TRAIN-INDUCED VIBRATION PREDICTION IN MULTI-STORY BUILDINGS USING SUPPORT VECTOR MACHINE

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Abstract: Train-induced vibration prediction in multi-story buildings can effectively provide the effect of vibrations on buildings. With the results of prediction, the corresponding measures can be used to reduce the influence of the vibrations. To accurately predict the vibrations induced by train in multi-story buildings, support vector machine (SVM) is used in this paper. Since the parameters in SVM are very vital for the prediction accuracy, shuffled frog-leaping algorithm (SFLA) is used to optimize the parameters for SVM. The proposed model is evaluated with the data from field experiments. The results show SFLA can effectively provide better parameter values for SVM and the SVM models outperform a better performance than artificial neural network (ANN) for train-induced vibration prediction.

Key words: *Vibration, railway, train, building, support vector machine, shuffled frog-leaping algorithm*

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1. Introduction

With the emergence of railways in urban areas, there have been complaints of vibrations caused by the passage of trains. In particular, with the rapid development of high-speed railway and urban rail transit system, the environmental vibration induced by running trains has attracted more attentions. As one kind of vibration caused by train, building vibration from train has attracted the interests of researches due to the requirements of high-quality living conditions. Therefore, it is necessary to predict the vibration in multi-story buildings caused by train for building new railway or making corresponding control measures to the established rail.

Due to the complexity of civil structures, limitations of data acquisition systems, the inadequacy of modeling procedures and constraints with parameter estimation,

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the prediction of train-induced vibrations in buildings is very complicated. There are many literatures on the methods to predict train-induced vibrations. Krylov (1995, 1998) proposed an analytical prediction model for the ground vibrations induced by train, in the model, a quasi-static force transmitted by a sleeper was based on the deflection curve of the track modeled as a beam on an elastic foundation. Lombaert (2009) proposed a ground response prediction measure, in which the contributions of quasi-static excitation related to the axle loads and dynamic excitation of random track unevenness to the track and free-field responses can be acquired by a numerical prediction method. Ferrara (2013) proposed a numerical model to predict train induced vibrations, in which mutual interactions in vehicle/track coupled system were considered by means of a finite and discrete elements method. El Kacimi *et al.* (2013) attempted to propose a 3D finite element (FE) coupled train-track model for calculate the ground induced vibration by a single high speed train locomotive.

Some predictors considered lots of factors. However, most predictors have their specific constants. Therefore, these cannot be used in a generalized way. There is a need of a simple technique and relevant and reliable method with greater degree of accuracy for the prediction of vibration caused by train on buildings.

Artificial neural networks (ANNs), is a mathematical model or computational model which is motivated by emulating the intelligent data processing ability of biological neural networks. A neural network consists of an interconnected group of artificial neurons, and it processes information using a connectionist approach to computation. That is, the synaptic weights can be adjusted in a learning process to reflect the input-output relationship for the analyzed system automatically (Hagan *et al.* 1996; Wei and Wu 1997). From training a large amount of data, neural networks are used to model complex relationships between inputs and outputs. ANNs appear to be a promising approach to describe complex systems due to its versatile parallel distributed structures and adaptive learning processes. However, it has been commonly reported that ANN models require a large amount of training data to analyze the distribution of input pattern. Moreover, it is difficult for them to generalize the results due to their overfitting nature.

Support vector machine (SVM) has been proposed as a novel technique in time series forecasting (Mukherjee *et al.* 1997; Müller *et al.*, 1999). Like ANNs, SVM also depends on the similarity between historic and real-time traffic patterns. However, SVM has provided some breakthroughs and plausible performances, such as traffic-pattern recognition (Ren *et al.* 2002), head recognition (Reyna *et al.*, 2001), travel time prediction (Wu *et al.* 2004; Yu *et al.* 2010, 2011), pedestrian detection (Guo *et al.,* 2012) and tunnel surrounding rock displacement prediction (Yao *et al.* 2010). These successful applications motivate us to apply SVM for solving the incident detection problem.

