Energy Consumption Analysis and Prediction of Hot Mix Asphalt

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Abstract. Hot mix asphalt (HMA) mixture is a major building material in paving engineering. To decrease energy consumption in HMA, a prediction model of energy consumption was investigated systematically in this paper, employing kernel principal component analysis (KPCA) and a support vector machine (SVM). The purpose of the work is to optimize production and structure parameters of an HMA plant. A prediction model of energy consumption cannot only be used for understanding but can also be used to develop new asphalt mixing plants and to achieve optimization. The main relationships between energy consumption and production parameters are studied in some field tests. To build a multi-parameter model of energy consumption, eigenvectors of many factors are optimized employing KPCA. The three kernel principal components of higher contribution rates are chosen. A prediction model of energy consumption is built using KPCA and SVM. Energy consumption of aggregate drying is predicted using the constructed model. The prediction model is optimized by particle swarm optimization (PSO). Influence coefficients of energy consumption are obtained by SVM and piecewise least-squares regression (PLSR) and are found to be consistent with test results. There is about a 5% error in energy consumption between the model prediction and the test. The prediction error can meet engineering requirements in the hot mix asphalt mixing plant.

1. Introduction
The rapid development of highway construction has spurred an increasing demand for hot mix asphalt (HMA) mixture [1,2]. The discharge temperature of hot mix asphalt mixture is 170°C–180°C. Therefore, the production of hot mix asphalt consumes significant amounts of energy [3,4]. Considering current Chinese asphalt production, the annual fuel consumption of a hot mix asphalt plant is equivalent to about 1.2 million tons of diesel oil [4]. Energy consumption has become an important issue for HMA [5], and it is important to reduce it. Many factors with complex interrelationships influence energy consumption in HMA. Some researchers have investigated the influence of asphalt mixture temperature on properties of materials. A prediction model of energy consumption was developed using computational fluid dynamics (CFD). However, some important factors have been neglected in the prediction model of energy consumption. Others have mainly evaluated the combustion state, conducted aerodynamic simulations and structural optimizations of burners, and performed fluid-solid coupling simulations of dry cylinders in the process of HMA. For
example, Some scholars employed multiple-source information fusion to comprehensively evaluate a swirl burner based on fire detection and flame image features [6]; Some scholars studied the flow fields of different nozzle structures for different swirl angles [7]; and Li constructed a 3D model of a drying drum to simulate the effect of structural parameters, the flow field distribution, and the heat-transfer process [8]. Some scholars studied the effects of operation parameters on energy consumption and pollutant emission in hot recycling of asphalt (HRA) [5]. Lee found that asphalt affects organic matter in flue gas emissions [9]. Coleri, E and Harvey, JT conducted a systematic statistical study of HMA [10]. Paranhos RS studied a method of measuring the pollutant emissions of an asphalt mixing plant and found that the process of road paving and the performance of the asphalt mixture strongly affect the environmental performance [11].

In this paper, the moisture content and temperature of the aggregate as flue gas temperature were measured. The eigenvectors of energy consumption in HMA were reconstructed employing KPCA. Employing a parametric model, which was constructed using an SVM and a large number of experimental data for training, the prediction model of energy consumption was developed in HMA. The results show that the proposed model can predict the energy consumption and obtain the main factors that affect energy consumption. This research provides reasonable guidance for the optimization of parameters and equipment design such that a hot mix asphalt plant will have better energy consumption. The overall research scheme is shown in Figure 1.

2. Factors impacting energy consumption

2.1 The work process of HMA

The main methods of asphalt mixing are HMA, warm mix asphalt (WMA), and cold mix asphalt (CMA). This paper focuses on the processes of HMA, which require much more energy than the other processes. The main production process of HMA is as follows. Aggregates are delivered to a drum dryer, where they will be heated to 180 degrees centigrade by burners inside the dryer. Emissions are discharged into the atmosphere through a dust bag during heating and drying, and the dust is recycled. The heated and dried aggregates are stored in an incubation silo after being sieved. Asphalt is heated by thermal cycling. With the addition of powder and other additives, heated aggregates and asphalt are delivered directly by an asphalt pump to a stirring cylinder for stirring. The maximum temperature of the asphalt mixture is controlled according to the paving temperature requirements. Energy is mainly consumed by the drying and heating of the aggregates in HMA, and large amounts of pollutants are created from the burning of residual oil. Energy consumption is affected by many factors, such as the environmental temperature, combustion airflow, production, moisture content of aggregates, the finished aggregate temperature, drum pressure, and discharge temperature.
2.2 Factors influencing energy consumption

