HAND BOOK
of
CURRICULUM STRUCTURE AND SYLLABUS
Doctor of Philosophy - IET
(Programme Code: 3101)
Batch: 2020-21

Institute of Engineering and Technology

Vision

To be one of India's most innovative higher education institutions.

Mission

To realise its vision, the University will:

Practice teaching that inculcates critical thinking and problem solving,

Pursue research that leads to innovation and enhancement of real-life applications,

Offer experience that leads to all round development, and

Develop a culture that is strongly rooted in interdisciplinarity and learning by building, not just doing.

Values

Caring for people.

Integrity including intellectual honesty, openness, fairness, and trust.

Commitment to excellence.

IQAC Documentation

Document Name: Curriculum Structure and Syllabus Handbook, Doctor of Philosophy in Engineering (Session 2020-2021)

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Document Description: This document is prepared by the Institute of Engineering and Technology (IET), JKLU to serve as an information baseline for further planning and delivery of courses w.r.t Doctor of Philosophy in Engineering (Session 2020-2021).

It includes Curriculum Structure, collation of Semester wise Course Description, prepared by respective faculty members.

This document is in compliance with BoS (upto 13th meeting) and approvals of the Academic Council (upto 20th meeting).

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Basic Rules and Regulations

1. Credit Requirement in Pre-PhD Course Work:

S. No.	Qualifying Examination	Credits
1.	M. Phil, M. Tech	9
2.	MBA, M. Sc., MCA, M. Com	16
3.	B. Tech	32

2. Research Methodology, Pedagogy, Academic Writing, Credit-2 each course, would be compulsory courses for Pre-PhD Course work. Remaining credits can be earned through elective courses and/or MOOC courses offered by different departments/institutes.
3. Minimum CGPA requirement for passing Pre-PhD Course work is 6.
4. Minimum duration of the PhD Programme would be 3 years and one can complete PhD work within 6 years (UGC Norms).

Course Structure, Detailed Syllabus & Scheme of Examination

S. No.	Course Code	Course Title	Total Contact Hours	Credits	Target Students	Core/ Elective
Common Core Courses (Engineering and Management)						
1	IL2101	Research Methodology	2 0 0	2	Pre PhD	Core
2	IL2102	Pedagogy	2 0 0	2	Pre PhD	Core
3	IL2103	Academic Writing	2 0 0	2	Pre PhD	Core
Elective Courses in Engineering						
1	AS2102	Algebra of Random Variable	3 0 0	3	Pre PhD	Elective
2	AS2103	Software Reliability	3 0 0	3	Pre PhD	Elective
3	AS2105	Chemical kinetics and transition state theory	310	4	Pre PhD	Elective
4	CS2102	Machine Learning and Data Mining	3 0 4	5	Pre PhD	Elective
5	CE2401	Advanced Concrete Technology	12 Weeks	4	Pre PhD	MOOC (NPTEL)
6	CH2101	Basic Thermodynamics: Classical and Statistical Approaches	310	4	Pre PhD	Elective
7	CS2401	Advanced Statistics	12 Weeks	4	Pre PhD	Curative MOOC
8	CS2402	Data Structure and Algorithms	12 Weeks	4	Pre PhD	Curative MOOC
9	CE2202	Advanced Highway Materials	3 0 2	4	Pre PhD	Elective
10	AS2201	Multi-Objective Optimization	3 0 0	3	Pre PhD	Elective
11	CS2403A	Introduction to Machine Learning	12 Weeks	4	Pre PhD	Curative MOOC
12	EE2104	Optimisation and Control	3 0 0	3	Pre PhD	Elective
13	EE2101	Industrial Automation and IoT-I	3 0 2	4	Pre PhD	Elective
14	EE2201	Computer Vision	3 0 0	4	Pre PhD	Elective
15	EE2105	High Voltage Engineering	3 0 2	4	Pre PhD	Elective

16	CS2405	Deep Learning	11 Hrs. Per week	5	Pre PhD	Curative MOOC
17	IL2401	Statistics with Python	3 0 2	3	Pre PhD	Curative MOOC
18	CS2406	Emerging Technologies: IoT and Big Data	1 0 1	3	Pre PhD	Curative MOOC
19	CS2115	Applied Advanced Machine Learning	3 0 2	5	Pre PhD	Curative MOOC

CORE AND MANDATORY COURSES FOR ENGINEERING AND MANAGEMENT

Course code	Course Title	Teaching Scheme				
		L	T	P	S	Credits
IL2101	Research Methodology	20	0	0	0	2

Target Students: PhD Scholars.

Course Objectives: This course aims to familiarize the PhD students with basic elements of research thinking.

Learning Outcomes:

On successful completion of this course, the students should be able to:

1. critically analyze the strengths and weaknesses of one's own and other's intellectual work and also write a literature review on a topic.
2. identify, describe, and critique the methods used for research in engineering, management, and development.
3. define research problems from a coherent analysis of gaps in existing knowledge base.
4. formulate hypotheses and/or research questions
5. write research proposals describing research questions, purpose, context, metrics, sources and methodology.
6. undertake research work making systematic use of investigation or experimentation, to discover or revise knowledge of reality.

Assessment Scheme:

Prerequisites : Nil		**Research Methodology**
Teaching Scheme		20+ hrs of Lecture, Seminar
Credit		2
Sr. No.	**Evaluation Component**	**Marks**
1	Attendance	NA
2	Assignment	30
3	Class Participation	10
4	Quiz	NA
5	Theory Exam-I	NA
6	Theory Exam-II	NA
7	Theory Exam-III	NA
8	Report-I	30
9	Report-II	NA
10	Report-III	NA
11	Project-I	30
12	Project-II	NA
13	Project-III	NA

14	Lab Evaluation-I	NA
15	Lab Evaluation-II	NA
16	Course Portfolio	NA
	Total (100)	100

Course Syllabi:

Ways of knowing, nature of science and philosophy, research competencies, reasoning, critical thinking for researchers, fallacies, common errors in analysis, literature review, nature of theoretical and empirical world, research approaches, research process, research goal, basic research, applied research, empirical research, characteristics of good research, types of research results, framing research proposal, pitfalls in research proposals, ethical issues in research, data collection, sources of evidence,

Reference and Reference Sources:

1. Jerry Wellington et al, Succeeding with Your Doctorate, SAGE Publications, 2005
2. Holyoak, Keith J., and Robert G. Morrison, eds. The Cambridge Handbook of Thinking And Reasoning. Cambridge University Press, 2005.
3. McNabb, David E. Research methods for political science: Quantitative and qualitative methods. Routledge, 2004, 2015.
4. Yin, R. K. 2003. Case Study Research: Design and Methods, 2d Edition. Thousand Oaks, 3rd Edition, CA: Sage Publications.
5. Patten, Mildred L. Proposing empirical research: A guide to the fundamentals. Part E, Pyrczak Pub, 2005
6. http://philosophy.hku.hk/think/arg
7. http://158.132.155.107/posh97/private/ResearchMethods/150.htm

Many more references will be provided during the courses.

Facebook Group: **https://www.facebook.com/groups/746835115749631/**

Course code	Course Title	Teaching Scheme				
		L	**T**	**P**	**S**	**Credits**
IL2102	**Pedagogy**	**20**	**0**	**0**	**0**	**2**

Target Students: PhD Scholars.

Course Objectives: This course aims to familiarize the PhD students with modern approaches for teaching university level or continuing professional development courses.

Learning Outcomes:

On successful completion of this course, the students should be able to:

1. Plan appropriate learning outcomes for university level or continuing professional development courses in their discipline wrt the New Education Policy or National Skill Qualification Framework.
2. Design a variety of learning activities for university level or continuing professional development courses in their discipline wrt the desired learning outcomes.
3. Design appropriate assessment schemes for university level or continuing professional development courses in their discipline wrt the desired learning outcomes.
4. Use flipped class- room, team-teaching, and project based learning or other approaches ofinductive teaching to transform regular university level or continuing professional development courses in their disciplines.

