applied sciences

MDPI

Article

Research on the Fatigue Life Prediction for a New Modified Asphalt Mixture of a Support Vector Machine Based on Particle Swarm Optimization

Yu Sun [1,2], Dongpo He [1,*] and Jun Li [2]

[1] School of Civil Engineering, Northeast Forestry University, Harbin 150040, China; donglin_2016@163.com
[2] Department of Municipal and Environmental Engineering, Heilongjiang Institute of Construction Technology, Harbin 150000, China; jinbaobei_2008@163.com
* Correspondence: Hdp@nefu.edu.cn

Abstract: SMC (Styreneic Methyl Copolymers) is a novel normal temperature asphalt modifier with superior performance. It has the advantages of a low construction temperature, good road performance, good energy savings and an emission reduction effect, and can improve the performance of an asphalt mixture. The fatigue performance of an asphalt mixture is one of the important technical parameters in the structural design of asphalt pavements. The fatigue performance of an asphalt mixture under specific traffic and environmental conditions has an important guiding significance and normative function for the design, construction, and maintenance of asphalt pavement. In this paper, the mixture of an SMC normal-temperature-modified asphalt and styrene–butadiene styrene block copolymer (SBS)-modified asphalt (SMCSBS) compound-modified asphalt was investigated, and an SMCSBS composite modified asphalt mixture with a different SMC content was prepared. A semi-circular bending fatigue test (SCB) was conducted to analyze and compare the fatigue properties of the modified asphalt mixture. On this basis, this paper proposes a fatigue life prediction model of an SMCSBS composite modified asphalt mixture based on a particle swarm optimization support vector machine (PSO-SVM). SMC content (SMC accounts for the mass percentage of SMCSBS composite modified asphalt)/%, asphalt aggregate ratio, stress ratio and loading frequency/Hz were used as training data to establish the prediction model, and RMSE and R^2 were used to evaluate the performance of the model. Experimental results show that the prediction results of the PSO-SVM method are more accurate than the experimental observation data and can effectively improve the prediction accuracy of the model. Compared with the M5′ model tree (M5′), artificial neural network (ANN), and support vector machine (SVM) method, the PSO-SVM method can achieve better prediction performance and a better prediction effect.

Keywords: SMCSBS composite modified asphalt mixture; the fatigue life; support vector machine (SVM)

check for updates

Citation: Sun, Y.; He, D.; Li, J. Research on the Fatigue Life Prediction for a New Modified Asphalt Mixture of a Support Vector Machine Based on Particle Swarm Optimization. *Appl. Sci.* **2021**, *11*, 11867. https://doi.org/10.3390/app112411867

Academic Editor: Nikos D. Lagaros

Received: 10 November 2021
Accepted: 12 December 2021
Published: 14 December 2021

Publisher's Note: MDPI stays neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Copyright: © 2021 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https://creativecommons.org/licenses/by/4.0/).

1. Introduction

With increasing traffic volume and heavy load traffic, a large number of reflection cracks appear in a traditional pavement structure under fatigue load, and the service life of a road is greatly shortened [1]. Fatigue failure is one of the main forms of current asphalt pavement damage. It is very important to study the fatigue performance of asphalt pavement under specific traffic and environmental conditions [2]. In order to ensure good serviceability and durability of asphalt pavement, it is of great significance to study the fatigue performance of asphalt mixtures and establish an appropriate fatigue prediction model [3–6].

Hveem is the first scholar to study the fatigue failure of asphalt pavement based on elasticity. Hveem's research shows that there is a correlation between pavement cracks, fatigue damage types, and pavement deformation caused by wheel pressure [7]. Santucci and Schmidt obtained the result of a low fatigue life of an asphalt mixture with high void

content through a fatigue test of controlling strain mode [8]. Zhesheng Ge used the grey relational analysis method to study the influence of load interval time, loading frequency, test temperature, void fraction, asphalt penetration, and asphalt content on the fatigue performance of a mixture, and found that the order of influence degree from large to small is as follows: Load interval time, test temperature, asphalt type, gradation type, asphalt content, and loading frequency [9]. Hongzhou Zhu evaluated the influence of asphalt property, aggregate gradation, and mixture volume on fatigue performance by using a grey correlation. The research showed that the mixture saturation, the mixture void fraction, the rubber powder mass ratio, and the asphalt film thickness have a great influence on fatigue performance [10]. Jiangmiao Yu and Xiaoning Zhang studied the influence of the environment on the fatigue performance of a mixture. The study showed that, within a certain test temperature range, the fatigue life increased with the increase of temperature. The fatigue life of the asphalt mixture specimen decreased after long-term aging [11].

Styreneic Methyl Copolymers (SMC) are a kind of normal temperature asphalt modifier, with a methyl styrene block copolymer extracted from waste plastics, waste rubber, and other methyl styrene polymer materials as the main raw material, and epoxy resin, an epoxy resin curing agent, and other additives in a certain proportion with the polymer solution. After the epoxy modification of the SMC, it has good compatibility with the asphalt material, and then the asphalt material is liquid at a normal temperature and can be melted or dispersed in the asphalt to change the construction and workability of an asphalt binder at a normal temperature [12]. The mixture of an SMC normal-temperature-modified asphalt and styrene–butadiene styrene block copolymer (SBS)-modified asphalt (SMCSBS) composite modified asphalt mixture, compared with traditional hot mix asphalt mixtures, not only has the material composition structure, strength structure, and basic characteristics [13], but also has the advantages of an SMC normal temperature-modified asphalt with a low construction temperature, good road performance, good energy savings and an emission reduction effect [14]. Qu Hongwei [15] proposed to apply an SMC normal temperature-modified asphalt in a highway covering construction and elaborated the specific construction points, pointing out that an SMC normal temperature-modified asphalt has the advantages of energy savings and environmental protection, convenient construction, and significant economic benefits. Wang Jianjun [16] used SBS and SMC to prepare a compound-modified constant temperature warm-mix asphalt and applied it to an AC-13 (the mixture ratio of asphalt mixture is asphalt concrete (AC-13)) asphalt mixture. Through laboratory tests, the high-temperature performance, low-temperature performance, and moisture susceptibility of the mixture were evaluated, and a performance analysis was conducted for the road material. At present, the research on an SMC normal temperature asphalt modifier is still in the exploratory stage [17], and there are few studies on SMCSBS-modified asphalt mixtures. This paper tries to study the fatigue performance of an SMCSBS-modified asphalt mixture.

At present, there are many kinds of fatigue life prediction models for asphalt mixtures. As early as the 1960s, Jones, D. et al. [18] established a classic fatigue life prediction model based on strain control. Zhang, B et al. [19] used double load envelopes and twin cohesive models to predict composite fatigue delamination.

