Contemporary Engineering Sciences, Vol. 10, 2017, no. 21, 1047 - 1055
HIKARI Ltd, www.m-hikari.com
https://doi.org/10.12988/ces.2017.79107

Deep Regression Model for Predictive Control in a Vegetable Waste Carbonization Plant

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Abstract

This paper proposes the use of a deep regression model to predict the behavior of the temperature inside a carbonization furnace in an activated carbon (AC) factory. The intention is to anticipate the behavior of the variable to improve the scheme of control of fuel and feed of material in order to guarantee a high quality in the final product. According to the temporal dependence of temperature with respect to previous events, the use of a recurrent neural network is proposed. Experiments on real-world industrial datasets demonstrate the effectiveness of the proposed approach.

Keywords: activated carbon, deep learning, predictive control, sensor

1 Introduction

Due to the increased consumption of oils produced from oil palm (*Elaeis guineensis*) a lot of waste, in particular the shell covering the almond, and the resulting fibres of the pressing process of the fruit (cuesco) is generated in Colombia. These wastes have been used as a point solution in the generation of electricity, but its use is not massified. Some state-supported industries investigating the possible use of this waste for the production of AC.

In this moment, in Colombia concepts as automatization and control are in upgrade, for this reason, new companies want to begin the production of AC and they want that their finished product have the highly quality indices. For that, they must identify and control the critical process variables. During the automation of pilot plants, the temperature control in the furnace is defined as a critical variable to guarantee the quality of the product. Therefore, and according to the response time of the system, and to the variables involved, we proposed the implemented of a predictive control strategy which permit know with anhelation the behavior of the temperature in the furnace [8].

There are several types of predictive control strategies for industrial processes like this, where the system have a complex dynamic behavior (non-stationary) and its state evolves over time [5]. The Predictive Control Based in Models (MCP) [5], for example, is a control strategy based on a mathematical model that may to predict the behavior of system depend variables, which in turn are changing on account of variation of independent variables [13].

On the other hand, the PID controllers may be a good option [2]. The derivative function calculate the error, (the difference between the read data and the set point) in order to correct it and prevent from spreading. Also derivative functions allow with previously know the error, if the time of action of the derivative function is long, the answer will not suitable to the process. Conversely on any industrial process is necessary that the time of action of the derivative function be according to the set point, that is to say reduce oscillation of the system with optimal times of action of the derivative.

In this research we have chosen to identify the behavior of temperature through a recurrent neural network, with the intention of knowing the future state of the system from its past evolution. This particular type of data are known as time series, and are characterized by the output that is influenced by the previous events, in contrast to reactive systems whose output depends only on the current state [11]. For this we propose the use of a LSTM (Long Short-Term Memory) network [7].

The processing of the time series consists in finding models for the data that allow to discover hidden knowledge in them, unknown patterns that can be used in a determined action [10]. The different existing techniques can be classified into two categories: estimator of short-lived and estimator of long-range [10]. Estimator of short-lived is an estimator of one-ahead-step or short-term and forecast several minutes, hours, days or months ahead [1]. An estimator of long-range on the other hand, is a tool that allows taking long-term decisions [6]. Among the tools used in both cases we can highlight the use of temporary association rules [12] and neural networks [3].

We propose the use of a LSTM (Long Short-Term Memory) with one output target and a real numbered vector output. The LSTM is a recurrent neural network (RNN) architecture that unlike traditional neural networks has a high capacity to learn from experience to classify, process and predict time series when there are time lags of unknown size and bound between important events.

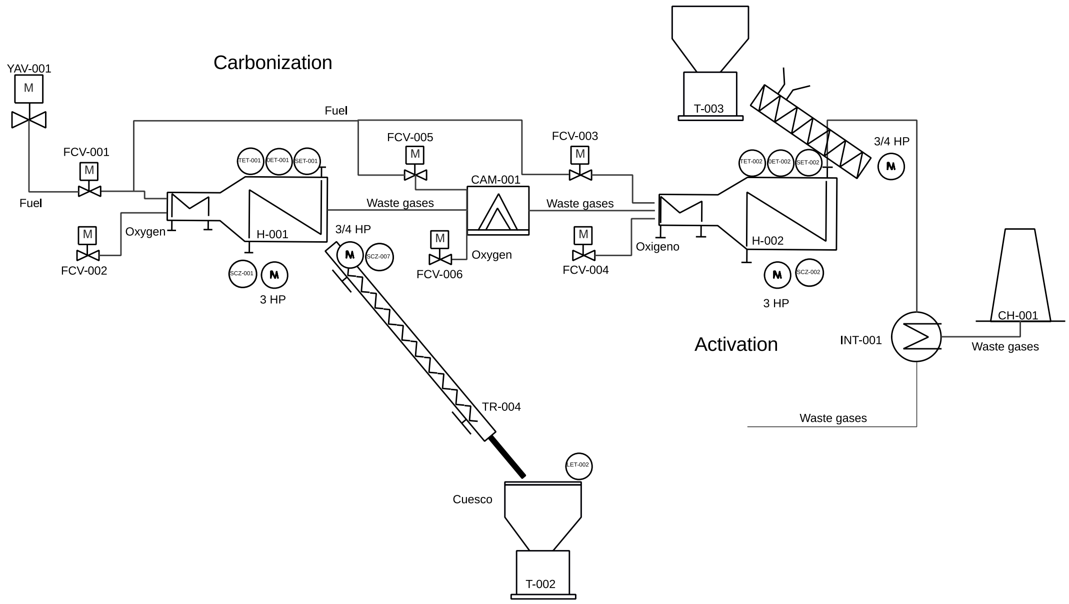

Figure 1: Cuesco thermal processing sequence [4]