Assessment Scheme:

Prerequisites : Nil		**Pedagogy**
Teaching Scheme		20+ hrs of Lecture, Seminar, and Observation of selected classes
Credit		2
Sr. No.	**Evaluation Component**	**Marks**
1	Attendance	NA
2	Assignment	30
3	Class Participation	10
4	Quiz	NA
5	Theory Exam-I	NA
6	Theory Exam-II	NA
7	Theory Exam-III	NA
8	Report-I	30
9	Report-II	NA
10	Report-III	NA

11	Project-I	30
12	Project-II	NA
13	Project-III	NA
14	Lab Evaluation-I	NA
15	Lab Evaluation-II	NA
16	Course Portfolio	NA
	Total (100)	100

Course Syllabi:

New Education Policy, NSQF, Levels of Expertise, Cognitive and Moral Development. Learning Styles, Deep learning, Bloom's Taxonomy of educational objectives, Dimensions of Learning, Solo Taxonomy of Educational Objectives, Merrill's Principles of Instruction, Deductive teaching, inductive teaching, flipped class, team-teaching, and hybrid teaching, Social learning theory, Experiential learning, Constructivism, Situated Learning,
Problem/Project based learning, etc.

Reference and Reference Sources:

1. New Education Policy, 2019
2. NSQF
3. https://www.learning-theories.com/
4. https://gsi.berkeley.edu/gsi-guide-contents/
5. https://eric.ed.gov/
6. https://tomprof.stanford.edu/
7. https://www.engr.ncsu.edu/stem-resources/legacy-site/education/
8. More specific references will suggested during the coursework.

Facebook Group: **https://www.facebook.com/groups/746835115749631/**

Course code	Course Title	Teaching Scheme				
		L	T	P	S	Credits
IL2103	Academic Writing	20	0	0	0	2

Target Students: PhD Scholars.

Course Objectives: Although they follow a well-defined format, writing scientific articles and getting them ready to be published, can be a difficult task. This course focuses on practicing necessary skills to write good academic prose.

Learning Outcomes:

On successful completion of this course, participants should be able to:

1) Write a scientific article to communicate about their research

2) Assess the quality of academic writing

3) Prepare a scientific article for publication, using different computational tools

Prerequisites : Nil

Teaching Scheme	20+ hrs of Lecture, Seminar, and Observation of selected classes
Credit	**2**

Assessment Scheme:

Sr. No.	Evaluation Component	Marks
1	Attendance	NA
2	Assignment	30
3	Class Participation	NA
4	Quiz	30
5	Theory Exam-I	NA
6	Theory Exam-II	NA
7	Theory Exam-III	NA
8	Report-I	NA
9	Report-II	NA
10	Report-III	40
11	Project-I	NA
12	Project-II	NA
13	Project-III	NA
14	Lab Evaluation-I	NA
15	Lab Evaluation-II	NA
16	Course Portfolio	NA
	Total (100)	100

Course Syllabus
1. The scientific paper. Sections: Title, Authors/Affiliation, Abstract, Introduction, Materials and methods, Results, Discussion, Conclusion, References, Bibliography, Footnotes, Appendix and Acknowledgements.

2. Tools and techniques for academic writing. Basic guidelines for text, equations, tables, figures, legends, graphs, quotes, references, captions, journal formats, etc. Using version control tools, using reference management tools.

3. Preparing to publish. Rewriting, final manuscript preparation, analysing written arguments and responding to referees. Ethics in research and publication. Plagiarism checkers, Peer Review Process, Social Impact, Ensuring Visibility

Reference and Reference Sources:

[1] E. Wager and S. Kleinert, "Responsible research publication: international standards for authors. A position statement developed at the 2nd World Conference on Research Integrity," presented at the Promoting Research Integrity in a Global Environment, 2011.

[2] S. A. Socolofsky, "How to write a research journal article in engineering and science," p. 17.

[3] M. J. Katz, From research to manuscript: a guide to scientific writing. Dordrecht, The Netherlands: Springer, 2006.

[4] Zemach Rumisek. Academic Writing, 2005. Macmillan ELT

[5] S. Bailey, Academic writing: a handbook for international students. London; New York: Routledge Falmer, 2004.

[6] I. Leki, Academic writing: exploring processes and strategies, 2. ed., 13th print. Cambridge: Cambridge Univ. Press, 2009.

[7] S. Kaye, Writing under pressure: the quick writing process. New York: Oxford University Press, 1989.

[8] E. J. Rothwell and M. J. Cloud, Engineering Writing by Design: Creating Formal Documents of Lasting Value, 1st ed. CRC Press, 2017.

[9] Silvia, P. J. 2015. Arcana and miscellany: From titles to footnotes. Write it up: Practical strategies for writing and publishing journal articles: 157-174. Washington, DC: American Psychological Association.

[10] Ballinger, G. A. & Johnson, R. E., 2015. Editor's comments: Your first AMR review. Academy of Management Review, 40(3): 315-322.

[11] Kamler, B. 2008. Rethinking doctoral publication practices: Writing from and beyond the thesis. Studies in Higher Education, 33(3): 283-294.

[12] Alvesson, M. & Sandberg, J. 2011. Generating research questions through problematization. Academy of Management Review, 36(2): 247-271.

IT Resources:

Elsevier Researcher Academy: https://researcheracademy.elsevier.com/

Coursera. Academic English: Writing. University of California, Irvine. https://www.coursera.org/specializations/academic-english

ELECTIVES IN ENGINEERING

Course Title: Algebra of Random Variables
Course Code: AS2102
Teaching Scheme: 3 0 0
Credits: 3

Course Objectives:

To familiarize students with the fundamentals of probability theory, random variables, random processes and algebraic operations on random variables and then finding solutions to some problems which requires applications of algebraic operations to random variables.

Syllabus

RANDOM VARIABLES
Random variables, Distribution and density functions of random variables, Discrete and continuous random variables, Gaussian, Exponential, Rayleigh, Uniform, discrete Uniform and conditional distributions, distribution mean, variance, moments and characteristics functions.

MULTIPLE RANDOM VARIABLES
Function of two random variables, Distributions of two random variables, correlation coefficient, Joint moments, Joint characteristics functions, Conditional distributions, conditional expected values, statistical independence. Multiple random variables, distribution of sums of random variables, Central limit theorem.

DISTRIBUTION OF SUM AND DIFFERENCE OF RANDOM VARIABLES
The Fourier convolution as the distribution of a sum, the distribution of sum and difference of continuous random variables, the distribution of the sum of mixtures of independent random variables.

DISTRIBUTION OF PRODUCTS AND QUOTIENTS OF RANDOM VARIABLES
The Mellin convolution and its relation with the distribution of product, the distribution of products and quotients of independent nonnegative random variables, the distribution of the products and quotients of continuous standardized Nonnegative random variables.

DISTRIBUTION OF PRODUCTS AND QUOTIENTS OF RANDOM VARIABLES THAT ARE NOT EVERYWHERE POSITIVE

The distribution of product of random variables that are not everywhere positive, the distribution of product of independent normal random variables. The distribution of product of discrete random variables.

Reference books

1. M.D. Springer, The Algebra of Random Variables, John Wiley & Sons.
2. J. Susan Milton and Jesse C. Arnold, 'Introduction to Probability and Statistics', McGraw Hill Education.
3. Papoulis, 'Probability, Random Variables And Stochastic Processes', TMH.
4. P. Kousalya, Probability, Statistics and Random Processes, Pearson.

Course code	Course Title	Teaching Scheme				
		L	T	P	S	Credits
AS2103	**Software Reliability**	**3**	**1**	**0**	**0**	**4**
Course Objectives: This Course aims to develop various concepts and tools to help students understand software metrics and software reliability models.						

Course Syllabi (Theory):

Unit – I: Introduction

Need for software reliability, Basic definition and terminology, introduction to reliability measures

Unit – II: Software Reliability Modelling

Introduction, Software metrics and software reliability models, Failure rate models, Reliability growth models, Markov structure models

Unit – III: NHPP Software Reliability Models

Introduction to Non-homogenous Poisson process models, Parameter estimation, NHPP models

Unit – IV: Fault-tolerant Techniques

Software fault tolerance, faults, errors and their management strategies, software defense, Fault recovery techniques

Course Title and Code : Chemical kinetics and transition state theory ((AS2105)	
Hours per Week	**L-T-P: One week** **3-1-0**
Credits	**04**
Students who can take	Ph.D.

Course Objective: This course provides an in-depth understanding of the kinetics of reactants and products. It covers two models: collision theory (CT) and transition state theory (TST). The course also aims to equip students with an understanding of rate theory, basic statistical mechanics, Boltzmann distribution and partition functions.

