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Prediction of thermal conductivity of underground tar-rich coal seam based on support vector machine

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ABSTRACT

The in-situ pyrolysis conversion of coal for extracting the tar is carried out to decrease the solid waste, reduce environmental pollution, and ensure energy safety. However, thermal conductivity, the most key thermal parameter, is quite indistinct for underground tar-rich coal seam under actual conditions. To obtain the thermal conductivity of underground tar-rich coal seam under actual conditions, the non-linear regression algorithm model of support vector machine was constructed. The results show that the training model demonstrates favorable generalization ability for predicting in-situ thermal conductivity of tar-rich coal seam. Moreover, the trained model subsequently predicts thermal conductivity of underground tar-rich coal seam with positive matching and reliability in the testing sets. The predicted study may promote further elucidation of the thermal conductivity evolution during the in-situ pyrolysis of tar-rich coal seam.

Keywords: tar-rich coal seam, in-situ pyrolysis, thermal conductivity, support vector machine.

1. INTRODUCTION

Tar-rich coal, a kind of coal-based oil and gas resources, is widely distributed in western China. Previous studies have demonstrated that the pyrolysis of one ton of tar-rich coal yields approximately 10% tar and 500 m^3 of combustible gas, as well as semi-coke that can replace anthracite and coke[1]. Obtained the tar content of 10%, potential oil resources extracted from tar-rich coal seam is of great significance to ensure energy security strategy of China. However, Conventional coal-to-liquid (CTL) approach is considered to have a number of distinct disadvantages[1]. To decrease the solid waste in the process of tar-rich coal mining and conversion, reduce environmental pollution, and prevent hazardous mining accidents in coal mines, the in-situ pyrolysis conversion of coal was carried out. The in-situ pyrolysis conversion of tar-rich coal seam is that underground tar-rich coal seam is heated and then converted into liquid organic matter, while the pyrolyzed semi-coke of tar-rich coal is still left underground. Therefore, thermal conductivity is one of the most desirable thermal properties of underground tar-rich coal seam that governs heat transfer.

In general, thermal conductivity of material can be gained by means of experimental test and prediction model[2-3]. Deng et al.[4] investigated the characteristics of thermal conductivity of coal versus temperature using pulverized coal. Besides, the particle size of coal was also found to have a significant effect on thermal conductivity[5]. Although thermal conductivity of coal powder has been tested by experimental means under atmospheric pressure, there are relatively few studies on the determination of thermal conductivity of underground tar-rich coal seam. Due to the requirement of sophisticated test procedures, experimental measurement of thermal conductivity of underground tar-rich coal seam becomes impractical[6]. Fortunately, prediction models about thermal conductivity of many materials were proposed[7]. In contrast to other prediction models, support vector machine exhibits a more accurate generalization performance in the presence of few dataset. Manoj[8] indicated that support vector machine model has the excellent prediction capability to predict the thermal conductivity of rocks using simple rock parameters. Cui et al.[6] demonstrated that the ternary fitting model has a higher thermal conductivity prediction accuracy for 7 types of frozen soils. In fact, thermal conductivity of underground tar-rich coal seam is influenced by numerous factors[9-10]. Conversely, many factors (density, porosity, P-wave

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velocity, and temperature, etc.) have been considered that may influence the thermal conductivity of material, but little studies have explored the pressure which plays a critical role in characterizing the actual underground state for tar-rich coal seam. Hence, it is extremely unclear for the thermal conductivity of underground tar-rich coal seam under actual conditions.

In this paper, to obtain the thermal conductivity of underground tar-rich coal seam under actual conditions, different affecting factors were discussed. Further, a variety of characteristic values that determine the thermal conductivity of underground tar-rich coal seam were put forward. The non-linear regression algorithm model of support vector machine was constructed by adopting the thermal conductivity of underground tar-rich coal as the label value. The underground condition of tar-rich coal seam could be simulated by this study, which may promote further elucidation of the thermal conductivity evolution during the in-situ pyrolysis of tar-rich coal seam.

