SPECIAL TOPIC — Smart design of materials and design of smart materials

Fast prediction of the mechanical response for layered pavement under instantaneous large impact based on random forest regression

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The layered pavements usually exhibit complicated mechanical properties with the effect of complex material properties under external environment. In some cases, such as launching missiles or rockets, layered pavements are required to bear large impulse load. However, traditional methods cannot non-destructively and quickly detect the internal structural of pavements. Thus, accurate and fast prediction of the mechanical properties of layered pavements is of great importance and necessity. In recent years, machine learning has shown great superiority in solving nonlinear problems. In this work, we present a method of predicting the maximum deflection and damage factor of layered pavements under instantaneous large impact based on random forest regression with the deflection basin parameters obtained from falling weight deflection testing. The regression coefficient R^2 of testing datasets are above 0.94 in the process of predicting the elastic moduli of structural layers and mechanical responses, which indicates that the prediction results have great consistency with finite element simulation results. This paper provides a novel method for fast and accurate prediction of pavement mechanical responses under instantaneous large impact load using partial structural parameters of pavements, and has application potential in non-destructive evaluation of pavement structure.

Keywords: deflection basin parameters, pavement condition assessment, instantaneous large impact, random forest regression

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1. Introduction

Layered pavements usually have relatively complex structures. Its mechanical properties, such as the elastic modulus of layers, are affected by ambient temperature and water content.[1,2] The elastic half-space foundation model assumes that the subgrade is continuous, isotropic, and completely elastic.[3] Further, layered elastic theory regards cement concrete pavements as a multi-layer structure composed of several elastic layers and elastic half-space ground.[4–6] In the mechanistic analysis of layered pavement structures, layered elastic theory is a powerful method, which has always been under constant extension in pavement engineering to make it more appropriate for real pavement conditions.[7] According to the JTJ 003-86 Standard of Climatic Zoning for Highway, each layer has different thickness and material mechanical properties. The cement concrete layer is the contact surface where the load acts. Concrete materials are characterized by the existence of a large number of randomly distributed micro-cracks and micro-cavities. During the process of loading, the microstructure of concrete undergoes a series of changes, leading to the initiation, propagation, and coalescence of damage, which ultimately results in the degradation of mechanical properties and even macroscopic cracking.[8,9] Moreover, previous studies has shown that the elastic modulus of subgrade have the most enormous implications for the bearing capacity of pavements.[10]

In order to crucially estimate the pavement health, the non-destructive testing devices such as falling weight deflectometer (FWD) have been widely applied. Considering the lack of pavement layer thickness information for all locations, studies have shown that deflection basin parameters (DBPs) calculated from FWD test data can make inferences regarding the structural condition of individual pavement layers.[11,12] In some cases, highways are required to have a certain bearing capacity for large instantaneous impact loads, such as the launching payloads. DBPs obtained from FWD testing can be used to assess the bearing capacity of the pavement to a certain extent, but they cannot directly measure the thickness and elastic modulus of the pavement layers. At the same time, the FWD load on the road surface generally consists of three im-

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pulse load levels (31 kN, 40 kN, and 49 kN), and the radius of action is 150 mm,[13] but the launching payload is a equivalent load of 200 tons, which can be fully loaded on 1 meter diameter area within 1 second.[14] The mechanical responses of pavements under large instantaneous impact load are different from those under FWD load, and they cannot be obtained from quick and non-destructive test method. Although mechanical responses[15,16] can be simulated from finite element (FE) models, this method may cost a lot of time and computing resources, which need all pavement structural parameters. Therefore, it is of great significance to study an accurate and rapid method for predicting the pavement bearing capacity under the instantaneous impact load.

With the rapid development of data science, data-driven machine learning methods have the potential to replace the expensive high-fidelity analyses with less expensive approximations.[17–19] So far, machine learning has been widely applied in flexible pavement assessment and prediction. Xie *et al.*[20] firstly determined the subgrade modulus by two DBPs, base damage index (BDI) and shape factor F_2, and then trained an artificial neural network (ANN) with the subgrade modules and other parameters to estimate the upper layer module. A few studies have found that the integration of the AI approach and FWD derived parameters is quite successful.[21,22] Li *et al.*[23] implemented DBPs to predict asphalt pavement responses with an artificial neural network (ANN)-based program combined with genetic algorithm (GA) optimization. Vyas *et al.*[12] performed the ANN modeling to obtain the desired outputs of deflection basin parameters by taking eight input parameters, including thickness of concrete layer, base layer, total pavement, and so on. Zhao *et al.*[24] utilized seven different methods to predict the air voids of asphalt layers: nonlinear data fitting, back propagation neural network (BPNN) algorithm, regression trees, random forest regression (RFR), and so on. Nevertheless, the machine learning method has not been widely applied in fast and accurate prediction of cement concrete pavement bearing capacity for instantaneous large impact load, which needs further investigation.

This paper develops a data-driven random forest regression model for fast prediction of the mechanical response of cement concrete pavements under instantaneous large impact load through the DBPs calculated from FWD testing. This method can predict the maximum pavement deflection and damage factor of layered pavements. We take the typical structure of cement concrete classified highways at all levels as an example, which are in the eastern part of the II district. The database for the machine learning is generated using numerical simulation of three-dimensional FE model of cement concrete layered pavements. Taking the BDI, F_2, base curvature index (BCI), FWD basin area A_{rea}, surface curvature index (SCI) as inputs and the elastic modulus of subgrade and the surface layer as outputs, an RFR model trained on hundreds of data sets calculated from simulation results is proposed with high consistency between prediction and the target elastic modulus. Based on the simulation results of three-dimensional FE model of pavements under instantaneous large impact, we propose another random forest model to predict the maximum deflection and damage factor of pavements. The input parameters are the elastic modulus of surface layer and subgrade which are predicted from the first RFR model, together with other checked parameters of classified pavements according to the standard. Compared with traditional nondestructive testing methods, the trained RFR model can get the targeted results in a few milliseconds, which greatly improves the efficiency of pavement dynamic response prediction under instantaneous large impact.

