| Course Type | Course Code | Name of Course | L | T | P | Credit |
|---|---|---|---|---|---|---|
| DE | NMED543 | Data-Driven Modelling for Mechanical Systems | 3 | 0 | 0 | 3 |

**Course Objective**

1. Develop foundations in linear algebra, signal processing, dynamical systems, optimization, regression, and numerical methods for data-driven modeling.
2. Introduce non-intrusive data-driven methods, including machine learning, physics-informed neural networks, and neural operators.
3. Introduce intrusive methods, including projection-based reduced-order modeling and POD–Galerkin formulations, for mechanical systems.

**Learning Outcomes**

By the end of the course, students will be able to:

1. Understand the foundational concepts in data-driven modeling: linear algebra, matrix decomposition, signal processing, optimization, and regression methods.
2. Formulate data-driven models using simulation data, experimental data, and governing equations.
3. Develop non-intrusive models using machine learning, physics-informed neural networks, and neural operators.
4. Construct intrusive projection-based reduced-order models using POD–Galerkin methods.
5. Implement and evaluate data-driven models for simulating physical systems.

| Unit No. | Topics to be Covered | Lecture Hours | Learning Outcome |
|---|---|---|---|
| 1 | **Linear Algebra:** A Geometric Viewpoint, Vector Space, Eigenvalue Problems, Singular Value Decomposition (SVD) | 5 | Interpret vectors, matrices, and linear transformations geometrically. Analyze vector spaces, bases, eigenvalues, and eigenvectors. Apply singular value decomposition to matrix approximation and data reduction. |
| 2 | **Dynamical Systems, Signal Processing and Transform Methods:** LTI, Fourier transform, FFT, Digital filters. | 5 | Analyze linear time-invariant systems and their response behavior. Use Fourier transforms and FFT to represent and process signals. Design and evaluate basic digital filters for signal conditioning. |
| 3 | **Numerical Solution of Differential Equations:** Nonlinear ODEs in Mechanics, Phase Portraits and Stability Analysis, Basic Numerical Methods for ODEs, PDEs. | 9 | Model and analyze nonlinear ODEs arising in mechanics, construct phase portraits to assess system stability, and apply numerical methods for ODEs and basic PDE discretizations. |
| 4 | **Computational Matrix Methods for Large-Scale Systems:** Sparse Matrix, Iterative Solvers: GMRES, BiCGSTAB, and Conjugate Gradient , Matrix Preconditioning Techniques | 4 | Represent and manipulate sparse matrices efficiently, select and apply iterative solvers such as GMRES, BiCGSTAB, and Conjugate Gradient, and use matrix preconditioning techniques to improve convergence and computational efficiency. |

| | | | |
|---|---|---|---|
| 5 | **Nonlinear Optimization with Multivariate Regression Methods:** Multivariate Regression and Statistical Inference, Least Squares, Regularization Techniques: Ridge, LASSO. | 6 | Formulate multivariate regression models and interpret statistical inference results, apply least-squares methods for parameter estimation, and use regularization techniques such as Ridge and LASSO to control overfitting. |
| 6 | **Non-intrusive data-driven modeling:** Machine-Learning Surrogates, Physics-Informed Neural Networks (PINNs), and Neural Operators (NOs), Gaussian Process Regression (GPR). | 7 | Build machine-learning surrogate models from input-output data, apply PINNs to embed governing equations into learning models, and use NOs to approximate mappings between functions or fields, implement GPR for surrogate modeling. |
| 7 | **Intrusive data-driven modeling:** Projection-Based Reduced-Order Modeling (pROM) including POD-Galerkin Methods. | 6 | Explain pROM and its computational advantages, apply POD-Galerkin methods to construct reduced-order models, and evaluate the accuracy, stability, and efficiency of reduced-order approximations. |
| | **Total** | 42 | |

## Text book:

1. Steven L. Brunton and J. Nathan Kutz, Data-Driven Science and Engineering: Machine Learning, Dynamical Systems, and Control, 2nd ed., Cambridge University Press, 2022.

2. Kutz, J. N. (2026). Data-Driven Modelling & Scientific Computation: Methods for Complex Systems & Big Data (2nd ed.). Oxford University Press.

## References:

1. Trefethen, L. N., & Bau, D. (1997). Numerical Linear Algebra. SIAM.

2. Herman, E. A., & Pepe, M. D. (2005). *Visual Linear Algebra*. John Wiley & Sons.

3. Deb, K., Optimization for engineering design: algorithms and examples, Prentice Hall India, New Delhi, 2nd Edition, 2012.

4. Benner, P., Grivet-Talocia, S., Quarteroni, A., Rozza, G., Schilders, W., & Silveira, L. M. (Eds.). (2021). Model Order Reduction: Volume 1—System- and Data-Driven Methods and Algorithms. De Gruyter. https://doi.org/10.1515/9783110498967

5. Thuerey, N., Holl, P., Mueller, M., Schnell, P., Trost, F., & Um, K. (2021). Physics-based deep learning. arXiv preprint arXiv:2109.05237.