Structural Engineering and Mechanics, *Vol. 63, No. 1 (2017) 115-124*
DOI: https://doi.org/10.12989/sem.2017.63.1.115

Seismic response of soil-structure interaction using the support vector regression

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(Received November 23, 2016, Revised April 28, 2017, Accepted April 29, 2017)

Abstract. In this paper, a different technique to predict the effects of soil-structure interaction (SSI) on seismic response of building systems is investigated. The technique use a machine learning algorithm called Support Vector Regression (SVR) with technical and analytical results as input features. Normally, the effects of SSI on seismic response of existing building systems can be identified by different types of large data sets. Therefore, predicting and estimating the seismic response of building is a difficult task. It is possible to approximate a real valued function of the seismic response and make accurate investing choices regarding the design of building system and reduce the risk involved, by giving the right experimental and/or numerical data to a machine learning regression, such as SVR. The seismic response of both single-degree-of-freedom system and six-storey RC frame which can be represent of a broad range of existing structures, is estimated using proposed SVR model, while allowing flexibility of the soil-foundation system and SSI effects. The seismic response of both single-degree-of-freedom system and six-storey RC frame which can be represent of a broad range of existing structures, is estimated using proposed SVR model, while allowing flexibility of the soil-foundation system and SSI effects. The results show that the performance of the technique can be predicted by reducing the number of real data input features. Further, performance enhancement was achieved by optimizing the RBF kernel and SVR parameters through grid search.

Keywords: seismic response; soil-structure interaction; support vector regression; kernel function

1. Introduction

Normally, the structure is built on a flexible layer of soil. Therefore, modeling of soil-foundation system should be done the same as structures. On the other hand, the structure with a fixed base and the same structure with flexible support have fundamental differences. Therefore, the main part of vibrational energy could be amortized by wave emission and the action of hysteresis rules. In the numerical studies it is shown, appropriating the effects of the flexibility of the soil under the foundation of the model, have a significant impact on the seismic response of structure and this issue will be affected by the soil type and the period of the structure (Chambers 1998, Sarkani *et al*. 1999, Tabatabaiefar *et al*. 2015).

During earthquake, behavior of the soil under a building foundation plays an important role in the structural response. In most cases, the soil under structure is not modeled and its significant impacts are ignored. Because the soil is unlimited, its modeling is more complex than modeling the structure. Many researchers have extensively studied this effect (Nguyen *et al*. 2016). Some researchers have modeled the elastic half-space under the structure as a concentrated mass and spring and in this model, the spring and the dampers were considered, independent of the load frequency content (Ribeiro and de Paivab 2015). Chore *et al*. have expressed a method that was based on finite element by using physical modeling of space frame- pile foundation and soil system (Chore *et al*. 2014). In 2000, the effect of the interaction on the nonlinear behavior of the structure was evaluated by determining the existing parameters of the system of one degree of freedom. These parameters were presented in ATC 3-06 regulations for common structures in Mexico, considering areas soil conditions concluded by period modification of the soil-structure interaction (Rodrigues and Montes 2000). Studies in the field of boundary elements in finite elements method is considered by many researchers. Yerli *et al*. (1998) have offered mixed finite elements and infinite elements method that are used in this research for evaluating the accuracy of the proposed soil model. Wolf (1994) used a viscous damper (called Cone model) take into account the radiation damping.

Arefi has gathered and sorted the dynamic response in a single-degree-of-freedom (SDOF) system and real buildings to calibrate the theoretical equations existing for dynamic characteristics of soil-structure systems (Arefi 2008).

The low status of the experimental data for SSI problems perhaps is due to the sparseness of recorded dynamic responses of known foundation on flexible soils with different soil characteristics and its high cost (Mihailo *et al*. 2001). A Support Vector Machine (SVM) is a smart learning algorithm that makes is used extensively by available experimental/numerical data to classify itself. Recently, studies show that the ability to predict dynamic response of a soil-pile-structure (SPS) system based on the neural networks and the support vector machines is possible

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 ISSN: 1225-4568 (Print), 1598-6217 (Online)

(Abbasi *et al*. 2015). The SVM method is a supervised learning algorithm that can use given data to solve certain problems by attempting to convert them into linearly separable problems (Cortes and Vapnik 1995). The SVM model gives input data called training data set that are linked to binary outputs in order to classify new observation to one of the two classes by creating a separating hyperplane with maximum margin between the two classes in the feature space (Vapnik 1998). The optimal separating hyperplane can be determined without any computations in the higher dimensional feature space by using kernel function in the input space.

The SVM algorithm usually can be divided into support vector classification and support vector regression. Support Vector Regression (SVR) is a powerful method that is able to approximate a real valued function in terms of a small subset (called support vectors) of the training examples (Shen *et al*. 2014).

The purpose of this paper is to explore the technique used to predict the dynamic response using numerical and technical analysis data set. By using this data set, an in-depth investigation using a SVR model is performed in order to create a model for predicting the seismic response of existing buildings with and without considering the SSI effects. The result of present work shows that numerical data set can be used as input to a machine learning algorithm such as SVR to create a prediction model that predicts if any similar buildings subjected to future earthquakes.

In the first step, the data results of SDOF systems are organized to evaluate the effect of SSI by varying important parameters. These parameters are: period of structure, level of flexibility of the soil, relative lateral strength of the structure, and soil mechanical properties. Then the effects of the parameters, especially the flexibility of the soil, and modeling issues are investigated on (SDOF) system response, which then followed by a approach predicting the SSI effects on their influence on similar systems using a SVR model with different kernel functions. For the second step, the data results of existing RC frame structure (built before 1970) are investigated to evaluate the effect of SSI by using the proposed SVR model.

