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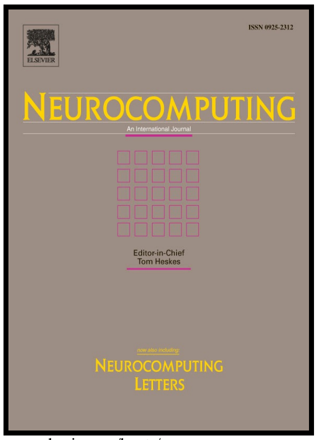

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Self-adaptive step fruit fly algorithm optimized support vector regression model for dynamic response prediction of magnetorheological elastomer base isolator

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Abstract
Parameter optimization of support vector regression (SVR) plays a challenging role in improving the generalization ability of machine learning. Fruit fly optimization algorithm (FFOA) is a recently developed swarm optimization algorithm for complicated multi-objective optimization problems and is also suitable for optimizing SVR parameters. In this work, parameter optimization in SVR using FFOA is investigated. In view of problems of premature and local optimum in FFOA, an improved FFOA algorithm based on self-adaptive step update strategy (SSFFOA) is presented to obtain the optimal SVR model. Moreover, the proposed method is utilized to characterize magnetorheological elastomer (MRE) base isolator, a typical hysteresis device. In this application, the obtained displacement, velocity and current level are used as SVR inputs while the output is the shear force response of the device. Experimental testing of the isolator with two types of excitations is applied for model performance evaluation. The results demonstrate that the proposed SSFFOA-optimized SVR (SSFFOA_SVR) has perfect generalization ability and more accurate prediction accuracy than other machine learning models, and it is a suitable and effective method to predict the dynamic behaviour of MRE isolator.

Keywords
Support vector regression, fruit fly optimization algorithm, self-adaptive step, magnetorheological elastomer base isolator, dynamic response prediction

1. Introduction
Support vector machine (SVM), based on structural risk minimization (SRM), is one of most commonly used machine learning methods, which is able to analyze data and identify patterns and is applied to classification and regression analysis [1]. Due to the low requirement on training samples, the SVM has the perfect generalization performance regarding small samples and could quickly deal with the problems of local optimum, over-fitting and slow convergence existing in other artificial intelligent techniques [2, 3]. Up to present, the SVM has obtained the wide applications in the fields of fault detection [4, 5], pattern recognition [6, 7], signal processing [8], robotics [9], and machine vision [10]. The SVM was then developed to process the nonlinear regression via the introduction of an insensitive loss function, named as SVR. SVR has been successfully applied to the areas of river flow prediction [11], wind speed prediction [12] and electric load prediction [13]. In the SVR model, the effectiveness and the generalization ability are mainly dependent on two parameters: regularization factor and loss function parameter. Once the values of above parameters are improperly selected, the prediction capacity of SVM will be greatly affected. Therefore, the main problem with SVR rests on the accurate identification of model parameters. There are several approaches developed for selecting the SVR parameters, including gradient-based methods, error evaluation method and gird search method. However, these approaches have similar disadvantages: excessive calculation and time consuming.

Recently, the swarm intelligence optimization algorithms were proposed to tackle optimization problems, which were also applied to optimize the SVR parameters, such as particle swarm optimization (PSO), ant colony optimization (ACO), bee colony algorithm (BCA), firefly algorithm (FA) and artificial fish swarm algorithm (AFSA). In [14], Li et al. put forward a hybrid self-adaptive learning approach based on SVR and PSO to estimate the ore grade. In [15], the SVR parameters are optimized by ant colony optimization, and then the trained model is applied to characterize NOx emissions with high forecast accuracy. Besides, Kavousi-Fard et al. presented a parameter identification approach for SVR using modified firefly algorithm (MFA-SVR), which is able to provide the satisfactory prediction results of electrical load [16]. However, there are still obvious differences between predictions and real data for some days, which signifies that MFA-SVR requires further study and validation.

Fruit fly optimization algorithm (FFOA) is a new swarm optimization algorithm which is inspired by the intrinsic behaviour of food search in fruit fly swarm [17-20]. The FFOA has been successfully adopted to deal with multi-objective optimization and scheduling problems. In [21], Lin combined the FFOA with general regression neural network (GRNN) to detect the logistics quality and service satisfaction of online auction sellers. This hybrid model is also compared with PSO-optimized GRNN and standard GRNN, and the comparison result demonstrates that FFOA is able to perfectly improve the classification and prediction accuracy of GRNN. In [22], Li et al. proposed a modified FFOA with the introduction of the escape local optimal factor to adjust the parameters of PID control with greatly stable outputs of step responses. In [23], the FFOA was used to solve the homogeneous fuzzy series-parallel redundancy allocation problem. Compared with PSO, GA and Tabu search (TS) algorithm, the FFOA has a relatively quick convergence while the identification accuracy is also higher than that of other algorithms. In terms of these advantages, the FFOA can be considered as a promising candidate for SVR parameter identification.

Magnetorheological elastomer (MRE) base isolator is an adaptive smart device used for vibration control and structure protection from the earthquakes [24-26]. Due to the unique property of controllable stiffness in MRE, the device is able to quickly adjust its property to avoid the resonance and protect the structure with the assistance of the control system [27-29]. Hence, to fully utilize the advantage of the device, an accurate and robust model should be developed for the controller design. However, because of nonlinear and hysteretic force-displacement/velocity responses, how to effectively characterize this novel device poses a challenging task for its engineering applications. So far, several models have been proposed to portray the nonlinear responses of the device, such as Bouc-Wen model [30, 31], LuGre friction model [32] and strain stiffening model [33]. These models are designed based on assumption of the device structure. When the model is fixed, model parameters will be calculated using optimization algorithms to minimize the errors between predicted responses and experimental measurements. This type of model heavily relies on the initial assumption, initial values and constraints of the model parameters. Once the information is inaccurate, the identification result may be unrealistic values such as negative damping and stiffness, which will affect the robustness of the designed controller.

On account of the problems in existing MRE models, this paper proposes a SVR-based model to forecast the dynamic response of MRE base isolator. In the proposed model, the captured displacement and velocity together with applied current level are used as the SVR inputs while the output is the shear force generated by the device. To obtain an optimal performance, the FFOA is employed to optimize the SVR parameters, which can make two parameters reach their optimal values in a short time. Considering that the standard FFOA may fall into the local optimum when dealing with some complex problems [34, 35], this paper introduces a self-adaptive step update mechanism into the standard FFOA, avoiding the premature and local optimum problems in algorithm. Then, the trained model is utilized to predict the dynamic behaviour of the device based on the inputted information of displacement, velocity and current. Eventually, to demonstrate the superiority of the proposed model, it is compared with other SVR-based models as well as two conventional soft computing methods: artificial neural network (ANN) and adaptive neuro fuzzy inference system (ANFIS). The result validates the proposed model with perfect performance in the evaluation indices.

2. Experimental testing of MRE base isolator

2.1. Core materials

Magnetorheological elastomer (MRE) is a novel type of field dependent intelligent material, which is made up of magnetic particles fluidized in the rubber matrix [25]. Generally, the MRE acts as a soft rubber without the magnetic field. However, when it is applied to the current, the modulus of elasticity of MRE will be significantly enhanced, which is related to the material property design and applied magnetic field intensity. Due to this unique characteristic, MRE has the great potential to be applied in automatic suspensions, rotor dynamics, motion-based isolator in infrastructure, etc [28].

