Data Driven Design of Load Bearing Components

VI semester B.Tech Project Thesis report

Department of Mechanical Engineering

by

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Chapter 1

Data Driven Design: Introduction and motivation

In engineering, design refers to the method or process of solving problems. A proposed design offers solutions to an issue that leads to the creation of a product or process. Engineering design is the method of using our knowledge of mathematics and natural sciences to devise a device, part, or process to meet desired needs.

Mechanical design focuses primarily on the design of load bearing components with the aim of determining the best size, shape, and material to ensure the component's protection under load. As a result, a mechanical design procedure has often been carried out using relevant constitutive models in the past. These constitutive models have historically been important for structural design and material certification, and have been accomplished primarily through uni-axial tests aimed at determining elastic material properties.

1.1 Limitations of constitutive models

The aforementioned constitutive models which form the basis of mechanical properties

6used for traditional design problems, have their own limitations. These models are complex and slow to process when dealing with complex problems for systems with high dimensional design variables. In certain cases, the design domain is much too large for a constitutive model to handle.

The nonexistence of knowledge of a design problem also makes getting to the correct constitutive model almost impossible. Constitutive models bring with them material modelling empiricism, modelling error and uncertainty.

1.2 Data Driven Design

In mechanical design, Data-Driven Design is proposed as a way to remove the epistemic uncertainties associated with conventional constitutive models. Data driven design can minimise modelling error and uncertainty by avoiding empirical models, and there is no loss of experimental knowledge. A data-driven model-free approach can not only eradicate the explicit postulation of a particular constitutive model, but it can also produce databases of material states that follow some relevant sampling guidelines. Further, for orthosis and prostheses, the designs that are data –driven are more engaging and tailored to users' preferences. In data driven design where a large number of relevant data is collected and processed to be used as the model (guiding the behavior of the component instead of constitutive model) for design.

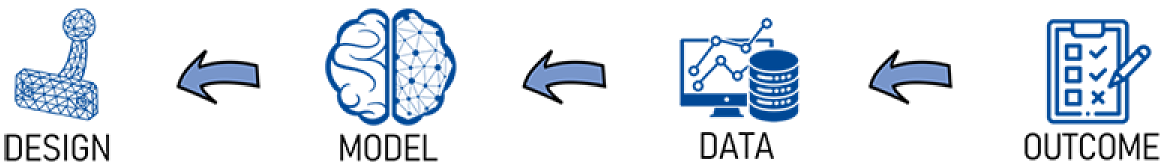
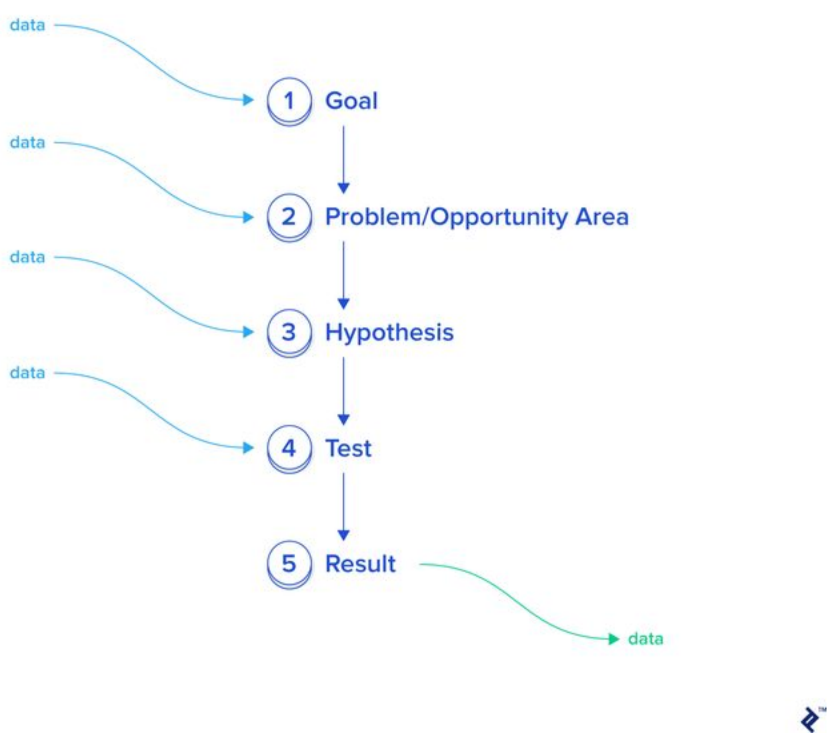


Fig. 1.1 data driven design method flow



Chapter 2

Review

2.1 Literature review

Stainier et al [1] propose an integrated model-free data-driven approach to solid mechanics and show how principles and techniques of data driven computational mechanics leads to elimination of epistemic uncertainty linked to traditional constitutive models. Qualitative as well as quantitative results obtained using a data-driven approach were more accurate. The methodology proposed in the paper is to generate a material database using the Data-Driven Identification method, which is used to solve the classical boundary value problem. This is done by employing a distance minimization algorithm to find a compatible mechanical state (stress-strain field) in equilibrium. Acquired data is used to train a model to predict responses from different geometric structures of the same material. This method thus eliminates the postulation of a constitutive model entirely, thus getting rid of its uncertainties.

