5-2013

Noise-Insensitive Prognostic Evaluation of Historic Masonry Structures

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NOISE-INSENSITIVE PROGNOSTIC EVALUATION
OF HISTORIC MASONRY STRUCTURES

A Thesis
Presented to
the Graduate School of
Clemson University

In Partial Fulfillment
of the Requirements for the Degree
Master of Science
Civil Engineering

by
Ashley Haydock
May 2013

Accepted by:
Dr. Sez Atamturktur, Committee Chair
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ABSTRACT

In recent years, a significant amount of research has been directed towards the development of prognostic methodologies to forecast the future health state of an engineering system assisting condition based maintenance. These prognostic methods, having furthered the maintenance practices for mechanical systems, have yet to be applied to historic masonry structures, many of which stand in an aged and degraded state. Implementation of prognostic methodologies to historic masonry structures can advance the planning of successful conservation and restoration efforts, ultimately prolonging the life of these heritage structures. This thesis presents a review of prognostic concepts and techniques available in the literature as applied to various engineering disciplines, and evaluates the well-established prognostic techniques for their applicability to historic masonry structures. Challenges of adapting the existing prognostic techniques to historic masonry are discussed, and the future direction in research, development, and application of prognostic methods to masonry structures is highlighted.

One particular prognostic technique, known as support vector regression, has had successful applications due to its ability to compromise between fitting accuracy and generalizability (i.e. flatness) in the training of prediction models. Optimal tradeoff between these two aspects depends on the amount of extraneous noise in the measurements, which in civil engineering applications, is typically caused by loading conditions unaccounted for in the development of the prediction model. Such extraneous loading, often variable with time affects the optimal tradeoff. This thesis presents an

approach for optimally weighing fitting accuracy and flatness of a support vector regression model in an iterative manner as new measurements become available. The proposed approach is demonstrated in prognostic evaluation of the structural condition of a historic masonry coastal fortification, Fort Sumter located in Charleston, SC. A finite element model is used to simulate responses of a casemate within the fort considering differential settlement of supports. Within the case study, the adaptive optimal weighting approach proved to have increased prediction accuracy over the non-weighted option.

DEDICATION

I would like to dedicate this thesis to my parents June Fender and Jimmy Fender

for all of their support, love, and prayers during this journey.

ACKNOWLEDGMENTS

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CHAPTER ONE

INTRODUCTION

1.1.   Motivation and Background

Prognostic techniques, in the context of structural health management of engineering systems, aim to forecast the future performance of a system to aid in maintenance decisions. Such forecasts are achieved by building a prediction model based on measurements collected from the system over a certain period of time. Motivated by the recent success of prognostic techniques as applied to mechanical systems, this thesis examines the applicability of prognosis in evaluating the future structural integrity of historic masonry structures. Many historic unreinforced masonry monuments stand in a structurally degraded state due to accumulated effects of aging, which makes timely maintenance of these structures even more crucial compared to newer construction. Successful implementation of prognostic techniques for historic masonry has potential to aid in planning of such timely maintenance programs and thus in prolonging the remaining life of these culturally and historically important monuments.

In monitoring long-term structural performance, however, nondestructive measurements are often corrupted by extraneous noise caused by the response of the structure to short-term loads and effects that are not of primary concern in the prognostic evaluation. For instance, if prognostic evaluations are conducted by exploiting the measured displacements to evaluate long term settlement of the foundation, then deformations caused by short term loads, for instance wind, would induce what is referred to herein as *noise*. Such noise convolutes the relevancy of the measured

responses for long-term prognostic evaluation, and thus, negatively affects the prognostic predictions. Consequences of such errors may result in unconservative (or overly conservative) predictions of the remaining useful life of a structure, thereby reducing the value of the prognostic evaluations. Only if the prognostic techniques are matured to become insensitive to such unavoidable noise present in measurements, will this useful technology begin to gain practical application in the civil engineering community, and in particular, for maintenance planning of masonry heritage structures.

This thesis addresses precisely the problem of developing a prediction model that is robust to non-stationary extraneous noise for prognostic evaluation of long-term structural health of existing structures.

1.2. Summary of Main Contributions

This thesis contributes to the structural health assessment of historic masonry structures by both examining the appropriateness of prognostic techniques for the aforementioned application and improving upon an existing prognostic technique.

The types of damage suitable for such a framework must occur gradually and must be detectable through non-destructive evaluation tools available for masonry construction. One type of damage that is common to masonry construction and is amenable to be implemented in a prognostic framework is structural damage induced by long term, gradual settlement of foundation, which is the focus of this study. However, many other forms of structural degradation caused by thermal loads and overloading, for example, are also identified as suitable for prognosis.

Inspection techniques for monitoring these damages must be able to globally assess the effect of these damages on the structural integrity of the system. Measurements of structural response, such as vibrations and strains, are viable response features for use in prognosis provided that their sensitivity to damage is confirmed *a priori*. These damage sensitive measurements can be utilized to form a prediction model in order to forecast future responses of the structure.

Among the available techniques for prognostic evaluation, Support Vector Regression (SVR) shows particular potential for applicability to historic masonry structures as it is capable of handling the nonlinear responses of masonry assemblies due to the complexity of their materials and geometry. Although SVR has an inherent capability to achieve a compromise between fitting accuracy and complexity of a model, the established literature lacks a clear definition for the optimality of this trade-off. In this study, this optimality condition is identified to be dependent on the noise level present in the measurements. This thesis contributes to the body of knowledge by proposing an approach for selecting the optimal trade-off between fitting accuracy and complexity of the trained SVR model in an adaptive manner. The proposed approach, referred to as adaptively weighted Support Vector Regression, focuses on achieving optimal prediction accuracy (instead of fitting accuracy) such that the amount of flatness in the model best accounts for noise. The procedure is repeated in an iterative manner as new data become available, thus updating the optimal trade-off.

The performance of this approach is demonstrated on simulated settlement data obtained from a finite element model of a historic masonry coastal fortification, Fort

Sumter located in Charleston, SC. The findings presented in this study reveal that the proposed approach is superior in the accuracy of the prognostic evaluation compared to the other approaches that primarily focus on improving the fitting accuracy.

1.3.   Organization of the Thesis

Chapter Two of this thesis presents a review of not only the established literature on prognostic evaluation but also the available inspection techniques for masonry construction with an objective to relate these two disassociated areas of knowledge, thus laying the foundation for prognostic evaluation of historic masonry. The findings obtained in Chapter Two are submitted to the Journal of Cultural Heritage and are currently under review.