2. The soil-structure models for considering SSI effects

The analysis methods of soil-structure interaction are divided into three categories of direct method, under structure method and mixed method. In the direct method, the soil-structure system response is obtained with analysis of the soil-structure system simultaneously in one step. The finite element method is an example of this method. In situations where is not possible to model the soil under the structure as finite element, the under structure method is used. In this method the effect of soil on the structure is defined by a series of spring and damper which its characteristics is introduced as a function of frequency of vibration. The most important advantage of this method is un-modeling of soil layers which greatly reduce the volume of operations, but this method has limitations which reduces its performance. The main assumption of this method, is establishing the principle of superposition which ensures linear behavior of the soil. In this method the soil-structure collection is divided into two parts of soil plus structure that each one are individually solved and in the final step of the analysis, based on superposition principle, the results of the analysis are combined together. This method especially, when the system has a complicated geometry, is less used. In the mixed method the model is divided into two sub-structures, one of them is called near field, which contains the structure and a certain area of soil surrounding, another one is called far field, which contains the rest space of the semi-infinite soil. In this method the stress and displacement values are first calculated in the position of surface contact in the far field, and then they are applied as force in finite element analysis of the near field. The problem of this method is the inefficiency in finding a solution for the problem of scattering of waves in the near and far field (Jaya and Prasad 2002).

3. Support vector machine method

A Support Vector Machine (SVM) method is a supervised learning algorithm that can use given data to solve certain problems by attempting to convert them into linearly separable problems. The SVM gives input data called training data set that are linked to binary outputs in order to classify new observation to one of the two classes by creating a separating hyperplane with maximum margin between the two classes in the feature space (Vapnik 1998). The optimal separating hyperplane can be determined without any computations in the higher dimensional feature space by using kernel function in the input space. The principle of a SVM is to produce a model based on the training data which predicts the target values of the test data given only the test data attributes.

The support vector machine (SVM) can be divided into support vector classification and support vector regression. The Support Vector Regression (SVR) is a powerful method that is able to approximate a real valued function in terms of a small subset (called support vectors) of the training examples using many different kernels, (Mallinson and Gammerman 2003).

Given a training set of instance-label pairs $\{(x_1, y_1), (x_2, y_2), ...(x_i, y_i)\}$, $i = 1, ..., m$ where $x_i \in R^n$, $y_i \in R$ are the training data patterns, x_i the value of the input and y_i the value of the output. The goal of SVR algorithm is to find a function f such that, for (x, y) drawn according to the same distribution as the training set, $f(x) = y$. The y values are often referred to as the ‘labels’ for each x. The function describes a non-linear regression surface that interpolates the data.

The regression function for the SVR model estimation is given by

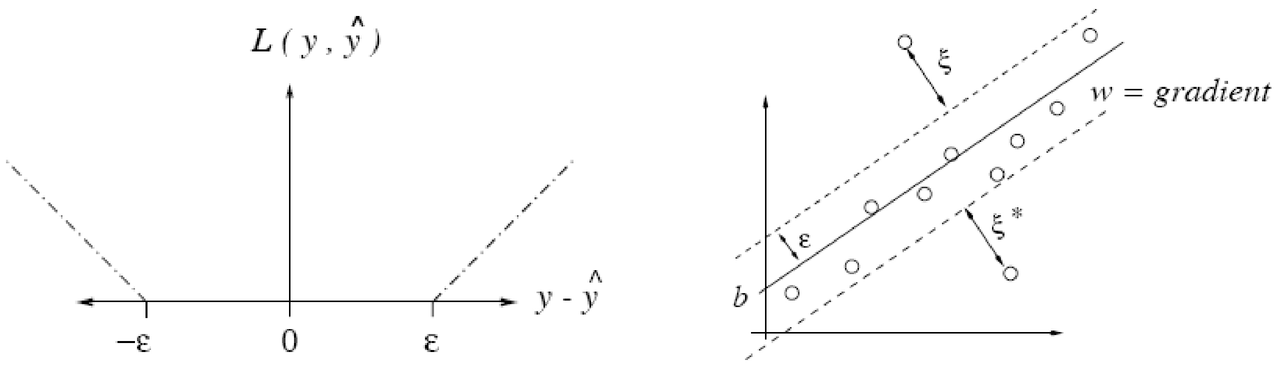


Fig. 1 SVR model estimation (Mallinson and Gammerman 2003)

$$f(x) = \langle \overline{w}, x \rangle + \overline{b} = \sum_{SVs} (\overline{\alpha}_i - \overline{\alpha}_i^*) K(x_i, x) + \overline{b} \tag{1}$$

where

$$\langle \overline{w}, x \rangle = \sum_{i=1}^{m} (\alpha_i - \alpha_i^*) K(x_i, x_j) \tag{2}$$

$$\overline{b} = -\frac{1}{2} \sum_{i=1}^{m} (\alpha_i - \alpha_i^*)(K(x_i, x_r) + K(x_i, x_s)) \tag{3}$$

The non-linear SVR solution, using an ε-insensitive loss function is given by

$$\max_{\alpha,\alpha^*} W(\alpha,\alpha^*) = \max_{\alpha,\alpha^*} \sum_{i=1}^{m} \alpha_i^* (y_i - \varepsilon) - \alpha_i (y_i + \varepsilon) - \frac{1}{2} \sum_{i=1}^{m} \sum_{j=1}^{m} (\alpha_i^* - \alpha_i)(\alpha_j^* - \alpha_j) K(x_i, x_j) \tag{4}$$

with constraints

$$0 \le \alpha_i, \alpha_i^* \le C, \quad i = 1, \ldots, m$$
$$\sum_{i=1}^{m} (\alpha_i - \alpha_i^*) = 0 \tag{5}$$

Solving Eq. (4) with constraints Eq. (5) determines the Lagrange multipliers, α, α^* besides, in high feature dimension space, the dot products can be replaced by the kernel function as

$$K(x_i, x_j) = \langle \phi(x_i) \phi(x_j) \rangle \tag{6}$$

where the parameters w, b are the gradient and the intercept respectively. Parameters are sought that minimize some measure of error on the training set between its prediction $\hat{y}$ and the true label y of an example x, subject to a penalty for overly complex models. In the case of regression estimation the label y is a real value. Sometimes it is useful to define the loss function by fixing some tolerance limit (or "insensitivity zone" $\varepsilon > 0$) so that errors of less than ε will not be punished. As shown in Fig. 1, the following absolute loss function will be used

$$L(y_i, \hat{y}_i) = |y_i - \hat{y}_i|_\varepsilon = \begin{cases} 0 & if \quad |y_i - \hat{y}_i| \le \varepsilon \\ |y_i - \hat{y}_i| - \varepsilon & otherwise \end{cases} \tag{7}$$