Shin et al. [2] presents a data-driven approach for developing a one-dimensional thin-walled beam model. In order to analyze complicated deformations occurring in a thin-walled beam by a beam theory, it is important to identify core cross-sectional deformations that are the bases for the one-dimensional beam analysis. For data processing, we use principal component analysis to obtain the desired core cross-sectional deformations without making any assumptions about the behaviour of the beam's sectional deformations. The core cross-sectional deformations can then be expressed in explicit functional forms (shape functions) to make the one-dimensional higher-order beam analysis construction easier.

Kirchdoerfer et al. [3] developed a new computing paradigm known as data-driven computing, in which calculations are performed directly from experimental material data as well as relevant constraints and conservation laws, such as compatibility and equilibrium, bypassing the empirical material modelling phase of traditional computing entirely. Data-driven solvers try to allocate the state from a predefined data set that comes closest to satisfying the conservation laws to each material point. Data-driven solvers try to find the state that is nearest to the data set while satisfying the conservation laws. The resulting data-driven problem thus consists of the minimization of a distance function to the data set in phase space subject to constraints introduced by the conservation laws.

2.2 Conclusion

The aforementioned papers shed more light into the conditions and criterion under which a model-free data driven design methodology would be more preferred over traditional modeling using the constitutive relations. In our report, we shall discuss one such methodology where we employ a similar distance-minimization algorithm to further predict the response of different geometric structures of the same material from a given set of phase space points.

Chapter 3

Objective and work-plan

3.1 Methodology

The model-free approach we'll look at, known as data-driven computing, involves formulating calculations directly from experimental material data and relevant critical constraints and conservation rules, bypassing the need for empirical material modelling in traditional computing. The data-driven solver aims to allocate the closest possible state from a predefined material-data set to and material point of the computational model while also meeting the necessary constraints and conservation rules. The local state assignment's best fit is calculated using a figure of merit that penalises the distance from the data set in phase space.

The resulting data-driven problem thus consists of the minimization of a distance function to the data set in phase space subject to constraints set forth by the essential constraints and conservation laws.

3.2 Algorithm

we consider discrete, or discretized, systems consisting of N nodes and M material points. Such systems typically arise from Finite Element (FE) discretization. The system undergoes displacement $u = \{u_a\}_{a=1}^{N}$, with $\mathbf{u}_a \in R^{n_a}$ and n_a the dimension of the displacement at node a, under the action of applied forces $\mathbf{f} = \{\mathbf{f}_a\}_{a=1}^{N}$, with $\mathbf{f}_a \in R^{n_a}$. The local state of the system is characterized by stress and strain pairs $\{(\boldsymbol{\varepsilon}_e, \boldsymbol{\sigma}_e)\}_{e=1}^{M}$, with $\boldsymbol{\varepsilon}_e, \boldsymbol{\sigma}_e \in R^{m_e}$ and m_e e the dimension of stress and strain at material point e. We regard $\mathbf{z}_e = (\boldsymbol{\varepsilon}_e, \boldsymbol{\sigma}_e)$ as a point in a local phase space $Z_e = R^{m_e} \times R^{m_e}$ and $\mathbf{z} = \{(\boldsymbol{\varepsilon}_e, \boldsymbol{\sigma}_e)\}_{e=1}^{M}$ as a point in the global phase space $Z = Z_1 \times \cdots \times Z_M$.

The internal state of the system is subject to the compatibility and equilibrium constraints of the general form:

$$\boldsymbol{\varepsilon}_e = \mathbf{B}_e \mathbf{u}, \quad e = 1, \ldots, M \tag{3.1}$$

$$\sum_{e=1}^{M} w_e \mathbf{B}_e^T \boldsymbol{\sigma}_e = \mathbf{f} \tag{3.2}$$

where $\{w_e\}_{e=1}^{M}$ are elements of volume and $\mathbf{B}_e$ is a discrete strain operator for material point e.

