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Advancements in Machine Learning Modeling of Co-firing Systems: A Mini Review

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ABSTRACTS

Accurate modeling of biomass co-firing systems is essential to enhance renewable energy usage by optimizing efficiency and minimizing harmful emissions. Traditional modeling approaches, such as mathematical models and simulations, have limitations in capturing the complex dynamics and non-linear relationships inherent in co-firing systems. In contrast to traditional modeling, machine learning provides a promising approach by utilizing historical data patterns to create precise prediction models. This paper reviews recent machine learning techniques applied in modeling biomass co-firing systems, focusing specifically on models for predicting thermal efficiency and emissions. The examined studies exhibit machine learning's potential to accurately forecast and enhance thermal efficiency factors like feed water, fuel, and air properties. Deep learning methods, including Deep Neural Networks (DNN) and Artificial Neural Networks (ANN), have shown superior modeling capabilities in optimizing thermal efficiency. Regression tree, random forest, and fuzzy logic algorithms have also proved effective in optimizing thermal energy production and power estimation. Moreover, machine learning algorithms such as Support Vector Machine (SVM), Gaussian process (GP), polynomial regression, and fuzzy logic have demonstrated accurate predictions of emissions, including CO2, NOx, and other pollutants. Challenges related to data availability, model interpretability, and scalability need to be addressed for further advancements in machine learning modeling.

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INTRODUCTION

The combined combustion of biomass and fossil fuels, known as co-firing, has become a favorable technique to minimize greenhouse emissions and utilize renewable bioenergy for power generation. Co-firing provides a relatively simple way to cut down CO_2, SO_x, and NO_x emissions by substituting biomass for portions of fossil fuel usage. Additionally, biomass co-firing has the potential to maintain total boiler efficiency even when adjusting combustion output for the new fuel mixture. However, the successful implementation of biomass co-firing relies on various factors, including biomass supply, delivery systems, biomass characterization, and addressing technical challenges [1], [2].

Creating precise models of biomass co-firing systems is vital for the assessment, enhancement, and

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effective management of this technology. Traditional modeling approaches, such as mathematical models and simulations, provide valuable insights but have limitations in capturing the complex dynamics and non-linear relationships inherent in co-firing systems.

Methods in machine learning (ML) have arisen as a potential solution for constructing and improving models of biomass co-firing systems. ML algorithms can learn from historical data and discover complex patterns, enabling accurate prediction of important parameters such as combustion efficiency and emission [3].

This paper aims to provide a comprehensive review of the advancements in machine learning modeling of biomass co-firing systems, with a specific focus on thermal efficiency and emission modeling. Although the literature covers diverse research on biomass combustion, our analysis concentrates distinctly on the machine learning techniques used for modeling and enhancing thermal efficiency and emissions forecasts. By analyzing the relevant methods and assessing their potential, strengths, limitations, and potential challenges, this review aims to identify the applicability of ML modeling in biomass combustion systems. Additionally, we explore the implications of these advancements and provide insights into future research directions.

The remainder of this paper is organized as follows: Section 2 focuses on modeling thermal efficiency in co-firing systems using machine learning techniques. Section 3 explores the application of machine learning in emission modeling for co-firing. Section 4 presents the conclusions drawn from the review and discusses future research opportunities.

This review examines several machine learning approaches relevant to modeling thermal efficiency and other facets of biomass co-firing, offering important understanding and recommendations for researchers, policy creators, and industry experts striving to improve renewable energy generation.

THERMAL EFFICIENCY MODELING USING MACHINE LEARNING

This section examines the use of machine learning approaches to model thermal efficiency in biomass co-firing systems. Thermal efficiency plays a crucial role in optimizing the performance of co-firing processes and reducing energy wastage. By utilizing machine learning methods, researchers have explored various approaches to analyze and predict thermal efficiency in co-firing systems.

A key study by Wang et al. [4] examined enhancing thermal efficiency through deep learning techniques, including Deep Neural Networks (DNN), Artificial Neural Networks (ANN), and Partial Least Squares (PLS). They investigated the relationship between thermal efficiency and eight input parameters associated with feed water, fuel, and air. Through their analysis, they found that DNN outperformed both ANN and PLS, demonstrating superior modeling capabilities. Notably, the DNN model showcased the ability to leverage unlabeled data, leading to an average improvement in thermal efficiency by 0.61%.

C. Wang et al. [5] aimed to reduce Unburned Carbon Content in Fly Ash (UCC-FA), which is the most important indicator of boiler combustion efficiency in a boiler system by employing the Gaussian process (GP) algorithm. They optimized the GP model's hyperparameters using the Genetic Algorithm (GA) and achieved a significant decrease in UCC-FA from 2.7% to 1.7%. This study demonstrates the effectiveness of machine learning in enhancing thermal efficiency and optimizing boiler combustion operations.

