Ain Shams Engineering Journal (2015) xxx, xxx–xxx

Ain Shams University

Ain Shams Engineering Journal

www.elsevier.com/locate/asej
www.sciencedirect.com

CIVIL ENGINEERING

Estimating hysteretic energy demand in steel moment resisting frames using Multivariate Adaptive Regression Spline and Least Square Support Vector Machine

Jatin Alreja [a,*], **Shantaram Parab** [a,1], **Shivam Mathur** [a,2], **Pijush Samui** [b]

[a] *School of Mechanical and Building Sciences (SMBS), VIT University, Vellore 632014, Tamil Nadu, India*
[b] *Centre for Disaster Mitigation and Management (CDMM), VIT University, Vellore 632014, Tamil Nadu, India*

Received 25 April 2014; revised 29 October 2014; accepted 13 December 2014

KEYWORDS

Multivariate Adaptive Regression Spline;
Least Squares Support Vector Machines;
Hysteretic energy;
Mathematical Modeling

Abstract This paper uses Multivariate Adaptive Regression Spline (MARS) and Least Squares Support Vector Machines (LSSVMs) to predict hysteretic energy demand in steel moment resisting frames. These models are used to establish a relation between the hysteretic energy demand and several effective parameters such as earthquake intensity, number of stories, soil type, period, strength index, and the energy imparted to the structure. A total of 27 datasets (input–output pairs) are used, 23 of which are used to train the model and 4 are used to test the models. The data-sets used in this study are derived from experimental results. The performance and validity of the model are further tested on different steel moment resisting structures. The developed models have been compared with Genetic-based simulated annealing method (GSA) and accurate results portray the strong potential of MARS and LSSVM as reliable tools to predict the hysteretic energy demand.

1. Introduction

The hysteretic energy, absorbed by a structural system during a seismic event that is strong enough to induce a certain amount of nonlinearity to the system, has been recognized by several researchers as a potentially useful seismic performance indicator [1–3]. The energy dissipated by hysteresis in structures under reversible load patterns is one of the most widely used parameters to evaluate cumulative effect of load history (cumulative damage). It is used to identify different behaviors between elements whose failure is dominated by flexion or shear, but also many others phenomena. However, it is

* Corresponding author. Tel.: +91 8870481352.
E-mail addresses: jateen_alreja2005@yahoo.com (J. Alreja), shantaram_186@hotmail.com (S. Parab), shivam02mathur@gmail.com (S. Mathur), pijush.phd@gmail.com (P. Samui).
[1] Tel.: +91 8870516272.
[2] Tel.: +91 7639811604.

Peer review under responsibility of Ain Shams University.

ELSEVIER Production and hosting by Elsevier

http://dx.doi.org/10.1016/j.asej.2014.12.006
2090-4479 © 2015 Faculty of Engineering, Ain Shams University. Production and hosting by Elsevier B.V.

necessary to evaluate this parameter to have a complete record of load–displacement history of each member of the studied structure [4,5].

Hysteretic energy is a parameter to measure effects of duration caused to a building after an earthquake strike [6]. It also takes into account the cyclic elastic behavior of the structure. Out of the different energy components the hysteretic energy is more important since it is directly in relation with the cumulative ductility. The hysteretic energy and its distribution throughout the structure are dependent on both the structural systems and the ground motion. The structural failure happens when the earthquake-induced hysteretic energy demand for a structure is larger than the hysteretic energy dissipation capacity of the structure [7–9]. It is considered as the key parameter to construct earthquake resistant buildings or to fix already existing structures and modify them into earthquake resistant structures. Hence it is important to calculate the hysteretic energy for buildings exceptionally for low rise buildings.

The hysteretic energy demand takes into account the effects of the duration of the earthquake and the cyclic-plastic deformation behavior of the structure. A monotonic demand parameter, such as peak inelastic drift or displacement, cannot represent this cumulative cyclic damage [10]. A design approach based on hysteretic energy demand, thus, has the potential to account for the damage potential explicitly. Hence, the modeling of hysteretic energy demand is necessary [11].