The values of parameters in SVM have a great influence on the performance of SVM, which need to be set by users. Therefore, there are many literatures on the parameters optimization for SVM. Lin *et al.* (2006) attempted to use a structural risk minimization principle to optimize appropriate parameters for SVM prediction model. Hou and Li (2009) presented evolution strategy with covariance matrix adaptation to determine the values for parameters in SVM. Due to the effectiveness of heuristic algorithm (Yao *et al.*, 2013, 2014), for example, ant colony optimization

(Yu *et al.* 2009, 2011, 2012), heuristic algorithm is the first choice to optimize the parameters for SVM. Lorena *et al.* (2008) proposed a set of parameter values for tuning the parameters in SVM by using genetic algorithms. Lin *et al.* (2008) introduced a particle swarm optimization to optimize the parameters in SVM. Zhang *et al.* (2010) developed ant colony optimization to select the optimal parameters for SVM. The shuffled frog-leaping algorithm (SFLA) is a meta-heuristic optimisation method proposed by Eusuff and Lansey (2003), which is inspired from the memetic evolution of frogs seeking food in a pond. The algorithm combines the advantages of the genetic-based mimetic algorithm and the social behaviour-based particle swarm optimization. It has been successfully applied in solving some classic compounding optimization problems (Eusuff and Lansey, 2003; Luo *et al.* 2009; Alireza 2007). Thus, SFLA is also used to optimize the parameters for SVM in this paper.

This paper presents a prediction model based on SVM for train-induced vibration prediction in multi-story buildings and shuffled frog-leaping algorithm (SFLA) is used for parameters optimization for SVM. The remainder of the paper is organized as follows. In Section 2 we provide a brief introduction about a prediction model on SVM, parameters optimization on SFLA and SVM for train-induced vibration prediction in multi-story buildings is presented. In section 3, some computational results are discussed and lastly, the conclusions are provided in section 4.

2. SVM for Train-Induced Vibration prediction in Multi-Story Buildings

2.1 The support vector machine (SVM) basic principle

SVM is a machine learning method based on statistical learning theory which was proposed by Vapnik (1999, 2000). By applying a set of high dimensional linear functions, it is shown that SVM has a strong learning ability and can get a smaller error on the independent testing set.

Given the training data set $\{x_k, y_k\}$, $k = 1, 2, \ldots, s$, $x_k \in R^m, y_k \in R^n, k$ is the number of training samples. These points are randomly and independently generated from an unknown function. SVM estimates the function by the following function:

$$f(x) = \langle w, x\rangle + b, \quad w, x \in R^m, b \in R^n \tag{1}$$

here, $\langle w, x\rangle$ is the feature of the inputs. The coefficients w and b are estimated by the so-called regularized risk functional:

$$MinJ = \frac{1}{2}\|w\|^2 + C \cdot R_{emp}[f] \tag{2}$$

The first term $\frac{1}{2}\|w\|^2$ is called the regularized term which is used as a measurement of function flatness. The second term $R_{emp}[f]$ is the so-called loss function to measuring the empirical error. C is regularization constant to determine the trade-off between the training error and the generalization performance. Here, we use the ε-insensitive loss function to measure empirical error:

$$|y - f(x)|_\varepsilon = \max\{0, |y - f(x)| - \varepsilon\} \tag{3}$$

The loss is zero if the predicted value is within the tube ε. If the predicted point is outside the tube, the loss is the magnitude of the difference between the predicted value and the radius ε of the tube (Yao *et al.*, 2012; Vapnik, 1999; Cao *et al.*,2003). Both C and ε are user-determined parameters. Two positive slack variables ξ, ξ^* are used to cope with infeasible constraints of the optimization problem. To get the estimation of w and b, the Eq.(2) can be transformed to a primal objective function(4).

$$MinJ = \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{s}(\xi_i^* + \xi_i) \tag{4}$$

$$s.t. \begin{cases} y_i - \langle w, x_i\rangle - b \le \varepsilon + \xi_i^* \\ \langle w, x_i\rangle + b - y_i \le \varepsilon + \xi_i \\ \xi_i^*, \xi_i \ge 0 \end{cases}$$