The insensitivity to gap length gives an advantage to LSTM over alternative RNNs and hidden Markov models and other sequence learning methods in numerous applications.

The paper is organized as follows. In Section 2 presents a description of the problem of determining the quality of combustion to control the carbonization process. Section 3 describes the strategies used to estimate the behavior of the temperature during the process of manufacture of AC in the carbonization furnace. Section 4 introduces some results obtained with the proposed strategy. Finally, conclusion and discussion are presented in section 5.

2 Problem statement

The production of AC (in physical process) entails two thermal processes: carbonization and activation (Fig. 1). Carbonization is a process of thermal decomposition of organic waste in the absence of air. The idea is to remove from the vegetable material hydrogen, oxygen and nitrogen to increase the proportion of carbon. During this heating the process undergoes three phases: a gaseous phase composed of the volatile material, a liquid phase containing tars, and a solid or carbonized phase. This process has as main variables the process temperature, the heating rate, the feed velocity of material, and the residence or retention time. These variables determine the quality of the carbonized material.

A rotary cylindrical furnace (6.6 m long and 0.7 m internal diameter) with

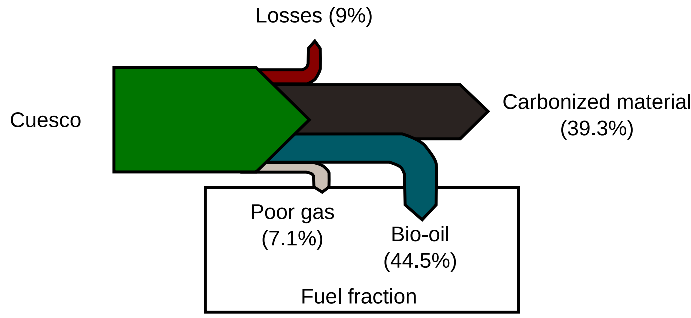

Figure 2: Sankey diagram of material proportion (carbonization furnace) [4]

a capacity of up to 200 kg/h, is used in a production plant. The nominal carbonization temperature is 500°C, with a nominal residence time of 67 minutes. During carbonization, about 40% of the processed material is converted into carbonized material, and more than 50% in combustible material [4] (Fig. 2). When the carbonization furnace reaches its steady state of operation, it ceases to require fuel feed (in our case, natural gas). The carbonization process enters a state of thermal self-support thanks to the combustible material contained in the cuesco. At this point the fuel feed to the furnace is eliminated, and the process control is performed by adjusting the furnace cuesco supply, in conjunction with the furnace rotation and the air content control [9].

Given the interrelationship of the variables, and their strong incidence on temperature, we try to implement a control that minimizes the temperature error. A theoretical model of behavior can hardly consider the interaction of these variables, which is why it is proposed to construct a regression model in order to predict the behavior, in this case using a LSTM (Long Short-Term Memory). LSTM is a recurrent neural network (RNN) architecture that unlike traditional neural networks has a high capacity to learn from experience to classify, process and predict time series when there are time lags of unknown size and bound between important events [14]. The temperature in the carbonization furnace behaves as a time series (Fig. 3). The prediction of the behavior of a time series is a complex problem of predictive modeling due to the strong dependence of the sequence with respect to the variables of the system. In addition, in the Tecsol AC plant, the sensed temperature is transmitted to the control unit wirelessly, which means that the sampling intervals are not constant.

3 Materials and Methods

The Fig. 3 shows some periodicity in the data set that probably corresponds to cycles on and off of the screw that feeds material to the furnace. In addition,

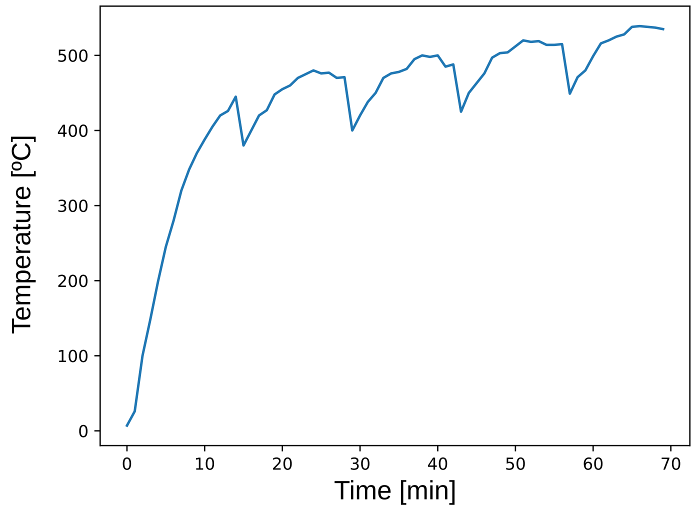

Figure 3: Plot of the furnace temperature dataset

it is possible to see an upward trend in the data set over time. To estimate the behavioral model of these data we use an LSTM. The LSTM network is a recurrent network that is trained using backpropagation over time.

