Prediction Of Boilers Emission Using Polynomial Networks

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Summary

In this paper we investigate the problem of NOx pollution using a model of furnace of an industrial boiler, and propose Functional Networks (FunNets) for high performance prediction of NOx as well as O2. The objective is to develop low cost inferential sensing techniques that would help in operating the boiler at the maximum possible efficiency while maintaining the NOx production within a specified limit. The studied boiler is 160 MW, gas fired with natural gas, water-tube boiler, having two vertically aligned burners. The boiler model is a 3D problem that involves turbulence, combustion, radiation in addition to NOx modeling. The 3D computational fluid dynamic model is developed using Fluent simulation package, where the volume of the furnace was divided into 371000 control volumes with more concentration of grids near solid walls and regions of high property gradients. The model provides calculations of the 3D temperature distribution as well as the rate of formation of the NOx pollutant, enabling a better understanding on how and where NOx are produced. The boiler was simulated under various operating conditions. The generated data is then used to train and test the developed neural network softsensors for emission prediction based on the conventional process variable measurements. The softsensors were constructed using Polynomial Networks (PolyNets), which are a special class of the recently introduced Functional Networks. PolyNets compose complex Neural Networks from simple transfer polynomials with weights that are computed efficiently by ordinary least-squares. The performance of the proposed PolyNet softsensor is evaluated in detail in the paper and compared with the traditional MLP neural networks. It is shown that PolyNets achieve better accuracy

with simpler structures, and could be trained faster than MLP NN by a factor of 6-8 times.

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