MECHANICAL ENGINEERING

Data-Driven Methods for Engineers (MECH0107)

- Coursework 2 -

Dr Lama Hamadeh
Office 429 |Roberts Building
Mechanical Engineering Department
(l.hamadeh@ucl.ac.uk)

Dr Llewellyn Morse
Office 503D |Roberts Building
Mechanical Engineering Department
(l.morse@ucl.ac.uk)

2024 - 2025

Coursework Brief and General Instructions

Module code	MECH0107
Module name	Data-Driven Methods for Engineers
Module tutor	Dr Llewellyn Morse
Academic year	2024/25
Term	Term 2
Individual/group assessment	Individual
Page count limit	12 Pages
% contribution to module	60

Submission Date

Please see the submission portal on Moodle for the due date for this assessment.

Page Count Penalty

Work that exceeds the word/page count by more than 10% will be reduced by 10 percentage points. This must not take the mark below the Pass Mark. Any material in addition to the 10% excess may not be taken into account in grading.

Eligibility for Delayed Assessment Permit (DAP)

This assessment is eligible for Delayed Assessment Permit.

Use of Generative AI

1. This assignment is classified as Category 2 where AI tools can be used in an assistive role.
2. You are not permitted to use AI tools for code writing or generate any idea related to your coursework.
3. You can use these tools to receive feedback on or proofread your code.
4. You can use these tools to explain error messages generated by your code.
5. You can use these tools to check your written English's grammar and/or spelling.

6. If you use any of these tools, you need to state the tool name, the output, and how you used it within your submission.
7. Please note that if you fail to adhere to these instructions, you might face academic misconduct and receive a 0 mark in this assessment.

Submission

1. Submission requirements:
   (a) **Report:** Submit a single `.pdf` file. The page count limit for this report can be seen at the start of this brief. See the end of this brief for the required contents of the report. You should **NOT** add snippets of codes into your report to explain how these are implemented, as this would make the report very long. This is why the codes and comments should be self-explanatory.
   (b) **Codes:** Submit all relevant code files that you have used. If you have modified the codes that were provided to you, include them as well. Include any datasets you have generated. Please name your code files, and your dataset files, in simple-to-follow manner. Your code files should be commented, and the comments should be clear.

   You should **put everything (written report AND codes)** into a zip folder, then submit the zip folder onto the submission point on Moodle. Note: please do not submit .rar file – only .zip is allowed.
2. Anonymity requirements:
   - Do not include your name, student number, or any identifiable information in any part of your submission. This includes your report, and your code files.
3. The marking rubric is available on Moodle.

Module's Intended Learning Outcomes

1. Identify the foundational concepts of artificial intelligence, machine learning, and data-driven modeling and their applications in science and engineering systems.

2. Develop and refine various supervised and unsupervised algorithms and appreciate their underlying mathematical backgrounds.

3. Examine the reliability and robustness of data-driven models

4. Extract features and patterns from data and discover new knowledge from it.

5. Identify the need to use neural networks and deep learning algorithms in some applications, compare their efficiency with machine learning algorithms, and interpret their predictions.

Coursework 2

Surrogate Models for the Shape Optimisation of an Aircraft Wing Maintenance Panel

Introduction

Aircraft structures are designed to achieve an optimal balance between safety and weight. Among various structural components, maintenance panels—such as the one shown in Figure 1b—play a crucial role by providing access to internal systems for inspection, repair, and servicing. However, these panels can introduce stress concentrations and affect the overall structural performance of the wing. Optimising the shape of these panels is essential to enhance safety, reduce weight, and maintain accessibility. Reducing the weight of aircraft structures such as this, not only enhances aircraft performance, but also contributes to sustainability by lowering fuel consumption and reducing carbon emissions.

(a) (b)

Figure 1: (a) A Boeing 737 Aircraft, (b) A square maintenance panel with an oval-shaped port on the wing of a Boeing 737 aircraft.

Traditional shape optimisation methods typically depend on computationally expensive Finite Element Analyses (FEA) to assess design performance. However, surrogate modelling techniques, such as Gaussian Process Regression (GPR) and Neural Networks (NN), offer efficient alternatives by approximating the relationship between design variables and performance metrics. These models facilitate rapid exploration of the design space, making them particularly valuable for iterative optimisation tasks that would otherwise be prohibitively time-consuming.

