MACHINE LEARNING AS A MEANS TO MODEL CURE KINETICS

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The cure kinetic relationship of a thermoset resin is important to understand in order to properly predict the curing profile of the material during a cure cycle. Understanding the cure profile of the material allows manufacturers to cure parts more effectively while avoiding potential defects like incomplete cure, and part deformation. Traditionally, the cure kinetic relationship is modeled by a parametric equation which requires the researcher to choose an equation to which they believe the relationship will fit, and to determine the value of the parameters in the equation. The accuracy of the model will be limited by the parametric equation chosen. Machine learning can be used to create models of relationships represented by large data sets which may be able to capture more of the local trends in a relationship than can be captured by traditional parametric models.

In this work, Gaussian Process Regression was used to create a model for the cure kinetic relationship of a thermoset material, Cycom© 5276-1. The Gaussian Process Regression method can calculate most likely predictions of the cure kinetic relationship, in addition to giving a confidence value for each prediction. In order to evaluate the accuracy of the model, the resulting predictions were compared to those of the traditional Arrhenius equation model with both models being compared to experimental results.

The machine learning model shows different levels of accuracy and confidence depending on the data used to train the model. In some conditions it outperforms the traditional model, and in other conditions it is outperformed. It is less capable of making predictions in ranges outside of the observed data than is a traditional parametric model. The machine learning method can also incorporate a prior assumption that bring the predictions towards the traditional model in regions of sparse data. Including the prior assumption decreased the error of the machine learning model when the traditional model had outperformed the machine learning method.

While the machine learning model was not consistently more accurate than the traditional model, there are other reasons why the model may be preferable in certain cases. This machine learning method allows for the automatic creation of a model which may require less time and effort to fit than would a traditional model, and as more training data becomes available it can be added to the model readily, increasing the precision of the model.