2. Theory model and simulation

2.1. Theory model

2.1.1. Pavement structure and layer properties

Table 1 summarizes layer materials and thicknesses of classified highways for the representative pavement cross section.[14] The expressway has four layers above subgrade, while the first grade highway, secondary road, and tertiary highway have three layers and the township roads only have two layers. The thickness and compressive strength of expressway cement concrete surface layer are the largest compared with the other four classified highways. Obviously, the expressway has the optimal bearing capacity theoretically, and the bearing capacity of the township road is relatively the weakest.

Table 1. Typical structure parameters of cement concrete classified highways at all levels in the second district. The thickness is in units of mm.

Expressway		First grade highway		Secondary road		Tertiary highway		Township road	
Material	Thickness	Material	Thickness	Material	Thickness	Material	Thickness	Material	Thickness
C50[a]	300	C40	270	C35	220	C30	220	C25	200
AC-25[b]	80	ATB30[c]	100	CCR-5[d]	150	CR[e]	150	CCR-5	180
LC[f]	150	CCR-3	250	CSG[g]	150	LFS[h]	100	–	–
CCR-3	200	–	–	–	–	–	–	–	–
subgrade	∞	subgrade	∞	subgrade	∞	subgrade	∞	subgrade	∞

[a]C: cement concrete, 50: the standard value of compressive strength of concrete cubes is 50 MPa, and the rest can be explain in the same manner; [b]AC: asphalt concrete, 25: the nominal maximum particle size of the mixed pellet; [c]ATB: asphalt-treated base, 30: the grade of ATB; [d]CCR: cement stabilized macadam, 5: the percentage of cement content is 5%; [e]CR: graded crushed stone; [f]LC: lightweight concrete; [g]CSG: cement sand and gravel; [h]LFS: lime-fly ash.

The layered elastic structure of pavements under the circular vertical load is shown in Fig. 1. In order to simplify the analysis, we only consider the damage failure of concrete materials and subgrage when establishing the theoretical model. In this paper, the concrete material is regarded as an isotropic homogeneous material.[25] According to the Code for design of concrete structures (GB 50010-2010) in 2015, the uniaxial compressive and tensile stress–strain equations of concrete can be obtained.[26]

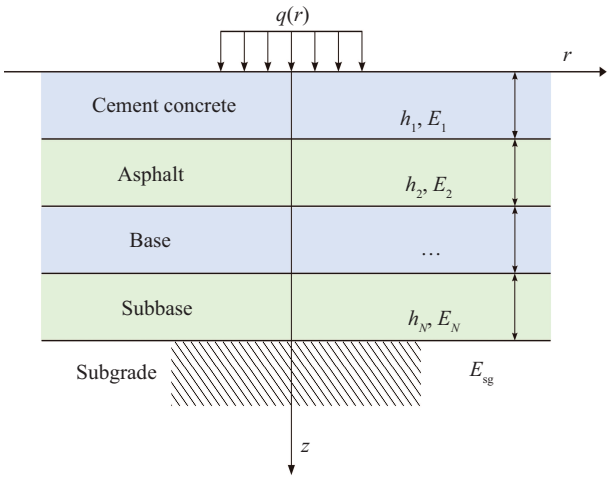


Fig. 1. The half space subgrade layered elastic model of layered pavements.

The stress–strain formula of concrete uniaxial compression y is

$$y=\begin{cases}\alpha_{\rm a}x+(3-2\alpha_{\rm a})x^2+(\alpha_{\rm a}-2)x^3, & x\geq 1,\\ \dfrac{x}{\alpha_{\rm d}(x-1)^2+x}, & x\geq 1,\end{cases} \tag{1}$$

where $x=\varepsilon/\varepsilon_{\rm c}$, $y=\sigma/f_{\rm c}^*$; $\alpha_{\rm a},\alpha_{\rm d}$ are the ascending and descending parameters of the uniaxial compression stress–strain curve, $f_{\rm c}^*$ is the uniaxial compressive strength of concrete, $\varepsilon_{\rm c}$ is the peak compressive strain of concrete corresponding to $f_{\rm c}^*$.

The stress–strain formula of concrete uniaxial tension is

$$y=\begin{cases}1.2x-0.2x^6, & x\leq 1,\\ \dfrac{x}{\alpha_{\rm t}(x-1)^{1.7}+x}, & x\geq 1,\end{cases} \tag{2}$$

where $x=\varepsilon/\varepsilon_{\rm t}$, $y=\sigma/f_{\rm t}^*$; $\alpha_{\rm t}$ is the descending parameter of the uniaxial tension stress–strain curve, $f_{\rm t}^*$ is the uniaxial tensile strength of concrete, $\varepsilon_{\rm c}$ is the peak tensile strain of concrete corresponding to $f_{\rm c}^*$.

In this paper, concrete damaged plasticity (CDP) model, which provides a universal material model for the mechanical response of concrete under cyclic and dynamic load conditions,[27,28] is chosen for dynamic simulation. In order to characterize the weakness of concrete mechanical properties caused by the presence of micro-cracks in the loading process, damage factors $d_{\rm c}$ and $d_{\rm t}$[29] are introduced to reflect the stiffness degradation degree of concrete caused by damage. Lemaitre's equivalence principle[30] indicates that if the effective stress under damage is used to replace the nominal stress in the constitutive equation of the nondestructive material, the constitutive equation of the damaged material can be derived from the constitutive equation of the nondestructive material. Then, the damage of concrete can be measured by damage factor.