In this coursework, you will develop two surrogate models—a Gaussian Process

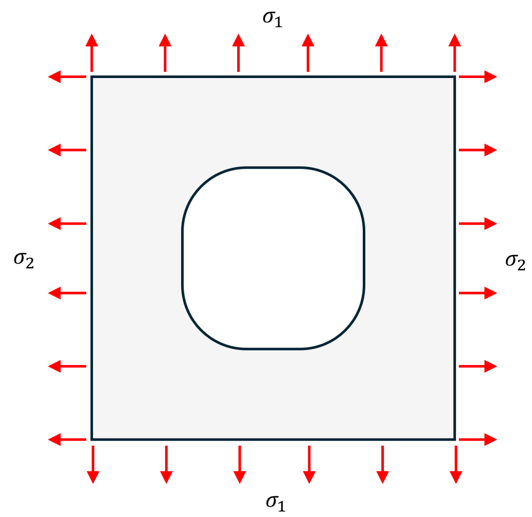
Regression (GPR) model and a Neural Network (NN) model—to optimise the shape of an aircraft maintenance panel. Using data from FEA simulations, you will train these models on various panel designs. These surrogate models will then be integrated into a multi-objective shape optimisation algorithm to refine the maintenance panel design. The optimisation aims to:

1. **Maximise** the safety of the panel.
2. **Minimise** the weight of the panel.

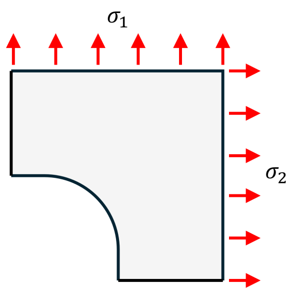
Additionally, the optimised design must satisfy specific functional constraints arising from the presence of neighbouring plates and the requirement for engineers to easily access the internal systems of the wing. These constraints are outlined later in this brief.

Problem

The maintenance plate shown in Figure 1b can be modelled as a thin square plate with subjected to biaxial loading (σ_1 and σ_2), as shown in Figure 2a. The symmetry of the plate can be exploited such that only one-quarter of the plate needs to be modelled in FEA, as shown in Figure 2b.



(a)



(b)

Figure 2: (a) The maintenance plate subjected to biaxial loading, (b) exploiting symmetry in FEA.

The biaxiality ratio is fixed at $\sigma_1/\sigma_2 = 2$. The plate is made of an aluminium alloy, with material properties $E = 70$ GPa (Young's modulus), and $\nu = 0.33$ (Poission's ratio). The geometry of this plate can be described in terms of the design variables shown in Figure 3. It has an out-of-plane thickness t.

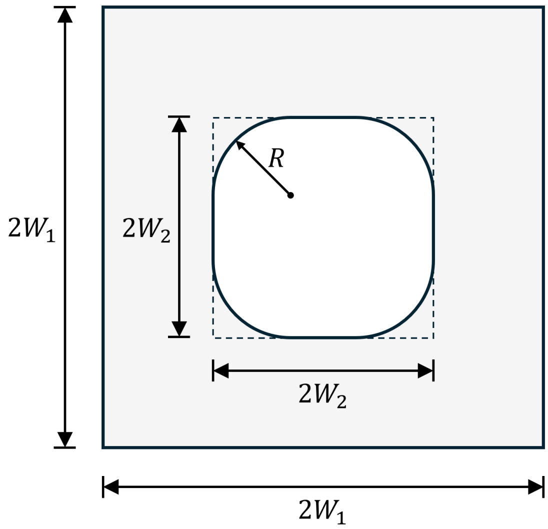


Figure 3: The geometry of the maintenance plate.

As you have learned in your studies, von Mises stress is a useful metric for assessing structural safety due to its relationship with a material's yield strength. In this optimisation, the goal is to minimise the maximum von Mises stress $\sigma_{\max}$ (which corresponds to maximising safety) and minimise the mass of the plate m. These objective functions, $\sigma_{\max}$ and m, depend on the design variables listed in Table 1.

The optimisation must also satisfy functional constraints related to the proximity of neighbouring plates while ensuring that the port remains easily accessible for engineers. To meet these requirements, the design variables can only be explored within the lower and upper bounds specified in Table 1.

Variable	**Description**	**Lower & upper bounds**	**Units**
W_1	Plate half-width	[0.4, 0.6]	m
W_2	Maintenance port half-width	[0.1, 0.2]	m
R	Maintenance port fillet radius	[0.04, 0.06]	m
t	Plate thickness	[0.01, 0.02]	m

Table 1: The design variables for the shape optimisation of the maintenance plate.

