Modeling the Permanent Deformation Behavior of Asphalt Mixtures Using a Novel Hybrid Computational Intelligence

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Abstract –

One of the main causes of pavement rutting is the repetitive action of traffic loads which results in the accumulation of permanent deformations. As a result, it is important to understand the characteristics of the permanent deformation behavior of asphalt mixes under repeated loading and to build the accurate mix model before they are placed in roadways. This study proposed a hybrid computational intelligence system named SOS-LSSVM for modelling the permanent pavement deformation behavior of asphalt mixtures. The SOS-LSSVM fuses Least Squares Support Vector Machine (LSSVM) and Symbiotic Organisms Search (SOS). LSSVM is employed for establishing the relationship model between the flow number, which is obtained from the laboratory test, and the parameters of the asphalt mix design. SOS is used to find the best LSSVM tuning parameters. A total 118 historical cases were used to establish the intelligence prediction model. Obtained results validate the ability of SOS-LSSVM to model the pavement rutting behavior of asphalt mixture with a relatively high accuracy measured by four error indicators. Therefore, the proposed computational intelligence systems can offer a high benefit for road designers and engineers in decision-making processes.

Keywords –

Symbiotic Organisms Search; Least Squares Support Vector Machine; Asphalt concrete mixture; Flow number; Prediction

1 Introduction

Over the last decades, the permanent pavement deformation or rutting of asphalt mixtures has gained great attention in the field of pavement engineering. Rutting progressively develops in asphalt pavements and increases the number of vehicle load cycles. It became a major concern because pavement rutting decreases the useful life service of the pavement and creates serious hazards for highway users. As a result, it is important to understand the characteristics of the permanent deformation behavior of asphalt mixes under repeated loading and consequently construct the accurate asphalt mixture before they are placed in roadways [1].

Recently, dynamic creep test is found to be one of the best methods for assessing the permanent deformation potential of asphalt mixtures [2]. The most important output of the dynamic creep test is the curve of accumulated strain against number of load cycles. The flow number, defined as the loading cycle number where the permanent deformation starts [3], is a good indicator of the rutting resistance of a given asphalt mixture. However, the dynamic creep test is sensitive and costly and cannot always be performed. Therefore, developing a relationship model based on the collectible historical data between the flow number obtained from the dynamic creep test and the parameters from the asphalt mix design leads to considerable savings in construction costs and time.

The prediction of the asphalt mixture performance of asphalt mixtures is a significantly important matter. However, building that accurate relationship model has traditionally been a complicated task. It is because the permanent deformation of asphalt mixtures is influenced by several factors which are also complex and highly nonlinear. The conventional approaches such as linear regression or decision tree are not sufficient to build a satisfactory model in terms of accuracy and computational cost. The artificial intelligence (AI) approaches have been reported to outperform the conventional approaches due to the excellence of their learning features [4-8]. Yet, only a few researches have utilized AI methods to predict the flow number of the asphalt mixtures [1,9,10].

The primary objective of this research work is to build the accurate prediction model using the advanced AI methods for enhancing the permanent deformation analysis. This research proposes a new computational intelligence system called Symbiotic Organisms Search – Least Squares Support Vector Machine (SOS-LSSVM). SOS-LSSVM fuses an accurate prediction technique, Least Squares Support Vector Machine (LSSVM) [11], and a very promising optimization tool, Symbiotic Organisms Search (SOS) [12]. The proposed model will be investigated alongside other prediction methods in building an accurate prediction model of the permanent deformation of asphalt mixtures.

In presenting the SOS-LSSVM as a novel computational intelligence system, this study makes three important contributions. First, SOS-LSSVM is a new variant of the nature-inspired based LSSVM. It integrates a recent promising metaheuristic algorithm (SOS) to the widely used and robust predictive method of LSSVM. Second, this study uses a cross validation technique that was adopted to validate the training and testing process. Third, three performance measurements are also used to evaluate the performance of the methods.

2 Model Construction

2.1 Least Squares Support Vector Machine

LSSVM is a modified version of the Support Vector Machine (SVM) [13]. The LSSVM is a statistical learning theory that adopts a least squares linear system as a loss function instead of the quadratic program in the original support vector machine (SVM) [14]. Notably, in LSSVM training process, a least squares cost function is proposed to obtain a linear set of equations in the dual space. One main difference between LSSVM and the original SVM is that LSSVM requires equality constraints instead of inequality ones while operating with a least squares cost function. The optimization problem and the constraints for LSSVM can be stated by the following formulation.