CDP model mainly includes the following parameters: yield stress $\sigma_{\rm c}$, *e.g.*, inelastic strain $\varepsilon^{\rm in}$, damage factor $d_{\rm c}$, *e.g.*, inelastic strain $\varepsilon^{\rm in}$ under the compression; yield stress $\sigma_{\rm t}$, *e.g.*, cracking strain $\varepsilon^{\rm ck}$, and damage factor $d_{\rm t}$, *e.g.*, cracking strain $\varepsilon^{\rm ck}$ under the tension. These parameters can be obtained from the constitutive equations above. The uniaxial tensile stress-strain curve of concrete is shown in Fig. 2. Before reaching the failure stress $\sigma_{\rm t0}$, the material is in a linear stage, followed by the strain softening and stiffness degradation stage which describes the relationship between yield stress $\sigma_{\rm t}$ and cracking strain $\varepsilon^{\rm ck}$.

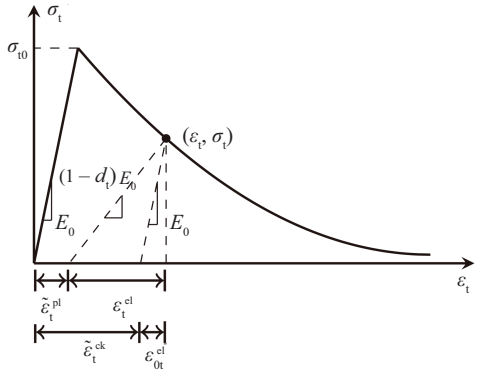


Fig. 2. Stress–strain curves of concrete under uniaxial tension.

Figure 3 shows the uniaxial compressive stress–strain curve of concrete, which indicates that concrete undergoes the elastic stage ($0\sim\sigma_{\rm c0}$), strengthening stage ($\sigma_{\rm c0}\sim\sigma_{\rm cu}$) and softening stage respectively when it is compressed.

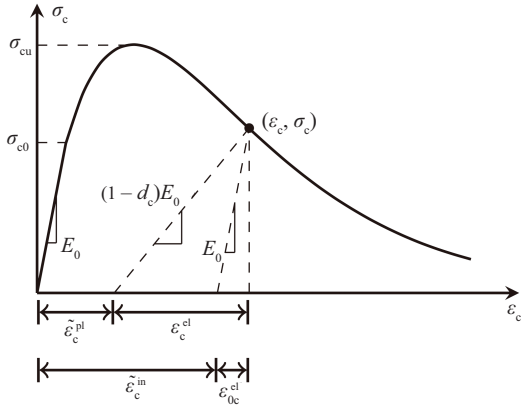


Fig. 3. Stress–strain curves of concrete under uniaxial compression.

Assuming that E_0 is the initial elastic modulus of concrete, the following formulas can be obtained from Fig. 2:

$$\tilde{\varepsilon}_{\rm t}^{\rm ck}=\varepsilon_{\rm t}-\varepsilon_{\rm 0t}^{\rm el}, \tag{3}$$

$$\tilde{\varepsilon}_{\rm t}^{\rm pl}=\tilde{\varepsilon}_{\rm t}^{\rm ck}-\left(\frac{\sigma_{\rm t}}{(1-d_{\rm t})E_0}-\frac{\sigma_{\rm t}}{E_0}\right)=\tilde{\varepsilon}_{\rm t}^{\rm ck}-\frac{d_{\rm t}\sigma_{\rm t}}{(1-d_{\rm t})E_0}, \tag{4}$$

$$\sigma_{\rm t}=(1-d_{\rm t})E_0(\varepsilon_{\rm t}-\tilde{\varepsilon}_{\rm t}^{\rm pl}), \tag{5}$$

where the tensile elastic strain $\varepsilon_{0t}^{el} = \sigma_t/E_0$, $\tilde{\varepsilon}_t^{ck}$ is the tensile cracking strain, ε_t and σ_t are the tension strain and stress, $\tilde{\varepsilon}_t^{pl}$ is the tensile equivalent plastic strain, d_t is the damage factor in the tensile process of concrete. By substituting Eqs. (3) and (4) into Eq. (5), the formula to calculate of the tensile damage factor is as follows:

$$d_t = 1 - \frac{\sigma_t}{\tilde{\varepsilon}_t^{pl}(1/b_t - 1)E_0 + \sigma_t}, \tag{6}$$

where $b_t = \tilde{\varepsilon}_t^{pl}/\tilde{\varepsilon}_t^{ck}$.

Similarly, the expressions of inelastic strain, equivalent plastic strain, and damage factor of concrete under compression can be obtained from Fig. 3 as

$$\tilde{\varepsilon}_c^{in} = \varepsilon_c - \varepsilon_{0c}^{el}, \tag{7}$$

$$\tilde{\varepsilon}_c^{pl} = \tilde{\varepsilon}_c^{in} - \left(\frac{\sigma_c}{(1-d_c)E_0} - \frac{\sigma_c}{E_0}\right) = \tilde{\varepsilon}_c^{in} - \frac{d_c\sigma_c}{(1-d_c)E_0}, \tag{8}$$

$$d_c = 1 - \frac{\sigma_c}{\tilde{\varepsilon}_c^{pl}(1/b_c - 1)E_0 + \sigma_c}, \tag{9}$$

where the compressive elastic strain $\varepsilon_{0c}^{el} = \sigma_c/E_0$, $b_c = \tilde{\varepsilon}_c^{pl}/\tilde{\varepsilon}_c^{in}$, $\tilde{\varepsilon}_t^{ck}$ is the tensile cracking strain, ε_t and σ_t are the tension strain and stress, $\tilde{\varepsilon}_t^{pl}$ is the tensile equivalent plastic strain, d_t is the damage factor in the tensile process of concrete.

