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ORIGINAL ARTICLE

Prediction of permanent deformation in asphalt pavements using a novel symbiotic organisms search–least squares support vector regression

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Abstract
The prediction of asphalt performance can be very important in terms of increasing service life and performance while saving energy and money. In this study, a new hybrid artificial intelligence (AI) system, SOS–LSSVR, has been proposed to predict the permanent deformation potential of asphalt pavement mixtures. SOS–LSSVR utilizes the symbiotic organisms search (SOS) and the least squares support vector regression (LSSVR), which are seen as a complementary system. The prediction model can be established from all input and output data pairs for LSSVR, while SOS optimizes the system's tuning parameters. To avoid sampling bias and to partition the dataset into testing and training, a cross-validation technique was chosen. The results can be compared to those of previous studies and other predictive methods. Through the use of four error indicators, SOS–LSSVR accuracy was verified in predicting the permanent deformation behavior of an asphalt mixture. The present study demonstrates that the proposed AI system is a valuable decision-making tool for road designers. Additionally, the success of SOS–LSSVR in building an accurate prediction model suggests that the proposed self-optimized prediction framework has found an underlying pattern in the current database and thus can potentially be implemented in various disciplines.

Keywords Asphalt mixtures · Artificial intelligence · Permanent deformation · Least squares support vector regression · Symbiotic organisms search

1 Introduction

Over the past decades, the number of vehicles on the road has significantly increased, causing deformation in pavement. Accumulated traffic load repetition permanently deforms asphalt pavement [1]. The side effects of permanent deformation can be devastating and include a reduction in the service life of the pavement and the creation of risky conditions for roadway users [2]. Increasing the thickness of asphalt pavement is one possible solution for road designers. However, it is often abandoned due to budget limitations. Predicting the appropriate asphalt mixtures may increase performance and service life at little additional construction cost. However, establishing a model that accurately depicts the relationship between asphalt mixtures and permanent deformation is a complicated task because of the dynamic and complex characteristics of asphalt mixtures.

There has been growing interest in the development of artificial intelligence (AI), particularly in predictive techniques due to their excellent learning features [3]. The main idea behind predictive approaches in AI is to develop a prediction model from a collection of input–output data pairs using a specific learning procedure. Once trained, the prediction model can forecast with high accuracy and

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handle nonlinear problems. As a result, much effort has been invested in improving the computational time and accuracy of AI predictive approaches [4–8].

The laboratory dynamic creep test and its flow number are commonly used as indicators that an asphalt mixture has a permanent deformation [9]. In the dynamic creep test result, the flow number can be determined as the load cycle number at which the tertiary deformation begins [10]. The tertiary deformation denotes the phase at which the progressive permanent deformations accelerate and permanent deformations grow rapidly. Determining the flow number within asphalt mixtures requires various AI approaches. For example, Gandomi et al. [11] built prediction models using an AI method called gene expression programming (GEP) by collecting dynamic creep test samples. Alavi et al. [12] utilized the genetic programming-simulated annealing (GP/SA) method to build prediction models for asphalt mixtures' performance. Mirzahosseini et al. [13] subsequently used two artificial neural network (ANN) models, multilayer perceptron (MLP) and multiexpression programming (MEP), to investigate asphalt pavement performance. These studies showed AI predictive techniques' strong potential to deal with the difficult input–output relationship of asphalt mixtures.

Despite the effective performance of the AI approaches that have been reported, previous studies in this area have made limited use of AI techniques. Furthermore, these studies have used only a simple, random division of training and testing sets in the validation process. A more advanced validation method is necessary to eliminate the potential for bias in dividing data points between these two sets. To that end, a serious need exists for more accurate systems in estimating the flow number of asphalt mixtures.

The present study proposes an AI system called SOS–LSSVR to predict permanent deformation in asphalt pavement. SOS–LSSVR integrates an accurate prediction technique, least squares support vector regression (LSSVR), with a new nature-inspired optimization technique, symbiotic organisms search (SOS). With the use of radial basis function kernel (RBF), LSSVR is considered an effective AI technique when dealing with prediction problems [14–16]. To improve the modeling performance, LSSVR needs two tuning parameters set correctly: the regularization parameter (γ) and the kernel parameter (σ). The selection process of parameters can be formulated as an optimization problem. As a new nature-inspired algorithm, SOS is considered a powerful and effective continuous-based global optimization method [4]. In previous research, experiments showed that SOS was superior to other nature-inspired techniques [4, 17–21]. Nevertheless, the algorithm's capability has not yet been tested in terms of obtaining the best LSSVR parameters.

The proposed method is investigated alongside other predictive techniques in terms of its efficacy as a viable prediction model for asphalt mixtures and their permanent deformation potential. The proposed method will use cross-validation, allowing for the validation of the training and testing processes. Furthermore, four different measures are employed to judge the accuracy of each prediction model. Obtained results are then compared with those of previous studies.

