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Review

Graphical methods for diagnosis of dynamic systems: Review

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ABSTRACT

This paper presents an overview of graphical methods used for robust Fault Detection and Isolation (FDI) that can be employed for monitorability and diagnosability analysis and/or online diagnosis of dynamic systems. We review the modeling approaches used by the different methods, and then study properties, such as detectability, isolability, and robustness of each one of the methods. The different properties of each method are reviewed in the paper.

Contents

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Acronyms

FDI	Fault Detection and Isolation	CR	compensatory response
FMEA	Failure Mode Effects Analysis	ESFA	extended symptom-fault association
FTC	Fault Tolerant Control	SCC	strongly connected component
FAC	Fault Adaptive Control	QTA	qualitative trend analysis
PCA	Principal Component Analysis	PCs	possible conflicts
PLS	Partial Least-Squares analysis	MECs	minimal evaluation chains
DEDS	discrete event diagnosis systems	AOG	AND–OR graph
ARR	analytical redundancy relation	MEM	Minimal Evaluation Model
AI	Artificial Intelligent	MASS	Minimal Additional Sensors Sets
BG	bond graph	EKF	extended Kalman filter
ODE	Ordinary Differential Equation	MMI	man machine interface
DAE	Differential–Algebraic Equation	GTST-MPLD	Goal Tree Success Tree-Master Plant Logic Diagram
LFT	Linear Fractional Transformation	GT	Goal Tree
FSM	Fault Signature Matrix	ST	Success Tree
BN	Bayesian Network	USOM	User Operating Mode
HBN	Hybrid Bayesian Network	FM	functional model
DBN	Dynamic Bayesian Network	FMA	failure model analysis
MSS	minimal structurally singular	CPD	conditional probability distribution
MSO	minimal structurally overdetermined	PF	particle filter
SDG	signed directed graph	RBPF	Rao–Blackwellized particle filter
TCG	temporal causal graph	RSPF	Risk Sensitive Particle Filters
MFM	Multilevel Flow Model	VRPF	Variable Resolution Particle Filters
IR	inverse response		

1. Introduction

In the past, automation in production systems has assisted operators in controlling processes and equipment with the goal of maintaining quality of the finished product, efficiency of operations, and overall safety of the plant. The main objective was to increase overall productivity by monitoring performance and allowing the operators to input corrective commands when deviations from expected behaviors were observed. Typically fault isolation was initiated using off line methods, such as Failure Mode Effects Analysis (i.e., FMEA's) or fault trees, when sufficient degradation of performance or a breakdown in the plant occured. More recently, the complexity and safety critical needs of systems such as power generation plants, automotive systems, aircraft, and medical systems have motivated the need for automated monitoring and diagnosis as part of the intelligent control loop. The need for safety and efficient control under a variety of operating conditions requires on line Fault Detection and Isolation (FDI) procedures that can inform intelligent Fault Tolerant and Fault Adaptive Control (FTC and FAC) schemes (Blanke & Lorentzen, 2006a). Therefore, FDI algorithms must be designed to operate online, which means they operate by comparing the observed behavior of the process against a reference behavior provided by a nominal model of the system. When the observed behavior differs from the nominal behavior, the diagnosis method uses this difference, expressed as a non-zero *residual vector* as the basis for the isolation task. Fig. 1 illustrates a generic on line fault detection and isolation scheme. This scheme is essentially composed of a characterization or *residual generation* phase that can be based on model-based and signal analysis approaches, and a *decision making* phase that is typically based on logical analysis or pattern recognition approaches. Ideally, residual analysis should be easy, but the presence of noise in the measurements, disturbances in the plant and its environment, and model uncertainties can complicate this task, leading to false alarms, missed alarms, incorrect diagnosis, and at the very least, delays in the detection and isolation of the fault. One of the goals of online schemes is to devise *robust* schemes that keep the overall FDI performance at high levels even in the presence of noise and uncertainties.

Different approaches have been developed for designing and implementing robust FDI procedures. These methods depend on the kind of knowledge used to describe the plant operation. They may be broadly categorized into two groups:

- *Methods that do not use explicit models of the plant and its behaviors.* Many of these approaches are based on *artificial intelligence* techniques derived from the knowledge of human experts or from *data-driven*, schemes, such as classifiers and machine

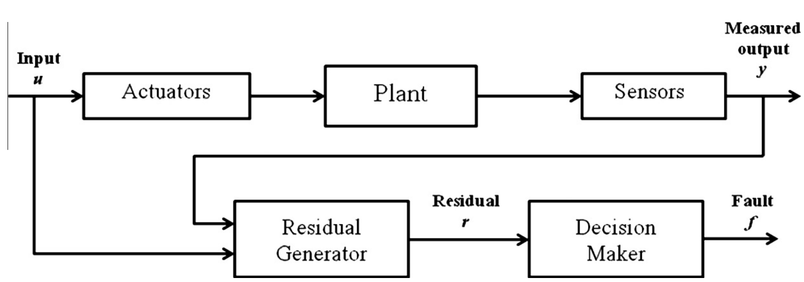

Fig. 1. Computational architecture of generic fault diagnosis scheme.

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