Computers in Industry 99 (2018) 294–302

Contents lists available at ScienceDirect

Computers in Industry

journal homepage: www.elsevier.com/locate/compind

Road surface temperature prediction based on gradient extreme learning machine boosting

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ARTICLE INFO

Keywords:
Road surface temperature
Prediction
Neural networks
Gradient boosting

ABSTRACT

The expressway is extremely important to transportation, but high road-surface temperatures (RST) can cause many traffic accidents. Most of the hourly RST prediction models are based on numerical methods, but the parameters are difficult to determine. Statistical methods cannot achieve the desired accuracy. To address these problems, this paper proposes a machine learning algorithm that utilizes gradient-boosting to assemble a ReLU (rectified linear unit)/softplus Extreme Learning Machine (ELM). By using historical data from the airport and Badaling expressways collected between November 2012 and September 2014, sigmoid ELM, ReLU ELM, softplus ELM, ReLU gradient ELM boosting (GBELM) and softplus GBELM were applied for RST forecasting, RMSE (root mean squared error), PCC (Pearson Correlation Coefficient), and the accuracy of these methods were analyzed. The experimental results show that ReLU/softplus can improve the performance of traditional ELM, and gradient boosting can further improve its performance. Thus, we obtain a more accurate model that utilizes GBELM with ReLU/softplus to forecast RST. For the airport expressway, our proposed model achieves an RMSE within 3 °C, an accuracy of 81.8% and a PCC of 0.954. For the Badaling expressway, our model achieves an RMSE within 2 °C, an accuracy of 87.4% and a PCC of 0.949.

1. Introduction

Expressways have been extremely important to the transportation industry, but bad road conditions often cause many accidents. One of the most serious problems is high road-surface temperature (RST), which can make tires easily explode. In this case, it is easy for the driver to operate the vehicle improperly, which results in the occurrence of traffic accidents. High RST also causes the asphalt in the road to swell, pit and be otherwise damaged; any increase in vehicle traffic can also cause large areas of intense damage. Thus, a high RST not only leads to accidents but also damages roads. Therefore, forecasting RST is a significant method to prevent traffic accidents and road damage. With the use of big data, expressway RST forecasting can be determined more easily than using a traditional way. Meteorological institutions have accumulated large amounts of road data in past decades. By applying data mining algorithms to these data, we can build a more accurate model.

RST is being studied all over the world. European researchers began researching RST earlier and established a complete road monitoring and RST forecasting system. For example, Germany [1] can forecast road weather for the next 1–3 days. The United Kingdom [2] uses road radar to monitor the road conditions. China started late but also established a road monitoring system; for example, Beijing has built many road monitoring stations, which can use the BJ-RUC (Beijing rapidly updating cycle) to forecast the weather of the roads in Beijing. So far, there are two methods to forecast the road temperature: numerical and statistical.

Numerical methods use a combination of physics and math to establish an equation that can forecast the RST. Chapman [3] built a model based on GIS (Geographic Information System). Bouilloud et al. [4] established a model that can forecast RST and snow depth in France. Sokol et al. [5] used a numerical method to forecast RST and used an ensemble method to eliminate uncertainty. Liu et al. [6] built a model

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https://doi.org/10.1016/j.compind.2018.03.026
Received 1 June 2017; Received in revised form 26 February 2018; Accepted 20 March 2018
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based on the conservation of energy; the model can forecast up to a range of 24 h. Jia et al. [7] utilized basic principles of heat conduction and built a model that can forecast RST for 4 moments per day. Feng et al. [8] utilized conservation of energy and built an hourly RST forecasting model. Meng et al. [9] combined the numerical simulation products Common Land Mode (CoLM) [10] and BJ-RUC to build a model that can forecast up to a range of 3–24 h. Yang et al. [11] established a numerical model in Korea. Other researchers, such as Han et al. [12] and Gan et al. [13], also used a numerical method to develop a forecasting model.

Statistical methods build a model based on historical data and are often easier to implement than numerical methods. Diefenderfer et al. [14] and Qu et al. [15] used linear regression to build a daily highest and lowest RST prediction model for multiple areas. Recently, researchers have been able to obtain higher-quality data; Li et al. [16] Ma et al. [17] used linear regression to build an hourly model and achieved good results. Additionally, Lukanen et al. [18], Hua Tian et al. [19], and Wu et al. [20] also built models based on statistical methods.

Numerical methods that are based on physics and that can simulate the various factors of RST have strong universality. The numerical method does not require observational data; in the early exploration of a system, when there is a lack of data, the numerical method is the best choice. The parameters of the numerical method are difficult to obtain; therefore, depending on the historical data and the limited amount of experimental information, the parameters of the model will be reduced since there is no effective method to determine them. Thus, any parameters the model does have are low quality [21]. Additionally, numerical methods are also very difficult to solve because they are based on a system of equations.

