THE UNIVERSITY OF BRITISH COLUMBIA
School of Engineering

Development and Optimization of a Basic Industry 4.0 Framework for Composites Manufacturing

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Group # 34

Introduction

The curing process is a critical part of the composites manufacturing industry. Optimizing this process can produce higher quality materials and reduce energy consumption. A problem currently facing manufacturers is accurately predicting the time needed for a part to reach its desired cure, as the part temperature lags behind the air temperature. This problem can be addressed through Industry 4.0 principles. By combining machine learning and digital sensors, accurate estimates of the soak time can be provided to manufacturers. For this project, an Industry 4.0 framework is applied for improving the curing process.

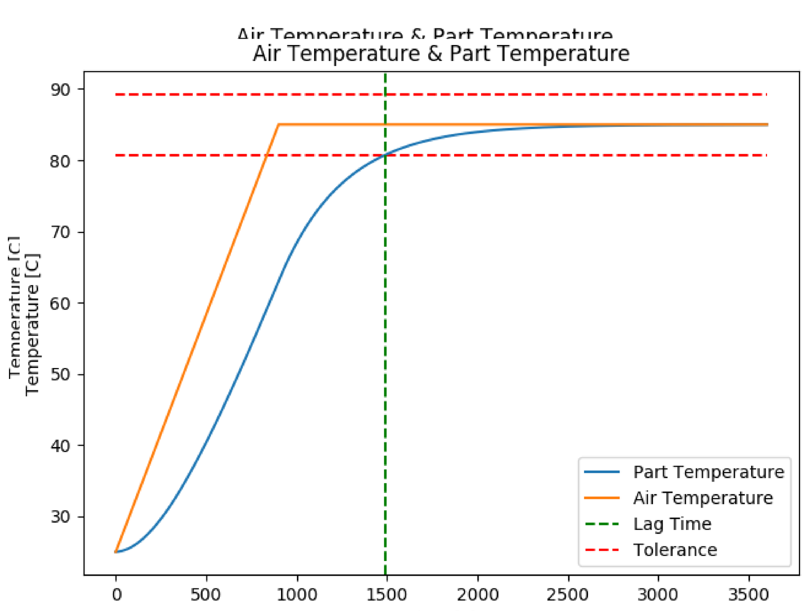

Fig. 1. This graph conveys the main objective of our project which is, predicting when a part is within the desired curing tolerance, known as the soak time, by using machine learning.

Methods and Materials

This project used a combination of software and hardware to complete the main objectives. The hardware included using four NTC 100kΩ thermistors, 16-bit ADC microcontroller, and a Raspberry Pi for acquiring data from the heat chamber. These data acquisition devices record all the data required for our machine learning (ML) algorithms. The software component included coding the ML and the data acquisition device and control software, and using MATLAB to for heat simulations

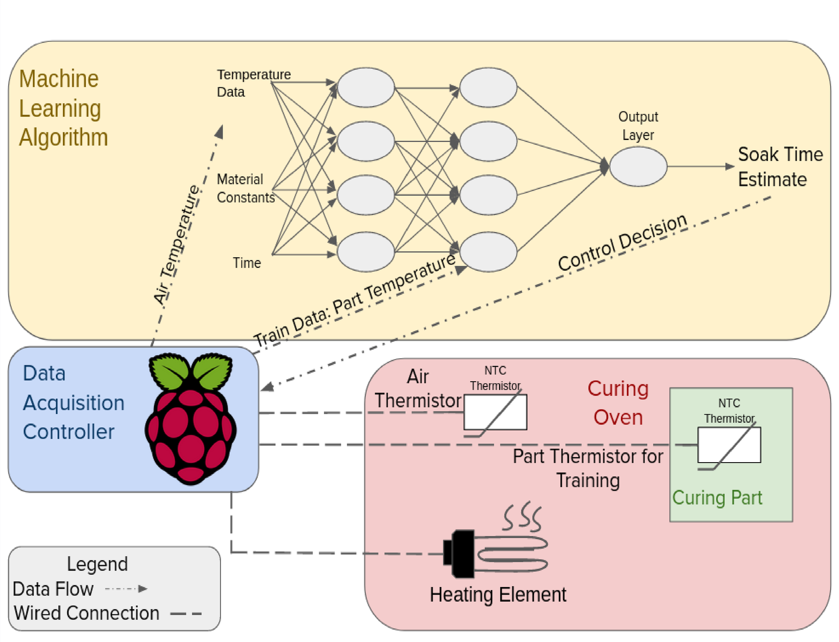

Fig. 2. Network diagram summarizing the overall experimental setup. On top is the neural network, left in blue is the data acquisition unit reading thermistors in the heat chamber (red). First the model is trained from the thermistor curing part data. Then the model can make new soak time predictions which determine the run time which is used to make a control decision for the heating lamp.

