Meta-Learning Prediction Framework for Asphalt Mixtures Fatigue Life Modeling

Longmeng Tan[1], Krzysztof Kowalski[2]*
Quality Supervision and Law Enforcement Detachment of Guizhou Province Traffic Construction Engineering, Guiyang 550081, Guizhou, China[1]
Poznan University of Technology, Poznań 100026, Poland[2]

***Abstract*—In order to improve the accuracy and generalization ability of asphalt mixture fatigue life prediction, this study introduces the meta-learning method, which aims to solve the problems of poor adaptability and strong data dependence of the traditional prediction model under complex working conditions. In this study, a prediction framework based on the Model-Agnostic Meta-Learning (MAML) algorithm is constructed, which realizes the fast and accurate prediction of asphalt mixture fatigue life under multi-task conditions through feature extraction, meta-knowledge learning, and a fast adaptive mechanism. The experiments were conducted using multi-class mixture data and compared with linear regression and BP neural network methods under the MATLAB platform. The results show that the meta-learning model achieves a prediction accuracy of 0.98 within 500 iterations, which is significantly better than that of the BP neural network (0.89) and linear regression (0.84), and the prediction error is controlled to be between 40 and 60 under typical working conditions, while the traditional method has an error of up to 150. Further analysis shows that the meta-learning method has a faster convergence rate (the convergence index is 0.9 for 100 iterations) and a higher convergence index of 0.9 for 100 iterations. 0.9) with higher robustness. In conclusion, the meta-learning-based prediction method shows excellent performance in fatigue life modeling, which is suitable for rapid application in real-world engineering with diverse materials and loading environments.**

Keywords*—Asphalt mixtures; fatigue life; meta-learning prediction; mechanism analysis

I. Introduction

With the rapid development of the economy, the cause of transportation has also made great progress, asphalt pavement as one of the main forms of highway, its performance is directly related to the service life of the road and driving safety [1, 2]. Asphalt mixture is the main constituent material of asphalt pavement, which is prone to fatigue damage under the repeated action of long-term traffic load, which in turn leads to cracks, potholes and other disorders on the road surface, affecting the normal use of the road [3]. Accurately predicting the fatigue life of asphalt mixtures is of great significance for the rational design of pavement structure, optimization of material composition, development of scientific maintenance plans, and reduction of road construction and maintenance costs [4]. Therefore, exploring new prediction methods has important theoretical and practical application value.

Asphalt mixture fatigue life prediction is an important research field in transportation engineering and materials science, and its core objective is to accurately predict the service life of asphalt mixtures under long-term repeated loading through theoretical analysis, experimental research, and numerical simulation [5], so as to provide a scientific basis for road design, construction, and maintenance [6]. Asphalt mixture fatigue life prediction research mainly includes asphalt mixture fatigue mechanism research [7], fatigue life influencing factors analysis [8], fatigue life prediction method research [9], fatigue life prediction without model validation and optimization [10], and so on. Currently, asphalt mixture fatigue life prediction research started relatively early, and after years of development, has achieved a series of more mature results [11]. Wang et al. [12], based on experimental observation and theoretical derivation, put forward the classical fatigue life prediction model represented by linear cumulative damage theory. Abdulmawjoud [13] used a deep neural network to predict the fatigue life of asphalt mixture under different asphalt types, aggregate gradation, and loading frequency, and achieved better prediction results. Zhao et al. [14] used a deep learning algorithm, combined a convolutional neural network and Long Short-Term Memory (LSTM) structure to predict the fatigue life of asphalt mixtures containing dynamic fatigue test data, material composition parameters, environmental monitoring data, and other multi-source information. Ameri and Ebrahimzadeh [15] utilized the viscoelastic continuum damage model and successfully predicted the mid-temperature fatigue performance of aged asphalt binder through a linear amplitude scanning test, indicating that the nonlinear prediction model can well fit the fatigue performance of asphalt binder with different aging times, showing that the nonlinear prediction model can fit the fatigue life of asphalt binder with different aging times well. Harne et al. [16] proposed a fatigue life prediction method for green mixtures based on support vector machines, which transforms the fatigue life prediction problem of asphalt mixtures into a classification or regression problem by searching for the optimal classification hyperplane with good generalization ability and prediction accuracy. Yue et al. [17] adopted an optimization neural network-based method using genetic algorithms for the architecture of the neural network is optimized to further improve the prediction performance of the asphalt fatigue life prediction model. Although extensive and in-depth research has been carried out at home and abroad in the field of fatigue life prediction of asphalt mixtures and a series of fruitful results have been achieved [18], there are still some urgent deficiencies and challenges faced by the existing technology: 1) the traditional prediction model lacks an in-depth portrayal of the fatigue

*Corresponding author.

mechanism of the material, and it is difficult to accurately reflect the complex process of fatigue damage accumulation in asphalt mixtures [19]; 2) the Machine learning method models usually require a large amount of high-quality data for training, and in practice, there are greater difficulties in obtaining a sufficient amount of representative fatigue data, which to a certain extent restricts the model's performance improvement [20].

Based on the shortcomings of the existing research, this study is dedicated to introducing the cutting-edge technology of meta-learning [21] into the field of fatigue life prediction of asphalt mixtures, with a view to provide an innovative methodology and ideas for solving the existing technical problems. The main contributions of this study are reflected in the following: 1) constructing a fatigue life prediction model system for asphalt mixtures based on meta-learning; 2) combining the fatigue damage mechanism of asphalt mixtures with the material properties, exploring how to integrate the a priori knowledge in the physical model into the meta-learning model; and 3) verifying the validity and superiority of the proposed model through a large number of simulation experiments.

This study centers on the fatigue life prediction problem of asphalt mixtures, and constructs a meta-learning-centered intelligent prediction framework.

The structure of the whole study is arranged as follows: Firstly, the fatigue mechanism and life prediction of asphalt mixture are systematically analyzed in Section II, which clarifies the influencing factors and the demand of prediction model. Section III describes the basic principle of meta-learning, the classification of the method and the typical application, which provides theoretical support for the subsequent construction of the model. Section IV focuses on proposing the fatigue life prediction model based on meta-learning, and describes the design of its structure in detail. Section V carries out experimental validation to evaluate the model performance from multiple dimensions, such as prediction accuracy, error control, convergence speed and generalization ability, by comparing and analyzing with the traditional methods. Finally, Section VI summarizes the research results, points out the limitations of the current research, and proposes the direction of improvement in the future. Through the above structural arrangement, this study aims to provide an innovative, low-sample, and highly adaptable solution idea for the efficient prediction of asphalt mixture fatigue life.