2.2. Device design

Inspired by the benefits of MRE, Li et al. have proposed an innovative adaptive base isolator based on conventional structure of laminated rubber bearing [25]. The soft MRE material, with significant MR effect, is adopted in this new device, which is demonstrated by great increase of shear modulus when subjected to magnetic field. Fig. 1 illustrates real object and cross-sectional view of the device. As can be seen from the figure, the layout of the MRE base isolator is designed by substituting the traditional rubber with MRE material. In the core of the isolator, 26 layers of steel plate and 25 layers of MRE sheet, each of a 1 mm thickness, are vulcanised together alternatively so as to form a laminated structure. In the core, the MRE sheets endow the isolator great flexibility in the horizontal direction while the steel plates supplies vertical loading capacity to the device. In order to take full advantage of the MR effect of the material, an electromagnetic coil is mounted outside the laminated core so as to generate uniformed magnetic flux throughout the MRE sheets. Therefore, the stiffness of the isolator is adaptable by altering the input electric current of the solenoid and certain relationship between the stiffness and applied current can be acquired. A steel yoke is placed around the coil so as to provide protection and needed vertical support for the device. The inner diameter of the coil is 30 mm larger than that of the laminated core so as to allow the deformation in the horizontal direction of the core. The core, coil and yoke are joined together by the bottom plate and the whole structure is enclosed by the top plate. There is a small gap between the top plate and steel yoke to avoid he friction between them.

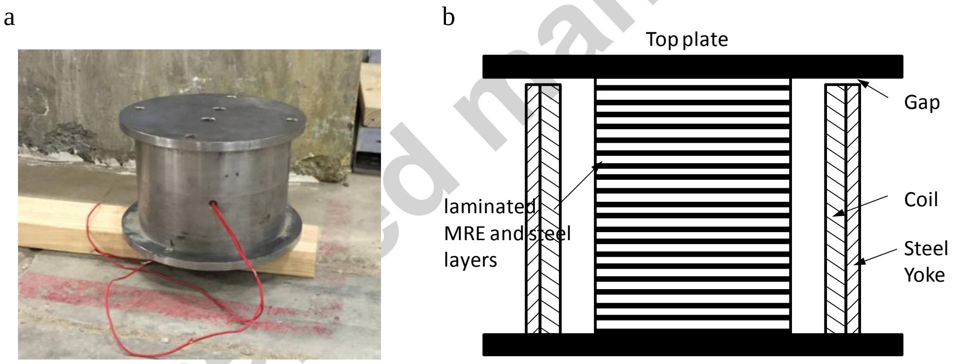


Fig. 1. Adaptive MRE base isolator, (a) real objective and (b) cross-section view

2.3. Performance testing

To assess the performance of this new developed MRE-based device, several groups of dynamic tests were conducted employing a 3 x 3 m^2, 10 t capacity MTS uni-axial shake table, which was utilized to generate the horizontal loading to the device. In the test, the MRE base isolator was installed on the table and moves together with the movement of the table. Besides, a load cell (Model SLS410, METTLER TOLEDO) and a LVDT displacement transducer with range of ±25 mm (Model DCTH1000, RDP GROUP) were installed on the fixed ground near the shake table to measure shear force and displacement responses of the isolator, respectively. To avoid the undesired fictions force generation, the load cell should keep static with the top surface of the device. A DC power conditioner (SOLA ELECTRIC), with the capacity of 5.3 A and 240 V, and a slider (Model SS-260-10, YAMABISHI ELECTRIC COMPANY LTD.) were also employed to generate and adjust DC current to simulate the magnetic coils. Moreover, a multi-meter (Model MS5208, MASTECH) was adopted to supervise the output currents from the slider in the tests. The detailed experimental setup is described in Fig. 2.

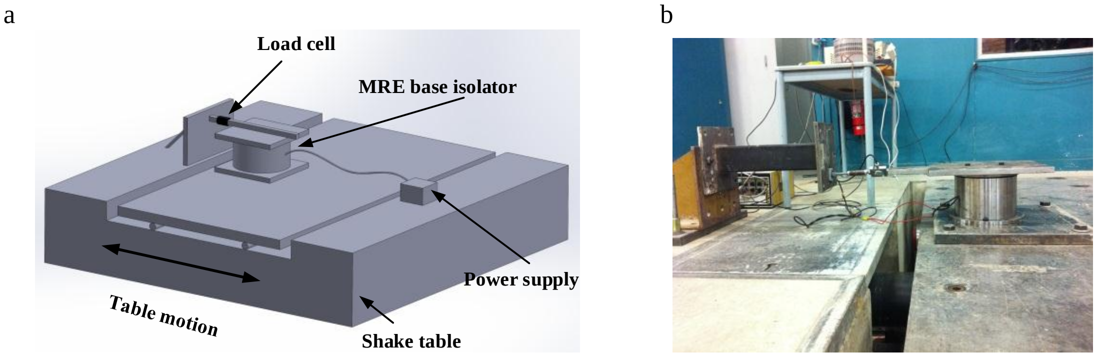
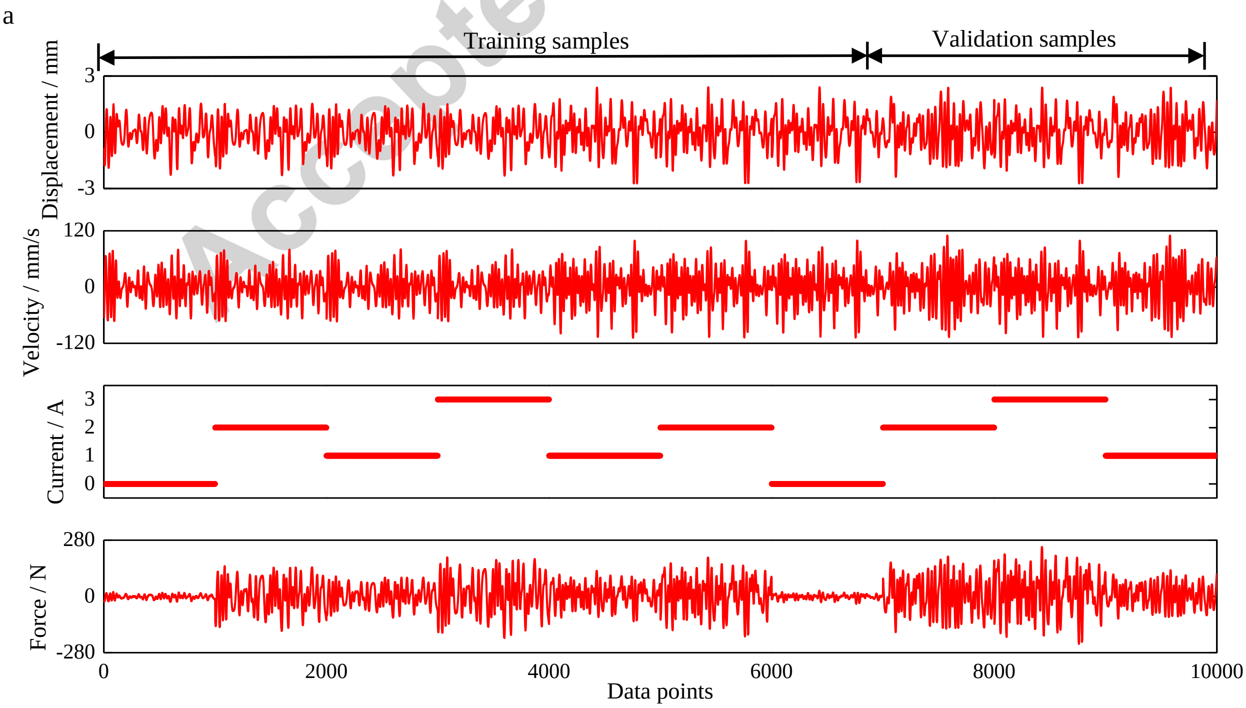


Fig. 2. Experimental setup. (a) 3D sketch, and (b) real setup.