Subsequently, Chapter Three of this thesis presents the proposed adaptively weighted SVR approach. In this chapter, theoretical background for SVR as well as the algorithmic development for adaptive weighting are presented. Furthermore, the application of this proposed approach is demonstrated on the settlement induced damage of a coastal fortification, Fort Sumter in Charleston. The findings obtained in Chapter Three will be submitted to the Journal of Performance of Constructed Facilities.

CHAPTER TWO

A REVIEW ON PROGNOSTIC EVALUATION OF HISTORIC MASONRY STRUCTURES: PRESENT CHALLENGES AND FUTURE DIRECTION

2.1.   Introduction

In the context of structural health management of engineering systems, prognosis is defined as the estimation of a system's *remaining useful life* (RUL) to aid in maintenance decisions [1]. In essence, RUL is the remaining time in which the system is usable before corrective action is required. The RUL depends on the rate of degradation of a system, which in turn depends on the system's initial design and construction, operational and environmental conditions, and current state of disrepair. All of these qualities that must be considered in prognostic evaluation are imprecisely known and thus, uncertainties are inevitably introduced to the prognostic evaluations. Therefore, a prognostic technique should not only provide an estimation of the RUL, but also specify the confidence level associated with such predictions [2].

Prognostic evaluation consists of four main stages: monitoring, diagnostics, prediction, and maintenance [1]. The first step entails monitoring user selected, damage-sensitive *features* of a system (e.g. vibration modes frequencies, modal parameters, peak values, etc.) obtained from the system through a series of sensors or onsite inspections beginning at time t_0 [3]. In the diagnostic phase, these features, monitored continuously or intermittently, are then pre-processed to assess the current health state or performance of the system. When repeated successively, diagnosis supplies information that can be used to train statistical models that can forecast the system's future health state. The remaining

time prior to the point at which the predicted health state intersects the corresponding user-defined failure threshold at the system's end of life, t_{EoL}, defines the remaining useful life (RUL) of the system (see Figure 2.1). This failure threshold is a conservative limit on damage level, beyond which the system is inadequate for its intended use. Therefore, t_{EoL} does not necessarily signify complete system failure. In the final step, based upon the estimated RUL, maintenance actions are scheduled for time t_m to extend the RUL of the system (see Figure 2.1) [1], [4].

Figure 2.1. Estimation of the RUL.

There are three significant technological and financial advantages in using prognostic evaluation for determining the well-being of historic masonry monuments: (i) ensuring structural safety, (ii) reducing unnecessary maintenance, and (iii) preventing secondary damage. These advantages are due to the ability of establishing condition-based maintenance, in which the predicted condition of the system determines when maintenance is required, unlike time-based maintenance, which predetermines the maintenance schedule based on time-steps in the system's life, regardless of the system's

health state [5]. The prognostic evaluation has been widely applied across many fields including medicine [6], weather and climate [7], nuclear energy [8], finance [9], economics [10], automotive [11], aerospace [12], and electronics [13]. However, prognostics have yet to be applied to masonry heritage structures.

In this chapter, prognostic concepts available in the literature are evaluated for their potential applicability to masonry structures. The limitations and challenges of using prognostic techniques for masonry are discussed. Finally, necessary future advancements for prognostic evaluation to be a practical solution for historic masonry monuments are identified. The organization of the chapter begins with a discussion in Section 2.2 of crucial factors contributing to the degradation of masonry that are amenable for incorporation into a prognostic framework using appropriate inspection methods. In Sections 2.3 and 2.4, common prognostic approaches are introduced and various established prognostic techniques are reviewed. An overview of the challenges faced as well as the future direction in the application of prognostic techniques to masonry follows in Section 2.5. Finally, concluding remarks are provided in Section 6.

2.2. Masonry Degradation and Inspection

This section details the types and sources of degradation of masonry structures along with inspection techniques suitable for prognostic evaluation.

2.2.1 Masonry Degradation Suitable for Prognosis

Prognosis is limited to predictable loads and environmental conditions and is challenged when the system responds to conditions that alter the rate of RUL depletion

[2]. Therefore, prognosis is unable to predict performance degradation resulting from uncontrollable events such as earthquakes or abrupt support settlements. Hence, for a form of structural degradation in masonry construction to be amenable for prognostic evaluation, it should be gradual.

The types of damage prevalent in historic masonry structures can be classified into two main categories, material degradations and structural degradations. Material degradation is essentially a durability problem that originates from a wide range of local physical, chemical, or biological processes that attack the composition of the material. If widespread or progressing in a compounding manner, material degradation can lead to structural degradations reducing the system's structural performance [14].

Historic masonry monuments are exposed to many environmental impacts such as wind, weather, water, ice, and temperature variations that can cause erosion, cracking, loss of material, and other defects [14]. Moisture is a key factor in many of these processes causing damage from weathering, ice formation, capillary flow, and biological effects such as mold growth. Water is also a significant cause of chemical degradation as it acts as an agent that carries potentially hazardous particles to components of the masonry and is easily involved in any chemical reactions that cause degradation [15].

Fluctuations of ambient temperature are also a significant cause of material degradations (Figure 2.2). In the summer months, increased exposure to direct sunlight elevates daytime surface temperatures, which can drop up to 50°C to air temperature at night. In winter, low temperatures of the stone surfaces can result in significant tensile stresses in the materials. These temperature variations cause strains in the stones, mortar,

and bond region due to the mutual deformation restraint, causing cracks in the masonry assembly [16].

Figure 2.2. Deformation of natural stones in historical masonry as a result of thermal elongation [16].

Structural degradation is a reduction in resistance properties, such as load carrying capacity of structural elements [17]. Processes such as foundation movement, thermal loads, and overloading as well as accumulated effects of material degradation can cause time-dependent structural degradations, which can take the form of cracks, inelastic hinges, and other structural discontinuities and present a safety issue that must be counteracted with condition-based maintenance [14].

Foundation movement is a particularly common problem for historic masonry structures due to the heaviness of the construction, coupled with inadequate bearing capacities of deteriorating soil conditions [18]. As masonry is primarily designed to carry loads in compression, the tensile stresses resulting from differential support settlement cause cracks, which in severe cases, can lead to structural discontinuities and inelastic internal hinges [19].

2.2.2 Masonry Inspection Suitable for Prognosis

For an inspection technique of historic masonry to be suitable within a prognostic framework, it should (i) be automated, (ii) provide quantitative, objective information, (iii) implement non-destructive analysis, (iv) assess the global condition of the structure, and (v) present an indication of the system's structural integrity. Manual inspection techniques, although frequently used, are not only laborious, but in some cases are limited to being qualitative and subjective [14]. Furthermore, manual inspection cannot practically obtain the continuous monitoring necessary to effectively track the structural condition of the monument. Therefore, quantitative, objective techniques suitable for automation are desired for prognostic application.