Based on the above analysis of the HMA process, parameters of a hot mix asphalt plant producing 240 t/h were measured at the site. Air flow was controlled by a frequency converter. Heavy oil was measured by a medium oil mass flowmeter. Figure 2(a) shows the relationship between combustion air and fuel consumption. The amount of combustion air is expressed by the blower frequency of the converter. It is seen that fuel consumption gradually increases with the amount of combustion air. Fuel consumption begins to decrease when the amount of combustion air reaches a certain value, which illustrates that many factors influence the fuel consumption of the drying drum for heating and drying. Similarly, fuel consumption increases with the output of aggregate temperature. Therefore, the output temperature and fuel consumption have a proportional relationship. Appropriate airflow is important to save energy. High airflow in a burner ensures complete fuel combustion. However, excessive airflow results in significant smoke emission, taking away heat and thus decreasing thermal efficiency. Conversely, if the airflow is too low, fuel cannot be fully burned, which increases energy consumption. The designed production of the drum dryer is 240 t/h. The production of the roll dryer was changed from 200 t/h to 310 t/h while holding other operating parameters constant. Fuel consumption was measured for different values of production. Figure 2(b) shows the relationship between productivity and fuel consumption. Higher production will lead to a model that is insufficient for analyzing fuel consumption, owing to the contact of the material curtain and hot air. Lower production will lead to a wind tunnel of the material curtain and hot air leakage. The aggregate temperature was adjusted by changing the load ratio of the burner. The aggregate temperature was measured using infrared radiation thermometers. The flue gas temperature of the de-dusting system was adjusted by changing the load ratio of the burner. The flue gas temperature was measured according to the thermal resistance. Figures 2(c) and 2(d) show that the aggregate temperature and flue gas temperature directly affect fuel consumption. It is seen that fuel consumption increases with the aggregate temperature and flue gas temperature. The above analysis shows that many factors affect energy consumption in the process of asphalt mixing. To consider all these factors will add to the complexity of the prediction model for energy consumption.

![Figure 2](image-url)

**Figure 2.** Relationship between important parameters and energy consumption
3. Experiment and method

3.1. Kernel principal component analysis (KPCA)

Many factors affect energy consumption during asphalt mixing. It is difficult to build a model owing to data dimensionality, large sample requirements, and high costs of data acquisition. This paper optimizes the fuel consumption feature vector employing KPCA to reduce the dimensionality of the parametric analysis [12,13,14,15]. Principal component analysis (PCA) is a statistical method that employs a plurality of variables to select characteristic transformation parameters that are less linear [16]. Multiple nonlinear characteristics affect energy consumption. KPCA is a nonlinear extension of PCA. The assumed input space sample data are \( x_1, x_2, \ldots, x_{n_1}, x_1, x_2, \ldots, x_{n_2}, \ldots, x_1, x_2, \ldots, x_{n_n} \) and the nonlinear mapping function is \( \varphi(x) \). So, the covariance matrix of \( \varphi(x) \) is

\[
C = \frac{1}{n} \sum_{i=1}^{n} \varphi(x_i)\varphi(x_j)^T
\]

and C can be decomposed into formulas (2) and (3):

\[
\lambda V = CV \quad (2)
\]

\[
V = \sum_{i=1}^{n} \alpha_i \varphi(x_i) \quad (3)
\]

\( V \) is the feature vector of characteristic value \( \lambda \). Formula (4) can be described by formulas (1), (2), and (3):

\[
\lambda \sum_{i=1}^{n} \alpha_i \left( \varphi(x_i) \varphi(x_i) \right) = \frac{1}{n} \sum_{i=1}^{n} \alpha_i \sum_{j=1}^{n} \left( \varphi(x_i) \varphi(x_j) \right) \left( \varphi(x_j) \varphi(x_j) \right)
\]