Once a linear function $f(x)$ is chosen it show that the best parameters (w, b) can be formulated as the solution to a standard constrained optimization problem as follow

$$\begin{aligned} &\min \quad \frac{1}{2} w^T w + C \left(\sum_{i=1}^{m} (\xi_i^* + \xi_i) \right) \\ &\qquad \mathrm{y_i} - (w^T \phi(x_i) - b) \le \varepsilon - \xi_i^* \\ &\text{subject to} \quad (w^T \phi(x_i) + b - \mathrm{y_i}) \le \varepsilon + \xi_i \\ &\qquad \xi_i, \xi_i^* \ge 0, \quad i = 1,2,\ldots,m \end{aligned} \tag{8}$$

where ξ_i, ξ_i^* are slack variables determining the degree to which data points will be penalized if the error is larger than precision parameter ε (see Fig. 1).

Here training vectors x_i are mapped into a higher dimensional space by the function ϕ. SVR model finds a linear separating hyperplane with the maximal margin in this higher dimensional space. *C*>0 is the penalty parameter of the error term. Furthermore, $K(x_i, x_j) \equiv \phi(x_i)^T \phi(x_j)$ is called the kernel function. These kernels map the input vectors into a very high dimensional space, possibly of infinite dimension, where a linear hyperplane is more likely. There are many types of kernel functions such as linear, polynomial, sigmoid and Radial basis function (RBF) kernels. The mathematical formulation for four known kernel functions is shown here (Girma 2009)

Linear: $K(x_i, x_j) \equiv x_i^T \cdot x_j$.

Polynomial: $K(x_i, x_j) \equiv (\gamma \cdot x_i^T \cdot x_j + r)^d$.

Sigmoid: $K(x_i, x_j) \equiv \tanh(\gamma \cdot x_i^T \cdot x_j + r)$.

Radial basis function (RBF):

$K(x_i, x_j) \equiv \exp(-\gamma \|x_i - x_j\|^2), \quad \gamma > 0$.

Exponential radial basis function:

Table 1 Range of input variables

No.	Variables	Values
1	Soil Shear Wave Velocity (m/s)	150-180
2	Poisson Ratio ν	0.3-0.33
3	Mass Density (kg/m^3)	1700-1900
4	F_y (kg/cm^2)	0.1W-0.5W
5	RDUCT	60-80%
6	DUCT	2-5
7	G	0.1G_{max}- G_{max}
8	Period of structure (sec)	0.5-1.5

F_y: the initial yield strength, W: total weight of superstructure
RDUCT: the residual strength as a fraction of the initial yield strength
DUCT: ductility (or cycle number)
G: the initial soil stiffness

$$K(x_i, x_j) \equiv \exp(-\gamma\|x_i - x_j\|), \qquad \gamma > 0\,.$$

Here γ, r and d are kernel function parameters.

The RBF kernel is a most successful kernel in many application problems.

4. Development of SVR model based on SSI effects

4.1 Data construction

Numerical data sets considering SSI effects having dynamic characteristics were selected from different studies for the training and testing of the SVR model (Arefi 2008). In this case, a number of data sets (approximately 850 data points) considered in this work are provided from different range of input variables, as summarized in Table 1. They were each used separately and then combined together with the aim of possibly achieving the highest accuracy in prediction. The data sets are divided into two subsets: training and testing. The training data are used to train the model to recognize the patterns between input and output data. The final model is tested with the testing data set, to ensure that predictions are real and not artifacts of the training process. It should be noted that, the testing data are used to evaluate the effectiveness of the developed model in generalizing the underlying relationships and achieving good performance when new data are introduced. Before training, the data sets were normalized within the range of 0.0-1.0 in accordance with the following equation. This preprocessing step increases the efficiency of the SVR training.

4.2 Normalizing

Because data can be calculated differently and results in different representation to the data, certain data will have high numbers compared to the rest while others may be small. In data mining or machine learning, it is best practice to have the data pre-processed or normalized before the models are built and make use of the data.

The function ‘normalize’ normalizes the data in the vector to become between 0 and 1 and scales the rest of the values appropriately. The normalized vector is computed as the following

$$N(n) = \frac{X(n) - X_{\min}}{X_{\max} - X_{\min}} \tag{9}$$

where $N(n)$=normalized value of each parameter; $X(n)$ =actual value of each parameter; and $X_{\min}$ and $X_{\max}$ =minimum and maximum values of each parameter. For SVR training, eight input variables were selected as shown in Table 1. The seismic response with and without SSI effects was the single output.

4.3 Model development

The data are divided into two subsets: training and testing. Because there is no precise method for partitioning the data sets, the SVR model was trained with randomly selected 25% of the total data sets, while 75% was used for testing. In the training process, the R-squared value (R^2) were used as the main criteria to evaluate the performance of the SVR model.

The R^2 is a measure of correlation between the predicted and the measured values and therefore, determines accuracy of the fitting model (higher R^2 equates to higher accuracy), which are calculated as follows

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i^t - y_i^p)^2}{\sqrt{\sum_{i=1}^{n}(\bar{y}_i^t - \bar{y}_i^p)^2}} \tag{10}$$

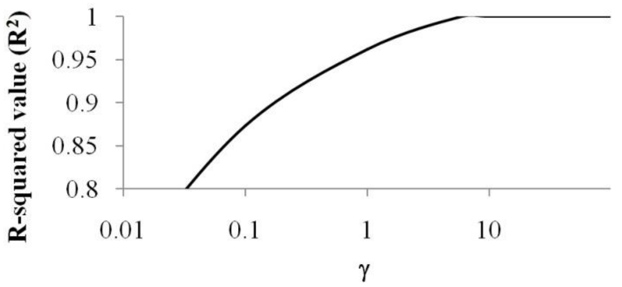
where y_i^t and y_i^p are target and predicted modulus values, respectively, and $\bar{y}_i^t$ and $\bar{y}_i^p$ are mean of the target and predicted modulus values corresponding to n patterns.