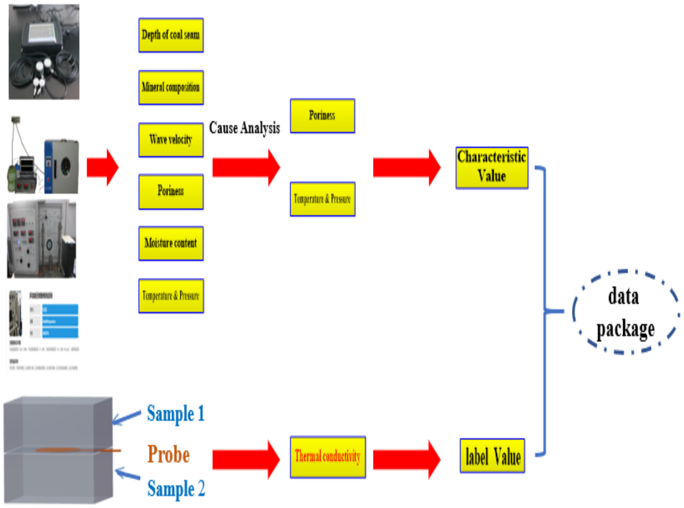
2. MODELING AND CODING ALGORITHM

When support vector machine (SVM) is employed to tackle the problems of regression estimation by the introduction of an alternative loss function, it is called as support vector regression (SVR). To get a clear look at the thermal conductivity of underground tar-rich coal seam under actual conditions, the principal component analysis method was used to research the influential factors. Pressure, temperature, and porosity were preliminarily employed as characteristic values in thermal conductivity during in-situ pyrolysis of tar-rich coal seam, and thermal conductivity was label value. The oral data was preprocessed by cross-validation to obtain the data set. Figure 1a shows the frame diagram of the data package establishment. Additionally, the LIBSVM prediction package was used in MATLAB to improve the algorithm. It was predominantly composed of data embedding and preprocessing, parameter optimization, and prediction models. Figure 1b depicts the SVR algorithm.

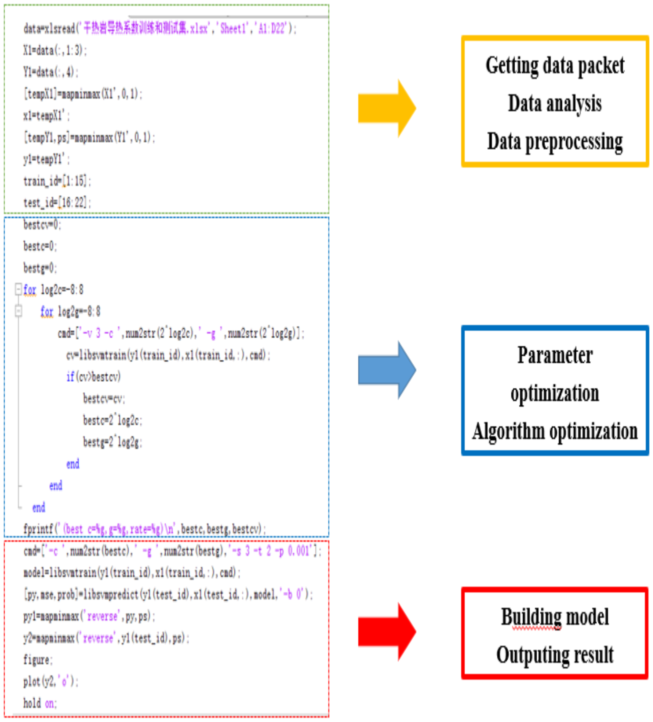
3. RESULTS AND DISCUSSION

3.1 *Training sets*

According to the algorithm steps, prediction SVR model for thermal conductivity of underground tar-rich coal is established, 30% of the data volume in the data package is used for training, and the best parameter *C* and *g* are determined in the training sets. It can be seen from Fig 2 that the actual value of the training sets has an excellent match with the predicted value, and its mean square error (*MSE*) and R^2 are also shown as 0.000 94 and 0.999, respectively. This evidences that the established support vector regression model has the outstanding generalization ability for predicting the thermal conductivity of underground tar-rich coal.



(a) data package



```
data=xlsread('干热岩导热系数训练和测试集.xlsx','Sheet1','A1:D22');
X1=data(:,1:3);
Y1=data(:,4);
[tempX1]=mapminmax(X1',0,1);
x1=tempX1';
[tempY1,ps]=mapminmax(Y1',0,1);
y1=tempY1';
train_id=[1:15];
test_id=[16:22];
bestcv=0;
bestc=0;
bestg=0;
for log2c=-8:8
    for log2g=-8:8
        cmd=['-v 3 -c ',num2str(2^log2c),' -g ',num2str(2^log2g)];
        cv=libsvmtrain(y1(train_id),x1(train_id,:),cmd);
        if(cv>bestcv)
            bestcv=cv;
            bestc=2^log2c;
            bestg=2^log2g;
        end
    end
end
fprintf('(best c=%g,g=%g,rate=%g)\n',bestc,bestg,bestcv);
cmd=['-c ',num2str(bestc),' -g ',num2str(bestg),'-s 3 -t 2 -p 0.001'];
model=libsvmtrain(y1(train_id),x1(train_id,:),cmd);
[py,mse,prob]=libsvmpredict(y1(test_id),x1(test_id,:),model,'-b 0');
py1=mapminmax('reverse',py,ps);
y2=mapminmax('reverse',y1(test_id),ps);
figure;
plot(y2,'o');
hold on;
```

