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Full Length Article

Application of artificial neural networks and response surface methodology approaches for the prediction of oil agglomeration process

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ABSTRACT

Oil agglomeration can be a promising technique to recover fines and ultra-fines coal particles from the discarded tailing generated from coal preparation plants. In the present study, an artificial neural network (ANN) and response surface methodology (RSM) was used to predict the behavior of coal oil agglomeration in terms of % ash rejection (% AR) and % combustible matter recovery (% CMR). A three layered Feed Forward Neural Network was developed by varying process variables such as solid concentration (SC), oil dosage (OD) and agglomeration time (AT). Waste soybean oil was used as bridging liquid. An approach of Multilayer Forward Back Propagation Neural Network has been used in conjugation with the hyperbolic tangent sigmoid (tansig) as transfer function. The network is well trained (learning) with Levenberg-Marquardt (LM) algorithm. For further improvement in the generalization of the developed ANN model Bayesian regularization technique has been adopted. Sensitivity analysis was performed using Garson's algorithm, Pearson correlation coefficient and Connection weight approach. The % CMR values predicted from ANN have been in good agreement with the obtained experimental values (R^2 0.9965) and shows better correlation between predicted and observed values than RSM (R^2 0.9892). Also, for % AR the correlation (R^2 0.9965) obtained using ANN found to be higher than RSM (R^2 0.9956).

1. Introduction

The low reserves of good quality coal, modern mining methods and use of highly mechanized equipments has led to the mining of inferior quality coal, which has ultimately route to the generation of more fines and ultra-fine coal particles [1–3]. The steps involved in coal beneficiation process are also the cause of increment in the production of coal fines and ultra-fines. In fine coal particles, the oxidation caused by weathering during coal mine site, transportation and storage results in the formation of a number of sites which reduces hydrophobicity of coal because of hydrogen binds with water molecules [4,5]. The finer the coal particles, less efficient and costlier will be the conventional method of coal cleaning. Conventional methods such as jigging, cyclones, dense media separation, and spiral concentrator are less effective for fine particles. Froth flotation is widely used for particle below 500 µm, but has the drawback that its efficiency drastically reduced for recovery of coal particles below 75 µm, coal with high clay content, oxidized and low-rank coal, under these circumstances, oil agglomeration has proven to be efficient with high recovery, cleaner product and easy dewatering [6–8].

Oil agglomeration is a size enlargement, a surface phenomenon based process in which intense mixing of oil and slurry of fine coal is done. The oil selectively adheres to the carbonaceous surfaces and acts as a bridging liquid to gather other oil-coated coal particles and form into an agglomerate of larger size. The size of the agglomerates increases with time and the difference in surface hydrophobicity causes the oil to agglomerate preferentially the hydrophobic combustible coal material, thus enabling separation of the organic carbon portion from the hydrophilic inorganic mineral matter [9–11]. The capillary forces within the bridging liquid are the reason for the bond strength between particles, when particles come in contact to each other. Thus, with reduction in particle size, surface area available for adsorbed oil coated particle will increase, which leads to the formation of stronger agglomerates [12].

There are several parameters which affect the oil agglomeration process such as coal rank, solid concentration, oil dosage, agglomeration time, pH, particle size, agitation speed, conditioning time, angle of contact, wetting characteristics, interfacial surface tension, ionic-strength, pretreatment methods (bacterial/microwave/ultrasonic), presence of salts, oil type, amount of washing water, temperature,

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recovery sieves etc. [2,3,7–9,13–23].

It can be difficult and time taking to analyze any process by using conventional univariate (one-factor-at-a-time) approach. Also, the study of main and interactional effect of variables is difficult and incomplete using univariate approach. Thus, to overcome this problem various researchers have used multivariate approach using design of experiments [1,15,19]. Response surface methodology combined with artificial neural network has been applied successfully in different fields and processes [24–26]. The artificial neural network has been utilized effectively as another statistical approach with high prediction. ANN has been the noteworthy aptitude to derive significance from intricate or imprecise noisy data, and could be used to extract a pattern in nonlinear, complex and noisy data sets to detect the trends with high accuracy. Numerous advances have been made in the development of intelligent systems, some of them inspired by biological neural networks are the artificial neural network to solve a variety of problems in medical as well as engineering such as pattern recognition, estimation, prediction, optimization, fault diagnosis, control, forecasting, production, sensitivity analysis and data compression [27–36]. Response surface methodology (RSM) is a mathematical and statistical tool to study the individual and interactional effects of variables on responses and is usually fitted by a polynomial equation (quadratic, cubic or higher order functions). Box-Behnken design (BBD) was chosen from other RSM designs due to its simplicity, feasibility, efficiency and also the minimum number of test runs than other RSM designs [37–39].