Akbas and Özdemir [6] aimed to model thermal energy production (TEP) and utilized regression tree, random forest, non-linear regression, Support Vector Regression (SVR), and Artificial Neural Networks (ANN). By employing an integrated ANN-Particle Swarm Optimization (PSO) model, they achieved a significant 4.24% increase in thermal energy production, emphasizing the effectiveness of the applied machine learning models.

Ashraf et al. [7] proposed a comprehensive step-wise methodology for implementing Industry 4.0 in a coal power plant to enhance thermal efficiency. They considered ten characteristic parameters and employed Artificial Neural Networks (ANN) and Least Square Support Vector Machine (LSSVM) algorithms. Their research demonstrated the potential of integrating Industry 4.0 practices and machine learning algorithms to improve thermal efficiency in coal power plants.

Karaçor et al. [8] focused on power estimation and utilized fuzzy logic (FL) and artificial neural network (ANN) algorithms. Their results showed accurate power estimation, with FL exhibiting error values between 0.59% and 3.54%, and ANN demonstrating error values ranging from 0.001% to 0.84%.

Han et al. [9] investigated the modeling of combustion operation conditions using machine learning techniques. The accurate modeling and prediction of these operation conditions contribute to optimizing thermal efficiency by enabling better control of combustion processes under different scenarios. They employed a combination of Convolutional Sparse Autoencoder (CSAE) and Least Support Vector Machine (LSSVM) algorithms. Their findings demonstrated a high prediction accuracy of 98.06%, and a fast prediction time of 3.06 ms per image, highlighting the effectiveness of machine learning in capturing thermal efficiency-related factors through flame imaging.

Effendy et al. [10] aimed to predict the oxygen content in a thermal system and utilized Artificial Neural Networks (ANN) and random forest-based soft sensor models. Both models provided relatively accurate predictions, showcasing the effectiveness of machine learning in optimizing thermal efficiency.

Hong and Kim [11] focused on predicting exhaust temperature in a thermal system. Exhaust temperature is a key indicator of combustion efficiency in gas turbines. Higher exhaust temperatures signify better utilization of fuel energy, resulting in improved thermal efficiency. They employed a CNN-RNN-based time series prediction model combining Convolutional Neural

Networks (CNN) and Recurrent Neural Networks (RNN). Their research demonstrated accurate predictions of exhaust temperature, with a comparison between Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) algorithms revealing the trade-off between prediction accuracy and calculation time.

These studies collectively contribute to the advancement of machine learning models for thermal efficiency modeling, highlighting their potential in optimizing various aspects of thermal systems. **Table 1** summarizes the application of machine learning approaches for modeling thermal efficiency.

Table 1. Summary of the application of machine learning approaches for modeling thermal efficiency.

Author	Year	Characteristic parameters	Algorithm	Result
J. Wang et al. [4]	2017	8 input parameters • feed water-related: flow rate (F_{fw}), temperature before the economizer (T_{fwa}), temperature after economizer (T_{fwb}), pressure (P_{fw}) • fuel related: coal flow rate (F_{COAL}), BFG flow rate (F_{BFG}), BFG heating value (H_{BFG}) • air related: airflow rate (F_{air})	Deep Learning (DNN, ANN, PLS)	DNN has better modeling than ANN and PLS and can use a large number of unlabeled data. The improvement of thermal efficiency averages 0.61% after optimization
C. Wang et al. [5]	2017	Four-first air speeds (AA, BB, CC, DD), Five-second air speeds (A, B, C, D, E), Over fired air speed (OFA), Oxygen concentration at the outlet of the furnace (O2), The load of the boiler (Load), Total air rate (Tar), Four pulverized coal feeder speeds (C1, C2, C3, C4), Four coal properties (Mt, Aar, Vdaf, Qnet.ar)	Gaussian Process (GP) and genetic algorithm (GA)	Unburned Carbon Content in Fly Ash (UCC-FA), which is the most important indicator of boiler combustion efficiency, decreases from 2.7% to 1.7%
H. Akbas and G. Özdemir [6]	2020	The dataset includes 22 inputs: grate load (GL), primary air fan passage ratio (PFPR), sanding dust and sawdust load (SDSL), secondary air fan passage ratio (SFPR), flue gas inlet temperature to radiation (FGTR), flue gas inlet temperature to mixing chamber (FGTMC), ambient air fan passage ratio (AFPR), thermal fan passage ratio (TFPR), the internal pressure of boiler (IPB), oil flow rate (OFR), oil inlet temperature to convection (OITC), oil exit temperature from radiation (OETR), boiler stack by-pass damper passage ratio (BSPR), total steam flow to refiner (TSFR), pressure of dryer (PD), dryer stack by-pass damper passage ratio (DSPR), main fan damper passage ratio (MFPR), steam control valve passage ratio (SVPR), heated	• Prediction: Regression tree (RT), random forest (RF), non-linear regression (NLR), SVR, and ANN • Optimization: integrated ANN–PSO model	Thermal energy production has increased by 4.24%

