

Exercises

1	2	3	4	5	6	7	8	9	10
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Surname, First name

Modelling, Uncertainty and Data for Engineers (CEGM1000)

Exam 22/23 Q2

1	1	1	1	1	1	1
2	2	2	2	2	2	2
3	3	3	3	3	3	3
4	4	4	4	4	4	4
5	5	5	5	5	5	5
6	6	6	6	6	6	6
7	7	7	7	7	7	7
8	8	8	8	8	8	8
9	9	9	9	9	9	9
0	0	0	0	0	0	0

Do not open the exam until given permission by the instructor!

(You can write your name and student ID on this page)

The exam is 180 minutes. The table below gives an overview. On the following pages, some questions have a specific box for you to answer: anything written outside the boxes will not be graded. Note that we have provided a lot of space for answers. The answer space size is not an indicator of how long we expect your answers to be! (shorter is generally better). **Points** indicate the relative amount of time expected to be spent for each question. Scratch paper is available to use during the exam, but will not be collected or graded. You may use pen or pencil and a scientific calculator. Any required equations are generally provided in the question description.

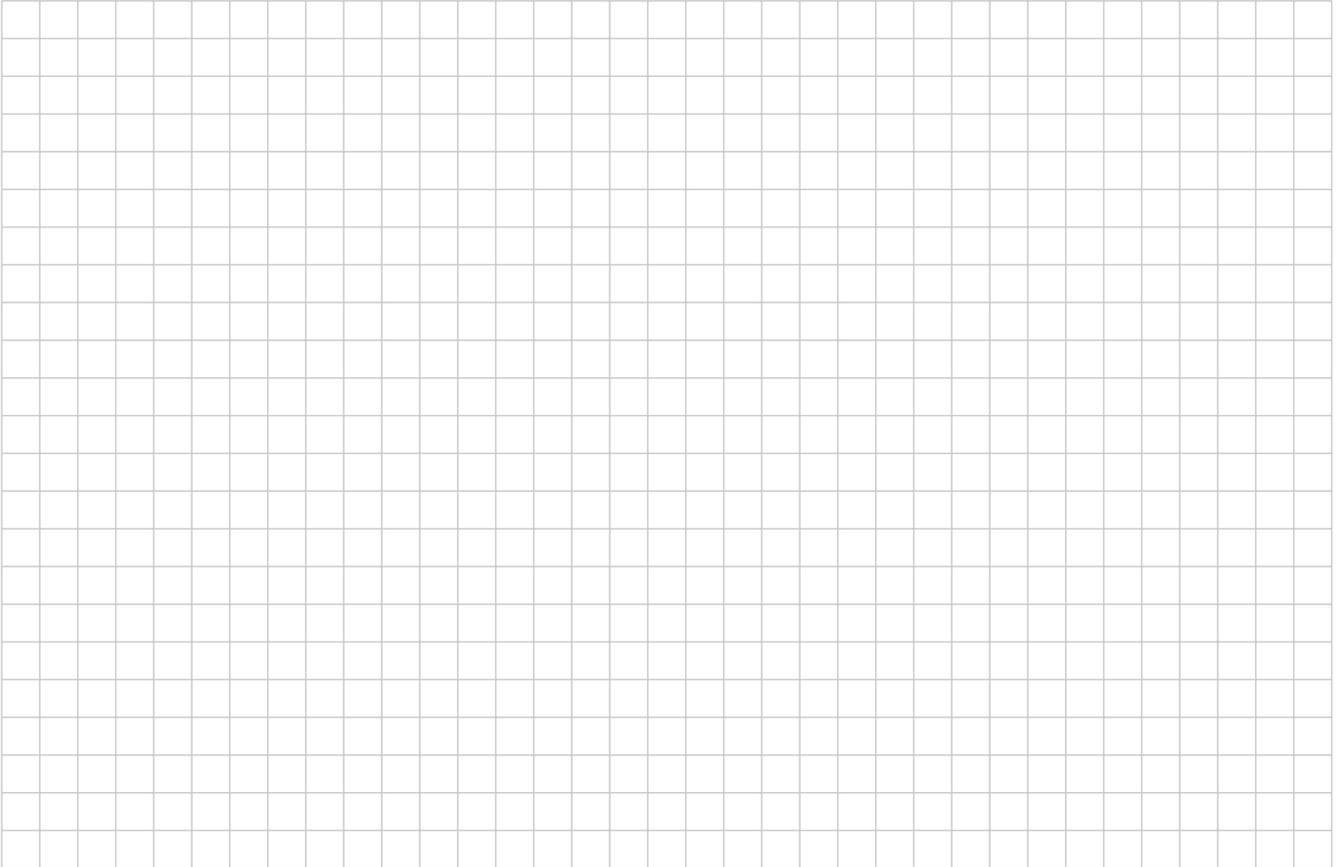
Don't forget to write your student ID and fill in the bubbles on the top right of this page. Good luck!

No.	Question	Sub-Q	Type	Points
1	Coding	a, b, c, d	MC	4
2	Finite Difference Methods	a	MC	2
2		b, c	Open	8
3	Finite Element Methods	a, b	MC	10
3		c	Open	3
4	Optimization		Open	5
5	Optimization		Open	5
6	Optimization		Open	5
7	Signal Processing	a, b, c	Open	15
8	Time Series	a, b, c, d	Open	14
9	Machine Learning	a, b, c, d, e	MC/MS	14
10	Risk and Reliability	a	Open	5
		b, c, d	MC	6
		e	Open	4
		Total:		100

Part 1: Coding

- 1p **1a** What does the acronym FAIR stand for?
- a Flexible, Available, Interoperable, Reusable
 - b Findable, Accessible, Interoperable, Repeatable
 - c Flexible, Available, Interoperable, Repeatable
 - d Findable, Accessible, Interoperable, Reusable
- 1p **1b** What does the adjective "Interoperable" stand for in FAIR data?
- a It means that data can be used by multiple operators concurrently, regardless of who they are (e.g., researchers, publishers, stakeholders, ...).
 - b It means that data can be integrated with other data. To this end, data must be standardised.
 - c It means that data can be used across multiple operating systems (e.g., Windows, Linux, ...).
 - d It means that data can be operated regardless of its origins.
- 1p **1c** Is FAIR data Open Data?
- a Sometimes it can be the case. But FAIR and Open Data must be kept separate
 - b Yes, every FAIR data is Open Data
 - c Yes, and the converse is also true: every Open Data is FAIR
 - d FAIR data is never Open data
- 1p **1d** Can FAIR principles prevent the fabrication of data (i.e., deliberate creation of data to propound a particular hypothesis with greater conviction)?
- a Yes
 - b No

- 3p **2c** If nothing is added to the code above, what kind of boundary conditions are applied by default?
Motivate your answer.

