A data-driven fusion model for energy consumption prediction of hot extrusion forming

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Abstract. Hot extrusion forming is widely used to process lightweight parts in automobile, aircraft manufacturing, and subway industry. However, hot extrusion forming is an energy-intensive process with high environmental emissions. Because hot extrusion forming is a complex thermal-mechanical coupling process, it is difficult to develop its energy consumption prediction model based on the process mechanism. With the increasing application of data intelligent acquisition, this paper proposed a fusion data model integrating bagging enhanced ELM (Extreme Learning Machine) and GPR (Gaussian Process Regression) using their entropy weight. The energy-related data collected by energy management system are purified using the local outlier factor (LOF) algorithm and RreliefF method. The bootstrap sampling method is used to obtain the training set and test set from the processed data. Then, the ELM and GPR are improved by the bagging algorithm for constructing the B-ELM learning model and the B-GPR learning model. Furthermore, the entropy weight method is used to further integrate the B-ELM and the B-GPR. Finally, an experiment validates the accuracy and reliability of the proposed model.

1. Introduction

From 2001 to 2019, the total aluminum consumption of China grew at a compound annual rate of 11.2 percent, much higher than the average of other countries. China's share of world aluminum consumption has increased from 14.8% in 2000 to 46.5% [1]. With the widespread application of extrusion forming technology and the worsening of global energy crisis, the energy consumption of extrusion forming process has been paid more and more attention. Life cycle assessment of extrusion process is implemented to evaluate energy consumption performance and analyzed the impact of different process parameters [2-3]. Specially, Ingarao et al. compared the energy efficiency of hot-extrusion forming and the traditional turning process for processing the same axisymmetric aluminum alloy parts [4]. Smadi et al. developed numerical methods to extract real data features from power consumption cycle [5]. Jo et al. estimated the energy consumption and CO2 emission for production of A7003 with different process variables [6]. However, there is still lack of energy consumption performance prediction approach, even though the energy prediction is the prerequisites of improving the energy efficiency of hot extrusion forming process. The existing energy prediction models can be grouped into theoretical, empirical, and data-driven models. Both theoretical and empirical modes need to simplify the process and establish feasible mathematical equations under some assumptions. Thus, the data-driven methods
are increasingly used to predict energy consumption performance of manufacturing processes. In order to accurately predict energy consumption performance, this paper proposed a fusion data model integrating bagging enhanced ELM and GPR using data from an energy management system.

2. Energy consumption characteristics of hot extrusion process

The extrusion process system consists of aluminum rod heating furnace, die heating furnace, extruder, straightening machine, cutting machine, and aging furnace. The forming process is a nonlinear thermo-mechanical coupling process, which is controlled by multi-parameters as shown in Figure 1. During extrusion process, the aluminum rod, the ingot tube and the die are heated to the preset temperature range simultaneously. Then the heated aluminum billets are forced to flow through die orifices of smaller cross-sectional area. The energy of extrusion process is used for aluminum rod heating, die heating, extrusion forming and ingot heating as shown in Figure 1. The extrusion forwarding force is used for metal deformation work and to overcome friction. During forming process, the deformation heat, friction heat, and the heat conduction of aluminum bar, die, extrusion container and extrusion spacer results in complex heat flow behavior. Finally, the microstructure and mechanical property homogeneity are impacted by energy consumption behaviour.

3. Energy consumption modeling of extrusion forming process

According to the above analysis, this paper proposed a fusion data model through integrating bagging enhanced (ELM) extreme learning machine and gaussian process regression (GPR) based on their entropy weight, as shown in Figure 2. Firstly, the data in the energy management system of extrusion process are extracted. The local outlier factor (LOF) algorithm and RReliefF method are used to remove...
the data anomalies. Then, the processed data are used to obtain the training set and test set by bootstrap sampling method. The ELM and GPR learning models are improved by the bagging algorithm for constructing the B-ELM learning model and the B-GPR learning model. Then, the entropy weight method is used to further integrate the B-ELM learning model and the B-GPR learning model.