Data Acquisition

- Collected data is filtered, scaled, and processed to train and test the machine learning algorithms

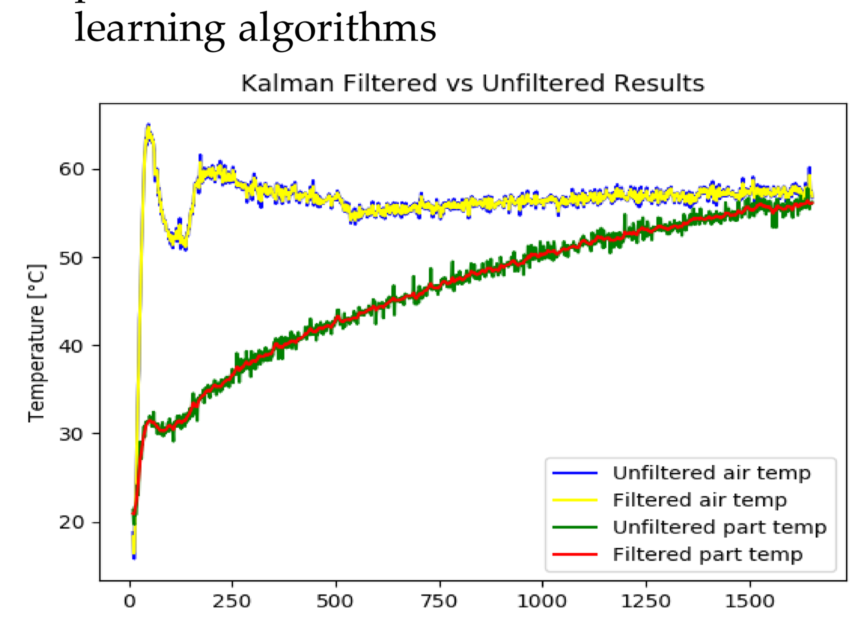

Fig. 3. Collected data from a run on using an aluminum cylinder as the part using our data acquisition system. Both the part and air temperatures are acquired for training and testing our machine learning models.

- Doing transient heat simulations to acquire data sets saves time and costs of running the heat chamber.
- Using programs like MATLAB is a common technique used in industry for generating sample data to train a neural network [1, 2].

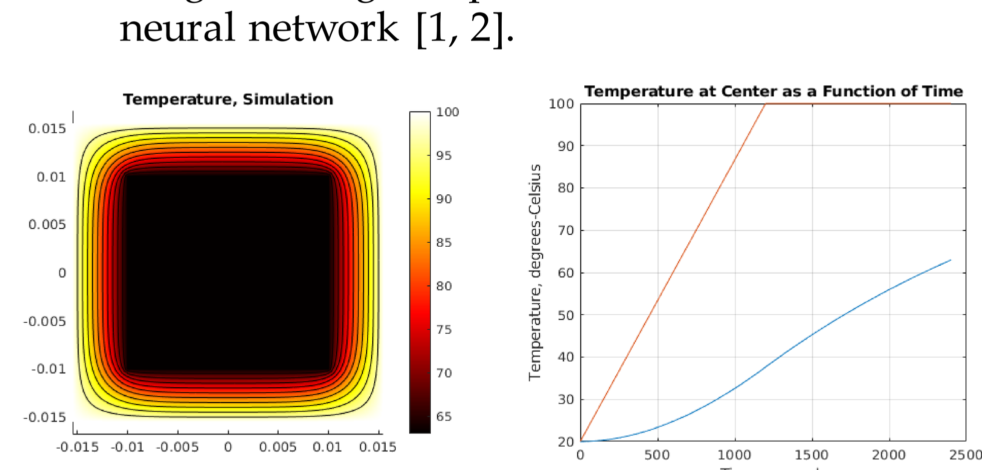

Fig. 4. An output from a transient heat simulation done using MATLAB. The air temperature is set to ramp up to 100°C and the part's internal temperature is simulated lagging behind the air temperature, mimicking a real curing cycle.

Machine Learning Algorithms

Long Short Term Memory (LSTM) Network

- Network implementing traditional feed forward connections along with recurrent connections which feed backward.
- Useful for time dependent data, network is designed to make prediction using past time steps to make a future prediction.