After course completion, the student will be able to:

1. Describe the concept of rate change associated with chemical change and how it can be measured.
2. Determine rate law of chemical change based on experimental data. And would able to identify the reaction order for a chemical change.
3. Apply integrated rate equations to solve for the concentration of chemical species during a reaction of different orders.
4. Explain the Arrhenius Law/Equation and the function of a catalyst.
5. Apply the transition theory between products and reactants, and calculate their transition state.

	Prerequisites	
Sr. No	**Specifications**	**Marks**
1	Attendance	**Nil**
2	Assignment	**20**
3	Class Participation	**Nil**

4	Quiz	**20**
5	Theory Exam-I	**Nil**
6	Theory Exam-II	**3**0 (From NPTEL completion certificates)
7	Theory Exam-III	**30**
8	Report-I	**NIL**
9	Report-II	Nil
10	Report-III	Nil
11	Project-I	Nil
12	Project-II	Nil
13	Project-III	Nil
14	Lab Evaluation-I (Contus.)	Nil
15	Lab Evaluation-II (exam)	Nil
16	Course Portfolio	Nil
	Total (100)	**100**
Evaluation Scheme for Retest:		
S. No.	**Specifications Marks**	**Marks**
1	Theory Exam-III	30
	TOTAL	30

SYLLABUS:

The Rate of a reaction; the rate law; the relation between reactant concentrations and time; activation energy and temperature dependence of rate constants; reaction mechanism; catalysis.; The kinetic molecular theory of gases; pressure of a gas; the gas law; the ideal gas equation; gas stoichiometry; deviation of gas law from ideal behavior; Daltons law; Maxwell's distribution; Boltzmann distribution: a story of Hamilton; Liouville and Boltzmann; Maxwell Boltzmann distribution; Boltzmann distribution and the kinetic theory of collisions;

thermodynamic functions of an ideal monoatomic and diatomic gas.

Reference Books:

1. Physical chemistry; Atkins; W. H. Freeman and Company New York; ISBN: 0-7167-8759-8
2. Chemistry; Raymond Chang; Tata McGraw Hill , Ninth edition 2010, ISBN 13: 978-0-07-064819-7
3. Chemistry; by John Mc Murry & Robert C. Fay; Pearson Education, ISBN: 81-297-0416-1
4. Pricipal of Physical Chemistry; Puri, Sharma, Pathania, Vishal publication ISBN13:9789387015814
5. A text book of physical chemistry by A. S. Negi and S. C. Anand; New Age publisher; ISBN:0-85226-020-2 https://books.google.co.in/books?id=wyP_V3X8YOIC&pg=PR1&source=gbs_selected_pages&cad=3#v=onepage&q&f=false }
6. ONLINE NPTL Chemistry Lecture : https://onlinecourses.nptel.ac.in/noc21_cy17/preview

Course Title and Code: Machine Learning and Data Mining: CS2102	
Hours per Week	**L-T-P: 3-0-4**
Credits	**5**
Students who can take	M. Tech & PhD (2020-2021)

Course Objective: This course introduces the fundamental concepts of machine learning and data mining techniques. The course will cover the state-of-the art data mining techniques along with its usage with machine learning algorithms on real-world data (or big data). This course helps the students to pursue project related ML and data mining with real-world research problems.

Learning Outcome:

On successful completion of this course, the students should be able to:

1. Utilize advanced knowledge of data mining, data warehousing and KDD concepts and techniques.
2. Organize and Prepare the data needed for data mining using pre-preprocessing techniques.
3. Generate and apply different mining techniques such as rule generation, association mining, Bayesian techniques and Frequent Itemset generation.
4. Apply the techniques of clustering, classification, association finding, feature selection and visualization on real world data.
5. Demonstrate knowledge in scalability and management of large dataset.
6. Identify machine learning techniques suitable for a given problem.
7. Interpret fundamental issues and challenges of machine learning: data, model selection, model complexity, etc.
8. Apply dimensionality reduction techniques.
9. Appreciate the underlying mathematical relationships within and across Machine Learning algorithms and the paradigms of supervised and un-supervised learning.
10. Utilize state-of-the art algorithms of Machine Learning for building applications.

Prerequisites		Linear Algebra, Basic Statistics
Sr. No	**Specifications**	**Marks**
1	Attendance	Nil
2	Assignment	10
3	Class Participation	10
4	Quiz	10
5	Theory Exam	20
6	Theory Exam	Nil
7	Theory Exam	Nil
8	Report-1	10
9	Report-2	Nil
10	Report-3	Nil
11	Project -1	20
12	Project -2	Nil
13	Project -3	Nil
14	Lab Evaluation1	Nil
15	Lab Evaluation2	20

16	Course portfolio	Nil
	Total (100)	100

Syllabus (Theory)

UNIT – I: Introduction: Data warehouse – Difference between Operational DBs and Data warehouses – Multidimensional Data Model, The process of knowledge discovery in databases, predictive and descriptive data mining techniques, supervised and unsupervised learning techniques.

UNIT – II: Techniques of Data Mining: Link analysis, predictive modeling, database segmentation, score functions for data mining algorithms, Bayesian techniques in data mining, Association Analysis: Problem Definition; Frequent Itemset generation; Rule Generation; Compact representation of frequent itemsets; Alternative methods for generating frequent item-sets

UNIT – III: Issues in Data Mining: Scalability and data management issues in data mining algorithms, parallel and distributed data mining, privacy, social, ethical issues in Knowledge Discovery in Databases (KDD) and data mining, pitfalls of KDD and data mining.

UNIT – IV: Introduction to Machine Learning, Supervised Learning: Classification: Preliminaries; General approach to solving a classification problem; Decision tree induction; Rule-based classifier; Simple and Multiple Linear Regression ; Nearest-neighbor classifier, SVM, Unsupervised Learning: Clustering; K-Means, Hierarchical Clustering

UNIT – V: Model Evaluation Measures: Cross-Validation Technique, Confusion matrix for evaluation, Class probabilities and class predictions, ROC Curve, Model evaluation metrics, Fitting dataset and evaluating their performance set, Evaluation of selected features, Model evaluation metrics, making predictions on new data

Usage of AI and ML Techniques for achieving sustainable practices, NIST and IEEE standards for AI and ML libraries, tools and techniques.

Reference Books:

1. Mitchell, Tom. Machine Learning, McGraw Hill 1997.
2. Murphy, Kevin P. Machine learning: a probabilistic perspective. MIT press, 2012. (Electronic copy available through the Bodleian library.)
3. Bishop, Christopher M. Pattern recognition and machine learning. Springer, 2006.
4. Han, Jiawei, Jian Pei, and Micheline Kamber. Data mining: concepts and techniques. Elsevier, 2011.
5. Tan, Pang-Ning, Michael Steinbach, Vipin Kumar, and Anuj Karpatne. Introduction to Data Mining, Global Edition. Pearson Education Limited, 2019.
6. Witten, Ian H., Eibe Frank, Mark A. Hall, and Christopher J. Pal. Data Mining: Practical machine learning tools and techniques. Morgan Kaufmann, 2016.

Course Code: CS2401
Course Name: Advanced Statistics
Credits: 4
Course Offered to: Pre Ph.D (Curated MOOC)

Course Description: This course will introduce and explore various statistical modeling techniques, including linear regression, logistic regression, generalized linear models, hierarchical and mixed effects (or multilevel) models, and Bayesian inference techniques. All techniques will be illustrated using a variety of real data sets, and the course will emphasize different modeling approaches for different types of data sets, depending on the study design underlying the data, Understanding and Visualizing Data with Python.

PREREQUISITES: Linear Algebra, Basic Statistics

Evaluation Scheme:

Sr. No	Specifications	Marks
1	Attendance	Nil
2	Assignment	20
3	Class Participation	Nil
4	Quiz	Nil
5	Theory Exam I	20
6	Theory Exam II	Nil
7	Theory Exam III	40
8	Report-1	Nil
9	Report-2	Nil
10	Report-3	Nil
11	Project -1	20
12	Project -2	Nil
13	Project -3	Nil
14	Lab Evaluation1	Nil
15	Lab Evaluation2	Nil
16	Course portfolio	Nil
	Total (100)	100

COURSE CONTENTS:

Overview & Considerations for Statistical Modeling, Fitting Models to Independent Data, Fitting Models to Dependent Data, Case Studies, Assignments & Lab Sessions.

SUGGESTED READING MATERIALS:
This course is part of the **Statistics with Python Specialization** Offered by **University of Michigan** through **Coursera**. Student may refer course notes, videos & ppts. Advanced Statistics text books as optional background material.