3.1. Energy prediction using bagging extreme learning machine

In a set of \( L \) samples \( D = \{ (x_t, y_t) \} \), \( x_t \) represents the parameters affecting the energy consumption, \( y_t \) represents the real extrusion energy consumption. Through multiple rounds of bootstrap sampling, the training subset \( \{ D_1, D_2, \ldots, D_M \} \) with differences can be obtained, and the base learner \( \{ f_1, f_2, \ldots, f_M \} \) can be obtained by using these training subsets. In ELM, assuming that the dataset \( \{(x_t, y_t)\} \) contains a set of \( L \) samples, \( x_t \) represents the parameters affecting energy consumption (Machine speed, torque, and actual current), and \( y_t \) represents true extrusion energy consumption (actual power). Setting the number of hidden layers as \( k \) and the activation function as \( g(x) \), the network output can be expressed as Equation (1).

\[
y(x, b, \beta) = \sum_{i=1}^{k} \beta_i g(w_i x + b_i), j = 1, \ldots, L
\]

where \( \omega_i \) is the input weight vector of the \( i \)-th hidden layer node, and \( b_i \) is the threshold (bias) of the \( i \)-th hidden node, \( \beta_i = \{ \beta_{i1}, \beta_{i2}, \ldots, \beta_{ik} \} \) is the output weight. Then the equation of \( L \) samples can be expressed as Equation (2) and (3).

\[
H = g(w_i x + b_i) \\
B = \begin{bmatrix} \beta_{i1}^T \\ \vdots \\ \beta_{ik}^T \end{bmatrix}_{N \times m}, T = \begin{bmatrix} t_{i1}^T \\ \vdots \\ t_{iL}^T \end{bmatrix}_{N \times m}
\]

where \( H \) is the hidden layer output matrix of ELM (i.e., the predicted value of energy consumption), and \( T \) is the expected output (i.e., the real output of energy consumption). The output weights can be expressed by Equation (4).

\[
\beta = H^{-1}T
\]

When the number of hidden neurons \( K \) is far less than the number of training samples \( L \), the solution of equation (4) does not exist. Therefore, it is turned to find the solution that minimizes the cost function \( C \), as shown in Equation (5) and (6).

\[
\text{Minimize:} \frac{1}{2} \| \beta \|^2 + \frac{1}{2} \sum_{i=1}^{L} \| \xi_i \|^2
\]

subject to: \( h(x_i)\beta = t_i \), \( i = 1, \ldots, L \)

Then Equation (5) has the following solution:

\[
\beta = H^{-1}T
\]

Where, \( H^+ \) is the Moore-Penrose generalized inverse of the output matrix \( H \), referred to as the pseudo-inverse. For improving the accuracy and generalization ability of the ELM, the bagging algorithm is shown in Table1.

Table 1. The bagging algorithm of ELM and GPR

| B-ELM | B-GPR |
|-------|-------|
| Step 1: Set the number \( M \) of learning machines | Step 1: Obtaining training sample \( D = \{(x_t, y_t)\} \) \( t = 1, 2, \ldots, L, x_t \in \mathbb{R}^3, y_t \in \mathbb{R} \) \( M \) |
| Step 2: Obtaining the bootstrap samples, establishing the training sample \( \{(x_t, y_t)\} \) \( c = 1, \ldots, M \) of each ELM model, and setting \( c = 1 \) | Step 2: From the obtained samples, there are \( h \) samples that have been replaced, and the bootstrap samples are obtained. |
| Step 3: Randomly inputting initial weight \( w_i \) and threshold \( b_i \) \( i = 1, \ldots, K \), and training the ELM model using bootstrap sample. Calculating matrix \( H \) and output weight \( \beta \). Testing the accuracy of the model using the rest data set, and setting \( c = c + 1 \) | Step 3: Performing the corresponding GPR model training through the obtained bootstrap training samples, and obtaining the GPR model output value |
| Step 4: If \( c \leq M \), go back to step 3. Otherwise, the average prediction results of each test observation set are calculated as the final model output. | Step 4: Obtain the GPR energy consumption model \( f_1 \). |
| Step 5: Repeat step 2 to 4 above for \( m \) times to obtain model sets \( \{f_1, f_2, \ldots, f_m\} \) | Step 5: Repeat step 2 to 4 above for \( m \) times to obtain model sets \( \{f_1, f_2, \ldots, f_m\} \) |
| Step 6: The average of the predicted results of the observation set is used as the final model output. | Step 6: The average of the predicted results of the observation set is used as the final model output. |
3.2. Energy prediction using bagging gaussian process regression

