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Machine learning algorithm hypothesis on smart gyroscopic tuned dampers for earthquake resistance buildings

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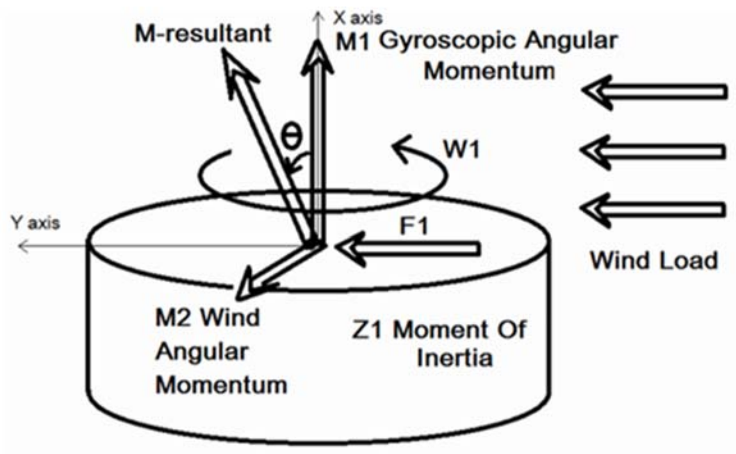
Abstract
The Research involves the hypothesis study of algorithms design for tuned mass dampers use in smart buildings for damping out earthquake and wind vibrations. Recent researches are done in the field of modifying tuned mass damper to improvise the reaction time and response range of the damper system. With the help of high end sensors an machine learning algorithm can be hypothesized that can help in developing self-learning damping system that utilizes the raw data from test vibration caused by wind loads and small scale earthquakes with well-defined and deeply studied vibration systems.

Keywords: Structural Analysis, Machine Learning, Tuned Mass Damper, Gyroscopic Damping.

1. Introduction
The design of gyroscope is described below for the smart damper to collect the raw data collection of the machine learning data. Gyroscope is designed to have controllable axis of rotation using hydraulic jack system. The resultant of angular momentum caused by wind with the gyroscopic angular momentum thus can be controlled. The higher value of M1 will reduce the angle made by the resultant angular momentum with the vertical. A set of such gyroscopes with high moment of inertia can be programmed to balance out any angular momentum dis-balance, either by wind load or by earthquake. A combination of such variable axis flywheel gyros can together damp any kind of vibration in the structure of installation. Above figure shows a gyroscope subjected to high wind loads. The M1 represents the flywheel angular momentum, while M2 represents the wind angular momentum by the Wind Load-F1. The resultant caused by these two combinations is inclined at an angle from the vertical axis. Z1 represents the moment of inertia of the flywheel. W1 is the anticlockwise angular velocity of the flywheel. Due to rotation kinetic energy an angular momentum M1 is induced in the gyroscope. This axis of rotation is now with an extra inertia or resistance towards any external force.



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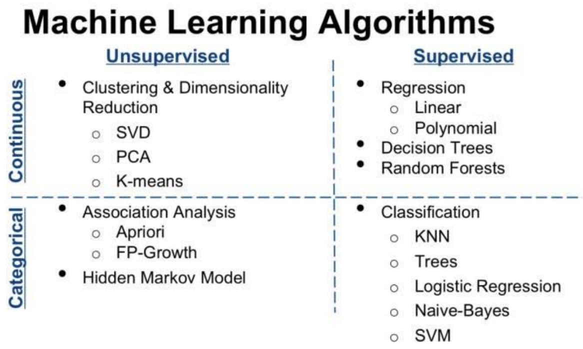
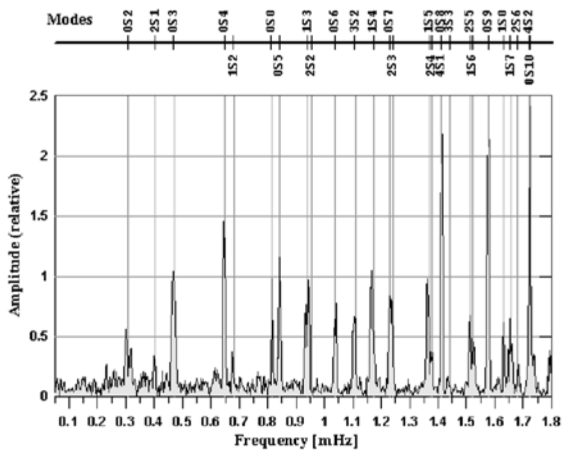
2 Raw Interpretation Mechanisms



The Raw data of the amplitude vibrations caused by well-defined wind load is collected as the raw data for the machine learning platform. The following shown algorithm methodologies are involved in the processing outline of the vibrational data from the self-stabilizing tuned mass damper.

3. Modes of Vibrations



Above shown is the vibrational modes collected by a raw data collecting device that calculates the behavior of the structures in an imposed vibrating load condition. The modes can be defined by calculating the relative amplitudes of the vibrations. The raw data collection is represented and processed in the form of relative amplitudes and the self-stabilizing logics of the damper is recorded for a well-studied and simplified vibration i.e. wind load. The relative behavior of the damper that is self-stabilizing in its nature can generate a fuzzy logic that will help in generating algorithms for machine learning process.