II. Fatigue Life Prediction Problems of Asphalt Mixture

A. Fatigue Mechanism Analysis of Asphalt Mixtures

Asphalt mixture fatigue refers to the phenomenon of gradual deterioration of the internal structure of asphalt mixtures under the repeated action of cyclic loading with decreasing strength and stiffness, which ultimately leads to the destruction of the material [22], as shown in Fig. 1.

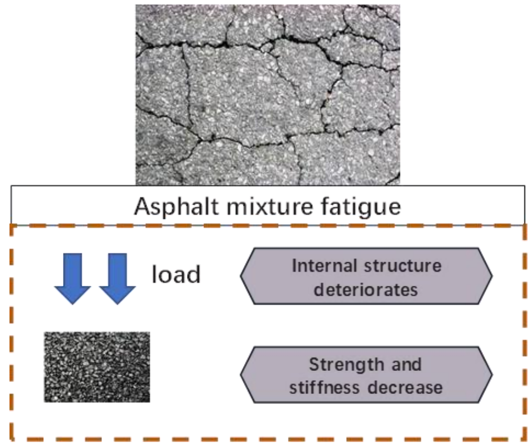

Fig. 1. Fatigue phenomenon in asphalt mixture.

1) Fatigue damage analysis: Asphalt mixture is a typical composite material, which consists of a variety of components such as asphalt, aggregate, filler, etc., as shown in Fig. 2. Under the action of loading, the interactions between the constituents jointly affect the fatigue performance of the material. From a microscopic point of view, the fatigue damage of asphalt mixtures is mainly reflected in three aspects, as shown in Fig. 3.

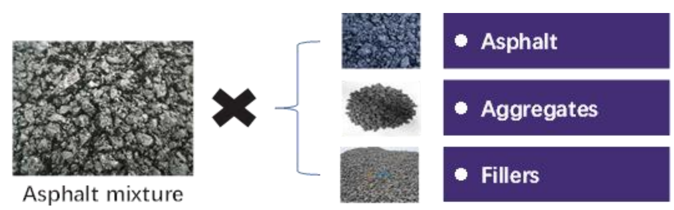

Fig. 2. Asphalt mixture.

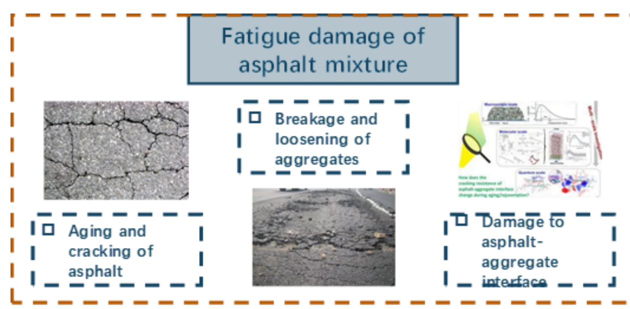

Fig. 3. Fatigue damage of asphalt mixture.

- Aging and rupture of asphalt: Under repeated loading, the lightweight components in asphalt gradually evaporate, resulting in asphalt hardening, its viscosity and elasticity decrease, and resistance to deformation is weakened. At the same time, under the repeated action of the load, the asphalt will also produce small cracks within the asphalt, and these cracks gradually expand, eventually leading to asphalt rupture.
- Aggregate fracture and loosening: Aggregate will produce micro-cracks under the action of load, and these cracks expand with the repeated action of load, which ultimately leads to the fracture of aggregate particles. In addition, the friction and misalignment between the

aggregate particles will also loosen the aggregate and reduce the embedding effect of the aggregate, thus affecting the overall strength of the asphalt mixture.

- Damage at the asphalt-aggregate interface: The bond at the interface between asphalt and aggregate is an important source of asphalt mixture strength. Under the action of load, the stress concentration at the interface will lead to a gradual weakening of the bond, and even the phenomenon of debonding. Once the bond at the interface fails, the aggregate particles will undergo relative displacement under load, accelerating the fatigue damage of asphalt mixture.

2) Fatigue damage principle: The fatigue damage of asphalt mixture is a complex physicochemical process, and its principle is mainly based on energy dissipation theory, microcrack extension theory and other parties [23], as shown in Fig. 4. As can be seen from Fig. 4, one is the energy dissipation theory, with the repeated action of the load, the energy dissipation within the material is increasing, resulting in a gradual decrease in the internal energy of the material, the structure is gradually loosened, and eventually fatigue damage occurs; the second is the theory of micro-crack expansion, the micro-cracks generated within the asphalt mixture under the repeated action of the load continue to expand and interpenetrate, the formation of macroscopic cracks, which ultimately leads to the fracture of the material.

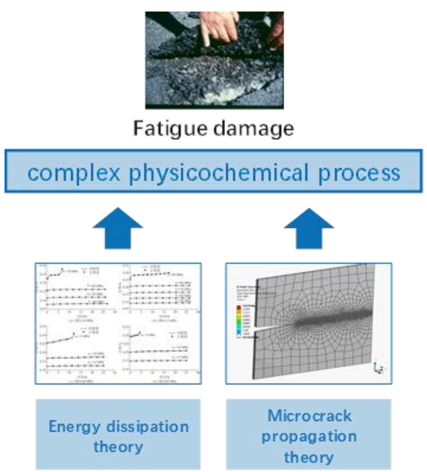

Fig. 4. Fatigue damage principle of asphalt mixture.

3) Characteristics: The fatigue of asphalt mixture has the following characteristics: 1) with the increase of load, the deformation of the material will gradually increase, showing obvious nonlinear characteristics; 2) asphalt mixture has both viscous and elasticity, and its mechanical behavior changes with time; 3) each load action will cause some damage to the asphalt mixture, and it continues to accumulate, which ultimately leads to the fatigue damage of the material [24]. The fatigue characteristics of asphalt mixtures are shown in Fig. 5.

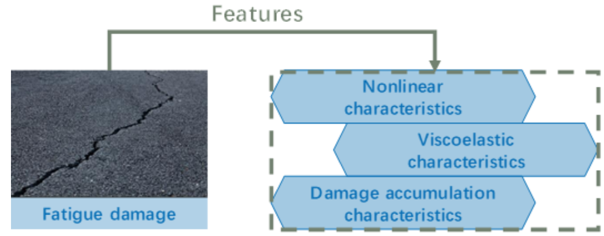

Fig. 5. Fatigue damage characteristics of the asphalt mixture.