Artificial intelligence has a wide range of applications in various fields. Compared with classical statistical methods, artificial intelligence models have better a prediction and recognition ability. In order to save testing time, meet equipment requirements, and cost and complexity, various prediction models, such as Bayesian, artificial neural network (ANN) [20], and support vector machine regression (SVM), have been introduced. Yan et al. proposed a Bayesian damage identification method based on the analysis probability model of scattering coefficient estimation and ultra-fast wave scattering simulation scheme [21]. Tan et al. pointed out that the error between the prediction results of the low-temperature flexural strain of asphalt and the actual measurement results based on the BP (back propagation) neural network model of the MATLAB platform is within the accuracy range of the engineering requirements [22]. As a powerful new learning machine, the support vector

machine (SVM), based on statistical learning theory, has attracted extensive attention from its initial application in pattern recognition, to its application in regression estimation [23]. For example, Pal investigates classification based on support vector machines to predict the liquefaction potential from the actual standard penetration test and cone penetration test field data [24]. Maalouf, Khoury and Trafalis investigated the application of SVM in the resilient modulus (M_R) prediction of hot mix asphalt samples [25]. In a study by Soltani et al., an Support Vector Machine Firefly Algorithm (SVM-FFA) was used to predict the stiffness of polyethylene terephthalate (PET)-modified asphalt mixtures [26]. Compared with the artificial neural network, genetic algorithm, and the support vector machine, this method is effective in stiffness prediction.

To sum up, in this paper, the fatigue performance of an asphalt mixture is studied from the following aspects: SMC content (SMC accounts for the mass percentage of SMCSBS composite modified asphalt)/%, asphalt stone ratio, stress ratio, and load frequency/Hz. So far, the research of AI models in predicting the fatigue life of asphalt mixtures is very limited. Therefore, the main goal of this study is to use an artificial intelligence method to predict the fatigue life of an SMCSBS asphalt mixture with different dosages and find the best prediction model.

2. Objectives

In this paper, the main objectives of the work presented are as follows:

(1) Disperse an SMC modifier into the SBS asphalt to prepare an SMCSBS-modified asphalt with different SMC contents, including 8%, 10%, and 12%, and then prepare the SMCSBS-modified asphalt mixture for a semi-circular bending test and semi-circular bending fatigue test (SCB).

(2) Establish the M5′ model tree (M5), artificial neural network (ANN), support vector machine (SVM), and PSO-SVM models to find the best prediction model for the fatigue life of different SMCSBS asphalt mixtures.

3. Materials

Under the condition of the same amount of SBS (4%), different amounts of SMC normal temperature-modified asphalt were added. According to the content of SMC, an asphalt modifier is 10%–12% of the asphalt quality (DBJ 64/T060-2016) [27], and the literature [28] on the properties of SMCSBS composite modified asphalts, 8%, 10%, and 12% of SMC content are selected to prepare a composite modified asphalt. The SMC normal temperature-modified asphalt was added into the SBS-modified asphalt according to the above content, the heating temperature was 110–120 °C, and the mixing time was 1–2 h (DBJ 64/T060-2016). Referring to the SMC Normal Temperature Modified Asphalt and Asphalt Mixture Design and Construction Technical Guide by the Scientific Research Institute of the Ministry of Transport (2014) testing method, the main technical indexes of normal temperature modified asphalts with different SMC contents were obtained through testing. The test results are shown in Table 1.

Table 1. Process indexes of modified asphalts with different content.

SMC Content/%	25 °C Penetration/0.1 mm		Softening Point °C		5 °C Ductility	
	Average	Standard Deviation	Average	Standard Deviation	Average	Standard Deviation
8	191	0.211	74	0.050	89.7	0.531
10	228	0.325	56.5	0.400	>100	0
12	248	0.561	55	0.636	>100	0

One dense-graded asphalt mixture (AC-16) was used for evaluation in this research. AC-16 mixtures are commonly used in China for the surface course of expressway bituminous concrete pavements. According to the JTG F40-2004 standard [29], the recommended mid-value gradation for this mixture was selected. The aggregate gradation and mix design are shown in Table 2.

Table 2. Aggregate gradation and mix design.

Sieve Size(mm)	Passing Rate (by Mass)		
	Up Limits	**Bottom Limits**	**Composite Gradation**
19	100	100	100.0
16.0	100	90	99.6
13.2	92	76	84.2
9.5	80	60	76.7
4.75	62	34	52.0
2.36	48	20	34.6
1.18	36	13	25.1
0.60	26	9	15.3
0.30	18	7	10.1
0.15	14	5	5.2
0.075	8	4	2.4
Binder	PG64-34 SMCSBS modified asphalt		
Apparent density (g/cm^3)	2.766		

The fatigue performance of SBSSMC modified asphalt mixtures are studied by selecting 4.3%, 4.8%, and 5.3% of the asphalt aggregate ratio as specimens.

4. Methods

4.1. Specimen Forming and Semi-Circular Bending (SCB) Fatigue Test

At present, the fatigue test methods of asphalt mixtures mainly include the four-point bending fatigue test, direct tensile fatigue test, indirect tensile fatigue test, and semi-circular bending (SCB) fatigue test. Hasan et al. compared and analyzed the difference between the four-point bending fatigue and semi-circular bending (SCB) test by studying the fatigue performance of coarse and fine asphalt mixtures [30]. Both mixtures have similar fatigue properties (crack resistance). Dong et al. found that, compared with the indirect tensile fatigue test, the SCB and beam fatigue test had a faster failure rate and were more sensitive to stress ratio [31]. Considering this comprehensively, this paper chose the semi-circular bending fatigue test.

The semi-circular bending fatigue test evolved from the semi-circular bending test. The test uses a semi-circular specimen, and the load is applied by a round rod in the middle of its top. At the same time, there are two supporting round rods at the bottom of the semi-circular specimen, and the distance between the supporting points is determined to be 0.8 times the diameter of the specimen, as shown in Figure 1. A cylindrical specimen of φ100 × 63.5 was made by a rotary compaction method for the asphalt mixture fatigue test, which was directly cut into two parts along the diameter and used as a semi-circular bending fatigue test specimen.



(**a**) (**b**)

Figure 1. Implementation of SCB testing: (**a**) preparation of specimen; (**b**) setup for SCB test.

4.2. Experimental Scheme Design

The UTM-30 universal testing machine, equipped with a temperature control room, was used for the SCB strength and fatigue test at 15 °C. The fatigue test conducted was a stress-controlled loading method with four different stress ratios of 0.2, 0.3, 0.4, and 0.5. The loading frequencies of the fatigue test were 10 Hz and 15 Hz, respectively. The fatigue test scheme of the SMCSBS composite modified asphalt mixtures is shown in Table 3.

Table 3. Fatigue test scheme of SMCSBS composite modified asphalt mixtures.