Often, conventional masonry inspection techniques are semi-invasive involving either drilling coupons or cutting slots [20]. Therefore, non-destructive techniques that facilitate the monitoring of unaltered historic masonry structures without inflicting any additional harm on cultural heritage are preferable. On the other hand, many existing non-destructive techniques such as the acoustic impact method [21], the impact-echo method [22], and the ultrasonic wave propagation method [23] are localized, requiring *a priori* knowledge of and access to the damage location. In practical applications, however, the presence and/or vicinity of structural degradation is unknown. Contrarily, inspection techniques that encompass the effects of the structural degradation on the structure as a whole can eliminate the need for preliminary knowledge regarding structural damage and degradation. Such techniques typically monitor global properties of the structure [24].

Furthermore, masonry inspection techniques that supply direct information on the structural health are preferable. For instance, the masonry moisture content, although identifiable using radar and thermography tests [25] [26], yields little information regarding the potential degradation in the structural integrity. Material deterioration due to moisture, which results in structural degradation, requires time to progress, during which moisture content can fluctuate making it difficult to directly link the moisture content to structural health. Likewise, direct measurements of other damage causing features, masonry temperature and degree of settlement for example, often do not explicitly indicate the extent of damage and overall structural performance of the masonry structure.

Dynamic or vibration testing employs sensors attached to a structure to measure the structure's vibration responses. These methods most commonly measure modal parameters (e.g. frequencies, mode shapes, and modal damping) which are functions of the structural properties (e.g. mass, stiffness, and damping) such that changes in the structural properties are indicated by changes in the modal parameters [27] [28]. When sensors are advantageously located to collect vibration data identifying the parameters of interest, this inspection method is valuable for monitoring historic masonry structures within a prognostic process [18] [3]. However, there remains a need to directly link the vibration response measurements to the remaining load carrying capacity of the masonry monument, which is the main property of concern in prognostic evaluation [29].

2.3. Prognostic Approaches

The choice of prognostic approach is determined by factors including data availability, dominant failure or degradation mode of interest, knowledge of the system at hand, modeling capabilities, accuracies required, and importance of the application. Prognostic methods can be classified into two main approaches: *model-based* and *data-driven*. The model-based approach exploits mathematical models for system representation and prediction, while data-driven assessment draws on previous measurements of the healthy system to estimate the future damage state [30].

Model-based prognostics are based on the assumption that an accurate numerical model can be developed to predict the system response. Consistency checks between the measurements of the real system and outputs of the numerical model produce residuals for detecting irregularities. The principle assumption is that the residuals are large in the presence of damage and small in the existence of normal disruptions, noise, and modeling errors. Statistical techniques (e.g. minimization of total cost per unit time) or, more commonly, utilization of prior knowledge or engineering judgment is employed to define the threshold, beyond which the system is considered to be significantly damaged [31]. The main advantage of the model-based approach using a physics-based model is its ability to incorporate a physical understanding of the system in monitoring. Since variations in response features are related to the model parameters, deviations in the model parameters resulting from either structural degradation or damage can be back-calculated by exploiting the measured changes in response features from the healthy system to the current system. Therefore, model-based methods can establish a functional

mapping between the physical parameters and the selected prognostic features. Also, model-based approaches can predict the response of a system under new loading conditions and system configurations [30]. Thus, model-based approaches can significantly outperform data-driven approaches [31].

The data-driven prognostic approach, also referred to as the data mining approach in the prognostic literature, is based upon previous system data that is a collection of measurements over time from sensors of damage indicators [32]. Features are extracted from the previous measurements and analyzed for trends during the system's lifetime. The assumption is that the statistical parameters of data are relatively identical unless malfunctioning occurs in the system. RUL predictions can then be extrapolated from the data-driven model. The strength of data-driven methods lies in the transformation of high-dimensional noisy data into lower dimensional 'information' for diagnostic and prognostic decisions. However, these methods have the inherent disadvantages of untoward reliance upon the quantity and quality of the system operational data for efficacy. In other words, data-driven methods perform poorly when the engineer wishes to either classify the nature of the change or if the structure is overly complex [33]. Also, data-driven prognostics require historical data to train the model, but often there is insufficient historical or operational data to obtain health estimates and determine trend thresholds used for RUL predictions [34] [19].

2.4. Prognostic Algorithms

While by no means is an exhaustive compilation of all prognostic algorithms provided, this section presents a brief description of widely implemented prognostic approaches.

A form of model-based prognostic evaluation, the physics of failure approach, assumes that the dominant failure modes (i.e. types of failure) and mechanisms (i.e. processes leading to failure) of a system at a particular life-cycle loading condition can be identified and used to develop physics-based damage models of expected system operating conditions [35]. However, this approach, conceived for systems in which life-cycle loading and failure mechanisms are known and multiple replicates of the system are available, is not suitable for inimitable historic masonry structures [36].

Data-driven approaches use supervised learning methods, namely machine learning, to recognize patterns in input-output training data and utilize the defined patterns to predict outputs given new input data [37]. Machine learning methods include for instance support vector machines, autoregressive moving average models, neural networks and grey prediction models. The support vector machine is reported to outperform both the autoregressive moving average model and the recurrent neural network in the accuracy of RUL predictions [38]. Support vector regression is noted to offer high accuracy, provide good generalization, and handle very high non-linearity, all of which are essential for prognostic schemes applicable to masonry structures [39] [40]. The grey prediction model is reported to achieve similar accuracy to autoregressive

moving average models while requiring less data [41] [42] and yielding conservative results [43].

Machine learning methods, such as support vector machines and grey prediction models, have great potential and appear to provide a feasible approach to prognostic evaluation of historic masonry. Model-based prognostics implemented in combination with data-driven approaches may however be the most ideal prognostic approach to historic masonry when sufficient data about the structure is available to support the development of the damage model.

2.5. Challenges and Future Direction in Prognostics as Applied to Historic Masonry Construction

The presence of uncertainties is a major issue in the prognostic health monitoring of historic masonry construction. In model-based approaches, uncertainties arise from assumptions made during model creation. Masonry construction tends to be very complex and behaves non-linearly because of the properties of its multiple components (i.e. brick/stone, mortar, grout, and accessory materials) and even more so when accumulated degradation and damage is present. These properties must be acknowledged to accurately model a masonry structure and assess its damage state [44]. Uncertainties in model input data are caused by variability in material properties, construction inconsistency, and the often necessary estimation of the initial state of the system. In data-driven approaches, uncertainties inevitably exist in measurements due to the inability to accurately detect the global structural response, the dependency of the measured structural response to input force levels, and the nonlinearity introduced by existing structural damage (i.e. opening

and closing of existing cracks) during non-destructive evaluation as well as the loss of information in data reduction. Within either prognostic approach, the accuracy of the prognostic method is affected by how well these relevant uncertainties are addressed [2].