Since the MRE base isolator will be applied to seismic protection of buildings [28], the performance of the device under random excitation input will be examined. In the dynamic testing, two types of excitations were selected to drive the device, i.e. random and EI-Centro seismic inputs. For the random excitation, in consideration of main frequency bands of earthquakes, the input frequencies were controlled between 1 Hz and 20 Hz. The maximum loading amplitude was set as 5 mm. For the EI-Centro seismic excitation, the input displacements were also scaled down to around 4 mm. During the testing, for each excitation type, the current would be regulated from 0 A to 3 A to evaluate the force responses of MRE isolator under various magnetic fields. Because of the high resistance design in the device, the performance of the isolator is susceptible to the heat generated from the coil after subjected to the currents. As a result, temperature control was employed to make temperature at a stable level during the testing. The sampling frequency was set as 256 Hz. The displacement and force responses were able to be directly acquired from the sensor readings while the velocity responses were obtained by computing displacement data using high-order finite-difference approximation algorithm.

Experimental data on displacement, velocity, applied current and shear force are shown in Fig. 3. In this work, the modeling task of the MRE base isolator is to find a suitable SVR model to demonstrate the highly nonlinear relationship between generated shear force and other condition parameters of the device i.e. displacement, velocity and applied current. In these captured responses, the data obtained in the first 7000 points are selected as the training samples to build up the SVR model while the rest of data (3000 points) are utilized as validation data to evaluate the performance of the trained model.



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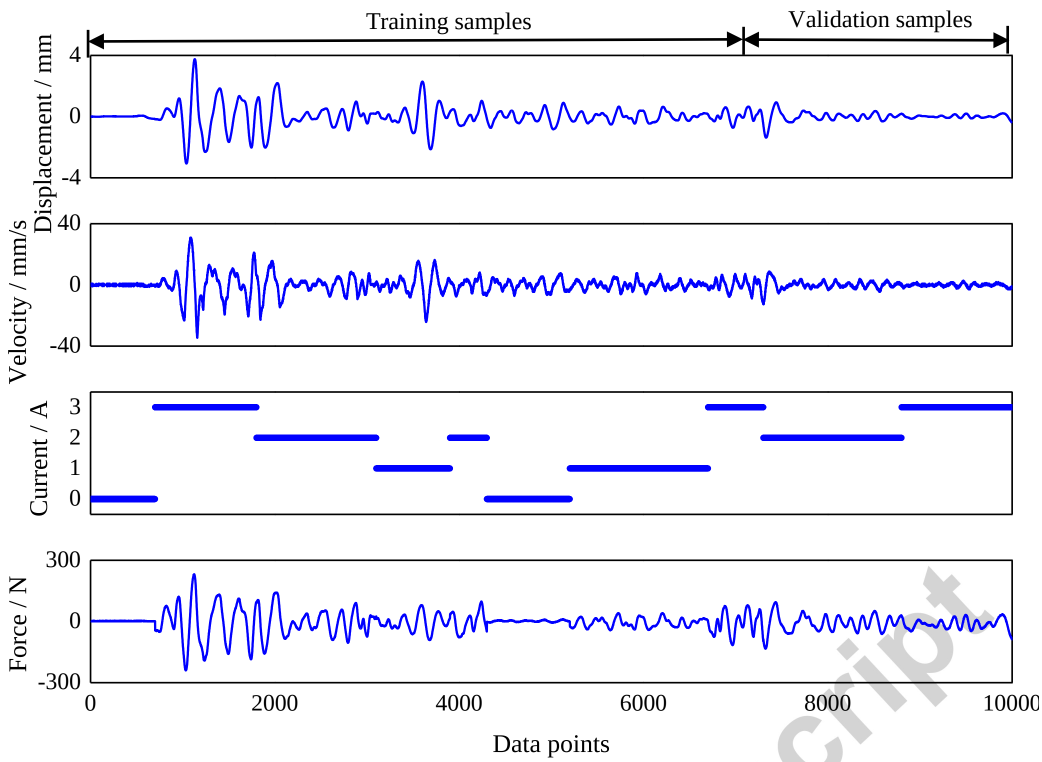


Fig. 3. Experimental data of displacement, velocity, current and shear force, (a) random excitation and (b) scaled EI-Centro seismic excitation

3. Self-adaptive step fruit fly optimization algorithm-optimized SVR model

3.1. Support vector regression

Support vector regression has been proved to be a useful technique to process the nonlinear regression problem in many application fields, which is on basis of the theory of structural risk minimization [36]. Different from other classical regression methods, SVR is developed to map the training data into a high dimensional feature space. Suppose a given data set $H=\{(x_i, y_i), i=1,\ldots,l\}$ in which element x_i denotes ith input value, y_i denotes corresponding output target and l denotes the number of elements in the data set. In accordance with [36], the approximation function of SVR is given as follows:

$$f(x) = w\varphi(x) + b \tag{1}$$

$$R(C) = \frac{1}{2}\|w\|^2 + C\frac{1}{N}\sum_{i=1}^{N} D_\varepsilon(y_i, d_i) \tag{2}$$

$$D_\varepsilon(y_i, d_i) = \begin{cases} 0, & \text{if } |y_i - d_i| < \varepsilon \\ |y_i - d_i| - \varepsilon, & \text{or else} \end{cases} \tag{3}$$

where $\varphi(x)$ is a nonlinear function as high dimensional feature space of input x. w and b represent the normal vector and a scalar, respectively. $\frac{1}{2}\|w\|^2$ is the regularization term, which is used to measure the flatness of the regression function. $C\frac{1}{N}\sum_{i=1}^{N} D_\varepsilon(y_i, d_i)$ denotes the empirical error evaluated by ε-insensitive loss function, the expression of which is shown in Eq. (3). The value of w and b can be calculated through solving the following minimization optimization problem (regularized risk function):

$$\begin{aligned} &\min R(w, \xi_i, \xi_i^*) = \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{N}(\xi_i + \xi_i^*) \\ &s.t.\ \ d_i - w\varphi(x_i) + b_i \le \varepsilon + \xi_i;\ w\varphi(x_i) + b_i - d_i \le \varepsilon + \xi_i^*;\ \xi_i, \xi_i^* \ge 0,\ i = 1, 2, \ldots, N \end{aligned} \tag{4}$$

where ξ_i and ξ_i^* denote slack variables, which are used to evaluate the distance between real value and related boundary. C and ε denote the error penalty factor and the loss function, respectively. By adding the Lagrange function as well as dual set of variables, the optimal nonlinear regression function will be acquired, given in Eq. (5):

$$f(x,\alpha,\alpha^*) = \sum_{i=1}^{N} (\alpha_i - \alpha_i^*) K(x_i, x_j) + b \tag{5}$$

where α_i and α_i^* denote the Lagrange multipliers and meet the relationship of $\alpha_i \times \alpha_i^* = 0$. $K(x_i, x_j)$ represents the kernel function, and can be expressed as $K(x_i, x_j) = \varphi(x_i) \cdot \varphi(x_j)$. Kernel function plays a significant role in constructing the nonlinear regression function. A good selection of kernel function makes the data easy to be classified in the feature space although they are inseparable in the original space [37]. The functions which meet the mercer condition are considered as the kernel functions [1].

3.2. SVR parameter analysis

In general, the prediction accuracy and generalization ability of SVR are dependent on the proper selection of SVR parameters including ε, C and parameters in kernel function. However, how to obtain the optimal SVR parameters becomes more complex because the model complicacy of SVR is also related to these parameters. Present algorithm implementation of SVR in software generally considers the assignment of these parameters as the pre-set inputs, which is based on the user's experience or priori knowledge. Especially for the kernel function, its type and parameter selection in on basis of knowledge in the application fields and may influence distributions of inputs in the training samples. As a consequence, in this work, the optimization of ε and C are just considered:

- Regularization factor C is a parameter to regulate the trade off cost between training error and model flatness (complicacy). If the value of C is too large, the target is to reduce the empirical risk as much as possible, regardless of model complicacy in the optimization problem [38].
- Parameter ε is a factor to adjust the size of the ε-insensitive area, which is employed to match the training data. The value of ε will bring about certain influence on the number of support vectors, which is utilized to set up the regression function. Generally, a larger ε will lead to fewer support vectors to be chosen, therefore causing less complicated regression estimation.

