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Subset Measurement Selection for Globally Self-Optimizing Control of Tennessee Eastman Process ⋆

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Abstract: The concept of globally optimal controlled variable selection has recently been proposed to improve self-optimizing control performance of traditional local approaches. However, the associated measurement subset selection problem has not be studied. In this paper, we consider the measurement subset selection problem for globally self-optimizing control (gSOC) of Tennessee Eastman (TE) process. The TE process contains substantial measurements and had been studied for SOC with controlled variables selected from individual measurements through exhaustive search. This process has been revisited with improved performance recently through a retrofit approach of gSOC. To extend the improvement further, the measurement subset selection problem for gSOC is considered in this work and solved through a modification of an existing partially bidirectional branch and bound (PB^3) algorithm originally developed for local SOC. The modified PB^3 algorithm efficiently identifies the best measurement candidates among the full set which obtains the globally minimal economic loss. Dynamic simulations are conducted to demonstrate the optimality of proposed results.

Keywords: Tennessee Eastman, self-optimizing control, controlled variable, plant-wide control

1. INTRODUCTION

Since published in 1993, the well-known Tennessee Eastman (TE) process (Downs and Vogel, 1993) has been extensively studied by researchers from the field of process control. Various control strategies and algorithms were proposed to address the control problems posed by Downs and Vogel. McAvoy and Ye (1994) used the relative gain array and other controllability analysis tools to configure a basic PID control system, which operates the process around the base case point and met basic requirements posed in the problem. Later, Ricker (1995) identified the optimal steady-state point of process operation, he also presented a well-configured decentralized control structure (Ricker, 1996), which achieved excellent performances for various control tasks. Meanwhile, nonlinear model predictive control (NMPC) algorithm (Ricker and Lee, 1995) was also considered. Jockenhövel et al. (2003) performed dynamic optimization of the TE process using a MATLAB-based OptControlCentre toolbox.

On the other hand, although there are many approaches developed for either control or optimization of the TE process, only a few were concerned with the economic performance by means of selecting controlled variables (CVs), which are of critical importance for a control system. The control system designed by Ricker (1996) controls the active constraints identified from steady state optimization, however, the sensitivity part is not appropriately addressed. Another successful one is the work of Larsson et al. (2001), where the self-optimizing control (SOC) methodology (Skogestad, 2000) was applied to select the best CVs to achieve economic improvements. The SOC is a control strategy that by means of selecting particular CVs, the economic performance of plant operation is automatically "self-optimizing" with an acceptable loss, in spite of disturbances and uncertainties. Such a strategy is particularly appealing for large scale process plants, such as the TE process, where installing and maintaining an extra computationally expensive "real-time optimization" (RTO) layer is unnecessary for economically optimal operation if a well-designed SOC system is implemented.

However, the self-optimizing control structure designed by Larsson et al. (2001) has several limitations. Firstly, only the individual measurements are considered as the CV candidates. It has been well recognized that one achieves better self-optimizing performance by controlling the measurement combinations, because they provide more intrinsic knowledge of the process (Alstad and Skogestad, 2007; Kariwala, 2007; Kariwala et al., 2008; Alstad et al., 2009; Ye et al., 2013). However, an application of measurement combination CVs to the TE process has not yet been

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Table 1. Manipulated variables for TE process

Number	Variable name
XMV(1)	D feed flow
XMV(2)	E feed flow
XMV(3)	A feed flow
XMV(4)	A and C feed flow
XMV(5)	Compressor recycle valve
XMV(6)	Purge value
XMV(7)	Separator liquid flow
XMV(8)	Stripper liquid product flow
XMV(9)	Stripper steam valve
XMV(10)	Reactor cooling water flow
XMV(11)	Condenser cooling water flow
XMV(12)	Agitator speed

reported elsewhere. Moreover, to select out the CVs, the full measurement set was screened largely according to their heuristic judgements of the process characteristics. Although easily understood from an engineer's perspective, too much subjective judgements may omit promising CV candidates that cannot be obviously detected. Since selecting a measurement subset to constitute CV is a combination problem in nature, an exhaustive search way is intractable with substantial measurements. In recent years, a number of algorithms for fast identifying a measurement subset were reported, e.g. the bidirectional branch and bound (BAB) (Cao and Kariwala, 2008; Kariwala and Cao, 2009, 2010) and the mixed integer quadratic programming algorithms (Yelchuru and Skogestad, 2012).