2.1.2. Deflection basin parameters of FWD testing

The DBPs derived from deflections at different radial offsets of FWD testing can indicate pavement deflection basin and eventually its strength.[12] As listed in Table 2, the proposed DBPs include base damage index (BDI), shape factor F_2, area under pavement profile A_{rea}, surface curvature index (SCI), and base curvature index (BCI) in this paper. For the parameters BDI and F_2, the only parameter that affects the BDI–F_2 curve is the elastic modulus of subgrade E_{sg}. When the other parameters are obtained, the elastic modulus of surface layer E_1 can be calculated from the function between A_{rea}, the maximum deflection (D_0), h_1, E_1, and E_{sg} for layered structures.[20] SCI is a measure parameter of the structural quality of the upper pavement layers, while BCI can characterize the quality of the base and subgrade.

Table 2. The equations and concerned layers of DBPs.

DBPs	Equations	Concerned layers
BDI	$\mathrm{BDI} = D_{300} - D_{900}$	subgrade, $F_2/\mathrm{BDI} \propto E_{sg}$
F_2	$F_2 = (D_{300} - D_{900})/D_{600}$	
A_{rea}	$A_{rea} = 6(D_0 + 2D_{300} + 2D_{600} + D_{900})/D_0$	surface layer
SCI	$\mathrm{SCI} = D_0 - D_{300}$	surface layer
BCI	$\mathrm{BCI} = D_{600} - D_{900}$	subgrade

2.2. Numerical simulation

2.2.1. Finite element model description

FE models are developed based on the representative pavement structures of classified highways form Table 1. The axisymmetric model is widely used to simulate the pavement responses when subjected to a circular load. In this paper, a 1/4 axisymmetric pavement structure model is established to decrease the computing costs without significant accuracy loss. The constitutive model of each pavement layer is critical for the mechanistic analysis of pavement responses. Since the concrete surface layer and subgrade are particularly important to the mechanical properties of pavement structure, the material non-linearity must be considered. Therefore, the elastoplasticity of concrete is modeled with CDP constitutive, and the mechanical behavior of subgrade is modeled with Drucker–Prager model. The material properties of the remaining layers are simplified to linear elasticity. Previous studies have found that if the domain size is larger than 20 times radius of the loading area in the horizontal direction, and larger than 140 times the radius in the vertical direction, the boundary condition effects can be eliminated.[31] The domain size of the model established in this paper is 15 m (length) × 15 m (width) × 10 m (depth), which reduce the calculation amount and ensure high accuracy of simulation. Moreover, as shown in Fig. 4, infinite boundaries are set up at the bottom of the subgrade and sides besides the symmetric planes. Because of the large gap between the load radius and the model size, a finer mesh is applied to the area near the loading center where the accurate mechanical responses are obtained.

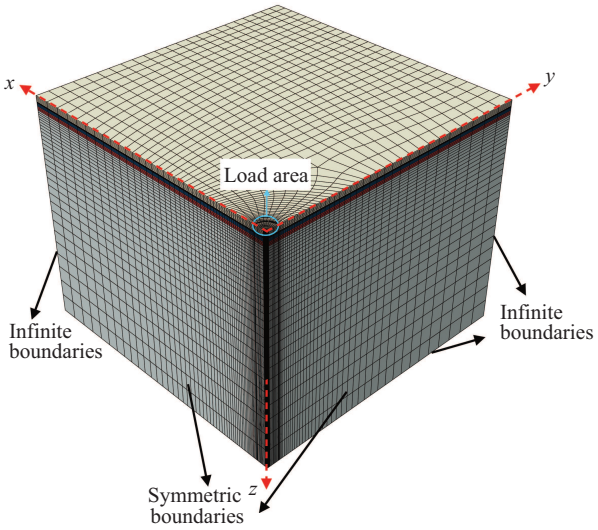


Fig. 4. Mesh and boundary conditions of the three-dimensional pavement FE model.

2.2.2. Loading configuration

During FE model development, both FWD load and instantaneous large impact analyses are conducted and compared to set up the database for pavement response prediction. Figure 5 is the cross-section of representative highway three-dimensional pavement FE model, which shows the load area and different types. FWD produces a pulse load on the pavement through the free fall of falling weight. The FWD load is simplified as a uniformly distributed half-sine wave load under an equivalent circle area, and the radius of load is 150 mm.[32] The amplitude of FWD load is 40 kN (0.55 MPa), and the loading time is 0.03 s,[13] as shown in Fig. 6. Furthermore, in order to predict the pavement responses under instantaneous large impact load, it is also necessary to establish an FE model under this load, and its loading curve is shown in Fig. 7. Assuming that the acting time of the load is 1.0 s, which gradually increases to 1.0 MPa in 0 s–0.25 s, remains 1.0 MPa in 0.25 s–0.75 s, and unloads to 0 in 0.75 s–1.0 s, with a load radius of 500 mm.

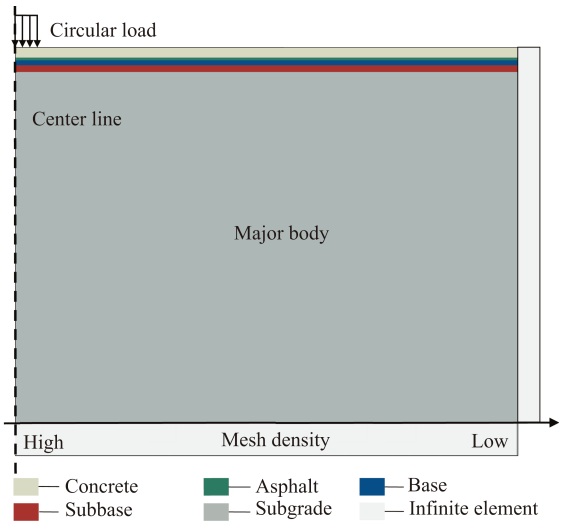


Fig. 5. The cross-section of highway three-dimensional pavement FE model.

