

ON-LINE CLASSIFICATION OF COAL COMBUSTION QUALITY USING NONLINEAR SVM FOR IMPROVED NEURAL NETWORK OPTIMIZER PERFORMANCE

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Abstract Overview

A nonlinear support vector machine (SVM) is used in real-time to classify the currently combusting quality of coal as it is used to generate electricity in an operating electric utility generator. The classification results are used to select a unique neural network model used in a downstream particle swarm optimizer to reduce the formation of nitrogen oxide (NO_x). The SVM structure is chosen using an exhaustive cross-validation routine, determining the radial bias kernel as the best choice, achieving a classification accuracy of greater than 67%. By using the SVM classifier to aid in reducing existing variance in the neural network model, the overall performance of the neural network optimizer is improved by 2% - 6% during online performance, depending on unit generation level.

Keywords

Neural Networks, Nonlinear SVM, Coal-Fired Power Generation.

Introduction

Machine learning technologies have led to a transformation of practices within many industries. Machine learning modeling and prediction methods are proving beneficial in applications ranging from genetic sequencing to business marketing (Chen, Fan, and Sun 2015; Libbrecht 2015). Computer systems have the distinct advantage over humans of being able to rapidly process substantial amounts of data, making them ideal for complex processes. As such, combustion systems (particularly utility electrical generators) have steadily adopted intelligent systems to aid in emission reduction and performance optimization (Hasler and Rosenquist 2009). These applications typically involve using a neural network regression model to represent the boiler. Optimization then manipulates the air flow rates around the unit to reduce emissions – e.g. nitrogen oxides (NO_x) and carbon monoxide (CO) – and/or improve overall net unit heat rate (NUHR).

A major obstacle faced at many coal-fired power plants comes from the fluctuating fuel quality. There are identified attempts in the literature to use machine learning methods to characterize coal quality, but most of these use

computer vision to assess the coal and none are known to be performed on-site at a combustion facility (Chaves et al. 2018; Le et al. 2019; Mao et al. 2019; Mohapatra 2016; Suljic, Banjanovic-mehmedovic, and Džananovic 2014; Zhang et al. 2014). The nature of the system typically requires that fuel analysis occur before fuel is loaded into storage silos. Such systems can be unreliable, and it can also be very difficult to then determine when the sampled fuel is actually combusted due to unknown traversal pathways through these storage silos. Furthermore, not all units have coal analyzers on the loading system, and some depend on daily or weekly manually sampled fuel quality analyses. In these situations, optimization systems are limited as they are lacking significant inputs to the process. Including certain system parameters in the neural networks can aid systems in responding to fuel changes, but a high level of stratification of these inputs has been observed in practice to introduce variance to the models and reduces the overall prediction quality. To reduce this variance, a technique reminiscent of bagging (Breiman 1996) is proposed in which a support vector machine (SVM) is used to classify the currently combusting coal quality using

on-line system parameters. The use of SVM to perform classification of data was first proposed by Vapnik (1995) and has since gained popularity for use in many industrial applications (Yin and Hou 2016).

Separating the combustion dataset based upon the results of the trained SVM, multiple neural networks having identical structures to the original, overall model are trained on the classified datasets. During operation, the SVM is interrogated using live combustion conditions and the appropriate unique neural network model is used to optimize the system for the desired output. This classification technique and its effects on the subsequent neural network prediction are the major focus of this project.

Methods

There are three components to this work: 1. Data collection from the on-line coal-fired power plant and labeled dataset creation, 2. Training, validation, and testing of SVM for coal quality classification, and 3. Neural network regression and optimization. Each of these components is discussed briefly below.

Data Collection and Labeled Set Generation

Working in conjunction with an online coal-fired power plant, data is collected from this site using multiple sources. Combustion parameters and firing data is obtained from currently operating combustion optimization system, Griffin Open Systems™. For its neural network training and control purposes, this system is collecting real-time information on the combustion process and system parameters throughout its service lifetime (about 2 years). This data is extracted and used to create the coal quality indicative parameters and training set for the SVM. Little pre-processing is performed by the Griffin system on this data, only filtering based on minimum and maximum values of key parameters (such as NO_x and CO₂ emission rates and generation level). Coal quality information is obtained from an upstream in-process ThermoFisher Scientific™ coal analyzer (Anderson et. al., 2007). This device performs prompt gamma neutron activation analysis (PGNAA) on coal samples to directly determine the elemental composition of the sample, as well as to determine calorific value (HHV), overall ash content, and moisture content.