The kernel matrix \( K \) is

\[
K = \varphi(x_i)\varphi(x_j)
\]

Formula (4) can be simplified to

\[
n\lambda \alpha = K \alpha
\]

where \( \alpha_1=(\alpha_1, \alpha_2, \ldots, \alpha_n) \) and \( \alpha=(\alpha_1, \alpha_2, \ldots, \alpha_n) \). The vector \( \alpha \) is the feature vector of kernel function \( K \), and \( \lambda \) is the characteristic value of kernel function \( K \), where \( K \) is chosen as a radial basis function (RBF) expressed as

\[
K(x,y) = \exp \left( \frac{-||x-y||^2}{2\sigma^2} \right)
\]

The parameter \( \sigma \) has a significant impact on KPCA in formula (7). Define a class \( k \) data sample \( x_{i1}, x_{i2}, \ldots, x_{im} \) \((i=1,2,\ldots,k)\) and class \( \lambda \) data sample \( \lambda_{i1}, \lambda_{i2}, \ldots, \lambda_{in} \) \((i=1,2,\ldots,k)\). A low-dimensional kernel principal component can be obtained as \( \gamma_{i1}, \gamma_{i2}, \ldots, \gamma_{in} \) \((i=1,2,\ldots,k)\). Within-class distance and between classes distance can be obtained as

\[
c_\sigma = \sum_{i=1}^{k} \sum_{j=1}^{n} \| \gamma_{ij} - \gamma_{ij} \|
\]

\[
d_\sigma = \sum_{i=1}^{k} \sum_{j=1}^{n} \| \gamma_{ij} - \gamma_{ij} \|
\]

The optimal function of \( \sigma \) is defined as
\[ F(\sigma) = \max \left( \frac{d_\sigma}{c_\sigma} \right) \]  

(10)

3.2. Support vector machine (SVM) model of energy consumption

The SVM is a new statistical learning tool for neural networks. It provides a good solution to practical problems such as those involving a small sample size, nonlinearity, or high dimensionality, owing to the improvement of generalization achieved via the risk-minimization principle. The present paper uses a least-squares SVM to model and forecast the fuel consumption of asphalt mixing equipment. This converts the problem to one of solving linear equations. The accumulative contribution rate is mainly determined by the three principal components obtained in KPCA. The first 23 samples and corresponding measured fuel consumption are treated as the training data set: \((x_i, y_i), i=1,2,\ldots,n, x_i \in \mathbb{R}, y_i \in \mathbb{R}\). A linear function with a high-dimensional feature space \((y(x) = W^T\phi + B)\) is used to fit the input sample set, where the mapping function \(\phi\) maps data from the input space to the feature space, and the nonlinear fit is converted to a linear fit. The above regression problem then transforms into a constrained optimization problem of formula (11):

\[
\min J(\omega, \xi) = \frac{1}{2} \omega^T \gamma \omega + \gamma \sum_{i=1}^{n} \xi_i^2 \\
y_i = \Phi(x_i^o \omega + b + \xi_i) i = 1, 2, 3, \ldots, n
\]  

(11)

where \(\xi_i\) is the loss function error in target optimization and \(\gamma\) is a regularization parameter. The construction of the Lagrange function simplifies the optimization calculation of formula (12), and the undetermined coefficients \(\alpha_i\) and \(b\) are obtained by the least-squares method. The nonlinear prediction model is

\[
y = \sum_{i=1}^{n} \alpha_i K(x_i, x) + b
\]  

(12)

where \(K\) is the kernel function. The radial basis function is taken as the kernel function.

