

Module 1

Lecture 8: Uncertainties in SHM process

- In situ monitoring, which is a continuous monitoring system is capable of identifying major differences for vibration-based measurements and environmental-based changes

- Continuous monitoring is expensive
 - It handles a big volume of data
 - communication
 - analysis
 - retrieval
- other alternative
 - numerical simulation
 - numerical structural analysis
 - standard loads

- It can also avoid complexities that arise from continuous monitoring

for example, continuous monitoring of a bridge is considered

- blocking of traffic
- conducting expensive static and dynamic load tests

conformance procedures

Alternatively,

damage status & deck status of the bridge can also be detected by analyzing eigen frequency and stiffness (degradation)

one of the important elements of this alternative method is that effects caused by local damage cannot be detected by this method.

Other specific issues are

- (1) Difficult to capture time-dependant change in material properties
- (2) Time-dependant change in structural geometry and the loading pattern

There are the actual sources of uncertainties

Sources of uncertainties in STM

- (1) Exact modeling of external load events, including its time and space dependency is approximated by a set of independent events
- (2) Strength & stiffness degradation with space & time dependence are disregarded
- (3) Measurements of geometric data such as
 - member deflection & the deck slab
 - displacement under dynamic load testsare subjected to large human errors & inaccuracies

(b) Modeling Uncertainties

(1) structural modifications such as

- construction errors
- changes in structural geometry (rebar growth, crack propagation)
- change in material characteristics due to ageing, physical, chemical & mechanical degradation

cannot be captured completely

(2) uncertainties from load variations

space & time dependency characteristics of load variations - is also not captured completely