Parameter	Levels
SMC content	8%, 10%, 12%
Asphalt aggregate ratio	4.3%, 4.8%, 5.3%
Stress ratio	0.2, 0.3, 0.4, 0.5
Loading frequency	10 Hz, 15 Hz
Test temperature	15 °C

In order to determine the control amplitude of the semi-sine wave load, the crack resistance of the semi-circular bending test was tested, referring to research results, such as Molenaar [32]. The calculation formula is shown as Equation (1).

$$\sigma_m = \frac{4.8P}{dt} \quad (1)$$

where, σ_m is at the bottom of the specimen tensile strength value, MPa; P is the specimen of peak load, N; d is the thickness of the specimen, mm; and t is the specimen diameter, mm.

In the stress control mode, the relationship between the fatigue life and control stress in the fatigue test is the fatigue equation. Referring to the research results of Liao et al. [33] on the anti-fatigue performance of asphalt mixtures, the double logarithmic regression equation can generally be used as the fatigue equation of the mixture, such as Equation (2).

$$lgN_f = k - nlg\sigma \quad (2)$$

where, N_f is the fatigue life; σ is the control stress, MPa; and k, n is the regression coefficient of fatigue equation.

4.3. Test Results

4.3.1. Analysis of the Influence of SMC Content on Fatigue Performance

For the sake of comparison, the loading frequency 10 Hz, fatigue life of different SMC content, and different asphalt aggregate ratio were selected, as shown in Figure 2. It can be seen from Figure 2a that under the same stress ratio conditions, the fatigue life of the mixture with a 10% SMCSBS asphalt aggregate ratio of 4.3 was the largest, followed by the fatigue life of the mixture with an 8% SMCSBS asphalt aggregate ratio of 4.8, which is consistent with Sun et al.'s research on the properties of SMCSBS composite modified asphalts [28]. As shown in Figure 2b, under the same stress amplitude, it is obvious that the mixture with the 10% SMCSBS asphalt aggregate ratio of 4.3 had the maximum fatigue life, the mixture with the 12% asphalt aggregate ratio of 4.3 had the minimum fatigue life, and the others were close. The results show that the effect of SMC content on fatigue performance is that the fatigue life of the mixture was the largest when the SMC content was 10%.

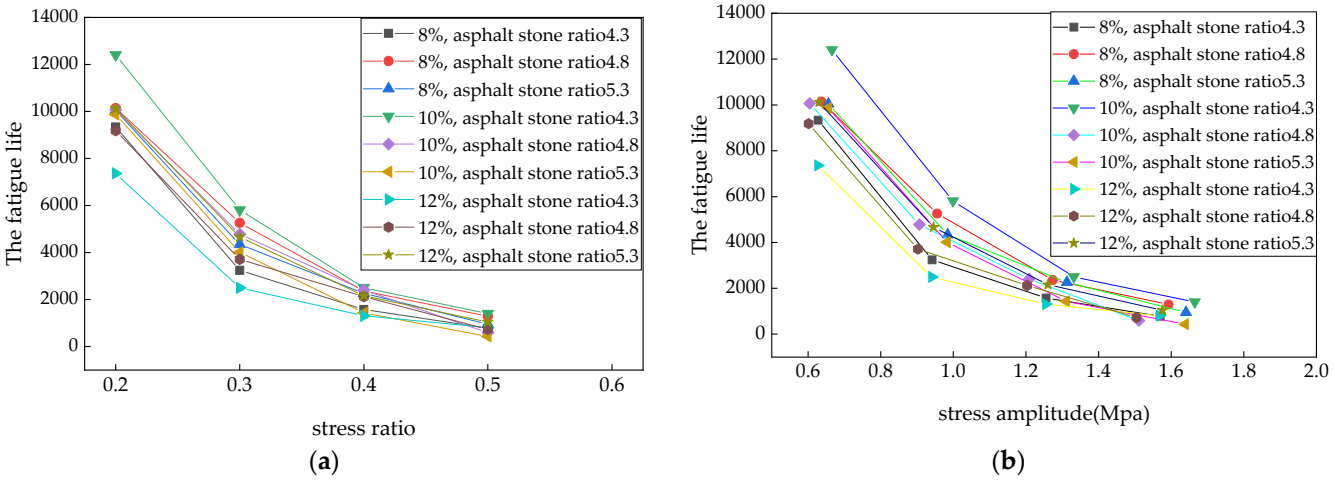


Figure 2. Values of different SMC content in the SCB fatigue test: (**a**) stress ratio; (**b**) stress amplitude.

4.3.2. Analysis of the Influence of Loading Frequencies on Fatigue Performance

From the influence of different SMC contents on fatigue performance, it can be seen that the fatigue life of the mixture of 10% SMCSBS was the largest. Therefore, only under this condition, the fatigue performance of different asphalt aggregate ratios and different loading frequencies was analyzed, as shown in Figure 3. It can be seen from Figure 3 that no matter under the same stress ratio condition or under the same stress amplitude condition, the greater the loading frequency, the greater the fatigue life. The fatigue life was the largest when the asphalt aggregate ratio was 4.3 and the loading frequency was 15 Hz.

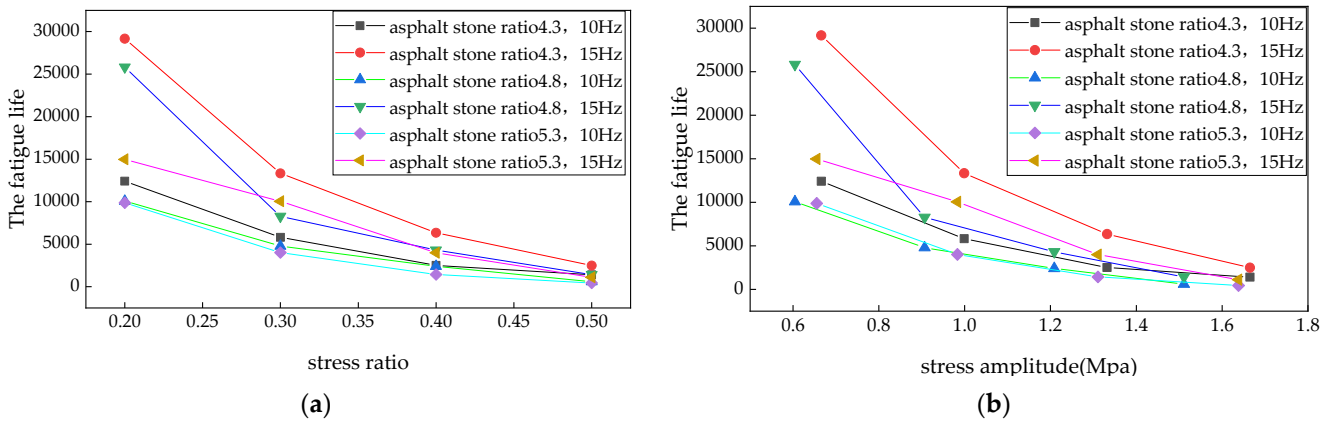


Figure 3. Values of different loading frequencies in the SCB fatigue test: (**a**) stress ratio; (**b**) stress amplitude.