2 Literature review

2.1 Least squares support vector regression (LSSVR)

Considered an alternative to the support vector machine (SVM), LSSVR is employed for regression analysis and solving the function estimation. Adopting a statistical learning theory, this AI method focuses on replacing the quadratic program with a least squares linear system as its loss function [22]. The formulation of the optimization problem and the constraints for LSSVR are shown as follows:

$$\text{Minimize } J_p(w, e) = \frac{1}{2} w^T w + \gamma \frac{1}{2} \sum_{k=1}^{N} e_k^2 \tag{1}$$

$$\text{Subjected to } y_k = w^T \phi(x_k) + b + e_k, \; k = 1, \ldots, N \tag{2}$$

where $e_k \in R$ denote slack variable, $\gamma > 0$ is a regularization constant, and $\phi(x_k)$ denotes an input mapping to a higher-dimensional feature space.

The Lagrangian is given by:

$$L(w, b, e; \alpha) = J_p(w, e) - \sum_{k=1}^{N} \alpha_k \{w^T \varphi(x_k) + b + e_k - y_k\} \tag{3}$$

where α_k are Lagrange multipliers. The conditions for optimality are given by:

$$\begin{cases} \frac{\partial L}{\partial w} = 0 \rightarrow w = \sum_{k=1}^{N} \alpha_k \varphi(x_k) \\ \frac{\partial L}{\partial b} = 0 \rightarrow \sum_{k=1}^{N} \alpha_k = 0 \\ \frac{\partial L}{\partial e_k} = 0 \rightarrow \alpha_k = \gamma e_k, \quad k = 1, \ldots, N \\ \frac{\partial L}{\partial \alpha_k} = 0 \rightarrow w^T \varphi(x_k) + b + e_k - y_k = 0, \quad k = 1, \ldots N \end{cases} \tag{4}$$

After elimination of e and w, the following linear system is obtained:

$$\begin{bmatrix} 0 & 1_v^T \\ 1_v & \omega + I/\gamma \end{bmatrix} \begin{bmatrix} b \\ \alpha \end{bmatrix} = \begin{bmatrix} 0 \\ y \end{bmatrix} \tag{5}$$

where $y = y_1, \ldots, y_N$, $1_v = [1; \ldots; 1]$, and $\alpha = [\alpha_1; \ldots; \alpha_N]$. The following formula represents the kernel function:

$$\omega = \varphi(x_k)^T \varphi(x_l) = K(x_k, x_l) \tag{6}$$

The resulting LSSVR model may be stated as:

$$y(x) = \sum_{k=1}^{N} \alpha_k K(x_k, x_l) + b. \tag{7}$$

where α_k and b are the solution to the linear system. The RBF kernel is the most frequently used kernel function. The RBF may be expressed as:

$$K(x_k, x_l) = \exp\left(-\frac{x_k - x_l^2}{2\sigma^2}\right) \tag{8}$$

where σ is the kernel function parameter.

While using the RBF kernel, LSSVR needs two parameters: the regularization parameter (γ) and the kernel parameter (σ). While the parameter impacts the smoothness of the regression function, the γ parameter takes control of all penalties imposed on data points that deviate from the regression function.

2.2 Symbiotic organisms search (SOS)

Many areas of research employ nature-inspired algorithms for the most complex optimization issues [23, 24]. Introduced by Cheng and Prayogo [4], SOS emerges as a newly promising nature-inspired algorithm. In the search for the optimal global solution, the attempt is to reach promising areas by simulating all symbiotic interactions that move an ecosystem of organisms. Within the ecosystem, each organism receives a certain fitness value that reflects the level of adaptation to the objective.

With SOS, the main searching strategy is divided into three phases: mutualism, commensalism, and parasitism. The developed searching strategy simulates the three types of actual symbiotic interactions that occur in the real world. With mutualism, all interactions between organisms are mutually beneficial. The commensalism phase sees one organism benefit, and another have no impact at all. Finally, one organism benefits, while the other suffers from parasitism. The detailed structure of the SOS algorithm is explained in Algorithm 1.

Algorithm 1. Pseudo-code of SOS algorithm

Input:	n: population size	UB: upper bound of the solution
	D: dimensions of problem	LB: lower bound of the solution
	$iter_{max}$: maximum number of iterations	F(X): objective function

```
Generate an initial population X={X_1, X_2, ..., X_n}, and evaluate its fitness
Identify the best solution of the initial population Xbest
for iter = 1 to iter_max do
    for i = 1 to n do
    /* Mutualism Phase /*
        Choose randomly index ii ∈ {1,2, ..., n}, which ii ≠ i
        BF_1 = (1 + round(rand(0,1))
        BF_2 = (1 + round(rand(0,1))
        X_mutual = ((X_i + X_ii) / 2)
        for j = 1 to D do
            X'_i[j] = X_i[j] + rand(0,1) * (X_best[j] − BF_1 * X_mutual[j])
            X'_ii[j] = X_ii[j] + rand(0,1) * (X_best[j] − BF_2 * X_mutual[j])
        end for
        if F(X'_i) < F(X_i)
            X_i = X'_i
        end if
        if F(X'_ii) < F(X_ii)
            X_ii = X'_ii
        end if
    /* Commensalism Phase /*
        Choose randomly index ii ∈ {1,2, ..., n}, which ii ≠ i;
        for j = 1 to D do
            X'_i[j] = X_i[j] + rand(−1,1) * (X_best[j] − X_ii[j])
        end for
        if F(X'_i) < F(X_i)
            X_i = X'_i
        end if
    /* Parasitism Phase /*
        Choose randomly index ii ∈ {1,2, ..., n}, which ii ≠ i
        for j = 1 to D do
            if rand(0,1) < rand(0,1)
                X_parasite[j] = X_i[j]
            else
                X_parasite[j] = rand(0,1) * (UB[j] − LB[j]) + LB[j]
            end if
        end for
        if F(X_parasite) < F(X_ii)
            X_ii = X_parasite
        end if
        Update the best solution of the current population Xbest
    end for
end for
```

Output: the final best solution of the population Xbest

Since its publication, SOS has been increasingly used in a variety of research fields [17–19, 25–31]. Today, the algorithm has huge potential in the ever-growing search for optimality.