Among statistical methods, multiple linear regression (MLR) is the most commonly used approach. Statistical methods are easier than numerical methods and only obtain the statistical relationship between various factors and RST. Because statistical methods only consider the influence of the environment on the RST, they have low accuracy. The integrity and accuracy of statistical data can also affect the results. However, obtaining parameters are easy to find and implement [22]. Moreover, many researchers work on statistical method to enhance accuracy, generalization, and impact on the system; therefore, statistical methods are becoming increasingly popular [21].

Parameters of most numerical methods are difficult to obtain. Building an accurate, hourly forecast model based on traditional statistical methods is difficult but frequently done. In the big data era, many problems have been solved by using big data in many domains, such as health care [23], medicine [24], recommendation systems [25] and so on. Machine learning (ML) plays a very important role in the big data research field. Like statistical methods, ML forecasts RSTs based on historical data, but the method can approximate more complex functions. To get good results, statistical methods need a large amount of data and accurate feature selection; however, ML can also achieve good results with only limited feature selection and minimal data. The parameters of ML are easy to obtain via an optimization algorithm.

In this paper, we utilize an ML algorithm called extreme learning machine (ELM) [26] to forecast RST. ELM is well known because it has a fast training speed and good generalized performance, but it also has some disadvantages. The sigmoid function is a very important activation function used in traditional ELM training. Recently, ReLU [27] and softplus [27] activation functions are very popular in deep learning because they have sparsity limits that are seldom used in ELM. Although some researchers [28,29] have applied ReLU and softplus to ELM classification problems and have demonstrated that ReLU and softplus improved the performance of ELM, little research attention is given to regression problems such as RST forecasting. In this work, we replaced the sigmoid function with ReLU or softplus. Then, we applied ELM with ReLU and softplus for RST forecasting. Because the weights and bias between the input layer and hidden layer are randomly assigned in ELM, the performance of ELM is a little random. To reduce the randomness of ELM, applying ensemble methods is a good idea. Among the ensemble methods, gradient boosting [30] is very popular in data mining research and always gets good results. Thus, we utilized gradient boosting to ELM to reduce randomness effectively. To build an accurate hourly forecasting model, an accurate weather forecasting system is necessary. We have BJ-RUC data, which is an accurate weather forecasting system. Therefore, we combined the proposed ML method with BJ-RUC and achieved good results.

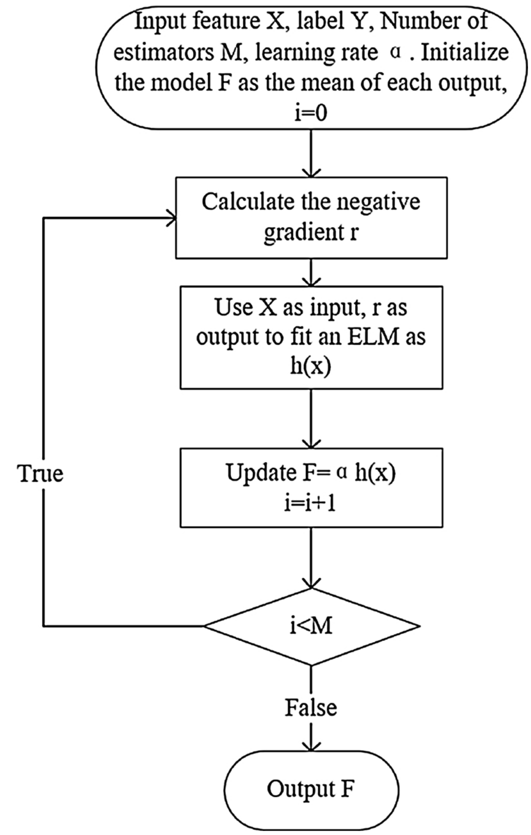

Fig. 1. The basic Gradient Extreme Learning Machine Boosting process.

2. Methodology

The main idea of the method described herein is to apply gradient boosting to ensemble ELM via an ReLU/softplus activation function. In this paper, gradient boosting was used to optimize a cost function over the function space by iteratively choosing an ELM that points in the negative gradient direction. The basic GBELM process is shown in Fig. 1.

2.1. Extreme learning machine

ELM is a type of SLFNs created by Guangbin Huang. Huang thought that training SLFNs based on the BP algorithm and gradient descent is not only inefficient but can also easily get stuck in a locally optimal solution. If an input matrix X, and an activation function g(x), are given, then an SLFNs can be represented as follows:

$$T = g(W*X+b)\beta \tag{1}$$

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