Thus it can be concluded that although in a different way, the values of both ε and C will influence the effectiveness and generalization performance of SVR model. Inappropriate combinations of SVR model will cause over-fitting or under-fitting problem. So as to acquire the perfect modeling accuracy, SVR parameters should be optimized during the process of model training and the optimal model is finalized based on best parameter combination. Accordingly, a useful and robust method to identify optimal SVR parameters should be investigated to obtain a well-performing prediction model.

3.3. Parameter-optimized SVR for characterizing MRE base isolator

In this work, the SVR model is developed to capture the dynamic behaviour of the MRE base isolator, in which the input vector is made up of displacement and velocity of the device as well as applied current level while the output is the predicted shear force. For the SVR model, there are a lot of kernel functions to be selected to construct the nonlinear optimal hyperplane on the input domain [39]. Here, in view of the few parameters and perfect prediction ability, the radial basis function (RBF) is chosen and its expression is given as follows:

$$k(x,y) = \exp(-\frac{|x-y|^2}{2\sigma^2}) \tag{6}$$

where x and y denote two feature vectors in the input space; σ denotes the parameter variable of RBF kernel function. The configuration of SVR model for MRE base isolator can be described by Fig. 4.

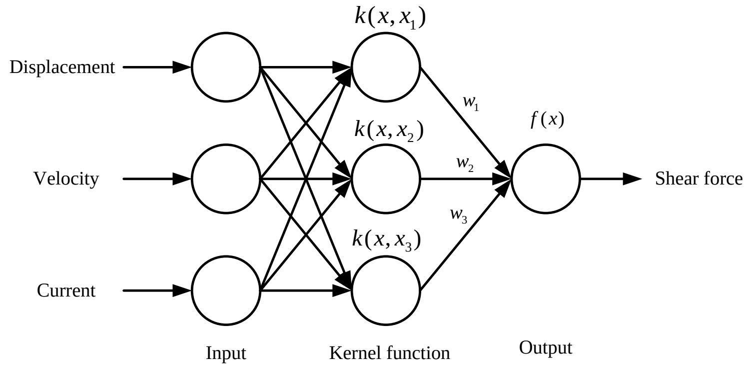


Fig. 4. Configuration of the proposed SVR model.

To obtain the optimal prediction capacity of trained SVR model, FFOA is employed to adjust the parameter values in this paper. However, although this newly developed algorithm seems to be an excellent solution to complex optimization problems, there is still no efficiency in search strategy, in which the fly movement step is always set as a constant. In the standard FFOA, the individual fruit fly randomly seeks the food source near the swarm location by osphresis based on the pre-set step size. Obviously, under the circumstance of determined swarm population, the larger step value will bring about the wider search space. In this case, the algorithm has the stronger global search ability but its local search ability will become weaker in the meantime. On the contrary, if the step size is too small, the individual fly has the strong local search ability leading to limited search space, and this will cause the algorithm to trap into the local optimum. Therefore, an appropriate step, with strong global search ability to prevent local optimum as well as strong local search ability to enhance the search accuracy, is imperiously demanding.

To deal with above issues, this work introduces a self-adaptive step update mechanism to adjust the flying distance of individual fly at each iteration process and proposes a novel FFOA with a self-adaptive step factor (SSFFOA). In the initial phase of iteration process, the fly is assigned with larger step size, which makes fly quickly find the approximate position of food source. On the other hand, in the later stage the fly is assigned with smaller step value, which makes the fly converge to the accurate food position with high accuracy. The detailed update mechanism could be demonstrated in the following expressions:

$$h = h_0 \cdot e^{[-20(\frac{n}{N_t})^a]} \tag{7}$$

$$X_i = X\_axis + h \cdot (2 \cdot rand - 1) \tag{8}$$

$$Y_i = Y\_axis + h \cdot (2 \cdot rand - 1) \tag{9}$$

$$Dist_i = \sqrt{X_i + Y_i} \tag{10}$$

$$S_i = \frac{1}{Dist_i} \tag{11}$$

where h is the step factor with the initial value of h_0; a denotes the parameter to regulate the fly location change; n and N_t denote the current and maximum iteration numbers, respectively; (X_i, Y_i) denotes the position coordinate of ith fruit fly; *rand* denotes a random number between 0 and 1; $Dist_i$ represents the distance between ith fruit fly position and original point while S_i is its reciprocal and denotes the smell concentration decision value. Fig. 5 depicts the algorithm step variations relating to different values of a. Obviously, the step gradually decreases from h_0 to 0 with the increasing iteration although different values will contribute to different step change trends. In this work, the value of parameter a is set as 5 because it is able to provide a relatively symmetrical step change. That is, in the early phase of optimization, the algorithm has a larger step value with a slowly reducing rate and the step quickly reaches its minimal value in the later period.

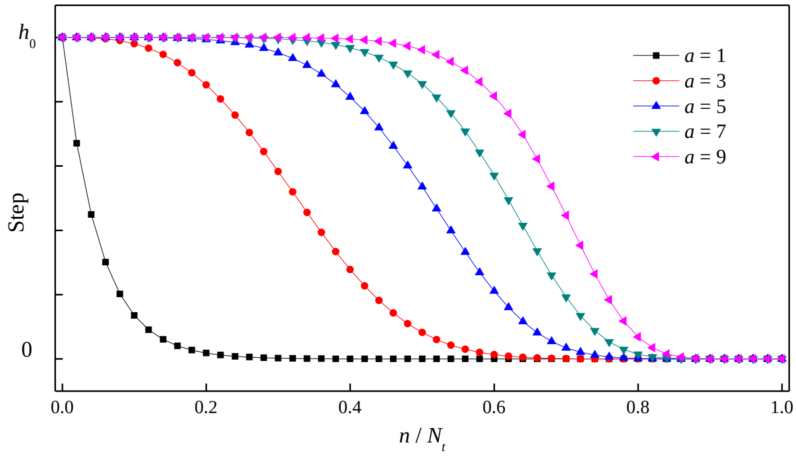


Fig. 5. Step variation corresponding to different values of *a*.

SVR parameter identification using proposed SSFFOA can be considered as calculating an optimization problem, in which the key work is to construct a rational fitness function. In this work, the normalized mean square error (NMSE) between the predicted values and target values is employed as the fitness to optimize the model parameters and its expression is:

$$NMSE = \frac{1}{\theta^2 N}\sum_{k=1}^{N}[F_a(k) - F_p(k)]^2 \tag{12}$$

$$\theta^2 = \frac{1}{N}\sum_{k=1}^{N}[F_a(k) - \overline{F_a}]^2 \tag{13}$$

where $F_a(k)$ and $F_p(k)$ are the actual values and predictions from SVR model, respectively; $\overline{F_a}$ denotes the average value of actual measurements; N denotes the total number of training samples. In essence, SVR parameter optimization is to make the fitness value as small as possible utilizing SSFFOA. When the fitness is closed to zero, the corresponding parameters [C, ε] are deemed as the optimal solution. The specific procedure of SSFFOA-optimized SVR (SSFFOA_SVR) training and validation can be summarized as following steps:

Step 1. Determine kernel function and initialize the SVR parameters: C and ε.

Step 2. Set SSFFOA algorithm parameters: fruit fly swarm size N_{size}, swarm initial location (X_0, Y_0), maximum iteration number N_t, initial value of step factor h_0 and position change parameter a.

Step 3. Update the position of ith fly according to Eqs. (7), (8) and (9).

Step 4. Calculate the distance $Dist_i$ between ith fly location and origin as well as corresponding judgment factor of smell concentration S_i according to Eqs. (10) and (11).

Step 5. In training samples, input the displacement and velocity responses, current levels and corresponding output shear forces to the SVR model, and compute the fitness value based on S_i, denoted as: $Smell_i$ = Fitness(S_i). Find and record the optimal smell concentration and fly coordinate, and meanwhile all flies fly towards that location based on vision organ.

Step 6. Check the termination rule. If the current iteration arrives at its maximum value, turn to Step 7. Otherwise, execute Steps 3-6.