4.4 Regression data processing kernel

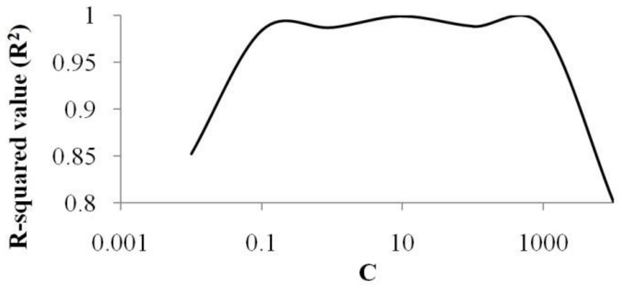
In the proposed model, three different SVM kernels were investigated. The goal was to find the best kernel to classify the data and have a good separation hyperplane between the data sets. Not in all cases the data can be separated, SVM in this case tends to soften the margin in order to separate as much as possible of the data. The kernels used are Linear, RBF, and ExponentialRBF. Finding the best parameters for the RBF classifier to soften the margin was done using grid search method. The RBF has a better success rate compared to the rest of the kernels when considering both with and without SSI effects accuracy.

4.5 Sensitivity of model to SVR parameters

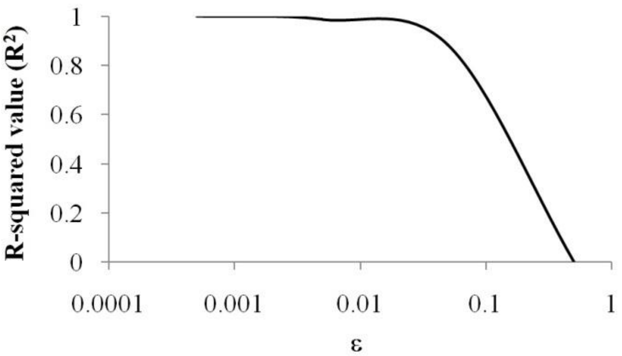
In this study, considering the good performance under general smoothness assumptions, the three different functions are used as the kernel function of the SVR model. By comparing the results obtained using the RBF with those



(a) The results of various γ in which C=10 and ε=0.005



(b) The results of various C in which $\gamma = 6$ and ε=0.005



(c) The results of various ε in which C=10 and $\gamma = 6$

Fig. 2 Sensitivity of the R^2 to SVR model control parameters (C, ε and γ)

results obtained by the other kernel functions, it is concluded that the RBF function give better results for data prediction. Also, the linear kernel gives inferior results and takes a longer time in the training of SVR. One of the important steps in SVR model development was the setting up of the appropriate Kernel function, parameters C and ε for training the SVR. The γ, parameters C and ε were chosen by a trial and error approach. The choice of $\gamma = 6$; C=10 and $\varepsilon = 0.005$ in this study is because these values produced the best possible results according to the validation set.

Sensitivity analysis of SVR control parameters (C, ε and γ) on the R-squared value (R^2) of the SVR based predictive SSI effects models is investigated. Fig. 2 gives the R^2 of SVRs at various γ, C and ε parameters.

5. Results and discussion

To verify the satisfactory performance of the training process, the SVR model is used to predict the seismic response of building systems from the training data set using the eight input variables. The results obtained with SVR model are compared with those of the dynamic analysis of the same problem as well as the available numerical data.

At the first step, the dynamic analyses results of SSI effects on the response of both SDOF and MDOF systems in the presence of other influential factors are selected from different studies (Galli 2005, Arefi 2008). Different nonlinear hysteretic rules were considered for SDOF structure to represent the behaviour of some typical MDOF structures. Moreover, two levels of flexibility in the soil were assumed that can be considered the two extreme cases of stiffness in soil, where soil can be in its initial stage and degraded stage. All the structural analyses have been resulted using the inelastic dynamic analysis program Ruaumoko (Carr 2008).

At the second step, using similar data as of the numerical analysis, the parameters of the most suitable model are proved to be $\gamma = 6$; C=10 and $\varepsilon = 0.005$. The results of the analysis with the SVR for the same data used for test of the numerical data are shown in following plotted figures. The maximum and minimum differences between the SVR model (with different kernel function) and test results are 11% and 0.2% corresponding to both SDOF and MDOF cases.

5.1 Results of SDOF analyses

In this section, the effects of the parameters and modeling issues considering the flexibility of the soil are investigated on single-degree-of-freedom (SDOF) system response, which then followed by a approach predicting the SSI effects on their influence on similar systems using the proposed SVR model. Therefore, a particular SDOF system has been assumed as a benchmark and other factors vary appropriately in order to observe the sensitivity of SSI effects to those parameters.

The benchmark SDOF system has been assumed with following characteristics:

- The intensity of the ground motion: BSE-1 (Basic Safety Earthquake) level earthquake, (FEMA 1997).
- Yield force (In the case with nonlinearity in the superstructure): Fy = 0.2 W.

where W is the weight of the superstructure.

- The pinching Pampanin hysteresis rule is employed (Fig. 3).
- No reduction in strength and P-Δ effects.

Three elements i.e., Poisson's ratio, stiffness and damping, are required to model the soil and foundation appropriately, among which a single multi-spring model is used as shown in Fig. 4.

The mechanical characteristics of the SDOF foundation support are represented by the effective shear modulus G, the mass density (ρ=1700 kg/m^3) and Poisson's ratio (v=0.33). At low strain, the maximum shear modulus Gmax is related to the shear wave velocity (C_s=150 m/s).