4. Results and discussion

4.1. KPCA model of energy consumption

With full consideration of the main factors affecting energy consumption, an intermittent hot mix asphalt plant (productivity is 240 t/h) is analyzed to predict energy consumption. Using the flue gas temperature, airflow, productivity, drum pressure, finished aggregate temperature and water content of feed aggregate as input samples. The flue gas temperature was measured by removing the armored thermoelectric resistance. The amount of airflow was measured and adjusted by the frequency converter of the blower. Drum pressure was measured by air pressure gauge. The finished aggregate temperature was measured by Infrared temperature instrument. Energy consumption was measured by the mass flowmeter of the fuel. The finished aggregate temperature was guaranteed to be constant, and different flue gas temperatures were obtained by changing the burner load ratio. To ensure that the finished aggregate temperature was constant and the burner load ratio could be changed to obtain different productivity. The finished aggregate temperature was guaranteed to be constant, changing the power of the blower to get different drum pressure. The finished aggregate temperature was guaranteed to be constant, and different water content of feed aggregate was obtained by changing the burner load ratio. Changing burner load to obtain different finished aggregate temperature. Giving a total of 43 samples for each parameter, and a \(6 \times 43\) sample matrix. The interaction between factors leads to direct analysis is very difficult. The method of principal component analysis can not be influenced by the interaction of all factors, and it can play a role in reducing dimension. Since the parameters have different dimensions, all data are normalized to obtain the raw data for principal component analysis (PCA).
To find which kernel function is suitable for the model in the present paper, the RBF radial basis, multilayer preceptor, and polynomial kernel function are used employing KPCA separately. The RBF radial basis is expressed as formula (13).

$$K(\|x - x_c\|) = \exp\left\{-\frac{\|x - x_c\|^2}{2\sigma^2}\right\}$$

(13)

$x_c$ is kernel function center, $\sigma$ is the width of a kernel function. Cumulative contribution rates for each principal component are calculated using formula (14). The threshold of cumulative contribution rates is set to 87%; the contribution rate $\lambda_i$ for each kernel principal component is calculated using formula (1),

$$C_k = \frac{\sum_{i=1}^{k} \lambda_i}{\sum_{i=1}^{n} \lambda_i}$$

(14)

where $C_k$ is the cumulative contribution rate of the top $k$ kernel principal components. The kernel function will affect the result of the kernel principal component analysis. Cumulative contribution rates for the principal components of the various kernel functions are shown in Figure 3. The figure shows that for the multilayer preceptor kernel function (MPK), polynomial kernel function (PKF), and RBF cumulative contributions of the first three principal components are 80%, 85%, and 89%, respectively, and the RBF is thus the most suitable. The $\sigma$ in the RBF function will affect the cumulative contribution rate of the kernel principal component analysis. This paper uses the RBF for KPCA of different parameters $\sigma$. Results are shown in Figure (4). The value of $\sigma$ in formula (10) was optimized by particle swarm optimization (PSO). When $\sigma = 1.7$ or 2.1, the cumulative contribution rate of the first three principal components is 89%. After the data are reduced from six dimensions to three dimensions, the KPCA still retains many features from the original data.

![Figure 3](image_url)

**Figure 3.** Cumulative contributions of principal components for different kernel functions

![Figure 4](image_url)

**Figure 4.** Cumulative contributions of principal components for different radial basis functions
4.2. Analysis of factors influencing energy consumption