This constrained optimization problem is solved using the following primal Lagrangian form:

$$\begin{aligned} L \; &= \; \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{s}(\xi_i^* + \xi_i) - \sum_{i=1}^{s}(\eta_i\xi_i + \eta_i^*\xi_i^*) - \\ &- \; \sum_{i=1}^{s}\alpha_i(\varepsilon + \xi_i - y_i + \langle w, x_i\rangle + b) - \sum_{i=1}^{s}\alpha_i^*(\varepsilon + \xi^* - y_i + \langle w, x_i\rangle + b) \end{aligned} \tag{5}$$

Here, L is the Lagrangian and $\eta_i, \eta_i^*, \alpha_i, \alpha_i^*$ are Lagrange multipliers. Hence the dual variables in (5) have to satisfy the positive constraints.

$$\eta_i, \eta_i^*, \alpha_i, \alpha_i^* \ge 0 \tag{6}$$

The above problem can be converted into a dual problem where the task is to optimize the Lagrangian multipliers α_i, and α_i^*. The dual problem contains a quadratic objective function of α_i and α_i^* with one linear constraint:

$$MaxJ = -\frac{1}{2}\sum_{i,j=1}^{s}(\alpha_i^* - \alpha_i)(\alpha_j^* - \alpha_j)\langle x_i, x_j\rangle + \sum_{i=1}^{s}\alpha_i^*(y_i - \varepsilon) - \sum_{i=1}^{s}\alpha_i(y_i + \varepsilon) \tag{7}$$

$$s.t. \begin{cases} \sum\limits_{i=1}^{s}\alpha_i = \sum\limits_{i=1}^{s}\alpha_i^* \\ 0 \le \alpha_i \le C \\ 0 \le \alpha_i^* \le C \end{cases}$$

$$\text{Let } w = \sum_{i=1}^{s}(\alpha_i - \alpha_i^*)x_i \tag{8}$$

$$\text{Thus, } f(x) = \sum_{i=1}^{s} (\alpha_i - \alpha_i^*) \langle x_i, x_j \rangle + b \tag{9}$$

By introducing kernel function $K(x_i, x_j)$ the Eq. (8) can be rewritten as follows:

$$f(x) = \sum_{i=1}^{s} (\alpha_i - \alpha_i^*) K(x_i, x_j) + b \tag{10}$$

where $K(x_i, x_j)$ is the so-called kernel function which is proven to simplify the use of a mapping. The value of $K(x_i, x_j)$ is equal to the inner product of two vectors. x_i and x_j in the feature space $\phi(x_i)$ and $\phi(x_j)$, that is, $K(x_i, x_j) = \phi(x_i) \cdot \phi(x_j)$.

Therefore, most of the non-linear problems in original space can be transformed into a linear separable problem after space conversion, as is shown in Fig. 1.

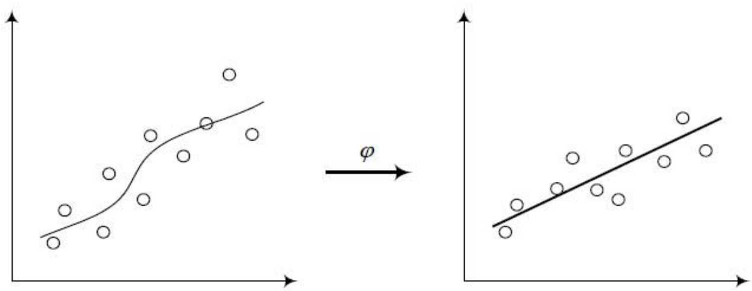

Fig. 1 *The mapping from the original space to the feature space.*

However, the difficulty of transforming the nonlinear problem into a high dimensional space is that the non-linear mapping in this process may be very complex. In order to avoid complex calculations in such high-dimensional space, the kernel function $K(x_i, x_j)$ is used to performed all necessary computations directly in input space, without having to compute the map $\phi(x)$. Some common kernel functions can be seen in Tab I.