4.3.3. Fatigue Equation

Under different loading frequencies (10 Hz, 15 Hz), a mixture with an SMC content of 10% and asphalt aggregate ratio of 4.3 was taken to establish the logarithmic equation of fatigue life and stress ratio/stress amplitude, as shown in Figure 4. The correlation coefficients of all fitting equations were >0.96. The fatigue life of the specimens decreased with the increase of stress ratio/stress amplitude. At the same time, the more SMC content was not better; when the content of SMC was more than 10%, the fatigue life was lower with more SMC content.

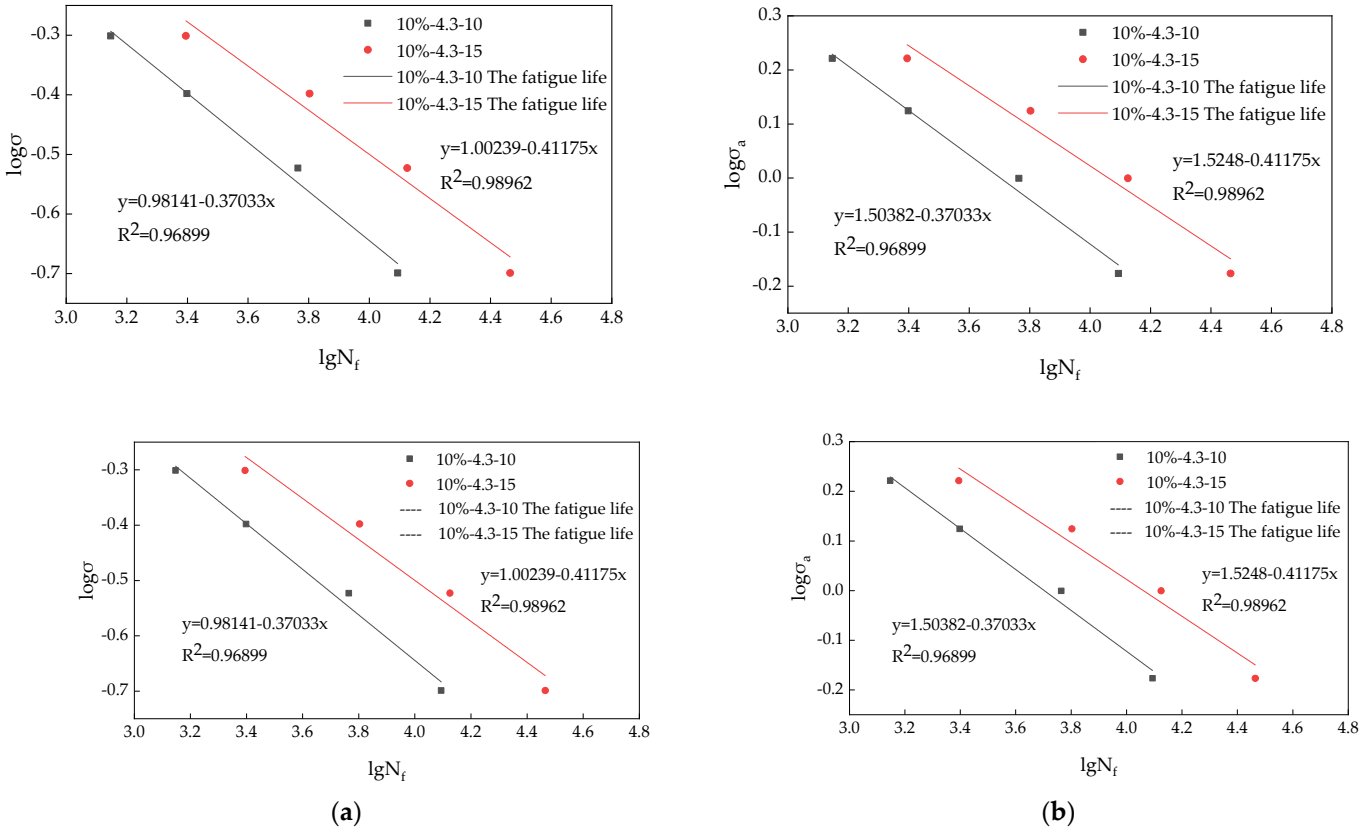


Figure 4. Comparison of fatigue equations of 10% SMC and asphalt aggregate ratio 4.3 in the SCB fatigue test: (**a**) stress ratio; (**b**) stress amplitude.

5. Predictive Simulation and Analysis

5.1. Particle Swarm Optimization (PSO)

Particle swarm optimization (PSO), introduced by Eberhart and Kennedy [34,35], is a group intelligence algorithm that has been successful in both continuous and discrete optimization. The feasible solution of each optimization problem is abstracted into a "particle" without volume and mass in the search space. The PSO algorithm generates the initial population and the population of each particle motion in the feasible solution space, decides its own speed position and orientation of each particle movement following the current optimum particles, and obtains an optimal solution. In the PSO algorithm, if it selects particles as the random initial population, the position of each particle in the dimensional space can be expressed as the solution of the optimization problem; the degree of its performance depends on the fitness value determined by the objective function of the optimization problem and, through constant iteration, adjusts its direction change and speed size, finally finding the global optimal solution. The velocity of the particle is as follows [36]:

$$v_i(t+1) = w \cdot v_i(t) + c_1 r_1 (pbest_i(t) + x_i(t)) + c_2 r_2 (gbest(t) + x_i(t)), \quad (3)$$

$$x_i(t+1) = x_i(t) + v_i(t+1), \quad (4)$$

In Equations (3) and (4), $i = 1, 2, \cdots, m$; $j = 1, 2, \cdots, n$; t is the number of iterations; c_1, c_2 is the learning factor, which measures the individual learning ability of $pbest_i(t)$ and the global learning ability of $gbest(t)$, respectively. r_1, r_2 is the random number transformed within the range of [0,1], $x_i(t)$ is the position information of the particle i at time t, $v_i(t)$ is the velocity information of the particle i at time t, $pbest_i(t)$ is the current optimal position of the particle i (namely, the optimal solution), $gbest(t)$ is the best location found by the whole population (namely, the global optimal solution), and w is the inertia factor, which

is calculated according to Equation (5) and used to control the influence of the last velocity on the current state.

$$w = (w_1 - w_2) \cdot \frac{H_{axgen} - G_{generation}}{H_{axgen}} \tag{5}$$

where, w_1, w_2 is the weight factor; H_{axgen} is the maximum number of iterations; and $G_{generation}$ is the number of current iterations.