Limitations in budget make it impracticable to fully detect every form of damage in a historic masonry structure. Non-destructive or semi-invasive inspection techniques, which are required for the analysis of historic masonries, are unable to provide equivalent knowledge of the strength and performance of a structure obtained from destructive testing [45] [29]. Therefore, research should carefully determine appropriate response features monitorable using non-destructive techniques.

Selected response features must be sensitive to the damage types of interest. However, sensitivity of these features to damage depends on each unique structure as well as the type and severity of damage present. As no one particular response feature is sensitive to all damage types, collection and assimilation of multiple response features would increase the likelihood of encompassing various damages attributing to the overall health state. Furthermore, past research has shown that the sensitivity of response features may vary with damage level [46]; thus future studies should evaluate the sensitivity of response features for variable damage levels.

Additionally, response features that are insensitive to extraneous noise due to natural variability in environmental and/or operational conditions are desireable. Many response features, especially those that are indicative of the dynamic behavior of the structure, are influenced by operational or environmental conditions, such as wind, temperature, and excitation level. Although it is a customary practice to incorporate

measured temperature and wind in the diagnostic processes applied to civil infrastructure systems, for historic masonry structures the effect of moisture absorbtion on the structure's stiffness and mass and consequently its dynamic response must also be considered [47].

Monitored features must provide a global assessment of the structural system instead of indicating localized behavior. The difficulty of exciting the structure uniformly through controlled excitation devices makes obtaining global vibration responses challenging. Because of the flexibility of masonry structural joints, the behavior of connections between structural components relies on frictional and mechanical properties of the material and thus tends to be load dependent. Practical difficulties such as optimal sensor and excitation placement [46] for identification of the global response must also be resolved.

An alternative to global assessment is *distributed prognostics*. Because historic masonry structures are often large in size and complex in behavior, it may be cost and time effective to analyze different parts of the system separately. A decomposition of the prediction can be developed into local predictions in order to attain a completely distributed prognostics process using several sub-models of the whole model. Separate predictions can be estimated according to the results of each component [48].

Information provided by the selected response features must be straightforwardly linked to the structural integrity of the historic masonry structure. As the relationship between structural health quantities, such as remaining load carrying capacity, and commonly implemented response features in diagnostic evaluations of civil infrastructure

systems is currently unknown, future research establishing this link between features and structural integrity is imperative.

Hence, not only must the most appropriate damage sensitive features for monitoring historic masonry be determined, but these features must be interpreted to gauge structural stability and overall performance of the structure. Measuring these features through a continuous structural health monitoring process, could increase the availability of data collection for more accurate RUL predictions, providing advanced warning of unfavorable structural conditions.

2.6. Conclusion

In this chapter, several masonry degradation schemes and inspection methods were elucidated for their applicability to be used in a prognostics process. General concepts in prognostics were emphasized in the Introduction prior to a subsequent literature review of existing prognostic techniques. Model-based and data-driven prognostic approaches were also presented coupled with a discussion of specific methodologies that may be adaptable to masonry structures. Depending on data availability and prior knowledge of the structure, an appropriate approach should be selected for predicting the RUL of the particular historical masonry structure. Finally, challenges and future work in employing prognostic techniques to masonry were discussed.

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CHAPTER THREE

ADAPTIVELY WEIGHTED SUPPORT VECTOR REGRESSION: PROGNOSTIC APPLICATION TO A HISTORIC MASONRY COASTAL FORTIFICATION

3.1.   Introduction

In recent years, a significant amount of research has been directed towards the development of prognostic methodologies to forecast the future health state of an engineering system assisting condition based maintenance. However, applications of these potentially useful and informative techniques to historic masonry structures are rare, if any. Developing prognostic methodologies for deteriorating historic masonry monuments and infrastructure affords the possibility of ensuring structural safety, reducing maintenance costs, and preventing secondary damage of such cultural heritage.

Among available prognostic models, Support Vector Regression (SVR) shows a distinct potential for application to historic masonry construction as it offers high accuracy, provides good generalization, and handles nonlinearity (Müller et al. 1997; Samanta and Nataraj 2008; Haydock and Atamturktur 2013). The predictive performance of SVR however, relies on the complexity of the model determined by the tradeoff between fitting accuracy and flatness. The dual objective of SVR then seeks to find the flattest possible model while simultaneously minimizing fitting error (Smola and Schölkopf 2004). The theory of SVR recognizes that more complex models may have greater fitting accuracy but are less generalizable to other datasets of similar underlying processes (Myung 2000). The optimal *weight*, defining the relative importance of flatness to fitting accuracy, however is dependent upon the noise resulting from extraneous

loading conditions, such as live, wind, or temperature loads that are time-variant. It must be noted that such extraneous loading conditions are different than causal effects of long term deterioration. Therefore, it becomes important to adjust the *weight* as new measurements become available to obtain a model complex enough to provide a close fit to data but simple enough to predict global trends well.

The article begins with a review of established literature on prognostic evaluation in Section 3.2. Main concepts and governing equations for SVR are given in Section 3.3 followed by a discussion on the adaptively weighted SVR approach. Section 3.4 then presents the historic masonry case study structure and applies the adaptively weighted SVR to improve forecasting accuracy in the prognostic evaluation. A discussion of the results as well as a summary of the contributions of this study concludes the chapter in Sections 3.5 and 3.6.

3.2. Background on Prognostic Evaluation of Historic Masonry

Prognosis, in the context of structural health management of engineering systems, is the estimation of a system's remaining useful life, beyond which, corrective action is required (Saxena et al. 2009). Prognostic techniques are suitable for forecasting gradual degradation processes as opposed to damages caused by sudden unpredictable events. Thus, prognosis is an acausal problem, meaning that it requires knowledge of future loading and operating conditions to make accurate predictions. As future conditions are typically unknown and uncontrollable, conjectures of expected future loading environments must be made based on the history of the structure (Saxena et al. 2010).

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The main objective in the implementation of prognostic techniques therefore is to enable educated planning of maintenance of the evaluated system (EI-Tawil et al., 2011). Such improvement in the management of engineering systems has been made possible by prognostic evaluation in many fields; however, prognostic evaluation of masonry heritage structures is in its infancy. With prognostic techniques fully developed and successfully applied to historic masonry monuments, timely condition-based maintenance and restoration efforts can be planned and the life of such heritage structures can be prolonged.

Masonry construction is prone to experience gradual degradations affecting structural integrity in two forms: material degradations resulting mainly from environmental impacts, and structural degradations resulting mainly due to applied loads or movement of supports (Haydock and Atamturktur 2013). Of the latter, differential support settlements are common in masonry structures due to the heavy weight of the construction and are particularly detrimental to the integrity of the structure due to the low tensile capacity of unreinforced masonry.

