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Optimal Shape Investigation of Masonry Arch Bridges under Dynamic Loads Using Support Vector Machine

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Abstract

The objective of this study is to determine the optimal shape of masonry arches under dynamic loads using the Support Vector Machine (SVM) technique. This approach utilizes the principles of Structural Risk Minimization (SRM), which demonstrate superior performance compared to methods based on Empirical Risk Minimization (ERM). The research particularly focuses on the types of arches commonly used in traditional structures and their significance in ensuring structural stability and performance. The modeling, dynamic analysis, and shape optimization of a semi-circular arch are comprehensively explained using ANSYS 11 software and the SVM method. The necessity of this study lies in the critical role that the optimal shape of arches plays in enhancing the resilience and reducing the vulnerability of masonry structures against dynamic loads, especially given their widespread application in both historical and modern constructions. The main innovation of this research is the application of the Support Vector Machine as an advanced and less commonly employed method for arch shape optimization. For the first time, SRM principles are integrated with dynamic modeling and computational analysis, offering a novel framework for optimizing traditional structures.

1. Introduction

Masonry arch bridges have been integral components of architectural and engineering heritage for centuries, known for their aesthetic appeal and structural efficiency. These structures, prevalent in both historical and modern applications, require meticulous analysis to ensure their resilience, particularly under dynamic loads such as seismic activity and vehicular traffic. A critical aspect of their performance lies in the optimization of their geometric shape, which significantly influences their ability to withstand dynamic forces while maintaining stability and durability [1].

Dynamic analysis is a comprehensive time-history analytical method that evaluates the responses of structures to time-dependent excitations, such as earthquakes. By numerically integrating the equations of motion, this method provides a detailed understanding of time-varying displacements, strains, stresses, and forces within a structure. Such insights are essential for predicting the behavior of masonry arches under dynamic loads, enabling engineers to design and optimize structures that meet safety and performance requirements [2].

Previous research has explored various aspects of modeling, dynamic analysis, and shape optimization of masonry arches. These studies have demonstrated the significance of employing advanced computational tools like ANSYS software for conducting dynamic analyses. However, these methods are often computationally intensive, requiring significant time and resources to achieve accurate results. The reliance on traditional optimization techniques, primarily based on Empirical Risk Minimization (ERM), has further limited the efficiency and applicability of these approaches [3].

Despite the progress made, a notable gap exists in the integration of advanced machine learning techniques, such as Support Vector Machines (SVM), into the dynamic analysis and optimization of masonry arches. Traditional methods have struggled to balance computational efficiency with the precision required for analyzing complex structural behaviors. Furthermore, existing studies have not fully leveraged the principles of Structural Risk Minimization (SRM), which offer a more robust framework for predictive modeling compared to ERM-based techniques [4].

To address these limitations, the present study introduces an innovative framework that combines SVM with SRM principles for the dynamic analysis and shape optimization of masonry arches. By employing this approach, the computational burden of dynamic analysis is significantly reduced while maintaining high accuracy in results. Additionally, the integration of SVM into the optimization process represents a novel application in the field, filling a critical void in the current body of knowledge. This research not only advances the methodological tools available for structural optimization but also sets a precedent for future studies aiming to enhance the resilience and performance of masonry arch bridges under dynamic loads.