The mass of the plate can be expressed in terms of the design variables as:

$$m(W_1, W_2, R, t) = \rho t \left[4W_1^2 - 4W_2^2 + (4 - \pi)R^2\right] \tag{1}$$

where ρ is the density of the aluminum alloy (2700 kg/m^3). The maximum von Mises stress can be expressed as:

$$\sigma_{max}(W_1, W_2, R, t) = f(W_1, W_2, R, t) \tag{2}$$

where f can either be an FEA model, a GPR surrogate model, or a NN surrogate model.

At the end of the multi-objective optimisation, a Pareto front diagram can be obtained, as shown in Figure 4. The Pareto front (blue dots) represents the optimal designs, while the grey dots represent the sub-optimal designs.

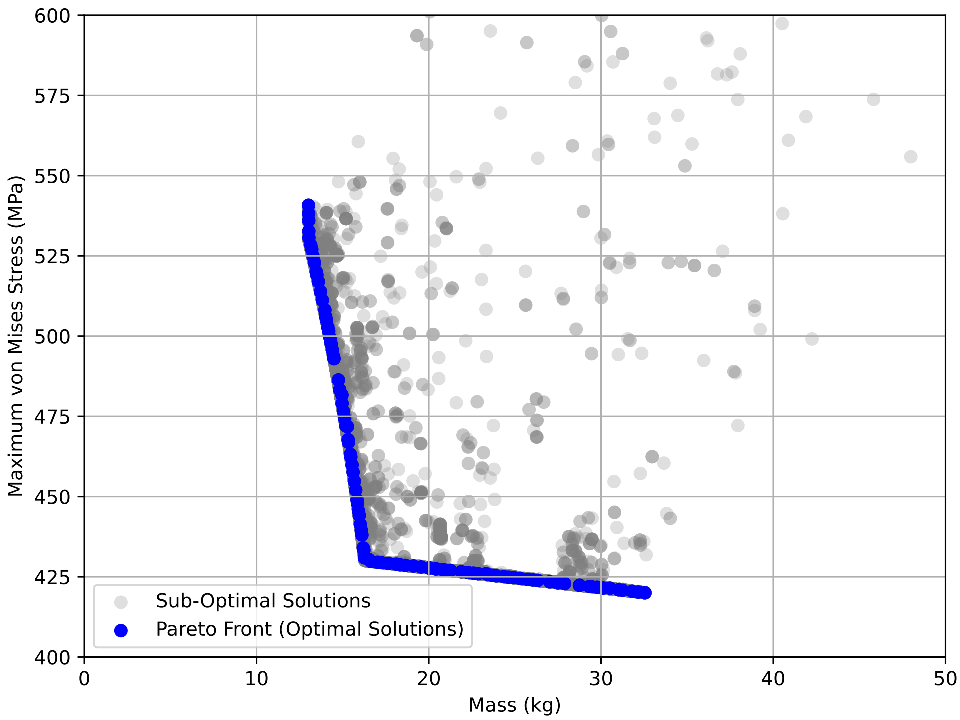


Figure 4: An example of the Pareto front obtained from the shape optimization of the maintenance panel. (These results are for illustration purposes only and may not reflect the outcomes you should expect from your surrogate models.)

Resources

To complete your coursework, you will need to download 6 files from Moodle:

1. The Abaqus FEA model of the maintenance plate `MaintenancePlate.cae`.

2. The text file `MaintenancePlate_StressExtract_Input.txt`. This file contains the values of the geometrical parameters W_1, W_2, R, and t. It is the input to `MaintenancePlate_StressExtract.py`. This text file is created by `MaintenancePlate_StressExtract_Function.m`.

3. The Python script `MaintenancePlate_StressExtract.py`. This script automates the workflow for modifying the geometry of a plate model in Abaqus, running a FEA job, and extracting the maximum von Mises stress. It also measures and logs the total runtime of the script and outputs the results to a specified file.

4. The text file `MaintenancePlate_StressExtract_Output.txt`. This file contains the value of the maximum von Mises stress and the total runtime of the Python script. It is the output of `MaintenancePlate_StressExtract.py`.

5. The Matlab function `MaintenancePlate_StressExtract_Function.m`. This function writes features to `MaintenancePlate_StressExtract_Input.txt`, runs the Abaqus script `MaintenancePlate_StressExtract.py`, and extracts the results from `MaintenancePlate_StressExtract_Output.txt`. To run this function, ensure that Abaqus is not open, otherwise it will give an error.