Artificial Neural Networks have been widely used to evaluate the hysteretic energy demand. Akbas used ANN to determine the hysteretic energy demand [12]. Despite the acceptable performance of ANN's, they do not give a certain function to calculate the outcome using the input values. Gandomi et al. used Genetic-simulated Annealing Algorithm to assess the hysteretic energy demand [13]. However, there is no absolute assurance that GSA will find a global optimum. Also, it cannot assure constant optimization response times.

Over the past few years, different modeling methods have become very popular and used by many researchers for a wide range of engineering applications [14]. This study uses Multivariate Adaptive Regression Splines (MARSs) and Least Squares Support Vector Machines (LSSVMs) for the prediction of Hysteretic Energy Demand in Steel Moment resisting Frames. MARS and LSSVM have strong potential for predicting the output (hysteretic energy) with high correlation and precision to the experimental value. MARS is a form of regression analysis introduced by Friedman [15]. MARS models are more flexible than linear regression models. It can handle both continuous and categorical data and it is simple to understand and interpret [16–19]. The LSSVM is a statistical learning theory which adopts a least squares linear system as a loss functions instead of the quadratic program in original support vector machine (SVM) [20–24]. It is closely related to Gaussian processes and regularization networks. It requires solving a set of only linear equations (linear programming), which is much easier and computationally very simple.

The aim of this study was to predict the hysteretic energy demand of steel moment resisting structures. Totally 27 input–output data-sets were collected, trained and tested by means of MARS and LSSVM models. These models have been developed using MATLAB software with the input parameters: Earthquake intensity (I), Number of stories (Ns), Soil type (Z), Fundamental period (T), Strength index (η) and hysteretic energy to energy imparted to the structure (E_I) ratio (E_H/E_I) and the output parameter hysteretic energy (E_H/m). The obtained results have been compared by experimental ones to evaluate both the models for calculating the hysteretic energy demand.

2. Multivariate Adaptive Regression Splines (MARSs)

Multivariate Adaptive Regression Spline is an implementation of techniques introduced by Friedman which is used for predicting the values of a continuous dependent variable using a set of predictor or independent variables [15]. This method makes no assumption about the functional relationship between the dependent and independent variables, instead MARS derives this relationship from a set of coefficients and basis functions that are directed from the regression data. MARS model is implemented in 2 steps where in the first step we build the model and add basis functions to increase the complexity until maximum complexity is achieved. Then in the second step we do a backward calculation to eliminate the least significant basis function from the model. Given below is an algorithm to explain MARS modeling.

The MARS algorithm builds models from two sided truncated functions of the predictors (x) of the form:

$$(x-t)_+ = \begin{cases} x-t, & x>t \\ 0, & \text{otherwise} \end{cases} \quad (1)$$

These serve as basis functions for linear or nonlinear expansion that approximates some true underlying function $f(x)$.

The MARSs model for a dependent (outcome) variable y, and M terms, can be summarized in the following equation:

$$Y = f(x) = \beta_0 + \sum_{m-1}^{M} \beta_m H_{\mathrm{km}}(x_v(k,m)) \quad (2)$$

where the summation is over the M terms in the model, and β_0 and β_m are parameters of the model (along with the knots t for each basis function, which are also estimated from the data). Function H is defined as follows:

$$H_{\mathrm{km}}(x_{v(k,m)}) = \prod_{k} -1^{K} h_{\mathrm{km}} \quad (3)$$

where $x_{v(k,m)}$ is the predictor in the kth of the mth product. For order of interactions $K = 1$, the model is additive and for $K = 2$ the model pairwise interactive.

During forward stepwise, a number of basis functions are added to the model according to a pre-determined maximum which should be considerably larger (twice as much at least) than the optimal (best least-squares fit).