Creation of the labeled training set for the SVM is performed by analyzing the available coal quality information and correlating this information to the combustion data. The coal quality parameters of interest are the calorific value (BTU/lb), percent ash (%), moisture content (%), and percent elemental sulfur (%). In practice, these indexes are most indicative of overall coal quality and firing performance (Mishra et al. 2016). To represent these values using combustion parameters available in real-time, the following points are created from the data: load-to-coal, drying air, hardness, and sulfur-to-coal.

To generate coal quality labels for the combustion dataset, a point system is created using expert knowledge of the combustion process obtained from plant personnel. This point system attempts to balance the contribution of each parameter to overall firing conditions and coal quality.

Training, Validation, and Testing of SVM

Training and validation of the SVM are performed in R™ using the “e1071” package (Meyer et al. 2019) which is based on the popular “libSVM” library (Chang and Lin 2011). The SVM model is created by solving the following optimization problem:

$$\min_{w,b,\xi} \frac{1}{2} w^T w + C \sum_{i=1}^l \xi_i \quad (1)$$

$$s.t. \quad y_i(w^T \phi(x_i) + b) \geq 1 - \xi_i, \quad \xi_i \geq 0$$

Transformation of this problem into the dual form allows for nonlinear kernel functions – higher dimensional mapping of the input features represented by, $K(x_i, x_j) = \phi(x_i)^T \phi_j(x_j)$ – to be utilized (Hsu, Chang, and Lin 2016). A 5-fold cross-validation procedure (Li et al. 2013) is performed to determine the optimal kernel function, kernel parameters, and hyperparameter cost (C) in the problem. The final optimal SVM parameters are further tested on an isolated testing set to determine adequate generalizability.

To utilize the optimal SVM within the existing plant control structure, the resulting optimal SVM is then reconstructed within the Griffin Open Systems™ software to enable seamless online classification and control.

Neural Network Regression and Optimization

The online control structure is implemented within the Griffin AI Toolkit™ environment. The methods of this system are detailed in multiple US patents (Radl 2010), but it will suffice to say that the general neural network structure is a feed-forward system trained through back-propagation. The models are optimized using particle swarm optimization (PSO) according to the general structure provided by Kennedy and Eberhart (1995). To evaluate the effect on optimizer performance, datasets consisting of one month of operation data and emission rate values immediately before implementing the SVM coal quality classifier and immediately after are compared across the generation range of the unit, evaluating the percent change in realized emission rates of NO_x.

Results and Discussion

The overall control system is modified by introducing the SVM classifier before optimization of the neural network model and allowing the control system to switch evaluation pathways based on the results of the classifier. This is shown in Figure 1.

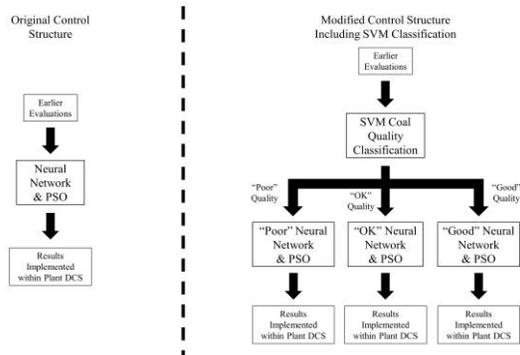


Figure 1 – Comparison of original and modified control methodologies, utilizing the SVM classifier

From the 5-fold cross-validation procedure, a wide range of accuracies are identified. The optimal configuration consists of using a radial bias kernel to transform the input data which results in an average accuracy greater than 67% on the validation set. Similar results are obtained with the isolated testing data. In practice, the modified control methodology presented above realizes improved optimizer performance of 2% - 6% (depending on unit generation level) between the comparison dataset NO_x emission levels.

Conclusion

Many existing coal-fired power plant combustion optimization systems are limited by the inability to account for coal quality fluctuations. By creating an upstream classification system using a nonlinear support vector machine to reduce variance within neural network models of the system, a 2% - 6% improvement in optimizer performance is realized in practice at an online coal-fired thermal power plant.

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