Equations (3) and (4) are used to update the velocity and position of each particle. In order to limit the particle velocity and reduce some poor results, the contraction coefficient is applied to the PSO algorithm [37]. In the PSO algorithm with the contraction coefficient, the update velocity is changed as follows:

$$v_i'(t+1) = x\Big(v_i(t) + c_1 r_1\big(pbest_i(t) + x_i(t)\big) + c_2 r_2\big(gbest(t) + x_i(t)\big)\Big), \tag{6}$$

where, the contraction factor x is as follows:

$$x = \frac{2}{\left|2 - \phi - \sqrt{\phi^2 - 4\phi}\right|}, \phi = c_1 + c_2 > 4 \tag{7}$$

5.2. Support Vector Machine (SVM)

A support vector machine (SVM) is a machine learning method based on statistical theory. It is a classification regression method [38]. The principle of optimal classification is a statistical concept for the classification methods of support vector machines. Through Vapnik [38], the value of the smallest generalization error in the separable class is selected. It comes from the principle of structural risk minimization. The different classes separate a plane so that the boundaries between them are at maximum. The boundary is the sum of the distances from the partition plane to the vertical. For two inseparable classes, a hyperplane with a maximum edge value and minimum misclassification error is identified. A predefined constant controls the margin and the size of the error. The design method of the support vector machine extends to the nonlinear decision surface, and the data projects into a feature space to generate a classification problem.

5.2.1. SVM Basic Principles

The SVM basic model is defined as a linear classifier, with the largest interval on the feature space. For a given training sample set (x_i, y_i), the interval maximization learning strategy can be used to solve a convex quadratic programming problem. Then, a Lagrange function is introduced to solve the dual problem, and finally, the optimal classification decision function is obtained. The specific process is as follows:

Given the training sample set (x_i, y_i), $i = 1, \ldots, l; x \in R^n, y \in \{+1, -1\}$, the hyperplane is denoted as $(w \cdot x) + b = 0$. In order for the classification to be correctly classified and have the classification interval for all samples, it is required to meet the following constraints:

$$y_i[(w \cdot x_i) + b] \geq 1 \; i = 1, 2, \cdots, l, \tag{8}$$

The classification interval is calculated as $\frac{2}{\|w\|}$, so the problem of constructing an optimal hyperplane is transformed into an optimization problem under constraints:

$$\min_w \phi(w) = \frac{1}{2}\|w\|^2 = \frac{1}{2}\left(w^T \cdot w\right), \tag{9}$$

The above problems are transformed into quadratic programming problems under constraint conditions:

$$\begin{gathered} \min_w \tfrac{1}{2} w^T \cdot w + C \textstyle\sum_{i=1}^{n} \xi_i, \\ \text{s.t. } y_i\left(w^T x_i + b \geq 1 - \xi_i\right), \\ \xi_i \geq 0, i = 1, 2, \cdots, n \end{gathered} \tag{10}$$

where, ξ_i is the non-negative relaxation variable introduced to measure the classification error, w is the normal vector of the hyperplane, and C is the penalty factor of the error term $\sum_i^n \xi_i$.

To solve the constrained optimization problems, a Lagrange function is introduced:

$$L(w, b, \lambda) = \frac{1}{2} w^T \cdot w + C \sum_{i=1}^{n} \xi_i - \sum_{i=1}^{n} \lambda_i [y_i (w^T x_i + b) - 1 + \xi_i] - \sum_{i=1}^{n} \alpha_i \xi_i, \quad (11)$$

where $\lambda_i \geq 0, i = 1, 2, \cdots, n$. The dual problem of the Equation (10) is:

$$\begin{aligned} \max Q(\lambda) &= \sum_{i=1}^{n} \lambda_i - \frac{1}{2} \sum_{i,j=1}^{n} y_i y_j \lambda_i \lambda_j (x_i \cdot x_j), \\ s.t. \sum_{i=1}^{n} y_i \lambda_i &= 0, 0 \leq \lambda_i \leq C \end{aligned} \quad (12)$$

Finally, the optimal classification decision function is:

$$f(x, \lambda) = \operatorname{sgn}\left(\sum_{SV} y_i \lambda_i (x_i \cdot x_j) + b\right), \quad (13)$$

For the linear indivisible case, the dual problem is:

$$\begin{aligned} \max Q(\lambda) &= \sum_{i=1}^{n} \lambda_i - \frac{1}{2} \sum_{i,j=1}^{n} y_i y_j \lambda_i \lambda_j \left(\phi(x_i)^T \cdot \phi(x_j)\right), \\ s.t. \sum_{i=1}^{n} y_i \lambda_i &= 0, 0 \leq \lambda_i \leq C \end{aligned} \quad (14)$$

where, $\phi(x_i)^T \cdot \phi(x_j) = K(x_i, x_j)$ is the kernel function.

The corresponding optimal classification decision function can be obtained as follows:

$$f(x, \lambda) = \operatorname{sgn}\left(\sum_{SV} y_i \lambda_i K(x_i, x_j) + b\right), \quad (15)$$

In fact, the whole process is to transform a linear indivisible problem into a simpler high-dimensional linear separable problem, which depends on the kernel function of SVM, and is defined as: $K(x_i, x_j) = \phi(x_i)^T \cdot \phi(x_j)$.

5.2.2. SVM Parameter Optimization and Kernel Function

For a given sample, SVM penalty factor C, selection of the kernel function and the determination of kernel parameter δ are key issues affecting SVM learning ability and generalization ability. The purpose of introducing penalty factor C into SVM is to deal with fault tolerance at fault points near hyperplane boundaries. The penalty factor of an appropriate value can improve the system's robust fault tolerance. On the contrary, overfitting or underfitting will result in classification problems.

The kernel function is very important to SVM. It makes raw data linearly separable and avoids the difficulty of a dimension disaster. There are many types of SVM kernel functions. The commonly used kernel functions include the linear kernel function, the polynomial kernel function, and the radial basis function (RBF) kernel function, respectively:

$$K(x_i, x_j) = {x_i}^T x_j, \quad (16)$$

$$K(x_i, x_j) = \left({x_i}^T x_j + 1\right)^{\delta}, \quad (17)$$

$$K(x_i, x_j) = \exp\left(-\frac{\|x_i - x_j\|^2}{2\delta^2}\right) \quad (18)$$

For a linear kernel, the form of a function is simple. Therefore, it is more suitable for dealing with the linear separable problems. For the polynomial kernel function, its function form is more complex, and requires extensive calculation time. For the RBF

kernel function, it can realize nonlinear mapping, the required number of the RBF kernel function parameters is smaller, and the numerical difficulty is also small. A large number of experimental results show that RBF kernel functions have better performance than other commonly used kernel functions.

5.3. Simulation of the PSO-SVM

5.3.1. Main Steps

Follows the following main steps (as shown in Figure 5):

Step 1: Load the obtained data set and divide it into two parts. The first part includes 70% of the data for training and building AI "black boxes," with the remaining 30% for model validation. Input parameters are SMC content (/%), asphalt aggregate ratio, stress ratio, and loading frequency (/Hz). The output of an AI numerical tool is the fatigue life.

Step 2: Build the model using the training data set. Use particle swarm optimization to optimize the SVM penalty factor C and kernel function parameter δ to generate the optimal PSO-SVM prediction model.

Step 3: Validate the model with test data. Various standards, namely, R^2 and RMSE, are used to validate four developed models in training and testing data sets.

Step 4: Predict fatigue life, and predict results.