Step 7. Output the optimal SVR parameters (C, ε) and based on these optimal values, set up the SVR model for force prediction of MRE base isolator.

Step 8. Input the validation samples to the trained SVR model for shear force prediction. The algorithm procedure is over.

Overall, the training and validation procedure of SSFFOA-optimized SVR for MRE base isolator could be depicted in Fig. 6.

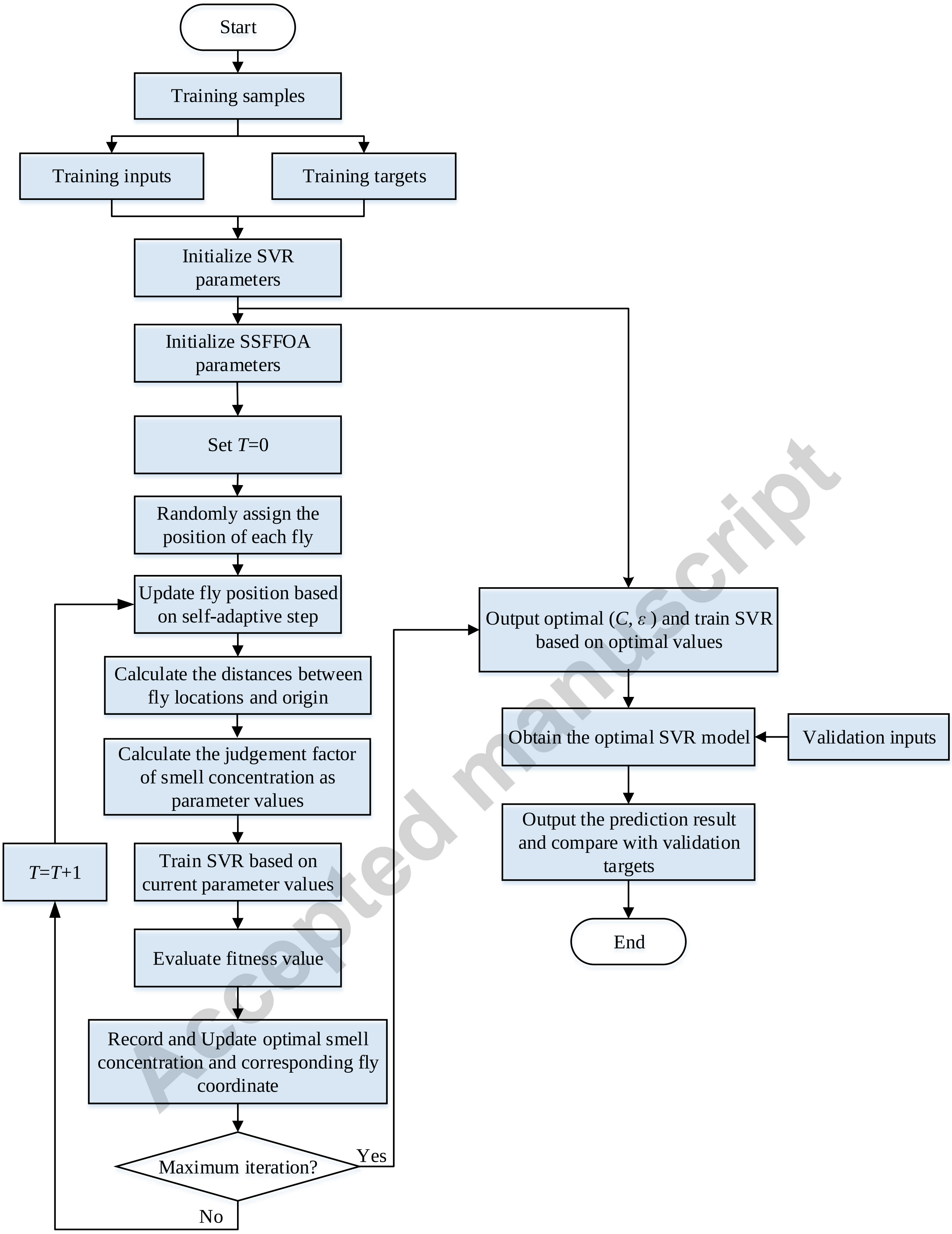


Fig. 6. Training and validation procedure of SSFFOA-optimized SVR model

4. Result and discussion

The SSFFOA-optimized SVR model is realized based on Matlab v.2012b LibSVM toolbox. For two types of excitations, two corresponding SVR models, represented as *Model 1* and *Model 2*, should be constructed to predict the dynamic behaviours of the device, respectively. SSFFOA algorithm parameters and kernel function parameter are set as: swarm size $N_{size} = 30$, maximum iteration $N_t = 200$, $h_0 = 2$, $a = 5$ and $\sigma = 0.1$. Furthermore, to enhance the generalization accuracy of the model, the input training and validation samples should be normalized to eliminate the effect caused by multi-dimension of input vector. In this work, all the input samples are scaled between 0 and 1 using maximum-minimum method, described by:

$$x_i^{norm} = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}} \tag{14}$$

where x_i denotes the ith raw data; x_{min} and x_{max} represent the minimum and maximum values in data set, respectively.

Then, the normalized training samples are entered into the SVR models for machine learning, and SSFFOA is used to optimize the model parameters for best prediction performance. Fig. 7 shows one example of optimal fly flight path to find the parameter C and algorithm convergence in the optimization procedure when the device is driven with random excitations. It is noticeably seen that all the fruit flies fly to optimal solution in a relatively complicated path with many inflexions after several flight trials. Besides, it is also clear that algorithm has a rapid convergence that makes the optimal solution obtained within approximate 70 iterations. In this way, the optimal coordinates for C and ε are obtained with coordinates of (-0.08593, 1.28596) and (0.31861, 2.54647), respectively. Similarly, the parameters of SVR for scaled EI-Centro earthquake excitations could be optimized. The detailed values for both models are shown in Table 1.

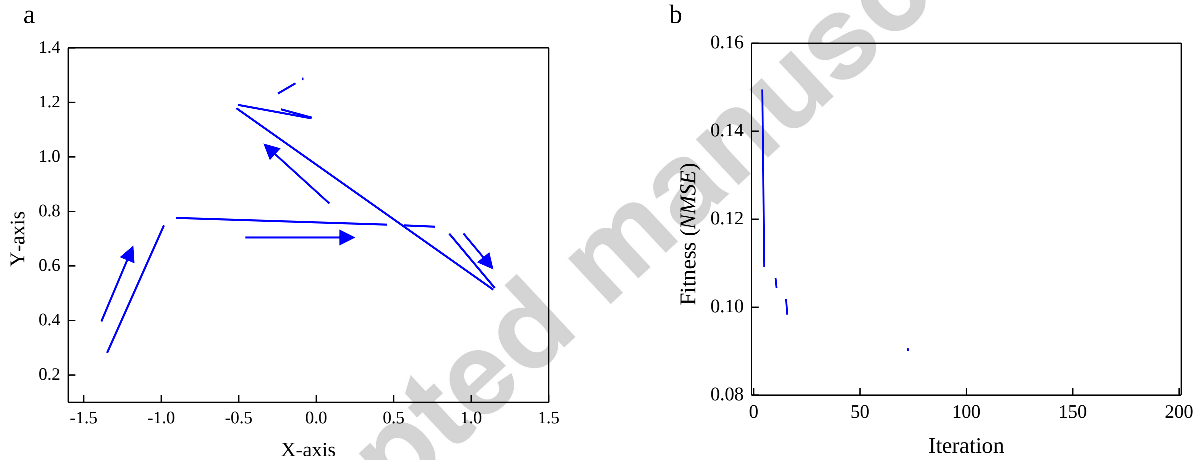


Fig. 7. Optimization process: (a) optimal flight paths, and (b) algorithm convergence.