B. Fatigue Life Prediction of Asphalt Mixtures

1) Definition and analysis: Fatigue life prediction of asphalt mixtures refers to the prediction of the number of cycles or service time, i.e., fatigue life that the material can withstand under a certain load, based on factors such as its composition, structure, and loading conditions [25]. The concept of fatigue life prediction for asphalt mixtures is shown in Fig. 6.

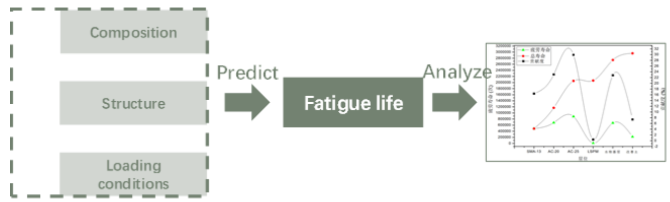

Fig. 6. Concept of fatigue life prediction for asphalt mixtures.

The key to fatigue life prediction is to establish a quantitative relationship between fatigue life and various influencing factors. There are many factors affecting the fatigue life of asphalt mixtures, including material composition, loading conditions, environmental factors, and so on. Material composition determines the basic physical and mechanical properties of asphalt mixtures, such as asphalt type and aggregate gradation. Load conditions include load size, frequency, loading mode, etc., which directly determine the level of stress and strain on the material. Environmental factors such as temperature and humidity also have a significant effect on the fatigue properties of the material (see Fig. 7).

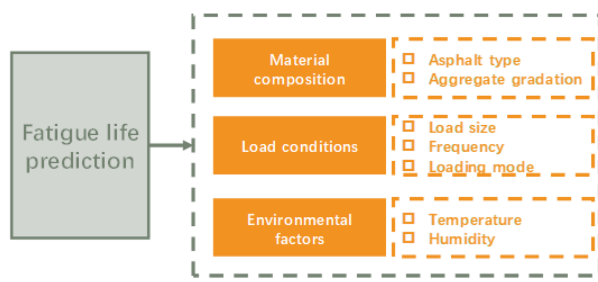

Fig. 7. Fatigue life prediction influencing factors.

2) Principles and characteristics: The principles of fatigue life prediction include fatigue damage accumulation model and material mechanics model. Fatigue damage accumulation model is to predict the fatigue life of materials by establishing the relationship between the fatigue damage and the number of loading cycles; material mechanics model: according to the mechanical properties of materials, establish the stress-strain relationship of materials, combined with the fatigue damage mechanism, to predict the fatigue life of materials [26].

Fatigue life prediction has the following characteristics: 1) uncertainty; 2) multi-factor coupling; 3) model dependence.

III. Meta-Learning

A. Principles and Methods

1) Principle of meta-learning: Meta-learning, i.e., "learning to learn", is an advanced machine learning concept, which aims to enable the model to quickly adapt to new tasks through the accumulation of experience, and significantly improve the learning efficiency and generalization ability [27]. The principle of meta-learning is shown in Fig. 8.

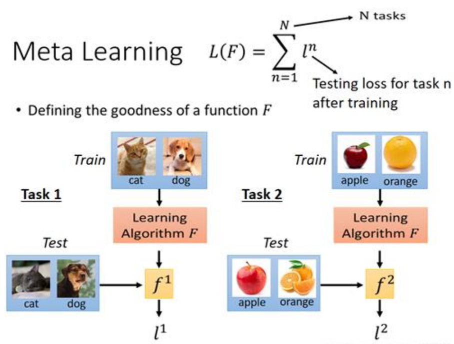

Fig. 8. Principle of meta-learning.

Traditional learning methods usually train models for a single task, while meta-learning extracts common knowledge from multiple related tasks to form a common knowledge base. When faced with a new task, the model utilizes the meta-knowledge to quickly adjust and efficiently find a solution with little data and computational resources.

2) Types of methods: Meta-learning methods are divided into optimization-based meta-learning, metric-based meta-learning, model-based meta-learning, etc., as shown in Fig. 9.

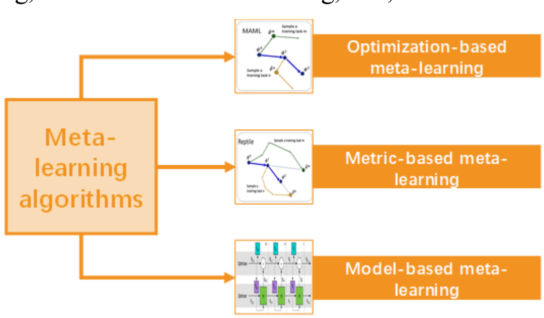

Fig. 9. Classification of meta-learning algorithms.

Optimization-based meta-learning makes the model learn quickly on a small amount of new data by adjusting the initial parameters or learning rate, the typical representative is MAML (Model-Agnostic Meta-Learning). Metric-based meta-learning constructs metric space to facilitate sample similarity metrics and classification, the representative algorithm is Prototypical Networks. Model-based meta-learning constructs models to quickly adapt to new tasks.

B. Applications and Characteristics

1) Meta-learning applications: In the field of image classification, meta-learning can be used to quickly classify new categories of images. A large amount of image data covering multiple categories and scenes is collected to train the classification model. When new image categories, the model uses meta-knowledge to quickly and accurately classify them, saving time and computational resources.

In the field of natural language processing, meta-learning can be used for tasks such as text categorization, sentiment analysis, and machine translation, as shown in Fig. 10. In the field of material science, meta-learning can be used for material performance prediction, such as predicting the strength, hardness, and fatigue life of materials. Performance data of multiple materials are collected to train the prediction model. When new material properties are predicted, the model utilizes meta-knowledge to predict quickly and accurately, accelerating research and development.

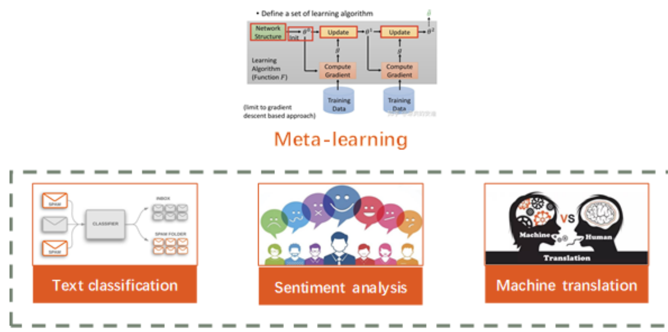

Fig. 10. Meta-learning application analysis.