Different kernel functions can produce different support vector machines. In general, the RBF kernel, as a nonlinearly kernel function, is a reasonable first choice (Dong *et al.*, 2005). Therefore, RBF kernel was also selected in this study.

linear kernel	$K(x_i, x_j) = x_i \bullet x_j$	
polynomial kernel	$K(x_i, x_j) = (x_i \bullet x_j + 1)^d$	d
RBF kernel	$K(x_i, x_j) = \exp(-\gamma \lVert x_i - x_j \rVert^2)$	$\gamma > 0$
sigmoid kernel	$K(x_i, x_j) = \tanh(b(x_i \bullet x_j) + c)$	b, c

Tab. I *Common kernel functions.*

2.2 SFLA for parameter optimization

The performance of SVM mainly referred to the ability of classifying unknown data samples correctly (That is the generalization ability). The kernel function is the core of SVM, which provide a simple bridge from linearity to non-linearity for SVM. In the RBF kernel, there are three parameters C, ε and σ, which are the key elements of the RBF kernel. And the three parameters directly exert a considerable influence on the generalization ability of SVM. So the parameter optimization is an important factor for improving the prediction accuracy of SVM. In this paper, SFLA is applied to optimize the parameters in SVM.

2.2.1 Encoding scheme

SFLA is firstly represented by an initial population that is composed of "frogs". Each location of each frog is a solution which is thought as $F_i = (f_{i1}, f_{i2}, \ldots, f_{iD})$. For parameter optimizations in SVM, since the parameters C, ε and σ are continuous-valued, the real encoding is adopted. To represent the parameters in SVM, the coordinate of each frog F_i is denoted as $F_i = (C_i, \varepsilon_i, \sigma_i)$. The algorithm first randomly generated n frogs as the initial population, noted them in descending order according to the fitness of each frog. Then the entire population is divided into m subgroups, and each subgroup contains n frogs. From the initial population, the first frog is selected in the first subgroup; the second frog is selected in the second group, until the first m frog is selected in the m^{th} subgroup. Then, the $(m + 1)^{\text{th}}$ frog is selected in the first subgroup. Repeat the process, until all frogs are distributed. In each subgroup, the frog with the best fitness and the worst fitness are denoted as F_b and F_w respectively. While in the total population the frog with the best fitness is denoted as F_g. The main work of SFLA is to update the position of the worst-performing frog through iterative operation in each sub-memeplex. Its position is improved by learning from the best frog of the sub-memeplex or its own population and position. In each sub-memeplex, the new position of the worst frog is updated according to the following equation.

$$d_i = \text{rand}() \times (F_b - F_w) \tag{11}$$

$$F'_w = F_w + d_i(-d_{\max} \leq d_i \leq d_{max}) \tag{12}$$

Formula (11) is used to calculate the updating step d_i. Rand () is the random number between 0 and 1; Formula (12) updates the position of F_w. d_{max} is the maximum step size. If a better solution is attained, the better solution will replace the worst individual. Otherwise, F_g will instead of F_b. Then recalculate Formula (11). If you still cannot get better solution, new explanation generated randomly will replace the worst individual. Repeat until a predetermined number of iterations. And complete the round local search of various subgroups. Then all subgroups of the frogs are re-ranked in mixed sort, and divided into sub-group to the next round of local search.

2.2.2 Fitness Function

Fitness function, determines possible solutions to the problem, is used to estimate the quality of the represented solution. For parameter optimizations in SVM, the best solution is able to minimize the error of prediction. Generally, the frog with minimum quality of food will tend to jump toward a position with more food. SFLA is a heuristic algorithm to find the maximum fitness of the individual frog. Thus, negative root mean squared error (RMSE) which is used in the literature (Yao *et al.* 2010) is also adopted in this paper.

$$\mathrm{RMSE} = \left[\frac{\sum_{i=1}^{n}(V_i - \hat{V}_i)}{n-p}\right]^{1/2} \tag{13}$$

where $\hat{V}$ is the prediction value by the model; V is the observed value; n is the number of observations and p is the number of model parameters.