The variable $\lambda_i$ in formula (14) represents the contribution of each influence factor in kernel principal components, and the mean influence degree of every factor on energy consumption. The results of employing the characteristic value $\lambda_i$ and regression coefficient $L_i$ of least-squares regression analysis to analyze the degree of influence of all factors [17] are shown in Figure 5. The influencing factors are the combustion airflow, production, discharge temperature, drum pressure, aggregate temperature, and moisture content. When the influence factor and the energy consumption are nonlinear, there may be positive correlation and negative correlation. As shown in Figures 5(a) and (b). Figure 5(a) presents the analysis of the characteristic value $\lambda_i$ of kernel principal components. The optimal combustion airflow can save energy consumption. Greater combustion airflow results in greater heat loss, and lower combustion airflow leads to insufficient combustion. The discharge temperature has the strongest effect on energy consumption, which increases with discharge temperature because a higher exhaust discharge temperature results in greater heat loss and higher energy consumption. The drum pressure negatively influences energy consumption. A decrease in drum pressure results in negative pressure and an increase in the air leakage rate in the drying drum, which leads to a combustion excess air coefficient and heat loss increase. The drum pressure increase results in negative pressure and a decrease in the air leakage rate in the drying drum, which leads to dust leakage and a rise in the combustion chamber temperature. Production has a positive influence on energy consumption, because there is a thicker material layer on the inner wall of the drum and less energy consumption. Aggregate temperature and moisture content positively influence energy consumption. The aggregate temperature is decided by paving process requirements. Good storage can reduce aggregate moisture content and energy consumption. The analysis results for different influence factors obtained from partial least-squares linear regression are shown in Figure 5(b). Figures 5(a) and 5(b) reveal that the effect of airflow on fuel consumption differs depending on the range. When airflow is relatively high, an increase in airflow suggests higher energy consumption due to higher heat loss. However, when airflow is low, increasing the airflow suggests less energy consumption because of better combustion. Therefore, there are positive and negative effects of airflow in different ranges. Drum pressure mainly affects discharge emissions and heat exchange effect. The excessive or too small pressure of the drum will lead to the increase of energy consumption. In actual production, the pressure fluctuation of the roller should be less. The above analysis shows that the aggregate temperature has the greatest effect and airflow the least effect on fuel consumption.

![Figure 5. Analysis of influence degree of different factors in HMA](image)

4.3. Energy consumption prediction of HMA

There are three key parameters: $\xi$, $\gamma$, and $\sigma_1^2, \sigma_2^2$. The variable $\gamma$ is the regularization parameter of the SVM model, i.e., the penalty coefficient. $\sigma_1^2, \sigma_2^2$ consists of the $K(x_i, x)K(x_i, x)$ kernel parameters of
equation 4. \( \zeta \) denotes the insensitive loss parameters of the SVM model \([18,19,20]\). We see that \( \zeta, \gamma, \) and \( \sigma_1^2 \) affect the simulation results of the SVM \([21,22]\). To obtain the appropriate model parameters, a parameter optimization model of the SVM is constructed based on particle swarm optimization \([23,24,25]\). The optimal combination of parameters of the SVM model is obtained by performing a regional search many times, achieving better prediction performance of the SVM model. The parameters of the SVM model are \( \gamma=25, \sigma_1^2=0.215, \sigma_1^2=0.215 \) and \( \xi=0.021, \xi=0.021 \).

Results of measured and predicted fuel consumption with parameter optimization are shown in Figure 6. The error rate is almost within \( \pm5\% \), and the error rate of the predicted fuel consumption has been reduced appreciably. The prediction error is mainly due to changes in oil quality and other unmonitored variables. Future research must consider as many factors as possible, such as changes in the aggregate moisture content and the structure of the curtain blade. Meanwhile, a change in the operation state of asphalt mixing equipment will lead to greater fluctuations in fuel consumption. The training data are limited and cannot cover all conditions, leading inevitably to prediction error.

![Figure 6](image)

**Figure 6.** Comparison of measured and predicted fuel consumption for optimization of SVM model

5. Conclusions

The present paper has analyzed various factors affecting fuel consumption in aggregate drying, which were measured. Based on KPCA, the main features affecting energy consumption were obtained. Using the first three principal component variables, an SVM model was built to predict energy consumption. The energy consumption model was then parametrically optimized. The relationship between selected factors and energy consumption was studied employing KPCA sensitivity and partial least-squares regression. Results show that production, the temperature of the finished aggregate has the greatest influence on energy consumption. With the increase of aggregate temperature, the energy consumption is gradually increased. The flue gas temperature, production, and aggregate moisture content have a certain influence on the energy consumption, and the energy consumption increases with the increase of these factors. Drum pressure and airflow have positive or negative effects on energy consumption. The roller pressure and air flow have the best value in different production conditions. Controlled airflow and drum pressure are very important to energy savings. The difference between measured and predicted fuel consumptions was about \( \pm5\% \), which meets the required prediction accuracy. The results have important implications for hot mix asphalt mixing process in terms of energy savings.
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