(b) SVR algorithm

Fig 1 Support vector machine data package establishment framework and support vector machine nonlinear regression algorithm programming

3.2 *Testing sets*

Figure 3 indicates the results of actual and predicted values when the remaining 70% of the data package is selected as the testing sets. It can be seen from the Fig 3 that, except for the defective pixels, the actual and predicted results are still quite close. The regression trend of thermal conductivity of underground tar-rich coal seam predicted by SVR is generally consistent with the actual change trend. Hence, the SVR has a better return effect. For unknown sample data, SVR displays strong predictive ability and confirms that SVR can adapt to the learning of small sample data. In the process of using the SVR prediction model to study the thermal conductivity of underground tar-rich coal seam, the efficiency of the SVR model is very high, no matter in the training sets or the testing sets. Consequently, the SVR prediction model has good adaptability after training, and this prediction method can be further applied and popularized, which provides a new way to determine the in-situ thermal conductivity of tar-rich coal seam.

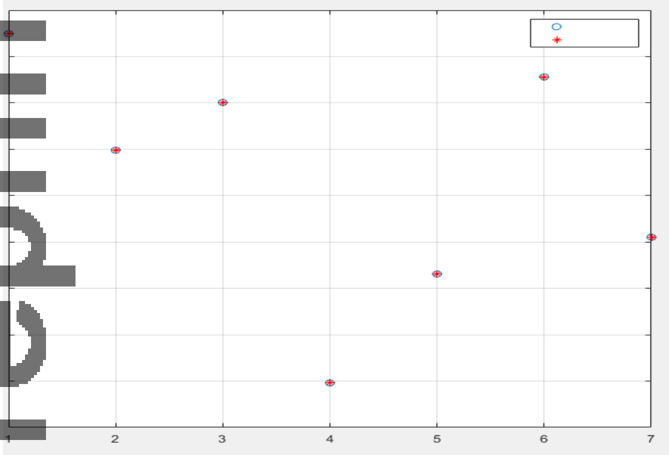


Fig 2 The results of support vector regression model training sets (* Actual value, ○ Predicted value)

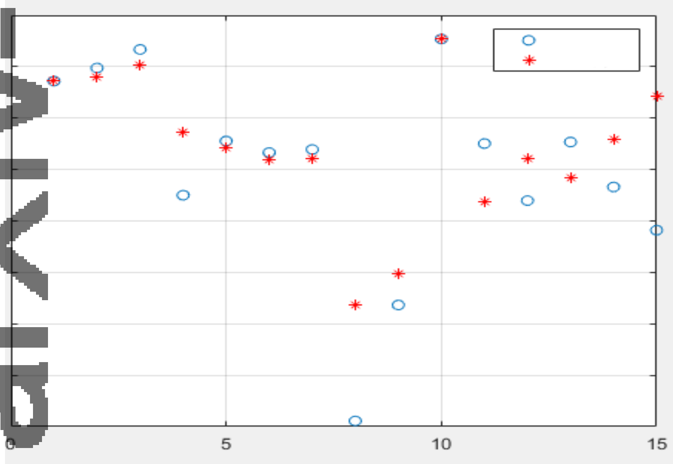


Fig 3 Predicted results of thermal conductivity of underground tar-rich coal seam (* Actual value, ○ Predicted value)

4. CONCLUSION

In this paper, three decisive factors were selected by principal component analysis as the characteristic values of the support vector machine. SVR model was then adopted to predict the thermal conductivity of underground tar-rich coal seam under actual conditions. The proposed model comprehensively considers the physical properties of underground the tar-rich coal seam. The training model obviously demonstrates the outstanding generalization ability for predicting in-situ thermal conductivity of tar-rich coal seam. Furthermore, the predicted value of the in-situ thermal conductivity of the tar-rich coal seam calculated by the SVR model is quite close to the actual measured value, and the SVR model has a high fitting accuracy. Therefore, it is convenient, fast and accurate to predict the thermal conductivity of underground tar-rich coal seam based on support vector machine.

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