Preprints of the 21st IFAC World Congress (Virtual)
Berlin, Germany, July 12-17, 2020

Abnormal Condition Prediction via Adaptive Deep Learning for Fused Magnesium Furnaces

Gaochang Wu*. Tianyou Chai*
Zhiwei Wu*

** State Key Laboratory of Synthetical Automation for Process Industries, Northeastern University, Shenyang 110819, P. R. China*
(e-mail: ahwgc2009@163.com; tychai@mail.neu.edu.cn; wuzhiwei@mail.neu.edu.cn)}

Abstract: Fused magnesia possesses numerous properties such as high melting point, dense structure, strong oxidation resistance, high compressive strength, strong corrosion resistance and stable chemical properties. It is an indispensable strategic resource in industry, military and even aerospace industry field. Fused magnesium furnace (FMF) is the main equipment for producing fused magnesia [Fuchs et al. 2008, Zhang et al. 2005, Zhang et al. 2006], which heats and melts the powdered raw materials through electrical arc. FMF is a typical high temperature submerged arc furnace that achieves the full-size smelting process through the continuous alternation of feeding and melting. Caused by the low-grade, complex mineral composition and large variations in the composition, the optimal setting value of the melting current in a FMF will change dynamically with the melting process and the feeding of the raw materials. Since the controlled current cannot traces the optimal setting value accurately and in time, semi-molten abnormal condition will appear high-frequently along with the production process. The substantial mechanism of semi-molten condition is due to the rising of the local melting point caused by the impurities in the feeding material, and thus the temperature in that local area will be lower than the melting temperature of the fused magnesia due to the unchanged current setting; after a period of time, the melting pool will be too thick to allow the exhausting of carbon dioxide gas, forcing the high temperature molten magnesia to penetrate the protection layer and touch the iron shell of the furnace directly. The semi-molten condition will heat up the furnace shell dramatically, resulting in the leakage of molten magnesia when dispose improperly. Therefore, the semi-molten abnormal condition not only has a huge impact on the energy consumption and product quality, but also is a potential threat to the production safety and workers.

Since the melting pool temperature in FMF is nearly 3000 degree Centigrade (the melting point of magnesia is about 2800 degree Centigrade), it is impossible to directly observe the inside of the melting pool. Currently, the detection of semi-molten condition usually depends on the regular observation of the inspection workers [Chai et al. 2017], that is, judging whether a certain area of the furnace shell is turning red. However, each worker usually needs to take a routing inspection for three FMFs in each workshop. In comparison, it only takes two to three minutes for the transformation of the melting state from the normal condition to the semi-molten condition [Wu et al. 2015]. Therefore, the missing alerts can frequently occur for the manual inspections. In addition, the objective standards of the inspection, especially for the semi-molten condition, differ from worker to worker, which may also lead to false or missing alerts. Therefore, an automatic working condition prediction method is urgently needed. From the perspective of visual prediction and detection, the method is expected to predict the semi-molten abnormal before the FMF has shown obvious visual features. Besides, the method should provide an accurate signal or information for subsequent operation control and production policy, for achieving the goal of energy saving, emission reduction and production efficiency improvement.

The main challenge of semi-molten condition prediction from the perspective of computer vision lies in the representation of dynamic features. The training and testing sets adopted by typical deep learning-based visual prediction and detection methods are sampled in a closed set, that is, the network is trained and tested in the same operation state. However, under the influences of opening factors, e.g., continuous alternation of feeding and melting, composition variations in the raw material, the set value of the process engineer, the decision of the enterprise manager, etc., the operation of FMF is always in a dynamic state, and its condition features transfers along time. In other words, the deep neural network may handle the prediction effectively for the recent data regarding to the training source, while yield more and more errors for the condition features after the transference. Another challenge for the prediction is overcoming the interference brought by the open environment. Different from laboratory under a controllable

environment, there exists heavy dust, spray from cooling water and occlusions from workers, causing unexpected interferences to the prediction from a single image (or video frame).

In this paper, we consider the two challenges, the representation of dynamic features and the interference from open environment, within a novel deep learning framework [LeCun et al. 2015] for the prediction of semi-molten condition using video data from an in-situ industrial camera. For the first challenge, an adaptive deep learning framework is developed mimicking the adaptive concept in control theory. Different from the fixed parameters in the commonly-used deep neural network, the proposed framework continuously updates the network parameters by using not only the historical data but also newly collected data that reflects the condition features after the transference. The framework is composed of two sets of neural networks: an upper neural network that learns an initial set of parameters (weight and bias) from scratch by using the existing historical data, and continuously corrects the parameters by using the newly collected data based on the fine-tuning technique with a small learning rate; a lower neural network receives the fine-tuned parameters from the upper network to keep the capability of representing dynamic features, and uses the real-time video stream to predict the semi-molten condition.

For the challenge of the interference from open environment, we combine the long-short term visual features of the semi-molten condition with convolutional recurrent neural network (CRNN) [Donahue et al. 2017] to introduce a time-aware neural network. Specifically, in terms of the temporal features, the semi-molten condition appears a long-term feature, while other interfering factors (such as the mentioned dust, spray and occlusions) show short-term features, i.e., they are in a state of rapid change (or move). The overall network design incorporates a convolutional neural network (CNN)-based spatial feature extractor and a recurrent neural network (RNN)-based temporal feature extractor within an encoder-decoder architecture. For the basic RNN unit, we employ the long short-term memory (LSTM) [Hochreiter and Schmidhuber 1997] which has a stronger perception ability of temporal information than the conventional RNN unit. In addition, instead of using the Hadamard product of a feature vector and network weight in the inner LSTM unit, the convolution between matrix is applied to achieve the integration of CNN and RNN. To support the adaptive deep learning framework mentioned above and prevent the tedious and time-consuming video labeling frame-by-frame, we introduce a semi-automatic labeling strategy by combining the specific characteristics of the semi-molten condition and weighted median filter-based label refinement scheme. The labeling strategy is able to generate a large number of high-quality label data with only two frame marking. By using image sequences from production processes of a real FMF, the proposed method is evaluated, and compared with other two baseline approaches based on deep learning techniques. The results show that the proposed method is effective and superior in forecasting advance and prediction accuracy.

Keywords: Adaptive deep learning, abnormal condition prediction, convolutional neural network (CNN), recurrent neural network (RNN).

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