After implementing the forward stepwise selection of basis functions, a backward procedure is applied in which the model is pruned by removing those basis functions that are associated with the smallest increase in the (least squares) goodness-of-fit. A least squares error function (inverse of goodness-of-fit) is computed. The so-called Generalized Cross Validation error is a measure of the goodness of fit that takes into account not only the residual error but also the model complexity as well. It is given by

$$\mathrm{GCV} = \frac{\sum_{i=1}^{N} (y_i - f(x_i))^2}{\left(1 - \frac{C}{N}\right)^2} \quad (4)$$

Please cite this article in press as: Alreja J et al., Estimating hysteretic energy demand in steel moment resisting frames using Multivariate Adaptive Regression Spline and Least Square Support Vector Machine, Ain Shams Eng J (2015), http://dx.doi.org/10.1016/j.asej.2014.12.006

with

$$C = 1 + cd \tag{5}$$

where N is the number of cases in the dataset, d is the effective degrees of freedom, which is equal to the number of independent basis functions. The quantity c is the penalty for adding a basis function. Experiments have shown that the best value for C can be found somewhere in the range $2 < d < 3$.

3. Least Squares Support Vector Machine (LSSVM)

SVM is a novel machine tool and especially useful for the classification and prediction with small sample cases. This novel approach motivated by statistical learning theory led to a class of algorithms characterized by the use of nonlinear kernels, high generalization of abilities and the sparseness of solution. Unlike the classical neural network approach the SVM formulation of the learning problem leads to quadratic programming with linear constraints. However the size of the matrix involved in the QP problem is directly proportional to the number of training points. Hence to reduce the complexity of optimization processes, a modified version called LS-SVM is proposed by taking equality instead of inequality constraints to obtain a linear set of equations instead of a QP problem in dual space. Instead of solving a QP problem by SVM, LS-SVM can obtain the solution of a set of linear equations. The formation of LS-SVM introduced is as follows. The following regression model can be constructed by using non-linear mapping function $\varphi(x)$.

$$y(x) = w^T\varphi(x) + b \tag{6}$$

where w is the weight vector and b is the bias term. By mapping the original input data into a high dimensional space, the nonlinear separable problem becomes linearly separable in space. Then the following cost function is formulated in the framework of empirical risk minimization

$$\min J(w, e) = \frac{1}{2}w^T w + \gamma\frac{1}{2}\sum_{k=1}^{N} e_k^2 \tag{7}$$

subject to equality constraints

$$y_k = w^T\varphi(x_k) + b + e_k \quad (k = 1, 2, 3 \ldots N) \tag{8}$$

where e_k is the random error and gamma is a regularization parameter in determining the trade-off between minimizing the training error and minimizing the model complexity. To solve this optimization problem Lagrange function is constructed as follows:

$$L(w, b, e; \alpha) = J(w, e) - \sum_{k=1}^{N}\alpha_k\{w^T\varphi(x_k) + b + e_k - y_k\} \tag{9}$$

where α_k are Lagrange multiplier. The solution of Eq. (9) can be obtained by partially differentiating it with respect to w, b, e_k and α_k.

$$\frac{\partial L}{\partial w} = 0 \rightarrow w = \sum_{k=1}^{N}\alpha_k\varphi(x_k) \tag{10}$$

$$\frac{\partial L}{\partial b} = 0 \rightarrow \sum_{k=1}^{N}\alpha_k = 0 \tag{11}$$

$$\frac{\partial L}{\partial e_k} = 0 \rightarrow \alpha_k = \gamma e_k \quad k = 1, \ldots, N \tag{12}$$

$$\frac{\partial L}{\partial \alpha_k} = 0 \rightarrow w^T\varphi(x_k) + b + e_k - y_k = 0, \quad k = 1, \ldots, N \tag{13}$$

The Eqs. (10)–(13) can be rewritten as follows:

$$\begin{bmatrix} 0 & \vec{1} \\ \vec{1} & \Omega + y^{-1}I \end{bmatrix} \tag{14}$$

where,

$$y = [y_1, \ldots, y_n]$$

$$\vec{1} = [1, \ldots, 1]$$

$$\alpha = [\alpha_1, \ldots, \alpha_n]$$

$$\Omega_{kl} = \varphi(x_k)^T\varphi(x_l) \ldots k, \quad l = 1, \ldots, N$$

Finally b and α_k can be obtained by the solution to the linear equation:

$$\hat{b} = \frac{\vec{1}^T(\Omega + \gamma^{-1}I_n)^{-1}y}{\vec{1}^T(\Omega + \gamma^{-1}I_n)^{-1}\vec{1}} \tag{15}$$

According to mercer's theorem the LS-SVM model can be expressed as follows:

$$y(x) = \sum_{k=1}^{N}\alpha_k K(x, x_k) + b \tag{16}$$

where $K(x, x_k)$ is the nonlinear kernel function. In comparison with some other feasible kernel functions, the RBF functions as a more compact supported kernel and is able to reduce a more computational complexity of the training process and improve generalization performance of LS-SVM. As a result RBF kernel was selected as kernel function as follows:

$$K(x, x_k) = \exp(||x - x_k||_2^2\sigma^{-2}) \tag{17}$$

where σ is the scale factor for tuning.