Non-destructive inspection techniques with potential to be automated that provide an indication of the global (rather than local) structural integrity are desired for prognostic evaluation of historic masonry structures. Particularly, vibration responses that monitor damage sensitive features supply a viable solution to providing a diagnostic assessment of the structure.

3.3.   Methodology

This section briefly discusses the theory behind support vector machines for regression (SVR) and introduces an approach for adaptively weighting the flatness to fitting accuracy in training SVR models to improve prediction accuracy.

3.3.1   Support Vector Regression

Motivated by results of the statistical learning theory (Vapnik 1998), Support Vector Machine (SVM) is a learning algorithm based on the structural risk-minimization principle, which finds a balance between model complexity and fitting error (Xu et al. 2012). In contrast to other machine learning approaches, such as neural networks, that are prone to overfitting the data and having poor generalization capabilities, SVM can allow a predetermined degree of flatness in the model to avoid overfitting (Burges 1998; Xu et al. 2012). Furthermore, most SVMs solve a quadratic programming problem, which finds the optimal solution and assures that the obtained solution is the unique global solution

Originally created for cluster analysis of datasets belonging to separate classes or categories, SVM seeks to maximize the margin around the linear hyperplane dividing the linearly separable classes (Schölkopf et al. 1995; Xu et al. 2012). In cases where a linear hyperplane (i.e. model) is inappropriate for adequately separating data, a nonlinear model must be obtained by mapping the original data into a new high dimensional feature space through the use of kernels. With the use of kernel functions, the SVM operations are performed in the input space rather than the higher dimensional feature space, thereby reducing the computational demands of high dimensional problems (Gunn, 1998).

SVMs were extended to solve regression problems for model estimation with the addition of an appropriate cost function called the *loss function* (Vapnik 1998). Several types of loss functions have been offered (e.g. quadratic, ε-insensitive, Huber, etc.); thus, the user must select the loss function that best suits the problem (Smola and Schölkopf 2004).

The basic principles of SVM for regression, known as Support Vector Regression (SVR), can be illustrated for a training dataset $\{(x_1, y_1),(x_2, y_2),\ldots,(x_n, y_n)\}$ of size n. Although more complex kernel functions are available and will be mentioned later, this discussion begins by using a linear kernel function (i.e. linear hyperplane) for simplicity. The linear kernel function, $f(x)$, can be used to solve the following regression problem,

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

where w is the coefficient and b is the constant offset known as bias. The model given in Eq. (1) is trained using a subset of the training dataset that constitutes the decision boundaries or margin bounds as shown in Figure 3.1 (Schölkopf et al. 1995). This subset of data points is referred to as the *support vectors*. The complexity of the model depends on the number of support vectors by which it is represented and is independent of the dimensionality of the input space (i.e. size of input data) (Smola and Schölkopf 2004; Drucker et al. 1997). Generally, seeking a small w in Eq. (1) decreases the percentage of data points utilized as support vectors thus, reducing model complexity and increasing model flatness (Smola and Schölkopf 2004).
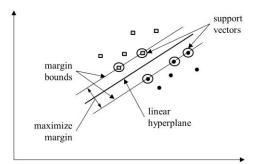
Figure 3.1. Support vectors and margin bounds.

The regression model is determined by the convex optimization problem:

$$\text{minimize} \quad \tfrac{1}{2}\|w\|^2 + \frac{1}{\lambda}\sum_{i=1}^{n}(\xi_i + \xi_i^{*}).$$

$$\text{subject to} \quad \begin{cases} y_i - \langle \mathrm{w}, \mathrm{x_i} \rangle - b \leq \xi_i \\ \langle \mathrm{w}, \mathrm{x_i} \rangle + b - y_i \leq \xi_i^{*} \\ \xi_i, \xi_i^{*} \geq 0 \end{cases} \tag{2}$$

in which the regularization parameter λ is traditionally a pre-specified constant that determines the effect of the slack parameters, ξ, ξ^{*} (i.e. the errors calculated by the loss function) on the objective function. When λ→0, maximizing fitting accuracy (i.e. minimizing fitting error) is the main objective of the optimization. Conversely, when λ→infinity, maximizing model flatness (i.e. minimizing complexity) becomes the main objective of the optimization. Therefore, applying λ>0 achieves a compromise between fitting accuracy and flatness is achieved.

By minimizing Eq. (2), a balance is found between complexity, $\tfrac{1}{2}\|w\|^2$, and overall fitting loss, $\frac{1}{\lambda}\sum_{i=1}^{n}(\xi_i + \xi_i^{*})$. This balance ensures that the obtained model

generalizes well preventing the model from fitting to noise, also known as overfitting. As a result, the model sensitivity to noise is reduced.

The loss function used in this study is the quadratic loss function, however other loss functions, such as ε-insensitive or Huber (Gunn 1998) are also available. The quadratic loss function can be written as follows:

$$L_{quad}\left(f(x)-y\right)=\left(f(x)-y\right)^{2},$$
(3)

To measure the error between the observed and estimated outputs for a given input, Eq. (3) uses the conventional least squares error criterion as shown in Figure 3.2.
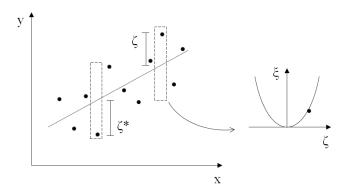

Figure 3.2. Quadratic loss function for a linear SVR.

The solution to Eq. (2) in the quadratic loss function formulation is given by,

$$\max_{\alpha,\alpha*}W(\alpha,\alpha*)=\max_{\alpha,\alpha*}-\frac{1}{2}\sum_{i=1}^{l}\sum_{j=1}^{l}(\alpha_i-\alpha_i*)(\alpha_j-\alpha_j*)\left\langle x_i,x_j\right\rangle+\sum_{i=1}^{l}(\alpha_i-\alpha_i*)y_i$$
$$-\lambda\sum_{i=1}^{l}(\alpha_i^2-\left(\alpha_i*\right)^2).$$
(4)

By exploiting Karush-Kuhn-Tucker conditions,

$$\overline{\alpha}_i,\overline{\alpha}_i*=0,\quad i=1,\ldots,l,$$
(5)

the optimization problem can be simplified as,

$$\min_{\beta} \frac{1}{2} \sum_{i=1}^{l} \sum_{j=1}^{l} \beta_i \beta_j \langle x_i, x_j \rangle - \sum_{i=1}^{l} \beta_i y_i + \lambda \sum_{i=1}^{l} \beta_i^{2} \ . \tag{6}$$

with constraints,

$$\sum_{i=1}^{l} \beta_i = 0 \ . \tag{7}$$

The regression model is given by Eq. (1) where

$$\bar{\omega} = \sum_{i=1}^{l} \beta_i x_i$$
$$\bar{b} = -\frac{1}{2} \langle \bar{\omega}, (x_r + x_s) \rangle. \tag{8}$$

In Eqs. (4, 6 and 8), the dot product, $\langle x_i, x_j \rangle$, can be replaced by a kernel function

to map the linear SVR formulation to solve a nonlinear problem, a process widely known

as nonlinear mapping (Gunn 1998). Various kernel functions, such as polynomial, spline

and radial basis functions are available for nonlinear mapping. Due to their flexibility and

consistency of fitting and predicting with minimal residual error in comparison to other

kernels, splines are a common kernel function of choice in SVR modeling (Gunn 1998;

Mammen 1997; Rajasekaran et al. 2008); thus, the remainder of the chapter will focus on

the spline kernel.

