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Assessing slagging propensity of coal from their slagging indices

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ABSTRACT

Energy production by coal combustion is the most commonly used energy technology. At this time, the correlation between the existing coal slagging indices and the actual observations made in most conventional boilers is poor. Some of the conventional test results and empirical ratios frequently offer misleading information, especially, when their use is extended to other coals or blends. For better understanding of the coal properties related to slagging problems, here a multi-variable regression (MR) analysis equation to predict slagging propensity and new models based on multi-resolution wavelet neural network (MWNN) and vague sets are proposed. Coal samples collected from a wide range of Chinese power plants are evaluated. The results of predictions correlate well with the reported field performance of the coals and the new models offer better predictive capability for understanding the field slagging observations than the conventional indices. The methods proposed here provide an encouraging development towards the search for a generic technique of assessing the slagging potential of pulverized coals/blends in boilers.

1. Introduction

The combustion of pulverized coal in power stations is expected to continue to be used for electricity generation for many years to come. In pulverized coal combustion, slagging and ash deposition are a set of the serious operational problems associated with power station boilers [1]. Slagging itself affects not only the heat transfer in the boiler, but also leads to mechanical damages and failures of the water/steam cycle [2]. The general features of ash deposition in boilers are still not fully understood, but it is generally agreed that inertial impaction, thermophoresis, heterogeneous reactions and condensation are the major pathways for ash particle transport to the boiler walls [3]. Many attempts have been made to accurately predict slagging tendency in boilers [19], such as empirical indices [4,5], new indices [1,6], numerical simulation [2,3,6–9], mechanism modeling [10,11] and so on.

Traditionally, empirical indices have been used to predict coal deposition tendencies, and they are still widely used due to their easy application, in spite of their shortcomings [4]. The standard test for ash fusion temperatures (AFT) was originally devised for assessing the clinker formation of ash from lump coal in stoker boilers [1]. There are still many other conventional empirical slagging indices, such as base to acid ratio [5], iron oxide percentage [4] and silica ratio derived from the chemical analysis of coal ash [4,5]. Angela [5] and Ruhul [12] provided abundant information about definitions and practical use of many of these indices. However, it has been shown, for example, by Jenkins et al. [13] and Degereji et al. [3] that so far, there is no single slagging index that is suitable to predict the slagging tendencies for a variety of coals. The applicability of such indices is mainly restricted to the particular coals for which they were obtained, and that their success rate is very low when trying to predict the slagging behavior for new coals. As a consequence, there is a need to question research findings that predict the slagging and fouling tendencies based on some of these indices [5]. Here, we propose new models to assess the slagging propensity of coals based on some indices. The evaluation of the different approaches is invariably done by comparing predictions with experimental observations on slagging behavior.

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2. Materials and methodology

2.1. Database

Here, in order to develop a comprehensive model, a wide range of coal samples which come from 50 coal mines in China's 18 provinces [14], including anthracite, lean coal, soft coal, lignite according to GB/T5751-2009 [15], are considered. For data selection process, similarity analysis is performed. After an analysis, the potential outliers are eliminated. After this process, 157 data of coal samples are selected to use in this study. This data set is separated randomly into two subsets as 120 for training and rest for testing purposes. The statistical characteristics of all the samples are shown in Table 1.

2.2. Multi-resolution wavelet neural network (MWNN)

2.2.1. Characteristics of orthogonal wavelets

The close subspace $\{V_j\}$ ($j \in Z$, the number of closed-loop subspace) which belong to the square integrable space L^2 has these features [20]:

$$\text{consistency and monotony: } V_j \subset V_{j+1} \tag{1}$$

$$\text{gradual progress: } \bigcap_{j\in Z} V_j = \{0\}; \bigcup_{j\in Z} V_j = L^2(R) \tag{2}$$

$$f(t) \in V_j \Leftrightarrow f\left(2^j t\right) \in V_0 \tag{3}$$

$$f(t) \in V_0 \Rightarrow f(t-n) \in V_0 \tag{4}$$

there must be $\{\phi(t-n)\}$ ($\phi \in V_0$), being the orthogonal basis of V_0 (j, k$\in$Z, the number of the orthogonal basis):

$$V_j = span\left\{\phi_{j,k} \quad \phi_{j,k}(t) = 2^{\frac{j}{2}}\phi\left(2^j t - n\right)\right\}, (j,k\in Z) \tag{5}$$

$$W_j = span\left\{\psi_{j,k} \quad \psi_{j,k}(t) = 2^{\frac{j}{2}}\psi\left(2^j t - n\right)\right\}, (j,k\in Z) \tag{6}$$

$\phi(x)$ and $\Psi(x)$ have the relationship:

$$\phi(x) = \sum_k h_k \phi(2x-k) \tag{7}$$

$$\psi(x) = \sum_k g_k \phi(2x-k) \tag{8}$$

Table 1
The number of samples and ranges of analyses for different provinces.