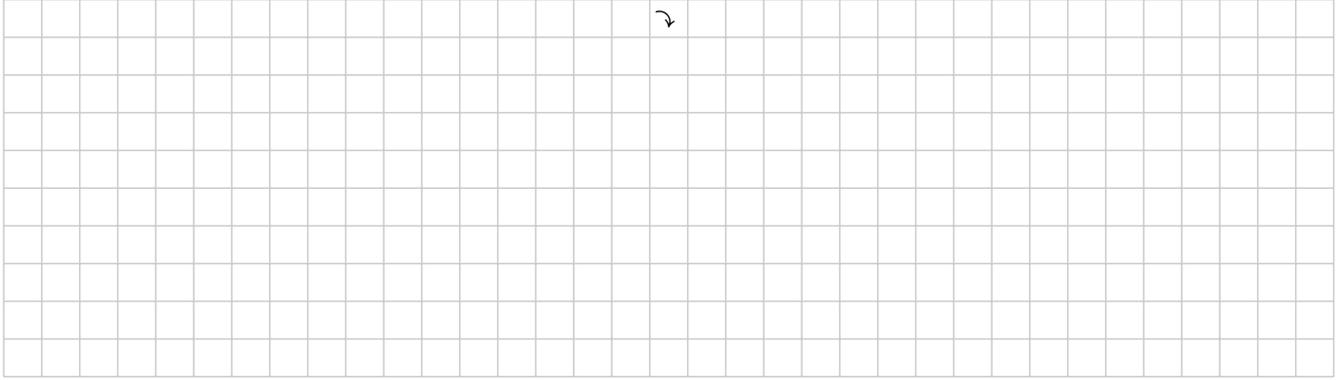


Part 4: Optimization 1

Three cities (C_1, C_2, C_3) are supplied with water from three different sources (S_1, S_2, S_3). The first (S_1) is a major reservoir, the other two are local sources (S_2, S_3). Sources S_2 can supply cities C_1 and C_3 and S_1 and S_3 can supply all cities. The cities have a consumption of a minimum of R_1, R_2, R_3 respectively. The local sources can only supply a maximum of Q_2 and Q_3 of water volume. The reservoir can supply a maximum of Q_1 , but there is a minimum supply of Q_{min} to be imposed.

- 5p **4** Establish the model that allows obtaining the optimum solution for the problem of supplying the cities in the most economical way knowing that the cost of supplying city j from source i is given by c_{ij} expressed in monetary units (m.u.) per unit of water volume.

A large grid of graph paper for solving the optimization problem. The grid is approximately 30 columns wide and 40 rows high. A small mouse cursor is visible near the bottom center of the grid.



Part 5: Optimization 2

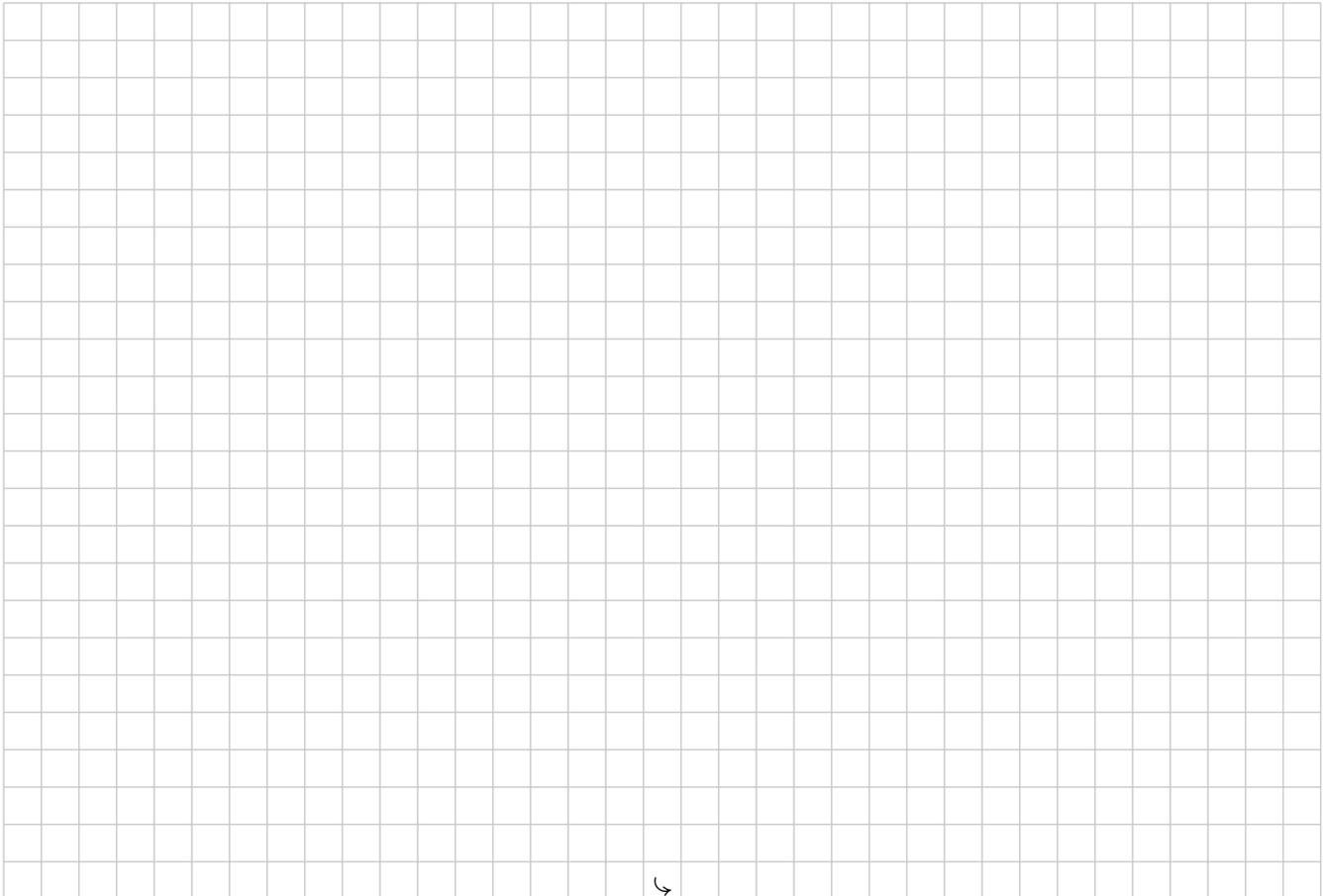
Consider the following table of the SIMPLEX method for solving an LP maximization problem:

5p

5

	Z	X1	X2	S1	S2	S3	b
Z	1	-1	-3	0	0	0	0
s1	0	0	1	1	0	0	5
s2	0	1	0	0	1	0	6
s3	0	1	3	0	0	1	21

Solve the problem.





Part 7: Signal Processing

A continuous time signal $x(t)$ is given as:

$$x(t) = A_1 \cos(2\pi f_1 t) + A_2 \cos(2\pi f_2 t)$$

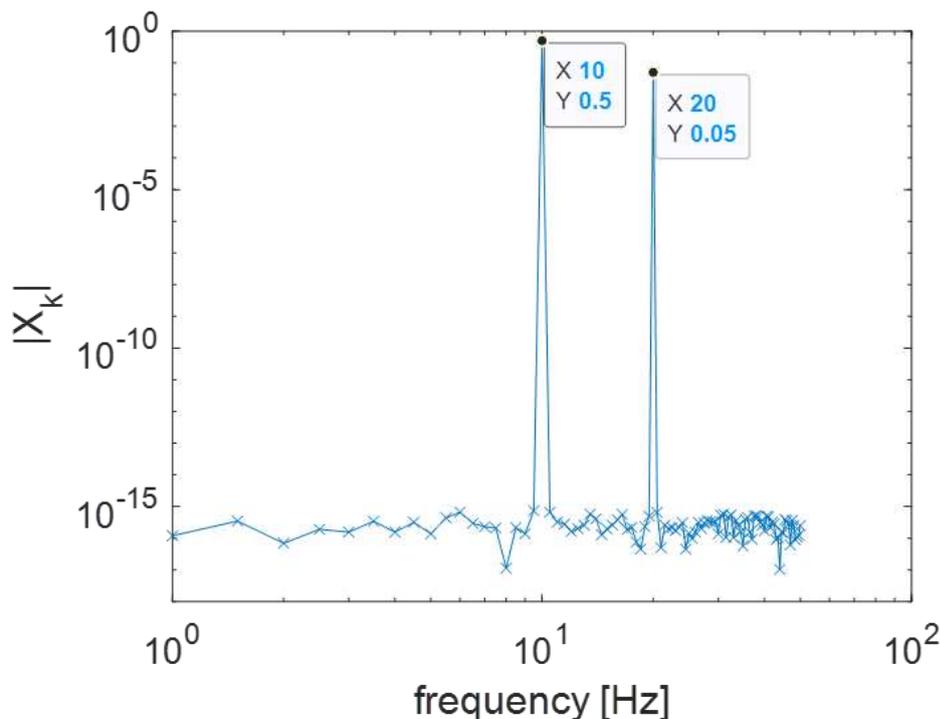
With $A_1 = 1$, $A_2 = 0.1$, $f_1 = 10$ Hz and $f_2 = 80$ Hz.

The signal has been sampled in three experiments, each time using a different sampling frequency f_s and a different measurement duration T_{meas} . The frequency domain plots (magnitude spectrum in logarithmic scale, as a result of the DFT) are shown below; the spectrum is double sided, but only shown for positive frequencies and, as commonly done in practice, up to the Nyquist frequency. The values of X_k , straight from the fft-implementation, have been divided by N , the number of samples.

Determine, for each experiment, the sampling frequency f_s , as well as the measurement duration T_{meas} . Only the final numerical answers are asked!