2) Meta-learning characteristics: Meta-learning is characterized by rapid adaptability, strong knowledge transfer, high learning efficiency, and wide applicability, as follows: 1) Rapid adaptability. The meta-learning model is trained by multi-tasks and has the ability to adapt quickly; 2) Strong knowledge migration. Meta-learning can extract generalized knowledge from multi-tasks to form a strong knowledge base, which can be shared and utilized for different but related tasks to enhance the learning effect of new tasks; 3) High learning efficiency. Meta-learning uses multi-task experience to optimize the learning process, improve efficiency, quickly adapt to new tasks, and reduce data and computational resource requirements; 4) Wide applicability. Meta-learning is applicable to multiple fields such as image classification, natural language processing, material science, robot control, etc.

IV. Meta-Learning Based Fatigue Life Prediction Method for Asphalt Mixtures

A. Structure of the Prediction Model

1) Overall framework of the model: The overall framework of the meta-learning-based fatigue life prediction model for asphalt mixtures integrates a meta-learner, a feature extractor, and a task-specific model, aiming to efficiently process multi-task learning and accurately predict the fatigue life of a new task, as shown in Fig. 11. As can be seen in Fig. 11, the meta-learner extracts generic features and initial parameters from multi-task data, the feature extractor deeply processes the input data to generate high-dimensional feature representations, and the task-specific model is fine-tuned with a small amount of data based on the meta-knowledge provided by the meta-learner to achieve fast adaptation and accurate prediction of new tasks.

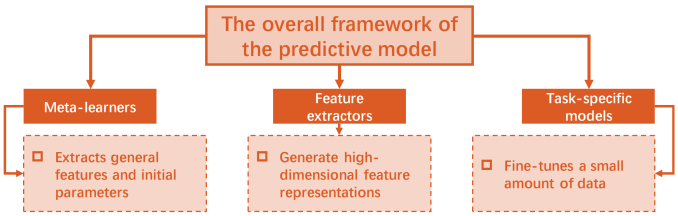

Fig. 11. Overall framework of the prediction model.

B. Key Technologies

The meta-learning-based fatigue life prediction model construction for asphalt mixtures includes key technologies such as feature extraction and fusion, meta-knowledge learning, and fast adaptive algorithms, as shown in Fig. 12.

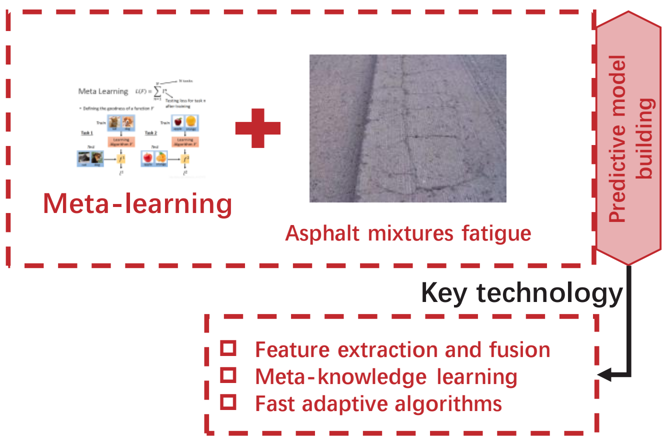

Fig. 12. Key techniques for predictive model construction.

1) Feature extraction and fusion: For fatigue life prediction of asphalt mixtures, the input data include material composition (e.g., asphalt type, aggregate gradation, etc.), structural parameters (e.g., void ratio, mineral gap ratio, etc.), and loading conditions (e.g., stress level, loading frequency, etc.). The model needs to automatically extract and fuse the key features of these multi-source heterogeneous data. A multi-layer neural network is used as the feature extractor, with different layers extracting different levels of semantic information.

2) Meta-knowledge learning: The model needs to learn generic meta-knowledge from multiple related tasks, which can help the model quickly adapt to new tasks. The meta-knowledge includes generic feature representations and initial values of model parameters. The generic feature representations are common features extracted from the data of multiple tasks, which can reflect the basic laws of fatigue life of asphalt mixtures. The initial values of the model parameters are the optimal initial values obtained after multiple task training, which can make the model converge quickly in the new task.

3) Fast adaptive algorithm: The fast adaptive algorithm is the core of meta-learning, which enables the model to use a small amount of new task data to quickly adjust the model parameters. In optimization-based meta-learning methods, the fast adaptive algorithm uses gradient descent for parameter updating. In the new task, the model first uses a small amount of data to calculate the gradient of the loss function, and then combines the initial parameters provided by the meta-learner to quickly adjust to get the parameters adapted to the new task.

C. Methodological Steps

Combined with the meta-learning algorithm, a data-driven fatigue life prediction method based on asphalt mixtures was designed, and the process is shown in Fig. 13 with the following steps:

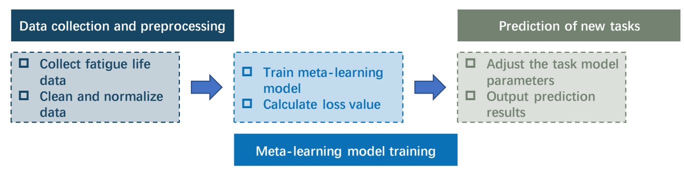

Fig. 13. Fatigue life prediction method for asphalt mixtures.

Step 1: Data collection and pre-processing. Collect fatigue life data under different asphalt mixture types and loading conditions, including material composition parameters, structural parameters and fatigue life. Clean and normalize the data to remove outliers and missing values.

Step 2: Meta-learning model training. The meta-learning model is trained using the training set. Each task data in the training set is input into the model, and the parameters of the meta-learner are updated by the optimization algorithm. First, initialize the parameters of the meta-learner, and then for each task, perform a gradient descent update based on the parameters of the meta-learner to obtain the model parameters for that task. Calculate the value of the loss function for that task and update the meta-learner's parameters by backpropagation. Repeat this process until the performance of the meta-learner is optimized on all tasks.

Step 3: New task prediction. When a new asphalt mixture fatigue life prediction is required, a small amount of data from the new task is fed into the trained meta-learning model. The model uses the meta-knowledge provided by the meta-learner to quickly adjust the parameters of the task-specific model. The adjusted model is then used to predict the fatigue life of the new task and the predictions are output.

V. Experimental Validation

A. Experimental Setup

In order to verify the effectiveness and superiority of the meta-learning based fatigue life prediction method for asphalt mixtures, the following experimental setup was conducted:

1) Data set preparation: Fatigue life data of multiple types of asphalt mixtures, including different asphalt types, aggregate gradation, and loading conditions, were collected from public databases and laboratory tests. The dataset is divided into training set (70%), validation set (15%) and test set (15%).

2) Experimental environment: MATLAB 2021a platform was used for the experiment, and the appropriate meta-learning algorithm (MAML) and neural network architecture (multilayer perceptual machine) were selected. Set the experimental parameters: the learning rate is 0.01, the training period is 500 times, and the batch size is 32.