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

Subjected to: $y_k = w^T \phi(x_k) + b + e_k, k = 1, \ldots, N$ (2)

where $w \in R$ is an undetermined parameter vector; $\phi(\cdot)$ is the nonlinear function that is usually introduced by a kernel function that maps the input space to a high-dimensional feature space; $e_k \in R$ are error variables; $\gamma > 0$ denotes a regularization constant.

The resulting LS-SVM model for function estimation is expressed as:

$$y(x) = \sum_{k=1}^{N} \alpha_k K(x_k, x_l) + b \quad (3)$$

where α_k and b are the solution to the linear system (4). The kernel function that is often utilized is the Radial Basis Function (RBF) kernel. Description of RBF kernel is given as follows:

$$K(x_k, x_l) = exp\left(\frac{\|x_k - x_l\|^2}{2\sigma^2}\right) \quad (4)$$

where σ is the kernel function parameter.

The accuracy of LSSVM depends on searched problem parameters. The regularization parameter (γ) is a positive cost parameter similar to the C in SVM, while the Kernel parameter (σ) is an additional parameter since LSSVM utilized the RBF kernel function. These two parameters need to be specified in order to find the best prediction model.

2.2 Symbiotic Organisms Search

Symbiotic Organisms Search (SOS) is one of the newly promising metaheuristic algorithms proposed by Cheng and Prayogo [12]. SOS simulates symbiotic interactions to iteratively move a population (ecosystem) of candidate solutions (organisms) to promising areas in the search space during the process of seeking the optimal global solution. Each organism in the ecosystem is associated with a certain fitness value, which reflects a degree of adaptation to the desired objective. The basic steps of the algorithm are summarized below.

1. Generate initial population
2. **Do**
3. Mutualism phase
4. Commensalism phase
5. Parasitism phase
6. Update the best solution
7. **Until** stopping criteria are satisfied

In [12], the performance of SOS has been compared with other metaheuristic techniques such as Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Differential Evolution (DE), and Bees Algorithm (BA) in numerous mathematical test functions and engineering problems. The comparison results indicate that SOS was able to achieve a better performance in terms of effectiveness and efficiency. Furthermore, SOS has been proven to successfully solve various problems in different fields of research [15-24].

2.3 Symbiotic Organisms Search – Least Squares Support Vector Machine

The Symbiotic Organisms Search – Least Squares Support Vector Machine (SOS-LSSVM) model is a hybrid artificial Intelligence (AI) system that combines the two different techniques of SOS and LSSVM. In this system, the LSSVM acts as a supervised-learning-based predictor to build the accurate input-output relationship of the dataset; and the SOS works to optimize the LSSVM parameters, the σ and γ parameters.

The SOS-LSSVM involves eight major steps which are categorized into two phases, beginning with training phase followed by the testing phase. The whole procedure of SOS-LSSVM is shown in Figure 1. An explanation of the major steps involved in SOS-LSSVM is given below:

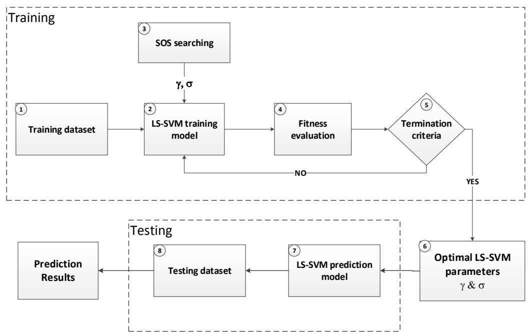

Figure 1. SOS-LSSVM procedure.