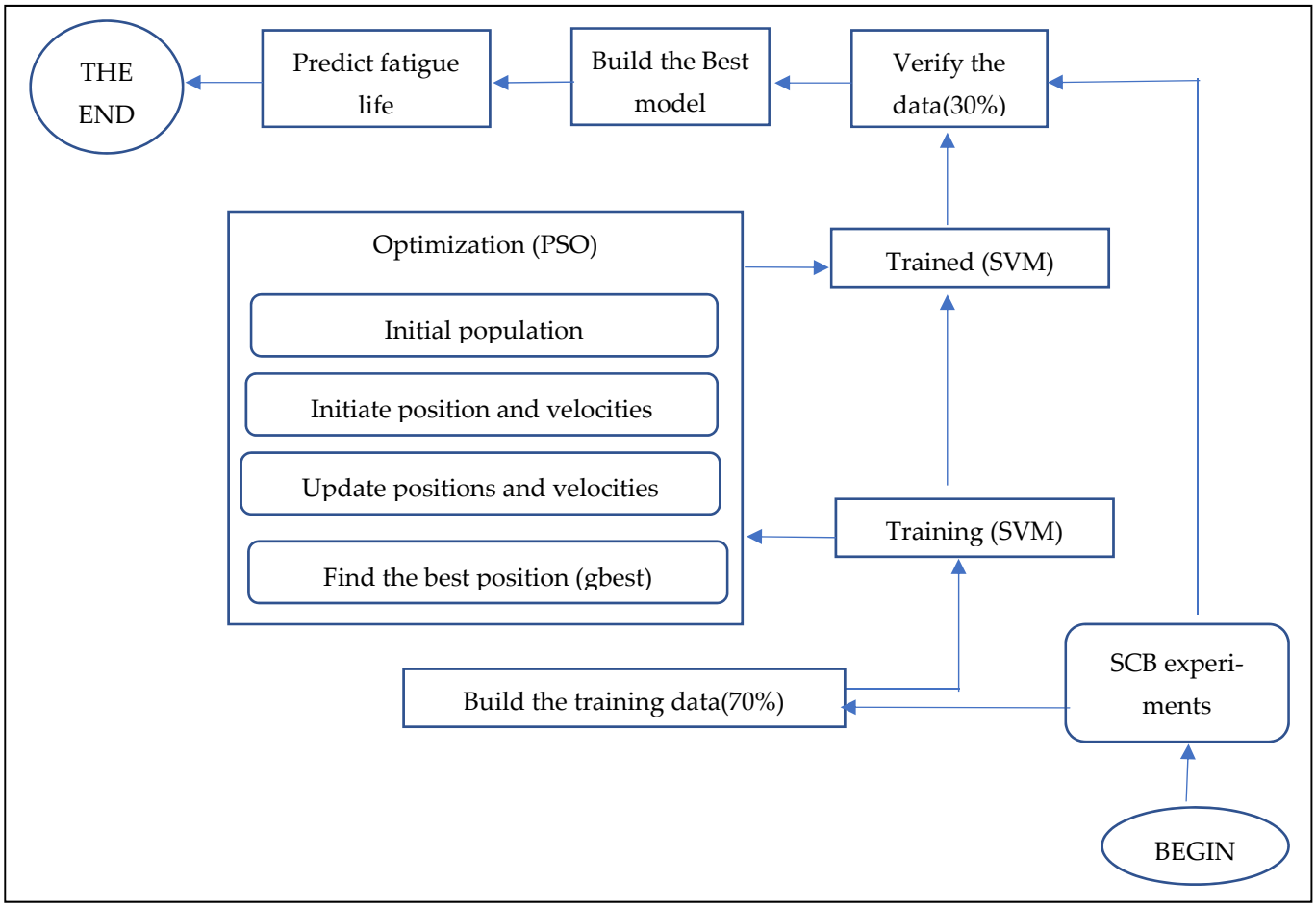


Figure 5. The methodological chart of the present study.

5.3.2. Model Performance Evaluation

In this study, subsequent statistical indicators were specified to evaluate the performance of M5′, ANN, SVM, and the PSO-SVM. The Root Mean Square Error (RMSE) and R^2 were used as fitness functions to determine the applicability of each factor. Equations (19) and (20) respectively represent RSME and R^2 equations:

(1) RMSE

$$\mathrm{MSE} = \sqrt{\frac{\sum_{i=1}^{n} P_{i1} - P_{i2}}{n}}, \tag{19}$$

(2) R^2

$$R^2 = \frac{\left[\sum_{i=1}^{n} \left(P_{i2} - \overline{P}_{i2}\right)\left(P_{i1} - \overline{P}_{i1}\right)\right]}{\sum_{i=1}^{n} \left(P_{i2} - \overline{P}_{i2}\right) \sum_{i=1}^{n} \left(P_{i1} - \overline{P}_{i1}\right)} \tag{20}$$

where, P_{i2} and P_{i1} are the fatigue life value predicted by the model and the measured value, respectively, and n is the total number of test data.

5.3.3. Performance Analysis

There were 72 samples in this study—70% of the training set and 30% of the test set.

In order to verify the advantages of the proposed PSO-SVM method, its performance was compared with that of other commonly used intelligent computing-based methods, such as M5′, ANN, and SVM. The predicted fatigue lives are represented in Figure 6 in the form of scatter plots. Table 4 summarizes performance indices of different methods to predict the fatigue life. The comparison presented in Table 4 leads to the conclusion that the PSO-SVM outperformed other methods in terms of accuracy of prediction of the output.