3) Comparison method: In order to highlight the advantages of meta-learning based methods, traditional methods (including linear regression and BP neural network) are selected for comparison. The parameter settings of the three algorithms are shown in Table I.

TABLE I. ALGORITHM PARAMETER SETTINGS

ID	Algorithm	Parameter Settings
1	Linear Regression	L2 regularization (ridge regression); Regularization coefficient initial value: 0.1
2	BP Neural Network	Multi-layer perceptron (MLP) architecture; Initial learning rate: 0.001; Batch size: 32; Training epochs: 500
3	Meta-Learning (MAML)	Base learning rate: 0.01; Meta-learning rate: 0.001; Outer optimizer: Adam; Tasks per batch: 20; Training epochs: 500; MLP architecture; Hidden layers activated by ReLU

B. Analysis of Results

In order to deeply evaluate the practical efficacy of the fatigue life prediction model for asphalt mixtures based on meta-learning, this section compares it with the traditional linear regression and BP neural network methods, and carries out the analysis of the results in terms of prediction accuracy, error control, convergence speed, and generalization ability, and obtains the results shown in Fig. 14 to Fig. 17, Table II to Table IV.

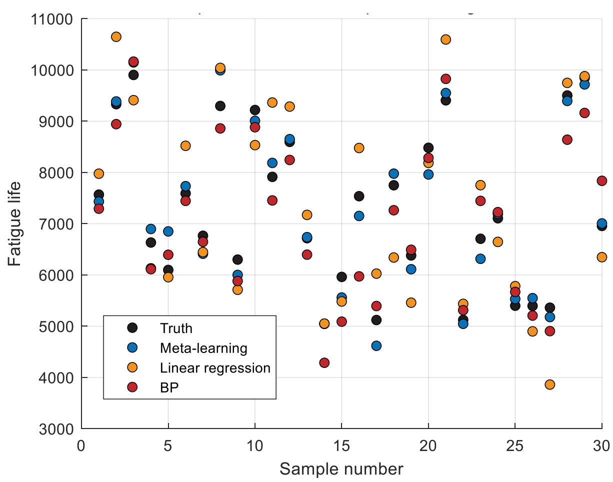

Fig. 14. Comparison of actual and predicted fatigue life.

Fig. 14 shows the comparison between the actual values of fatigue life of asphalt mixtures and the results obtained by three prediction methods: meta-learning method, traditional linear regression method, and BP neural network method. From the figure, it can be visualized that the meta-learning method is closest to the real value in the overall trend, and its prediction curve closely follows the actual life data, showing superior fitting accuracy. In contrast, the traditional method shows large deviations at several points, especially in the fatigue life of higher or lower conditions, and the BP neural network, although improved compared with the traditional linear method, still shows a certain degree of volatility and instability in some segments.

Further discussion and analysis of Fig. 14 shows that the meta-learning method shows a strong generalization ability and adaptivity, not only in the high value zone can be accurately predicted, but also maintains a good fit in the low value zone. This performance is attributed to the “meta-knowledge” extracted from multi-task learning, which enables the model to quickly adjust the parameters and give accurate results even in the face of unseen samples. This method outperforms the traditional model in responding to new conditions and data fluctuations, which shows that it has a stronger practical value and potential for popularization in road engineering. This also verifies the effectiveness of the meta-learning-based prediction method proposed in this study in improving the accuracy of fatigue life prediction of asphalt mixtures.

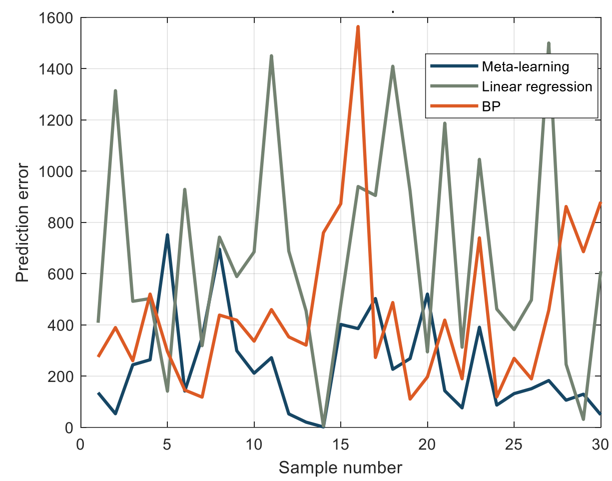

Fig. 15. Comparison of prediction errors.

Fig. 15 shows the error comparison of the three prediction methods (meta-learning, linear regression, and BP neural network) in the fatigue life prediction task of asphalt mixtures. It can be clearly seen in the figure that the meta-learning method has the lowest prediction error as a whole, and the error distribution is more concentrated and less fluctuating, indicating that it has stronger stability and accuracy. In contrast, the traditional linear regression method has the largest range of error fluctuations, with multiple high error points, indicating that its ability to fit the nonlinear law of fatigue life is limited, and it cannot effectively capture the complex feature interactions. While the BP neural network reduces the error to a certain extent, the overall error level is still higher than that of the meta-learning method, especially in some of the test samples where large deviations still occur.

Further observing the trend of the error curves, the meta-learning method keeps the error in a lower range in several data segments, showing its good adaptability to different working conditions and sample types. Its lower maximum error and standard deviation indicate that meta-learning has obvious advantages in generalization and robustness. This is due to the "meta-knowledge" accumulated through multi-task learning, which can be quickly and accurately adapted to new tasks. In contrast, BP neural network still relies on a large number of samples for training, while linear regression lacks the ability to model nonlinear factors. Therefore, Fig. 15 further verifies that the meta-learning method is more stable and practical than traditional methods in real engineering prediction.

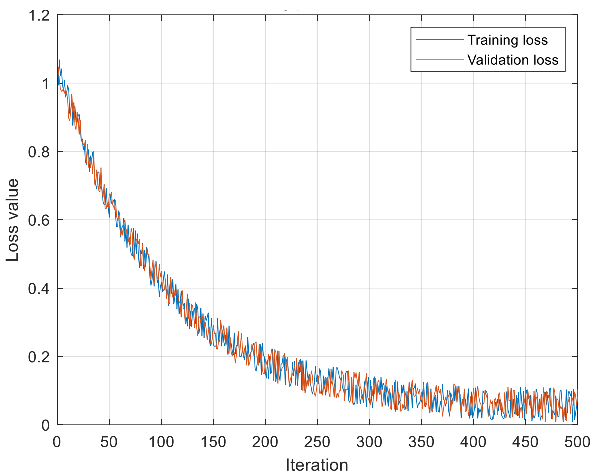

Fig. 16. Training process curve.