2.3 Hybridization of prediction and optimization approaches

In recent years, the collaborative integration between the prediction method and optimization technique has been studied extensively. The prediction methods learn from the given data inputs and outputs until an underlying pattern exists. However, some modeling techniques require advanced parameter settings to produce an acceptable level of accuracy [32]. Many studies have utilized optimization techniques to find suitable parameters so that the prediction methods can determine the complicated input and output relationship and thus increase their accuracy. Table 1 summarizes the recent studies for hybridizing the prediction method with the optimization technique.

3 The symbiotic organisms search–least squares support vector regression (SOS–LSSVR)

As a hybrid system, SOS–LSSVR integrates two computational intelligence methods with the LSSVR accurately portraying the input/output relationship as a predictor and with the SOS optimizing all LSSVR parameters ensuring the highest level of accuracy. Figure 1 explains the framework of SOS–LSSVR.

For SOS–LSSVR, there are eight key steps when used across training and testing phases:

1. Training data
   Training data are used for creating the prediction model. To prevent greater numeric ranges of input variables from dominating the process, the data were normalized into a (0,1) range [33].
2. LSSVR training
   With a hybrid system, the complex relationship between output and input variables is addressed by LSSVR. This learning process requires two tuning parameters, γ and σ parameters. Within the boundary range, the parameters are initialized randomly for the first iteration. As the optimizer, SOS simulates the searching for the best tuning parameters, allowing the LSSVR to then build the prediction model with higher accuracy.
3. SOS searching
   SOS is used to test the many combinations of both parameters that allow for the best set to be found. The generation of the population that best represents the candidate solution allows the search process to begin (consisting of both parameters). Utilizing all three phases—mutualism, commensalism, and parasitism—the fitness value of each solution will gradually improve.
4. Fitness evaluation
   LSSVR can have a low accuracy when predicting a new and unseen dataset despite its solid performance on all training data. This issue is known as the overfitting problem [34]. To overcome this problem, the training data were separated into learning subsample and validation subsamples. The learning subsample

Table 1 Summary of recent studies for hybrid prediction–optimization method

Previous work	Description	Techniques
Gandomi et al. [11]	Prediction of flow number of asphalt mixtures	Prediction: genetic programming Optimization: simulated annealing
Alavi et al. [12]	Prediction of flow number of asphalt mixtures	Prediction: genetic programming Optimization: simulated annealing
Cao et al. [38]	Prediction of construction cost index in Taiwan	Prediction: radial basis function neural network Optimization: artificial bee colony
Hoang et al. [6]	Prediction of groutability estimation of grouting process	Prediction: support vector machine Optimization: flower pollination algorithm
Chou and Ngo [39]	Prediction of fiber-reinforced soil	Prediction: least squares support vector regression Optimization: smart firefly algorithm
Tien Bui et al. [40]	Prediction of rainfall-induced shallow landslides	Prediction: least squares support vector machine Optimization: differential evolution

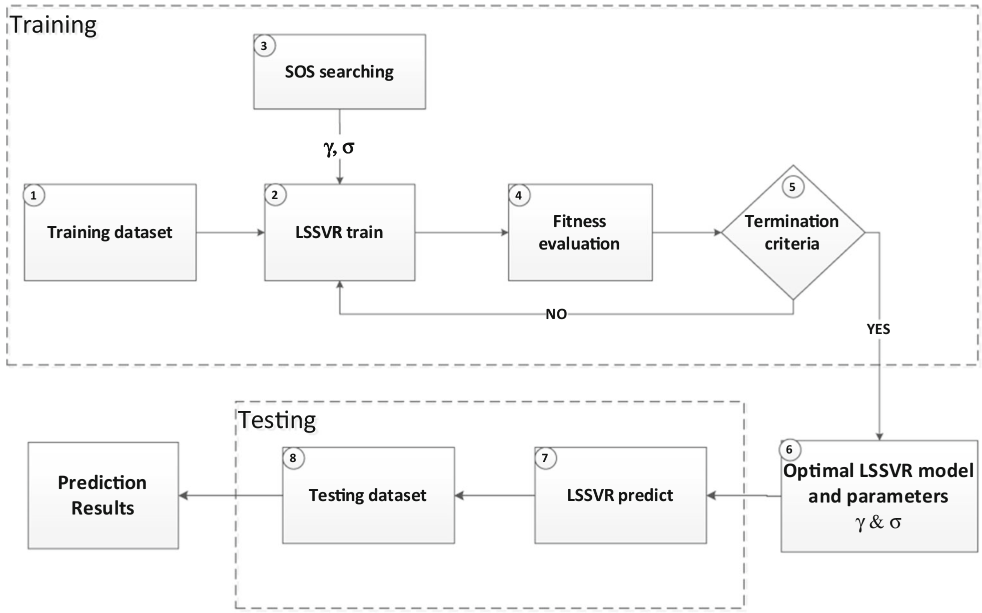

Fig. 1 SOS–LSSVR architecture

was used for building the prediction model. The validation subsample has no rule in building the actual model. However, it was used for supporting the generalization capability. To avoid the sampling bias, the tenfold cross-validation technique was used to split the training data into smaller subsamples.