Course Code: CS2402
Course Name: Data Structure and Algorithms
Credits: 4
Course Offered to: Pre Ph.D (Curated MOOC)

Course Description: This course will introduce Advanced Algorithms and Complexity. Essentially, a linear programming problem needs to optimize a linear function of real variables constrained by some system of linear inequalities. This course will study the classical NP-complete problems and the reductions between them. Also practice solving large instances of some of these problems despite their hardness using very efficient specialized software based on tons of research in the area of NP-complete problems. It will first show that some special caseson NP-complete problems can, in fact, be solved in polynomial time then consider exact algorithms that find a solution much faster than the brute force algorithm. This course will conclude with approximation algorithms that work in polynomial time and find a solution that is close to being optimal.

PREREQUISITES: Linear Algebra, Basic Statistics

Evaluation Scheme:

Sr. No	Specifications	Marks
1	Attendance	Nil
2	Assignment	20
3	Class Participation	Nil
4	Quiz	Nil
5	Theory Exam I	20
6	Theory Exam II	Nil
7	Theory Exam III	40
8	Report-1	Nil
9	Report-2	Nil
10	Report-3	Nil
11	Project -1	20
12	Project -2	Nil
13	Project -3	Nil
14	Lab Evaluation1	Nil
15	Lab Evaluation2	Nil
16	Course portfolio	Nil
	Total (100)	100

COURSE CONTENTS:
Advanced Algorithms and Complexity, Linear Programming, NP-complete Problems, Coping with NP-completeness & Flows in Networks, Case Studies, Assignments & Lab Sessions.

SUGGESTED READING MATERIALS:

This course is part of the Data Structures and Algorithms Specialization Offered by
UNIVERSITY OF CALIFORNIA SAN DIEGO and NATIONAL RESEARCH UNIVERSITY HIGHER SCHOOL OF ECONOMICS through **Coursera**. Student may refer course notes, videos & ppts. Advanced Data Stuctures & Algorithms textbooks as optional background material.

Course Title: Advanced Concrete Technology (NPTEL)
Course Code: CE2401
Duration: 12 weeks
Credit: 4

Syllabus:

Cement Chemistry & Aggregates for concrete

Chemical and mineral admixtures

High performance concrete proportioning Tests for

fresh concrete and hardened concrete Creep and

shrinkage in concrete

Durability of concrete

Course Title and Code: **Basic Thermodynamics: Classical and Statistical Approaches (CH2101)**	
Hours per Week	**L-T-P: 3-1-0**
Credits	**4**
Students who can take	Ph.D.

Course Objective:

This course provides an in-depth understanding laws of thermodynamics, thermodynamic relations, Solution thermodynamics, phase equilibrium and chemical reaction equilibrium. The key elements include the adaptation of classical, statistical, and postulate-based thermodynamics approaches to understanding entropy and related thermodynamic potentials for different flow processes.

After course completion, the student will be able to:

CH2101.1 Apply the basic laws of thermodynamics to calculate heat and work requirement for industrial processes.

CH2101.2 Apply mass, energy and entropy balances to flow processes.

CH2101.3 Evaluate and apply the concepts of phase equilibrium.

CH2101.4 Evaluate and apply the physical and chemical equilibrium

CH2101.5 Analyze and evaluate data from PVT behavior of fluids and ideal gas systems

	Prerequisites	
Sr. No	**Specifications**	**Marks**
1	Attendance	-
2	Assignment	20
3	Class Participation	-
4	Quiz	20
5	Theory Exam-I	-
6	Theory Exam-II	30 (From NPTEL Completion Certificates)
7	Theory Exam-III	30

8	Report-I	-
9	Report-II	-
10	Report-III	-
11	Project-I	-
12	Project-II	-
13	Project-III	-
14	Lab Evaluation-I	-
15	Lab Evaluation-II	-
16	Course Portfolio	-
	Total (100)	**100**

Evaluation Scheme for Retest:

S. No.	Specifications	Marks
1	Theory Exam-III	30
	Total	30

SYLLABUS

Thermodynamics everywhere; historical development of thermodynamics; Zeroth Law of Thermodynamics and concept of temperature; Discussion on internal energy heat and work; First Law of Thermodynamics ; State function and path function; calculation of p-V work ; Heat Capacities; Joule and Joule-Thomson expansion; some practice problems; thermochemistry; Second Law of thermodynamics (various statements and their equivalence); Carnot cycle; definition of entropy; Heat engines and their efficiencies; practice problems on the classical second law; Statistical Formulation of the Second Law; Statistical formulation of the Second Law continued; Calculation of entropy for various processes using Boltzmann entropy formula; Fundamental equation and entropy postulates; introduction to free energies; Maxwell Relations and conversion of thermodynamic derivatives; Applications of free energy

References

1. Smith, J. M., Van Ness, H. C., and Abbott, M. M., Introduction to Chemical Engineering Thermodynamics, 6th ed., McGraw-Hill, 2001.
2. Kyle, B.G., Chemical and Process Thermodynamics, 3rd ed., PHI, New Delhi, 1999.
3. Rao, Y.V.C., Chemical Engineering Thermodynamics, University Press, 1997.
4. Kumar A S K, Classical thermodynamics - A Basic Approach, Surya Infotainment Products Pvt. Ltd - Bangalore
5. Hanna A Rizk, Classical and Statistical Thermodynamic.

Online : https://nptel.ac.in/courses/104/106/104106107/#

Course Title and Code: Advanced Highway Materials CE2202	
Hours per Week	**L-T-P: 3-0-2**
Credits	**4**
Students who can take	**M.Tech. & Ph.D.**

Course Syllabus:

Introduction: Components of pavement structure, functions of subgrade, subbase, base course and wearing courses**.**

Soil: Classification, identification and strength tests, soil moisture movement, sub-soil drainage, soil stabilization.

Aggregates: Classification, physical and strength characteristics with MORTH specifications, proportioning of aggregates, skid resistance and polishing of aggregates. Sustainable materials as aggregates for green highways.

Bitumen: Bitumen sources and manufacturing, Bitumen constituents, structure & Rheology, Tests on bitumen and MORTH specifications, Emulsions – types & properties, Adhesion of bitumen, Modified bitumen.

Bituminous Mixes: Desirable properties of mixes, various bituminous mixes used in India, Design of bituminous mixes, tests on bituminous mixes, Fillers and their specifications.

Cement Concrete Mixes: Constituents and their requirements, Physical and structural properties of concrete, Factors influencing mix design, Design of concrete mixes, Specifications of concrete as per IRC:58 for concrete pavements. Sustainable materials for concrete pavements.

List of Practicals:

1. Identification tests on soils (Sieve analysis and Atterburg limits)
2. Compaction test on subgrade soil
3. CBR test on subgrade soil
4. Strength tests on aggregate

5. Aggregate polishing and skid resistance test (demonstration)
6. Granular Sub Base (GSB) mix design
7. Elastic recovery test on binder
8. Marshall bituminous mix design
9. Concrete Mix Design

Suggested books:

1. Highway Engineering by S.K. Khanna, C.E.G. Justo & A. Veeraragavan, Nem Chand and Bros., Roorkee.
2. Hot Mix Asphalt: Materials, Mixture Design and Construction by Freddy L. Roberts, National Asphalt Pavement Association, Research and Education Foundation, Lanham, Maryland.
3. Principles of Transportation Engineering by Partha Chakroborty & Animesh Das, PHI, New Delhi.
4. Bituminous Road Construction in India by Prithvi Singh Kandal, PHI Learning Private Limited, Delhi.
5. Principles of Transportation Engineering by Partha Chakroborty & Animesh Das, PHI, New Delhi.
6. Highway Materials and Pavement Testing by S.K. Khanna, C.E.G. Justo & A. Veeraragavan, Nem Chand and Bros., Roorkee.
7. Specifications for Road and Bridge Works, Fifth Revision, Ministry of Road Transport and Highways (MORTH), Indian Roads Congress, New Delhi.
8. Relevant IRC and IS codes

Course Code: AS 2201
Course Title: Multi-objective Optimization
Teaching Scheme: 3 0 0
Credits: 3

Course Overview:

This is an introductory course to multi-objective optimization. It will start with the details and mathematical models of problems with multiple objectives. This course includes most fundamental concepts in the field of multi-objective optimization covering conventional and evolutionary methods.

