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Fundamental evaluation of petrographic effects on coal grindability by seasonal autoregressive integrated moving average (SARIMA)

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ABSTRACT

A series of coal Hardgrove grindability index (HGI) tests were performed to determine each iteration's content of the monomacerite microlithotypes vitrite (Vt) and inertite (In), the bimacerite microlithotypes clarite (Cl) and durite (Du), and the trimacerite microlithotypes duroclarite (Dc) and clarodurite (Cd). In HGI tests, larger particles are broken in grinding, the resulting daughter particles can be composed of different microlithotypes than the parent particle. Therefore, predicting the overall composition of the later iterations is complicated. A time series of the compositions values was constructed by sequencing the contents of all iteration (in different mesh sizes) by the order of iterations. Seasonal autoregressive integrated moving average (SARIMA), a widely used method of time series analysis, was employed for forecasting the final iteration's content of Vt, In, Cl, Du, Dc, and Cd. The proposed methodology was able to forecast the last iteration's composition, comparable to the actual observation.

1. Introduction

The Hardgrove grindability index (HGI), a commonly used coal quality parameter, is fundamentally a function of the inorganic and organic portions of the coal (coal type) and the degree of metamorphism (coal rank) (Hower and Wild, 1988; Hower, 1998). With respect to the coal petrology, while macerals are the basic microscopic entities in coal (Hower and Wild, 1988), microlithotypes, which are the microscopic associations of macerals and minerals, control the behavior of coal in grinding and pulverization (Hower et al., 1987; Hower and Wild, 1994; Hower and Calder, 1997; Hower, 1998; Trimble and Hower, 2000; Hower and Wagner, 2012; Hansen and Hower, 2014; Hower, 2008). The maceral composition of the individual microlithotypes further influences the behavior of coal in grinding (Hansen and Hower, 2014). Attempts have been made to investigate the effects of different parameters such as elemental analysis, mineral matter, and moisture on HGI. For example, Ural and Akiylidz (2004) investigated the relation between HGI and mineral matter for low rank Turkish coal. Vuthaluru et al. (2003) studied the effects of moisture and coal blending on Hardgrove Grindability Index (HGI) for Collie coal of Western Australia. Jorjani et al. (2008) investigated the effect of macerals, ash oxides, and moisture on HGI of Kentucky coals. Several researchers examined the predictability of HGI, based on petrography and other coal quality parameters, by neural networks (Bagherieh et al., 2008; Chelgani et al., 2008; Modarres et al., 2009).

Trimble and Hower (2000) staged progressive grindability tests on coal sample KCER-92563, the raw Central Appalachian-source feed coal at a Kentucky utility power plant. Their initial test procedure was based on the Hardgrove grindability index procedures but deviated from the procedure in their subsequent runs. For their "fines-removed" path, the <74 μm (200-mesh) coal was removed from the test fraction. In other words, instead of a 50-g 16- × 30-mesh (1.19 mm × 0.595 mm) test fraction as used in the original test, the subsequent tests used the >74 μm (>200-mesh) fraction from the previous iteration. Up to 13 iterations of the modified HGI test were performed. In their "fines retained" path, the <74 μm (<200-mesh) coal was kept in the test fraction. Neither path exactly follows typical industrial-scale pulverization procedures since, although fines are removed continuously in the ball mill at the power plant, some <74 μm (the <200-mesh) coal is going to be present in mill.

In this study, we are using autoregressive integrated moving average (ARIMA) in the evaluation of the fines-removed portion of the Trimble and Hower (2000) experiments, with particular attention to the amount of microlithotypes in the fractions. This is the first time

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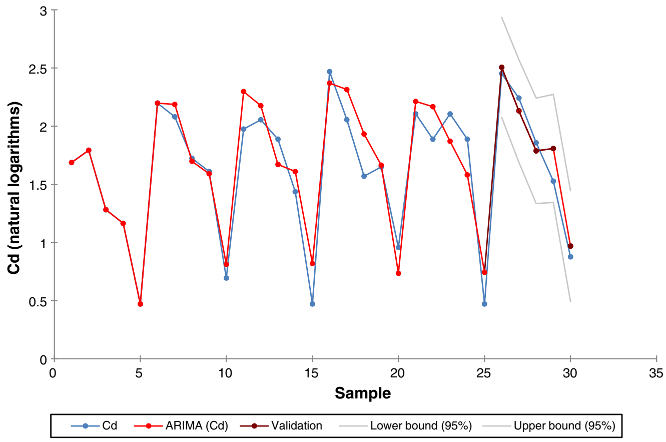

Fig. 1. Variation of actual Cd contents for all iterations vs. model estimation.