The prediction model with the highest accuracy is determined based on the combination of two γ and σ tuning parameters that has the lowest error on the validation subsample. An objective function is now developed based on the model accuracy in predicting the validation subsample. The root-mean-square error (RMSE) is used to represent model accuracy in the objective function, as shown in Eq. 9.

$$\text{Min Fitness Value} = \frac{\sum_{k=1}^{S} \text{RMSE}(\text{validation}_k)}{S} \quad (9)$$

where S indicates the total number of folds and $\text{RMSE}(\text{validation}_k)$ indicates the value of root-mean-squared error between the actual and predicted values for the k-th validation subsample.

5. Termination criteria
   Once the stopping conditions have been met, the process terminates or else proceeds to the next iteration. The total number of SOS iterations was used as the termination criterion.
6. Optimal LSSVR model and parameters
   As soon as the termination criteria have been met, the loop will come to a complete stop and this suggests the prediction model has found the ideal input–output mapping relationship along with the optimal parameters.
7. LSSVR predicting
   With the two parameters at the optimum level obtained from the training phase, the prediction model can be established and then used to predict all test data.
8. Testing data
   Finally, to measure the general accuracy and the prediction performance, the testing data are applied to the trained model.

4 Experimental results

4.1 Historical dataset

In this study, 118 dynamic creep test samples from a laboratory test were used, and this allowed a prediction to be made of the proposed solution's performance [11, 12]. The dataset included 10 different input variables (influencing factors) as well as one output variable. All statistical descriptions of input and output variables are described in Table 2. The historical dataset is listed in Table 3.

The dataset was employed for modeling the asphalt pavement performance in [11–13, 35]. It was revealed that the previous studies have only used a partial amount of all possible input variables. Table 4 lists all previous models that have been employed to predict the flow number of asphalt mixtures.

In Case 1, Alavi et al. [12] and Mirzahosseini et al. [13] used IF3, IF4, IF6, and IF10 as their input variables. Gandomi et al. [11] employed IF1, IF5, IF6, and IF10 as the input variables in Case 2. Meanwhile, Mirzahosseini

Table 2 Input/output variables and statistical descriptions

Variable	Definition	Min	Max	Average	SD
IF1	Percentage of coarse aggregate (%)	33	81	57.31	14.33
IF2	Percentage of fine aggregate (%)	18	57	37.15	11.31
IF3	Percentage of filler (%)	1	10	5.54	3.17
IF4	Percentage of bitumen (%)	4	7	5.51	0.81
IF5	Percentage of air voids (%)	1.71	8.77	4.54	1.52
IF6	Percentage of voids in mineral aggregate (%)	13.20	19.04	16.55	1.41
IF7	Marshall stability (kN)	2.73	15.3	10.16	2.04
IF8	Marshall flow (mm)	2.1	4.75	3.50	0.62
IF9	Coarse aggregate-to-fine aggregate ratio	0.58	4.5	1.84	1.05
IF10	Marshall stability to flow ratio/Marshal quotient	0.61	4.81	2.99	0.74
Output	Flow number	22	510	227	143.97

Table 3 Historical dataset

No.	IF1	IF2	IF3	IF4	IF5	IF6	IF7	IF8	IF9	IF10	Output
1	55	38	7	4	7.69	16.3	11.74	3.27	1.4474	3.5902	260
2	55	38	7	4	7.52	16.16	9.49	2.9	1.4474	3.2724	350
3	55	38	7	4.5	5.6	15.45	11.58	3.4	1.4474	3.4059	300
4	55	38	7	4.5	5.67	15.51	11.42	3.72	1.4474	3.0699	310
5	55	38	7	5	4.55	15.54	11.38	3.73	1.4474	3.0509	310
6	55	38	7	5	4.08	15.12	12.88	3.8	1.4474	3.3895	340
…	…	…	…	…	…	…	…	…	…	…	…
112	68	30	2	6	3.42	16.55	9.57	3.3	2.2667	2.9000	60
113	68	30	2	6	4	17.05	9.71	3.4	2.2667	2.8559	55
114	68	30	2	6.5	3.46	17.59	9.12	3.48	2.2667	2.6207	50
115	68	30	2	6.5	3.36	17.51	9.22	3.25	2.2667	2.8369	60
116	68	30	2	6.5	3.02	17.21	9.55	3.36	2.2667	2.8423	60
117	68	30	2	7	3.36	18.49	9.01	3.51	2.2667	2.5670	50
118	68	30	2	7	2.74	17.97	8.24	3.37	2.2667	2.4451	45

Table 4 Previous models for predicting the flow number of asphalt mixtures

Model	Previous works	No. of input variables	List of input variables
Case 1	GP/SA [12]	4	IF3, IF4, IF6, IF10
	MEP, MLP [13]		
Case 2	GEP [11]	4	IF1, IF5, IF6, IF10
Case 3	LGP, ANN [35]	6	IF1, IF3, IF4, IF5, IF6, IF10

et al. [35] utilized IF1, IF3, IF4, IF5, IF6, and IF10 as the input variables in Case 3.

