Modeling gasification of forest residues using deep learning algorithms

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Keywords: Forest residues, biomass gasification, deep learning, neural networks.
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Introduction

Forest residues (FR) are by-product of wood harvesting and forest management activities. They are the biomass left on the forest floor as waste material, which should be removed for sanitary and forest fire protection reasons (Nurek et al., 2019). Although excessive removal of these residues could have an impact of depleting soil nutrients, moderate removal (30-70%) has no significant effect on soil nutrients (Börjesson, 2000). In the Italian alpine region of South Tyrol, they primarily comprise of small branches, twigs, pine needles, and pinecones (Figure 1). These residues were tested for their suitability as feedstock for gasification and were found to give a producer gas (PG) similar in average composition to gasifying standard wood chips (WC). However, one major problem associated with using FR was that of unpredictability in the biomass flow rates in the reactor due to the different physical characteristic of the FR constituent components. This in turn was found to change the air flow in the reactor caused changes in the equivalence ratio leading to an unpredictable and unsteady producer gas output.

Figure 1. Different components of forest residues

Studies have shown that artificial neural networks (ANN) are efficient models to predict the producer gas output given a set of input-output data collected from experiments. In this study a custom ANN model was developed to predict the producer gas composition and its flow rate when gasifying different FR feedstock. While there are a few published works on ANN modeling of biomass gasification with popular methods of hyperparameters optimization (Ascher et al., 2022; Sharma et al., 2022), little has been reported on developing custom model architectures or leveraging the capabilities of deep learning frameworks to improve model performance. The present study reports on these aspects to improve the overall performance of a base model.

Materials and methods

The deep learning frameworks used in the present study are TensorFlow and Keras. The data used for training and validating the model have been collected from experiments conducted on an open top, downdraft gasifier. The feedstock composition, the reactor temperatures, and the air flow rate were taken as input variables, while the major producer gas components and its flow rate out of the gasifier were the outputs. The first step involved pre-processing the data. Due to the uneven sizes of input and output datasets, the output data was augmented using linear interpolation between adjacent data points. Further, the datasets were shuffled to avoid any sequence bias and the total dataset was split into training (80% data) and validation (20% data) sets.

For the base model architecture, the RandomSearch tuner in the Keras API was used to tune three hyperparameters of the base model: the number of hidden layers, the number of neurons in each hidden layer, and the learning rate of the optimization algorithm. It provided the best results on the validation set with the architecture comprising of three hidden layers 96, 64, and 48 neurons from input to output. The model is compiled with the Adam optimizer with a learning rate of 0.001, the loss function used is the Mean Squared Error (MSE), and the 'accuracy' metric is used to determine how often the predictions equal the actual values.

Results

The base show reasonably good results with an accuracy of 89.67% on the training dataset and 89.48% on the validation dataset (Figure 2). However, it is possible that this could be improved by architecting custom models better suited to the current problem. As gasification as a very complex process, which involves several reactants, products, and reactions that occur simultaneously in the various different zones of the gasifier leading to non-linearities due to interactions among the variables, custom layers with non-linear forward pass computations in the hidden layers could improve model performance. Hence, a custom layer class defined with quadratic forward pass functions which was found to perform significantly better than the standard Dense layers. Preliminary results show an increase in accuracy over 93% on both training and validation sets.

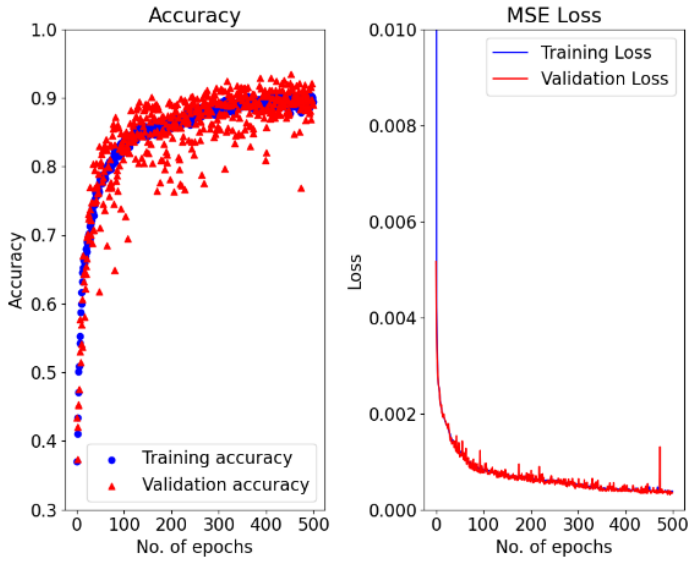

Figure 2. Accuracy and loss of the base neural network model.

Conclusions

In the current literature, several researchers have successfully demonstrated the use of neural network models to predict producer gas composition in biomass gasification. However, to the best of the authors' knowledge, no such study has reported on leveraging the capabilities of such models to improve performance. From preliminary model development, it was found that a custom-built ANN, designed to suit the specific needs of the current problem, performed better than the base Sequential model. The final accuracy of the model increased by over 4%. Further optimization of the model could lead to even better performance.

References

Ascher, S., Sloan, W., Watson, I., & You, S. (2022). A comprehensive artificial neural network model for gasification process prediction. *Applied Energy*, *320*, 119289. https://doi.org/10.1016/J.APENERGY.2022.119289

Börjesson, P. (2000). Economic valuation of the environmental impact of logging residue recovery and nutrient compensation. *Biomass and Bioenergy*, *19*(3). https://doi.org/10.1016/S0961-9534(00)00028-3

Nurek, T., Gendek, A., & Roman, K. (2019). Forest residues as a renewable source of energy: Elemental composition and physical properties. *BioResources*, *14*(1). https://doi.org/10.15376/biores.14.1.6-20

Sharma, K. G., Kaisare, N. S., & Goyal, H. (2022). A recurrent neural network model for biomass gasification chemistry. *Reaction Chemistry \& Engineering*, *7*(3), 570–579. https://doi.org/10.1039/D1RE00409C