Course Plan:

Optimality concept, Introduction to multi-objective optimization, comparison of single objective optimization and multi-objective optimization, Non-linear programming Weighted sum method, □-constraint method, No-preference Methods, Posteriori Methods, Priori Methods
Goal programming, Dominance relations, Dominance partial order, Pareto optimality
Introduction to Evolutionary Computation: Biological and artificial evolution, different historical branches of EC, a simple genetic algorithm. Search Operators: Crossover, mutation, crossover and mutation rates, Crossover for real-valued representations, mutation for real-valued representations
Applications of multi-objective optimizations

References:

1. Wayne L. Winston, Operations Research: Applications and Algorithms. Duxbury Press, 2003.
2. Godfrey C. Onwubolu and B. V. Babu. New optimization techniques in engineering. Springer, 2004.
3. K. Deb. Multi-objective optimization using evolutionary algorithms. Chichester, UK: Wiley; 2001.
4. Osyczka A. Evolutionary algorithms for single and multicriteria design optimization. Heidelberg: Physica-Verlag; 2002.

Course Title and Code: Introduction to Machine Learning, CS2403	
Hours per Week	**Curated MOOC**
Credits	**4**
Students who can take	**Pre-Ph.D, Post Graduate, Under graduate**

Course Objective: With the increased availability of data from varied sources there has been increasing attention paid to the various data driven discipline such as analytics and machine learning. This course introduces concepts of machine learning from a mathematically well motivated perspective. Different learning paradigms and some of the more popular algorithms and architectures used in each of these paradigms would be
covered in the course.

Learning Outcome:
On successful completion of this course, the students should be able to:

1. Identify machine learning techniques suitable for a given problem.
2. Interpret fundamental issues and challenges of machine learning: data, model selection, model complexity, etc.
3. Apply dimensionality reduction techniques.
4. Appreciate the underlying mathematical relationships within and across Machine Learning algorithms and the paradigms of supervised and un-supervised learning.
5. Apply Suitable Machine Learning Technique.
6. Build Neural Network for Prediction
7. Utilize Reinforcement Learning concepts to improvise precision of models.

Prerequisites: Linear Algebra, Basic Statistics, Programming Langauge

Evaluation Scheme

Sr. No	Specifications	Marks
1	Attendance	Nil
2	Assignment	40
3	Class Participation	Nil
4	Quiz	Nil
5	Theory Exam I	Nil
6	Theory Exam	15
7	Theory Exam (End Term)	25
8	Report-1	Nil

9	Report-2	Nil
10	Report-3	Nil
11	Project -1	Nil
12	Project -2	Nil
13	Project -3	Nil
14	Lab Evaluation1	10
15	Lab Evaluation2	10
16	Course portfolio	Nil
	Total (100)	**100**

Retest

1	Theory Exam	25
2	Lab Evaluation	10

Course Contents:

Probability Theory, Linear Algebra, Convex Optimization - (Recap), Introduction:
Statistical Decision Theory - Regression, Classification, Bias Variance

Linear Regression, Multivariate Regression, Subset Selection, Shrinkage Methods, Principal Component, Partial Least squares

Linear Classification, Logistic Regression, Linear Discriminant Analysis, Perceptron, Support Vector Machines

Neural Networks - Introduction, Early Models, Perceptron Learning, Backpropagation, Initialization,
Training & Validation, Parameter Estimation - MLE, MAP, Bayesian Estimation

Decision Trees, Regression Trees, Stopping Criterion & Pruning loss functions, Categorical Attributes, Multiway Splits, Missing Values, Decision Trees - Instability Evaluation Measures

Bootstrapping & Cross Validation, Class Evaluation Measures, ROC curve, MDL, Ensemble Methods - Bagging, Committee Machines and Stacking, Boosting

Gradient Boosting, Random Forests, Multi-class Classification, Naive Bayes, Bayesian Networks
Undirected Graphical Models, HMM, Variable Elimination, Belief Propagation

Partitional Clustering, Hierarchical Clustering, Birch Algorithm, CURE Algorithm, Density-based Clustering

Gaussian Mixture Models, Expectation Maximization, Learning Theory, Introduction to Reinforcement Learning, Optional videos (RL framework, TD learning, Solution Methods, Applications)

Suggested Reading Materials:

The Elements of Statistical Learning, by Trevor Hastie, Robert Tibshirani, Jerome H. Friedman (freely available online)

Pattern Recognition and Machine Learning, by Christopher Bishop

This course would be delivered on SWAYAM from 27th January, 2020 to 17th April, 2020 by Prof. Balaraman Ravindran, Professor in Computer Science at IIT Madras and Mindtree Faculty Fellow Student may refer course notes, videos & ppts.

Course Title and Code: Optimisation and Control (EE2104)	
Hours per Week	**L-T-P: 3-0-0**
Credits	**3**
Students who can take	**M.Tech. & Ph.D.**

This course aims at equipping students with the conceptual tools necessary to solve estimation and control problems, maximizing performance and minimizing cost.

Learning Outcomes

On successful completion of this course, the students should be able to:

1. analyze the requirements of a given estimation and control problem
2. design and implement a solution for a given estimation and control problem
3. efficiently use Computer Aided Control Systems Design (CACSD) tools
4. assess, troubleshoot, improve and document a given estimation and control system
5. apply relevant engineering standards to meet technical, safety, regulatory, societal and market needs

Syllabus:

1) Mathematics refresher: linear algebra, optimization, dynamic systems, modelling identification and simulation.
2) Control system project planning and documentation.
3) Discrete-event control systems. Typical models, counters, and timers. State machines, Petri nets, Sequential Flow Charts. Queuing systems.
4) Continuous control systems: Stability, time domain, frequency domain, design specifications, compensation. State variable modelling of linear continuous systems, controllability and observability. Introduction to LQR
5) Introduction to stochastic and robust control. Performance assessment.

Teaching Scheme and Credits

Hrs. per Week		Credits	Duration in Weeks
In Class	Out Class	3	
3 (L) + 0 (T) + 0(L)	2		

Course Feedback: Online - Every Fortnight

Evaluation Scheme

Sr. No	Specifications	Marks
1	Attendance	Nil
2	Assignment (4)	40
3	Class Participation	Nil
4	Quiz	Nil
5	Theory Exam I	Nil
6	Theory Exam	Nil
7	Theory Exam (End Term)	30
8	Report-1	30
9	Report-2	Nil
10	Report-3	Nil

11	Project -1	Nil
12	Project -2	Nil
13	Project -3	Nil
14	Lab Evaluation1	Nil
15	Lab Evaluation2	Nil
16	Course portfolio	Nil
	Total (100)	**100**

Books:

R. F. Stengel (1994). Optimal control and estimation. Dover Publications.

C.-T. Chen, Linear System Theory and Design, 3rd ed. USA: Oxford University Press, Inc., 1998.

B. Hrúz and M. Zhoum (2007). Modeling and control of discrete-event dynamical systems: with Petri nets and other tools. London: Springer.

D. H. Hanssen, Programmable Logic Controllers A Practical Approach TO IEC 61131-3 Using CoDeSys. Wiley, 2015.

IT Resources
https://nptel.ac.in/courses/107/106/107106081/
https://nptel.ac.in/courses/108/105/108105019/
https://nptel.ac.in/courses/112/107/112107220/
https://www.controldraw.co.uk/
https://www.codesys.com/
https://web.math.princeton.edu/~cwrowley/python-control/index.html

Course Title and Course Code	Industrial Automation and IoT - I (EE2101)
Hours per Week	**L T P: 3 0 2**
Credits	4
Students who can take	**M. Tech & Ph. D.**

Course Objectives

Industrial automation is the application of technology to control the production and delivery of industrial products and services. On the other hand, the Internet of Things (IoT) is transforming the way we work and live, extending the power of Internet to a whole range of objects different from computers or smartphones. This course aims to provide an introduction to industrial automation and IoT technologies and standards.

Learning Outcomes:

On successful completion of this course, the students should be able to:

1. Analyze the link between Information Technology and Operational Technology.
2. Specify the key components to design an Industrial automation & IoT system.
3. Choose technologies for communication and real time data collection.
4. Design, deploy and test a basic Industrial automation & IoT system.
5. Apply recommended engineering practices to meet desired requirements for applications, considering sustainability, security and safety as design constraints.