Some useful formulas: $f_{nyquist} = f_s/2$ $T_{meas} = 1/f_0$

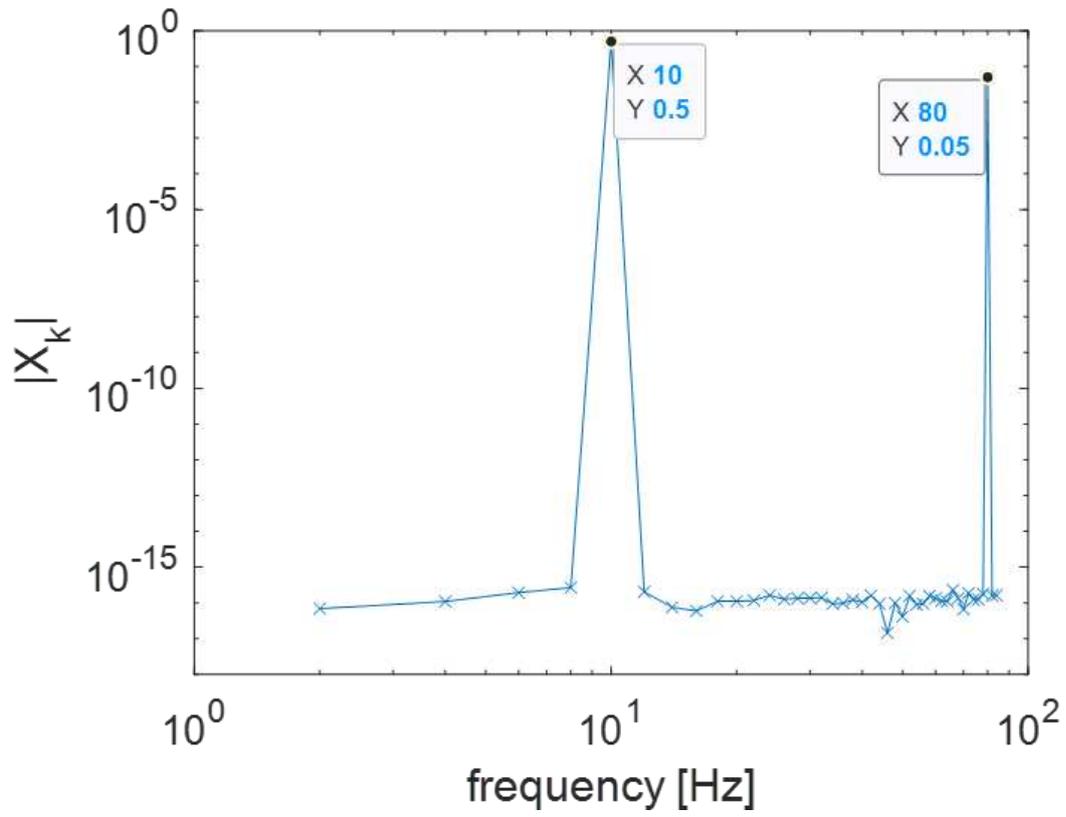
5p 7a Experiment A



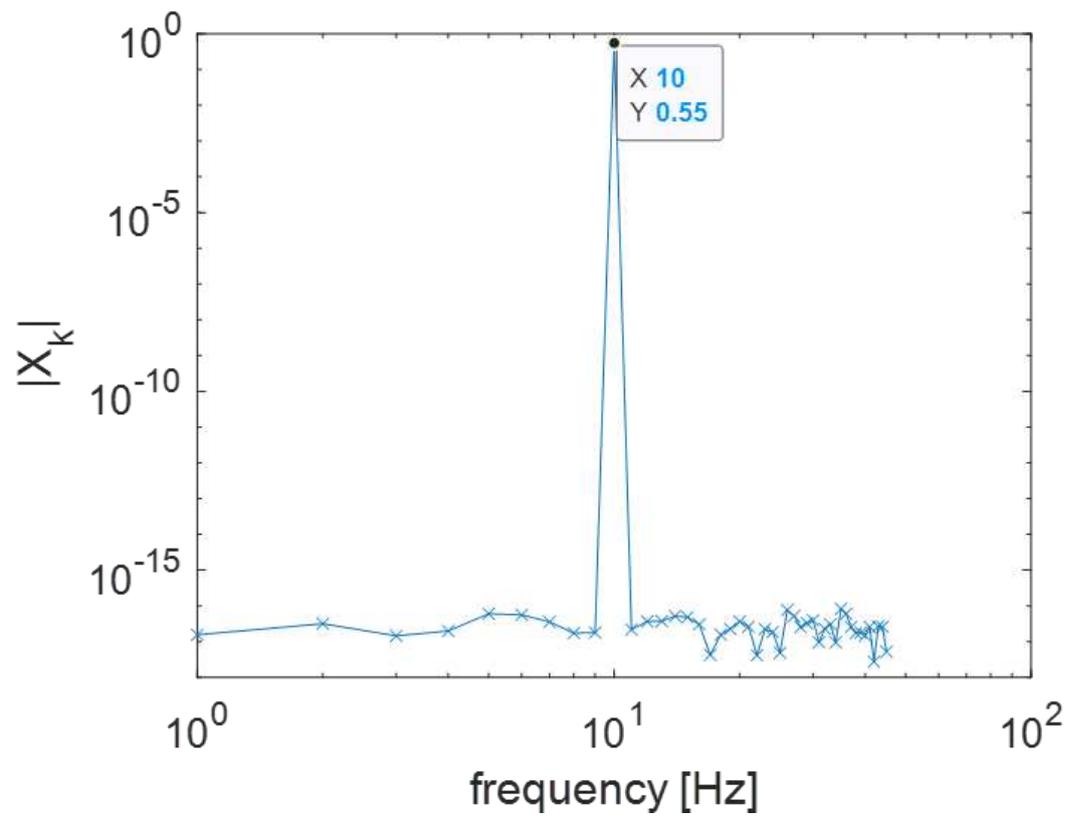
$f_s =$

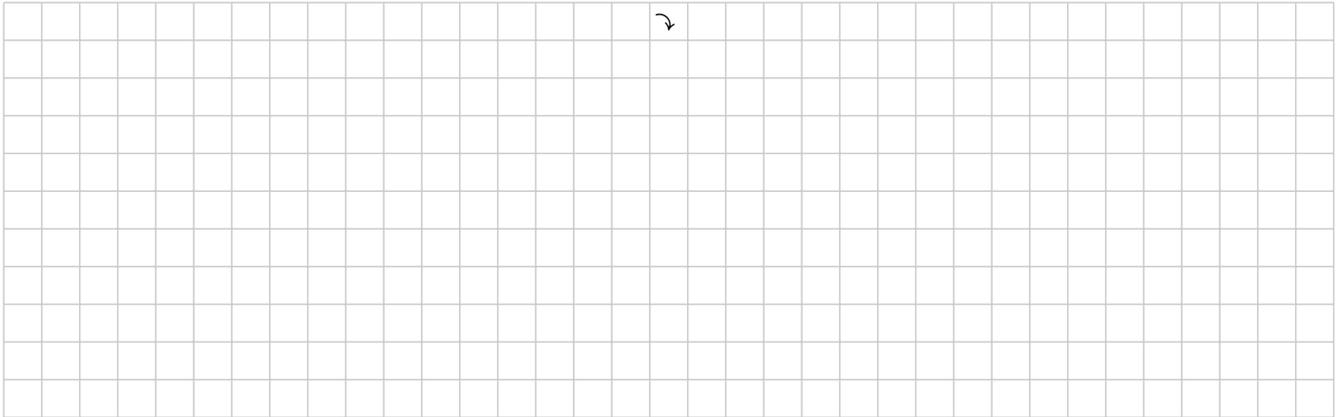
$T_{meas} =$

5p 7b Experiment B

 $f_s =$ $T_{meas} =$

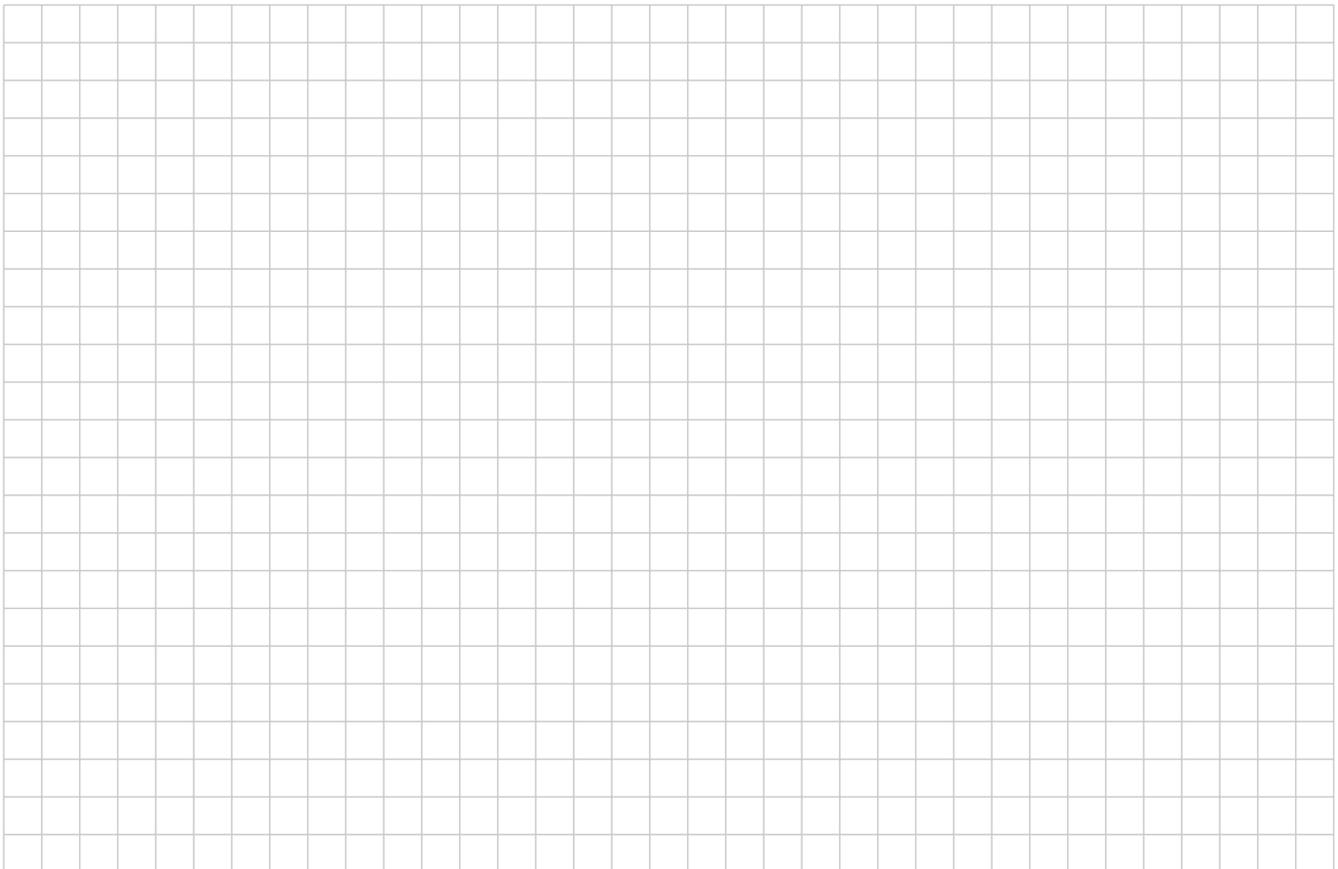
5p 7c Experiment C

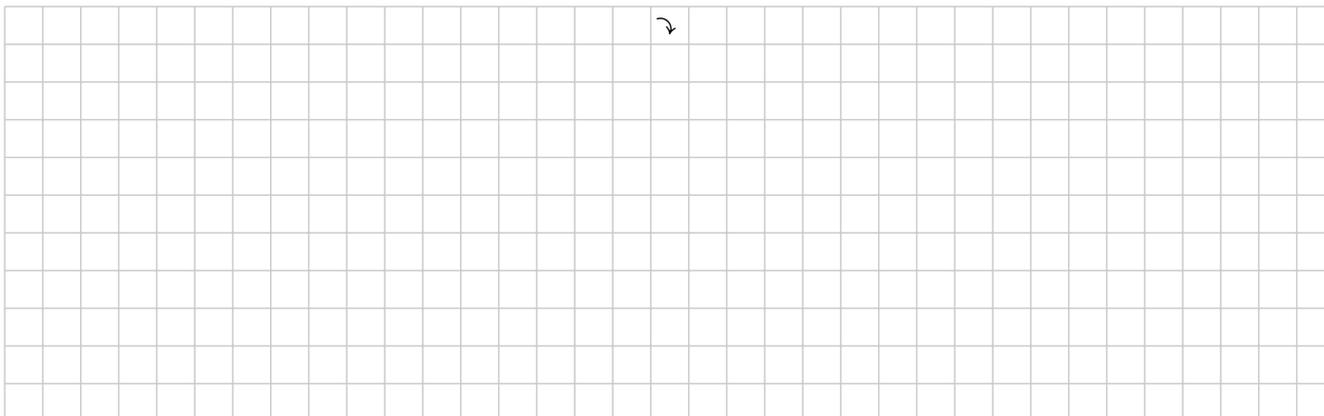
 $f_s =$ $T_{meas} =$



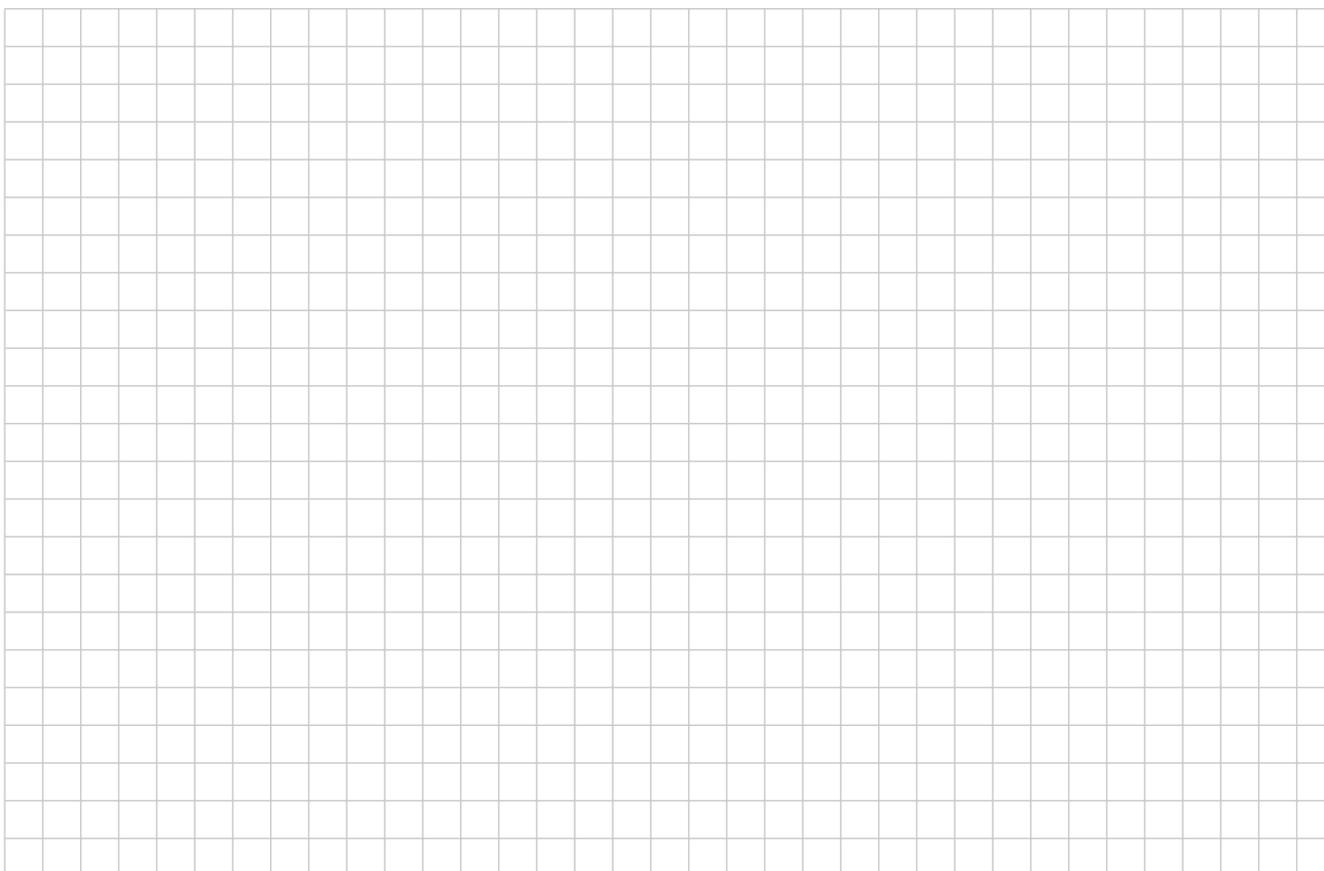
Assume that the two tidal constituents are not known a-priori, so we want to use spectral analysis technique to identify them. We want to compute the power spectral densities (PSD) using the least-squares harmonic estimation (LS-HE).

- 4p **8b** Sketch a plot of the expected PSD from the data set, where the horizontal axis is the frequency (cycle/hour). Add relevant numerical values on the horizontal axis.