To achieve a high level performance with LS-SVM models, some parameters have to be tuned including regularization parameters γ and the kernel parameter corresponding to the kernel type, i.e. σ. These parameters have been determined using trial and error approach.

4. Development of MARS and LSSVM models

Out of the 27 datasets which are available, 23 datasets are used to train the models and 4 datasets are used to test the accuracy of the models. Table 1 shows the dataset used for developing the models. The data were normalized between 0 and 1 before being used in the model as following:

$$D_{norm} = \frac{D - D_{min}}{D_{max} - D_{min}} \tag{18}$$

The assessment of the model is done on the basis of coefficient of regression value R which is calculated using the formula:

Table 1 Database used for model development.

ID	I	Ns	Z	T (s)	η	E_H/E_I	E_H/m (cm/s)^2
1	1	3	1	1.0109	0.22	0.84	4160
2	1	3	2	1.0109	0.22	0.8	4011
3	1	3	3	1.0109	0.22	0.87	5751
4	1	9	2	2.2862	0.11	0.7	415
5	1	9	3	2.2862	0.11	0.81	835
6	1	20	1	3.7863	0.058	0.78	1503
7	1	20	2	3.7863	0.058	0.68	1081
8	1	20	3	3.7863	0.058	0.8	1849
9	2	3	1	1.0109	0.22	0.88	10,948
10	2	3	2	1.0109	0.22	0.86	11,219
11	2	3	3	1.0109	0.22	0.9	13,953
12	2	20	1	3.7863	0.058	0.83	4075
13	2	20	2	3.7863	0.058	0.75	3131
14	2	20	3	3.7863	0.058	0.83	4496
15	3	3	1	1.0109	0.22	0.9	20,140
16	3	3	2	1.0109	0.22	0.88	21,383
17	3	3	3	1.0109	0.22	0.91	24,613
18	3	9	2	2.2862	0.11	0.82	2484
19	3	9	3	2.2862	0.11	0.88	4387
20	3	20	1	3.7863	0.058	0.85	7656
21	3	20	2	3.7863	0.058	0.79	6202
22	3	20	3	3.7863	0.058	0.85	8173
23	1	9	1	2.2862	0.11	0.85	1760
24	2	9	1	2.2862	0.11	0.89	4809
25	2	9	2	2.2862	0.11	0.78	1241
26	3	9	1	2.2862	0.11	0.9	9042
27	2	9	3	2.2862	0.11	0.86	2361

$$R = \frac{\sum_{i=1}^{n}\left\{\left[\left(\frac{E_H}{m}\right)_{\mathrm{ai}} - \overline{\left(\frac{E_H}{m}\right)_a}\right]\left[\left(\frac{E_H}{m}\right)_{\mathrm{pi}} - \overline{\left(\frac{E_H}{m}\right)_p}\right]\right\}}{\sqrt{\sum_{i=1}^{n}\left[\left(\frac{E_H}{m}\right)_{\mathrm{ai}} - \overline{\left(\frac{E_H}{m}\right)_a}\right]}\sqrt{\sum_{i=1}^{n}\left[\left(\frac{E_H}{m}\right)_{\mathrm{pi}} - \overline{\left(\frac{E_H}{m}\right)_p}\right]}} \quad (19)$$

where $\left(\frac{E_H}{m}\right)_{\mathrm{ai}}$ and $\left(\frac{E_H}{m}\right)_{\mathrm{pi}}$ are the actual and predicted values, respectively, $\overline{\left(\frac{E_H}{m}\right)_{\mathrm{ai}}}$ and $\overline{\left(\frac{E_H}{m}\right)_p}$ are mean of actual and predicted E values. For an effective and good model the R value should be close to one. Also while comparing the models the values of R are compared and the model with R value closer to one and higher than the other is considered better and used.