2. Literature review

This section discusses related research on Masonry Arch Bridges under Dynamic Loads**.** In [5], Authors developed a hybrid optimization framework combining genetic algorithms with finite element analysis to investigate the optimal shapes of masonry arches. Although this approach demonstrated improvements in optimization outcomes, it faced challenges in handling high-dimensional design spaces efficiently. Our SVM-based methodology addresses this limitation by offering robust performance in high-dimensional settings and ensuring scalability.Another noteworthy contribution by [6] utilized deep learning models to predict the dynamic stability of semicircular masonry arches. While their neural network models achieved high accuracy, the need for extensive training data and the risk of overfitting limited the practical application of their approach. Our method overcomes these issues by leveraging SVM, which requires smaller datasets and inherently avoids overfitting through SRM principles.In [7], the influence of material properties on the seismic performance of masonry arches was investigated using parametric analyses. Although the research provided a detailed understanding of material behavior, it lacked a systematic framework for shape optimization. Our research extends beyond material analysis to include comprehensive shape optimization, enhancing the overall resilience of masonry arches. Finally, in [8] authors examined the impact of geometric irregularities on the dynamic performance of masonry arches through numerical simulations. While the study highlighted critical geometric factors affecting stability, it did not incorporate advanced optimization methodologies. Our work fills this gap by integrating machine learning techniques directly into the optimization process, providing a more efficient and effective framework for analyzing and improving structural performance. Despite the progress made, a notable gap exists in the integration of advanced machine learning techniques, such as Support Vector Machines (SVM), into the dynamic analysis and optimization of masonry arches. Traditional methods have struggled to balance computational efficiency with the precision required for analyzing complex structural behaviors. Furthermore, existing studies have not fully leveraged the principles of Structural Risk Minimization (SRM), which offer a more robust framework for predictive modeling compared to ERM-based techniques.To address these limitations, the present study introduces an innovative framework that combines SVM with SRM principles for the dynamic analysis and shape optimization of masonry arches. By employing this approach, the computational burden of dynamic analysis is significantly reduced while maintaining high accuracy in results. Additionally, the integration of SVM into the optimization process represents a novel application in the field, filling a critical void in the current body of knowledge. This research not only advances the methodological tools available for structural optimization but also sets a precedent for future studies aiming to enhance the resilience and performance of masonry arch bridges under dynamic loads.

3. Modeling, Analysis, and Shape Optimization of Arches Using ANSYS 11

Considering that in the optimization section, design variables, namely the thickness of the base and the thickness of the crown, need to be defined as parameters, key points in the modeling of the arch must be defined as follows[9].

4. Geometrical Modeling

For clarity, the semi-circular arch with the definition of key points as parameters is presented in (Figure 1), where the coordinates of the key points are defined as follows (Table1):

Table 1: Coordinates of Key Points of the Semi-Circular Arch

point	1	2	3	4	5	6	7
X coordinates	0	R	-R	0	R+t0	-(R+t0)	0
Y coordinates	0	0	0	R	0	0	R+t1

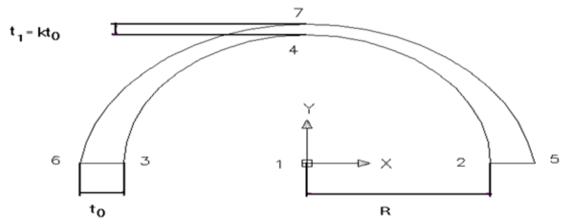

Figure 1: Semi-Circular Arch [8]

Modeling the arch in this way means that the gradual reduction in thickness from the base to the crown contributes to the stability of the arch. It is worth noting that in the modeled arch, the thickness decreases linearly from the base to the crown. Additionally, the thickness of the arch in the longitudinal direction is equal to 20 units. The displacements of the support nodes are set to zero, and the shear force is unable to displace them. Furthermore, the masonry consists of brick and mortar, considered as homogeneous materials with properties listed in Table 2, and the coefficients involved in the nonlinear and non-elastic analysis listed in Table 3 are taken into account.

Table 2: Characteristics of Masonry Materials

Density (ρ) kg/m^3	***1460*[6]**
Elastic Modulus (E) N/m^2	5×10^8 **[7]**
Allowable Tensile Stress (f_t) N/m^2	0.5×10^5 **[6,7,8]**
Poisson's Ratio (υ)	***0.17* [8]**

Table 3: Coefficients Influencing Nonlinear Non-Elastic Analysis

Shear Transfer Coefficient for Open Crack	0.1[6]
Shear Transfer Coefficient for closed Crack	0.9[7]
Allowable Tensile Stress N/m^2 (f_t)	5×10^4 [6, 7, 8]
Allowable compress Stress N/m^2 (f_c)	5×10^5 [6,7]

5. Support Vector Machine:

(SVM) is a machine learning method based on the statistical learning theory proposed by Vapnik and his colleagues in the 1990s. In SVM, the principles of Structural Risk Minimization (SRM) are employed, while other methods rely on Empirical Risk Minimization (ERM). It has been demonstrated that SRM principles perform better than ERM in terms of functionality. SVM is generally used for binary or multiclass classification and regression problems [10].