Set \( D = \{(x_t, y_t) | t=1, 2, \ldots, L, x_t \in R^d, y_t \in R\} \) containing L squeezed samples, where \( x_t \) represents a 4-dimensional input variable, and \( y_t \) represents an output variable. Assuming that there is a hidden function \( f \), the data set forms a set of \( \{f(x_1), f(x_2) \cdots f(x_L)\} \), and it obeys the joint Gaussian distribution. Its properties are completely determined by the mean function \( \hat{y}(x_t) \) and the kernel function determine \( k(x_t, y_t) \), and the Gaussian process can be uniquely determined by the mean function and the covariance function.

**Mean value:**
\[
\hat{y}(x_t) = k(x_t)K^{-1}y
\]

**Variance:**
\[
\sigma_y^2(x_t) = k(x_t, x_t) - k(x_t)K^{-1}k(x_t)
\]

Where, \( k(x_t) = [C(x_t, x_1), C(x_t, x_2), \ldots, C(x_t, x_n)]^T \) is the covariance vector between the input of the sample to be tested and the training sample. The square exponential covariance function is selected, and the hyperparameters \( \sigma_0, \sigma_f, l \) and the kernel function are solved through Gaussian likelihood estimation. The definition of the square exponential covariance function is Equation (9).

\[
k(x_t, y_t) = \sigma_f^2 \exp \left[ -\frac{1}{2} \sum_{i=1}^{d} \left( \frac{x_{ts} - x_{ti}}{l} \right)^2 \right]
\]

\( f(x) \sim GP(\hat{y}(x_t), k(x_t, y_t)) \)

Where, \( x, x_t \in R^d \) is an arbitrary random variable and its mean function is usually set to 0 for convenience. In this paper, the energy consumption prediction is a regression problem and the noise is taken into account. In this case, the general GPR model is expressed as Equation (11).

\[
y = f(x) + \epsilon
\]

Where \( \epsilon \) is an independent Gaussian distribution with mean 0 and variance \( \delta^2 \), denoted as \( \epsilon \sim N(0, \delta^2) \). Thus, the prior distribution of the true value of extrusion energy consumption is Equation (12).

\[
Y \sim N(0, K(X, X) + \sigma^2 I_n)
\]

The joint Gaussian distribution of the observed and predicted energy consumption of training samples is Equation (13).

\[
\begin{bmatrix} y \\ y^2 \end{bmatrix} \sim N \left( \begin{bmatrix} K(X, X) + \sigma^2 I_n & K(X, x_s) \\ K(x_s, X) & k(x_s, x_s) \end{bmatrix} \right)
\]

Where \( K(X, x_s) = K(x_s, X)^T \) is the \( n \times 1 \)-order covariance matrix between the test point, and the training set input, and \( k(x_s, x_s) \) is the covariance of the test point. Then the posterior distribution of \( f_t \) can be calculated by Equation (14).

\[
y_s, y, x_s \sim N(\hat{y}, cov(y))
\]

\[
\hat{y} = K(x_s, X)(K(X, X) + \sigma^2 I_n)^{-1}y
\]

\[
cov(y) = k(x_s, x_s) - K(x_s, X) \times [K(X, X) + \sigma^2 I_n]^{-1}K(X, x_s)
\]

The output of GPR energy consumption model is predicted mean vector \( \hat{y} \), which is the predicted value of output vector. In order to improve the accuracy and generalization ability of GPR energy consumption prediction model, the bagging algorithm of GPR is shown in Table1.