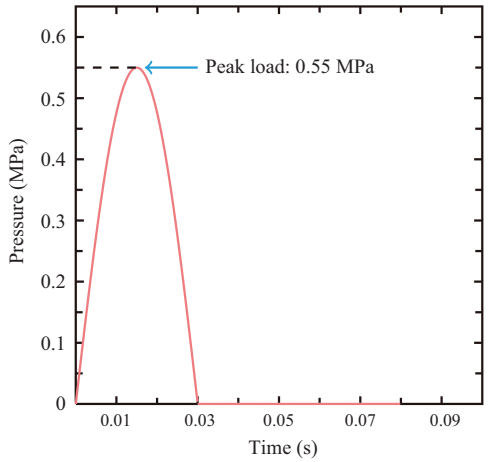


Fig. 6. Loading curve for simulation of FWD FE model.

The main differences between the two loads are the load amplitude and area, and the size effect of concrete will lead to different mechanical responses of pavements. Therefore, the rapid prediction method of pavement responses under large impact load based on pavement DBPs under FWD proposed in this paper has important research significance and necessity.

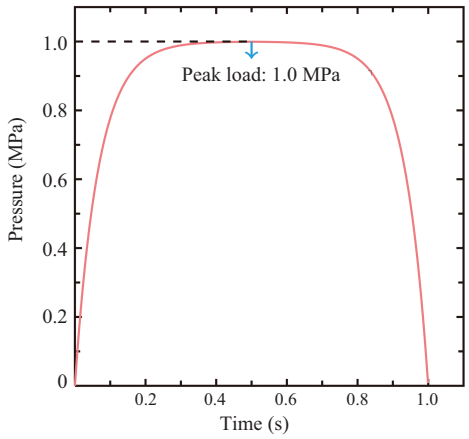


Fig. 7. The loading curve for simulation of instantaneous large impact FE model.

3. RFR model of mechanical responses prediction

Traditional FWD testing method has certain limitations for pavement evaluation. Many structural indicators are usually based on empirical methods without sufficient fundamental theory. At the same time, the peak and area of FWD load are relatively small, so the mechanical responses of pavement structure under transient large impact load cannot be evaluated directly in this way. Moreover, the mapping relationship between the evaluation results and the shape of deflection basin is highly nonlinear. Random forest is an ensemble machine learning classifier that uses multiple decision trees to train samples and predict values across a certain range by averaging. The random forest regression has shown excellent performance in settings where the number of variables is much larger than the number of observations. Furthermore, it is versatile enough to solve large-scale problems, easily adapted to various ad hoc learning tasks, and returns measures of variable importance.[33] Therefore, we try to introduce random forest regression into mechanical responses prediction of pavement to replace traditional FWD testing and numerical simulation methods.

Here, we provide an RFR machine learning model for moduli prediction of concrete layer and subgrade with the DBPs as inputs. Then the inputs will be the types of classified highways, modulus, and thickness of each layer. The mapping relationship between these inputs and evaluation parameters under instantaneous large load is constructed by RFR method, so as to realize the rapid prediction of mechanical responses. As shown in Figs. 8 and 9, the prediction method is divided into two steps, and the model of each step includes a data input module, a mapping module, and an output module. The input module is mainly applied to provide input information

for the method, including the DBPs for the first step and pavement structure parameters for the second step. The RFR model is the core for both steps, which takes into account many predictions by using their average bases on decision trees. And any changes in datasets may impact only one decision tree but not the whole random forest, so it is more accurate and stable. In this way, the given input features are mapped to the output module features in steps through a series of regressions.

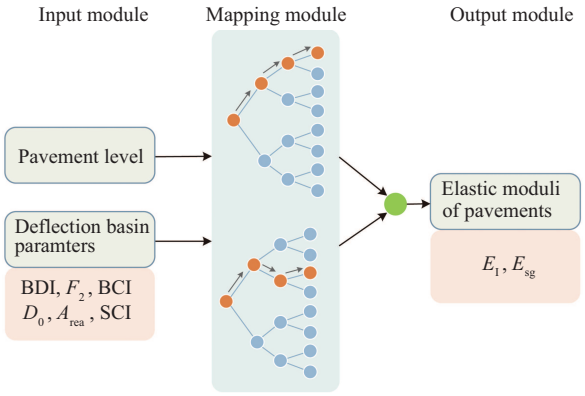


Fig. 8. Schematic diagram of the RFR model I for elastic moduli prediction of surface layer and subgrade.

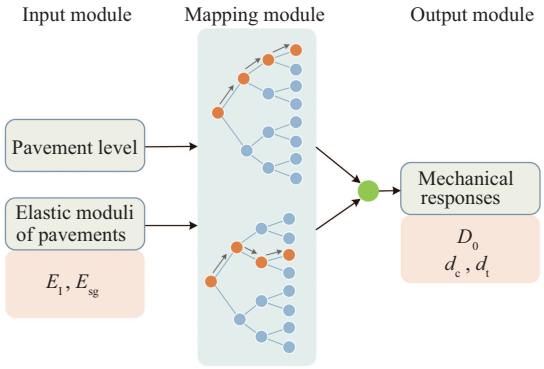


Fig. 9. Schematic diagram of the RFR model II for pavement mechanical response prediction.

Since the elastic moduli of surface layer and subgrade have important impact on the mechanical properties of pavements, and it will change with the external environment. Therefore, the first step is to use RFR model I to predict the elastic moduli of surface layer and subgrade with BDI, F_2, A_{rea}, SCI, and BCI as inputs. Then the output values obtained from first step together with other pavement structure parameters will be as input features for the RFR model II. Finally, through the mapping module, the pavement mechanical responses we need can be provided.