Author	Year	Characteristic parameters	Algorithm	Result
		oil flow rate to press (HOFP), heated oil flow rate to melamine press and impregnation (HOFMI), heated oil flow rate to steam generator (HOFSG), and fiber production rate (FPR).		
W. Ashraf et al. [7]	2020	10 variable: Superheated steam flow, Superheater outlet steam pressure, Superheater outlet steam temperature, Reheat steam flow, Reheater steam inlet pressure, Reheater steam outlet pressure, Reheater steam inlet temperature, Reheater steam outlet temperature, Feed-water pressure, and Feed-water temperature	Artificial neural network (ANN) and least square support vector machine (LSSVM)	Possible to enhance the thermal efficiency
M. Karaçor et al.[8]	2021	Year, Fuel, Temperature	Fuzzy logic (FL) and artificial neural network (ANN)	Error-values: FL between 0.59% and 3.54% ANN between 0.001% and 0.84%
Z. Han et al. [9]	2021	Flame imaging	A combination of convolutional sparse autoencoder (CSAE) and least support vector machine (LSSVM)	Prediction accuracy is 98.06% and prediction time is 3.06 ms/image.
N. Effendy et al. [10]	2022	19 Variable: Deaerator level, The feed flow rate of boiler water to the superheater, The temperature of advanced steam in the superheater, Feedwater flow rate, Main gas inlet flow rate to the furnace, Fuel gas pressure behind the control valve, Combustion airflow rate, Air pressure of burner box, Main steam temperature, Furnace exhaust gas pressure, The temperature of boiler Flue gas, Boiler steam pressure, Wind box pressure, Combustion air temperature, Steam drum boiler levels, Primary steam header flow rate, The water inlet temperature of the economizer, The water outlet temperature of the economizer, Oxygen content	Artificial neural network (ANN) and random forest-based soft sensor	RF MAE 0.0486, MSE 0.0052, RSME 0.0718 and Std Error 0.0719 ANN MAE 0.0715, MSE 0.0087, RMSE 0.0935, and Std Error 0.0935
C. Hong and J. Kim [11]	2023	13 sensor features, including gas flow, inlet pressure, and air temperature	CNN-RNN-based time series prediction model composed of six layers combining CNN and RNN	CNN-RNN algorithms accurately predicted the exhaust temperature. The accuracy and time required were compared when using LSTM and GRU among RNN algorithms in the CNN-RNN network model.

Author	Year	Characteristic parameters	Algorithm	Result
				The average calculation time of the GRU algorithm was short but LSTM predicted more accurately

EMISSION MODELING USING MACHINE LEARNING

In recent studies, several research efforts have focused on utilizing machine learning techniques to model and predict emissions in various domains. For instance, Saleh et al. [12] aimed to model CO2 emissions by considering energy consumption parameters such as electrical energy and burning coal. They employed the Support Vector Machine (SVM) algorithm, which yielded a promising outcome with a Root Mean Square Error (RMSE) of 0.004. This study demonstrates the effectiveness of SVM in accurately predicting CO2 emissions, offering valuable insights for monitoring and controlling emissions.

In their study, C. Wang et al. [13] aimed to reduce the NOx emissions of a 330MW boiler. They used the Gaussian process (GP) algorithm to model the relationship between NOx emissions and various boiler operation parameters. By optimizing the GP model's hyperparameters with the Genetic Algorithm (GA), they achieved a significant decrease in NOx emissions from 345 ppm to 238 ppm. The study demonstrated the effectiveness of machine learning, specifically GP modeling, in reducing emissions and optimizing combustion operations.

Elmaz et al. [14], performed another study to forecast emissions including CO, CO2, CH4, H2, and higher heating value (HHV) utilizing machine learning methods. They identified 16 characteristic features, including equivalence ratio, fuel flow rate, and temperature distribution. By employing polynomial regression, support vector regression, decision tree regression, and multilayer perceptron, they achieved high performance, with R2 values exceeding 0.9. This research showcases the potential of machine learning models in predicting emission levels and deepening our understanding of the relationships between characteristic parameters and emissions.

