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Dynamic model-based sensor network design algorithm for system efficiency maximization

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ABSTRACT

A dynamic model-based sensor network design (DMSND) algorithm has been developed for maximizing system efficiency for an estimator-based control system. The algorithm synthesizes the optimal sensor network in the face of disturbances or set point changes. Computational expense of the large-scale combinatorial optimization problem is significantly reduced by parallel computing and by using combination of three novel strategies: multi-rate sampling frequency, model order reduction, and use of an incumbent solution that enables early termination of evaluation of infeasible sensor sets. The developed algorithm is applied to an acid gas removal unit as part of an integrated gasification combined cycle power plant with carbon capture. Even though there are more than thousand process states and more than hundred candidate sensor locations, the optimal sensor network design problem for maximizing process efficiency could be solved within couple of hours for a given budget.

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1. Introduction

A systematic approach to sensor network design (SND) is of prime importance in order to achieve an economic and efficient measurement network for optimal plant operation, monitoring, and control. Typical chemical processes have a large number of possible locations for measurements and it is not economically or practically viable to measure all the variables. Some of the variables that are measured may have very low precision, low signal-to-noise ratio and low reliability. Such measurements might lead the process operation to a suboptimal condition and result in degraded process performance. In practice, process variables are measured either for monitoring or control purposes. Process monitoring is an indispensable part of any process operation to ensure compliance with environmental emission standards and avoidance of safety hazards and unwanted products. Monitoring equipment health is also very important to detect and circumvent any undesired conditions. Regarding process control, some controlled variables especially those obtained by steady-state economic analysis (Skogestad, 2004) can have significant impact on process performance. Thus, it is of prime importance to find an optimal sensor network that can ensure satisfactory process performance subject to the economic and operational constraints.

Sensor placement problem has been an active area of research in last several decades. Sahraei et al. (2014) have presented a comprehensive literature review on the sensor placement methodologies and control strategies to improve power plant efficiency. The traditional SND algorithms that have been presented in the existing literature have mostly considered static process conditions. These algorithms will be called steady-state SND (SSND) algorithms. Lee and Diwekar (2012) have developed an optimal sensor placement algorithm for advanced power plants where a stochastic integer programming problem is solved to maximize the Fisher information subject to budget constraints. Nabil and Narasimhan (2012) have considered static process operation for determining a redundant sensor network from a data reconciliation perspective and for minimizing the loss of operational profit due to measurement error subject to an available resource limit. Ali (1993) and Ali and Narasimhan (1993, 1995, 1996) have used a steady-state process model for maximizing reliability of the sensor network for given sensor failure rates. Kelly and Zyngier (2008) have minimized the overall instrumentation cost subject to the constraints on software and hardware redundancy of measured variables and observability of unmeasured variables and their precision. Carnero et al. (2001, 2005) have considered steady-state process operation and obtained an optimal design of non-redundant observable linear sensor

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Nomenclature

A	process transition matrix
a	power consumption coefficient due to solvent regeneration
B	input matrix
b	scalar budget ($)
C	measurement matrix
c_i	cost of individual sensor ($)
d	disturbance
F	flowrate (mol/h)
Gen	number of generations in GA
K	Kalman gain matrix
K_c	proportional gain of P-only controller
κ	weighting factor for incumbent solution
λ	weighting factor for estimation error
N_s	total number of candidate sensor
n	number of states
P	pressure
P	state error variance–covariance matrix
P_c	consumed power (MWh)
Q	process noise variance–covariance matrix
q	process variables for which a desired estimation accuracy is desired
R	measurement noise variance–covariance matrix
T	temperature, settling time
t	time (h)
τ_I	reset time
W	weighting factor
u	control inputs
u_d	vector of disturbance and control inputs
v	measurement noise vector
w	process noise vector
x	vector of states
$\hat{x}$	vector of estimated states
y	vector of measurements
$\hat{y}$	vector of estimated variables
$\varepsilon(t)$	deviation of the controlled variable from set point

