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Research article

Estimation of coal moisture content in convective drying process using ANFIS

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In this study, a new methodology was applied to estimate the coal moisture content during the drying process. Adaptive-network-based fuzzy inference system (ANFIS) was applied to predict the coal moisture content at any time during the drying process. The experiments were carried out for different drying air temperatures (70, 100, 130 and 160 °C), drying air velocities (0.4, 0.7 and 1.1 m/s), bed heights (80, 130 and 150 mm) and sample sizes (20, 35 and 50 mm), and the experimental results were used to validate applicability of the ANFIS in the coal drying process. The ANFIS network achieves quite satisfying scientific results with acceptable deviations. The MSE and R^2 values were calculated as 1.899 and 0.998, respectively, for the testing stage. The results of this study show the applicability of the ANFIS in the coal drying processes to predict the coal moisture content at any time. Therefore, it is not necessary to carry out all the experiments: by using the ANFIS, the drying curves of some other cases which are not performed can be estimated easily. Herewith, the necessary number of the experiments decreases.

1. Introduction

Coal is a very important source of energy for the world. Low rank coals (LRCs) are very substantial for the power plants, and the liquefaction and gasification processes [1]. The LRCs are known as having moisture content of up to 65% [1]. The moisture in the LRC causes lots of problems in transportation, handling, burning, storage and milling processes [1–2]. Therefore, efficient utilization of the LRCs depends on their moisture level. A new techno-economic model was proposed to specify the necessary critical cost point for coal fired power plants [3].

The LRCs should be dried to reduce the energy losses and the transportation costs, and to raise the quality of the LRCs [4–5]. The dried LRCs can be used efficiently in any process. There are some important attempts to review the coal drying literature [6–12].

The design of a suitable dryer mostly depends on the drying kinetics, and the drying kinetics of a product is determined by the experimental works [13]. However, all the drying conditions can't be analyzed experimentally due to high cost and long experiment time [13].

Drying models have been developed to estimate moisture level in any time and drying condition during coal drying process. Thin-layer drying models are one of the most popular one adopted to many organic and inorganic materials. Thin-layer drying models estimate the curve of moisture level and time. Thin-layer drying models have been applied in a few coal drying processes [13–17].

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Artificial neural networks (ANNs) have been used in many different processes and cases. There are lots of studies in the literature, which are on using of the ANNs for estimation. Razani et al.applied fuzzy inference system (FIS) for predicting roof fall rate by using 109 data from US coal mines [18]. Their proposed model utilizes subtractive clustering method and their dataset is evaluated with three indices such as coefficient of determination (R^2), mean absolute error (MAE), and root mean square error (RMSE). Abkhoshk et al. studied the effect of particle size on the flotation kinetics of coal in a batch flotation cell [19]. A multi input/single output (MISO) fuzzy model is applied with two input variables and one output variable. The performance of the proposed method is evaluated by correlation coefficient values of proposed fuzzy model.

Tutmez compared fuzzy and regression modeling for estimating calorific value of lignite [20]. Data driven models are used with linguistic fuzzy modeling structures. Sadighi et al.used kinetic base model and neuro-fuzzy logic model to simulate behavior of a reactor. They emphasize that neuro-fuzzy logic model gives more accurate estimations [21]. Jumah and Mujumdar studied the application of a hybrid neuro-fuzzy system called adaptive-network-based fuzzy inference system (ANFIS) to time dependent drying processes in a spouted bed [22]. Their proposed model is given satisfactory performance.

Basarir et al. proposed an adaptive neuro-fuzzy inference system and multiple regression model to predict the penetration rate of diamond drilling [23]. They emphasized that the proposed adaptive neuro-fuzzy inference model has shown better performance with more accurate predictions. Akkaya studied heating value predictions of low rank coals by using multi output neural network model [24]. The proposed network model has used a back-propagation learning algorithm and based on feed forward configuration. For high prediction performance, eight different back propagation algorithms are tested.

Aydın et al. developed an approach for forecasting of both cutting zone temperature and surface roughness by integrating neuro-fuzzy inference system with particle swarm optimization learning [25]. The ANFIS architecture consists of 12 fuzzy rules, three inputs and two outputs. Gaussian membership function is used to train the process. Azadeh et al. aimed to apply a predictive control of a drying process by using both neuro-fuzzy inference system and artificial neural network [26]. It is desired to predict the granule particle size in this study. The ANFIS architecture has Gaussian combination and Gaussian bell-shaped membership function, three inputs and one output.

Galetakis et al. used fuzzy inference system to estimate the exploitable reserves of a specified area in Greece [27]. Five inputs, one output, 13 fuzzy rules and Gaussian membership functions are used to construct the FIS. Khorami et al. aimed to predict of Free Swelling Index of coal according to the proximate and ultimate analysis, group-macerals, mineral matter and vitrinite maximum reflectance of coal [28]. The ANFIS architecture has three input sets (total 15 input parameters), one output, eight fuzzy rules and Gaussian membership function are used in the study.