5. Results and discussion

The MARS model is divided into two phrases that is forward and backward pass which is also used by recursive partitioning trees. Both the models have been developed using MATLAB software for training and prediction of the hysteretic energy. The models have been trained using 23 datasets and 4 datasets are used to validate the model. The relationship between the original training datasets and MARS predicted datasets is shown in Fig. 1. From the graph, we can infer that the predicted datasets are identical to the original datasets with a good coefficient of correlation (R). Fig. 2 shows the relation between original testing datasets and MARS predicted datasets. The identical values validate the performance of the MARS. The best value of R (Coefficient of Correlation) is 0.9864 for the training set and the value of R for the testing set is 0.9890.

The hysteretic energy Equation formulated according to MARS is given below:

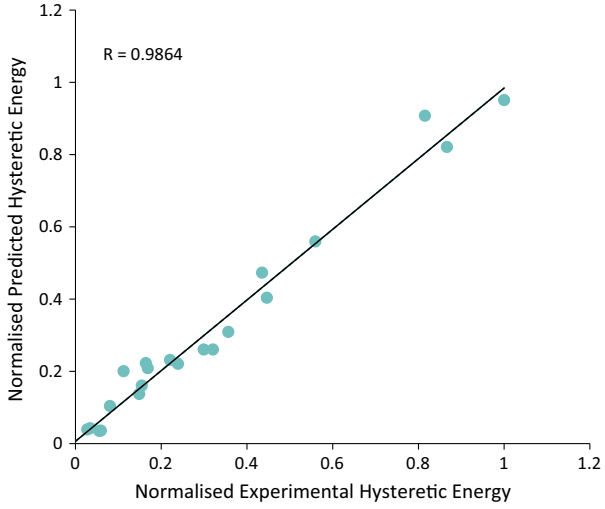

Figure 1 Performance of training datasets (MARS).

$$y = -0.0335 + \sum_{i=1}^{6} C_i \beta_i(x) \quad (20)$$

where $y = E_H/m$, C_i = coefficient, $\beta_i(x)$ = Basis Function. The details of basis functions have been shown in Table 2.

ANOVA decomposition has been done on the developed MARS model. The results of ANOVA decomposition have been shown in Table 3. The value of GCV is maximum for T. So T has the maximum effect on the predicted E_H/m.

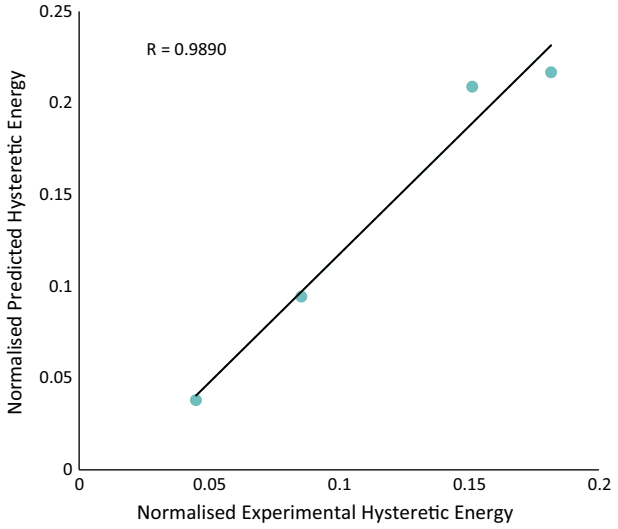

Figure 2 Performance of testing datasets (MARS).

Table 2 Details of basis function.

$B_i(x)$	C_i	Function
$B_1(x)$	0.9945	$B_1(x) = \max\left(0, \frac{E_h}{E_i} - 0.73913\right)$
$B_2(x)$	0.4756	$B_2(x) = \max(0,\ T - 0.45950)$
$B_3(x)$	0.7679	$B_3(x) = \max(0,\ 0.45950 - T)$
$B_4(x)$	1.6201	$B_4(x) = B3(x)$ ****** $\max(0,\ I - 0.5)$
$B_5(x)$	−0.7776	$B_5(x) = B3(x)$ * $\max(0,\ 0.5 - I)$
$B_6(x)$	−0.6819	$B_6(x) = B2(x)$ * $\max(0,\ 0.5 - I)$

Table 3 Results of anova decomposition.