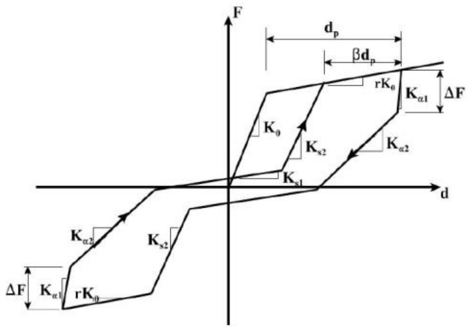


Fig. 3 Pampanin pinching and stiffness degrading hysteresis loop (Carr 2008)

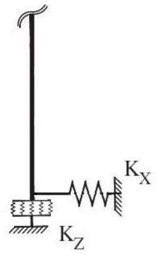


Fig. 4 Multi-spring model for the SDOF foundation support

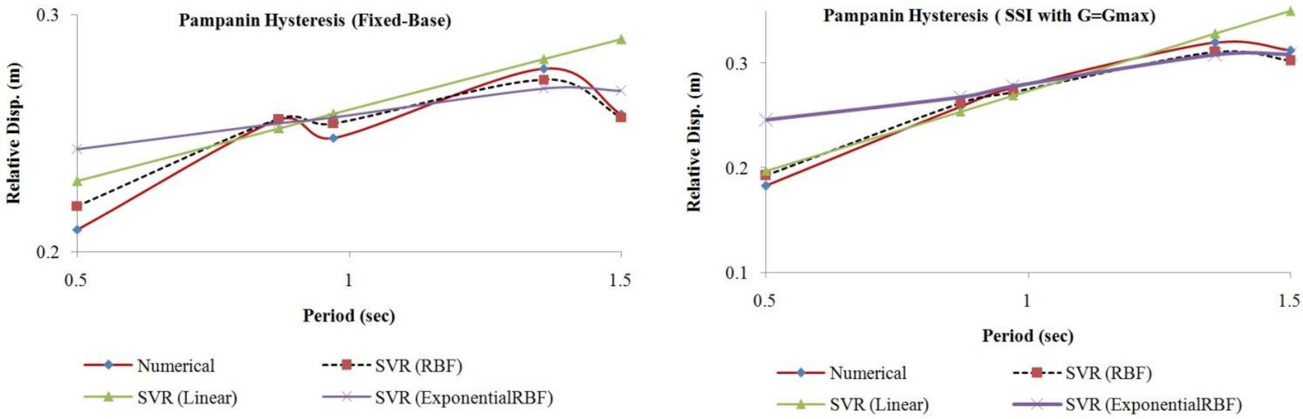


Fig. 5 Comparing numerical results (relative disp.) with the SVR results of SDOF system

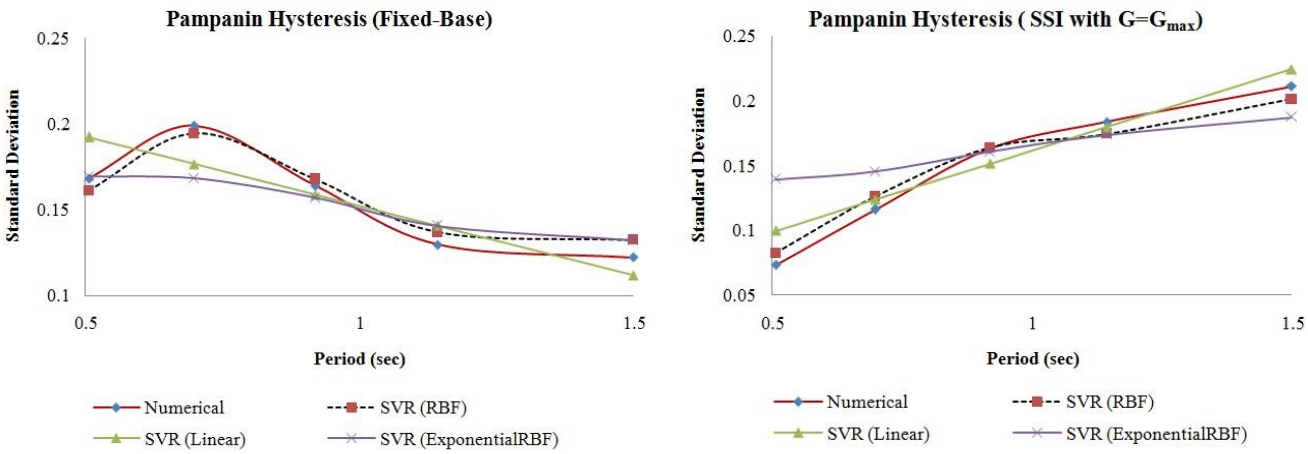


Fig 6 Comparing numerical results (standard deviation) with the SVR results of SDOF system

A set of ten recorded historical strong ground motion records has been selected to be used in time history analyses (Christopoulos *et al*. 2002). The BSE-1 response spectrum is targeted for a seismic zone 4 and soil type C or D to scale the ground motion records.

Fig. 5 shows comparing the relative displacements of SDOF mass to the moving base or in another word, they are obtained from numerical analysis and proposed SVR model with different kernel functions. It can be observed that the results predicted using the SVR model with the RBF kernel is in relatively good agreement with the numerical analysis results.

5.1.1 Influence of foundation flexibility

The standard deviation of the spectral displacement for ten different earthquakes exhibits the level of scattering and emphasizes the care to be taken on the selection of ground motion ensemble. As was investigated in the previous reference, two levels of stiffness in the foundation soil are considered. First, with the fixed-base (without SSI) and second when the initial soil stiffness G=Gmax. Variation of standard deviation for different periods is compared with those of the results obtained using SVR model and shown in Fig. 6. Comparison of the results of the SVR model with RBF kernel with other models indicated that RBF function has better results than the other kernel functions.