3.3.2 Adaptively Weighted Support Vector Regression

The trade-off between fitting accuracy and flatness of an SVR greatly affects the

predictive performance of the prognostic evaluation. This principle is evident in Figure

3.3: models that are *too simple*, as shown by λ=2 on the left in Figure 3.3, may neither be

able to fit the available data nor be able to generalize the trends well. Models that are *too*

complex on the other hand may accurately fit the available data, as shown by λ→0 on the left in Figure 3.3, but may not be able to generalize the trends well. Therefore, there is an optimal degree of flatness, as shown by λ=0.01 on the right in Figure 3.3 that finds a more suitable compromise between fitting error and flatness.
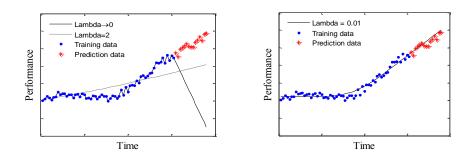

Figure 3.3. Trade-off between flatness and goodness of fit varying from (left) more

extreme λ values to (right) more compromising λ value.

This optimal flatness depends on the extraneous noise present in the measurement. In measuring the structural responses of a system as in the case of the present study, extraneous noise may be incurred in the measurements due to the responses of the structure to sources other than those that cause long term degradation. For example, in using vibration measurements to monitor damage within a historic masonry structure caused by long term, gradual settlement of the foundation, wind and other external short term loading effects can influence the response of the structure, consequently adding noise to the data. Thus, the optimal λ is that which generalizes global trends in the presence of noise.

The dependency of optimal flatness to noise levels is demonstrated in Figure 3.4. In noise-free datasets, λ→0 (i.e. giving zero weight to flatness) may provide a suitable model as shown in Figure 3.4 (a). As noise increases, however, a larger λ is required,

meaning that more weight is given to flatness than fitting accuracy, to achieve a similar trend as presented in Figures 3.4 (b) and (c). Therefore, λ must be correctly determined for a given dataset to ensure reliable predictions of the future health state of the system.
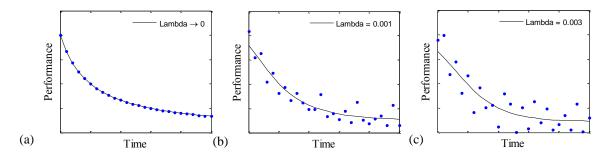

Figure 3.4. Magnitude of λ required to fit a given trend as noise is added.

Cross-validation has been used for selecting the λ by utilizing hold-out experiments; however, this technique focuses solely on fitting accuracy (in an interpolative manner) rather than prediction accuracy (in an extrapolative manner) (Stone 1974; Jaakkola and Haussler 1999; Smola and Schölkopf 2004). Because a prognostic evaluation requires accurate extrapolative projections of the future health of the structure, the focus in this chapter is to improve the forecasting accuracy of the model rather than its closeness of fit to available data. Hence, the optimal λ is selected by that which predicts with the least error a predetermined number of most recent measurements that are not used in training the SVR model. As the global trends and noise levels may change over time, a constant λ may not be the best approach to applying flatness. Here, the proposed method adaptively selects λ and thus that is referred to as adaptively weighted SVR.

The basic steps of this adaptively weighted prognostic approach can be demonstrated on an initial dataset of *n* points. In Figure 3.5, the dataset is divided into

three parts: the *preliminary training set* consisting of the first *m* points, the *hold-out set* consisting of the following *h* points, and the *forecasting set* consisting of the next *f* points. During the preliminary stage, optimal λ is selected. For this, multiple candidate λ values (ten λ values for each multiple of 10 from 10^{-15} to 10^5) are tested in their ability to predict the hold-out set of *h* points from *m* to *n*, where $n = m + h$. The resulting L1 norm prediction error of the hold-out set is summed for each model trained by a different candidate λ, and, by comparison, the candidate λ producing the model with the least prediction error over the hold-out set is chosen as the optimal λ. During the forecasting stage, this optimal λ is then used to train a refined model using the total dataset that was used in the preliminary stage (i.e. up to *n*) to predict the forecasting set (i.e. from *n* to *p*). The adaptively weighted approach then repeats this process as additional measurements become available by adding these *new* data points to the training set and updating λ accordingly. The detailed steps of this process are shown in Algorithm 1.
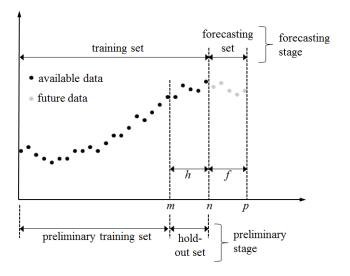

Figure 3.5. Dataset divisions for preliminary and forecasting stages of adaptively weighted SVR.

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Table 3.1. Pseudocode for adaptively weighted SVR.

Algorithm 1. Basic structure of adaptively weighted SVR

Begin
Input *SVR parameters*
- *X = independent variable*
- *Y = dependent variable*
- *h = number of hold-out points*
- *f = number of forecasting points*
- *P = total number of iterations*
- *m = index of final point in preliminary training set*
- *n = index of final point in hold-out set*
- *p = index of final point in forecasting set*

For *i = 1* **to** *P*
      For $\lambda = 10^{-15}$ **to** 10^{5}
- *Train a support vector regression model (see Gunn 1998) using preliminary training set, X_1 to X_m, and forecast the hold-out set, X_m to X_n*
- *Compute the L1 norm residual error of the predicted hold-out set by comparison to the corresponding subset of Y*

      End
- *Choose optimal λ as that which gave the least prediction error of the hold-out set*
- *Train a support vector regression model using training set, X_1 to X_n, and predict the forecasting set, X_n to X_p, where $X_{p = X_{(n+f)}}$*
- *Compute the residual error of the predicted forecasting set*
- *Define new input parameters:*
  - $X^{i+1}_m = X^i_n$
  - $X^{i+1}_n = X^i_p$

End
End

3.4. Case Study

Coastal fortifications built as defense mechanisms in protecting important seaports and harbors, were once the cornerstone of national defense in the United States (McGovern and Smith 2006). Today, these coastal fortifications, many of which are over 150 years old, are considered structures of national heritage. Over their lifetime, these structures are subject to harsh coastal environmental and operational conditions leading

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to material and structural degradations. To successfully preserve these important historic edifices for future generations, timely maintenance is imperative. Prognostic evaluation can assure such timely maintenance campaigns.