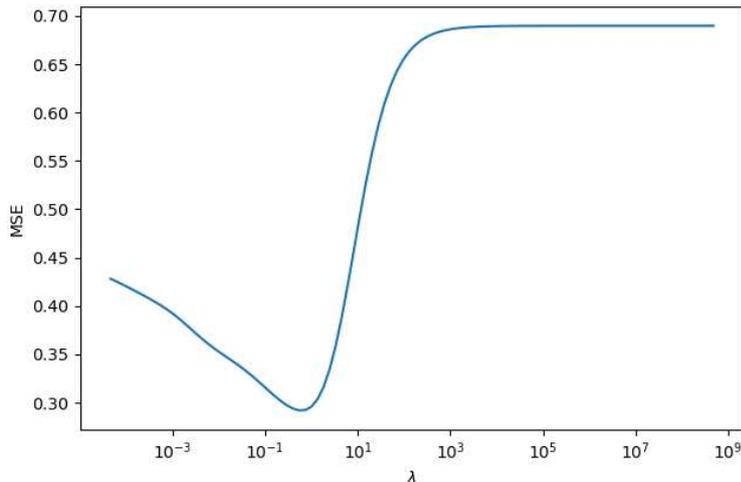
- 2p **8d** Based on the results for Question d, write an expression for y_S at the time instance $t = m + 1$, i.e. $y_S(m + 1) = ?$



Part 9: Machine Learning

- 3p **9a** Assume you have a dataset with $N = 100$ data points and would like to train a linear basis function model with weights \mathbf{w} which could potentially be too complex and overfit the data. You then decide to introduce an L_2 regularization term λ to the loss function and do a model selection study. Assume the number of basis functions is fixed and you cannot afford to collect more data.
- (a) You allocate 20 samples for training, 40 for validation and 40 for testing. You use the training loss to calibrate λ , the validation loss to calibrate \mathbf{w} and the test set to assess the final model
 - (b) You allocate all 100 samples for training and use those to obtain both λ and \mathbf{w} at the same time
 - (c) You allocate 70 samples for training, 20 for validation and 10 for testing. You use the validation loss to calibrate λ , the training loss to calibrate \mathbf{w} and the test set to assess the final model
 - (d) You allocate all 100 samples to the training set and use those to obtain \mathbf{w} . Then you move the samples for validation and use those to obtain λ . Finally, you move the samples to the test set and assess the final model.

4p



9b

A regularization term λ is added to the loss function of a neural network and a model selection study is performed by computing the mean squared error (MSE) over a validation dataset for different values of λ . The results of this study are shown above.