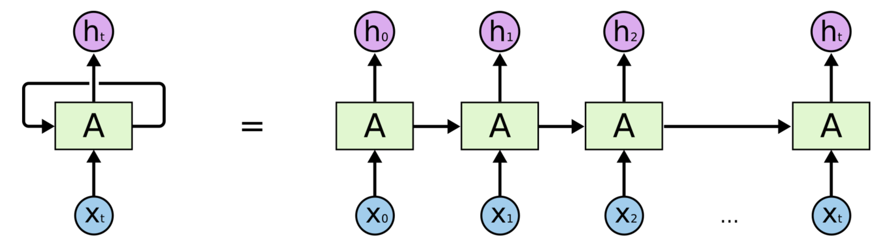

Fig. 5. Typical LSTM network diagram.

Random Forest

- Uses decision trees to train data for regression and predictions tasks
- Easy to implement and fast to train/test

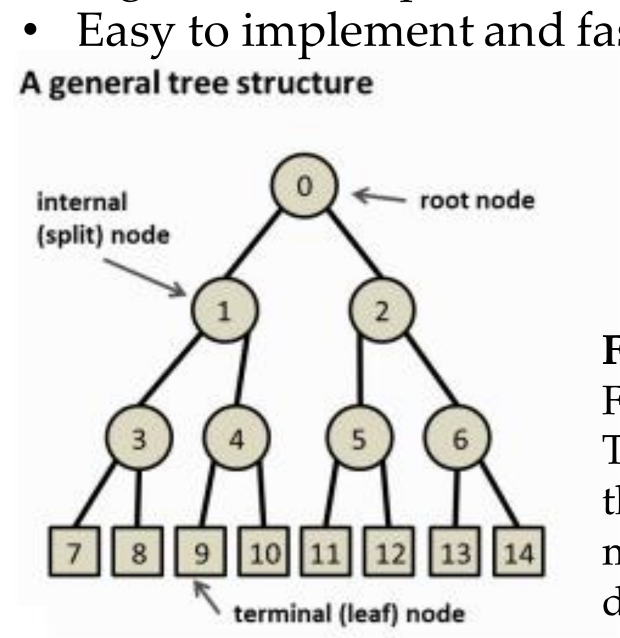

Fig. 6. Random Forest Decision Tree, many of these are used to make a 'forest' of decision trees.

Results Using Machine Learning Algorithms

- Internal part temperature predications from our long short-term memory (LSTM) and Random Forest algorithms show high accuracy with cross validation scores between 0.9608-0.998, with 1.0 being the best score.
- The LSTM algorithm performed better than Random Forest. Percent error at stable air temperature for the LSTM was typically below 2%, whereas the Random Forest algorithm was closer to 5% and more sporadic.
- Using our machine learning algorithms accurate soak time predictions could be made for curing tolerances of 5%. Requiring a minimum of two runs for training.
- Our algorithms give users better feedback on the curing process than the previous solution. This can be used for making smarter control decisions to reduce power consumption significantly.