Fig. 16 demonstrates the trend of training loss and validation loss with the number of iterations for the meta-learning-based approach in fatigue life prediction of asphalt mixtures. From the overall trend, both the training loss and the validation loss decrease rapidly with the increase of the number of iterations and level off at a certain stage, indicating that the model training process has good convergence. Especially in the first 100 iterations, the loss value shows a rapid decline, indicating that the meta-learning model is able to effectively capture the common knowledge among tasks and establish a stable prediction structure at the early stage. Compared with the slow convergence process of traditional neural networks, this feature significantly improves the training efficiency of the model.

From the change curve of the validation loss, the model does not show any obvious oscillation or overfitting trend throughout the training process, indicating its strong generalization ability. The change in loss on the validation set is consistent with the training set, indicating that the meta-learning method still maintains a stable performance in the face of unseen tasks or samples. This is because the model extracts more generalizable meta-parameters through the learning process of multiple tasks, allowing the model to adapt quickly with a small amount of fine-tuning even when faced with a new task with a slightly different distribution from the training set. This performance is of great practical importance for life prediction of asphalt mixtures under variable operating conditions.

From the final stabilized value of the loss curve, the loss value of the model after the training of the meta-learning method is significantly lower than that of the traditional method, which reflects its higher prediction accuracy and model robustness. Since the fatigue life prediction of asphalt mixtures involves the complex coupling of multiple factors, the traditional method is often difficult to fully express the deep relationship between variables due to the limited modeling capability. The meta-learning method not only accelerates the training convergence speed by extracting and utilizing multi-task synergistic information, but also improves the model's ability to fit the complex fatigue damage mechanism, which provides theoretical support for further popularizing the technology to road material performance prediction.

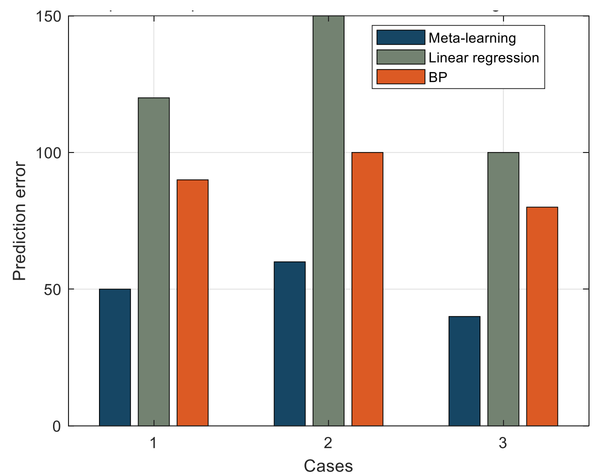

Fig. 17. Comparison of prediction errors under different working conditions.

Fig. 17 shows the comparison results of the errors of the three methods (meta-learning, BP neural network, and linear regression) in the fatigue life prediction of asphalt mixtures under different working conditions. It can be clearly seen that the meta-learning method shows the lowest prediction error under all kinds of working conditions, which is significantly better than the BP neural network and the traditional linear regression method, indicating that it has a stronger adaptive ability and robustness to working conditions. Especially under the more complex or nonlinear conditions such as working conditions 2 and 3, the error control ability of the meta-learning method is still stable with almost no obvious fluctuation, which demonstrates its strong modeling ability in the face of high-dimensional and multivariate input scenarios.

Further analysis shows that the linear regression method has the most significant error difference among different working conditions, and its prediction error is susceptible to drastic changes in variables, with poor stability, showing a typical underfitting problem. BP neural network, although improved compared with linear regression in most of the working conditions, still shows an increase in prediction deviation under high loads or complex material parameter combinations. This indicates that the traditional methods have limited ability to model the nonlinear interactions among multiple variables, such as environment, load, and material components, and are difficult to perform the task of predicting variable working conditions in engineering.

In contrast, the meta-learning approach, by accumulating rich "meta-knowledge" during the multi-task training phase, enables the model to adapt quickly to new working conditions, and can realize high-precision prediction with only a very small amount of new task data. The analysis results in Fig. 17 further demonstrate that the meta-learning method not only improves the prediction accuracy and efficiency, but also enhances the generalization ability of the model under different external environments or parameter fluctuations, which is an effective way to solve the problem of "poor adaptability to multiple working conditions" in the prediction of the life of asphalt mixtures.

TABLE II. ALGORITHM COMPARISON DATA

Iterations	Meta-Learning Accuracy	Linear Regression Accuracy	BP Neural Network Accuracy
100	0.95	0.80	0.85
200	0.96	0.82	0.87
300	0.97	0.83	0.88
400	0.98	0.84	0.89
500	0.98	0.84	0.89

Table II demonstrates the comparison of the prediction accuracies of the three methods (meta-learning, linear regression, and BP neural network) with different numbers of training iterations (100, 200, 300, 400, and 500), aiming to assess the evolutionary trend of the accuracy of each method with the upper bound performance as the training process advances.

First, from the overall trend, the prediction accuracies of all three methods increase with the number of iterations, indicating that continuous training helps the models to extract more effective features and laws. However, there are significant differences in the rise and final accuracy among the three. The meta-learning method achieves a high accuracy of 0.95 in the initial 100 iterations, much higher than the 0.80 of linear regression and the 0.85 of BP neural network, which indicates that it has a strong learning and fitting ability under a small amount of training, reflecting the core advantage of meta-learning of "fast adaptation with few samples".

Secondly, in terms of stability and final performance, the accuracy of the meta-learning model reaches 0.97 at 300 times of training, and stabilizes at 0.98 at 500 times, showing high training efficiency and convergence performance. In contrast, the BP neural network model can only approach 0.89 after 400 iterations, which is slow to improve and the accuracy fluctuates; the linear regression model almost stops the growth of accuracy after 200 iterations, and finally stays at 0.84, reflecting the existence of an obvious model upper limit, which is difficult to further approximate the actual data. This also indicates that the linear model has limited performance in the face of complex nonlinear relationships in asphalt mixtures.

Thirdly, from the perspective of model variability, the performance of meta-learning is much better than the other two, because it obtains "common initialization parameters" and "task adaptation ability" through multi-task learning, which makes the model jump out of the local optimum faster, and avoids the traditional method of high-dimensional nonlinear problems falling into the "common initialization parameters" and "task adaptation ability". It avoids the traditional methods from falling into the dilemma of "underfitting" or "overfitting" in high-dimensional nonlinear problems. Thus, the data in Table II not only verifies the significant advantage of the meta-learning method in training accuracy, but also further supports its potential as an efficient, stable and strongly generalized prediction tool in engineering practice.