Sr. No	Specifications	Marks
1	Attendance	NIL
2	Assignment	10
3	Class Participation	05
4	Quiz	05
5	Theory Exam-I	10
6	Theory Exam-II	10
7	Theory Exam-III	20
8	Report-I	NIL
9	Report-II	NIL
10	Report-III	NIL
11	Project-I	10
12	Project-II	NIL
13	Project-III	NIL
14	Lab Evaluation-I (Continuous)	10
15	Lab Evaluation-II (Exam)	10
16	Course Portfolio (MOOC Course)	10
Total (100)		**100**

Evaluation Scheme for Retest:

S. No.	Specifications	Marks
1	Theory Exam-III (End Term)	20
2	Lab Evaluation-II (Exam)	10
3	**Total**	**30**

Syllabus

Theory

UNIT1: Introduction. Classical hierarchical industrial automation model. Essential functions of each level. Elements of industrial control (sensors, actuators, transmitters, controllers, etc.). ISA 95 / ISA S88 – Enterprise integration. Emergent architectures.

UNIT2: Instrumentation. Characteristics of instruments: accuracy, precision, sensitivity, etc. Units and standards. Voltage, current and electrical power measurements. Measurement of temperature, position, speed, force, pressure, light, level, humidity and other variables. Signal conditioning and transmission. Indicators, recorders. Actuators. Valves and motors. Instrumentation symbols. Functional identification. Standards: ISA 5.1 – Instrument symbols and identification. IEC 61511 Safety Instrumented Systems.

UNIT3: IoT fundamentals, Architecture and protocols,

UNIT4: Industrial IoT fundamentals. Convergence of IT and OT. Industrial communication: principles, protocols and technologies. Design methodology. Design of IoT systems for industrial safety processes.

UNIT5: CASE STUDIES

Design and test a basic IIoT system involving prototyping, programming and data analysis. Application to sustainability problems: health, energy, water, smart cities, etc.

Practical

1. Characteristics of sensors. Calibration. Temperature, moisture, displacement, voltage, current, etc. Signal conditioning and processing.
2. Interfacing LEDs. Serial port. DC-motor.
3. IoT communication. Standards: MODBUS, OPC, MQTT, etc.
4. PLC programming.
5. Mini-project

Text Book(s)

- Krishna Kant. "*Computer-based Industrial Control*". PHI Learning Private Limited, 2010.
- Hanes, Salgueiro, Grossetete, Barton and Henry (2017). "*IoT Fundamentals: NetworkingTechnologies, Protocols and Use Cases for the Internet of Things*". Cisco Press
- Curtis Johnson. "*Process Control Instrumentation Technology*". PHI Learning Private Limited, 2013.

Reference Book(s)

- Gilchrist (2016). "*Industry 4.0: The Industrial Internet of Things*". Apress.
- John P. Bentley. Principles of Measurement Systems. 4th Edition, Addison Wesley Longman Ltd.,UK, 2004

Web Resources

https://nptel.ac.in/courses/108/105/108105062/
https://nptel.ac.in/courses/106/105/106105195/

Online Courses:

Developing Industrial Internet of Things
https://www.coursera.org/programs/j-k-lakshmipat-university-on-coursera-kzogk/browse?index=prod_enterprise_products&productId=84QbLYtsEeicuBLWaYsl_g&productType=s12n&query=industrial+iot&showMiniModal=true

Design of Internet of Things
https://nptel.ac.in/courses/108/108/108108098/

Course Code and Title	Computer Vision (**EE2201**)
Scheme	**L T P: 3 0 0**
Credits	**4**
Students who can take	**M. Tech: Semester II**

Course Objectives: This course aims to develop skills for building computer vision applications with Python, OpenCV, and Deep Learning.

Learning Outcomes:

On successful completion of this course, the students should be able to:

EE2201.1 Implement Image Processing Algorithms using OpenCV tools.

EE2201.2 Use supervised and unsupervised machine learning algorithms for image classification.

EE2201.3 Design, Train and Test Neural Networks and deploy suitable activation functions image processing function using Keras/Tensorflow libraries.

EE2201.4 Identify suitable Performance Parameters and evaluate valuate technique for best performance.

Syllabus:

Module 1: Introduction to Image Processing system-Image Sampling, Quantization, Thresholding, Image Enhancement, Contrast Stretching- Linear, Logarithmic, Power Law, Image Histograms-Histogram Equalization, Histogram Processing, Filters-Median, Min, max, Nonlinear Filters-Smoothing /Weighted Smoothing, Image Sharpening. Edge Detection and Segmentation

Module 2: Deep Learning for Computer Vision, Image Classification and Segmentation using Machine Learning, Understanding Neurons, Activation functions, Gradient Descent and Backpropagation in neural Networks, Building a Neural Network Model for Classification problems, Limitations of Neural Networks.

Module 3: Convolutional Neural Networks, Keras Basics, CNN architecture-Convolution, Pooling and Fully connected layers.

Assessment Scheme:

Sr. No.	Evaluation Component	Marks
1	Attendance	Nil
2	Assignment	20
3	Class Participation	Nil
4	Quiz	20
5	Theory Exam-I	Nil
6	Theory Exam-II	Nil
7	Theory Exam-III	30
8	Report I	Included with Project
9	Report II	Nil
10	Report III	Nil
11	Project I	Nil
12	Project II	Nil
13	Project III	30

14	Lab Evaluation I	Nil
15	Lab Evaluation II	Nil
16	Course Portfolio	Nil
	Total (100)	100
Evaluation Scheme for Re-Test		
1	**Theory Exam - III**	30
	Total (30)	30

References:

1. Digital Image Processing- S Jayaraman, S Esakkirajan, T Veerakumar
2. Introduction to Statistical Learning-Garet James
3. Deep Learning book by Ian Goodfellow, Yoshua Bengio, and Aaron Courville.

Web resource:

https://github.com/machine-perception-robotics-group/GoogleColabNotebooks/tree/eng1/MLDL_lecture_notebooks
https://www.tensorflow.org/api_docs/python/tf/keras/layers/Dense
https://www.tensorflow.org/api_docs/python/tf/keras/initializers

Course Title and Course Code	**High Voltage Engineering (EE2105)**
Hours per Week	**L T P: 3 0 2**
Credits	**4**
Students who can take	**Ph.D. Course work**

Course Objectives: This course focuses on the high-voltage technology used in electric power apparatuses and electric machinery. The course focuses on gas breakdown, discharge initiation, electric conduction and breakdown of liquid/solid/composite materials, the generation of DC, AC, pulsed high voltage/large current, measurement techniques, and surge voltage propagation and protection.

Learning Outcomes:

On successful completion of this course, the students will be able to:

1. Conceptualize the idea of high voltage and safety measures involved.
2. Analyse the breakdown mechanism of solids, liquids and gases.
3. Analyse and calculate the circuit parameters involved in generation of high voltages.
4. Measure direct, alternating and impulse high voltage signals.
5. Measure the dielectric loss and partial discharge involved in non-destructive high voltage tests.

Sr. No.	Specifications	Marks
1	Attendance	NIL
2	Assignment	20
3	Class Participation	05
4	Quiz	10
5	Theory Exam-I	NIL
6	Theory Exam-II	10
7	Theory Exam-III	20
8	Report-I	NIL
9	Report-II	NIL
10	Report-III	NIL
11	Project-I	10
12	Project-II	NIL
13	Project-III	NIL
14	Lab Evaluation-I (Continuous)	15
15	Lab Evaluation-II (Exam)	10
16	Course Portfolio (MOOC Course)	NIL
Total (100)		**100**

Evaluation Scheme for Retest:

S. No.	Specifications	Marks
1	Theory Exam-III (End Term)	20
2	Lab Evaluation-II (Exam)	10
3	**Total**	**30**

Syllabus:

Unit-1: Electrostatic fields and field stress control

Electrical field distribution and breakdown strength of insulating materials - fields in homogeneous, isotropic materials - fields in multi-dielectric, isotropic materials - numerical method: Finite Difference Method (FDM), Finite Element Method (FEM), charge simulation method (CSM)

Unit-2: Electrical breakdown in gases

Gases as insulating media, ionization and decay processes, Townsend mechanism, Paschen's law, thermal ionization, deionization by recombination, deionization by attachment negative ion formation, mobility of gaseous ions and deionization by diffusion, relation between diffusion and mobility, penning effect, the breakdown field strength, breakdown in non-uniform fields, partial breakdown, corona discharges.

