggested HSO-XGB achieves an MAE value of 1.08. A lower MAE indicates the improved exactness of the proposed approach for predicting the HHV of biomass heating value.

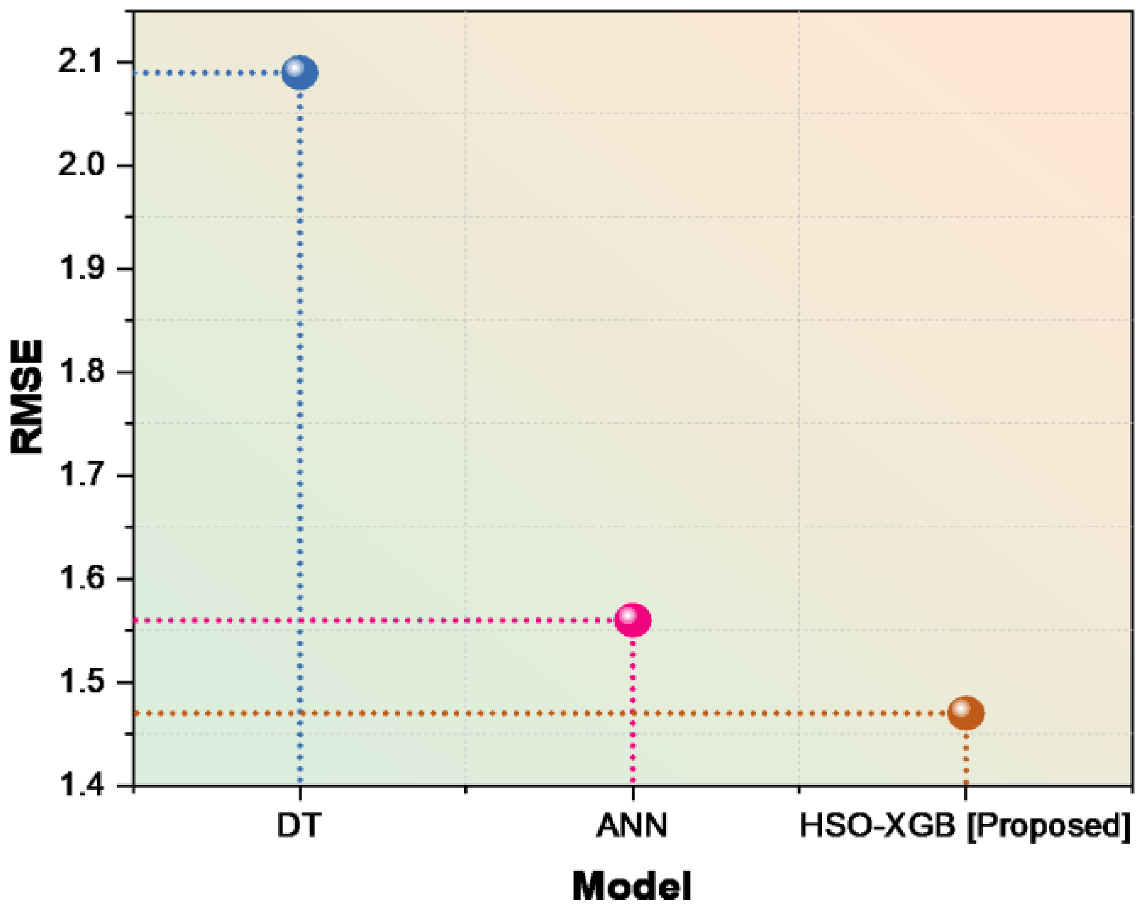

Figure 1. RMSE

Table 1. Comparison of RMSE, MSE, MAE

Model	DT	ANN	HSO-XGB [Proposed]
RMSE	2.09	1.56	1.47
MSE	4.36	2.43	1.97
MAE	1.48	1.21	1.08