Table 1. Optimal parameter values of SSFFOA_SVR model

Parameter	*Model 1* (Random input)	*Model 2* (Seismic input)
C	7.7591	13.1279
ε	0.3897	0.5256
Number of support vectors	7000	7000

From Table 1, it is clearly seen that the number of support vectors in training SVR model for random excitation is 7000, which is 100%. In the same way, the SSFFOA_SVR model for scaled seismic excitation also employs all the support vectors, which means that each training sample is used as support vector. Fig. 8 (a) and (b) portray the measured and forecasted shear force responses under two types of excitation conditions, respectively. The comparison of two responses demonstrates that the predictions from the SSFFOA_SVR models are able to satisfactorily meet with the experimental measurements in principle although several obvious deviations still appear in the strain stiffening areas (peak values in the figures). Especially for the scaled earthquake excitation, the corresponding model can perfectly predict the change tendency with the seismic wave propulsion, which is definitely beneficial in the application of vibration mitigation of building structures using adaptive MRE base isolator.

Fig. 9 and Fig. 10 describe the correlation coefficients of two excitation cases between measured and forecasted responses, which is defined as

$$CC = \frac{\sum_{i=1}^{N}[F_a(i) - \overline{F_a}] \cdot [F_p(i) - \overline{F_p}]}{\sqrt{\sum_{i=1}^{N}[F_a(i) - \overline{F_a}]^2} \cdot \sqrt{\sum_{i=1}^{N}[F_p(i) - \overline{F_p}]^2}} \tag{15}$$

where $F_a(k)$ and $F_p(k)$ denote the measurements and predictions from the proposed model, respectively; $\overline{F_a}$ and $\overline{F_p}$ denote the average values of measured and predicted responses, respectively; N denotes the total number of measured data. Generally, the higher the value of CC is, the better the agreement between two responses will be. According to the figures, the CC values of *Model 1* for both training and validation data respectively arrive at 0.9521 and 0.9418, meeting the accuracy requirement in modelling study. Besides, it is also noticeable that *Model 2* has better prediction capacity with correlation coefficient values 0.9577 and 0.9486 for training and validation samples, respectively. These results illustrate the good generalization performance of the proposed models in forecasting the shear force generated by MRE base isolator when device responses such as displacement, velocity and applied current are utilized as model inputs.

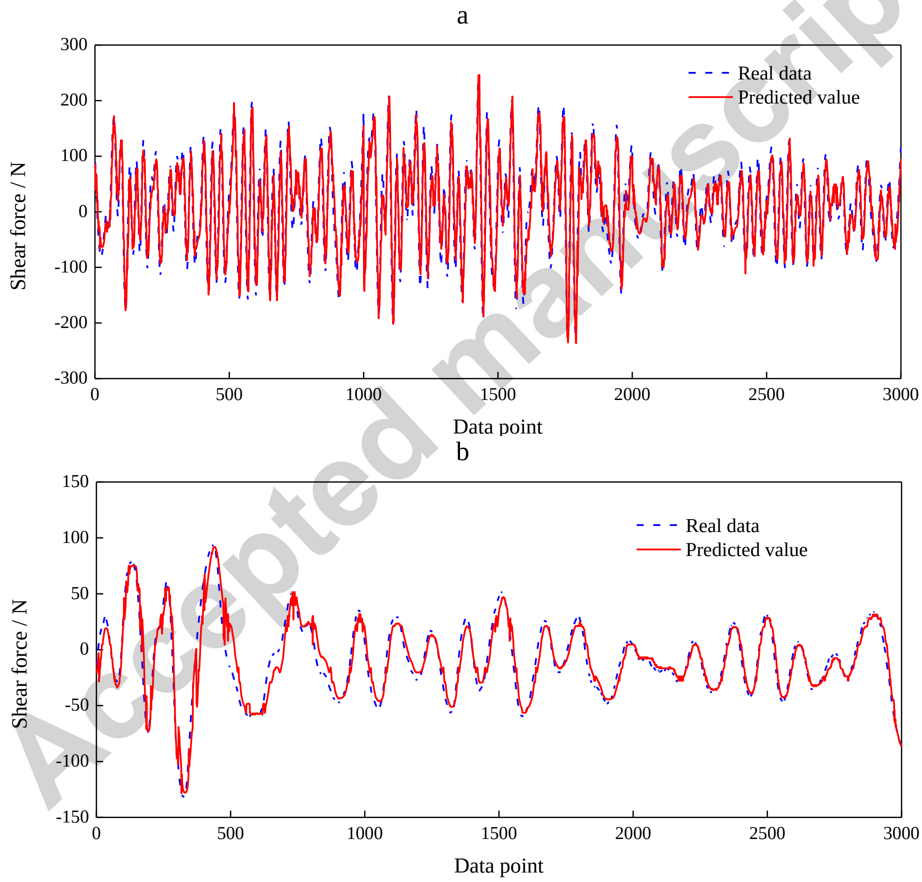


Fig. 8. Comparisons between measurements and predictions from the proposed model, (a) random excitation, and (b) scaled earthquake excitation.

a

b

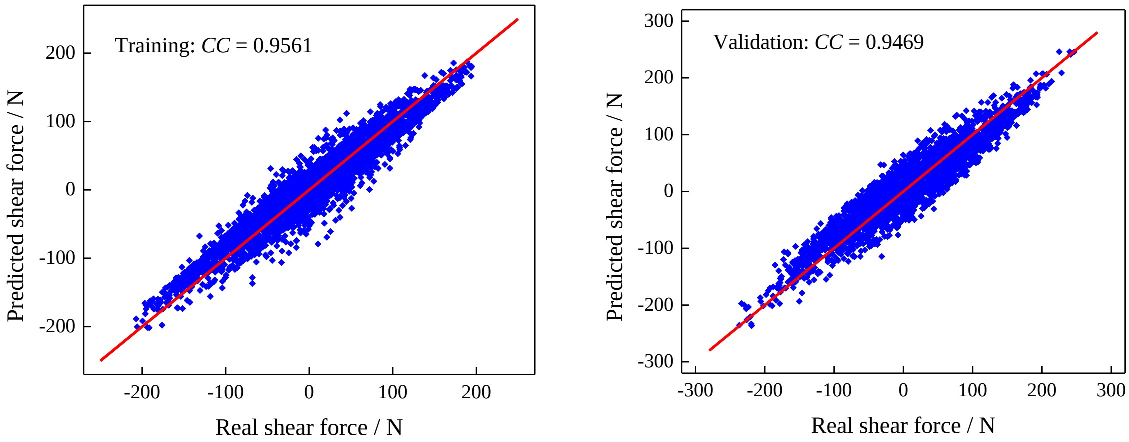


Fig. 9. Regression analysis of results from random excitation, (a) training data, and (b) validation data.

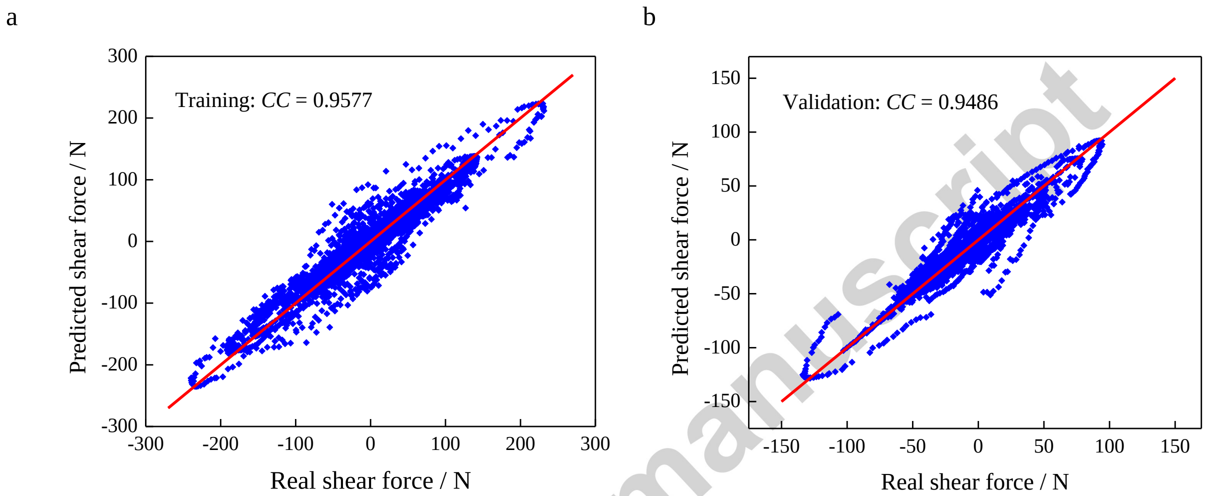


Fig. 10. Regression analysis of results from scaled earthquake excitation, (a) training data, and (b) validation data.