LSTM networks use memory blocks instead of neurons. The blocks have gates that handle both the state of the block and its output. These memory blocks are connected through the layers. This block structure provides higher performance than the classical neuron, and adds short-term memory to the system. The memory block receives an input sequence, and each gate inside uses sigmoid activation units to control its triggering. There are three types of gates in one unit: Forget Gate, Input Gate and Output Gate. Each unit is like a small state machine in which the gates have weights that are defined during training. The problem is in general terms a regression problem. That is, given the recorded behavior of the temperature in the carbonization furnace, what will be the value of the temperature in the following minutes?

The performance of the final model is evaluated using cross validation. To do this, we separate the dataset in an orderly manner, creating a training set and a test set. For training we use 67% of the data, and we use the rest to test the model. The network has a visible layer with one input, a hidden layer with eight LSTM blocks or neurons, and an output layer that makes a single value prediction. The default sigmoid activation function is used for the LSTM blocks. The network is trained for 100 epochs and a batch size of one is used.

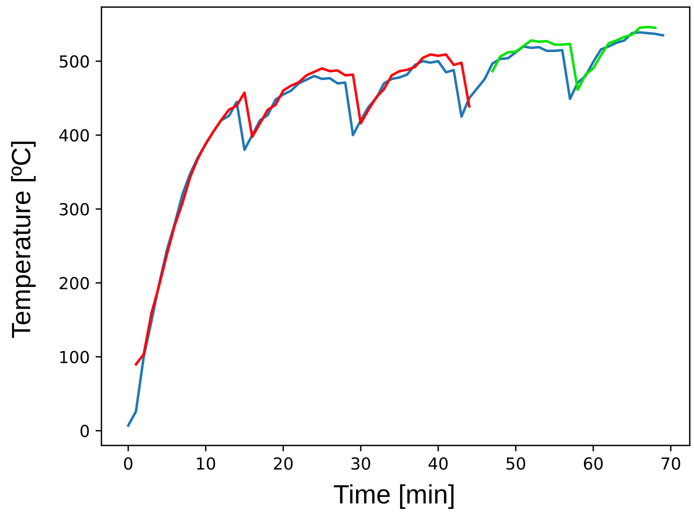

Figure 4: Plot of the furnace temperature dataset and model predictions

4 Results and Discussion

The model fit code was written in Python using Keras. We setup a SciPy work environment with Pandas support. The temperature data was sensed with a K-type thermocouple with a resolution of one degree centigrade. Therefore, temperature data are originally integer values, but are converted to floating point since in this format they are more suitable for working with neural networks. LSTM networks are quite sensitive to the scale of input data due to the behavior of the activation function. Therefore, the values are rescaled to the range of 0 to 1.

The results can be seen in Fig. 4. In the figure the original dataset is represented in blue, the predictions for the training dataset in green, and the predictions on the unseen test dataset in red. We can see that the model has an average error of about 21 degrees Celsius on the training dataset, and about 71 degrees Celsius on the test dataset. These values are calculated on the same scale and dimensions of the dataset, and at full scale of the temperature sensor correspond to an average error of 2% and 7%.

We attribute the high performance of the model to the structure of the LSTM network. The general structure of the data presents an ascending slope with short cycles, and the values are strongly dependent on the carbonization process, and therefore on the history of events. These characteristics are observed both during experiments and in the structure of the model. Models were evaluated using Keras 2.0.5, TensorFlow 1.2.0 and scikit-learn 0.18.2.

5 Conclusions

This work has presented the development of a model for the temperature inside a carbonization furnace in an AC manufacturing process, in order to construct a set of pattern for the predictive recognition of the furnace in a control scheme. Temperature signals were taken during an actual AC production process. The model for the signal was identified using an LSTM network. This neuronal structure was selected by observing the importance of the previous events in the behavior of the signals. The network structure was designed with an input layer, a hidden layer with eight LSTM blocks or neurons, and an output layer. The performance of the models are calculated by evaluating the average error on the training dataset, and the average error on the test dataset. According to the results, the model predict the behavior of the signals faithfully, since in the worst case the error does not exceed 7%. Consequently, this research will continue to generate models for a larger number of tests, establishing baseline behavior and designing metrics for comparing similarity between the sensor signals and references in real time.

Acknowledgements. This work was supported by District University Francisco José de Caldas. The views expressed in this paper are not necessarily endorsed by District University. The authors thank the research group ARMOS for the evaluation carried out on prototypes of ideas and strategies.

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Received: September 27, 2017; Published: November 9, 2017