ARIMA has been used for predicting grindability of coals. To the best of our knowledge this the first time that the monomacerite, bimacerite, and trimacerite microlithotypes content of HGI tests are modeled. Other researchers have examined coal grindability based on coal petrography (Modarres et al., 2009), metamorphism (Yusupov and Burdukov, 2013), and coal hardness (Tiryaki, 2005). However, the problem of modeling the microlithotype content of ground coal in a series of HGI test is not addressed in the literature. Researchers have employed a range of soft computing methods such as artificial neural networks, and statistical methods such as multiple regressions in the closely related areas (see e.g., Chelgani et al., 2008 and Peisheng et al., 2005). However, this problem cannot be addressed by employing multiple regression analysis because in this case there is only one dependent variable (i.e., the microlithotype content). Also, artificial neural networks have the major limitation of addressing the problem in the form of a “black box” solution. On the other hand, the proposed time series model is based on rigorous statistical theories, and renders a functional relationship instead of a black-box solution.

2. Methods

Autoregressive integrated moving average (ARIMA) models, developed by Box and Jenkins (Box et al., 2008), provide a robust approach to time series forecasting. ARIMA models are used to describe autocorrelations that exist within the data (Hyndman and Athanasopoulos, 2013). This technique is, essentially, a data-oriented approach that is adapted from the data structure. Forecasting is based on a linear combination of past observations that need a stationary series without any specific trend in the data (Pai and Lin, 2005). The future value of a variable in an ARIMA model is supposed to be a linear combination of the past values and past errors, expressed as follows:

$$\begin{aligned} y_t = {} & \vartheta_0 + \varphi_1 y_{t-1} + \varphi_2 y_{t-2} + \cdots + \varphi_p y_{t-p} \\ & + \varepsilon_t - \vartheta_1 \varepsilon_{t-1} - \vartheta_2 \varepsilon_{t-2} - \cdots - \vartheta_q \varepsilon_{t-q} \end{aligned} \tag{1}$$

where y_t is the actual value, ε_t is the random error at time t, φ_i and ϑ_j are the coefficients, and p and q are integers that are often referred to as autoregressive and moving average polynomials, respectively (Box et al., 2008).

A central feature in the development of time series models is an assumption of some form of statistical equilibrium (Hyndman and Athanasopoulos, 2013). A particular assumption of this kind is that of stationarity (Pai and Lin, 2005). A stationary time series can be usefully described by its mean, variance, and autocorrelation function (ACF) (Box et al., 2008). The internal correlation of the observations in a time series is usually expressed as a function of the time lag between observations. The autocorrelation at lag k, $\gamma(k)$, is defined as:

$$\gamma(k) = \frac{E(X_t-\mu)(X_{t+k}-\mu)}{E(X_t-\mu)^2} \tag{2}$$

where $X_t, t = 0, \pm 1, \pm 2, \ldots$ represents the values of the series, μ is the mean of the series, and E is the expected value. A plot of the autocorrelation's sample values against the lag is known as the autocorrelation function (or correlogram). The correlogram is a basic tool in the analysis of time series, particularly, for indicating possibly suitable models (Everitt, 2002). Partial autocorrelations (PACF) measure the degree of association between various lags when the effects of other lags are eliminated. Both ACF and PACF are primary graphical tools that are used to inspect a time series. They are also used to determine the order of autoregressive and moving average components (Box et al., 2008). ACF and PACF were used in this study to identify a class of candidate models. The Akaike Information Criterion (AIC) (Akaike, 1974), with minimum value, was used to select the optimal model among the candidate ones that were examined in the previous step (Dindarloo et al., 2015).

The application of differencing is often used to transfer data into a stationary series. One or two orders of differencing are typically enough to prepare data for the method. The combined autoregressive-moving average model in this case [i.e. ARMA(p,q)] is referred to as ARIMA(p,d,q), in which parameter d is the differencing order. The application of ARIMA in seasonal data needs further differencing in the seasonal portion. In this case, the model is

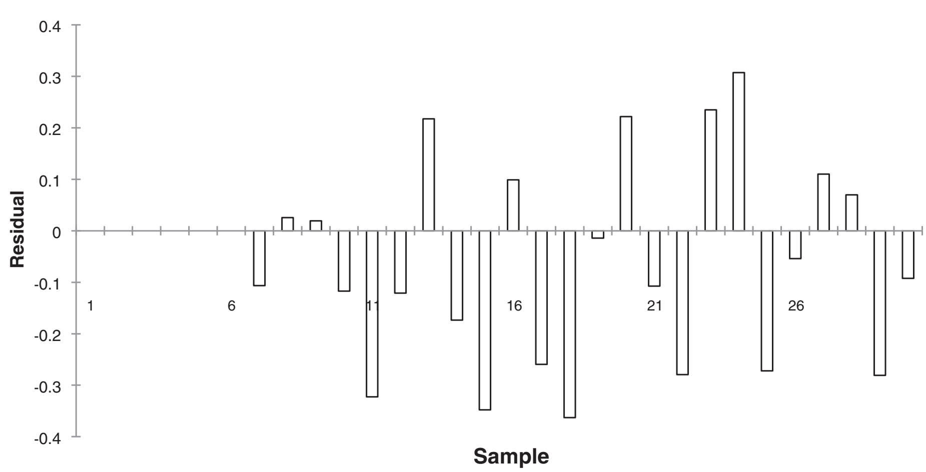

Fig. 2. Cd model's residuals.