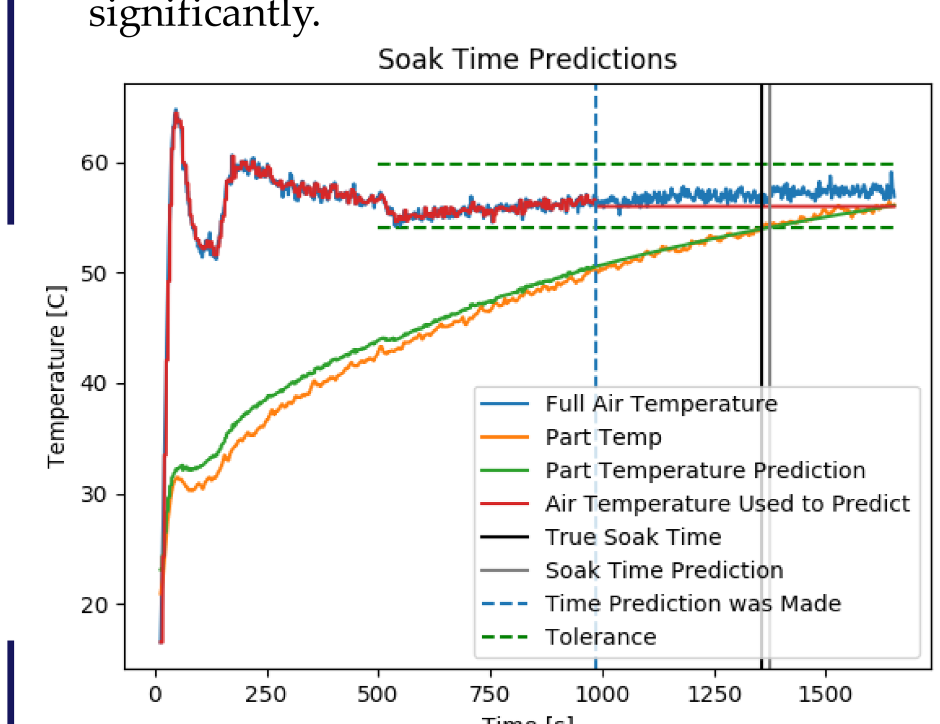

Fig. 7 The accuracy of the LSTM's soak time estimates is seen in this figure. A prediction is made at the time indicated (dashed blue) for a 5% tolerance (dashed green). The LSTM gives an estimate of soak time (grey) which is very close to the actual soak time (black).

- Implementing this LSTM algorithm can save users from costly trial and error test runs for determining the soak time.

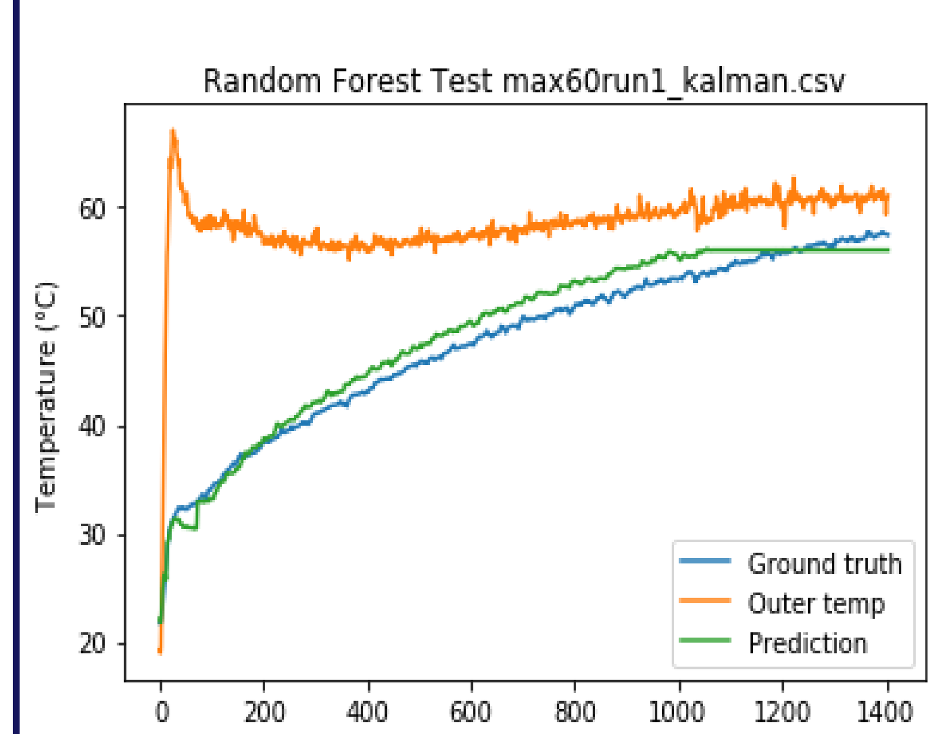

Fig. 8. Prediction of part temperature using Random Forest algorithm on real-time heat chamber data. This example had a percent error below 5% throughout the curing cycle.

- The Random Forest algorithm was on average less accurate at predicting soak time compared to the LSTM.
- With more data sets for training, the Random Forest algorithm's accuracy will improve.

Conclusions

Our main objective of developing an Industry 4.0 framework to accurately estimate soak time for a part was achieved. The framework was created using an array of thermistors and 16-bit ADC for the data acquisition system combined with our LSTM and Random Forest algorithms. The resulting soak time predictions were accurate within a set confidence interval. The project built a proof of concept for predicting soak time on objects with simple geometries but with further development could be used on composite materials.

We note that due to the COVID-19 situation the machine learning algorithms were not tested in the heat chamber's control system, so predictions could not be made in real-time. We would have also liked to acquire and generate more data to improve the prediction capability of our ML algorithms. With additional funding and development we are confident that this framework can be implemented on a larger scale for manufacturing of composite materials.

References

[1] D. Aleksendric, P. Carlone, and V. Cirovic, "Optimization of the temperature-time curve for the curing process of thermoset matrix composites," *Applied Composite Materials*, vol.23, pp. 1047–1063, Oct. 2016.

[2] P. Shah, V. Halls, J. Zheng, and R. Batra "Optimal cure cycle parameters for minimizing residual stresses in fiber-reinforced polymer composites laminates," *Journal of Composite Materials*, vol.52, no.6, pp. 773-792, 2017.

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