402g Probabilistic Sensor Fault Detection and Identification in Distributed Parameter Systems
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A method of sensor fault detection and identification in distributed parameter systems is presented. It is based on probabilistic inference using dynamic Bayesian Belief Networks (BBNs). The method involves constructing the structure of a dynamic BBN model of all sensors in a given process from individual sensor BBN models, calculating conditional probability data that describe correlations among the sensors, calculating a sensor fault detection index for each sensor, and choosing a proper fault detection threshold. A comparison of the value that a fault detection index takes and the threshold allows one to differentiate between operative and faulty sensors. A proper selection of the threshold provides reliable fault detection by minimizing the missed faults and false alarms. The sensor fault detection and identification method is applied to a tubular flow reactor in which an exothermic reaction takes place. Sensor faults of different types (bias, precision degradation and noise) are introduced into the measurements of a subset of sensors placed along the reactor, and the method is then used to detect and identify the faults.

Except for the method presented in [1], sensor fault detection and identification using BBNs has been limited to static belief networks which has been of little use to process industries. The focus of the work in [1] was on lumped-parameter systems. Distributed parameter systems are spatial and temporal in nature and hence require belief networks that can accommodate spatial as well as temporal knowledge. The spatial-temporal nature of the process warrants single sensor BBN models with discrete adaptable nodes [1] as building blocks for a dynamic BBN model representing all sensors in the process under consideration. The dynamic BBN includes a snapshot of process sensors that incorporates two time instants k and k+1. The next snapshot features time instants k+1 and k+2. In the snapshot representing process sensors at k+1 and k+2, it is assumed that measurements at k+2 are conditionally independent of those at k. In other words, time slices are assumed to obey Markov property; that is, the future is conditionally independent of the past given the present. Thus, process-sensor readings at consecutive time slices are used as evidence in inference process to update beliefs in the dynamic BBN. From the updated beliefs, a probability absolute difference (difference between updated beliefs and beliefs when all sensors are in the normal operating mode) for each sensor is calculated. A ratio of probability absolute difference of a sensor and the sum of probability absolute differences of all sensors is defined as a fault detection index for that sensor. For each sensor that appears in consecutive snapshots, an average of its fault detection index is considered. The fault detection threshold is selected such that it lies between (a) the maximum value that the fault detection indices take for operative sensors and (b) the minimum value that the fault detection indices take for faulty sensors when a specific number of sensors are faulty.

The sensor fault detection and identification method is applied to a tubular flow reactor in which an exothermic reaction takes place. The temperature of the reaction mixture and concentration of the reactant inside the reactor are measured with temperature and concentration sensors placed at equal distances along the reactor. The structure of a dynamic BBN representing all sensors used in the reactor is constructed considering cause-effect relation between the variables that the sensors measure. Profiles of these variables are calculated by numerically simulating the reactor operation. From expected values of the variables at all time instants, state bin ranges of discretized nodes for all time instants are calculated. Conditional probability data that correlate the process variables are calculated from the state bin ranges using Monte Carlo simulations. The optimum values of prior probability presented in [2] are used.

[1] Mehranbod, N., and M. Soroush, “A Method of Sensor Fault Detection and Identification,” J. of Process Contr., 15(3), 321-339 (2005).

[2] Mehranbod, N., M. Soroush, M. Piovoso, and B. A. Ogunnaike, “Probabilistic Model for Sensor fault Detection and Identification” AIChE J., 49(7), 1787-1802 (2003).