Since oil agglomeration, process has suffered a knockout in its commercialization due to the high oil costs; there is an imperative need to investigate such oils, which could bring down the process cost to the minimal. Waste oils can provide a solution to such problems and can prove a boon for this process. The growth in the food industry and production of waste vegetable oils are going hand in hand. Soybean oil being cheap and easily available in India, favors its utilization among the lower and the middle classes of family and thus, even its disposability after use has become a challenge that needs to be taken-up. Therefore, the utilization of these waste oils for recovering fines from the beneficiating plants and their quality up-gradation can be fruitful from both economic and environmental point of view.

In this study, an attempt is made to use oil agglomeration process for the beneficiation of coal fines, grounded to below 75 μm for their better improved liberation using waste soybean oil. In context of this, in the present study ANN with a feed forward back propagation neural network has been used to envisage the responses, % ash rejection (% AR) and % combustible matter recovery (% CMR), depending upon the input variables such as solid concentration (SC), oil dosage (OD), and agglomeration time (AT). The different approaches (ANN and RSM) to infer the significance of input to output parameters are also preconceived comprehensively. Models have been proposed for % AR and % CMR, based on input and output weights/variables of the designed ANN model.

2. Material and methods

2.1. Sample preparation and experimental procedure

The coal sample was collected from Jamadoba Coal Preparation plant (JCPP), Jharkhand, India. A fine coal sample of approximate 50 kg was collected from the cyclone underflow and feed to froth flotation. The particle size-by-size weight and ash distribution (air dried basis) of feed sample is given in Table 1. The samples were mixed thoroughly before riffling and coning-quartering. The sample was reduced to one-fourth (approximately 12–13 kg) by a series of riffling and coning-quartering, and to prepare a representative sample of approximately 100 g for proximate and ultimate analysis. The details of proximate and ultimate analysis are mentioned in Table 2. The sample was grounded by controlled dry grinding and sieved to obtain size fraction of −75 μm (−0.075 mm) for experiments. Samples were stored in airtight plastic bags. Waste Soybean oil was used as a bridging liquid. The specific gravity (0.893) was determined using a hydrometer. Kinematic viscosity (32.60 mm^2/s) was determined by using the Viscometer. The interfacial oil-water surface tension (9.20 mN/m) and surface tension (25.40 mN/m) was determined by using the tensiometer. All the tests were performed at Central Research Facility, IIT-ISM Dhanbad.

Table 1
Particle size distribution of feed sample.

Size (mm)	Weight %	Ash %
+0.5	3.57	37.58
−0.5 + 0.297	18.42	37.26
−0.297 + 0.212	12.61	36.05
−0.212 + 0.152	13.02	37.04
−0.152 + 0.105	12.48	35.38
−0.105 + 0.075	6.12	34.00
−0.075 + 0.053	21.32	31.43
−0.053	12.46	29.37
Total	**100.00**	**34.43**

Table 2
Characteristics of coal sample.

Proximate Analysis of coal sample	
% Moisture	2.33
% Volatile Matter	16.80
% Ash	34.43
% Fixed Carbon	46.44
Ultimate Analysis of coal sample	
% Carbon	59.18
% Hydrogen	2.08
% Nitrogen	1.79
% Sulphur	0.71
% Oxygen + % Ash	36.24

Several trial runs were conducted at different levels for each process variable. From the preliminary test runs, it was found that the increasing solid concentration beyond 10% solid concentration, the response of oil agglomeration were not satisfactory or encouraging. Similarly, levels for each process variable used in the present were set to obtain maximize ash rejection and combustible matter recovery. Thus, the levels were selected at equidistant for each variable. Experiments were performed in a rectangular cell equipped with detachable baffles placed above approx. 10 mm from the bottom. An agitair flotation cell (Galigher, Model LA-500) was used for the experiments without air addition. Aqueous slurries of coal fines of −75 μm, of solid concentration (SC) 3%, 6%, 9% (%w/w of coal-water mixture) were prepared respectively. For each oil agglomeration test, 1000 ml of freshly prepared slurry using tap water was poured into an agglomerating vessel of 1.5 L capacity. The bridging oil (5, 10 and 15%, %w/w of coal) was used in the experiments to analyze the effect of the waste soybean oil at different oil dosage, solid concentration and agglomeration time (5, 10, 15, 20 min). The experiments were performed at ambient pH of the mixture. The experiments were carried out at an impeller speed of 800 RPM and conditioning time of 3 min, and were kept constant throughout the experiments for better wettability of coal particles. For conditioning, pre-determined oil dosages were added and mixing was done with varying agglomeration time of 5, 10, 15 and 20 min respectively. The agglomerates formed were washed, and recovered by wet screening over a series of sieves (0.150 mm > 0.105 mm > 0.075 mm) to recover agglomerates from suspension of water and mineral matters. Agglomerates were further washed using equal amount of water for each test run to remove mineral matter adhering to the surface of agglomerates and then with ethanol/acetone (20 ml/g of feed) to ensure removal of oil and dried at 60–65 °C until constant weight was attained. The dried agglomerates were weighed,