Fort Sumter, in Charleston, South Carolina, where the first shots of the American Civil War were fired in 1861 (National Park Service 1984) is one such historically important fort that is in need of accurate structural assessment and prognostic evaluation. There is evidence that differential settlement of the foundation has been occurring at Fort Sumter leading to extensive cracks throughout the masonry casemates. Thus, this section demonstrates the weighted SVR prognostic technique as applied to one of the casemates of Fort Sumter considering gradual settlement of foundations.

3.4.1   Case Study Structure: Fort Sumter National Monument

The construction of the pentagonal-shaped clay masonry fort began in 1829 on a man-made island. In the years of the Civil War, Fort Sumter witnessed several battles that severely damaged the structure (National Park Service 1984). After several rounds of demolition and reconstruction, Fort Sumter was declared a national monument in 1948. The fort has since been maintained by the National Park Service and is currently accessible to visitors (see Figure 3.6).

Figure 3.6. Current aerial view of Fort Sumter (Courtesy: National Park Service).

3.4.2 Finite Element Model Development

The FE model of the single casemate used in this study as shown in Figure 3.7 is developed in Ansys 13.0 by incorporating data from on-site inspections and evaluations discussed in detail in (Atamturktur et al. 2013). Laboratory tests are conducted on core samples of the masonry and a masonry prism specimen from fallen debris in order to obtain the material properties. 3D laser scanning is performed to obtain the precise as-is geometry of the casemate with which the FE model geometry is constructed while preserving key geometrical features such as any permanent deformation, material deterioration, tilting of the walls. The FE model is developed using SOLID65 elements that are specialized for modeling concrete-like brittle materials (Özen 2006; Mahini et al. 2007). The SOLID65 element uses a smeared crack analogy to account for deformations due to cracking and crushing of the material. The linear material properties of the model are calibrated to experimentally obtained modal parameters (i.e. first two natural frequencies and mode shapes).
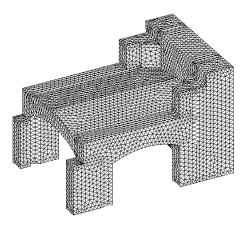

Figure 3.7. FE model of Fort Sumter casemate used in case study (refer to Atamturktur et al. 2013).

Because the barrel vaulted casemates are built adjacent to but detached from the scarp wall, the scarp wall and the casemate are two independent structural entities. Therefore, contact elements that allow sliding and separation (but do not allow penetration) of two adjacent components are used to model this interface. A dynamic hammer impact test was used to calibrate the friction coefficient accounting for the friction and cohesion (if any) at the interface to represent this possible sliding action in the FE model. To take into consideration the lateral interaction with the adjacent casemates, adjacent casemates are represented using substructuring techniques. To keep the size of the model to a manageable level, the foundations of the casemate are idealized as a series of linear springs having finite stiffness. Details of the model development process are provided in Atamturktur et al. (2013).

3.4.3   Simulations of Support Settlement

The FE model used to simulate support settlement is shown in Figure 3.8, where the casemate of interest is the center casemate with the adjacent casemates modeled as substructures. The ground below the casemates can be visualized as a rectangular plane as shown on the left of Figure 3.8. By tilting this rectangular plane in the direction perpendicular to the external wall as shown in Figure 3.8 (right), the settlement configuration is simulated. This configuration representing settlement of the external wall is used to obtain the structural response data for application of the proposed prognostic technique.
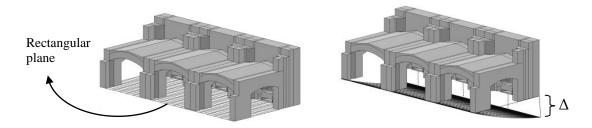
Figure 3.8. Initial model configuration on level surface (left) and settlement configuration

(right).

In the simulations, the ground plane of the casemate is gradually settled with a maximum displacement (Δ) under the scarp wall of from 2.5 mm to 100 mm at increments of 2.5 mm. The first principal strain at the two control point locations, Point 1 and Point 2, shown in Figure 3.9 are monitored during these settlement simulations. As shown in Figure 3.9, Point 1 is located at the base of the pier, and Point 2 is located at the springing of the arch. The resulting first principal strains at the two control points obtained from the simulated settlement are plotted in Figure 3.10 with randomly generated non-stationary noise added.
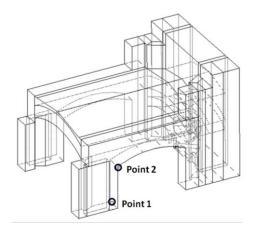

Figure 3.9. Locations Point 1 and Point 2 of monitored strains during settlement (circled).
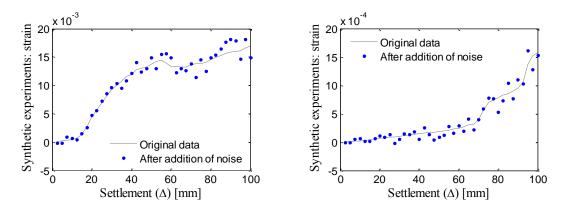
Figure 3.10. Settlement induced strains obtained from FE model of Point 1 (left) and

Point 2 (right) with added noise.

3.4.4   Prognostic Evaluation using Weighted SVR

The algorithm presented in the methodology section is deployed on the simulated dataset shown in the previous section. 15 data points simulating the strain response of the casemate under settlement up to 40 mm are assumed to be available for the prognostic evaluation. To determine the initial λ value, the first ten of these data points are used in the preliminary training set (up to 27.5 mm settlement) and the next five data points are used as the hold-out set (from 27.5 mm to 40 mm settlement) (refer back to Figure 3.5). Multiple candidate λ values between 10^{-15} and 10^5 are tested to find the optimal λ that yields the minimal error in predicting the hold-out set. With the identified optimal λ, a refined SVR model is trained and is executed to forecast the next five data points (from 40 mm to 52.5 mm settlement). This process is repeated as new measurement data become available, and the optimal λ is updated during each iteration. In this case study, a total of five iterations are completed to reach 100 mm settlement, thus the optimal λ is updated four times after it is initially determined in the first trial. The predicted response,

prediction error, and adaptively refined optimal λ obtained as a result of this analysis are

displayed in Figure 3.11 for Point 1 and Figure 3.12 for Point 2 (note that results shown

after the vertical dashed line in Figures 3.11 and 3.12 (a) and (b) are the compiled results

of the five forecasting iterations). For comparison, the predicted response and prediction

error of an SVR model trained using a constant λ of λ→0, which gives all weight to

fitting error and none to flatness, are also included in the figures.