A class of Data-Driven problems consists of finding the compatible and equilibrated internal state $\mathbf{z} \in E$ that minimizes the distance to the global material data set D = D1 ··· DM . To this end, we metrize the local phase spaces Z_e by means of norms of the form:

$$|\mathbf{z}_e|_e = \left(C_e \boldsymbol{\varepsilon}_e \cdot \boldsymbol{\varepsilon}_e + C_e^{-1} \boldsymbol{\sigma}_e \cdot \boldsymbol{\sigma}_e\right)^{1/2} \tag{3.3}$$

The local norms induce a metrization of the global phase Z by means of the global norm:

$$|\mathbf{z}| = \left(\sum_{e=1}^{M} w_e \, |\mathbf{z}_e|_e^2\right)^{1/2} \tag{3.4}$$

with associated distance:

$$d(\mathbf{z}, \mathbf{y}) = |\mathbf{z} - \mathbf{y}| \tag{3.5}$$

for y, z Z. The distance-minimizing Data-Driven problem is then,

$$\min_{\mathbf{y} \in D} \min_{\mathbf{z} \in E} d(\mathbf{z}, \mathbf{y}) = \min_{\mathbf{z} \in E} \min_{\mathbf{y} \in D} d(\mathbf{z}, \mathbf{y}), \tag{3.6}$$

i.e., we wish to find the point y D in the material data set that is closest to the constraint set E of compatible and equilibrated internal states or, equivalently, we wish to find the compatible and equilibrated internal state z E that is closest to the material data set D.

3.3 Data generation and implementation

The material dataset is generated through simulations of load bearing members on computer softwares, namely ANSYS. For the purpose of this project, A finite element simulation was run on a thick plate(E=217.5E+09, poisson's ratio= 0.3) with dimensions 200x128x50 mm with eccentric holes in it was biaxially loaded in the vertical and horizontal plane.

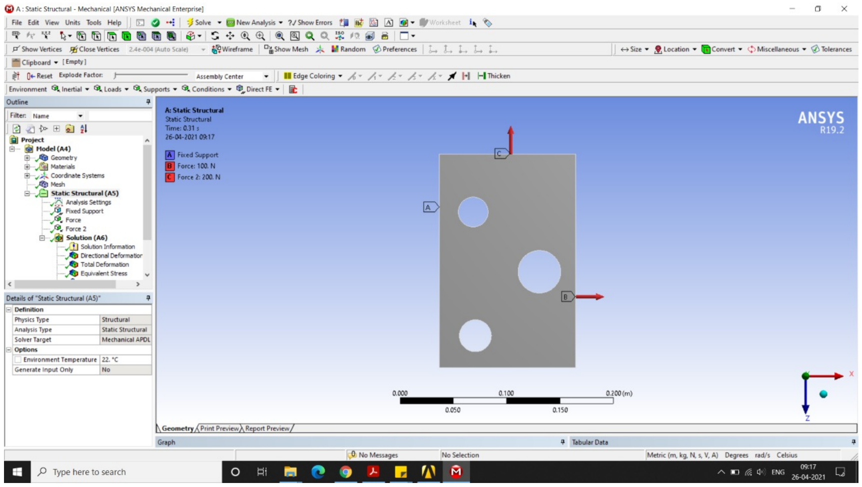
The plate was meshed with 300k+ nodes.

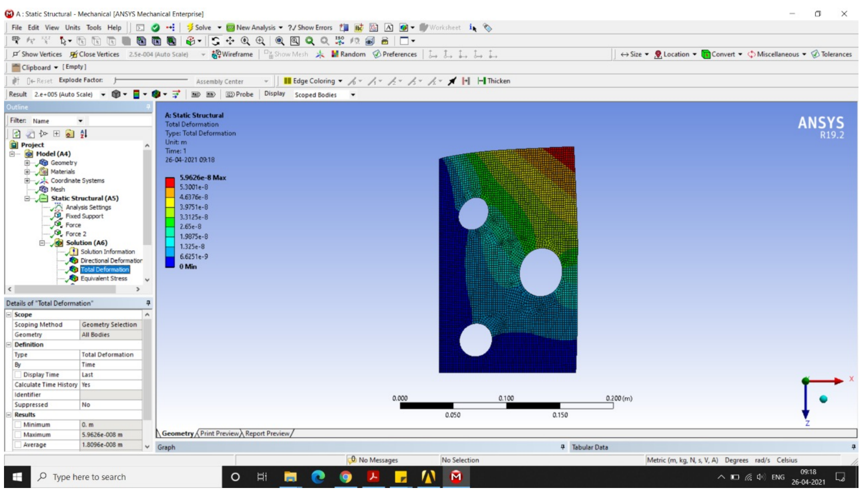
From the loading displacement fields; stress and strain fields were generated over the entire volume of the plate.