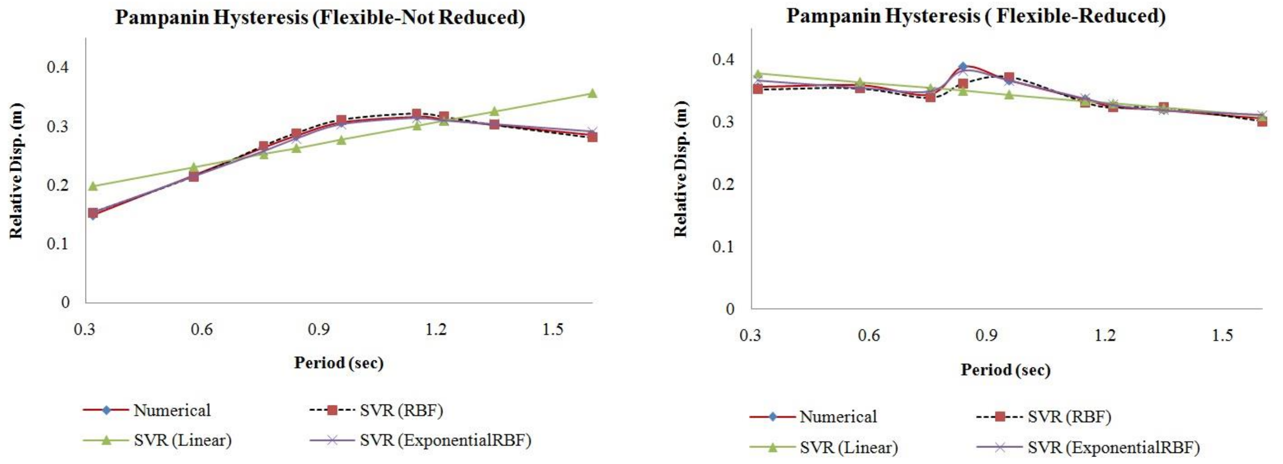


Fig. 7 Displacement spectra of with and without strength reduction of SDOF system obtained using numerical analysis and different SVR kernel outputs

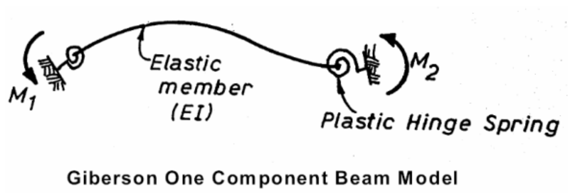


Fig. 8 Lumped plasticity beam-column element (Arefi 2008)

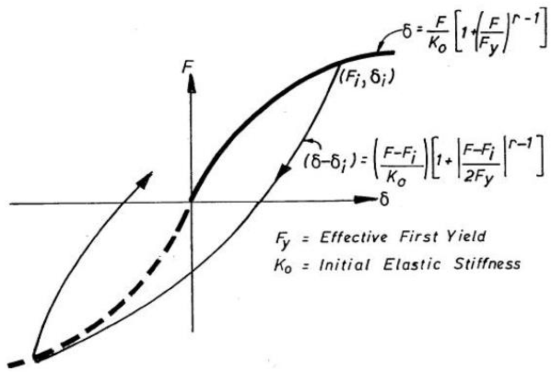


Fig. 9 Ramberg-Osgood Hysteresis, (Arefi 2008)

The average accuracy was 89% for the three different kernels. The performance for RBF kernel is the best with 95% accuracy with the other kernels. The RBF has a better success rate compared to the rest of the kernels when considering the sample accuracy.

5.1.2 Influence of strength reduction in superstructure

Different nonlinear displacement response spectra of SDOF in presence of soft soil and strength reduction in the structure are shown in Fig. 7.

It should be noted that cyclic response and nonlinear action can change the maximum relative displacement of SDOF system within the usual frequency range (Aydemir and Aydemir 2016). As illustrated in Table 1, the ductility (or cycle number) was provided from different range of input variable. As shown in Fig. 7, both RFB and ExponentialRBF kernel functions are found to have better prediction accuracy than the Linear kernel function.

5.2 Results of RC frame using time history analysis

As was explained in the previous section, the accuracy of proposed SVR model to predict the effects of SSI on a 2D six-storey existing building with different infill panel configurations is evaluated in the following. The original models considered by Galli (Galli 2005) were investigated to understand the global behaviour of the structure with different infill distributions along the height of the structure. These models exhibit different responses and have different fundamental periods; therefore SDOF models representing this range of structures can be sought from the results presented in the previous section.

5.2.1 Modelling of the superstructure using FEM

For comparing with the SVR results, the finite element model (FEM) of the RC frame is also constructed only for testing cases in the inelastic dynamic analysis program Ruaumoko (Carr 2008). As shown in Fig. 8, the lumped plasticity beam-column element is chosen because it is a good compromise between simplicity and accuracy. In the previous reference, all inelastic deformation of the frame member was concentrated at specifically identified parts of the member which are expected to undergo plastic deformations (Palanci *et al*. 2016). The other parts of the member were modelled as elastic elements. Furthermore, a modified hysteresis loop is adopted to describe the hysteretic behaviour of the plastic hinges. This model can describe the post-cracking shear deformation (Pampanin *et al*. 2006).

Wolf cone's model and equivalent lumped elements is employed for soil to capture the behaviour of the overall response of the RC frame in presence of flexible base. As shown in Fig. 9, a nonlinear Ramberg-Osgood model for spring force is implemented to capture the nonlinearity of the soil. As mentioned above, the ten known records have been employed as input motion to perform time history analysis and the average of the results has been calculated. All of these results of the finite element model (FEM) along