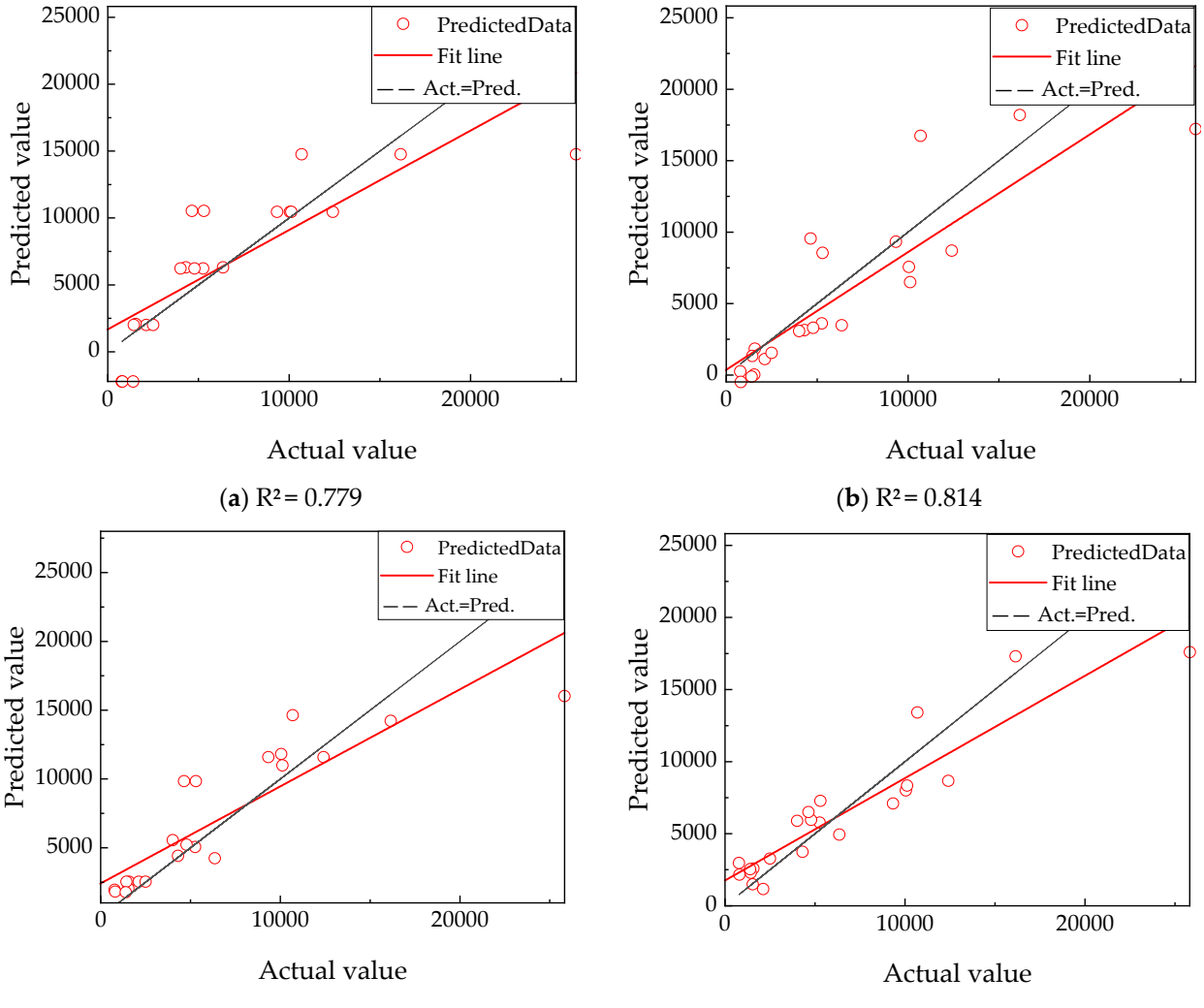


Figure 6. Fatigue life prediction by (**a**) M5′, (**b**) ANN, (**c**) SVM, and (**d**) PSO-SVM.

Table 4. Summary of prediction capability for testing parts using M5′, ANN, SVM, and the PSO-SVM.

Method	RMSE (mm/day)	R^2
M5′	4035.33	0.779
ANN	3988.36	0.814
SVM	3563.26	0.861
PSO-SVM	2253.71	0.903

6. Conclusions

The following conclusions can be drawn based on this investigation:

(1) Under the same load frequency (10 Hz), the fatigue life of different SMC contents is shown as follows: under the same stress ratio/stress amplitude, the fatigue life of a mixture reaches the maximum when the effect of SMC content on fatigue performance is 10%. This also shows that the more SMC content is not better; when the content of SMC is more than 10%, the fatigue life is lower with more SMC content.

(2) Taking the fatigue life of the mixture of 10% SMCSBS as an example, the fatigue performance of different asphalt aggregate ratios and different loading frequencies is shown as follows: whether under the same stress ratio/stress amplitude, the greater the loading frequency, the greater the fatigue life. The fatigue life is the largest when the asphalt aggregate ratio is 4.3 and the loading frequency is 15 Hz.

(3) Four artificial intelligence models M5′, ANN, SVM, and PSO-SVM were used to predict the fatigue life of an SMCSBS asphalt mixture, with input parameters (SMC content/%, asphalt aggregate ratio, stress ratio, and load frequency/Hz) and output parameters (fatigue life). The model was validated using standards, such as RMSE and R^2. The results show that M5′ (RMSE = 4035.33 and R^2 = 0.779), ANN (RMSE = 3988.36 and R^2 = 0.814), and SVM (RMSE = 3563.26 and R^2 = 0.861), but the PSO-SVM (RMSE = 2253.71 and R^2 = 0.903) with particle swarm optimization showed the most stable algorithm compared with other methods. Particle swarm optimization (PSO) support vector machine (SVM) ha good performance in predicting the fatigue life of an SMCSBS asphalt mixture.

Author Contributions: Conceptualization, Y.S. and D.H.; methodology, D.H.; software, Y.S.; validation, Y.S. and J.L.; investigation, J.L.; writing—original draft preparation, Y.S.; writing—review and editing, Y.S., D.H. and J.L. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Data sharing is not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Li, K.; Huang, M.; Zhong, H.; Li, B. Comprehensive evaluation of fatigue performance of modified asphalt mixtures in different fatigue tests. *Appl. Sci.* **2019**, *9*, 1850. [CrossRef]
2. Shafabakhsh, G.; Mirabdolazimi, S.M.; Sadeghnejad, M. Evaluation the effect of nano-TiO2 on the rutting and fatigue behavior of asphalt mixtures. *Constr. Build. Mater.* **2014**, *54*, 566–571. [CrossRef]
3. Ma, H.Y.; Chen, H.X.; Yang, P.W.; Xing, M.L.; Wang, K.; Kuang, D.L. Prediction of fatigue life of asphalt slurry based on improved S-VECD model. *J. Chang. Univ. Nat. Sci. Ed.* **2019**, *4*, 35–43.
4. Ren, R.B.; Geng, L.T.; Chen, M.M.; Yan, F.L. Study on fatigue performance test and prediction model of rubber—Plastic asphalt mixture. *J. Shandong Jianzhu Univ.* **2016**, *31*, 583–587.
5. Xie, C.L.; Zhang, Y.; Geng, H.B. Prediction model of asphalt mixture fatigue performance based on BP neural network. *J. Chongqing Jiaotong Univ. (Nat. Sci. Ed.)* **2018**, *02*, 35–40.