Functions	Standard deviation	GCV	Basis function	Variables
1	0.117	0.149	2	T
2	0.086	0.035	1	E_H/E_I
3	0.164	0.048	3	I, T

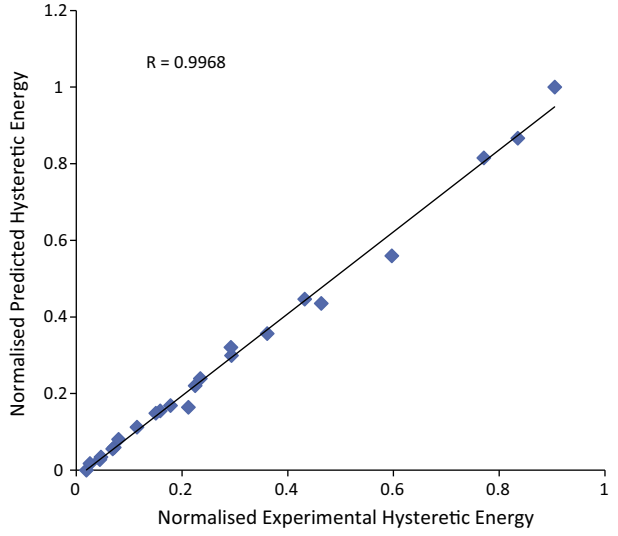

Figure 3 Performance of training datasets (LSSVM).

For the prediction of hysteretic energy demand, LSSVM model uses the same training and testing datasets as used in the MARS model. For the developed model, the design value of γ and σ is 8 and 0.99 respectively. The value of R in training is 0.9968 and in testing is 0.9907. Fig. 3 shows the relationship between the original training datasets and LSSVM predicted datasets and Fig. 4 shows the relation between original testing datasets and LSSVM predicted datasets.

The developed LSSVM model gives the following equation for the hysteretic energy demand:

$$\frac{E_H}{m} = \sum_{k=1}^{23} \alpha_k e^{\frac{-(x_k - x)(x_k - x)^T}{1.96}} - 0.1231 \tag{21}$$

Here x_k = Input of Training DataSet; x = Input of Data-Set whose output has to be determined.

The value of α_k is shown in Fig. 5. The comparison between Genetic-based Simulated Annealing (GSA), MARS and LSSVM models for modeling hysteretic energy in terms of Correlation Coefficient (R) is shown in Fig. 6.

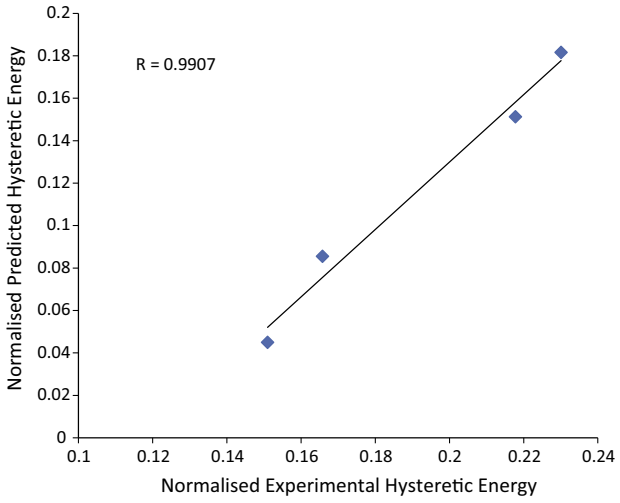

Figure 4 Performance of testing datasets (LSSVM).

Figure 5 Values of α_k for LSSVM model.

