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Fault Diagnosis Inverse Problems: Solution with Metaheuristics

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To my mother Luz Milagros, in memoriam
Lídice Camps Echevarría

To Xiomara, Maria Alejandra, and Maria Gabriela
Orestes Llanes Santiago

To Nádia
Haroldo Fraga de Campos Velho

To Gilsineida, Lucas, and Luísa
Antônio José da Silva Neto

Preface

Faults can occur in every system, but when they occur in control systems, they may cause not only economic losses but also damage to human being, material, and to the environment. But, how is a fault in a control system defined? A fault is defined *as an unpermitted deviation of at least one characteristic property or parameter of a system from the acceptable, usual, or standard operating condition* [57, 61, 78, 115]. The area of knowledge related to methods for diagnosing faults is called Fault Diagnosis or Fault Detection and Isolation (FDI). The name Fault Detection and Isolation indicates how are conceived many Fault Diagnosis methods: first detecting if there are faults that are affecting the system and then isolating them, i.e., deciding which fault is affecting the system.

On diagnosing a system relies a big interest. Topics so important in the industry such as reliability, safety, and efficiency are related to FDI. Fault Diagnosis is also crucial for the topic of maintenance. It is also recognized that the increase of the automation in the industry enhances the probability of faults occurrence [61]. Therefore, it is easy to conclude that Fault Diagnosis is a current area of intense research and real applications interest. But FDI is not a simple and easy problem to formulate and solve. For diagnosing faults in systems, measurements need to be used. These measurements are commonly corrupted by noise. Moreover, the measurements can be affected by spurious disturbances acting on the system. All these facts can lead to the conclusion that the system may be deviated from its acceptable behavior, even when no faults are affecting it. This implies in false alarms. In order to avoid this situation, the methods developed and applied for FDI should be *robust*. Robustness means rejection of false alarms, which are attributable to disturbances or spurious signals. With the increase of the robustness it could occur, that some faults can not be diagnosis, for example when the fault effects in the system output are within the range of deviation due to the noise. This fact is related to the system loss of *sensitivity*. Therefore, useful FDI methods must present two properties: *robustness* and *sensitivity*. Moreover, in complex systems, the propagation of faults can rapidly occur [57, 115]. As a consequence, Fault Diagnosis also take into consideration the diagnosis time [57, 115].

A great variety of FDI methods can be found in the literature, and they may be brought down to two types of methods: model-based methods and non-model-based methods. Model-based methods make use of a mathematical or a physical/mathematical model of the system.

In this book, it is presented and formalized a recent methodology for Fault Diagnosis which falls into the category of model-based methods. The name of the methodology is *Fault Diagnosis—Inverse Problem Methodology* (FD-IPM). It unifies the results of some years of cooperation among researchers from the fields of FDI, Inverse Problems, and Optimization. Some of the contributions that resulted from this cooperation are described in Refs. [1, 18–21]. As its name indicates, it is based on the formulation of Fault Diagnosis as an Inverse Problem. In particular, the Fault Diagnosis Inverse Problems are formulated as optimization problems, which are solved using metaheuristics. Therefore, in the proposed methodology, the areas of FDI, Inverse Problems, and Metaheuristics are linked.

The main objective of this book is to formalize, generalize, and present in a systematic, organized, and clear way the main ideas, concepts, and results obtained during the last years which are based on the formulation of Fault Diagnosis as Inverse Problems which are solved as optimization problems.

For readers familiarized with Inverse Problems, some questions could arise: why formulate FDI as an Inverse Problem, if it is well known that Inverse Problems are usually ill-posed problems (sometimes the ill- posed problems are called hard problems), there are already well established FDI methods, which are not based on the Inverse Problem approach?

It is true that Inverse Problems are usually not easy to solve. The main difficult point to deal with, when solving them, is the effect on the solution when the observed data (e.g., measurements) present noise, i.e., amplification of the noise which is always present in the observable variable affects the Inverse Problem solution. Inverse problems belong to the class of ill-posed problems: the existence or uniqueness of the solution are not guarantee; or it does not show continuous dependence on the input values. From the latter condition, the noise in the measurements can be amplified in the inverse solution. But, in turn FDI also deals with noisy data (measurements of the system), and it is very important to know how the noise in the data influences the diagnosis of the faults, in order to avoid, for example, false alarms or to identify faults that may be masked within the noise. It is recognized that obtaining robust and sensitive FDI methods, at the same time, continues to be a current research field of high interest [114]. Moreover, Inverse Problems is an interdisciplinary area that matches the mathematical model of a problem with its experimental data [94]. That is exactly the idea behind FDI, when a mathematical or physical/mathematical model of the system is considered known.

Formulating FDI as an Inverse Problem also brings some insight to the understanding of the FDI problem by means of the introduction of ideas and methodologies from Inverse Problems. Inverse Problems, which arise from practical applications, deal with observable information from the system. How this information can be used is a key issue for solving Inverse Problems. Fault Diagnosis can be understood as a problem based on information (e.g., model of the system and measurements). Therefore, the ideas from Inverse Problems allowed to identify some results that could help solve problems of the area of Faults Diagnosis.

Moreover, the formulation of the Fault Diagnosis Inverse Problems as optimization problems allows to apply metaheuristics for computing the solution, i.e., diagnosing the faults.