4.2 Experimental settings

To benchmark the performance of SOS–LSSVR, three different widely used predictive techniques were employed, including SVR [36], LSSVR [14], and BPNN [37]. The SVR and LSSVR methods belong to SVM class. Meanwhile, BPNN modifies the ANN by regulating the connection weights and bias values using back-propagation algorithm throughout the training process.

This study uses a default set for all parameters to ensure a fair comparison. All parameters for SOS–LSSVR, SVR, LSSVR, and BPNN are listed in Table 5. Four performance measures were used during the evaluation process for AI-based predictive methods throughout this research, as listed in Table 6. To evaluate all predictive methods, these performance measures were used, which allowed for more accurate results and a fairer test all around.

The historical dataset was now separated into training and testing dataset. Previously, Gandomi et al. [11], Alavi et al. [12], and Mirzahosseni et al. [13] used approximately 75% of the dataset for training and 25% of the dataset for

Table 5 Tuning parameters of the competing predictive methods

AI method	Parameters	Setting references
SVR	Regulation parameter $C = 1$	[33]
	RBF kernel parameter $\gamma = 1/N$	
LSSVR	Regulation parameter $\sigma = 1$	[14]
	RBF kernel parameter $\gamma = 1$	
BPNN	Training algorithm = Levenberg–Marquardt	[41]
	Maximum number of iterations = 1000	
	Initial $\mu = 0.01$	
	μ decrease factor = 0.1	
	μ increase factor = 10	
	Maximum $\mu = 10^{10}$	
SOS–LSSVR	γ searching boundary = 10^{-8}–10^{8}	
	σ searching boundary = 10^{-5}–10^{5}	
	Population size = 25	
	Maximum number of iterations = 100	

N is number of input variables, μ is learning rate of BPNN

Table 6 Performance measures

Performance measure	Formula
Coefficient of correlation (R)	$R = \frac{n\sum y.y' - (\sum y)(\sum y')}{\sqrt{n(\sum y^2) - (\sum y)^2}\sqrt{n(\sum y'^2) - (\sum y')^2}}$
Root-mean-squared error (RMSE)	$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y - y')^2}$
Mean absolute percentage error (MAPE)	$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left\vert\frac{y - y'}{y}\right\vert$
Mean absolute error (MAE)	$MAE = \frac{1}{n}\sum_{i=1}^{n}\vert y - y'\vert$

y is the actual value; y' is the predicted value; and n is the number of data samples

testing. To ensure the same proportion of training and testing data as the previous works, fourfold cross-validation was selected. The dataset was split into fourfold, which assigns the 3/4 (or 75%) portion of the dataset for training and assigns the remaining portion for validating the prediction model. A total of four distinct sets of training and testing data were performed. By using a fourfold cross-validation method for each model, the results were obtained, and they were based on average results for the testing and training datasets. Compared to considered models, cross-validation allowed the best validation capabilities, and this allowed the study to apply all training and testing datasets in both phases.

4.3 LSSVR–SOS training process and prediction results

As mentioned previously, SOS simulates the nature-inspired searching strategies to find the combination of LSSVR tuning parameters that produces the lowest fitness value (training error) during the training process. To ensure that the learning model is accurately generated, the *k*-fold cross-validation method was used. In the beginning, the *k*-fold cross-validation separates the dataset randomly into the training and testing data. The training data are employed to build the prediction model, while the testing data are treated as unseen data for verifying the trained model. To avoid the over-fitting, SOS–LSSVR also utilizes *k*-fold cross-validation to divide the training data into the learning and validation subsamples 10 times, where each subsample is used as a validation subsample.

In this study, every fitness value of LSSVR tuning parameters is determined using the objective function formulated in Eq. 5. The convergence curves of SOS searching are illustrated in Fig. 2. As shown in Fig. 2, the SOS searching improved the fitness value quickly from the starting iteration. The fitness value converged after several iterations, indicating that no further improvement of the