Like many other machine learning methods, SVM involves a model construction process consisting of two stages: training and testing. At the end of the training phase, the generalization capability of the trained model is evaluated using test data. In summary, the main operation of SVM in solving regression problems can be stated as follows:

1. Support Vector Machine approximates the regression function using a linear function.
2. Support Vector Machine performs regression operations with a function where the deviation from the actual value is less than ε (loss function).
3. By minimizing the structural risk, Support Vector Machine provides the best solution [11].

In methods such as artificial neural networks, empirical risk minimization principles are used to achieve the best solution. Minimizing empirical risk ensures the appropriate performance of the model on training data, but there is no guarantee of proper generalization. Therefore, in this method, proper network design is necessary to improve the generalization performance of the model. The goal of structural risk minimization is to optimize the

generalization capability of the model while minimizing empirical risk simultaneously [12].
Solving the regression problem in SVM involves approximating the regression function using a linear function f(x) =<w.x>+b. on a set containing a sample such as
{(x1,y1),….(x1,y1)ϵ Rn, yϵR} Translated academically, it becomes: to be able to estimate output values based on inputs. In the above equation, x is the input vector
(w,b) ϵ RN×R The controlling parameters of the function f are represented by <w.x>, indicating the inner product. For solving the regression problem, the Vapnik loss function is used, where a minimum error of ε can be ignored. This loss function is defined in equation (1) as follows:

$$L_\varepsilon(y) = |y - f(x)|_\varepsilon = \begin{cases} 0 & |y-f(x)|\le\varepsilon \\ |y - f(x)| - \varepsilon & otherwise \end{cases} \quad (1)$$

Lε(y) represents the loss function and ε is the allowable error in the loss function. The controlling parameters of the optimal regression function are obtained by solving the following optimization problem:

$$\begin{aligned} &Minimise\,\Phi(W,\zeta^*,\zeta) = \frac{\|w\|^2}{2} + C\left(\sum \zeta_i^* + \sum \zeta\right) \\ &y_i - \left((W.X_i) + b\right) \le \varepsilon + \zeta_i \\ &Subject\ to\ \left((W.X_i) + b\right) - y_i \le \varepsilon + {\zeta^*}_i \\ &\zeta_i, \zeta_i^* \ge 0 \end{aligned} \quad (2)$$

In the equation (2), ζ's are slack variables. These variables, along with the loss function, are depicted in Figure 2. To solve the optimization problem above, the Lagrange function is written according to equation (2) using the theory of Lagrange multipliers.

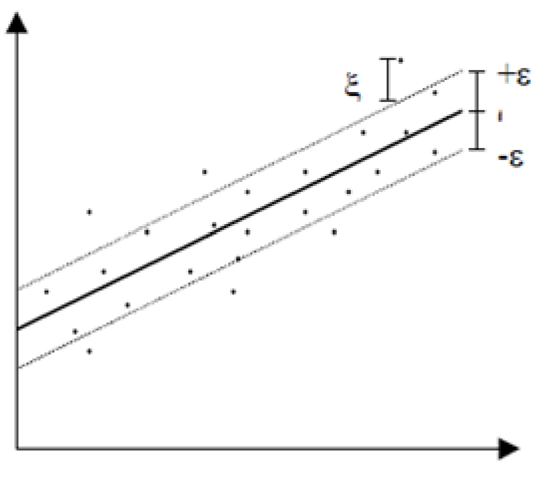

Figure 2: Vapnik's Loss Function and Slack Variables

With the maximization of the above function under the following constraints, the values of a and a* are obtained. These coefficients are referred to as Lagrange multipliers.
The optimization problem above can be solved using Quadratic Programming (QP) methods, thus achieving a definite global extremum. Consequently, the risk of overfitting these data points is higher. Therefore, support vectors do not lie within the margin band. Hence, controls the number of support vectors[13]. With the help of Lagrange multipliers and support vectors, the optimal response control parameters are calculated as follows:
In Equation 7, Xr and Xs are two support vectors.
For constructing a Support Vector Machine (SVM) model, the parameters C and are defined by the user. Parameter C is a regularization parameter and can take values from zero to infinity. Its role is to balance between minimizing empirical risk and maximizing generalization capability. Parameter can also take values from zero to infinity. Its value is crucial in the context of support vectors and consequently, the model's performance. Linear regression problem in SVM can be easily extended to non-linear regression. For this purpose, kernel functions are used [14]. Various kernels have been recognized so far, but the successful application of polynomial and radial basis function (rbf) kernels in geotechnical engineering problems has been reported. Thus, in the case of non-linear regression in SVM, the control parameters of the optimal function are calculated with the following equations:

6. Modeling arches using Support Vector Machines (SVM)

To generate and evaluate a Support Vector Machine (SVM)-based model for predicting the dynamic response of concrete arches under seismic force, 300 arch samples analyzed by ANSYS software are used. Each arch sample includes 3 independent variables: arch radius, base thickness, and crown thickness, and one dependent variable: maximum arch tensile stress. The range of these parameters in this study is defined as follows: arch radius (4 to 8 meters), base thickness (0.8 to 1.4 meters), and crown thickness (0.2 to 0.4 meters).
For creating the SVM model, the data are divided into two sets, training and evaluation, with a ratio of 70 to 30 (210 samples for training and 90 samples for evaluation). The desired model is generated using the training dataset, and its performance in predicting the desired population is evaluated using data not experienced during the model training (test dataset). Moreover, the radial

basis function (rbf) kernel, chosen as the best kernel function in various research studies, is used as the kernel function in this study[15]. To achieve a better model, multiple models are created by combining different combinations of kernel function parameters (C, and ζ), and their performance is evaluated. Additionally, the prediction results of the model are presented using statistical indices such as the correlation coefficient (R) and the root mean square error (RMSE). The correlation coefficient is a measure of the conformity of predicted values to measured values and is calculated according to the following equation.

Moreover, the value of RMSE, which is a measure for error estimation, is calculated according to the following equation.

Tables 4 to 6 present the results obtained from the generated models based on different combinations of parameters C, , and ζ.

Table 4: Model evaluation for various values of the kernel function parameter ζ

ζ	Train Set		Test Set	
	R	RMSE	R	RMSE
0.5	0.8324	0.2134	0.6914	0.1424
1	0.8873	0.2542	0.7105	0.1804
10	0.9132	0.0422	0.8123	0.1924
50	0.9732	0.1393	0.8012	0.0834
100	0.9023	0.2059	0.9145	0.1425
200	0.9802	0.1942	0.9014	0.1804
300	0.8931	0.1954	0.7204	0.1643
$\varepsilon = .002$ C=120				

Table 5: Model evaluation for various values of the kernel function parameter

ε	Train Set		Test Set	
	R	RMSE	R	RMSE
0.0001	0.8753	0.1246	0.7406	0.0245
0.001	0.8472	0.0754	0.8520	0.0810
0.005	0.9123	0.0864	0.9025	0.1149
0.01	0.7856	0.1825	0.8205	0.1820
0.05	0.7750	0.1342	0.7525	0.1025
0.1	0.8253	0.2305	0.8206	0.2150
$\zeta = 45$ C=120				

Table 6: Model evaluation for various values of the kernel function parameter c

C	Train Set		Test Set	
	R	RMSE	R	RMSE
0.1	0.6892	0.2025	0.6027	0.1486
1	0.8402	0.1840	0.8242	0.1085
10	0.7920	0.1820	0.8295	0.0895
50	0.8154	0.1234	0.7930	0.0702
100	0.8682	0.0804	0.8206	0.1079
150	0.9104	0.0865	0.9253	0.0802
200	0.9425	0.9104	0.9874	0.9795
ε = .002 ζ =45				

7. Conclusion

The overall goal of this research is to utilize a nonlinear Support Vector Machine (SVM) model along with a radial basis function (rbf) kernel for predicting the dynamic response of concrete arches under seismic force. To this end, a dataset consisting of 300 arch samples analyzed by

ANSYS software is divided into a 70 to 30 ratio for training and evaluation datasets (Figure 3).

Finally, after determining the best SVM model, which exhibits adequate accuracy in predicting the dynamic responses of arches compared to actual results, the kernel function parameters (C, , and ζ) as well as the values of R (correlation coefficient) and RMSE (root mean square error) are presented as determinant parameters in selecting the best SVM model. Figure 4 compares the maximum tensile stress calculation by Support Vector Machine and ANSYS software. The results of the study indicate that the Support Vector Machine has an error ranging from 11 to 17 compared to the results obtained by ANSYS software.

