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Thermal decomposition of rice husk: a comprehensive artificial intelligence predictive model

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Abstract

This study explored the predictive modelling of the pyrolysis of rice husk to determine the thermal degradation mechanism of rice husk. The study can ensure proper modelling and design of the system, towards optimising the industrial processes. The pyrolysis of rice husk was studied at 10, 15 and 20 °C min^{-1} heating rates in the presence of nitrogen using thermogravimetric analysis technique between room temperature and 800 °C. The thermal decomposition shows the presence of hemicellulose and some part of cellulose at 225–337 °C, the remaining cellulose and some part of lignin were degraded at 332–380 °C, and lignin was degraded completely at 480 °C. The predictive capability of artificial neural network model was studied using different architecture by varying the number of hidden neurone node, learning algorithm, hidden and output layer transfer functions. The residual mass, initial

degradation temperature and thermal degradation rate at the end of the experiment increased with an increase in the heating rate. Levenberg–Marquardt algorithm performed better than scaled conjugate gradient learning algorithm. This result shows that rice husk degradation is best described using nonlinear model rather than linear model. For hidden and output layer transfer functions, ‘log-sigmoid and tan-sigmoid', and ‘tan-sigmoid and tan-sigmoid' transfer functions showed remarkable results based on the coefficient of determination and root mean square error values. The accuracy of the results increases with an increasing number of hidden neurone. This result validates the suitability of an artificial neural network model in predicting the devolatilisation behaviour of biomass.

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