2.2.3 Extremal Optimisation

To further increase the stability of the modified SFLA to find the global optimum for high-dimensional continuous function optimization, extremal optimisation is adopted which is an optimisation heuristic inspired by the field of statistical physics. In this algorithm, each component f_{i1} in the current individual F_i is considered as a species and assigned a fitness value k_i. There is only mutation operator in extremal optimisation which will operate the worst species by the following equation:

$$F_k' = F_k + \delta_k \tag{14}$$

Where F_k is the worst species, F_k' is the mutation result of F_k. δ_k denotes the Cauchy random variable with the scale parameter equal to one and is generated anew for the k-th decision variable. In this way, the individual can be updated and evolve toward the optimal solution.

2.2.4 Termination

In this paper, the search continues until $\mathrm{RMSE}_n - \mathrm{RMSE}_{n-1} < 0.0001$ or the number of generation reaches the maximum number of generations T_{max}.

The flowchart of the proposed SFLA used to optimize the parameter optimization for support vector machine can be shown in Fig. 2.

2.3 Applying SVM for Train-Induced Vibration Prediction in Multi-Story Buildings

Since the earliest days of railways in urban areas, there have been complaints of building vibration caused by the passage of trains. In this paper we would like to predict the level of the vibration caused by trains on building. Since annoyance from the vibration induced by train is an indoor phenomenon. the effects of the building structure on the vibration must be considered. For example, wood frame buildings are more easily excited by ground vibration induced by train than heavier

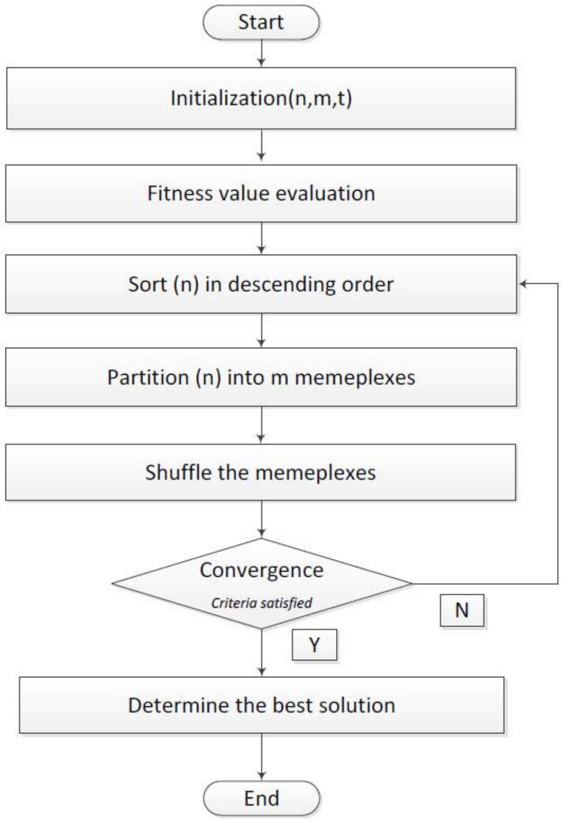

Fig. 2 *The flowchart of the proposed SFLA.*

buildings. And depending on the vibration measurements it has been concluded that the ground vibration induced by train affected by many factors (Suhairy, 2000). These factors can be summarized as:

- Ground quality(which is the most important factor)
- Train type
- Railway track and the embankment design
- Train speed
- Distance from the rail way track to the building(receiver)
- Building type and the foundation design.

To simply this problem, the factors are assumed to be frequency independent and directly related to the time weighting for the maximum velocity values. According to the previous studies and our experience, the vertical on the ground (Z direction) is the most dominating direction comparing with the others directions (X and Y). Therefore, the vertical vibrations are selected to be predicted.

3. Case study

The proposed SVM has been trained and tested on the data by the measurements carried out for more than 160 trains from different types, speeds and directions. To determine the reasonable point for testing, the height of building has been considered. Fig. 3 shows that the train-induced vibrations at each floor in 6-story building, 12-story building, 18-story building and 24-story building, respectively. In Fig. 3, there is the train speed with 89km/h, the distance from the rail way track to the building is 20m, the height of each floor is 3m and the building is made of frame structure. By analyzing the data of vibrations with different building height under the same conditions and it can be found that the building heights have little relation with the train-induced vibrations. In this paper, the seven story building is selected for the examine point in this paper. Thus, there are lots of data acquired by measurements. However, not all of the data is effective in processing, the outliers among the samples are removed by data preprocessing.