Subscripts

act	actual variable
β	decision variable vector of binary number (0 and 1)
cont	control/controlled variable
CO_2	carbon dioxide
est	estimated/estimator-based
in	inlet or, input
incum	incumbent
ma	process monitoring variables and active constraints
mon	monitoring variables
opt	optimal
r	reduced order model
set	desired set point
solvent	selexol solvent
ss	steady state
term	termination
$(.)_i$	*i*th tray

networks. Kretsovalis and Mah (1987) minimized an objective function of the weighted average of the cost of the measurements and the precision of the estimates. The authors used the trace of the steady-state process error covariance matrix and showed that redundancy in measurements improved the estimation accuracy. SND from an economic perspective has been presented by Bagajewicz and Markowski (2003), Bagajewicz (2005a) where the authors obtained an expression for assessing the value of precision. More recently, Bagajewicz (2005b) has extended the economic value of precision by introducing the effect of induced bias obtained by evaluating the economic value of accuracy. Bagajewicz et al. (2005), Bagajewicz (2006), Bagajewicz and Nguyen (2008) have also investigated economic value of data reconciliation and instrumentation upgrades. Peng and Chmielewski (2006, 2005) have placed sensors from the controls perspective. The authors have developed algorithm for simultaneous selection of sensors as well as minimal backed-off operating points by maximizing the operating profit.

Since the SSND algorithms optimize a steady-state objective, the transient performance of the sensor network can lead to sub-optimal plant performance. DMSND algorithms are limited in the existing literature. Kadu et al. (2008) have considered a discrete linear time invariant system with multi-rate extension of the basic Kalman filtering algorithm to show the effect of various measurement sampling rates on state estimation. To find Pareto optimal solutions for the optimal sensor network, they considered dual objective functions, namely maximizing the quality of estimates and minimizing the measurement cost subject to a constraint on system detectability. Mellefont and Sargent (1978) developed an implicit enumeration algorithm using a linear stochastic system for selection of measurements to be used in optimal feedback control. This algorithm minimizes both the measurement cost and a quadratic function of the covariance of state prediction error with minimum number of measurements.

Other than different objectives considered for the SND problem, different computational methods have also been developed in the open literature for designing optimal SND. A tree search approach has been used by Bagajewicz (1997), Bagajewicz and Sanchez (2000) and Bagajewicz and Cabrera (2002) to solve a mixed integer problem and obtain a cost optimal sensor network subject to the constraints on estimation precision, availability, resilience, error detectability, hardware redundancy, and reliability. Later an equation-based tree search method for the design of a nonlinear sensor network was presented by Nguyen and Bagajewicz (2008, 2013). The genetic algorithm (GA) has been used by Zumoffen and Basualdo (2010). A graph theoretic approach has been used by Meyer et al. (1994) and Luong et al. (1994) to design a sensor network for process monitoring. An approach combining the GA and graph theoretic approaches has been developed by Sen et al. (1998) to synthesize a non-redundant SND algorithm for linear processes. Madron and Veverka (1992) have adopted a Gauss-Jordan elimination method to optimize overall measurement cost and overall precision of a system. Recently, a stochastic optimization-based method has been proposed by Ghosh et al. (2014) to identify an optimal subset of measured variables for effective statistical process monitoring.

Computational expense is an issue for solving large-scale SND problems. Due to this difficulty, Chmielewski et al. (2002) have developed an alternative SND formulation to obtain the minimum cost sensor network. The authors improved computational efficiency by converting the nonlinear programming problem into a convex program through the use of linear matrix inequalities. They applied the SND approach to both steady-state and dynamic processes subject to single/multiple constraints on precision, gross-error detectability, resilience, and reliability. Nguyen and Bagajewicz (2008) have proposed a rigorous equation-based tree search method for designing nonlinear sensor networks but its performance is not satisfactory when dealing with large-scale problems ($\geq$35 measured variables and $\geq$25 balance equations). Later on, the same authors have proposed an approximate method (Nguyen and Bagajewicz, 2013) to solve a large-scale problem with 35 variables and 28 balance equations where the equation-based tree search method was used for initialization but still

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