1. Training data:
   The data for training are obtained from data collection.
2. LSSVM training model:
   LSSVM addresses the complex relationship between input and output variables. LSSVM requires two parameters, σ and γ, to finish the learning process. LSSVM will gradually obtain the tuning parameters from the optimizer – the SOS algorithm.
3. SOS parameters search:
   In this hybrid AI system, SOS is utilized to explore the various combinations of σ and γ parameters to look for the best set of them. SOS utilizes mutualism, commensalism, and parasitism phase to gradually improve the fitness value of each solution.
4. Fitness evaluation:
   A fitness function is now developed to evaluate accuracy of the learning system. This function has a correlation with the accuracy of the prediction model. The most accurate prediction model is represented by the combination of σ and γ parameters that produces the best fitness value. Instead of randomly splitting the data, it was partitioned into two subsets; learning subset and validation subset. To avoid the sampling bias, the 10-fold cross-validation technique is used in splitting the training data into learning and validation subsets. In this study, the fitness function utilizes mean square error (MSE) of the validation dataset.
5. Termination criteria:
   The process terminates when the termination criterion is satisfied. While still unsatisfied, the model will proceed to the next iteration. As SOS-LSSVM uses SOS, the termination criterion used in this study was the SOS iteration number.
6. Optimal LSSVM parameters:
   The loop stops when the termination criterion is fulfilled. This condition means that the prediction model has identified the input/output mapping relationship with the optimal σ and γ parameters.
7. LSSVM prediction model:
   The optimal LSSVM σ and γ parameters obtained from the training phase are used to establish the prediction model for predicting the testing data.
8. Testing data:
   The data for testing is obtained from data collection. The test set will be used to measure the performance of the LSSVM prediction model.

3 Experimental Results

The experimental dataset was obtained from [1]. A total of 118 samples of uniaxial dynamic creep tests were evaluated from the laboratory experiment at Iran University of Science and Technology, Asphalt Mixtures and Bitumen Research Center. The database includes the percentage of filler to the total aggregate (FP), percentage of binder to the total aggregate (BP), percentage voids in mineral aggregate (VMA), ratio of Marshall stability to Marshall flow (M/F), and the flow number which represents the number of loading cycles where the tertiary deformation starts (Fn). The characteristics of the aggregates, fillers, and the bitumen of the dataset can be seen in Table 1. It also shows the experimental dataset of 5 total input and output variables used in this study.

Table 1 Statistical description of permanent deformation analysis obtained from the dynamic creep test (I = input, O = output)

Variables	Unit	Type	Min	Max	Avg	Std. dev.
FP	%	I	1	10	5.54	3.17
BP	%	I	4	7	5.51	0.81
VMA	%	I	13.2	19.04	16.55	1.41
M/F	-	I	0.61	4.81	2.99	0.74
Fn	cycle	O	22	510	227	143.97

To validate the Symbiotic Organisms Search – Least Squares Support Vector Machine (SOS-LSSVM) performance, another comparison to other predictive models is performed. This includes the Least Squares Support Vector Machine (LSSVM) and the Artificial Neural Network (ANN). In this study, all parameters were set to default for fair comparison.

- For SOS-LSSVM, maximum number of iteration was set to 50; population size was set to 25; and search range for the σ and γ parameters starts from 10^{-5} to 10^{5}.
- For ANN, maximum hidden layers were set to 1; the number of neurons in the hidden layer was set to 4, which is equal to the number of input variables; the number of cycles was set to 1000; and the learning rate was set to 0.1.
- For LSSVM, the parameters of σ and γ were set to 1, as suggested in [13].

Three accuracy measures (coefficient of correlation R, root mean squared error RMSE, and mean absolute percentage error MAPE) were utilized to measure the performance of the predictive techniques. The data was split into 90/10 of training and testing sets. The training and testing processes are performed for each predictive model. The complete experimental results can be seen in Table 2. It can be seen that SOS-LSSVM has performed better in all measurement categories, not only in the training dataset but also in the testing dataset. LSSVM and ANN outputted a similar result in the testing dataset. In terms of R and MAPE, LSSVM earned a slightly better score. Meanwhile, in terms of RMSE, ANN earned a slightly better score.

Table 2 Comparative experimental results among predictive methods.

Performance measure	Predictive methods	Training Result	Testing Result
R	LSSVM	0.9816	0.9234
	ANN	0.9604	0.9161
	SOS-LSSVM	0.9882	0.9564
RMSE	LSSVM	32.37	47.62
(cycle)	ANN	40.91	46.57
	SOS-LSSVM	22.31	35.37
MAPE	LSSVM	23.59	13.88
(%)	ANN	19.09	14.35
	SOS-LSSVM	12.29	8.53

The detailed testing results for the LSSVM, ANN, and SOS-LSSVM are displayed in Table 3. As discussed before, there are 11 cases selected as testing data that represents approximately 10% of the total historical data. After the testing process is finished, the predicted Fn is recorded. Beside the aforementioned performance measures, the differences between the actual and predicted Fn were computed to further illustrate the accuracy of the competing methods. With respect to Table 3, the mean absolute deviation from actual Fn produced by LSSVM, ANN, and SOS-LSSVM are 35.2, 34.7, and 24.9, respectively. It can be concluded that the SOS-LSSVM produced less error than other methods.