TABLE III. PREDICTION ERROR DATA UNDER DIFFERENT WORKING CONDITIONS

Condition	Meta-Learning Error	Linear Regression Error	BP Neural Network Error
1	50	120	90
2	60	150	100
3	40	100	80

Table III lists the prediction errors of the three methods in three typical conditions: 50, 60, 40 for the meta-learning method, 120, 150, 100 for the linear regression, and 90, 100, 80 for the BP neural network, and the meta-learning method has the lowest error in all the conditions, which shows the strongest prediction accuracy and error control ability. Among them, Case 2 usually represents a more complex or extreme test scenario, in which the error of traditional methods rises significantly (up to 150 for linear regression and 100 for BP), while the meta-learning method still controls the error within 60, which shows that it still has a high stability and generalization ability under the high-complexity task. This advantage stems from the meta-learning's extraction and migration of common knowledge from multiple historical tasks, which gives the model the ability to be quickly tuned under new working conditions without the need for a large number of samples to be relearned.

Further analyzing the robustness of the model and its ability to adapt to the working conditions from the error fluctuation amplitude, we find that the error range of the meta-learning method is only 20 (from 40 to 60) under the three working conditions with the smallest variation, while that of the BP neural network is 20 (from 80 to 100), and that of linear regression is as high as 50 (from 100 to 150), which indicates that meta-learning not only predicts more accurately, but also performs more smoothly and reliably among the working conditions. Especially when the working condition parameters change significantly, the error of linear regression method fluctuates drastically and is prone to deviate significantly from the actual value, reflecting its lack of modeling ability for complex environments. Although BP neural network is more flexible, the error is still amplified when there are insufficient samples or complex feature interactions. In conclusion, the data in Table III fully reflects the system advantages of meta-learning in terms of "cross-operating conditions, consistency and fault tolerance", which is an effective means to construct a highly robust asphalt fatigue life prediction system.

TABLE IV. MODEL CONVERGENCE SPEED

Iterations	Meta-Learning Convergence Speed	Linear Regression Convergence Speed	BP Neural Network Convergence Speed
20	0.3	0.1	0.15
40	0.5	0.15	0.25
60	0.7	0.2	0.35
80	0.8	0.25	0.45
100	0.9	0.3	0.55

Table IV demonstrates the comparison of the convergence speed (i.e., the training accuracy or loss decline speed) of the three prediction methods (meta-learning, linear regression, and BP neural network) at different numbers of iterations (20, 40, 60, 80, and 100). From the data, it can be seen that the meta-learning method shows a clear lead in each iteration stage: at 20 iterations, the convergence speed has reached 0.3, while linear regression and BP neural networks are only 0.1 and 0.15; at 100 iterations, the meta-learning speed rises to 0.9, much higher than the BP's 0.55 and the linear regression's 0.3. This suggests that meta-learning has a much faster initial fitting ability and overall convergence efficiency, and is able to achieve a much higher training accuracy or loss decline speed at different numbers (20, 40, 60, 80, and 100). This can build an effective prediction model in a very short training cycle, saving training time and improving engineering efficiency. The reason is that the meta-learning method constructs a good “model initialization” by extracting the shared patterns and parameters among multiple tasks, thus speeding up the adaptation to new tasks.

In terms of the smoothness and cost of the convergence process, meta-learning not only improves the performance rapidly at the early stage of training, but also has a smooth and persistent convergence curve with almost linear growth trend, showing good controllability and stability. This is especially critical for engineering applications, especially in environments with restricted data or limited training resources, where fast convergence can significantly reduce computational costs. While linear regression converges slowly and is susceptible to data distribution interference, its convergence value is always low, indicating its natural limitation in complex feature modeling; BP neural network, although it has some nonlinear fitting ability, improves slowly in the initial stage (only from 0.15 to 0.55), has higher training cost, and is sensitive to the hyper-parameters and the number of samples, with the risk of training instability.

VI. CONCLUSION

This study focuses on the fatigue life prediction problem of asphalt mixture, innovatively introduces the meta-learning method, and proposes the fatigue life prediction method of asphalt mixture based on meta-learning algorithm. The method analyzes the fatigue mechanism of asphalt mixtures, extracts the influencing factors affecting fatigue, analyzes the fatigue life prediction problem of asphalt mixtures, and combines the meta-learning algorithm to construct the fatigue life prediction model of asphalt mixtures. Through systematic experimental simulation analysis, the significant advantages of the meta-learning method in terms of prediction accuracy, error control, convergence speed and generalization ability are verified. The study shows that the meta-learning method can effectively utilize the multi-task learning mechanism, quickly adapt to different working conditions, and provide an efficient and accurate solution for the fatigue life prediction of asphalt mixtures. Future research will focus on further optimizing the meta-learning model architecture and expanding its practicality and application scenarios, with a view of playing a greater role in practical engineering.

REFERENCES

[1] Qu L , Wang Y , Riara M , Mo L, Xiao Y. Study on fatigue-healing performance and life prediction of hot recycled asphalt mixture[J].*Construction and Building Materials*, 2024, 436:14.doi:https://doi.org/10.1016/j.conbuildmat.2024.136964.

[2] Wang L , Li Q , Liu K J K .Fatigue Performance Analysis and Life Prediction of Wood Tar-Based Rejuvenated Asphalt[J].*International Journal of Pavement Research and Technology*, 2024, 17(6):1531-1542. doi:https://doi.org/10.1007/s42947-023-00315-w.

[3] Silva L S V D , Bastos J B D S ,Lucas J, Jorge Luiz O, Babadopulos L F D A L, Soares, J B. Evaluation of moisture-induced damage on the fatigue life of asphalt mixtures using failure tests of asphalt binders, interfaces, and mixtures[J].*Fatigue & Fracture of Engineering Materials & Structures*, 2024, 47(7). doi:https://doi.org/10.1111/ffe.14280.

[4] Wang G , Sun E , Zhao Y .Study on fatigue performance and rutting prediction model of steel slag asphalt mixture[J].*Canadian Journal of Civil Engineering*, 2024, 52(2):228-245. doi:https://doi.org/10.1139/cjce-2024-0064.

[5] Lv S .Fatigue Life of Pre-Cut Seam Asphalt Mixture Composite Beams: A Combined Study of Fatigue Damage Evolution and Reflective Cracking Extension[J].*Buildings*, 2024, 15. doi:https://doi.org/10.3390/buildings15010050.