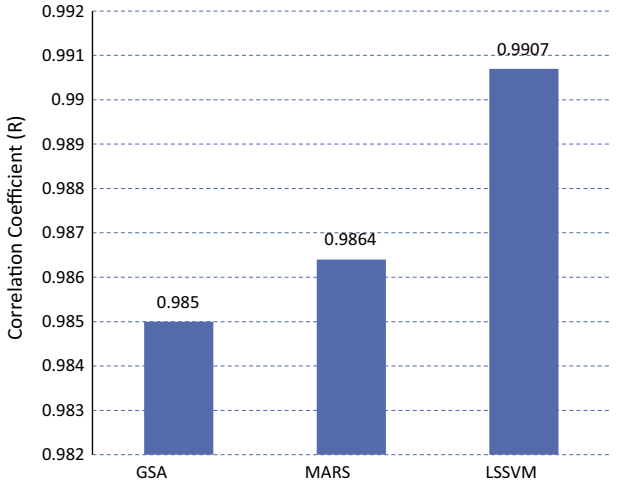

Figure 6 Comparison between GSA, MARS and LSSVM models for modeling hysteretic energy in terms of correlation coefficient (R).

These results prove that the MARS and LSSVM models are more accurate and reliable for the prediction of the hysteretic energy demand in Steel Moment resisting Structures.

6. Conclusion

This study shows the efficient and feasible use of MARS and LSSVM based approach for the prediction of Hysteretic Energy Demand in Steel Moment Resisting Frames. 27 data have been utilized to develop the MARS and LSSVM models. The performance of the MARS and LSSVM is better than that of the GSA model due to its better coefficient of correlation (R). The developed equations can be used by the users for determination of hysteretic energy demand in steel moment resisting frames. In summary, it can be concluded that MARS and LSSVM can be used for solving different problems in engineering.

References

[1] Park YJ, Reinhorn AM, Kunnath SK. IDARC: Inelastic damage analysis of reinforced concrete frame—shear-wall structures. Tech. Rep. NCEER-87-0008, State University of New York at Buffalo, Buffalo, NY; 1987.
[2] Bojorquez E, Teran-Gilmore A, Ruiz SE, Reyes-Salazar A. Evaluation of structural reliability of steel frames: interstory drift versus plastic hysteretic energy. Earthquake Spectra 2011;27(3):661–82.
[3] Kazantzi AK, Vamvatsikos D. A study on the correlation between dissipated hysteretic energy and seismic performance. In: 15th world conference on earthquake engineeering, National Technical University of Athens, Greece; 2012.
[4] Vera CO. Evaluation of energy dissipated by hysteresis in R/C shear walls using parameters of displacement. In: First European conference on earthquake engineering and seismology, Geneva, Switzerland; 2006.
[5] Prasanth T, Ghosh S, Collins KR. Estimation of hysteretic energy demand using concept of modal pushover analysis, vol. 37. John Wiley & Sons Ltd.; 2008, p. 975–90.
[6] Gandomi AH, Alavi AH. Expression programming techniques for formulation of structural engineering systems. Metaheuristic applications in structures and infrastructures. Waltham: Elsevier; 2013 [Chap. 18].
[7] Bertero VV, Teran-Gilmore A. Use of energy concepts in earthquake-resistant analysis and design: issues and future directions. The earthquake engineering online archive. Berkeley: University of California; 1993.
[8] Vision 2000 Committee. Structural Engineering Association of California (SEAOC); 2000.
[9] Riddell R, Garcia JE. Hysteretic energy spectrum and damage control. Earthquake Eng Struct Dynam 2001;30(12):1791–816.
[10] Chowdhary AR, Ghosh S. Inclusion of p–Δ effect in the estimation of hysteretic energy demand based on modal pushover analysis. ISET J Earthquake Technol 2010;47(2–4):75–86.
[11] Rathore M, Chowdhary AR, Ghosh S. Approximate method for estimating hysteretic energy demand on plan-asymmetric building. J Earthquake Eng 2012;15(1):99–123.
[12] Akbas B. A neural network model to assess the hysteretic energy demand in steel moment resisting frames. Struct Eng Mech 2006;23(2):177–94.
[13] Gandomi AH, Alavi AH, Asghari A, Niroomand H, Nazar AM. An innovative approach for modeling of hysteretic energy demand in steel moment resisting frames. Neural Comput Appl 2013;24(6):1285–91.
[14] Aminian P, Gandomi AH, Alavi AH, Arab Esmaeili M. New design equations for assessment of load carrying capacity of CSB: a machine learning approach. Neural Comput Appl 2013;23(1):119–31.
[15] Friedman JH. Multivariate adaptive regression splines. Annal Statistic 1991;19(1):1–141.
[16] Taylan P, Weber GW, Ozkurt FY. A new approach to multivariate adaptive regression splines by using Tikhonov regularization and continuous optimization. Top 2010;18:377–95.
[17] Andres JD, Lorca P, Juez FJDC, Sanchez-Lasheras F. Bankruptcy forecasting: a hybrid approach using fuzzy c- means clustering and multivariate adaptive regression splines (MARS). Expert Syst Appl 2011;38:1866–75.
[18] Yao D, Yang J, Zhan X. Predicting breast cancer Survivability using random forest and multivariate adaptive regression splines (MARS). In: Electronic and Mechanical Engineering and Information Technology (EMEIT) international conference on electronic & mechanical engineering and information technology, Harbin, Heilongjiang, China; 2011.
[19] Jalali-Heravi M, Asadollahi-Baboli M, Mani-Varnosfaderani A. Shuffling multivariate adaptive regression splines and adaptive neuro-fuzzy inference system as tools for QSAR study of SARS inhibi'tors. J Pharm Biomed Anal 2009;50:853–60.
[20] Suykans JAK, Vandewalle J. Least squares support vector machine classifiers. Neural Process Lett 1999;9:293–300.
[21] Baesens B, Viaene S, Gestel TV, Suykens JAK, Dedene G, Moor BD, et al. An empirical assessment of kernel type performance for least squares support vector machine classifiers. In: Fourth international conference on knowledge-based intelligent engineering systems & allied technologies, Brighton, United Kingdom; 2000.
[22] Espinoza M, Suykens JAK, Moor BD. Least squares support vector machines and primal space estimation. In: IEEE Conference on Decision and Control, Hawaii, USA; 2003.
[23] Lu C, Gestela TV, Suykens JAK, Huffel SV, Vergote I, Timmerman D. Preoperative prediction of malignancy of ovarian tumors using least squares support vector machines. Artif Intell Med 2003;28:281–306.
[24] Mitra V, Wang CJ, Banerjee S. Text classification: a least square support vector machine approach. Appl Soft Comput 2007;7:908–14.