Table 3 Detail of testing results.

Case number of testing data	Actual Fn (cycle)	Deviation from Actual Fn (cycle)		
		LSSVM	ANN	SOS-LSSVM
4	260	19.84	61.81	37.31
11	260	-4.79	7.20	-1.97
15	160	75.97	50.57	89.06
19	270	9.94	15.16	14.83
38	190	-12.35	-14.23	-14.99
44	150	37.95	62.40	39.27
57	420	-62.96	-11.77	-8.00
62	420	-25.39	-8.95	1.36
66	380	-107.90	-103.93	-44.88
67	360	-28.37	45.57	19.04
82	60	1.77	-0.04	-3.32

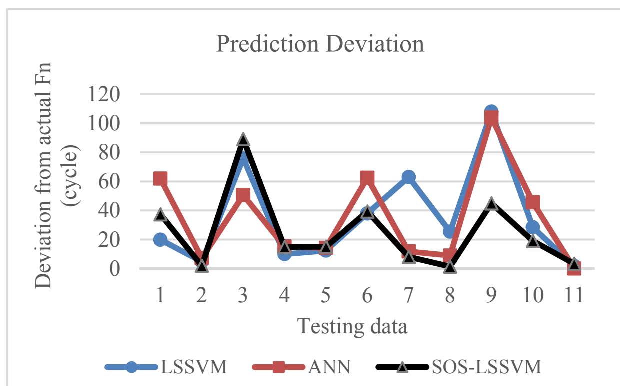

Figure 2. Prediction deviation of LSSVM, ANN, and SOS-LSSVM.

Figure 2 illustrates testing deviations between the actual and predicted values of the three prediction techniques. It can be seen that the SOS-LSSVM produced the best data fit among the other prediction techniques. This further supports that the SOS-LSSVM is the most reliable method for establishing the prediction model.

4 Conclusion

This study developed a new prediction method called Symbiotic Organisms Search – Least Squares Support Vector Machine (SOS-LSSVM) to predict the permanent deformation of asphalt mixtures. To investigate the accuracy of the proposed method, two prediction methods, LSSVM and ANN, were used as benchmarks for the SOS-LSSVM. The experimental data set was acquired from dynamic creep tests of 118 samples. In this investigation, the proposed predictive techniques were applied to the prepared training and testing datasets.

The proposed SOS-LSSVM was further compared for performance outcomes by using three different performance measures (R, RMSE, and MAPE) to obtain a comprehensive comparison of the applied predictive techniques. The findings showed that the proposed SOS-LSSVM achieved the best accuracy for all performance measures. The ANN was in the second place in terms of overall accuracy, while the LSSVM was in the last place.

This study presents a significant contribution to address the importance of the problem of permanent deformation in asphalt mixtures. By accurately predicting the appropriate flow number with the corresponding mixture, the SOS-LSSVM assists the road designers to select the asphalt mixtures accurately within the given specifications. Analytical results indicate that SOS-LSSVM is the most reliable model for building accurate asphalt mixtures based on the specific characteristics of permanent deformation.

References

[1] Alavi A. H., Ameri M., Gandomi A. H., Mirzahosseini M. R. Formulation of flow number of asphalt mixes using a hybrid computational method. *Construction and Building Materials,* 25(3): 1338-1355, 2011.

[2] K.E. Kaloush M. W. W. Tertiary flow characteristics of asphalt mixtures. *Journal of the Association of Asphalt Paving Technologists,* 71: 278–306, 2002.

[3] Witczak M. W., Kaloush K. E., Pellinen T., El-Basyouny M., Von Quintus H. Simple performance test for superpave mix design. *NCHRP Report*: 465, 2002.

[4] Cheng M.-Y., Firdausi P. M., Prayogo D. High-performance concrete compressive strength prediction using Genetic Weighted Pyramid Operation Tree (GWPOT). *Engineering Applications of Artificial Intelligence,* 29: 104-113, 2014.

[5] Cheng M.-Y., Prayogo D., Wu Y.-W. Novel Genetic Algorithm-Based Evolutionary Support Vector Machine for Optimizing High-Performance Concrete Mixture. *Journal of Computing in Civil Engineering,* 28(4): 06014003, 2014.