6. The shape optimization is performed using one of two scripts:

   - `MaintenancePlate_Optimisation.py` (Python version)
   - `MaintenancePlate_Optimisation.m` (Matlab version)

   These scripts include a key function responsible for computing the optimization objectives:

   - `_evaluate` (in the Python version)
   - `plateObjectives` (in the MATLAB version)

   These functions calculate the maximum von Mises stress, σ_{max}, and the mass, m. The calculation of m follows Equation (1), while σ_{max} is estimated using a simple dummy equation. This dummy equation is not physically accurate but serves as a placeholder for testing the optimization algorithm. You must replace this dummy equation with either your Gaussian Process Regression (GPR) surrogate model or your Neural Network (NN) surrogate model.

Files 1, 3, and 5 should not be modified. However, feel free to open them and have a look at them if you want to. Files 2, 4, and 6 can be freely modified.

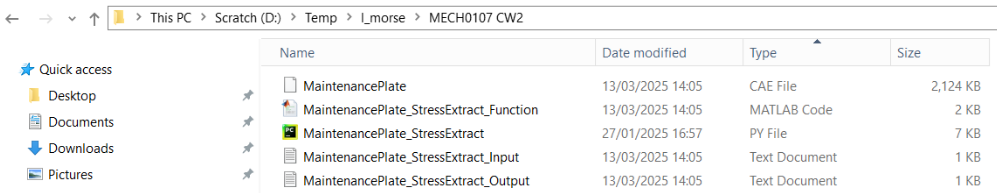
Files 1-5 will need to be placed in your Winion directory and run on Winion - see the instructions in the following section. File 6 cannot be run on Winion, so it should instead be run via your favourite Python programming application.

Instructions to Get Started

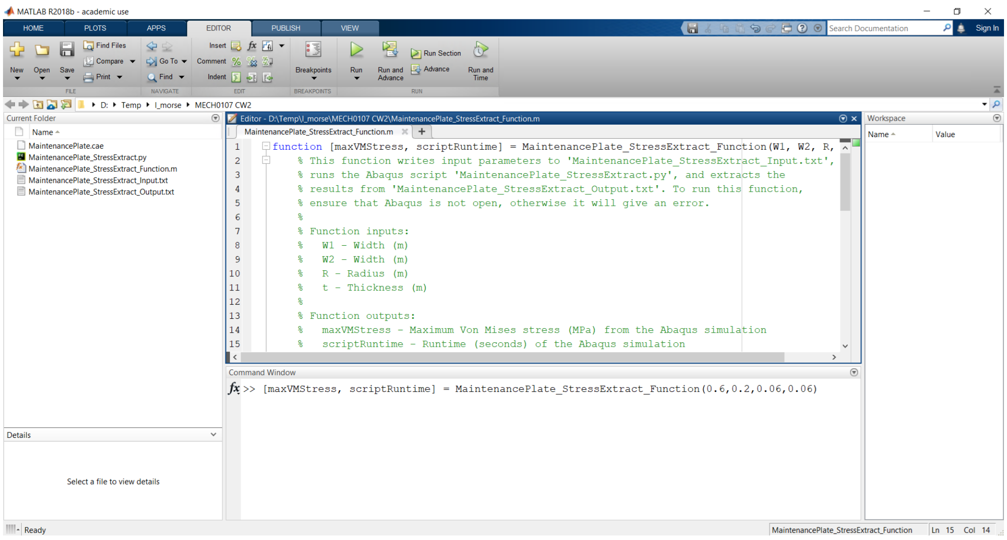
1. Open file explorer on Winion. A guide for connecting to Winion can be found on Moodle.

2. Create the folder "MECH0107 CW2" in your temporary directory on Winion (D:/Temp/YourUserName). Therefore, you'll have "D:/Temp/YourUserName/MECH0107_CW2".

3. Places files 1-5 in the folder "MECH0107 CW2". Therefore your folder will look like this:



4. Double-click the Matlab function `MaintenancePlate_StressExtract_Function.m`. This will bring up this function in Matlab:



5. You can run this Matlab function via the command window as shown below.

```
Command Window
>> [maxVMStress, scriptRuntime] = MaintenancePlate_StressExtract_Function(0.6,0.2,0.06,0.06)
```

6. You should now be ready to begin the coursework. To create the training data for your surrogate models, you will need to create an additional Matlab script to sample from the function `MaintenancePlate_StressExtract_Function.m` inside a loop.