Province	N	Minimum	Maximum	Mean	Std. dev	Classification of slagging tendency		
						LS	MS	SS
Anhui	8	1026[a]/67.6[b]/2.7[c]/0.2[d]	1476[a]/86.4[b]/10.6[c]/0.4[d]	1363[a]/77.3[b]/4.5[c]/0.3[d]	164.4[a]/6.6[b]/2.5[c]/0.1[d]	3	2	3
Beijing	7	1070[a]/52.8[b]/1.5[c]/0.1[d]	1500[a]/91.5[b]/3.2[c]/0.7[d]	1306[a]/74.3[b]/2.3[c]/0.3[d]	183.8[a]/13.0[b]/0.7[c]/0.2[d]	3	1	3
Fujian	8	1190[a]/73.0[b]/1.4[c]/0.1[d]	1500[a]/86.7[b]/2.9[c]/0.3[d]	1346[a]/79.1[b]/2.2[c]/0.2[d]	111.1[a]/4.5[b]/0.6[c]/0.1[d]	3	3	2
Guizhou	10	1130[a]/19.9[b]/1.1[c]/0.1[d]	1500[a]/91.9[b]/3.4[c]/3.0[d]	1333[a]/64.7[b]/2.1[c]/0.9[d]	151.1[a]/27.5[b]/0.8[c]/1.2[d]	4	1	5
Hebei	6	1115[a]/60.3[b]/1.1[c]/0.1[d]	1500[a]/83.2[b]/6.9[c]/0.4[d]	1328[a]/72.2[b]/2.5[c]/0.3[d]	147.4[a]/8.5[b]/2.3[c]/0.1[d]	2	2	2
Henan	10	1210[a]/62.2[b]/1.1[c]/0.1[d]	1500[a]/93.3[b]/2.8[c]/0.4[d]	1379[a]/77.7[b]/1.8[c]/0.2[d]	116.5[a]/10.4[b]/0.6[c]/0.1[d]	4	5	1
Heilongjiang	2	1320[a]/67.5[b]/1.5[c]/0.2[d]	1460[a]/80.8[b]/1.6[c]/0.3[d]	1390[a]/74.2[b]/1.5[c]/0.2[d]	99.0[a]/9.4[b]/0.1[c]/0.1[d]	1	1	0
Hubei	9	1150[a]/47.3[b]/1.1[c]/0.2[d]	1370[a]/79.7[b]/2.9[c]/0.9[d]	1226[a]/61.9[b]/2.1[c]/0.5[d]	65.2[a]/12.2[b]/0.7[c]/0.2[d]	1	3	5
Jilin	13	1130[a]/29.1[b]/1.1[c]/0.1[d]	1500[a]/91.3[b]/2.5[c]/1.3[d]	1375[a]/72.8[b]/1.6[c]/0.5[d]	132.4[a]/15.6[b]/0.5[c]/0.3[d]	7	4	2
Jiangsu	8	1170[a]/83.3[b]/1.9[c]/0.1[d]	1450[a]/90.2[b]/3.3[c]/0.6[d]	1349[a]/82.1[b]/2.5[c]/0.2[d]	86.5[a]/10.8[b]/0.3[c]/0.2[d]	4	3	1
Jiangxi	9	1245[a]/22.9[b]/0.8[c]/0.1[d]	1480[a]/93.5[b]/3.8[c]/1.8[d]	1334[a]/58.0[b]/2.4[c]/0.8[d]	69.4[a]/30.8[b]/1.2[c]/0.7[d]	1	3	5
Ningxia	7	1270[a]/20.3[b]/1.3[c]/0.2[d]	1340[a]/80.9[b]/2.8[c]/2.5[d]	1296[a]/41.5[b]/1.7[c]/1.4[d]	23.2[a]/22.9[b]/0.5[c]/0.9[d]	0	2	5
Qinghai	8	1100[a]/62.5[b]/1.2[c]/0.2[d]	1385[a]/80.3[b]/11.0[c]/0.5[d]	1224[a]/70.1[b]/3.9[c]/0.3[d]	107.3[a]/7.0[b]/3.1[c]/0.1[d]	1	1	6
Yunnan	9	1120[a]/67.4[b]/1.1[c]/0.1[d]	1500[a]/86.8[b]/3.3[c]/0.4[d]	1386[a]/81.3[b]/2.0[c]/0.2[d]	150.3[a]/6.1[b]/0.7[c]/0.1[d]	6	3	0
Chongqing	12	1020[a]/61.0[b]/1.2[c]/0.1[d]	1500[a]/86.0[b]/3.5[c]/0.5[d]	1323[a]/78.4[b]/2.4[c]/0.2[d]	143.9[a]/8.7[b]/0.9[c]/0.1[d]	5	4	3
Shanxi	10	1040[a]/19.6[b]/1.1[c]/0.1[d]	1580[a]/84.4[b]/9.4[c]/1.8[d]	1303[a]/65.7[b]/3.2[c]/0.4[d]	180.7[a]/23.5[b]/2.4[c]/0.5[d]	4	2	4
Xinjiang	10	1270[a]/53.2[b]/1.0[c]/0.1[d]	1700[a]/91.4[b]/1.7[c]/0.5[d]	1443[a]/73.3[b]/1.3[c]/0.2[d]	135.4[a]/12.1[b]/0.2[c]/0.1[d]	5	3	2
Guangxi	11	1100[a]/32.2[b]/1.4[c]/0.1[d]	1500[a]/87.0[b]/8.1[c]/1.4[d]	1288[a]/73.2[b]/3.0[c]/0.4[d]	136.5[a]/17.1[b]/1.8[c]/0.4[d]	4	1	6

[a] Softening temperature (ST).
[b] Silica ratio (SR).
[c] Silica to alumina ratio (SAR).
[d] Basic to acid oxides ratio (BAOR); LS – Low slagging, MS – Medium slagging, SS – Severe slagging.

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