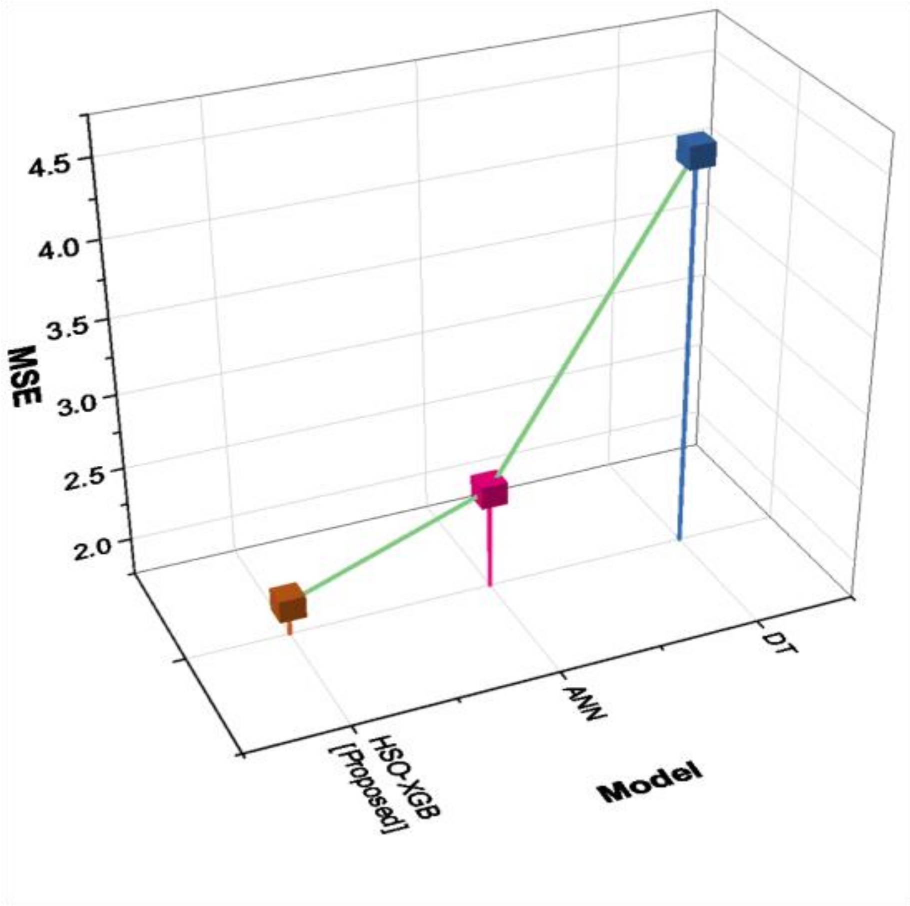

Figure 2. MSE

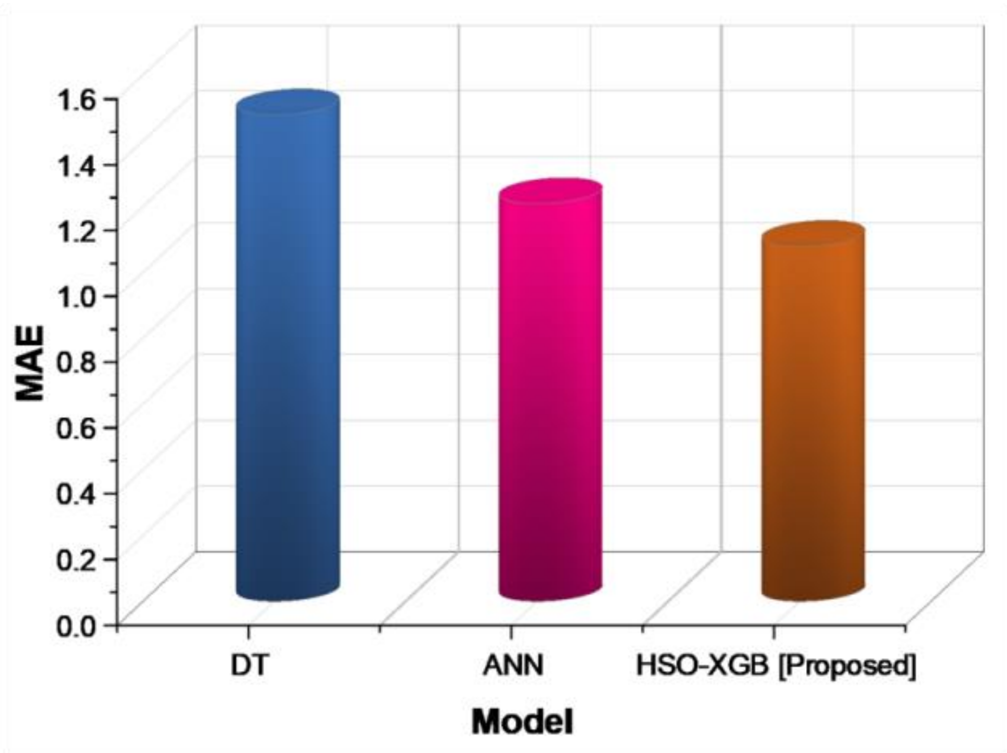

Figure 3. MAE

4. Conclusions

In this study, we introduced a novel approach Harmony Search optimized Extreme gradient boosting (HSO-XGB), accurately estimated heat generation from solid biomass sources. Experimental results showed RMSE(1.47),MSE(1.97),MAE(1.08). The results of the proposed method were compared to the other previously utilized algorithms, and the outcomes of the evaluations showed that the suggested strategy was more effective for predicting heat generation from solid biomass sources.ML models heavily rely on the availability and quality of data. Limited or poor-quality data on solid biomass fuels may hinder the model's accuracy. In future research Integration with other renewable energy sources and smart grid technologies to create a more robust and reliable energy system.

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