4. Prediction results and discussion

In Section 3, we provide an RFR-based method for nonlinear regression between DBPs and mechanical responses under instantaneous large impact. In this section, we will verify the feasibility and accuracy of the proposed method. Firstly, a DBP dataset of different pavement structures with different elastic moduli generated by FE model simulation is established. Following the process of Figs. 8 and 9, multiple unrelated decision trees are established by extracting random samples and features to obtain the prediction results in a parallel manner. Compared to the FE model simulation results, the accuracy analysis of the prediction results of elastic modulus and pavement mechanical responses is carried out to verify the reliability of the proposed RFR method.

4.1. Data preparation

The FE simulation results with high-fidelity are treated as the training dataset in the RFR method, and some of the results will be used as validation dataset to evaluate the accuracy of the prediction results. Using the numerical model in Subection 2.2, the elastic modulus of the surface layer and the subgrade are changed respectively to development the model in batches, and the models are applied two different loads as shown in Figs. 6 and 7 to create the database. Table 3 summarizes the elastic modulus, density, and Poisson ratio of pavement material database. The elastic modulus of cement concrete in Table 3 is the representative value at 20 °C. In fact, the effective elastic modulus of unsaturated concrete is affected by saturation, soil porosity, micro-cracks, and temperature. Previous studies have shown that temperature affects the viscous force in water contents and micro-cracks under compressive loads, which results in a decrease in the elastic modulus of concrete with increasing temperature.[34] The influence of saturation, water content and micro-cracks on the elastic modulus of cement concrete is directly related to temperature. Therefore, the temperature correction coefficient K_{E} with respect to 20 °C is introduced in this paper to define the possible variation range of the concrete elastic modulus. K_{E} is the ratio of the elastic modulus $E(T)$ at temperature T (in units of °C) to the elastic modulus at 20 °C, as shown below:

$$K_{\text{E}} = E(T)/E(T = 20\ ^{\circ}\text{C}), \tag{10}$$

$$K_{\text{E}} = 1.116 - 0.006T. \tag{11}$$

According to plenty experiments and calculation results, the approximate K_{E} can be calculated from Eq. (11). The temperature ranges from −80 °C to 70 °C, and then K_{E} approximately ranges from 0.7 to 1.6, which means the range of concrete elastic modulus for each type of pavement is $0.7E_1$–$1.6E_1$. For the training dataset, ten values of K_{E} ($K_{\text{E}} = 0.7, 0.8, 0.9, \ldots, 1.4, 1.5, 1.6$) are considered, and according to previous study,[11] the values of subgrade elastic modulus are assigned as 14 MPa, 28 MPa, 69 MPa, 138 MPa, 207 MPa, 276 MPa. There are five types of cement pavements with different elastic moduli corresponding to five different grades of highways. Thus, the dataset for each type of load contains a total of 300 cases, which are divided into training dataset and testing dataset. The testing dataset are designed to verify the ability of the RFR model to predict the moduli of surface and subgrade, and the mechanical responses under instantaneous large impact.

Table 3. Elastic modulus, density, and Poisson ratio of pavement material database.

	Elastic modulus (MPa, $T = 20$ °C)	Density (10^{-9} t/mm^3)	Poisson ratio		Elastic modulus (MPa, $T = 20$ °C)	Density (10^{-9} t/mm^3)	Poisson ratio
C50	34554	2.365	0.20	C40	32600	2.365	0.20
C35	31334	2.363	0.20	C30	29792	2.363	0.20
C25	27871	2.377	0.25	AC-25	1180	2.377	0.25
ATB30	1000	2.294	0.25	CCR-5	1500	2.300	0.20
CR	350	2.291	0.35	LC	12000	2.400	0.20
CCR-3	1000	2.300	0.20	CSG	200	1.180	0.35
LFS	700	1.180	0.35	subgrade	14 ∼ 276	1.800	0.35

4.2. Prediction results and analysis

4.2.1. Elastic modulus of subgrade layer prediction results

Based on the above method, the RFR model is used to predict the elastic modulus of the subgrade layer. The pavement level, I_{bd}, F_2, and BCI are the input features, and the subgrade elastic modulus is the predicted value. The traing dataset of 300 cases is developed by the FE simulation results, and for the testing dataset, the pavement type, the elastic modulus of subgrade are randomly sampled within the corresponding ranges mentioned in Subsection 4.1, and a total of 50 sets of data were obtained.

The random forest regression model contains hyper-parameters that need to be set manually, such as the number of decision trees, the number of features to be used when each node is split, and the number of leaves on each tree. In a limited time, the different estimators of hyper-parameters can be tuned by a heuristic search method, namely the grid search method. In this paper, the RandomizedSearchCV method provided by scikit-learn is selected to implement the random search of best estimators, which is able to find the optimal hyper-parameter estimator within the specified parameter ranges and searching times. Since predicting elastic modulus of subgrade is a regression problem, the scoring parameter is set to the regression coefficient R^2,[35]

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y}_i)^2}, \tag{12}$$

where n is the number of samples in the testing dataset, y_i is the true value of the i-th case of samples, $\bar{y}_i$ is the average of all the true values, and $\hat{y}_i$ is the prediction value of the i-th case of samples. When the R^2 is in close proximity to 1, it indicates that the accuracy of the prediction model is adequate. Furthermore, the mean absolute error (MAE) is applied to quantify the difference between prediction value by the RFR model and the FE value besides R^2,[36] which is denoted as follows:

$$\mathrm{MAE} = \frac{\sum_i^n |y_i - \hat{y}_i|}{n}. \tag{13}$$

Through 300 searching times, we get the best estimator with 500 decision trees and 20 leaves on each tree. The R^2 of the testing set predicted by the RFR is 0.99, and the MAE of prediction results is 5.10 MPa. The prediction results of 50 random inputs are plotted against the simulation results generated by FE model in Fig. 10(a). The points of the predicted values are concentrated in the vicinity of the dashed line the reference line $y = x$, indicating that the RFR predicting model has high reliability. In addition, we estimate the importance of the input features for the prediction results, as shown in Fig. 10(b). It can be seen that the DBPs which has the greatest influence on the prediction results of the subgrade elastic modulus is F_2, with a ratio of 0.66. That means F_2 is very important in the prediction of elastic modulus of subgrade and has a strong correlation with the prediction target. The importance ratio of BCI is 0.21, followed by I_{bd} (0.11), while the proportion of pavement type is 0.02, which has little effect on the elastic modulus prediction of subgrade. This is because the elastic modulus of subgrade is an artificially prescribed range and is not related to the type of pavement.