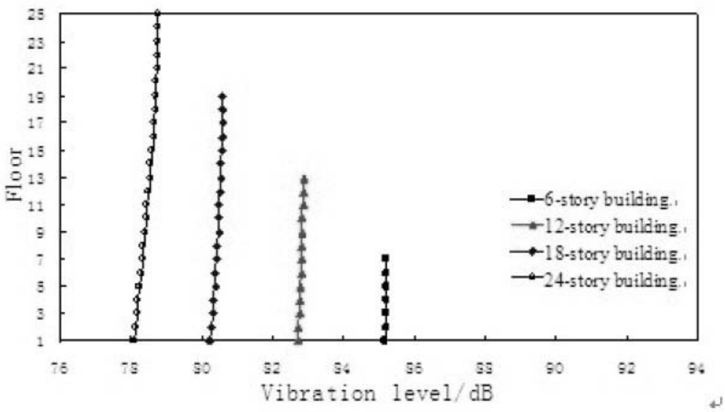

Fig. 3 *The vibrations of building with different floors by train under various storey heights.*

Since it is necessary for data collection and preprocessing before the application of SVM, a data filtering algorithm (Dion and Rakha, 2006; Tam and Lam, 2008) was then applied to the observations collected from the surveys in order to filter out the outliers. In the filtering algorithm, there are two kinds of data: one is the real-time train-induced vibrations by measurements and the other is the off-line train-induced vibrations by estimation. A weighting factor w_i is used to weight the effect of the measured data and the estimated data.

$$v_i = (1 - w_i)\overline{v_i} + w_i v_i' \tag{15}$$

where $\overline{v_i}$ is the off-line average train-induced vibration at point i. v_i' is mean train-induced vibration at point i. w_i is at point$i$is calculated by the following equation (16).

$$w_i = \begin{cases} 1 - (1 - \varphi)^{n_i} & \text{if} \quad n_i > 0 \\ w_i - 1 & \text{if} \quad n_i = 0 \end{cases} \tag{16}$$

where n_i is the number of valid data by measurements at point i and φ is a predetermined parameter to be calibrated by the empirical data. Based on the above data processing, the real-time vibration data after data preprocessing can be acquired. Thus, there are 780 samples in total from these experiments. The data is divided into three sub-sets, which represent training samples, testing samples and inspection samples respectively. There are about 70% samples for training, 10% samples for testing and the remaining samples for inspection.

The parameters setting of SFLA are performed as the literature (Elbeltagi *et al.* 2005), the population of n is 200, the number m of memeplexs is 20, and the generation number for the sub-memeplex is equal to 10. These values are found suitable to produce good solutions in terms of the processing time and the quality of the solution in accordance with our observation in experiments. There are 20 memplexes, each containing 10 frogs. Based on the triangular probability rule, eight out of the ten frogs are chosen to form the individual submemeplex. The local exploration in each submemeplex is executed for 10 iterations.

In this paper, SFLA continues running 10 times under the same condition. Fig. 4 shows the convergence of the ten calculations. It can be observed from Fig. 4 that the prediction error decreases fast before the 360th generation, and then it changes smoothly. The least prediction error appears at about the 400th generation, and it almost remains unchanged after the 400th generation. Further analysis found the differences between the results of the ten calculations changes little. This means SFLA has a good converge and the three parameters were optimized as (4.0623, 0.0064, and 1.0267) for the train-induced vibration prediction model.