Unit-3: Breakdown in liquid and solid dielectrics:

Liquid as insulators, breakdown in liquids, suspended solid particle mechanism, cavity breakdown, electroconvection and electro-hydrodynamic model of dielectric breakdown, breakdown in solids, intrinsic breakdown, streamer breakdown, electromechanical breakdown, edge breakdown and treeing, thermal breakdown, erosion breakdown, tracking - breakdown of solid dielectrics in practice, partial discharges in solid insulation.

Unit-4: Generation of high voltage:

Generation of high direct voltages, half and full wave rectifier circuits, voltage multiplier circuits, Van de Graff generators, electrostatic generators, impulse voltage generator circuits, impulse current generator.

Unit-5: Measurement of high voltage:

High direct voltage measurement, peak voltage measurements by spark gaps, sphere gaps, reference measuring systems, uniform field gaps, rod gaps, factors affecting sphere gap measurements.

Unit-6: High voltage testing:

Testing of insulators and bushings, testing of isolators and circuit breakers Testing of cables, testing of transformers, testing of surge diverters, radio interference measurements.

Standards

1. "IEEE Standard Techniques for High-Voltage Testing", 6th edition, IEEE Std. 4-1978.
2. "High-voltage test techniques, Part 1: General definitions and test requirements", IEC 60060-1, 1989.
3. "High Voltage Test Techniques, Part 2: Measuring Systems", IEC Publication 60060-2, 1994.
4. "High Voltage Test Techniques, Part 3: Measuring Devices", IEC Publication 60060-3, 1976.
5. "High Voltage Test Techniques, Part 4: Application Guide for Measuring Devices", 1st ed., IEC Publication 60060- 4, 1977.
6. Indian Standard specifications for High Voltage test techniques", Bureau of Indian Standard, IS 2071, New Delhi, 1991.

List of Experiments

1. To measure the dielectric Strength of transformer oil.
2. To Study the effect of different shape of electrodes on dielectric (air) breakdown.
3. To Study the gas actuated Buchholz relay for oil filled transformer.
4. Study of Impulse Voltage Generator
5. Parametric Analysis of Impulse Voltage Waveform
6. Study of Impulse Current Generator
7. Parametric Analysis of Impulse Current Waveform
8. Critical Flashover of a Sphere Gap using Impulse Voltage Generator (IVG).
9. Study of Rectangular Pulse Current Generator
10. Functioning of Voltage Doubler.
11. 3-Stage Cockroft Walton Voltage Multiplier

1. Power frequency AC Test Source.
2. Application of High Voltage D.C. Test Source (Half Wave)

Textbooks:

1. Naidu M. S. and Kamaraju V., “High Voltage Engineering”, fourth Edition, Tata McGraw- Hill Publishing Company Limited, New Delhi.
2. Wadhwa C.L., "High Voltage Engineering", third edition, New Age publishers, New Delhi.
3. Nagrath, I.J. and Kothari, D.P., Power System Engineering, Tata McGraw–Hill

E-Resources:

1. https://nptel.ac.in/courses/108/104/108104048/
2. NPTEL Web Course on High Voltage Engineering by Ravindra Arora, www.nptel.ac.in
3. https://bharatsrajpurohit.weebly.com/high-voltage-engineering-course.html

Course Title and Code: Deep Learning, CS2405	
Hours per Week	**Curated MOOC (approx.. 11 Hrs. per week)**
Credits	**5**
Students who can take	**Pre-Ph.D, Post Graduate, B.Tech Under graduate (Final Year)**

Course Objective:. This course includes the foundations of Deep Learning, building of neural networks, and discussion of successful machine learning projects. Students will learn about Convolutional networks, RNNs, LSTM, Adam, Dropout, BatchNorm, Xavier/He initialization, and more. Students will master not only the theory, but also see how it is applied in industry. Course includes practice of all these ideas in Python and Tensor-Flow.

Learning Outcome:
On successful completion of this course, the students should be able to:

1. Identify Deep learning techniques (Convolutional networks, RNNs, LSTM, Adam, Dropout, BatchNorm, Xavier/He initialization) suitable for a given problem.
2. Find creative ways to apply deep learning to solve real life problems.
3. Appreciate the underlying mathematical relationships within and across Deep Learning algorithms.
4. Utilize Reinforcement Learning concepts to improvise precision of models.
5. Analyze Case studies from healthcare, autonomous driving, sign language reading, music generation, and natural language processing.

erequisites: Linear Algebra, Basic Statistics, Programming Langauge (Python), Artificial Intelligence, Machine Learning

aluation Scheme

Sr. No	**Specifications**	**Marks**
1	Attendance	Nil
2	Assignment	20
3	Class Participation	Nil
4	Quiz	Nil
5	Theory Exam I	Nil
6	Theory Exam	Nil
7	Theory Exam (End Term)	30
8	Report-1	Nil
9	Report-2	Nil
10	Report-3	Nil
11	Project -1	40
12	Project -2	Nil
13	Project -3	Nil
14	Lab Evaluation1	Nil
15	Lab Evaluation2	10
16	Course portfolio	Nil
	Total (100)	**100**

Retest

1	Theory Exam	30
2	Lab Evaluation	10

Course Contents:

Introduction to Deep Learning, Neural Network Basics, Shallow Neural Networks, Improving Deep Neural Networks: Hyperparameter tuning, Regularisation and Optimisation, Practical Aspects of Deep Learning, Optimisation Algorithms, Hyperparameter tuning, Batch Normalisation and Programming Frameworks, Structuring Machine Learning Projects

Foundations of Convolutional Neural Networks: Deep Convolutional Models: Case studies, Object Detection: Special Applications: Face Recognition and Neural Style Transfer, Sequence Models, Recurrent Neural Networks

Natural Language Processing and Word Embeddings, Sequence models and Attention Mechanism

Suggested Reading Materials:

This course is regularly delivered on coursera by Andrew Ng, Founding Lead of Google Brain along with instructors at DeepLearning.ai. The specialization is divided into 5 courses with an approximate completion time of 3 months requiring a study time of 11
hours per week.

Course Title and Code: IL2401 Statistics with Python		
Course Description:		
Prerequisites		
Hours per Week		**L-T-P: 3-0-2**
Credits		3
Sr. No	**Specifications**	**Marks**
01	Attendance	Nil
02	Assignment	Nil
03	Class Participation	Nil
04	Quizzes	Nil
05	Theory Exam I	25
06	Theory Exam II	25
07	Theory Exam III	25
08	Report -1	Nil
11	Project -1	25
15	Lab Evaluation	Nil
16	Course portfolio	Nil
	Total (100)	**100**

Learning Outcomes:

On successful completion of this course students will be able to:

- Create and interpret data visualizations using the Python programming language and associated packages & libraries
- Apply and interpret inferential procedures when analyzing real data
- Apply statistical modeling techniques to data (ie. linear and logistic regression, linear models, multilevel models, Bayesian inference techniques)
- Connect data analysis methods to research questions.

Syllabus:

Unit 1 Understanding and Visualizing Data with Python

In this unit, learners will be introduced to the field of statistics, including where data come from, study design, data management, and exploring and visualizing data. Learners will identify different types of data, and learn how to visualize, analyze, and interpret summaries for both univariate and multivariate data. Learners will also be introduced to the differences between probability and non-probability sampling from larger populations, the idea of how sample estimates vary, and how inferences can be made about larger populations based on probability sampling.

At the end of each week, learners will apply the statistical concepts they've learned using Python within the course environment. During these lab-based sessions, learners will discover the different uses of Python as a tool, including the Numpy, Pandas, Statsmodels, Matplotlib, and Seaborn libraries. Tutorial videos are provided to walk learners through the creation of visualizations and data management, all within Python. This course utilizes the Jupyter Notebook environment within Coursera.

Unit 2 Inferential Statistical Analysis with Python
In this unit, we will explore basic principles behind using data for estimation and for assessing theories. We will analyze both categorical data and quantitative data, starting with one population techniques and expanding to handle comparisons of two populations. We will learn how to construct confidence intervals. We will also use sample data to assess whether or not a theory about the value of a parameter is consistent with the data. A major focus will be on interpreting inferential results appropriately.