Kovalnogov et al. [15] focused on improving the efficiency of burners and reducing emissions using machine learning. By considering various characteristic parameters like load, airflow, and fuel and oxidizer compositions, they applied mathematical modeling and machine learning algorithms. The results indicated that implementing flue gas recirculation and considering flow swirl significantly improved burner efficiency and reduced emissions. Furthermore, machine learning methods showed promising results in classifying the state of the burners, with random forest emerging as the best algorithm. This research emphasizes the potential of machine learning in optimizing burner efficiency and achieving emission reductions.

Han et al. [16] carried out a study to create models predicting exhaust emissions, particularly NOx and CO2, with flame imaging as the key parameter. They employed stacked denoising autoencoders (SDAE), artificial neural networks (ANN), and other algorithms. The results exhibited high prediction accuracy, with R2 values of 0.97 for NOx and 0.96 for CO2. This research highlights the effectiveness of machine learning techniques in accurately predicting exhaust emissions based on flame imaging data, enabling a better understanding of emission behavior and facilitating informed decisions for optimizing combustion processes.

Krzywanski et al. [17] focused on predicting SO2 and NOx emissions using machine learning. They considered nine input variables, including combustion mode, oxygen carrier, and fuel reactor temperature, utilizing fuzzy logic (FL) and artificial neural network (ANN) algorithms. The developed model successfully validated the emissions predictions, with relative errors below 10%. This research highlights the effectiveness of machine learning, particularly FL and ANN, in accurately predicting emissions based on various combustion-related variables, supporting emission control and mitigation strategies.

Zhou et al. [18] aimed to estimate CO2 emissions from coal-fired power plants (CFPPs) in near-real-time using machine learning. By utilizing a simulated CFPP dataset and characteristic parameters like capacity and temperature, they employed the Emission Estimation Network (EEN), a heterogeneous network-based deep learning algorithm. The results showcased the accuracy and ease of implementation of the EEN approach. This research underlines the potential of machine learning models, particularly EEN, in providing timely and reliable estimations of emissions from CFPPs, enabling effective monitoring and assessment of environmental impact.

Ren et al. [19] focused on predicting biomass gasification products, including N2, H2, CO, CO2, and CH4, using machine learning. By considering characteristic parameters such as equivalence ratio and temperature, they utilized the physics-informed neural network (PINN) method. The PINN models outperformed other algorithms, showcasing their superior prediction capabilities. This research demonstrates the effectiveness of machine learning, particularly PINN, in accurately predicting biomass gasification products, contributing to the development of sustainable energy solutions.

In Wang et al.'s [20] study, the researchers aimed to predict NOx emissions by considering characteristic parameters related to steam flow, pressure, temperature, and feed water temperature. By combining a random forest (RF) algorithm with a lightweight convolutional neural network (CNN), they achieved high prediction accuracy. This research showcases the effectiveness of machine learning in accurately estimating NOx emissions, providing valuable insights for optimizing emissions in power plants.

Overall, these studies highlight the significant potential of machine learning techniques in modeling and predicting emissions across different domains. By leveraging characteristic parameters and employing various algorithms, these models contribute to our understanding of emission patterns, facilitate emission reduction strategies, and support sustainable practices. A summary of the machine learning techniques to model and predict emissions is provided in **Table 2**.

Table 2. Summary of the Machine learning Techniques to Model and predict Emissions.

Author	Year	Characteristic parameters	Algorithm	Result
C. Saleh et al. [12]	2016	Energy consumption such as electrical energy and burning coal	Support Vector Machine (SVM)	Root Mean Square Error (RMSE) with an error value of 0.004
C. Wang et al. [13]	2018	Four-first air speeds (AA, BB, CC, DD), Five-second air speeds (A, B, C, D, E), Over fired air speed (OFA), Oxygen concentration at the outlet of the furnace (O2), The load of the boiler (Load), Total air rate (Tar), Four pulverized coal feeder speeds (C1, C2, C3, C4), Four coal properties (Mt, Aar, Vdaf, Qnet.ar)	Gaussian Process (GP), support vector machine (SVM), and genetic algorithm (GA)	NOx decreases from 345 ppm to 238 ppm
F. Elmaz et al. [14]	2020	16 Features: equivalence ratio (ER), fuel flow rate (FR), distribution of temperature (T0, T1, T2, T3, T4, T5), Carbon (C), Hydrogen (H), Oxygen (O), Nitrogen (N), Moisture (M), Volatile Matter (VM), Fixed Carbon (FC), Ash (A).	Polynomial regression, support vector regression, decision tree regression, and multilayer perceptron	Multilayer perceptron and decision tree regression achieving R2 > 0.9
V. Kovalnogov et al. [15]	2022	Load, Airflow, methane and biogas, fuel and oxidizer compositions, and others	Mathematical modeling for Efficiency of Burners. ML to Improve the Efficiency of Burners	Emission reduction of 15% with random forest is the best algorithm to classify the state of burners
Z. Han et al. [16]	2022	Flame imaging	Stacked denoising autoencoder (SDAE), ANN, extreme learning machine (ELM), SVM, LSSVM, and Gaussian process regression (GPR)	Prediction accuracy NOx (R2=0.97) and CO2 (R2=0.96) prediction time NOx (38.78 ms/f) and CO2 (38.76 ms/f)