Please note: The Winion nodes are reset periodically. You will lose all your data on Winion when this happens. Ensure that you regularly backup your files elsewhere. Loss of data is not a valid reason for Extenuating Circumstances (EC).

Tasks and Report

Your report should include the following sections:

1. **Description of the Surrogate Model Setup**
   (a) **GPR Surrogate Model**
   - Data sampling
   - Data preprocessing
   - Model design choices and justifications. For example, your kernel choice and justification for your choice

   (b) **NN Surrogate Model**
   - Data sampling
   - Data preprocessing
   - Model design choices and justifications. For example, your architecture choice and justification for your choice

   Where possible, you should support your justifications with your own **quantitative analyses**.

2. **Results**
   (a) **GPR Surrogate Model**
   - Error evaluation of the surrogate model
   - Shape optimisation results (i.e. the Pareto front diagram) for the surrogate model

   (b) **NN Surrogate Model**
   - Error evaluation of the surrogate model
   - Shape optimisation results (i.e. the Pareto front diagram) for the surrogate model

3. **Discussion**
   Your discussion should address the following questions. Where possible, you should support your answers with your own **quantitative analyses**.

   (a) The primary advantage of using a surrogate model for shape optimisation is the significant reduction in computational time compared to performing the optimisation directly with FEA. In this context, was the use of surrogate models justified in this coursework? In your answer, consider:

i. How much time was required to generate the data samples for each of your surrogate models?
ii. How much time was required to train your surrogate models?
iii. On average, how much faster were each of your surrogate models compared to the FEA model when obtaining a single estimate of the von Mises stress?
iv. How much time did the shape optimisation algorithm require to complete with your surrogate models?
v. If the shape optimisation algorithm were executed directly with FEA instead of using your surrogate models, estimate how much time it would take to complete.
(Note: Running the full optimisation with FEA would likely take a very long time, so there is no need to attempt this. You may estimate the duration based on your answers to (iii) and (iv) above.)

(b) In this coursework, you conducted the shape optimisation of the panel using two different machine learning models: a GPR model and an NN model. Which of these two models do you consider the most appropriate and least appropriate for this shape optimisation problem, considering both computational efficiency and predictive accuracy? In your answer, consider:

- The total computational time required by the GPR model vs. the NN model.
- The error of the GPR model compared to error of the NN model.

(c) For the model you considered the least appropriate for this problem in question (b), what conditions would need to change for this to become the most appropriate model? In your answer, consider the number of design variables, as well as other factors such as dataset size, training time, and model generalization ability.

(d) Your shape optimisation was conducted under specific functional constraints due to the presence of neighbouring plates and the requirement for engineers to easily access the internal systems of the wing. These constraints were outlined in Table 1.

Now, suppose the shape optimisation is conducted again with a revised set of constraints. However, you continue to use the surrogate models that were trained under the original constraints. Would these surrogate models still be valid and reliable for the new optimisation process? Why or why not? In your answer, consider:

- Tightened constraints: The lower bounds increase, and the upper bounds decrease. How would this affect the performance and predictive capability of your surrogate models?

- Relaxed constraints: The lower bounds decrease, and the upper bounds increase. How would this affect the performance and predictive capability of your surrogate models?
- If the performance of the surrogate models deteriorates under the new constraints, what strategies could you use to improve their accuracy and suitability for the new constraints?

(e) Consider the two Pareto fronts you presented in your results section. These Pareto fronts provide many optimal designs for the maintenance panel. Pick one of these Pareto fronts, then select one of the optimal designs and compare its $\sigma_{\max}$ and m with those of the average design, defined as follows:

$$W_1 = 0.5 \text{ m}, \quad W_2 = 0.15 \text{ m}, \quad R = 0.05 \text{ m}, \quad t = 0.015 \text{ m}$$

In your answer, consider:

- Is $\sigma_{\max}$ for your chosen design higher or lower than that of the average design? Calculate the percentage difference.
- Is m for your chosen design higher or lower than that of the average design? Calculate the percentage difference.
- From an engineering perspective, what additional practical considerations might influence the selection of a final design beyond the constaints outlined in Table 1, and beyond just minimising $\sigma_{\max}$ and m?
- How could you modify your surrogate models to incorporate these additional practical considerations in future optimizations?

If you are using any references, add them to a "References" section at the end of your report. This section is **NOT** included in the page count.

End of Coursework