3.3. Fusion of Bagging-ELM and Bagging-GPR based on entropy weight

According to the different prediction results of B-ELM and B-GPR energy consumption model, the entropy weight method is used to set different weights for the two models, and the above prediction model based on B-GPR and B-ELM are combined into a prediction model by weight. The following is the steps of entropy weight method fusion. First, according to the predicted and real values of each prediction model, the relative error of energy consumption is calculated Equation (17).

\[
e_{uq} = \begin{cases} \frac{|y_{uq} - y_q|}{\hat{y}_q}, & 0 \leq \frac{|y_{uq} - y_q|}{\hat{y}_q} \leq 1 \\ \frac{|y_{uq} - y_q|}{\hat{y}_q}, & \frac{|y_{uq} - y_q|}{\hat{y}_q} \geq 1 \end{cases}
\]

\( y_q \)
Where \( e_{uq} \) and \( y_{uq} \) represent the relative error and predicted energy consumption of the \( q \)th extrusion energy consumption observation value in the \( u \)th energy consumption model, respectively. \( \tilde{y}_q \) represents the \( q \)th observed value of extrusion energy consumption. According to Formula (17), the entropy of the \( u \)th prediction model is calculated by Equation (18).

\[
E_u = -\frac{1}{\ln N} \sum_{q=1}^{N} P_{uq} \ln P_{uq} \tag{18}
\]

\[
P_{uq} = \frac{e_{uq}}{\sum_{r=1}^{N} e_{uq}} \tag{19}
\]

Secondly, the weight of each prediction model is shown in Equation (20). Here \( u = 1, 2 \) representing the two prediction models proposed in this paper (B-ELM prediction model and B-GPR prediction model).

\[
Z_u = 1 - \frac{1 - E_u}{\sum_{u=1}^{N} (1 - E_u)} \tag{20}
\]

Finally, the comprehensive evaluation value of entropy weight of each evaluation index is determined. After multiplying the weight values of each index and their corresponding predicted values, the predicted values of the fusion model can be obtained as Equation (21).

\[
\tilde{y}_q = \sum_{u=1}^{2} Z_u y_{uq} \tag{21}
\]

4. Verification

4.1. Experiment setting
The hot extrusion forming of the 6063 aluminum alloy parts is studied in this experiment, and profile dimensions and extrusion die structure is shown in Figure 3. The welding height is 20mm, and there is a level of empty knife groove that supports the work belt and prevents contact between the die and the profile to reduce friction. The hot extrusion forming process parameters are shown in Table 2. The energy-related data are collected by IoT-based energy management system.

| No | Parameters                  | Value  |
|----|-----------------------------|--------|
| 1  | Die initial temperature (°C) | 450    |
| 2  | Diameter of Extrusion Tube (mm) | 130   |
| 3  | Extrusion ratio             | 11     |
| 4  | Aluminum rod diameter (mm)  | 120    |
| 6  | Upper die size (length×height) | φ100 mm × 50 mm |
| 7  | Lower die size (length×height) | φ100 mm × 50 mm |

![Figure 3: Profile dimensions and die structure](image)

4.2. Experiment simulation
In this experiment, the data comes from the monitoring data of energy management system. The experiment uses B-ELM, B-GPR, and B-EW to establish energy consumption models. In Figure 4(a) and (b), the maximum error of B-ELM prediction model appears in the 18s and the maximum error of B-GPR prediction model appears in the 30s. By comparing the above models, it can be concluded that B-ELM has the better prediction accuracy of the prediction model. In Figure 4(d), it shows the comparison between the predicted and real values of the fusion energy consumption prediction model. It can be obtained from the experimental simulation diagram that the maximum error between the real value and the predicted value of the B-EW energy consumption prediction model is 1.2.
Figure 4. Prediction performance comparison. (a) Energy prediction of B-ELM, (b) Energy prediction of B-GPR, (c) Energy prediction of B-EW, (d) Energy prediction error of B-EW

5. Conclusion
For accurately predicting energy consumption with a small number of data samples, this paper proposed a fusion data model integrating bagging enhanced ELM and GPR based on their entropy weight. The local outlier factor (LOF) algorithm and RreliefF method are used to remove the data anomalies. The experiment results indicate that the RMSE, MRE and MSE errors of B-EW model are better than those of B-ELM and B-GPR models, and the maximum error is less than 1%. The accuracy of B-EW is higher than that of B-ELM and B-GPR in predicting extrusion energy consumption.

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