# GAUTAM BUDDHA UNIVERSITY

## Course Name: PHM BASIC

| | PHM BASIC | |
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| S No | Topics | Total Hours: 60 |
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| 1 | **Introduction** | 4 |
| | | |
| | The various types of maintenance. Cost-Benefit Analysis. | 1 |
| | Condition-based Maintenance and Predictive Maintenance. When is predictive maintenance justified ? | 1 |
| | Detection. Diagnostics | 1 |
| | Prognostics. | 1 |
| | The PHM Process.The various stages according to IS0 13374 | |
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| 2 | **Data Acquisition** | 8 |
| | | |
| | Which data should be acquired? Determining critical components through FMMEA and experience | 2 |
| | How should data be acquired ? Sensor systems for PHM. Connected objects; the IoT | 2 |
| | Data acquisition characteristics (sampling rate, data communication). Data storage. Architecture. Edge vs Cloud. | 2 |
| | Data Quality . Data Cleansing. Dealing with outliers. Data Acquisition KPIs. | 2 |
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| 3 | **Specifying and Validating PHM** | 8 |
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| | PHM Requirements and Specification Development | 2 |
| | PHM Performance Evaluation | 3 |
| | Dealing with Uncertainty: epistemic, measurement and future profile uncertainty. | |
| | Health Indicator Validation. Test bench approach and virtual protptype approach. | |
| | Detection metrics :confusion matrix, sensitivity, recall, etc. ROC Curve | 3 |
| | Diagnostics metrics | |
| | Prognostics metrics | |
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| 4 | **Notions of Machine Learning (for PHM)** | 8 |
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| | Machine Learning and Artificial Intelligence | 1 |
| | Classification and Regression | 1 |
| | Supervised Learning . Training set and test set | 2 |
| | Unsupervised Learning. Clustering | 2 |
| | Cross-Validation | 1 |
| | Introduction to Neural Networks | 1 |

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| **5** | **Model-based PHM** | **11** |
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| | Physics-of-Failures degradation models: concept and examples: Paris-Erdogan law for crack growth; etc. | 2 |
| | Kalman filter, particle filter | 3 |
| | Model-based Detection, diagnostics and prognostics | 3 |
| | PHM for Electromechanical systems | 2 |
| | PHM for Electronics (e.g. capacitors) | 0.5 |
| | PHM for Electrochemical systems ( e.g. batteries) | 0.5 |
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| **6** | **Data-driven PHM** | **14** |
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| | Notion of Feature | 1 |
| | Problem Formulation.Data pre-processing.Feature Engineering. Feature Extraction and Selection. Expert validation.Context importance | 2 |
| | Feature Extraction.Time domain. Frequency Domain. Mixed. Wavelets; Hilbert-Huang transform. EMD | 2 |
| | Feature Reduction | 3 |
| | Parametric methods. Maximum Likelihood. Bayesian | 1 |
| | Dimensionality Reduction.Principal Components Analysis ( PCA) | 1 |
| | Notion of Health Indicator. Distance -based Classification (e.g. Mahalanobis) | 1 |
| | How to select a suitable classification or regression algorithms? Non -exhaustive list of methods (below) - may be modified. | |
| | k-NN (k-nearest neighbours), SVM ( Support vector machine), other. | 1 |
| | Regression Methods for Prognostics | 2 |
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| **7** | **RAMS and PHM** | **4** |
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| | FMMEA as first step of a PHM Model | 1 |
| | Relations beTween RUL , MRL ( Mean Residual Life) , reliability function, hazard rate | 1 |
| | Probability Distribution of RUL | 1 |
| | Impact of Predictive Maintenance on Availability | 1 |
| | Safety issues | |
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| **8** | **PHM Standards** | **2** |
| | ISO, IEEE, IEC | |
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| | **PHM ADVANCED** | **60** |
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| **1** | **Functional approaches** | **6** |
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| | Generative methods | 3 |
| | Functional PCA ( FPCA) | 3 |
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| **2** | **Hybrid approaches: combining model-based and data-driven techniques** | **5** |
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| **3** | **Decision Trees** | **5** |
| | Classification trees, regression trees, random forests | |
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| | **Artificial Neural Networks for PHM** | **18** |
| | Historical overview.Perceptron. Multi-layer perceptron | 2 |
| | Backward Propagation | 2 |
| | Convolutional Neural Networks ( CNN). | 2 |
| | Recurrent Neural Networks (RNN) /LSTM ( Long term-short term memory). | 2 |
| | Semi-supervised approaches | 2 |
| | Reinforcement learning | 2 |
| | Feature learning : stacked auto-encoders and related techniques | 2 |
| | Transfer Learning.Adversarial learning | 2 |
| | Challenges : interpretability and auditability | 2 |
| | | |
| **5** | **HMM ( Hidden-Markov Model)** | **4** |
| | Concept of HMM | 1 |
| | The three problems of HMM | 1 |
| | Viterbi algorithm, Baum-Welch algorithm | 2 |
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| **6** | **Combining multiple learners** | **1.5** |
| | Boosting, bagging | |
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| **7** | **PHM-Enabled Maintenance Decision Making** | **6** |
| | Value of Information vs Data Acquisition Cost. When is it worth acquiring new data ? | 2 |
| | Combining maintenance constraints and operational constraints: dynamic maintenance planning | 2 |
| | Closing the loop: maintenance decisions affect asset health. | 2 |
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| **8** | **PHM-based Product Qualification** | **4** |
| | Product Testability | 2 |
| | Designing PHM-Enabled Products | 2 |

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| **9** | **PHM and Digital Twins** | **4** |
| | Continuously learning model | 2 |
| | Digital transformation with digital twins | 2 |
| | Opportunities and Challenges | 1 |
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| **10** | **Safety and Cybersecurity. Data Ownership** | **4** |
| | How can safety be guaranteed in a predictive maintenance context? | 1 |
| | How can cyber-threats be detected and mitigated ? | 1 |
| | Whom do the data belong to ? How to ensure data integrity ? | 2 |
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| | **CASE STUDIES IN PHM ( LAB)** | |
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| | Aerospace | 15 |
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| | Railways | 15 |
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| | Process Industries | 15 |
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| | **TUTORIALS** | 45 |
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