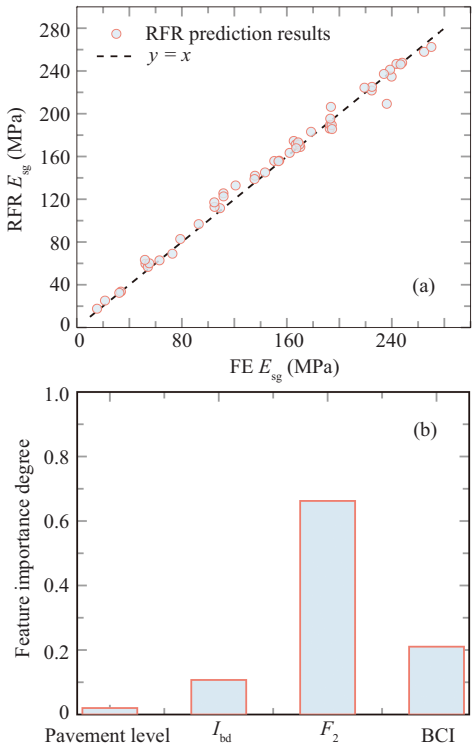


Fig. 10. (a) Prediction results of subgrade elastic modulus compared with FE simulation results and the black dashed line is the identity line serving as the reference. (b) The importance of each feature for subgrade elastic modulus prediction.

4.2.2. Elastic modulus of surface layer prediction results

Taking the pavement level, elastic modulus of subgrade E_{sg}, maximum deflection D_0, A_{rea}, and SCI as input features, we can obtain the predicting outcomes of surface elastic modulus, as shown in Fig. 11. Similar to Subsection 4.2.1, the optimal estimator is obtained through 300 searching times, which has 800 decision trees, 30 leaves on each tree, and takes sampling method without replacement. From Fig. 11(a), we can note that the R^2 is 0.95, indicating the accuracy of the prediction model is reliable. The value of MAE is 1392.83 MPa, which is one order of magnitude smaller than the target true value. Furthermore, we also analyze the importance of features for the prediction model. The results indicate that the SCI is most important with the importance score of 0.775, because the surface elastic modulus can directly determine the shape of the deflection basin. The importance score of the pavement level, which represents different concrete materials of surface is 0.169. Besides, the importance scores of D_0, A_{rea}, and E_{sg} are 0.049, 0.005, and 0.002 respectively, so the above features can be simplified to speed up the predicting process.

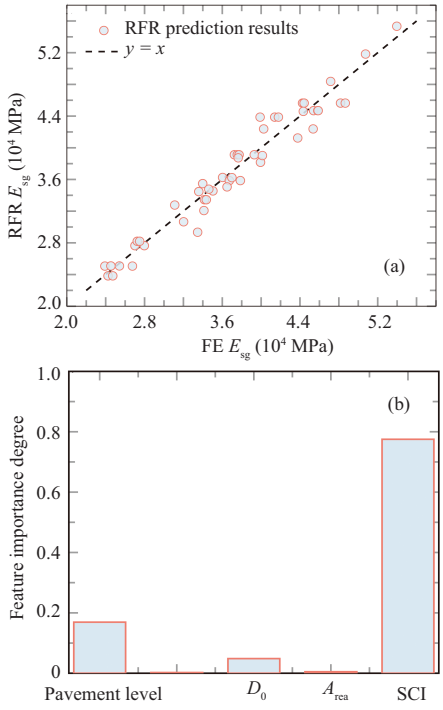


Fig. 11. (a) Prediction results of surface elastic modulus compared with FE simulation results and the black dashed line is the identity line serving as the reference. (b) The importance of each feature for surface elastic modulus prediction.

4.2.3. Prediction results of pavement responses

According to the elastic modulus of the structural layers predicted in the previous two subsections, we can further predict the pavement mechanical responses under instantaneous large impact load, mainly the maximum deflection D_0 and the tensile damage factor d_t. D_0 can directly reflect the bearing capacity of the pavements under instantaneous large impact, and d_t can quantify the damage degree of the pavements under the load. Comparing the FE simulation results between the FWD load and instantaneous large impact load, it can be found that the tensile and compressive damage factor of concrete surface are both zero under FWD load. Meanwhile, the tensile strength of cement concrete is much lower than the compressive strength, so serious tensile damage occurs under the large load in some samples, as shown in Fig. 12. At the center of load, the network cracks will appear at the bottom of the surface, and gradually spread around. In order to compare the different shapes of the deflection basin under the different two loads, figure 13 respectively shows the deflection basins of the lowest elastic modulus of concrete surface layer and subgrade in all classified highways. It can be seen that the bearing capacity of the expressway is much larger than other typical highways. The maximum deflections under the instantaneous large impact load are also greater than those under the FWD load.