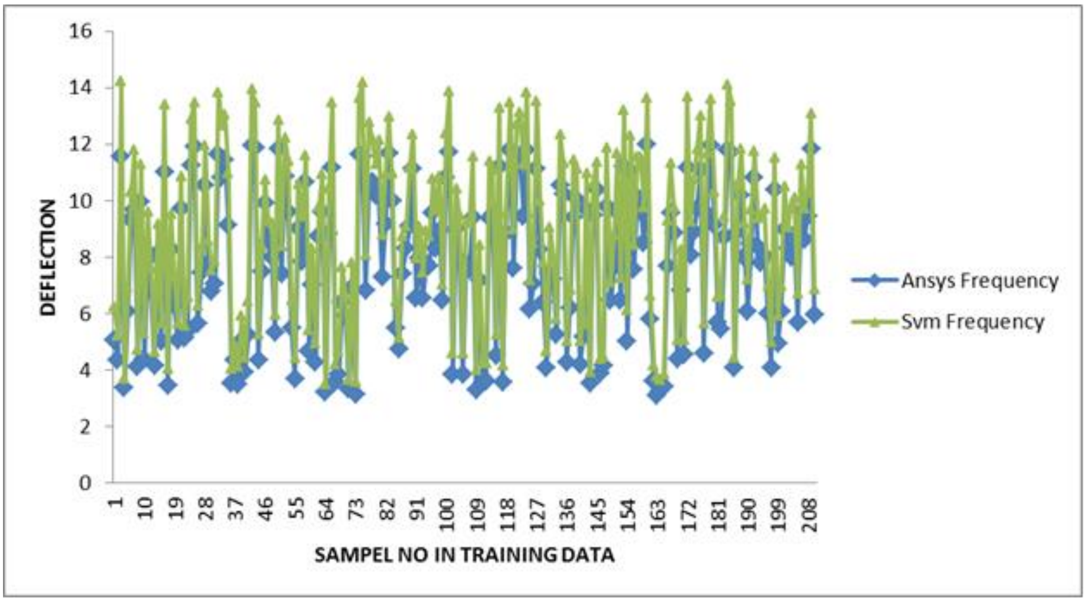

Figure 3: Comparison plot of maximum tensile stress calculated by ANSYS software and SVM

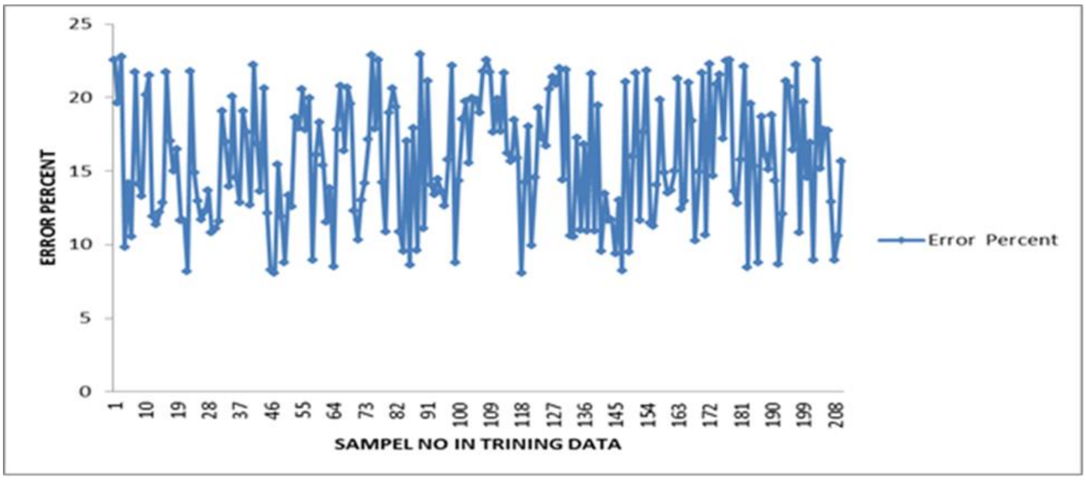

Figure 4: Percentage error plot of maximum tensile stress calculation by SVM software compared to ANSYS software

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