Fig. 2 Convergence curves of SOS in the training process

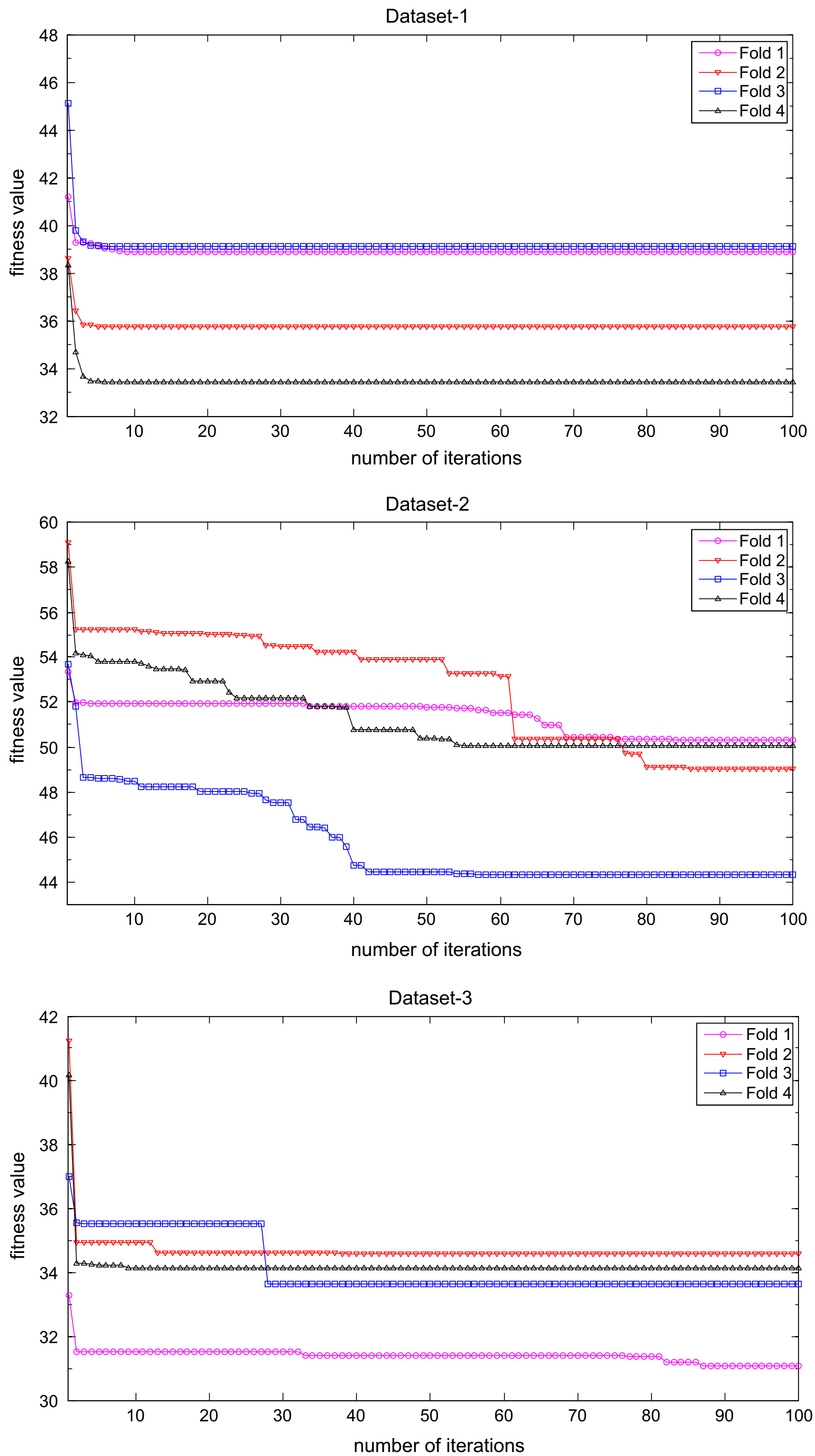

Table 7 Summary of the cross-validation results of the proposed SOS–LSSVR over various models

Model	No. of fold	Training dataset				Testing dataset				Optimal parameters	
		R	RMSE	MAPE (%)	MAE	R	RMSE	MAPE (%)	MAE	γ	σ
Case 1	1	0.9723	34.10	12.71	23.92	0.9815	29.30	17.95	23.91	189,827.5	11.3
	2	0.9759	31.12	13.14	21.98	0.9533	47.66	34.12	34.72	1706709.6	19.4
	3	0.9699	34.55	13.66	23.93	0.9778	32.79	12.22	23.04	440,099.6	15.3
	4	0.9804	28.07	12.27	20.52	0.9557	44.99	15.49	30.19	423,084.1	10.8
Case 2	1	0.9608	40.79	20.59	30.40	0.8952	58.57	30.04	45.26	18.2	2.6
	2	0.9536	42.48	18.89	30.30	0.9356	54.82	44.58	44.59	12.3	2.6
	3	0.9702	35.15	17.34	26.30	0.9020	60.96	26.11	41.08	121.0	2.9
	4	0.9670	36.28	17.21	26.87	0.9435	51.44	20.06	36.46	21.3	2.3
Case 3	1	0.9897	20.47	8.22	14.85	0.9740	33.93	12.69	22.88	127,896.4	22.4
	2	0.9866	22.70	10.98	17.08	0.9759	34.62	14.85	25.12	100,000,000.0	92.6
	3	0.9902	20.45	7.32	15.01	0.9670	33.48	14.59	26.20	11,418.1	14.6
	4	0.9863	23.77	11.32	17.87	0.9681	35.35	15.77	24.99	14,776,685.0	80.1

Table 8 Comparative testing results between SOS–LSSVR with other predictive methods over various models