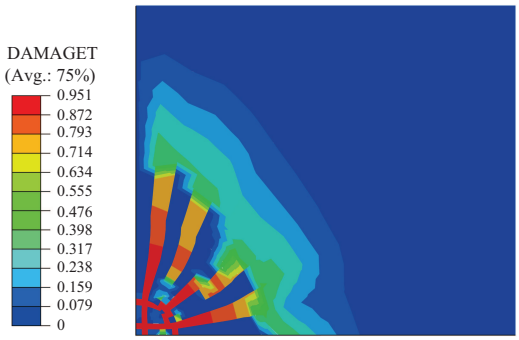


Fig. 12. A tensile damage cloud map of concrete surface layer of tertiary highway.

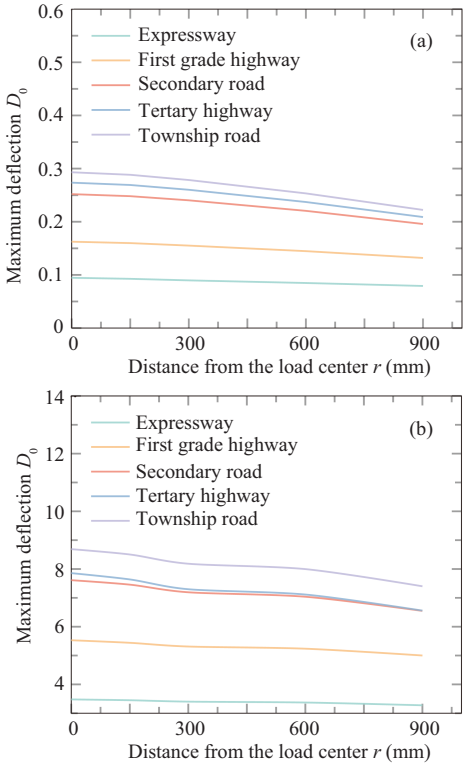


Fig. 13. (a) Deflection basins under FWD load of typical cement concrete classified highways with the lowest elastic moduli. (b) Deflection basins under instantaneous large impact of typical cement concrete classified highways with the lowest elastic moduli. The horizontal axis represents the distance from the load center.

The mechanical property prediction results of the RFR model are shown in Fig. 14. The regression coefficient R^2 of tensile damage factor d_t prediction is 0.98, and R^2 of D_0 prediction is 0.94. MAE values of these two targets are 0.03 and 0.15 mm, which shows the available performance of this RFR prediction model. The results of testing dataset demonstrate that the RFR model also works efficiently for the elastic moduli that have been predicted in the preceding training process. Meanwhile, the results indicate that the expressways almost have no tensile damage and the deflections under instantaneous large impact load are most minimum. The other four highways appear tensile damage in various ranges, and D_0 of these pavments also significantly increase compared to expressways. From Fig. 14, we can infer that under the same load, the greater the D_0 of pavements, the higher the d_t of pavements. Therefore, the elastic modulus of the structural layer can be backward calculated by the DBPs obtained from the FWD testing, and predicting the mechanical responses of the pavements under the impact load is feasible and reliable based on the RFR method. Furthermore, the whole procedure of prediction costs nearly 5 minutes to get the best estimator, while the FE simulation costs about 2 hours just to calculate a single case of pavement damage under instantaneous large impact. The calculation time differs by 24 times, which highlights the advantages of the RFR prediction model in terms of calculating speed and prediction accuracy.

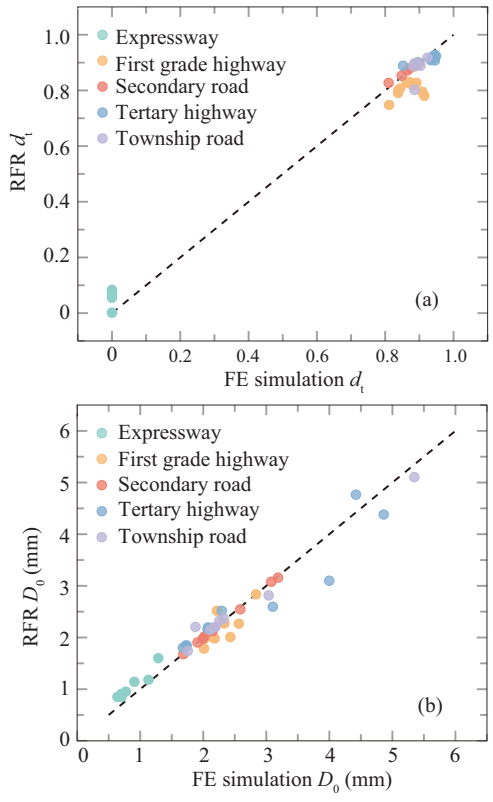


Fig. 14. (a) Prediction results of d_t compared with FE simulation results and the black dashed line is the reference line. (b) Prediction results of D_0 compared with FE simulation results.

5. Conclusion

In conclusion, we have proposed a data-driven RFR method to overcome the difficult problem of predicting mechanical responses of pavements under instantaneous large impact load. In order to verify the accuracy of this prediction method, a testing dataset with 50 cases are randomly generated. Firstly, the changeable elastic moduli of subgrade and surface layer are backward calculated from DPBs using RFR method, and the performance is quite feasible. Subsequently, the pavement mechanical responses are predicted by the obtained elastic moduli of the structural layers. The predicted results are basically consistent with the FE model simulation results, and show that our method can accurately and effectively obtain the tensile damage factor and maximum deflection value of five grades of highway under instantaneous large impact load. It is worth noting that we only consider the change of elastic moduli of two structural layers, while the actual situation will be more complicated. Non-singleness influence of complex environmental factors on pavement material properties should be analyzed in future study. Random forest regression has great advantages in solving such difficult problems, which can handle high-dimensional data without feature selection and is not sensitive to missing values or outliers. And it is proved in this work that RFR provides a novel way for fast and accurate prediction of pavement mechanical responses under instantaneous large impact load, and has application potential in prediction of non-destructive evaluation of pavement structure.

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