4. Non Linear Raw Data

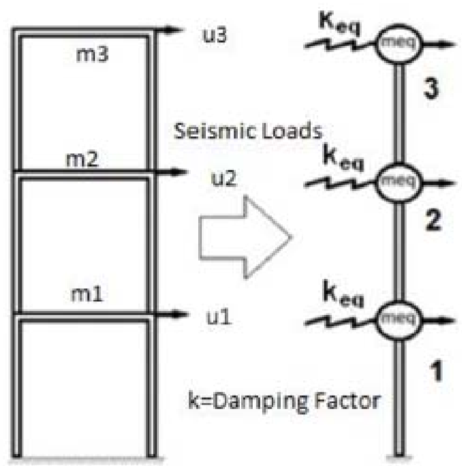
In general, linear procedures are applicable when the structure is expected to remain nearly elastic for the level of ground motion or when the design results in nearly uniform distribution of nonlinear response throughout the structure. As the performance objective of the structure implies greater inelastic demands, the uncertainty with linear procedures increases to a point that requires a high level of conservatism in demand assumptions and acceptability criteria to avoid unintended performance. Therefore, procedures incorporating inelastic analysis can reduce the uncertainty and conservatism. This approach is also known as "pushover" analysis. A pattern of forces is applied to a structural model that includes non-linear properties (such as steel yield), and the total force is plotted against a reference displacement to define a capacity curve. This can then be combined with a demand curve (typically in the form of an acceleration-displacement response spectrum (ADRS)). This essentially reduces the problem to a single degree of freedom (SDOF) system.

5. Unsupervised machine learning

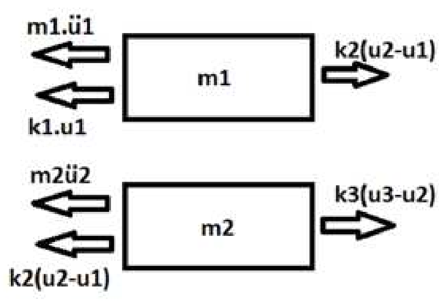
Unsupervised learning typically is tasked with finding relationships within data. There are no training examples used in this process. Instead, the system is given a set data and tasked with finding patterns and correlations therein. The use of Principle Component Analysis is described in the machine learning algorithms to be used; Principal component analysis (PCA) is a statistical procedure that uses an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components. The number of principal components is less than or equal to the number of original variables. This transformation is defined in such a way that the first principal component has the largest possible variance (that is, accounts for as much of the variability in the data as possible), and each succeeding component in turn has the highest variance possible under the constraint that it is orthogonal to the preceding components. The resulting vectors are an uncorrelated orthogonal basis set. The principal components are orthogonal because they are the eigenvectors of the covariance matrix, which is symmetric. PCA is sensitive to the relative scaling of the original variables.

6. Seismic Vibration Modes Algorithm

Seismic load on a three storied structure is analyzed to calculate the vibrational modes of the structure. The accurate calculate of these modes over time need to be calculated beforehand the sensors to retract the structure using the gyroscopic tuned mass damper. Complex algorithms are required to simplify the amplitude variation of structure to damp it efficiently. An algorithm of Mode calculation for seismic loads m1, m2 and m3 for three floors is described below.



Damping Forces Free Body Diagram



$$M=\begin{pmatrix} m1 & 0 & 0 \\ 0 & m2 & 0 \\ 0 & 0 & m3 \end{pmatrix} \; ; \; \ddot{U}=\begin{pmatrix} \ddot{u}1 \\ \ddot{u}2 \\ \ddot{u}3 \end{pmatrix}$$

$$K(eq.)=\frac{12EI}{L^3} = k1=k2=k3$$

$$\begin{pmatrix} m1 & 0 & 0 \\ 0 & m2 & 0 \\ 0 & 0 & m3 \end{pmatrix}\begin{pmatrix} \ddot{u}1 \\ \ddot{u}2 \\ \ddot{u}3 \end{pmatrix} + \begin{pmatrix} k1+k2 & -k2 & 0 \\ -k2 & k2+k3 & -k3 \\ 0 & -k3 & k3 \end{pmatrix}\begin{pmatrix} u1 \\ u2 \\ u3 \end{pmatrix} = 0$$

The Basic algorithm in terms of double differential equation of amplitude u is shown above. The modes of the vibrations can be calculated by using the differential matrix of the lambda values and angular frequencies value.

Substituting the value of k1, k2 and k3 ask(eq.) and taking the lambda values as A1,A2 and A3.

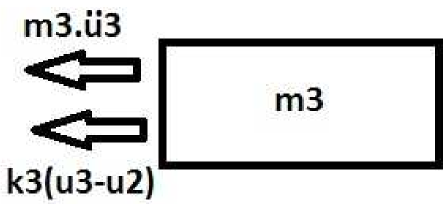
6.1 The First Vibrational Mode Algorithm:

$$\text{Mode 1}=\begin{pmatrix} (k1+k2-u1.A1) & -k2 & 0 \\ -k2 & (k2+k3-u2.A1) & -k3 \\ 0 & -k3 & (k3-u3.A1) \end{pmatrix}$$

$$A11\begin{pmatrix} -1 \\ 0 \end{pmatrix} + \begin{pmatrix} (k2+k3-u2.A1) & -k3 \\ -k3 & (k3-u3.A1) \end{pmatrix}\begin{pmatrix} A21 \\ A31 \end{pmatrix} = 0$$

Fundamental/First Vibrational Mode Matrix Equation

6.2 Mode 1 Amplitude Calculation



$$m1.\ddot{u}1+k1.u1=k2(u2-u1)$$
$$m2\ddot{u}2+k2(u2-u1)=k3(u3-u2)$$
$$m3.u3+k3(u3-u2)=0$$

Similarly other two mods can be found by using Lambda value variation in above equation as A2 and A3.
A11=1; for relative amplitude calculation.

7. Acknowledgment

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8. References

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