Author	Year	Characteristic parameters	Algorithm	Result
J. Krzywanski et al. [17]	2022	9 variables input: the IDmode tag defining the combustion mode, the kind of oxygen carrier OC, excess oxygen OE in the fuel reactor, the average fuel reactor temperature T, the FCad/VMad ratio (ad—air-dried basis), the Nad/Cad molar ratio, the sulfur content Sad and ash content Aad in the fuel (coal and biomass), the IDfuel tag defines the fuel type,	Fuzzy logic (FL) and artificial neural network (ANN)	Successfully validated maximum relative errors between the measured values and predicted by the developed model SO2 and NOx emissions are lower than 10%.
S. Zhou et al. [18]	2023	Simulated CFPP, Capacity (MW), TCHRFL, H, Range of χC, Range of HHV	Emission Estimation Network (EEN) heterogeneous network-based deep learning	A competitive approach that not only has accurate measurements but is also easy to implement
S. Ren et al. [19]	2023	ER, MC, amount of oxygen in oxidant agent, pressure, and T	Physics-informed neural network method (PINN)	PINN model can outperform all the other models (RF, GBR, XGB, SVM, and ANN) PINN models have outperformed prediction capability (average test R2 0.91–0.97)
Z. Wang et al. [20]	2023	Superheat outlet steam flow, Superheat outlet steam pressure, Superheat outlet steam temperature, Reheat steam flow, Reheater inlet steam pressure, Reheater outlet steam pressure, Reheater inlet steam temperature, Reheater outlet steam temperature and Economizer inlet feed water temperature	Combining a random forest (RF) algorithm and a lightweight CNN.	Model prediction • accuracy: RMSE = 13.52704 ± 0.21036 mg/m3, • MAE = 9.89313 ± 0.18288 mg/m3, • R2 = 0.93337 ± 0.00222),

CONCLUSION

Machine learning techniques have shown promise in accurately predicting and optimizing thermal efficiency parameters and emissions in biomass co-firing.

For thermal efficiency modeling, deep learning methods like Deep Neural Networks (DNN) and Artificial Neural Networks (ANN) have demonstrated superior modeling capabilities, while regression tree, random forest, and fuzzy logic (FL) algorithms have been effective in optimizing thermal energy production and power estimation. These models contribute to improved performance and energy savings in co-firing systems.

In emission modeling, machine learning algorithms such as Support Vector Machine (SVM), Gaussian process (GP), polynomial regression, and fuzzy logic (FL) have been successful in predicting emissions like CO_2, NO_x, and other pollutants. These models enhance our understanding of the relationships between characteristic parameters and emissions, enabling effective emission reduction strategies.

Looking forward, the direction of future research should emphasize the development of hybrid models that seamlessly integrate domain knowledge and physics-based frameworks, further enhancing the accuracy and interpretability of predictive models. By consolidating these insights, we can continue to drive the progress of sustainable energy generation and emission reduction practices in biomass co-firing.

Author Contributions

The paper titled "Advancements in Machine Learning Modeling of Co-firing Systems: A Mini Review" was authored by a team of researchers from the Department of Research Center for Transportation Technology at the National Research and Innovation Agency. Fauzi Dwi Setiawan is the corresponding author and played a key role in conceptualizing the study, designing the research methodology, collecting data, and drafting the main manuscript. Kurnia Fajar Adhi Sukra contributed significantly to data analysis, result interpretation, and writing. Nilam Sari Octaviani extensively contributed to the literature review, analyzing existing research and writing the introduction. Rizqon Fajar provided valuable guidance, supervision, and critical feedback throughout the research process. Fitra Hidiyanto reviewed the methodology, conducted statistical analysis, and contributed to the conclusion section. Together, their collaboration and expertise from the same institution have strengthened the quality and impact of this research.

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