Regarding these results, mark **all** the options that are **TRUE**; consider that each wrong answer will result in negative points, but the lowest score for this sub-question is 0 (we will not subtract points from the rest of the exam):

- High values of λ lead to very rigid models
- Even without regularization, this specific model would already be resistant to overfitting
- The weights w of the neural net most likely increase as λ is decreased
- Increasing the size of the validation dataset (N) would make the "U"-shaped behavior of this curve less pronounced
- For $\lambda = 10^3$, training the model on a different dataset of the same size will lead to a very different model

2p



9c

Consider the dataset with five data samples $\{x_1, x_2, x_3, x_4, x_5\} = \{-1.6, -0.2, 0, 1.6, 2.2\}$ shown above.

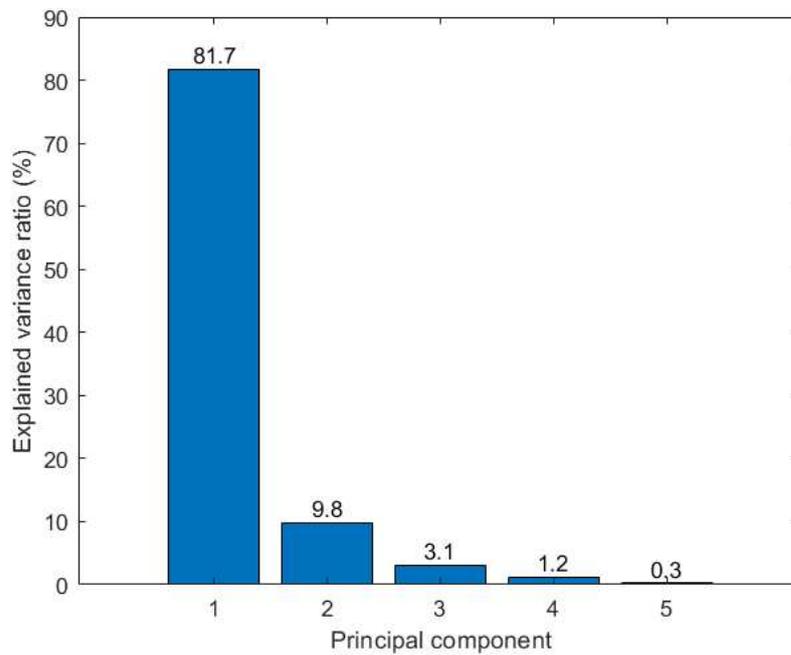
Using the Euclidean distance, we perform K-means clustering to find the global optimal (minimum objective) when the cluster number $K = 3$. Which single data sample forms one cluster? (Euclidean distance between a and b : $d = \sqrt{(a - b)^2}$)

- (a) x_1
- (b) x_2
- (c) x_3
- (d) x_4
- (e) x_5

3p **9d** Consider again the previous dataset. This time K-means clustering with Euclidean distance is used to find the global optimal (minimum objective) for $K = 2$. What are the centroids of the final clusters?

- (a) [-0.9, 1.9]
- (b) [-0.6, 1.9]
- (c) [-1.0, 2.0]
- (d) [-0.9, 1.3]
- (e) [-0.2, 1.6]

2p



9e

We perform *principal component analysis* on a given dataset. Consider the explained variance ratio with respect to the principal component number shown in the figure. What is the lowest dimension that guarantees a total explained variance ratio of 95%?

- (a) 2
- (b) 3
- (c) 4
- (d) 5

Part 10: Risk and Reliability

You are asked to evaluate the system reliability of a 2 m diameter oil pipeline that is currently operating in an earthquake region. The main objective is to evaluate the probability of failure, which in this case is defined as: the annual probability of a leak from the pipeline due to one of three different failure modes caused by an earthquake, M_i :

1. M_1 : buckling of the pipe from longitudinal stress
2. M_2 : high pressure failure (hoop stress)
3. M_3 : failure of welded joint

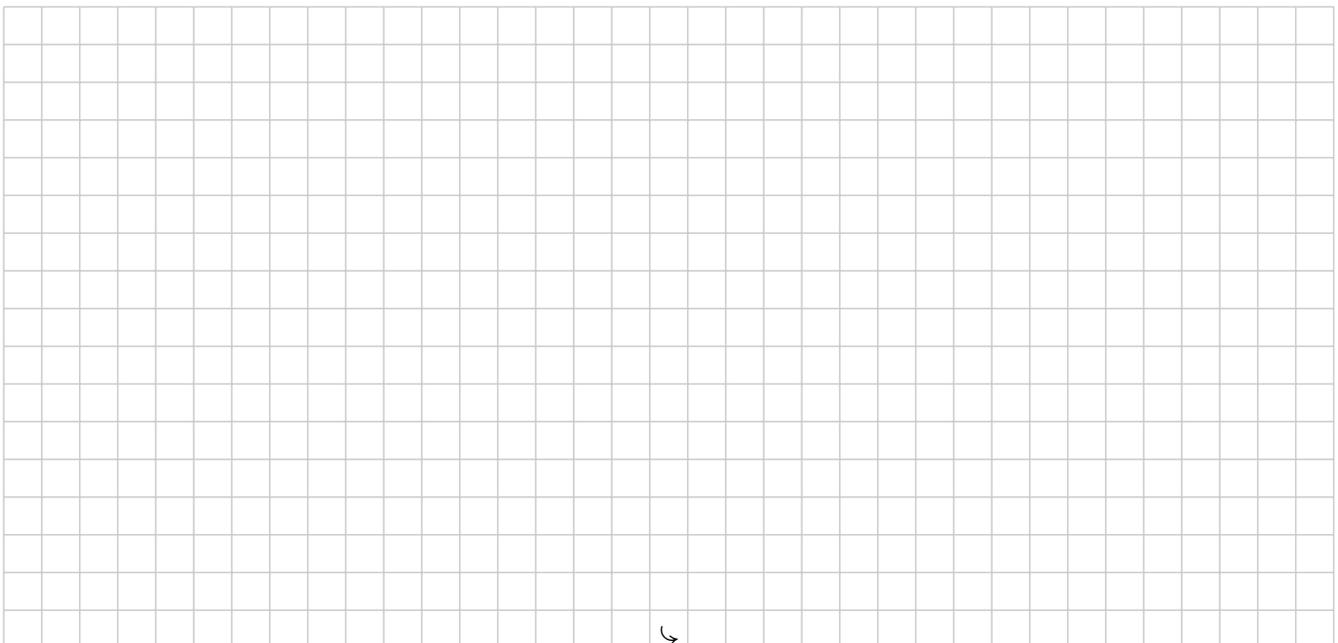
Each failure mode is dependent on whether or not an earthquake occurs, which has an annual probability of occurrence of 10%. For simplicity, consider each failure mode to be mutually exclusive, and that damage can only occur once per year per failure scenario. In other words:

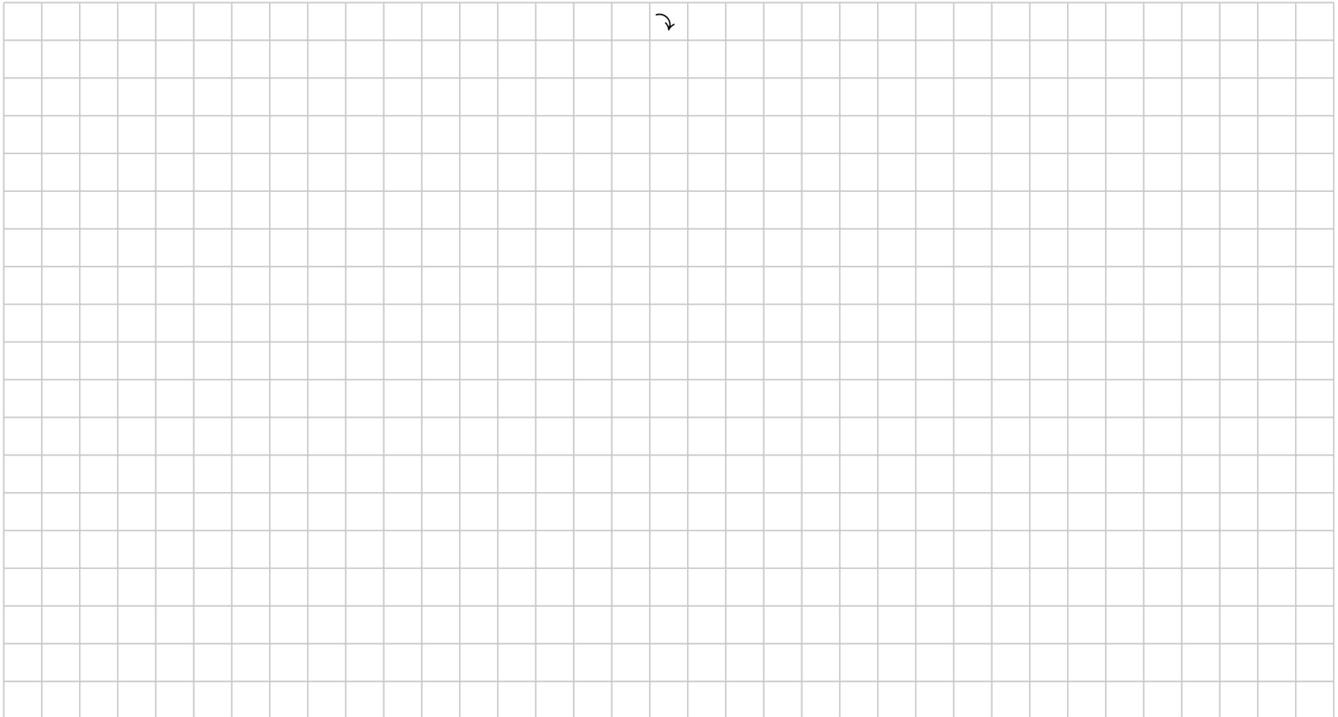
$$P(M_1 \cup M_2 \cup M_3) = P(M_1) + P(M_2) + P(M_3)$$

The probabilities of each failure mode have already been assessed and are summarized in the following table:

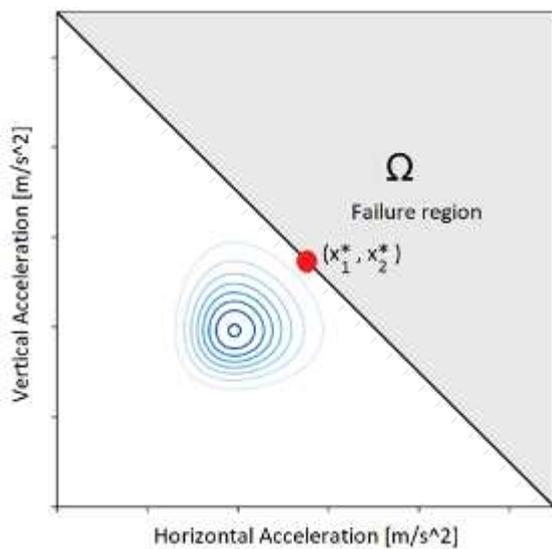
	$P(M_i EQ)$	Damage (k€)
M_1	0.5	1000
M_2	0.3	50
M_3	0.4	10

- 5p **10a** Construct the FD curve (i.e., the FN curve, except with damage in place of fatalities on the x-axis) for leakage of the pipeline segment due to each of the 3 failure modes. Don't worry about the scale of your plot being precise, so long as the FD values are clearly indicated at each point.





- 3p **10b** Failure of one of the pipeline segments is a function of the horizontal and vertical acceleration, X_1 and X_2 , respectively. The limit state can be described by a function, illustrated in the figure, where the failure region is represented by Ω . If $f_{X_1, X_2}(x_1, x_2)$ is the multivariate probability distribution of the random variables X_1 and X_2 . Which of the following best defines the probability of failure:



- (a) $\int_{\Omega} [f_{X_1}(x_1) + f_{X_2}(x_2)] dX_1 dX_2$
 (b) $P(X_1 > x_1^* \cup X_2 > x_2^*)$
 (c) $\int_{\Omega} f_{X_1|X_2}(x_1|X_2 = x_2^*) f_{X_2}(X_2 = x_2^*) dX_1$
 (d) $\int_{\Omega} f_{X_1, X_2}(x_1, x_2) dX_1 dX_2$