6. Zhu, H.Z.; Fan, S.P.; Lu, Z.T.; Yan, H. Analysis of fatigue life prediction model of aged asphalt based on dissipated energy. *Road Traffic Technol.* **2019**, *36*, 8–13, 30.
7. Hveem, F.N. *Pavement Deflections and Fatigue Failures*; Highway Research Board Bulletin 114; Transportation Research Board: Washington, DC, USA, 1955.
8. Santucci, L.E.; Schmidt, R.J. The Effect of Asphalt Properties on the Fatigue Cracking of Asphalt Concrete on the Zaca-Wigmore Test Project. *Proc. Assoc. Asphalt Paving Technol.* **1969**, *38*, 39–64.
9. Ge, Z.S. Grey correlation analysis of influencing factors on fatigue performance of asphalt mixture. *J. Transp. Eng.* **2002**, *2*, 8–11.
10. Zhu, H.Z. Analysis of key Influencing Factors of asphalt mixture fatigue performance. *J. Southeast Univ. (Nat. Sci. Ed.)* **2004**, *34*, 260–263.
11. Yu, J.M.; Zhang, X.N. Evaluation of environmental factors influencing the fatigue performance of asphalt mixtures. *J. Southeast Univ.* **2005**, *21*, 486–489.
12. Tan, Y.R.; Zhang, H.Y.; Cao, D.W.; Xia, L.; Du, R.J.; Shi, Z.Q.; Dong, R.; Wang, X.H. Study on cohesion and adhesion of high-viscosity modified asphalt. *Intern. J. Trans. Sci. Technol.* **2019**, *8*, 394–402.
13. Jia, X.; Zhang, Z.; Guo, C.; Gao, J. Mixture design of SMC recycled asphalt mixture at normal temperature. In Proceedings of the 10th Annual Conference of Maintenance and Management Branch of China Highway Society, Shenzhen, China, 9 January 2020; pp. 63–70.
14. Wei, W.; Jin, Y. Road performance analysis of waste plastics +SMC compound modified SMA10 asphalt mixture. *Highw. Traffic Technol.* **2019**, *35*, 43–46, 60.
15. Qu, H.W. Application of SMC Modified Asphalt at Room Temperature in Highway Overlay Engineering. *Shanxi Constr.* **2016**, *42*, 166–167.
16. Wang, J.J. Road performance analysis of AC-13 asphalt mixture at room temperature. *Urban. Roads Br. Flood Control* **2019**, *8*, 211–213.
17. Shu, P.; Wang, B.; Zhang, Y.; Wang, S. Properties of high RAP SMC recycled asphalt mixture at norma temperature in Panzhihua area. *Transp. Energy Sav. Environ. Prot.* **2020**, *80*, 83–87.
18. Jones, D.; Harvey, J.T.; Monismith, C.L. *Reflective Cracking Study: Summary Report*; Working Paper Series; Institute of Transportation Studies: California, CA, USA, 2008.
19. Zhang, B.; Kawashita, L.F.; Hallett, S.R. Composites fatigue delamination prediction using double load envelopes and twin cohesive models—Sciencedirect. *Compos. Part A Appl. Sci. Manuf.* **2020**, *129*, 105711. [CrossRef]
20. Park, H.I.; Kweon, G.C.; Lee, S.R. Prediction of resilient modulus of granular subgrade soils and subbase materials using artificial neural network. *Road Mater. Pavement Des.* **2009**, *10*, 647–665. [CrossRef]
21. Yan, W.J.; Chronopoulos, D.; Papadimitriou, C.; Cantero-Chinchilla, S.; Zhu, G.S. Bayesian inference for damage identification based on analytical probabilistic model of scattering coefficient estimators and ultrafast wave scattering simulation scheme. *J. Sound Vib.* **2020**, *468*, 115083. [CrossRef]
22. Tan, Y.; Song, X.; Zhou, C.; Gong, W. Research on the application of neural network in the model for solid volume parameters prediction of asphalt mixture. *Highw. Eng.* **2008**, 60–64. [CrossRef]
23. Vapnik, V. Statistical Learning Theory. *Ann. Inst. Stat. Math.* **2003**, *55*, 371–389.
24. Pal, M. Support vector machines-based modelling of seismic liquefaction potential. *Int. J. Numer. Anal. Methods Geomech.* **2006**, *30*, 983–996. [CrossRef]
25. Maalouf, M.; Khoury, N.; Trafalis, T.B. Support vector regression to predict asphalt mix performance. *Int. J. Numer. Anal. Methods Geomech.* **2008**, *32*, 1989–1996. [CrossRef]
26. Soltani, M.; Moghaddam, T.B.; Karim, M.R.; Shamshirband, S.; Sudheer, C. Stiffness performance of polyethylene terephthalate modified asphalt mixtures estimation using support vector machine-firefly algorithm. *Measurement* **2015**, *63*, 232–239. [CrossRef]
27. *DBJ 64/T060-2016, Technical Specification for Construction of SMC Modified Asphalt Pavement*; Standards of Ningxia Hui Autonomous Region: Yinchuan, China, 2016.
28. Sun, Y.; He, D. High and Low-Temperature Performance Evaluation and Microanalysis of SMCSBS Compound-Modified Asphalt. *Materials* **2021**, *14*, 771. [CrossRef] [PubMed]
29. *JTG F40-2004, Technical Specifications for Construction of Highway Asphalt*; Pavement, Renmin Communication Press: Beijing, China, 2004.
30. Hasan, M.M.; Ahmad, M.; Hasan, M.A.; Faisal, H.M.; Tarefder, R.A. Laboratory performance evaluation of fine and coarse-graded asphalt concrete mix. *J. Mater. Civ. Eng.* **2019**, *31*, 04019259. [CrossRef]
31. Dong, Q.; Zhao, X.; Chen, X.; Ma, X.; Cui, X. Long-term mechanical properties of in situ semi-rigid base materials. *Road Mater. Pavement Des.* **2020**, *22*, 1692–1707. [CrossRef]
32. Molenaar, A.A.A.; Scarpas, A.; Liu, X.; Erkens, S.M.J.G. Semi-circular bending test, simple but useful. *Asph. Paving Technol. Assoc. Asph. Paving Technol.-Proc. Tech. Sess.* **2002**, *71*, 794–815.
33. Liao, M.C.; Chen, J.S.; Tsou, K.W. Fatigue Characteristics of Bitumen-Filler Mastics and Asphalt Mixtures. *J. Mater. Civ. Eng.* **2012**, *24*, 916–923. [CrossRef]
34. Kennedy, J.; Eberhart, R. Particle swarm optimization. In Proceedings of the ICNN'95-International Conference on Neural Networks, Perth, Australia, 27 November–1 December 1995; Volume 4, pp. 1942–1948.

35. Shi, Y.; Eberhart, R.C. Empirical study of particle swarm optimization. In Proceedings of the 1999 Congress on Evolutionary Computation-CEC99 (Cat. No. 99TH8406), Washington, DC, USA, 6–9 July 1999; Volume 3, pp. 1945–1950.
36. Liu, Q.J.; Jing, L.H.; Wang, L.M.; Lin, Q.Z. A Method of Particle Swarm Optimized SVM Hyper-spectral Remote Sensing Image Classification. *IOP Conf. Ser. Earth Environ. Sci.* **2014**, *17*, 012205. [CrossRef]
37. Clerc, M.; Kennedy, J. The Particle Swarm: Explosion, Stability and Convergence in Multi-dimensional Complex space. *IEEE Trans. Evol. Comput.* **2002**, *20*, 1671–1676.
38. Vapnik, V. *The Nature of Statistical Learning Theory*, 2nd ed.; Springer: New York, NY, USA, 1999; ISBN 978-0-387-98780-4.