Metaheuristics are a group of nonexact algorithms that allow to solve optimization problems based on a search strategy in the feasible solution space. Metaheuristics may provide a sufficiently good solution to an optimization problem, especially with incomplete information. Naturally an obvious question comes to mind. Which is the best metaheuristic for Fault Diagnosis Inverse Problems? In [137], it is demonstrated that there is not a unique answer to this question. Instead, this book describes in an easy way, but with rigor, four well-known metaheuristics for optimization (Differential Evolution, Particle Collision Algorithm, Ant Colony Optimization, and Particle Swarm Optimization), which were also used during the application of the methodology to Fault Diagnosis in three benchmark problems (DC Motor, Inverted Pendulum System, and Two Tanks System) from the FDI area. These examples are useful for showing how to analyze and interpret the influence of some metaheuristics parameters in the quality of the diagnosis. Furthermore, this book presents the main ideas and concepts from optimization and metaheuristics, which may be useful for readers that are not familiarized with these topics.

The formulation of FDI as Inverse Problems also allowed to develop two new hybrid metaheuristics: *Particle Swarm Optimization with Memory* and *Differential Evolution with Particle Collision*. New metaheuristics constantly arise in the literature, but for being accepted by the computational community, they have to be formalized and validated, following the well-recognized methodology for metaheuristic validations [30, 45, 125]. This is also presented in this book.

The analysis of the results obtained along the experiments for the validation of the new metaheuristics, as well as in their application to the benchmark problems, made use of basic concepts and test from statistics. During the analysis of the experiments, different tables and graphics were constructed in order to facilitate the presentation of the results, as well as their interpretation.

Formulating Fault Diagnosis as an Inverse Problem and solving it by means of metaheuristics bring together readers from at least three different areas: Fault Diagnosis, Inverse Problems, and Metaheuristics. This represents the nature of the authors of this book.

The prerequisites to read this book are calculus of several variables and linear algebra. Some basics about programming are also useful for a better understanding of the chapter that presents the topic of metaheuristics.

The chapters of this book are summarized as follows:

- **Chapter 1:** In this chapter, the main concepts, ideas, advantages, and disadvantages related to the use of model-based FDI methods are presented. The main ideas on the formulation and solution of Inverse Problems are also briefly described.

- **Chapter 2:** This chapter presents and formalizes Fault Diagnosis as an Inverse Problem, as well as the new methodology for Fault Diagnosis: Fault Diagnosis—Inverse Problem Methodology. The three benchmark problems used during the experiments are also described.
- **Chapter 3:** This chapter makes an introduction to metaheuristics for optimization. In particular, the metaheuristics Differential Evolution, Particle Collision Algorithm, Ant Colony Optimization for continuous problems, and Particle Swarm Optimization are described. This chapter also presents two new metaheuristics: Particle Swarm Optimization with Memory and Differential Evolution with Particle Collision.
- **Chapter 4:** This chapter presents the application of Fault Diagnosis—Inverse Problem Methodology to the three benchmark problems considered. In particular, the experiments are designed in order to analyze robustness and sensitivity of the diagnosis obtained with FD-IPM.

Chapter 1 can be read independently when the reader is only interested in the main concepts and ideas from model-based Fault Diagnosis or Inverse Problems. For readers interested in metaheuristics, we recommend Chap. 3 which can be read independently. For the new methodology, Chap. 2 has to be read. We recommend to read Chap. 1 before reading Chap. 2. Chapter 4 presents the applications of the methodology to three benchmark problems. Before reading Chap. 4, we recommend reading Chap. 2.

Appendices A and B show the Matlab® codes for the algorithms of the new metaheuristics Differential Evolution with Particle Collision and Particle Swarm Optimization with Memory, respectively.

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Contents

Acronyms

ABC	Artificial Bee Colony
ACO	Ant Colony Optimization
BBO	Biogeography-Based Optimization
BMs	Bio-Inspired Metaheuristics
CS	Cuckoo Search
DC	Direct Current
DE	Differential Evolution
DEwPC	Differential Evolution with Particle Collision
EAs	Evolutionary Algorithms
EDAs	Estimation of Distribution Algorithms
EP	Evolutionary Programming
FA	Firefly Algorithm
FDI	Fault Detection and Isolation, Fault Diagnosis
FD-IPM	Fault Diagnosis—Inverse Problem Methodology
GAs	Genetic Algorithms
GEO	Generalized Extremal Optimization
GP	Genetic Programming
IP	Inverse Problems
IPS	Inverted Pendulum System
IWD	Intelligent Water Drops Algorithm
LTI	Linear Time Invariant
MAs	Memetic Algorithms
MPCA	Multiple Particle Collision Algorithm
NMs	Nature-Inspired Metaheuristics
NPMs	Non-population-Based Metaheuristics
PCA	Particle Collision Algorithm
PI	Proportional-Integral Controller
PID	Proportional-Integral-Derivative Controller
PMs	Population-Based Metaheuristics
PSO	Particle Swarm Optimization
PSO-M	Particle Swarm Optimization with Memory

SA	Simulated Annealing
SI	Swarm Intelligence
SIs	Swarm Intelligence algorithms
SISO	Single Input Single Output
TS	Tabu Search