Unit 3 Fitting Statistical Models to Data with Python
In this unit, we will expand our exploration of statistical inference techniques by focusing on the science and art of fitting statistical models to data. We will build on the concepts presented in unit 2 to emphasize the importance of connecting research questions to our data analysis methods. We will also focus on various modeling objectives, including making inference about relationships between variables and generating predictions for future observations.
This unit will introduce and explore various statistical modeling techniques, including linear regression, logistic regression, generalized linear models, hierarchical and mixed effects (or multilevel) models, and Bayesian inference techniques. All techniques will be illustrated using a variety of real data sets, and the course will emphasize different modeling approaches for different types of data sets, depending on the study design underlying the data.

Coursera link: https://www.coursera.org/specializations/statistics-with-python

Course code	Course Title	Teaching Scheme	
		NA	**Credits**
CS2406	Emerging Technologies: IoT to Big Data	1 0 1	3

Course Objectives: This course familiarises with fundamental concepts of three emerging technologies: Smart Mobile devices, IoT Wireless and Cloud Computing Technologies, and the Bigdata emerging technologies.

Learning Outcomes:
On successful completion of this course, the students should be able to:

- Explain the architecture of Smart Mobile Devices, appreciating the use of various sensors and processor types (CPU, DSP, GPU).
- Interface accelerometer/GPS sensor and use ML for device orientation recognition.
- Interface GPS Sensor and explore time synchronization.
- Recommend suitable wireless network for a particular application
- Explain the characteristics of Hadoop and Spark big data systems
- Evaluate Spark ML classification and regression algorithms based on linear models, Naïve-Bayes, and decision tree

Assessment Scheme:

Sr. No.	Evaluation Component	Marks
1	Attendance	Nil
2	Assignment	20
3	Class Participation	Nil
4	Quiz	20
5	Theory Exam-I	Nil
6	Theory Exam-II	Nil
7	Theory Exam-III	40
8	Report I	Nil
9	Report II	Nil
10	Report III	Nil
11	Project I	Nil
121	Project II	Nil
13	Project III (With Report)	20
14	Lab Evaluation I	Nil
15	Lab Evaluation II	Nil
16	Course Portfolio	Nil
	Total (100)	**100**
	Evaluation scheme for retest.	
	Theory III	40
	Total (100)	**40**

Syllabus:

Module 1. Smart Device and Emerging Mobile Technologies: Description of the smart device sensors (e.g., accelerometer, gyro (gyroscope sensor), heart rate sensor, optical IR (infrared) light sensor, barometer, and pressure altimeters) along with the GPS (Global Positioning System) and A-GPS (Assisted GPS, based on MSA (Mobile Station Assisted) and MSB (Mobile Station Based)).

Module 3: IoT Wireless and Cloud computing Emerging Technologies:
Functionality and characteristics of IoT wireless networks, the IoT network architecture, and wearable IoT networks. IoT wireless communication technologies based on WLAN (Wireless Local Area Network), WPAN (Wireless Personal Area Network), and LPWAN (Low-Power Wide Area Netw .Details on WPAN (which include Bluetooth, ZigBee, 6LoWPAN, and IEEE 802.15.4 technology) and LPWAN (which include LoRa, UNB, Sigfox, and NB-IoT)

Module3: Big Data Emerging Technologies: Characteristics and operations of Hadoop and Spark. Spark ML basic statistics algorithms based on correlation and hypothesis testing Spark ML classification and regression algorithms based on linear models, naive Bayes, and decision tree techniques

Learning resource: Coursera Course

(1) Big Data Emerging Technologies by Yonsei University
(2) Smart Device and Mobile Emerging Technologies
(3) IoT Wireless& Cloud computing Emerging Technologies

Course Title and Code **CS2115: Applied Advanced Machine Learning**	
Hours per Week	**L-T-P: 3-0-2**
Credits	**5**
Students who can take	B.Tech. Odd Sem (VIII)

Course Objective-

The course, Advanced Applied Machine Learning, offered for M.Tech students aims to develop deeper understanding of machine learning and its applications focusing on in-depth coverage of new and advanced methods in machine learning, as well as their underlying theory. It emphasizes approaches with practical relevance and discusses a number of recent applications of machine learning in areas like information retrieval, recommender systems, data mining, computer vision, natural language processing and robotics. An open research project is a major part of the course.

Learning Outcome:
On successful completion of this course, the students should be able to:

- Analyse the loss function and their convergence in various machine learning algorithms.
- Apply important problem-solving techniques like, Stochastic Gradient Descent, Backpropagation, Duality and Regularization in practical applications.
- Demonstrate expertise in Deep Learning, Ensemble Learning and Reinforcement Learning.
- Explore text and image data along with regular tables and graphs.
- Implement a real-life project using Machine Learning techniques.

Prerequisites		**Basic Machine learning, Linear algebra, Probability, Statistics, Python programming**
Sr. No	**Specifications**	**Marks**
01	Attendance	Nil
02	Assignments	20
03	Class Participation	Nil
04	Quiz (2)	10
05	Theory Exam	Nil
06	Theory Exam (Mid)	20
07	Theory Exam (Final)	20
08	Report-1	Nil
09	Report-2	Nil
10	Report	Nil
11	Project-1	10
12	Project-2	Nil
13	Project-3	Nil
14	Lab Evaluation (Mid)	10
15	Lab Evaluation (Final)	10
16	Course portfolio	Nil
	Total (100)	**100**

Retest

1	Quiz	20
2	Theory Exam (Final)	20

Syllabus (Theory)

1 **Introduction:** ML concepts
2 **Stochastic gradient descent:** Error Bounds, Random Forest, Naive Bayes and its convergence
3 **Perceptron Learning:** Learnability, VC dimensions, Occam's Razor Principles, Logistic Regression.
4 **Kernel tricks and regularizations:** Support vector machines (Quadratic optimization), Dual support vector machines.
5 **Backpropagation:** Neural Networks and its accuracies, Convolutional neural networks, Recurrent neural networks.
6 **Graphical models:** Expectation maximization, Bayesian network analysis.
7 **Structure Learning**: Principal components analysis, Clustering (Convergence and Initialization), Ranking
8 **Ensemble Learning:** Bagging, Boosting and Stacking
9 **Online learning**: Markov decision, k-arm Bandit, Reinforcement learning, DeepRL

Syllabus (Practical)

1. Write Python program to implement: stochastic gradient descent (SDG), overfitting, regularization, momentum, kernel learning, convergence, parameter optimization, learning rate and sparse matrix multiplication in standard ML algorithms and explore the efficiency.
2. Implement graphical models listed above.
3. Write program for PCA, K-Means and PageRank.
4. Write python program for ensemble learning algorithms.
5. Implement online learning algorithms.

Text Books:

1. Kevin P. Murphy, Machine Learning – A Probabilistic Perspective, MIT Press, 2012.
2. Bishop, "Pattern Recognition and Machine Learning", Springer, 2006.
3. Hastie, Tibshirani, Friedman, "The Elements of Statistical Learning", Springer, 2001.
4. Vapnik, "Statistical Learning Theory", Wiley, 1998.
5. Tom Mitchell, "Machine Learning", McGraw Hill, 1997.

Reference Courses:

1. Advance Machine Learning CS6780 - Advanced Machine Learning. Spring 2019. Prof. Thorsten Joachims Cornell University. https://www.cs.cornell.edu/courses/cs6780/2019sp/
2. Machine Learning by Andrew NG. https://www.coursera.org/learn/machine-learning

Reference Materials:

1. Tong Zheng. Solving large scale linear prediction problems using stochastic gradient descent algorithms. Proceedings of the International Conference on Machine Learning (ICML), 2004.

2. Martin Abadi et al. TensorFlow: Large-Scale Machine Learning on Heterogeneous Distributed Systems. Preliminary White Paper, 2015. Since this is a white paper and is a bit longer than what we'll usually be reading, we will cover Sections 1, 2, 4.1, 6, and 9 only.
3. Rich Caruana, Steve Lawrence, and C Lee Giles. Overfitting in neural nets: Backpropagation, conjugate gradient, and early stopping. In Advances in Neural Information Processing Systems (NeurIPS), 2001.
4. Sergey Ioffe, Christian Szegedy. Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift. Proceedings of the International Conference on Machine Learning (ICML), 2015.
5. Ilya Sutskever, James Martens, George Dahl, and Geoffrey Hinton. On the importance of initialization and momentum in deep learning. Proceedings of the International Conference on Machine Learning (ICML), 2013.
6. Suyog Gupta, Ankur Agrawal, Kailash Gopalakrishnan, and Pritish Narayanan. Deep learning with limited numerical precision. Proceedings of the International Conference on Machine Learning (ICML), 2015.