[6] Cheng M.-Y., Wibowo D. K., Prayogo D., Roy A. F. V. Predicting productivity loss caused by change orders using the evolutionary fuzzy support vector machine inference model. *Journal of Civil Engineering and Management,* 21(7): 881-892, 2015.

[7] Hoang N.-D., Pham A.-D. Hybrid artificial intelligence approach based on metaheuristic and machine learning for slope stability assessment: A multinational data analysis. *Expert Systems with Applications,* 46: 60-68, 2016.

[8] Cheng M.-Y., Hoang N.-D., Wu Y.-W. Hybrid intelligence approach based on LS-SVM and Differential Evolution for construction cost index estimation: A Taiwan case study. *Automation in Construction,* 35: 306-313, 2013.

[9] Gandomi A. H., Alavi A. H., Mirzahosseini M. R., Nejad F. M. Nonlinear Genetic-Based Models for Prediction of Flow Number of Asphalt Mixtures. *Journal of Materials in Civil Engineering,* 23(3): 248-263, 2011.

[10] Mirzahosseini M. R., Aghaeifar A., Alavi A. H., Gandomi A. H., Seyednour R. Permanent deformation analysis of asphalt mixtures using soft computing techniques. *Expert Systems with Applications,* 38(5): 6081-6100, 2011.

[11] Suykens J. A. K., Vandewalle J. Least Squares Support Vector Machine Classifiers. *Neural Process. Lett.,* 9(3): 293-300, 1999.

[12] Cheng M.-Y., Prayogo D. Symbiotic Organisms Search: A new metaheuristic optimization algorithm. *Computers & Structures,* 139: 98-112, 2014.

[13] Suykens J. A. K., Vandewalle J. Least squares support vector machine classifiers. *Neural Processing Letters,* 9(3): 293-300, 1999.

[14] S. K. K., Kim D., S.L.Sekar, Samui P. Model of least square support vector machine (LSSVM) for prediction of fracture parameters of concrete. *International Journal of Concrete Structures and Materials,* 5(1): 29-33, 2011.

[15] Tejani G. G., Savsani V. J., Patel V. K. Adaptive symbiotic organisms search (SOS) algorithm for structural design optimization. *Journal of Computational Design and Engineering*, 2016.

[16] Cheng M.-Y., Prayogo D., Tran D.-H. Optimizing Multiple-Resources Leveling in Multiple Projects Using Discrete Symbiotic Organisms Search. *Journal of Computing in Civil Engineering*: 04015036, 2015.

[17] Tran D.-H., Cheng M.-Y., Prayogo D. A novel Multiple Objective Symbiotic Organisms Search (MOSOS) for time–cost–labor utilization tradeoff problem. *Knowledge-Based Systems,* 94: 132-145, 2016.

[18] Cheng M.-Y., Chiu C.-K., Chiu Y.-F., Wu Y.-W., Syu Z.-L., Prayogo D., Lin C.-H. SOS optimization model for bridge life cycle risk evaluation and maintenance strategies. *Journal of the Chinese Institute of Civil and Hydraulic Engineering,* 26(4): 293-308, 2014.

[19] Duman S. Symbiotic organisms search algorithm for optimal power flow problem based on valve-point effect and prohibited zones. *Neural Computing and Applications*: 1-15, 2016.

[20] Prasad D., Mukherjee V. A novel symbiotic organisms search algorithm for optimal power flow of power system with FACTS devices. *Engineering Science and Technology, an International Journal,* 19(1): 79-89, 2016.

[21] Kamankesh H., Agelidis V. G., Kavousi-Fard A. Optimal scheduling of renewable micro-grids considering plug-in hybrid electric vehicle charging demand. *Energy,* 100: 285-297, 2016.

[22] Verma S., Saha S., Mukherjee V. A novel symbiotic organisms search algorithm for congestion management in deregulated environment. *Journal of Experimental & Theoretical Artificial Intelligence*: 1-21, 2015.

[23] Abdullahi M., Ngadi M. A., Abdulhamid S. i. M. Symbiotic Organism Search optimization based task scheduling in cloud computing environment. *Future Generation Computer Systems,* 56: 640-650, 2016.

[24] Ruskartina E., Yu V. F., Santosa B., Redi A. A. N. P. Symbiotic Organism Search (SOS) for Solving the Capacitated Vehicle Routing Problem. *International Journal of Mechanical, Aerospace, Industrial, Mechatronic and Manufacturing Engineering,* 101: 857-861, 2015.