Model	AI methods	R			RMSE			MAPE (%)			MAE		
		Best	Worst	Average	Best	Worst	Average	Best	Worst	Average	Best	Worst	Average
Case 1	SOS–LSSVR	**0.9815**	**0.9533**	**0.9671**	**29.30**	**47.66**	**38.68**	**12.22**	**34.12**	**19.94**	**23.04**	**34.72**	**27.96**
	LSSVR	0.9460	0.9199	0.9312	49.59	68.85	60.98	40.65	70.70	51.37	42.25	55.57	49.86
	BPNN	0.9700	0.9385	0.9589	38.38	53.65	43.56	16.69	32.18	22.17	28.89	36.65	33.09
	SVR	0.9249	0.8564	0.9002	135.09	137.50	136.54	108.57	177.44	139.45	112.34	121.05	117.80
Case 2	SOS–LSSVR	**0.9435**	**0.8952**	**0.9191**	**51.44**	**60.96**	**56.45**	**20.06**	**44.58**	**30.20**	**36.46**	**45.26**	**41.85**
	LSSVR	0.8457	0.6057	0.7497	91.33	104.30	97.24	70.05	114.57	81.40	77.23	87.90	80.11
	BPNN	0.9390	0.8181	0.8821	54.69	78.41	67.69	22.93	48.40	32.78	40.10	60.39	50.59
	SVR	0.8156	0.6095	0.7359	130.16	148.90	140.64	106.72	195.53	142.96	111.68	130.19	123.14
Case 3	SOS–LSSVR	**0.9759**	**0.9670**	**0.9713**	**33.48**	**35.35**	**34.35**	**12.69**	**15.77**	**14.47**	**22.88**	**26.20**	**24.80**
	LSSVR	0.9491	0.8694	0.9091	66.38	77.30	69.33	33.14	76.21	57.11	51.26	61.75	55.60
	BPNN	0.9499	0.8711	0.9241	43.13	80.39	56.71	24.81	43.96	32.33	35.34	61.97	43.42
	SVR	0.8707	0.8008	0.8406	134.04	151.91	141.47	113.71	163.32	145.62	110.60	134.63	122.43

Bold text denotes the best performance across the methods

fitness value can be obtained. It can be seen that the SOS delivers a great performance as the optimizer in this system.

Table 7 displays the performance of SOS–LSSVR for each fold on each dataset. Table 8 shows the complete statistical comparative results of the experiment among the predictive methods. These results show that SOS–LSSVR performed better compared to the rest of predictive methods. In each dataset, SOS–LSSVR earned the best score in overall measurement category (R, RMSE, MAPE, and MAE), followed by the BPNN, LSSVR, and SVR. Figure 3 depicts the performance measures that are described in Table 8.

Among three models of dataset, SOS–LSSVR achieved the best overall performance in Case 3. In Case 3, SOS–LSSVR produces the lowest RMSE, MAPE, and MAE scores of 34.35, 14.47%, and 24.80, respectively, while having the highest R score of 0.9713. To conclude, Case 3, the model with 6 input variables (IF1, IF3, IF4, IF5, IF6, IF10), enables SOS–LSSVR to build the most accurate model for predicting the flow number.

4.4 Comparison with previous works

Numerous studies have proposed AI methods for estimating the flow number of asphalt mixtures. For further verification, the prediction results of the proposed SOS–LSSVR were compared with those of previous works. Generally, it was not possible to compare the performance of the proposed method with the previous works because