Jatin Alreja: He is an undergraduate student in School of Mechanical and Building Science at VIT University. His research interest mainly includes Environmental Engineering, Structural Engineering and Geotechnical Engineering.

Shantaram Parab: He is an undergraduate student in School of Mechanical and Building Science at VIT University, Vellore. His research interests cover a wide range of subjects in civil engineering, including structural engineering, geotechnical engineering, slope stability, pile foundation, structural designs, and superstructure designs.

Shivam Mathur: He is an undergraduate student in School of Mechanical and Building Science at VIT University. His main areas of research interest are Structural Engineering, Geotechnical Engineering, Transport Management and Environmental Engineering.

Pijush Samui: He is a professor at Centre for Disaster Mitigation and Management in VIT University, Vellore, India. He obtained his B.E. at Bengal Engineering and Science University; M.Sc. at Indian Institute of Science; Ph.D. at Indian Institute of Science. He worked as a postdoctoral fellow at University of Pittsburgh (USA) and Tampere University of Technology (Finland). He is the recipient of CIMO fellowship from Finland. Dr. Samui worked as a guest editor in "Disaster Advances" journal. He also serves as an editorial board member in several international journals. Dr. Samui is editor of International Journal of Geomatics and Geosciences. He is the reviewer of several journal papers. Dr. Samui is a Fellow of the International Congress of Disaster Management and Earth Science India. He is the recipient of Shamsher Prakash Research Award for the year of 2011.

Please cite this article in press as: Alreja J et al., Estimating hysteretic energy demand in steel moment resisting frames using Multivariate Adaptive Regression Spline and Least Square Support Vector Machine, Ain Shams Eng J (2015), http://dx.doi.org/10.1016/j.asej.2014.12.006