(a)   (b)   (c)

Figure 3.11. Comparison of adaptively weighted SVR to non-weighted SVR using Point

1 data with increasing noise: (a) predicted response, (b) prediction error, and (c) λ value

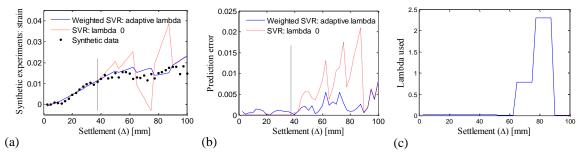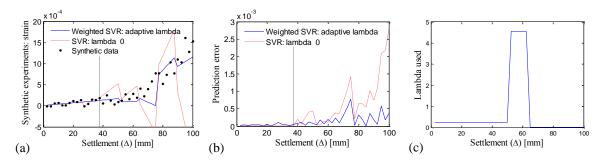used for prediction model.

(a)   (b)   (c)

Figure 3.12. Comparison of adaptively weighted SVR to non-weighted SVR using Point

2 data with increasing noise: (a) predicted response, (b) prediction error, and (c) λ value

used for prediction model.

As evidenced in Figures 3.11 and 3.12, the adaptively weighted SVR predicts the settlement induced strains with less than half as much error as the non-weighted approach (see Table 3.2). It must be noted that the noise added to the simulated data is non-stationary in nature. Therefore, the distinct advantage of the adaptive approach is its ability to recover the optimal λ as noise fluctuations occur over time, as is the case in practical *in situ* monitoring applications.

Table 3.2. Total prediction error for adaptively weighted SVR and non-weighted SVR.

SVR Approach	Point 1	Point 2
Adaptively weighted	0.0719	0.0057
Non-weighted	0.1898	0.0178

3.5. Conclusion

Although SVR is known for its superior prognostic abilities, the performance of this machine learning technique is reliant on the selection of an appropriate regularization parameter, λ, determining the tradeoff between fitting accuracy and model complexity (i.e. flatness). The optimal tradeoff is greatly affected by the presence of time-variant extraneous noise within measurements, which is common during *in situ* monitoring applications. Therefore, an ideal process for selecting optimal λ is one in which the model sensitivity to noise is decreased.

Within this chapter, an adaptive weighting approach for SVR is developed, which first determines the optimal λ based on forecasting accuracy, and then uses this optimal λ to develop a refined model for future predictions. As additional data becomes available in time, the optimal λ is updated allowing the new model to be adjusted for fluctuations in

noise intensity. Thus, the most suitable model complexity for a given dataset is selected for each set of predictions. In testing the performance of this approach on the simulated settlement response of a historic masonry coastal fortification, the adaptively weighted SVR shows greatly increased forecasting accuracy over the non-weighted approach.

The developed adaptively weighted SVR has potential to be incorporated in a structural health monitoring process to ultimately assist in preserving the cultural heritage by predicting its future structural integrity. However, future direction in research should focus on determination of appropriate damage sensitive features and corresponding monitoring techniques for prognosis of historic masonry structures. Furthermore, a failure threshold indicating the structure's end of life must also be defined. Such a threshold can only be defined by developing a link between nondestructive measurements and the remaining load carrying capacity of the masonry monument as suggested in Atamturktur et al. (2012), which is the primary attribute of concern in prognostic evaluation.

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CHAPTER FOUR

CONCLUSIONS

This thesis has first examined the necessary considerations in applying prognostic methodologies to forecast the future health state of historic masonry monuments. An evaluation of common masonry degradation schemes and the capabilities of existing prognostic frameworks suggests that forms of degradation appropriate for prognosis of historic masonry must be gradual in nature. One example of such degradation, which is studied in this thesis, is settlement induced damage resulting from differential support settlement. Such foundation settlement is common in masonry structures due to the heaviness of masonry materials. Periodic inspection techniques assessing these damages, to be applicable to prognosis, must provide quantitative measurements, be as sensitive as possible to the damage of interest, and reflect the global (rather than local) behavior of the structure eliminating the need for *a priori* knowledge of damage location. To be incorporated in a monitoring process, these inspection techniques must be conducted in an automated manner. However, these *in situ* measurements are often susceptible to detecting the responses of the structure to extraneous load conditions other than the primary loads of interest, thus corrupting the measurements with noise. Therefore, the prognostic technique chosen should attempt to eliminate the effect of this noise on predictions.

A prognostic technique known as Support Vector Regression (SVR) is particularly suitable for *in situ* prognostic evaluation of masonry not only because of its ability to handle nonlinearity in measurements, but because of its ability to avoid

overfitting to noise when training a prediction model. In SVR, the introduction of flatness in the prediction model decreases the model sensitivity to noise, thereby making the model more generalizable. In this thesis, SVR, which traditionally trains a prediction model with a predetermined constant degree of model complexity (or flatness), is enhanced to determine the optimal complexity of the model and allow the optimal complexity to be updated over time. In contrast to existing approaches that focus on improving the fitting accuracy, the approach proposed herein calculates the optimal complexity of the model based on forecasting accuracy. The adaptive selection of optimal flatness also increases the model robustness to variations in noise levels that might occur over time. When implemented in prognostic evaluation of a historic masonry coastal fortification, Fort Sumter, the adaptively weighted approach outperformed the non-weighted approach in forecasting accuracy.

As the application of this adaptively weighted Support Vector Regression technique for prognostic evaluation of Fort Sumter is among first efforts in applying prognostics to historic masonry, future research is necessary to further the potential of such prognostic evaluations. In this thesis, simulated strain measurements are exploited for development of the prediction model. In the future, studies should be conducted to determine the most sensitive features to the damage type of interest for implementation in a prognostic framework. Moreover, a link between these non-destructively measured features and the remaining load carrying capacity of the structure, an aspect that can be measured only through destructive measurements, should also be identified. This link is necessary to develop a *failure threshold* defining the level of damage at which the

structure reaches the end of its remaining useful life. With such information, timely maintenance campaigns can be planned. These important aspects, left out of the scope of this thesis, are essential for the future success of prognostic evaluation as applied to masonry construction.

With the prognostic methodologies for application to historic masonry structures matured, prognostic evaluation of the remaining structural integrity of masonry monuments and infrastructure can be implemented in a structural health monitoring process to provide early detection of damage and enable effective maintenance strategies of such cultural heritage.