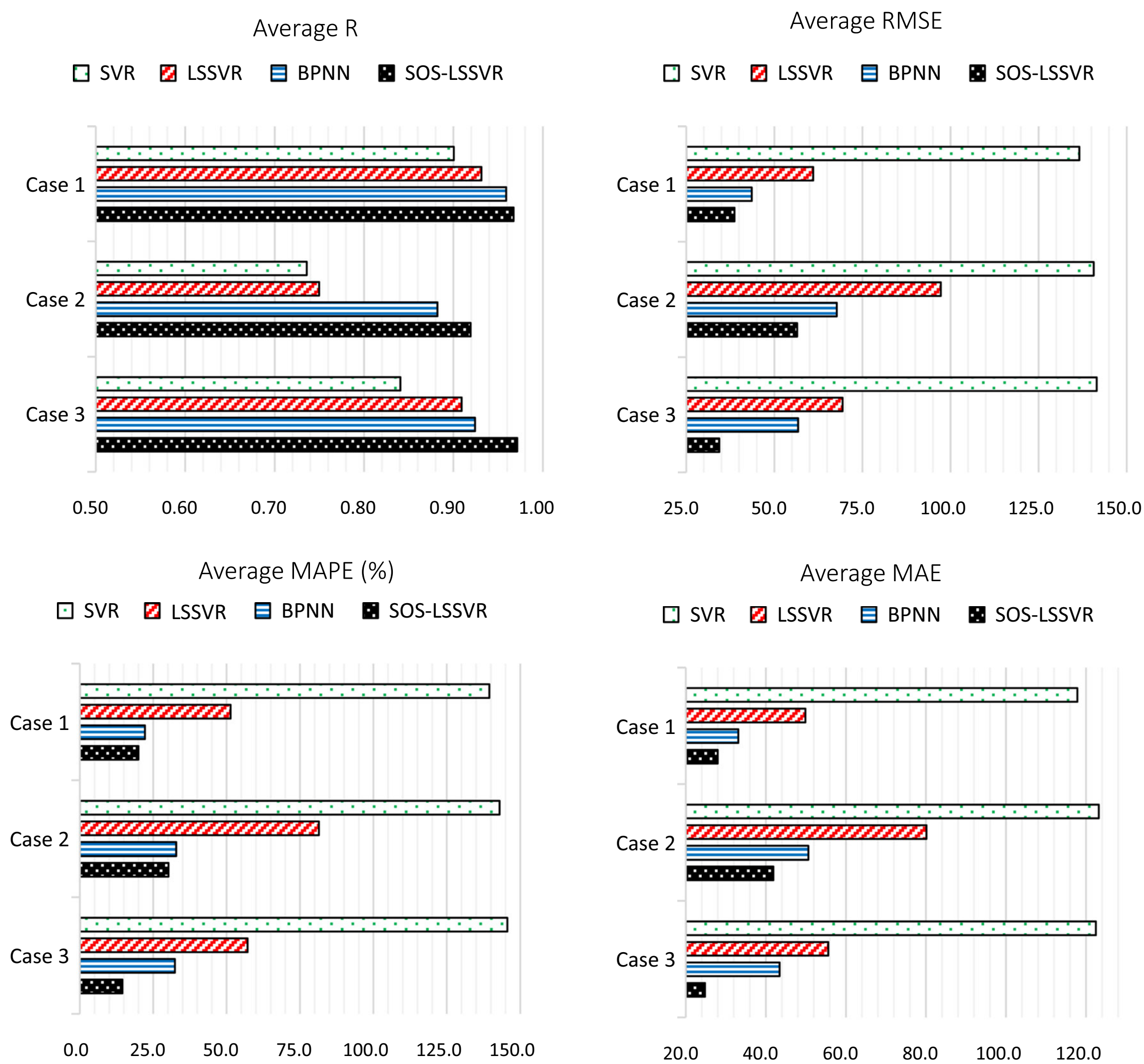

Fig. 3 Average testing results of the performance measures for the SOS–LSSVR and other methods through cross-validation

the data divisions for training and testing were different. As discussed previously, this study employed fourfold cross-validation to keep the same proportion of training and testing ratio (75/25) with the previous research. Table 9 summarizes the comparison results between the proposed method and previous works.

In Case 1, SOS–LSSVR outperforms GP/SA and MEP in all performance measure categories (R, RMSE, and MAE). MEP has slightly better R and MAE scores compared with GP/SA, while GP/SA is better than MEP in terms of RMSE. Overall, error rates (RMSE and MAE) improved by SOS–LSSVR method were 14.0–17.4% compared to those of previous methods in this case. Similar to Case 1, the obtained results of the SOS–LSSVR performance are better than those of GEP in every category in Case 2. The error rates of SOS–LSSVR were 13.2–16.5% lower than those of GEP. In Case 3, the SOS–LSSVR and

Table 9 Average testing results between SOS–LSSVR with previous researches over various datasets

Model	AI methods	R	RMSE	MAE
Case 1	MEP [13]	0.956	46.23	32.509
	GP/SA [12]	0.948	46.06	33.842
	SOS–LSSVR	**0.9671**	**38.68**	**27.96**
Case 2	GEP [11]	0.891	67.63	48.218
	SOS–LSSVR	**0.9191**	**56.45**	**41.85**
Case 3	LGP [35]	0.964	38.44	26.442
	ANN [35]	**0.974**	34.95	**23.102**
	SOS–LSSVR	0.9713	**34.35**	24.80

Bold text denotes the best performance across the methods

ANN produced better performance than LGP. SOS–LSSVR has the best score in terms of RMSE, while ANN has the best score in terms of R and MAE.

5 Conclusion

Permanent deformations in asphalt pavement have become a major issue in road engineering because it creates discomfort and often dangerous situations to the road users. Permanent deformations usually occur after a number of repeated loading cycles, known as flow number, applied to an asphalt pavement. Accurately predicting the flow number is essential for road designers in determining the proper asphalt binder properties. Thus, the present study developed a new predictive method called SOS–LSSVR to model the complex relationship of asphalt mixtures and predict their permanent deformation.

The dataset used in this study was obtained from a dynamic creep test containing 118 samples. All proposed predictive techniques used cross-validation through the varying dataset models. As a benchmark, three different predictive methods were used for SOS–LSSVR: SVR, BPNN, and LSSVR. The proposed SOS–LSSVR was compared with other methods through multiple performance measures to build an extensive comparison of the predictive methods.

In this study, the SOS–LSSVR is able to achieve better accuracy than all other comparative measures with the BPNN, LSSVR, and SVR achieving the second-, third-, and fourth-best overall accuracies, respectively. Furthermore, the results from SOS–LSSVR are compared with those of past research. It was revealed that the results from SOS–LSSVR outperform those of previous predictive methods.

The present study validates that the new predictive model SOS–LSSVR represents a significant step forward in assisting road designers in addressing the critical problem of permanent deformation in asphalt mixtures. Investigating the selection of relevant input factors of the given dataset represents an interesting direction for further study. Choosing a set of relevant input factors may increase the model performance and reduce the model complexity.

Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

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