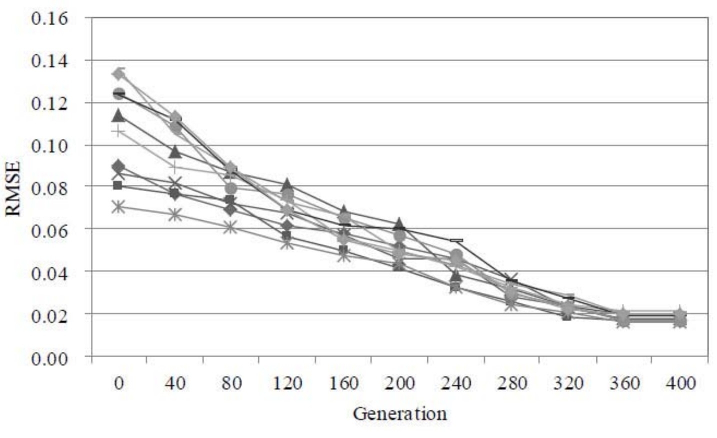

Fig. 4 *Fitness of each calculation by SFLA.*

To evaluate the performance of our SVM, a standard artificial neural network (ANN) model with three-layer is also introduced in this paper. To get a good comparison, the same input and output variables for ANN are equal to the ones for SVM. Fig. 5 depicts the prediction performance of the two models. It is obvious that the errors from SVM models generally are smaller than that of ANN. This can be explained that SVM uses the structural risk minimization principle to minimize the generalization error, while ANN uses the empirical risk minimization principle to minimize the training error. Thus, SVM easily seeks to find the global solution while ANN may tend to fall into a local optimal solution. Therefore, it is feasible to solve the train-induced vibration prediction with our model.

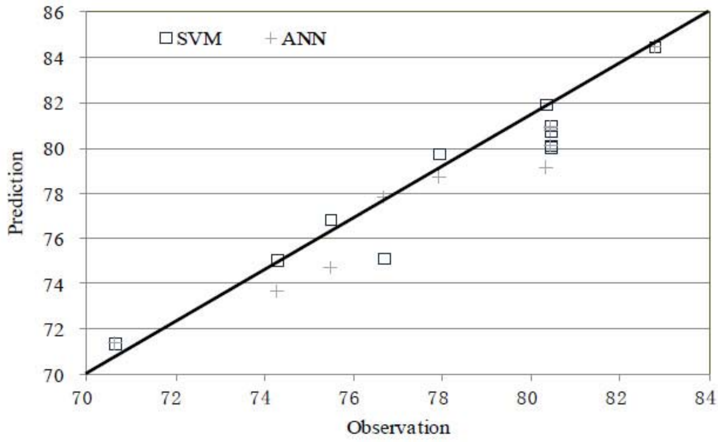

Fig. 5 *The comparison between the proposed SVM and ANN.*

4. Conclusions

The train-induced vibration in multi-story buildings is one of the major complaints of vibrations caused by passage of trains. In this paper, an effective prediction measure is proposed to provide the level of vibrations on building induced by train. The train-induced vibration in multi-story buildings is one of the major complaints of vibrations caused by passage of trains. In this paper, an effective prediction measure is proposed to provide the level of vibrations on building induced by train. Thus, it is very important to perceive the potential danger in timely and provide corresponding measures to decrease the effect of vibrations. This paper attempted to use support vector machines for train-induced vibration prediction in multi-story buildings. To improve the prediction performance of SVM, a SALF is used to optimize the parameters of SVM. The prediction model was tested on the data from field experiments. The results show that SALF has a good convergence and relative stable performance. Furthermore, to evaluate the prediction performance of the proposed SVM, ANN is used to predict the vibrations by the same data of SVM. The comparison results with the proposed SVM and ANN suggest that the SVM attains the lower prediction error. This indicates that the proposed SVM is to be a powerful tool for train-induced vibration prediction in multi-story building.

Thus, the main contributions of this paper to the literature can be summarized as follow: Firstly, it attempts to develop the models to predict rain-induced vibration in multi-story buildings using real-world data. It is expected to help to efficiently make reasonable and effective measures to reduce the harm of vibration. Secondly, in order to improving the prediction accuracy, shuffled frog-leaping algorithm is used to optimize the parameters for support vector machine. The performance of the proposed model can provide some valuable insight for researchers as well as practitioners.

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