To demonstrate the effectiveness of the proposed model, the predicted shear forces are also compared with that from other conventional soft computing models such as artificial neural network (ANN) and adaptive neuro-fuzzy inference system (ANFIS). Moreover, in order to evaluate the priority of SSFFOA in terms of optimizing SVR parameters, the uniform training and validation data sets are utilized to set up models and forecast shear force using standard SVR, FFOA-optimized SVR (FFOA_SVR), GA-optimized SVR (GA_SVR), PSO-optimized and SVR (PSO_SVR) together with ANN and ANFIS. To make an unbiased comparison, all the models have the same inputs (displacement, velocity and current) and output (shear force). The parameter setting for each model is given in Table 2.

Table 2. Model parameter setting

Model	**Parameter setting**
SVR	Regularization factor C = 1, loss function width ε = 0.01, kernel function and parameters: RBF and σ = 0.1.
FFOA_SVR	Kernel function and parameters: RBF and σ = 0.1, swarm size: 30, maximum iteration: 200, step length: 2.
GA_SVR	Kernel function and parameters: RBF and σ = 0.1, swarm size: 30, maximum iteration: 200, crossover probability: 0.7; mutation probability: 0.01.
PSO_SVR	Kernel function and parameters: RBF and σ = 0.1, swarm size: 30, maximum iteration: 200, inertia weight factor: 0.73, learning coefficients: $c_1 = c_2 = 1.5$.
ANN	Hidden layer number: 1, neuron number in the hidden layer: 12, transfer function: *log-sigmoid*, training function: *trainlm*.
ANFIS	Membership function number: 5, training times: 30, training function: *genfis2*.

In this work, apart from correlation coefficient, three other evaluation indices are selected to comprehensively examine the performance of each model and a comparative study will be conducted to contribute the best regression model. The expressions for evaluation indices are given as

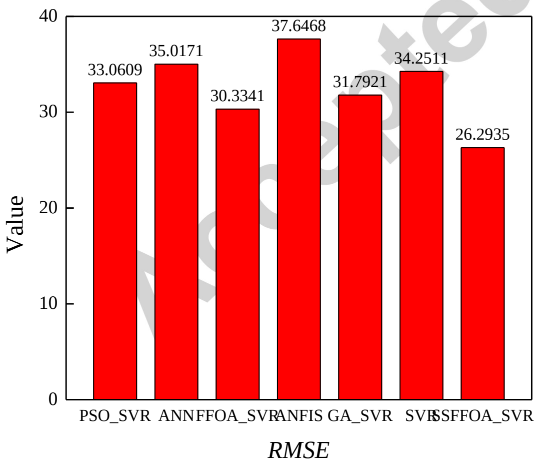
Root mean square error: $$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}[F_a(i) - F_p(i)]^2} \quad (16)$$

Mean absolute relative error: $$MARE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{F_p(i) - F_a(i)}{F_a(i)}\right| \times 100 \quad (17)$$

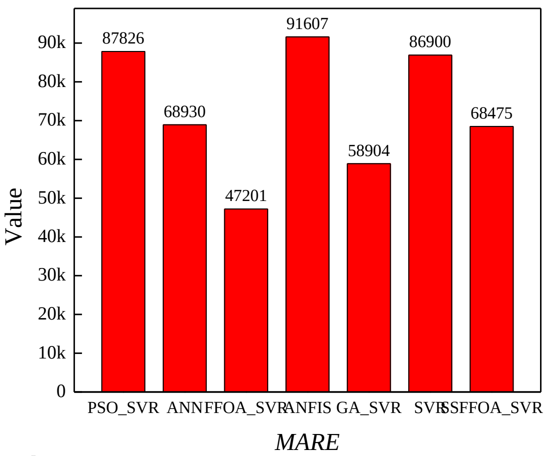
Mean absolute deviation: $$MAD = \frac{1}{N}\sum_{i=1}^{N}\left|F_a(i) - F_p(i)\right| \quad (18)$$

For above three indices, *RMSE* is a good measure of sample standard deviation of the differences between two groups of data (measured and predicted) [40], *MARE* provides a measure of accuracy of a model for setting up fitted time-series values in trend prediction, and *MAD* denotes the mean of absolute deviations from a central point. Generally, smaller index value will have better agreement between measurements and predictions from the model. Fig. 11 and Fig. 12 provide four indices values of different prediction models when the device is loaded with two types of excitations, respectively. The results clearly show that the SSFFOA_SVR model could offer a better performance and higher prediction accuracy than ANN and ANFIS models after four evaluation indices results are synthetically considered. The major factor to this phenomenon is that network optimization in ANN and ANFIS are mainly relied on gradient descent-based approaches, which are regarded as local search methods and may cause slow convergence therefore providing low identification accuracy. Furthermore, in SVR-based models, relative errors of *RMSE*, *MARE*, *MAD* and *CC* between SVR model with pre-set parameters and SSFFOA_SVR model are 30.26%, 26.91%, 32.11% and -4.19% in the case of random excitation, and 32.32%, 98.84%, 33.36% and -4.15% for scaled earthquake excitation. This result validates the efficiency and necessity of parameter optimization in SVR for improving model prediction capacity. Among all SVR based models, the SSFFOA_SVR has the best values in most indices though GA_SVR and FFOA_SVR models have better *MARE* values than SSFFOA_SVR. As a whole, the proposed model is considered as the best one due to its perfect model performance.

a



b



c

d

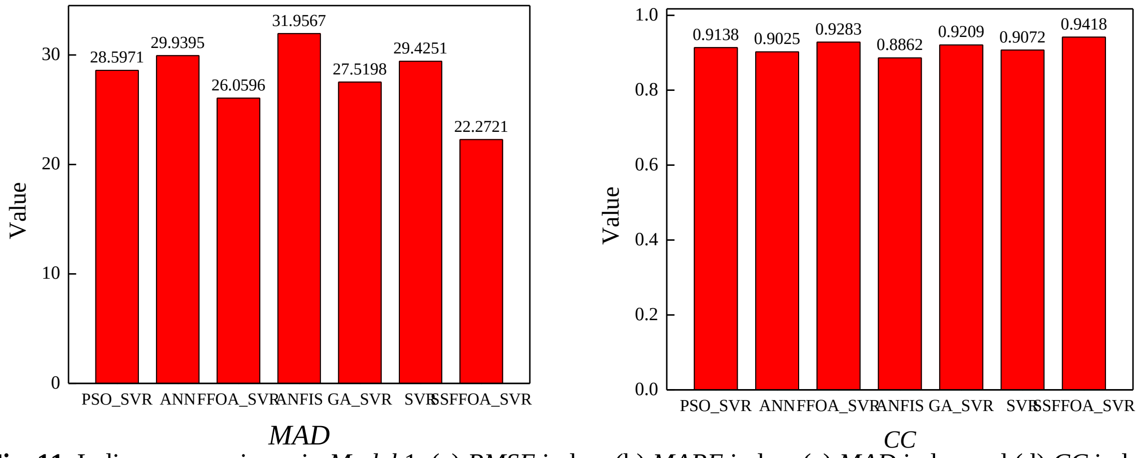


Fig. 11. Indices comparisons in *Model* 1, (a) *RMSE* index, (b) *MARE* index, (c) *MAD* index and (d) *CC* index

