 **RESPONSIBLES**

**PART I**
Nicola Pedroni
E-mail: nicola.pedroni@ecp.fr, nicola.pedroni@supelec.fr
Office: C428, Ecole Centrale Paris (ECP)
Phone: +33 (0)1 41 13 13 19

**PART II**
Yan-Fu Li
Email: yanfu.li@ecp.fr; yanfu.li@supelec.fr
Office: C441A, Ecole Centrale Paris (ECP)
Tel: +33 (0)1 41 13 16 71

**SYLLABUS**

**PART I**
The quantitative analyses of the phenomena occurring in safety-critical engineering applications (e.g., reliability optimization processes) are based on mathematical models. In practice, not all the characteristics of the system under analysis can be captured in the model. Thus, uncertainty is present in both the values of the model input parameters and hypotheses. Such uncertainty propagates within the model and causes uncertainty in its outputs: the quantification of this output uncertainty is of paramount importance for taking robust decisions. For more than 30 years, probabilistic frameworks and methods have been used as basis for reliability optimization, risk assessment and uncertainty analysis, but there is a growing concern, partly motivated by newly emerging risks like those related to security, that extensions and advancements are needed to effectively treat the different sources of uncertainty and related forms of information. Alternative approaches for
representing uncertainty have been proposed, e.g. those based on interval probability, possibility and evidence theory. It is argued that these approaches provide a more adequate treatment of uncertainty in situations of poor knowledge. However, many questions concerning the foundations of these approaches and their use remain unanswered. In this course some of these alternative methods are introduced within the contexts of risk assessment and reliability optimization problems.

**PART II**

Many real word optimization problems cannot be efficiently solved by conventional solution techniques, such as linear programming and mixed-integer programming, due to their large sizes and high complexities. One practical approach to tackle these problems resorts to mechanisms inspired by biological evolution, such as crossover and mutation. In this approach, a set of candidate solutions constitute a population and a fitness function is defined to determine the quality of each solution with respect to the objective of the optimization. At each cycle of the iterative search for the optimum, the candidate solutions of larger fitness values are selected with higher probability and processed by the above mentioned mechanisms to generate new solutions (on average of improved fitness) which, then, enter the next cycle of evolution. This procedure is repeated until a preset termination condition is satisfied, which stops the search. This type of approach, namely evolutionary algorithm (EA), is regarded as a heuristic which does not guarantee the global optimum but can return a quite good approximation (near-optimum). EAs have proven to be an effective tool across various application domains because they do not require any assumption about the fitness landscape. In this course, we introduce the basic concepts about EAs and the classical genetic algorithm (GA). Applications of GA for reliability optimization are introduced on simple conceptual system models as well as on realistic models where uncertainties become relevant and must be taken into account to achieve robust results in the optimization, which can be then used for confident decision making.

**TEACHING GOAL**

**PART I**

The aim of this part of the course is to illustrate the state of knowledge on the treatment of uncertainties in the quantitative assessment of system risk and reliability for practical optimization (minimization and maximization, respectively) in situations concerning high-consequence technologies, e.g. nuclear, oil and gas, transport etc. The areas of potential application of the theories and methods studied in the course are broad (engineering, medicine, environmental impacts, natural disasters, security and financial risk management): the focus of the course is, however, mainly on engineering applications and, in particular, on system risk and reliability assessment for optimization under uncertainty. By way of examples, the
applicability of different methods will be verified and discussed, highlighting strengths and weaknesses in dependence of the situation addressed.

**PART II**
The purpose of this part of the course is to equip the students with the knowledge needed to utilize EAs for solving practical engineering optimization problems under uncertainty. Exemplifications are made with respect to system reliability optimization problems in presence of uncertainty, with possible extensions to availability, maintainability and safety of different industrial systems, e.g. energy, transportation, computing, supply chains and logistic service systems.

**TEACHING OBJECTIVES**

**PART I**
The main objectives of the first part of the course are the following:

(i) *Methodological*: to learn the *state of the art* on the treatment of uncertainties in risk assessment for the optimization of reliability in situations concerning high-consequence technologies, and the *methods* for the representation and characterization of such uncertainties;

(ii) *Practical*: to derive *guidelines* for the *application* of different methods to different engineering problems, taking into account their strengths and weaknesses in dependence of the situation addressed;

(iii) *Computational*: to acquire *basic technical skills* to *implement* and apply the uncertainty representation methods learned to simple numerical examples.

**PART II**
This second part of the course will train the students:

(i) to understand the functioning of EAs for solving optimization problems;

(ii) to extract information from practice and formulate an optimization problem including the uncertainties;

(iii) to design a EA and fine-tune it;

(iv) to calibrate the EA to solve the optimization problem under uncertainty;

(v) to validate and report the results.

**INSTRUCTORS**
Nicola Pedroni, Assistant Professor at Ecole Centrale Paris and Supelec, nicola.pedroni@ecp.fr, nicola.pedroni@supelec.fr

Yanfu Li, Assistant Professor at Ecole Centrale Paris and Supelec, yanfu.li@ecp.fr, yanfu.li@supelec.fr
TEXTS/COURSE SUPPORT
Copies of presentation slides, scientific papers and book chapters.
The course materials in the form of PDF will be available on the website of the option.

REFERENCES
PART I

PART II

ASSIGNMENTS AND EVALUATION
Written exam:
open questions and exercises about the topics treated – 3h closed book.

OUTLINE/SCHEDULE
PART I
Lecture 1: Introduction (3 hrs)
  1.1 Introduction to the course
  1.2 Uncertainties in reliability and risk assessment
  1.3 The probabilistic approach for treating uncertainties
Lecture 2: Non-probabilistic representations of uncertainty (I): interval analysis and possibility theory (3 hrs)
  2.1 Interval analysis: basic principles
  2.2 Possibility theory
    2.2.1 Basic principles
2.2.2 Approaches for constructing possibility distributions and examples of necessity/possibility elicitations for reliability and risk assessment
2.2.3 Mixed probabilistic and possibilistic uncertainty representation: Fuzzy Random Variables
2.2.4 Numerical examples

Lecture 3: Non-probabilistic representations of uncertainty (II): possibility theory (ctd) and risk assessment application examples (3 hrs)
3.1 Possibility theory (continued): Mixed probabilistic and possibilistic uncertainty propagation
3.2 Reliability and risk assessment application examples
   3.2.1 Event tree analysis
   3.2.2 Renewable energies example

PART II
Lecture 4: Introduction to Evolutionary Algorithms (3 hrs)
4.1 Brief recall of exact optimization methods
4.2 What is an evolutionary algorithm?
4.3 Components of evolutionary algorithms
4.4 Example application: Knapsack problem

Lecture 5: Genetic Algorithms (3 hrs)
5.1 Introduction
5.2 Encoding and decoding of solutions
5.3 Genetic operators and elitist strategy
5.4 Constraints handling
5.5 Example application: reliability optimization problem

Lecture 6: Evolutionary Optimization under Uncertainty (3 hrs)
6.1 Noisy fitness functions
6.2 Search for robust solutions
6.3 Approximating fitness functions
6.4 Example application: reliability optimization problem under uncertainty