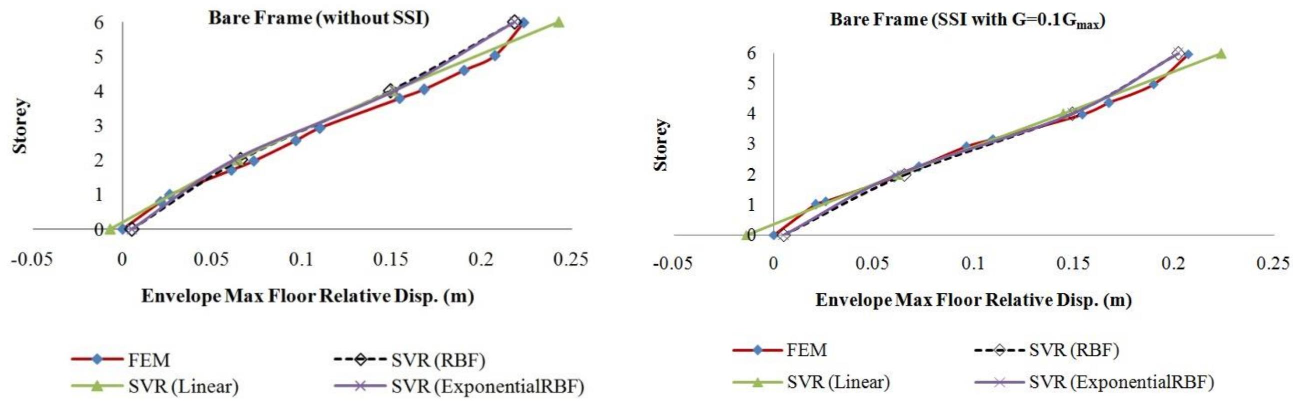


Fig. 10 Bare frame: comparing FEM results with predicted values using SVR model

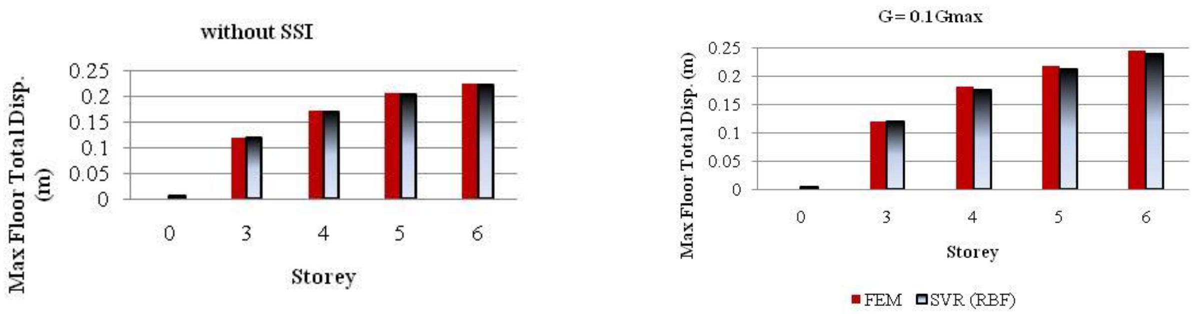


Fig. 11 Bare frame: comparing FEM results with the SVR predicted values

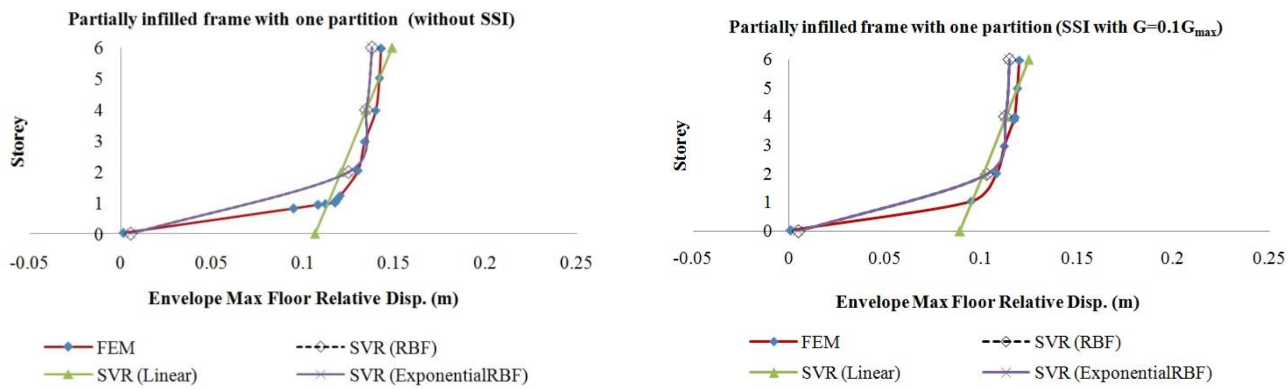


Fig. 12 Partially infilled frame: comparing FEM results with predicted values using SVR model

with the testing results of the SVR model are presented in Figs. 10-15 for comparison. While the FEM has been successful in following the trend of variation of the RC frame responses, overestimation or underestimation is observed at each floor.

To make a direct comparison possible, the same data as the FEM is used for the SVR model. As mentioned previously, 75% of the recorded data is used for training and 25% for testing. The parameters of the governing function come out as $\gamma = 6$; C=10 and $\varepsilon = 0.005$. Figs. 10-15 illustrate the results of analysis with the SVR. Further, the figures show a very good accuracy for proposed SVR model with RBF kernel compared with the numerical analysis results (FEM).

As shown in Fig. 10, the maximum and minimum differences between the FEM and the SVR model results are 2.12% and 0.52% corresponding to the cases without SSI and G=0.1Gmax, respectively. The overall average difference with respect to the results is 1.32%. In the following figure, a comparison of the results of the maximum response as above are presented in terms of envelope of maximum floor total displacement of each floor (see Fig. 11).

It has been suggested by previous references, time history analysis results on the partially infilled frame with one partition presented in Fig. 12 suggest a significant reduction in the elastic stiffness of the structure when SSI is considered. It is found that the results in absence of flexible foundation can be different by approximately 10% as

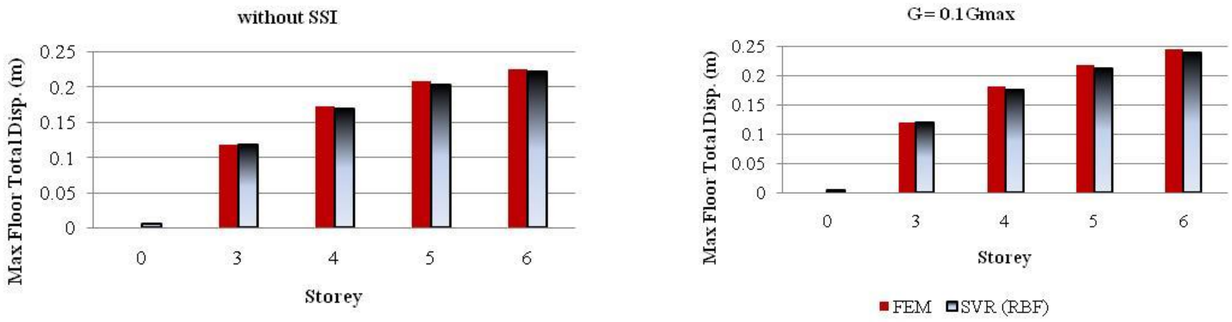


Fig. 13 Partially infilled frame: comparing FEM results with the SVR predicted values

