

Fault Diagnosis for Electric Power Systems and Electric Vehicles

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First Edition

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Preface

The aim of this monograph on "Fault diagnosis for electric power systems and electric vehicles" is to analyze methods for fault detection and isolation in electric power systems and in electric traction and propulsion systems. To this end, the following topics are treated:

(a) model-based fault diagnosis with the use of nonlinear estimation methods and statistical fault diagnosis criteria. Modelling of the fault-free condition of nonlinear systems with the use nonlinear Kalman filters and nonlinear observers are extensively presented. At a next stage statistical decision making for fault detection and isolation is analyzed. Statistical approaches to fault diagnosis are introduced as methods that allow for precise and optimized definition of fault thresholds and which permit for distinguishing for incipient parametric changes in the monitored systems and for minimizing the launching of false alarms. In this context, an approach for fault thresholds definition based on the confidence intervals of the χ^2 (chi-square) distribution is presented. Several application examples are given about fault detection and isolation in the electric power transmission and distribution system, interconnected electric power units, conventional AC power units, renewable energy sources, electric power microgrids, and electric machines.

(b) model-free fault diagnosis with the use of nonlinear estimation methods and statistical fault diagnosis criteria. In particular modelling of the fault-free condition of nonlinear systems with the use of nonlinear regressors (e.g. neural networks) and the associated nonlinear least squares techniques are explained. Neural networks with Gauss-Hermite activation functions are introduced as an approach for modelling nonlinear dynamical systems, and particularly electric power generation and electric traction and propulsion systems. Besides, the statistical processing of the residuals of these neural networks, which are the differences between the outputs of the neural models and the outputs of the monitored system is shown to provide clear indications about the existence of faults.

In the present monograph on *Fault diagnosis for electric power systems and electric vehicles*, the following issues are analyzed: Chapter 1 is on Fault diagnosis with model-based and model-free techniques (Model-based fault diagnosis techniques and Model-free fault diagnosis techniques). Chapter 2 is on Control and fault diagnosis for Synchronous Generator-based renewable energy systems (Control of the marine-turbine and synchronous-generator unit and Fault diagnosis of the marine-turbine and synchronous-generator unit). Chapter 3 is on Fault diagnosis for electricity microgrids and gas processing units (Fault diagnosis for electric power DC microgrids and Fault diagnosis for electrically actuated gas compressors). Chapter 4 is on Fault diagnosis for gas and steam-turbine power generation units (Fault diag-

nosis for the gas-turbine and Synchronous Generator electric power unit and for the steam-turbine and synchronous generator power unit). Finally, Chapter 5 is on Fault diagnosis for wind power units and for the distribution grid (Fault diagnosis for wind power generators and Fault diagnosis for the electric power distribution grid).

Through the detailed and in depth treatment of the aforementioned topics, this monograph is expected to have a meaningful contribution to the members of the research, academic and engineering community. It is anticipated that the monograph will be particularly useful to researchers and university tutors working on fault diagnosis problems of electric power systems and of electric traction and propulsion systems.

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