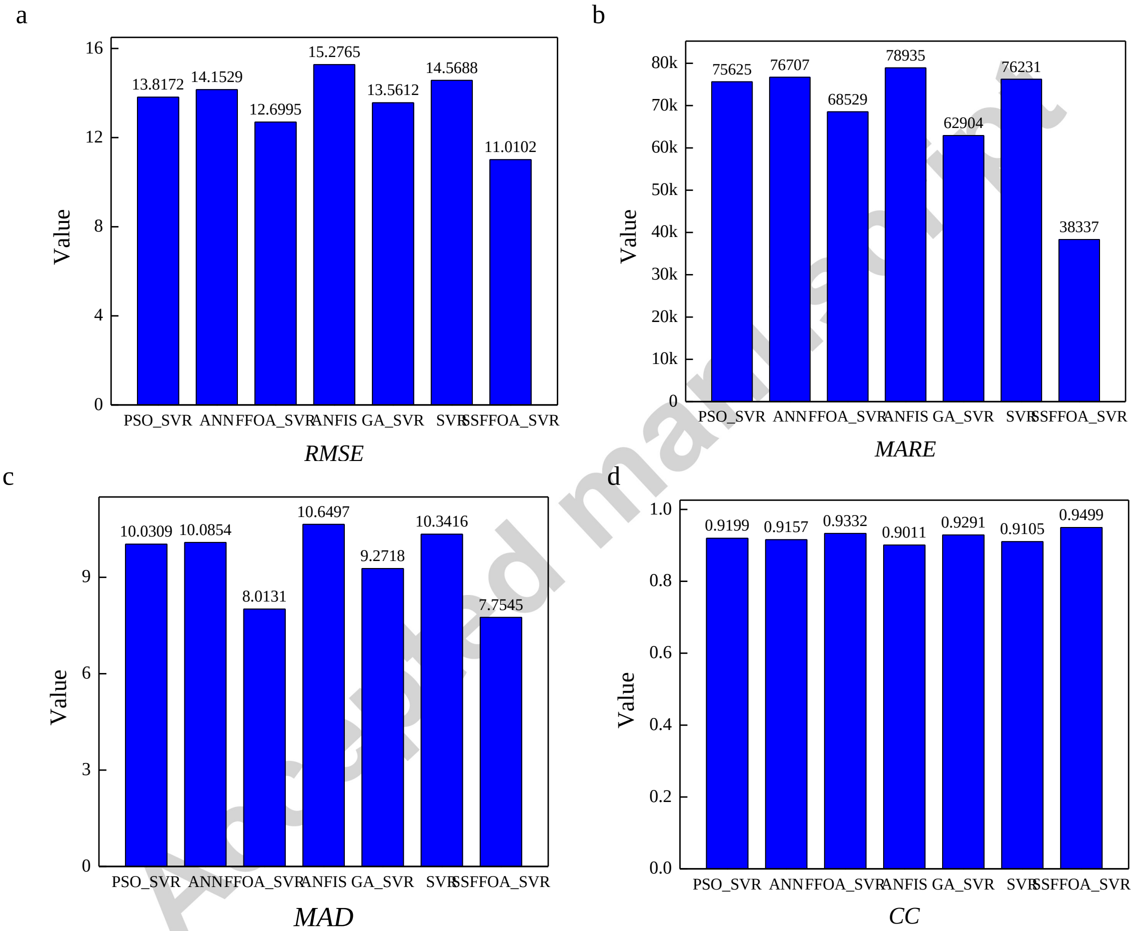


Fig. 12. Indices comparisons in *Model* 2, (a) *RMSE* index, (b) *MARE* index, (c) *MAD* index and (d) *CC* index

Finally, to investigate the role of self-adaptive step on SVR parameter optimization, a comparative study is undertaken on convergence and accuracy comparison among GA_SVR, PSO_SVR, FFOA_SVR and SSFFOA_SVR models. In this case, just experimental data from scaled earthquake excitation are selected as training data. Fig. 13 gives the acquired fitness values in 200 iterations. It can be seen that the fitness values will decline as the increment of iteration number for all SVR models. In four types of SVR models, PSO_SVR first reaches its optimum but it results in premature convergence. Different from PSO_SVR model, SSFFOA_SVR has the minimal fitness value and arrives at its optimal value much more quickly than GA_PSO and FFOA_SVR, which also outperform PSO_SVR in the respect of fitness. Accordingly, FFOA with self-adaptive step is perceived as an ideal candidate in optimizing model parameters during SVR training.

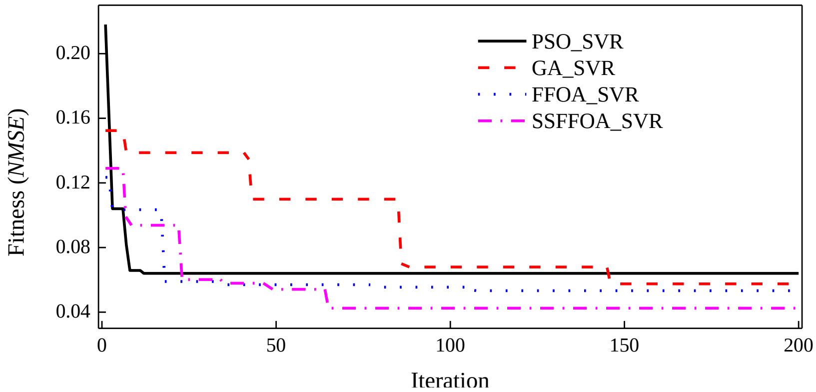


Fig. 13. Algorithm convergence and accuracy comparison

5. Conclusion

Support vector machine is one of the most conventional machine learning techniques for pattern recognition and statistical classification in various engineering fields. Besides, its varient, named as support vector regression, has been extensively applied in prediction and regression tasks. This work investigated the application of SVR in estimation of shear force for adaptive magnetorheolgical elastomer base isolator, which is a promising device used in vibration mitigation of building structures. A novel optimization method for SVR parameters based on fruit fly optimization algorithm was presented. To accelerate the convergence rate and enhance the identification accuracy of FFOA, a new self-adaptive variation mechanism was introduced to automatically update step length of fruit fly in each iteration. The performance of the proposed method was evaluated using responses measured from the device under two types of excitations. The prediction results demonstrate the perfect ability of the proposed SSFFOA_SVR model to portray the dynamic behaviour of the MRE base isolator. Additionally, compared with other optimization method applied in SVR parameters, the SSFFOA provides a faster convergence together with highest recognition accuracy. Final, through comparison with other SVR-based models and two classical soft computing methods, the proposed model also exhibits excellent performances in *RMSE*, *MARE*, *MAD* and *CC*.

Acknowledgement

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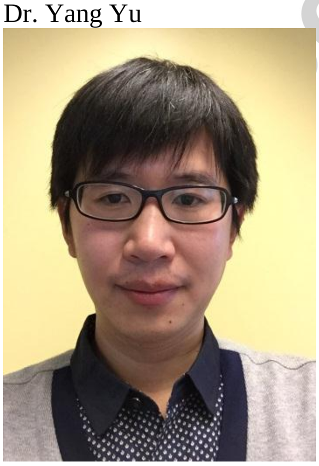

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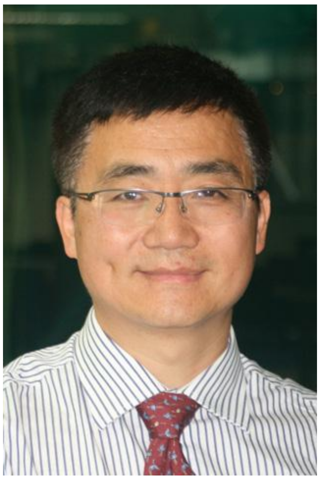

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