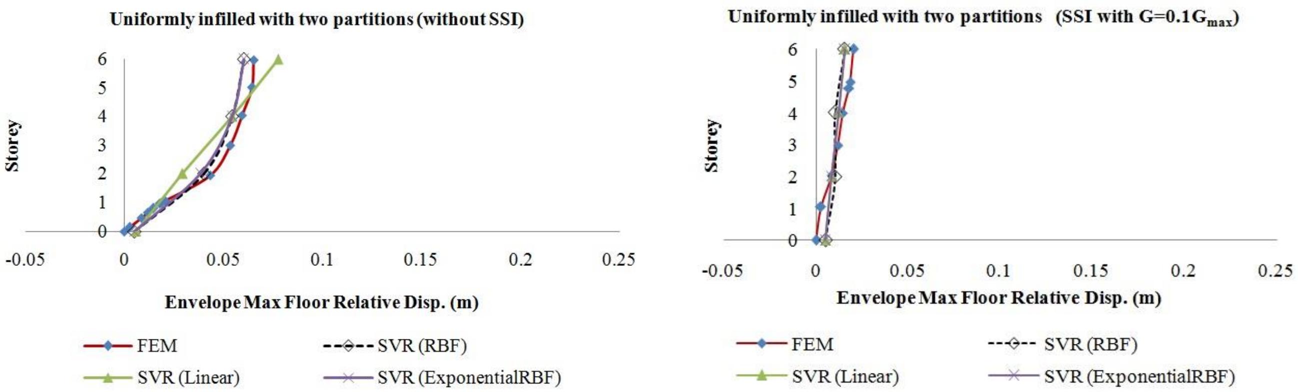


Fig. 14 Uniformly infilled frame: comparing FEM results with predicted values using SVR model

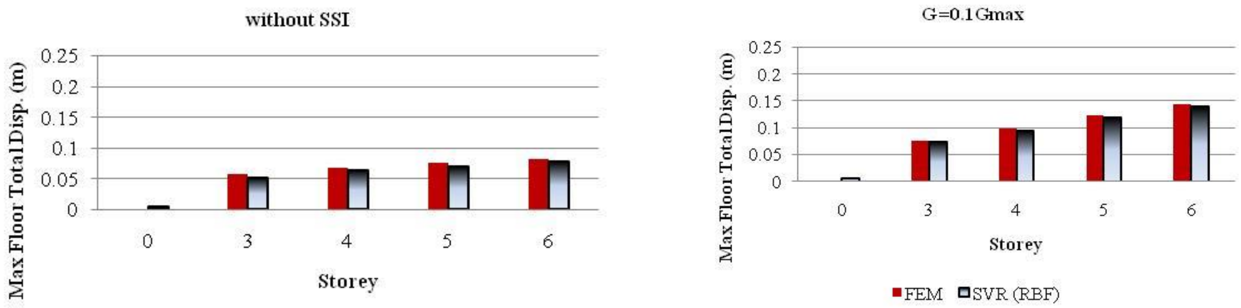


Fig. 15 Uniformly infilled frame: comparing FEM results with the SVR predicted values

compared to the SVR model with the different kernels. The little difference is clear in the roof floor displacements.

Similarly, comparisons of the maximum response of the frame results (partially infilled with one partition) are presented in terms of envelope of maximum floor total displacement of each floor (see Fig. 13). It has been found in predicted values that the support vector regression with RBF kernel function can achieve good performance for the partially infilled frames.

Fig. 14 illustrates the comparison between the numerical analysis (FEM) values and the SVR predicted values of the uniformly infilled frame with two partitions. Numerical analysis results shown in Fig. 14 emphasize the important contribution of the foundation rocking in total displacement of each floor in uniformly infilled structures. It is evident that the structure reaches to the plateau at a lower top drift demand compared to bare frame while the maximum base shear is higher for the infilled case. It has been found that the support vector regression with RBF kernel function can make the mathematical model for the uniformly infilled frames too.

The objectives of this example are to investigate the overall seismic response of existing buildings modelled on flexible foundation, and hence to evaluate the SSI effects on the structural response albeit through the use of relatively simple soil model.

As is noted in Fig. 13, the elastic stiffness of the frame with two panels is much higher than the frame with single panel.

It seems that, it has led to different behaviours in presence of SSI in terms of floor displacements. Flexibility of the soil foundation (G=0.1Gmax) has resulted to major improvement of maximum floor relative displacements for double-panel frame.

Correspondingly, comparisons of the maximum response of the uniformly infilled frame with two partitions are shown in terms of envelope of maximum floor total displacement of each floor (see Fig. 15). It has been concluded that the SVR model with RBF kernel function can achieve reasonable estimation for the uniformly infilled frames. The performance for RBF kernel has the highest accuracy (with more than 90%) in compared to the other kinds of kernels.

6. Conclusions

The support vector regression (SVR) model is used to predict the seismic response of the building systems with and without considering soil-structure interaction (SSI) effects from the training data set using the eight input variables. The γ, parameters C and ε of the SVR model are chosen by a trial and error approach. It is demonstrated that the proposed SVR model captured the input-output relationships exactly. Further, the sensitively analysis on R-squared values (R^2) is indicated that the performance of the proposed SVR model is satisfactory. The comparing plots of numerical analysis results of both SDOF and MDOF systems with the SVR predicted values are presented. The average database accuracy was 89% for the three different kernels. The performance for RBF kernel function is the best with 95% accuracy. It is concluded that the SVR model with RBF kernel function can achieve reasonable estimation for the different kinds of frames. Hence, the proposed method is highly suitable for the soil-structure systems that have complicated geometry where they have no prior knowledge about their hyperparameters.

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