[6] Krzysztof S, Baran J. Towards Data-Enabled Intelligent Road Construction: A Review of Hybrid Algorithms and Applications. *Data Engineering and Applications*. 2024, 4(2): 1–13. doi:https://doi.org/10.64972/dea.2024.v4i2.19.

[7] Xu X , Wan G , Kang F , Li S, Huang W, Li Y. Evaluation Method of Fatigue Life for Asphalt Pavement on the Steel Bridge Deck Based on the Inhomogeneous Poisson Stochastic Process[J].*Materials*, 2024, 17(4):12. doi:https://doi.org/10.3390/ma17040780.

[8] Yang H , Ouyang J , Feng L , Ou J. Fatigue-Healing Performance Evaluation of Fiber-Modified Asphalt Mixture[J].*Journal of Materials in Civil Engineering*, 2024, 36(1):9. doi:https://doi.org/10.1061/JMCEE7.MTENG-16828.

[9] Petcu C , Racanel C .Estimation of Asphalt Mixture Fatigue Behaviour Using the Two-Point Bending Test[J].*Journal of Applied Engineering Sciences*, 2024, 14(1):153-160. doi:https://doi.org/10.2478/jaes-2024-0019.

[10] Spinola J R , Melo J V S D , Manfro A L .Development of an asphalt mixture with polymer incorporation modified by industrial graphene nanoplatelets for high-performance to rutting[J].*The International Journal of Pavement Engineering*, 2024, 25(1):2337303.1-2337303.26.

[11] Peng X , Jiajun C , Aihong K , Heyu K, Xukang D, Yao Z. Performance of epoxy asphalt mixtures toughened with different fibers[J].*Experimental Technology & Management*, 2024, 41(1). doi:https://doi.org/10.16791/j.cnki.sjg.2024.01.006.

[12] Wang L , Cheng P , Zhao Q .Research on Fatigue–Healing Performance of Asphalt Mixture Based on the Semicircular Bending Test[J].*Materials*, 2023, 16(19):16. doi:https://doi.org/10.3390/ma16196382.

[13] Abdulmawjoud A A .Evaluation of Fatigue Characteristics of Reclaimed Asphalt Pavement Mixtures Through Dissipated Energy[J].*International Journal of Pavement Research and Technology*, 2023, 16(1):9. doi:https://doi.org/10.1007/s42947-021-00128-9.

[14] Zhao Y , Liu X , Yan D .Evaluation of drastic temperature change on temperature stress of asphalt mixture during microwave deicing[J].*Road Materials and Pavement Design: an International Journal*, 2024(7/9):25.

[15] Ameri M , Ebrahimzadeh Shiraz M .A Review of the Studies on the Effect of Different Additives on the Fatigue Behavior of Asphalt Mixtures[J].*Advances in Civil Engineering*, 2024, 2024. doi:https://doi.org/10.1155/2024/6695747.

[16] Harne V R , Tripathi R K , Guzzarlapudi S D .Effect of extrinsic and intrinsic parameters on fatigue performance of hot mix asphalt mixtures: a review[J].*Journal of Building Pathology and Rehabilitation*, 2024, 9(1). doi:https://doi.org/10.1007/s41024-024-00406-6.

[17] Yue M , Yue J , Wang R , Guo Y, Ma X. A Comprehensive Analysis of Fatigue and Healing Capacity of Sasobit Polymer-Modified Asphalt from Two Perspectives: Binder and FAM[J].*Journal of Materials in Civil Engineering*, 2023, 35(3):19. doi:https://doi.org/10.1061/(ASCE)MT.1943-5533.0004655.

[18] Ani O J , Shafabakhsh G A , Mirabdolazimi S M .Presenting the Self-Healing Potential Model by Induction Heating Method in Warm Asphalt Mixtures by Artificial Neural Network[J].*Journal of Advanced Research in Fluid Mechanics and Thermal Sciences*, 2023. doi:https://doi.org/10.37934/arfmts.105.2.120.

[19] Li Y , Tian G , Guo W , Wei Z, Zhou Z, Chen Z. Fatigue resistance of asphalt and asphalt mixture incorporated with high-elasticity anti-rutting additive[J].*Construction and Building Materials*, 2025, 459. doi:https://doi.org/10.1016/j.conbuildmat.2024.139730.

[20] Wei H , Xu B , Li J ,Zheng J, Liu Y, Lu R. Effect of temperature on fatigue damage evolution of asphalt mixture based on cluster analysis and acoustic emission parameters[J].*Engineering Fracture Mechanics*, 2025, 317. doi:https://doi.org/10.1016/j.engfracmech.2025.110954.

[21] Xiao H , Tian W , Liu W , Guo J, Zhang Z, Jin S. Knowledge-Driven Meta-Learning for CSI Feedback[J]. *IEEE Transactions on Wireless Communications*, 2024, 23(6):16. doi:https://doi.org/10.1109/TWC.2023.3327984.

[22] Wang Z , Liu D , Hu B , Zhu C, Luo W. An improved regression model to predict fatigue life of asphalt mixes incorporating low to moderate RAP contents[J].Construction and Building Materials, 2023, 374:13. doi:https://doi.org/10.1016/j.conbuildmat.2023.130904.

[23] Liu H , Kong D , Guo T , Jin D, Chu C, Yu H. Experimental study on creep-fatigue damage of hot central plant recycling asphalt mixture containing high RAP[J].Construction and Building Materials, 2024, 440(000):13. DOI:https://doi.org/10.1016/j.conbuildmat.2024.137348.

[24] Hong L , Yuan J , Sun L , Liu L. A model predicting mechanical properties of asphalt mixtures considering void ratio and loading conditions[J].Materials Today Communications, 2024, 39. DOI:https://doi.org/10.1016/j.mtcomm.2024.109221.

[25] Monteiro S N .Influence of the Bailey Gradation Method on the Mechanical Behavior of Asphalt Mixture Containing Steel Slag as an Alternative Aggregate[J].Buildings, 2024, 14. DOI:https://doi.org/10.3390/buildings14123942.

[26] Seitllari A .Investigating the fatigue life of asphalt pavements under different aging levels using the three-point bending cylinder (3PBC) test and mechanistic-empirical analysis[J].Materials and Structures, 2025, 58(4). DOI:https://doi.org/10.1617/s11527-025-02659-0.

[27] Dabrowski B, Walczak R. Intelligent Methods for Feature Extraction and Diagnosis of Rolling Bearing Composite Faults Based on Machine Learning: A Review. Journal of Applied Automation Technologies, 2025.3:39–51. DOI:https://doi.org/10.64972/jaat.2025v3.4.