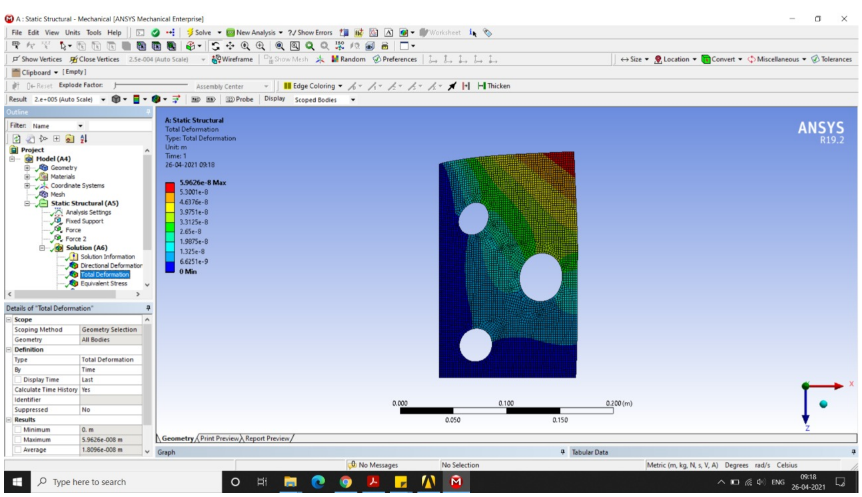
There are various robust libraries or tools which are useful for implementing such algorithms with optimum running complexities with large datasets. In this case, we had a material database generated from FEA with 800K+ datapoints.

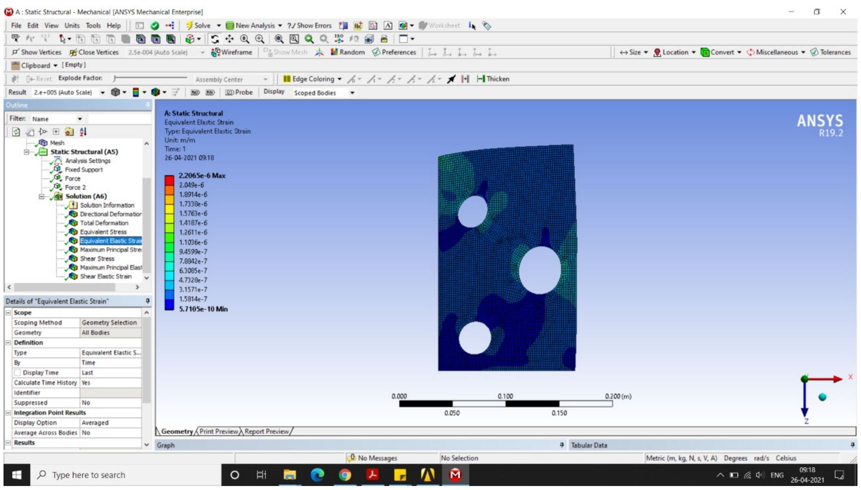
We used python packages SciPy and Scikit-learn to implement the distance minimization algorithm on our dataset, along with the mesh of an unknown complex deformity.

All following results were obtained with a uniform metric Ce, corresponding to an isotropic Hookean material with E = 100 GPa and poisson's ratio = 0.35.










```
from scipy.spatial.distance import cdist
from sklearn.metrics.pairwise import euclidean_distances
scipy_cdist = cdist(data_reduced, data_reduced, metric='euclidean')
sklearn_dist = euclidean_distances(data_reduced, data_reduced)
```

Fig. 3.1 Here, "data-reduced" refers to our cleaned and sorted dataset, which is input in the form of a NumPy array

Chapter 4

Miscellaneous

4.1 Work for the upcoming semester

-Selection of a load bearing member and the material property behaviour we want to study.
-Converge on a more inclusive methodology and pipeline for the selected design problem.
-Literature review of other Data Driven methodologies for solving design problems.

4.2 References

[1] Laurent Stainier, Adrien Leygue, Michael Ortiz, "Model-free data-driven methods in mechanics: material data identification and solvers" Published online: 4 June 2019, © Springer-Verlag GmbH Germany

[2] Data-driven approach for a one-dimensional thin-walled beam analysis- Dongil Shin, Yoon Young Kim School of Mechanical and Aerospace Engineering, Seoul National University, 1 Gwanak-ro, Gwanak-gu, Seoul 08826, Republic of Korea.

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