Farkas aimed to determine optimal topology and parameters for drying problem under uncertainties and difficulties [29]. The result of this study is that a properly selected ANN structure can be used to measure the moisture distribution in a fixed-bed dryer. Tutmez and Dag predicted reserve estimation parameters for lignite thickness by using fuzzy approach [30]. The FIS has two inputs, one output, Gaussian membership function and seven fuzzy rules are used.

Liu et al. dealt with optimizing the neural network topology in order to forecast the moisture of grain in drying process by using genetic algorithm [31]. Balbay et al. investigated the accurate influence of different air temperatures and air velocities to drying on a newly designed fixed-bed drying system by using the ANN [32].

ANN/ANFIS is a method that can be applied for estimation in distinct fields. The coal drying experiments are very difficult and expensive to repeat. There are numerous attempts to model drying process and to predict moisture level at any time and case by using ANN/ANFIS. ANN/ANFIS has high accuracy and is easy to use.

ANFIS has the ability to represent uncertainties of drying process with linguistic variables and easy interpretation of the result because of the natural rules representation. Therefore, ANFIS presents a more suitable structure to predict coal moisture content, and it may be a convenient and well alternative for thin-layer drying models.

However, the ANFIS has not been used to estimate the coal moisture content during drying process, as far as we know. In this study, the ANFIS is used to estimate moisture level in any time and experimental condition. Different drying parameters (drying air temperature, drying air velocity, bed height and sample sizes) were investigated by the experimental works. The main aim of this study is to show applicability of the ANFIS in coal drying processes. ANFIS in the coal drying processes provides to predict the coal moisture content easily at any time and the necessary number of the experiments decreases.

2. Method and materials

In this section, data about lignite used in the experiments, the experimental set-up and methodology are presented.

2.1. Experimental works

The proximate analysis and heating values of Konya–Ilgın lignite used in experimental works are shown in Table 1. The schematic diagram of the fixed-bed dryer is shown in Fig. 1. Details of the experimental set-up and the experimental procedure can be found in the references [33–36].

Table 1
Data for Konya–Ilgın lignite (original (wet) basis) [33–36].

Total moisture	%	52.42
Ash	%	8.79
Volatile matter	%	21.20
Fixed carbon	%	17.59
Lower heating value	kcal/kg	2144
Higher heating value	kcal/kg	2561

As can be seen, Konya–Ilgın lignite is a LRC with a very low heating value and high moisture content. A suitable drying process should be designed for Konya–Ilgın lignite to utilize it efficiently. The first objective of the experimental works is to understand the effects of different parameters on the drying process. The second aim of the experimental works is to describe the drying characteristics. For these aims, the drying experiments were carried out at different conditions. As a result of the experimental works, an appropriate drying process for Konya–Ilgın lignite can be designed.

2.2. ANFIS

Adaptive neuro-fuzzy inference system is a type of artificial neural network that is based on Takagi–Sugeno fuzzy and it uses a hybrid learning algorithm. The ANFIS has five layers which can be called inputs, if part, rules and normalization, then part and output. It is assumed that the fuzzy inference system has two inputs a and b and one output t when the rule base contains two fuzzy if-then rules of Takagi–Sugeno type and p, q and k are consequent parameters in Eqs. (1) and (2) [37].

$$\textit{Rule } 1: \textit{If } a \textit{ is } A_1 \text{ and b is } B_1, \text{then } f_1 = p_1 a + q_1 b + k_1 \quad (1)$$

$$\textit{Rule } 2: \textit{If } a \textit{ is } A_2 \text{ and b is } B_2, \text{then } f_2 = p_2 a + q_2 b + k_2 \quad (2)$$

Layer 1: required values such as membership functions for each ith node are defined in this layer that is shown in Eq. (3).

$$O_i^1 = \mu_{A_i}(a) \quad (3)$$

O_i^1 is the membership function of A_i and A_i represents the linguistic label (hot, warm, etc.) related with this node [37]. Mostly, bell-shaped function is chosen and other sigmoidal functions have rarely been used to describe the fuzzy membership functions.

Layer 2: each rule is a node in the ANFIS by using soft-min or product to determine the rule matching factor w_i. The incoming signals in Eq. (4) are multiplied in this layer and sent the product out.

$$w_i = \mu_{A_i}(a) \times \mu_{B_i}(b), \quad i = 1, 2 \quad (4)$$

Layer 3: each w_i is scaled into w_i in this layer. The ratio of the ith rule's weight to the sum of all rule's firing strength can be calculated as follows in Eq. (5):

$$\overline{w}_i = \frac{w_i}{w_1 + w_2}, \quad i = 1, 2 \quad (5)$$

Layer 4: each w_i sclaed with regard to the result of linear regression f_i in this function layer and finally output rule is generated in Eq. (6).

$$O^4 = \sum_i \overline{w}_i f_i \quad i = 1, 2 \quad (6)$$

Layer 5: each rule output is added to the output layer. Overall output can be calculated in Eq. (7) as follows:

$$O_i^5 = \sum_i \overline{w}_i f_i = \frac{\Sigma_i w_i f_i}{\Sigma_i w_i} \quad (7)$$