Solution to handle the above uncertainties

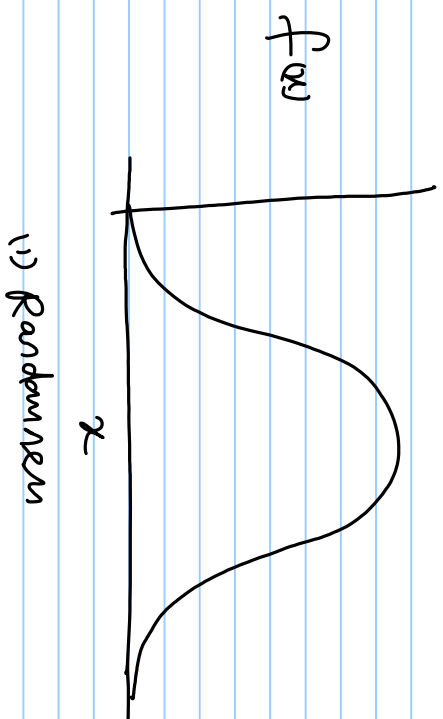
③ ways, by which these can be handled

(1) Using Random Variables

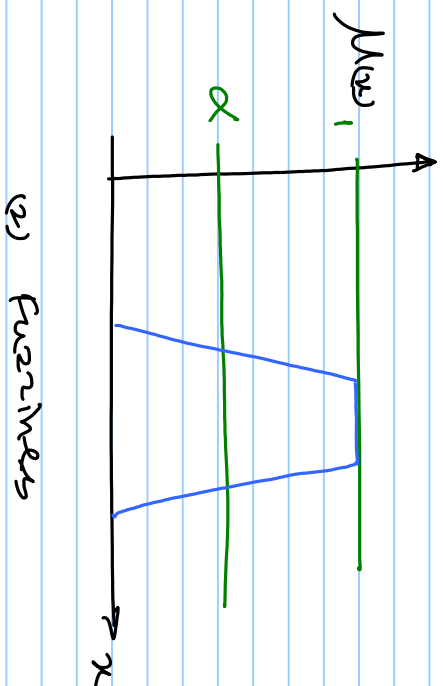
(2) Fuzzifiers

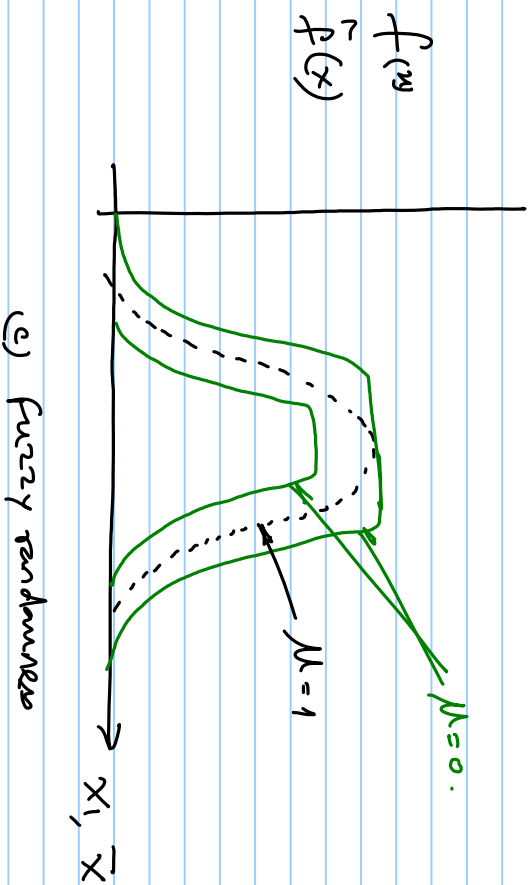
(3) fuzzy randomness

1) Randomness



(2) fuzziness





(c) fuzzy randomness

- selection of the model, depends on the availability of data
- Quantum & quality of data available to represent uncertainty - decide? model

For example,

if the data is statistically sound then
one parameter can be described stochastically

But, choice of probability distribution will affect
the results of simulation, significantly

If data of parameters are frequently fragmented
and not precise,

then fuzzy-randomness model is more
effective to model this uncertainty

other class of uncertainty - sth

(1) Uncertainty present in the observational data

- Experimental Analysis
- Numerical

Solution:

To characterize the effects caused by

{ Statistical sampling
Hypothesis testing
Input/output effect analysis

The uncertainty on

The output of the Analysis

Issues - related to Advancements in STM

- STM process, in the present context is highly advanced
- wireless, decentralized sensors, which are recent advancements in semi-conductor devices & MEMS technology
 - very useful to collect in-situ data, efficiently
- They are also capable of establishing communicable requirements between the sensors
 - This makes decision process much faster

However,

investigation of the collected data is an issue

- this needs a faster investigation process
- even though the data is huge, statistical tools should be able to handle this volume without any residual error

Solution

statistical Pattern Recognition (SPR)

- when the data is analyzed for a set of observations, they follow a specific pattern

Identify this statistical pattern

— It becomes easy and simple to perform data condensation & feature extraction, from the observed data

(SPK) — matrix structure to address uncertainty related to relevant data

— continuous manifesting structures

the most critical issue
is Data Normalization

- Qualitative separation of data & vibration-based results from that of environmental conditions

Statistical problems

In the data analysis, uncertainty assessment, therefore becomes very critical

one does structural prognosis

- Identification of future operation conditions & loading

Here also, uncertainty plays a role

- Service life prediction based on time-space dependency characteristics & material is very complex
- Load variations, which are time-space dependent add to this complexity

Critical issues of unreflexivity is silly (summary)

- Can arise from parametric data, which arise from physical experiment and numerical simulation output
- Imperfect knowledge of control parameters of the physical experiment & numerical simulations
 - imperfect knowledge on the input to numerical model
- It can also arise from
 - Stochastic Equations & models
 - Environmental variables
 - Measurement errors
 - Discretization & Numerical errors

— from the pdf of specific probability distributions
pdf - can handle problems related to uncertainty via
random theory

— one can choose a specific type of distribution to
include all possible values of the variable

other methods

- (1) Dempster-Shafer theory of possibility & belief
- (2) Theory of fuzzy sets
- (3) Information gap theory
- (4) Convex models of uncertainty

The most simpler way to address this uncertainty is Monte-Carlo technique

- idea - to randomly pick values of a parameter such that histogram of the chosen values approximates the PDF
- The computational model is analyzed (or evaluated) @ each point sampled in the input parameter space

summary

STM - advanced

- advantages

- critical issues

most important issue is the uncertainty

- physical exp
- numerical simulation

- Data collected
- Data proven
- structural properties

Future Reading

(1) Yager RR, Kacprzyk J, Pedrini M. 1996.

Advances in Dempster-Shafer Theory & Evidence,
John Wiley & Sons

(2) Dornikova D, Jain LC, Lazareni R. 2000.

Fuzzy sets & their applications to clustering & Training,
Int. Series on Computational Intelligence, CRC Press, NY

(3) Ben-Haim Y, Cogan S, Sandeide L. 1998.

Usability of Mathematical modeling in Mechanical
decision process, Mech System & Signal process
12(1): 121-134.

(A) Christian Jenkel, Wolfgang Graf, Jan-Dirk Sicker. 2001.
 sHM under consideration of uncertain data

Inst. of St Analysis, TU Dresden, Germany