

MODELING THE PYROLYSIS BEHAVIOUR OF PLASTIC MIXTURES USING ARTIFICAL NEURAL NETWORK

John and Willie Leone Family

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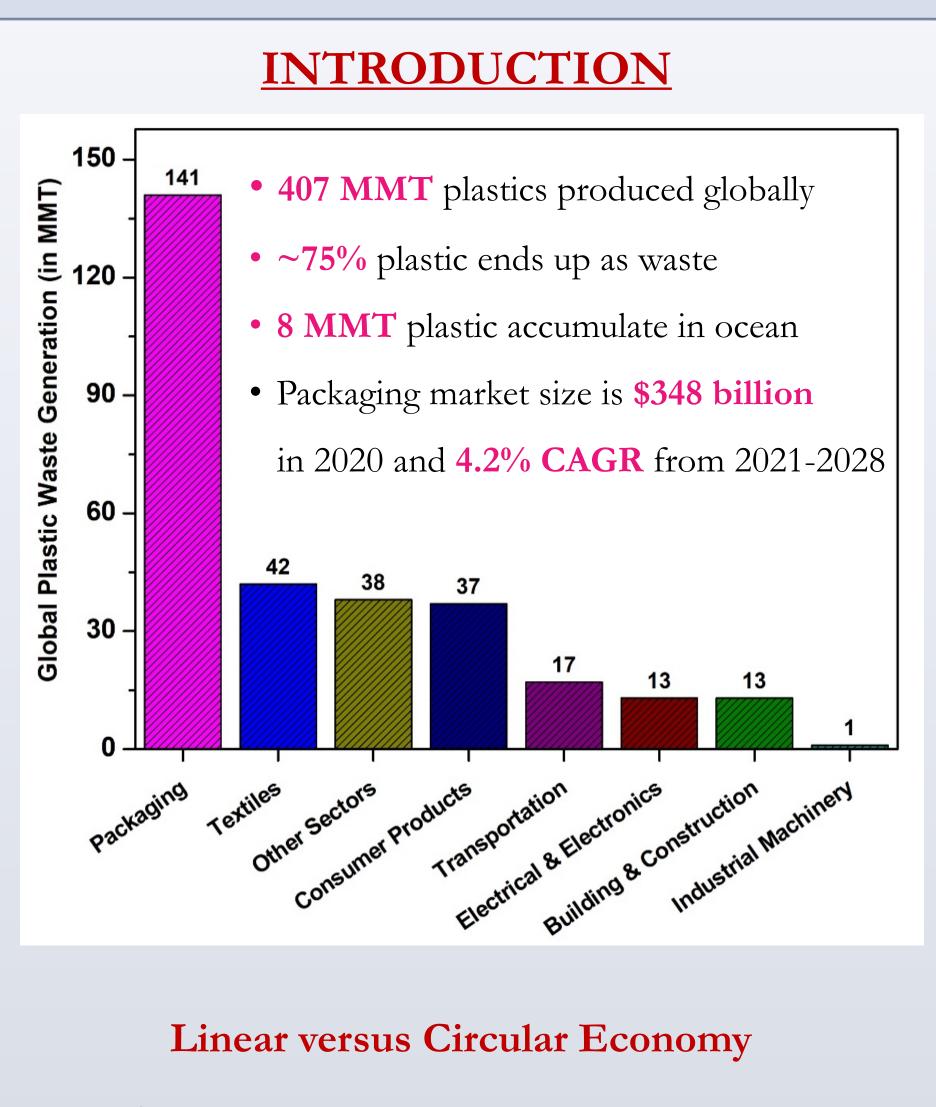
Mineral Engineering

J.V. Jayarama Krishna^a, P.A. Barbara^b, Hilal Ezgi Toraman *a,b,c

aDepartment of Energy and Mineral Engineering, Pennsylvania State University, University Park, PA- 16801, USA

bDepartment of Chemical Engineering, Pennsylvania State University, University Park, PA- 16801, USA

cInstitutes of Energy and the Environment, Pennsylvania State, E-mail: hzt5148@psu.edu



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- To study the pyrolysis behaviour of Polyethylene Terephthalate (PET) and Polyamide 6 (PA6) in different mixture ratios
- To evaluate the kinetic and statistical parameters and model the PET-PA6 mass loss behaviour using artificial neural network (ANN)
- To test the efficacy of ANN model on new dataset

MATERIAL & METHODS Flowchart for algorithm of ANN modeling Samples: PET: PA6 in 1:0, 0:1, 1:1, 1:3, 3:1 TGA Experimental Conditions: Train the network and test it • Heating rate = 10 K/min; Sample mass = 7 mg Collect TG experimental data @ 5, 10, 50 K/min • Nitrogen ambience (100 mL/min); T = 25-700 °C Evaluate RMSE and R2 ANN topology for PET-PA6 mixtures Normalization of data No **Parameters** Explore up to three hidden layers and up to **Parameter** three nodes in each hidden laver **PET Mass Fraction** Select ANN Model with best RMSE **PA6 Mass Fraction** and R² for both test and unseen data Fix network topology and transfer function Split data into training, validation and testing Denormalize the results of Input Layer Hidden Layer Output Layer selected model after training a = logsig(n)Nodes = 1 to 5 (1st HL), 0 to 5 (2nd HL), 0 to 5 (3rd HL) **RESULTS** Experimental and simulated DTG profile Experimental TG data for PET:PA6 (a) 1:0, for PET:PA (3:1) at 10 °C min⁻¹. (b) 0:1, (c) 1:1, (d) 3:1, (e) 1:3. Model Experimental Pc4 Performance plot of ANN511 model. The training, validation Experimental versus predicted TG curves on testing and testing plots overlap with each other. data at 10 °C/min using ANN511 for PET:PA6 mixtures (a) 1:0, (b) 0:1, (c) 1:1, (d) 3:1, and (e) 1:3. **Best Validation Performance is 0.00029021 at epoch 73**

79 Epochs

CONCLUSIONS

- The TGA results confirm that there are **significant** interactions among PET and PA6 mixtures.
- The kinetic study was carried out using isoconversional methods such as Kissinger-Akahira-Sunose (KAS) and Flynn-Wall-Ozawa (FWO), and a multi-Gaussian distributed activation energy model (DAEM).
- The average activation energy (E_a) obtained by KAS and FWO methods was in the range of **168-194 kJ mol**⁻¹, which is in good agreement with the value obtained by the DAEM model.
- The mass loss profiles of PET-PA6 mixtures were modelled using Artificial Neural Network (ANN).
- The model **ANN511** predicted the experimental mass loss behaviour reasonably well for both test data and new data at interpolated conditions of PET:PA6 in different ratios with root mean square error (RMSE) less than **3%**.

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