In this study, we consider the measurement subset selection problem for TE process in the framework of SOC. Firstly, we investigate the TE process by applying a new globally SOC (gSOC) method, which approximately minimizes the average loss for all operating conditions for a plant operation (Ye et al., 2015). The new gSOC method is developed in terms of "operating condition" instead of some perturbed "disturbance variables". This method allows us to derive measurement combinations as CVs for the TE process. Then, we investigate the measurement subset selection problem with a modified partially bidirectional branch and bound (PB^3) algorithm, which was earlier employed in local SOC methods based on local average loss minimization. Finally, we implement the derived subsets for gSOC of the TE process through a retrofit approach proposed recently (Ye et al., 2016), dynamic simulations are carried out to validate the optimality.

2. OVERVIEW OF THE PROCESS

2.1 Process description

The plant-wide TE process consists of the following 4 reactions

$$A(g) + C(g) + D(g) \rightarrow G(liq)$$
$$A(g) + C(g) + E(g) \rightarrow H(liq)$$
$$A(g) + E(g) \rightarrow F(liq)$$
$$3D(g) \rightarrow 2F(liq)$$

where A, C, D, E are the reactants, G and H are the products and F is the byproduct. Besides, there exists an inert component B in the material circle, which is contained in the feed and removed through purge to maintain inventory balance. The process includes 5 major operating units: the reactor, product condenser, vapor-liquid separator, recycle compressor and product stripper.

Table 2. Measurements for TE process

Number	Variable name
XMEAS(1)	A feed
XMEAS(2)	D feed
XMEAS(3)	E feed
XMEAS(4)	A and C feed
XMEAS(5)	Recycle flow
XMEAS(6)	Reactor feed rate
XMEAS(7)	Reactor pressure
XMEAS(8)	Reactor level
XMEAS(9)	Reactor temperature
XMEAS(10)	Purge rate
XMEAS(11)	Product separator temperature
XMEAS(12)	Product separator level
XMEAS(13)	Product separator pressure
XMEAS(14)	Product separator underflow
XMEAS(15)	Stripper level
XMEAS(16)	Stripper pressure
XMEAS(17)	Stripper underflow
XMEAS(18)	Stripper temperature
XMEAS(19)	Stripper steam flow
XMEAS(20)	Compressor work
XMEAS(21)	Reactor cooling water outlet temperature
XMEAS(22)	Separator cooling water outlet temperature
XMEAS(23–28)	mole fraction of A–F in feed
XMEAS(29–36)	mole fraction of A–H in purge
XMEAS(37–41)	mole fraction of D–H in product

The process includes 12 manipulated variables (MVs) and 41 measurements, as listed in Table 1 and Table 2. For the MVs, they have all been scaled within the 0-100% range, which are considered as valve positions. For the measurements, they are defined with different sampling frequencies and dead time to keep consistence with the industrial practice. An economic index is also introduced, which is composed of the cost/loss of raw materials and energy, see Downs and Vogel (1993) for more details.

2.2 Overview of control structure

In open literature, there have been many control structures developed for the TE process. However, in the remainder of this paper, we will mainly introduce two control systems proposed by Ricker (1996) and Larsson et al. (2001) to get an overview for controlling the TE process. (For the sake of convenience, they will be denoted as "CS_Ricker" and "CS_Skoge" after the corresponding authors respectively. Furthermore, the choice of CV selection is of particular interest in this study and outlined as below.

According to their control policies, the following process variables should be controlled in closed-loops:

(1) Separator level and stripper level. These two liquid levels are integrating variables and have no steady state effects, they must be stabilized in the first place.
(2) Production rate (stripper underflow) and product quality (mole %G in product). Manufacturing objective defines their targets under different operating modes and specifications, these equality constraints should be controlled to satisfy the targets.
(3) At the optimum, there are 5 active constraints that needs to be controlled at their boundaries: reactor pressure (maximum) and level (minimum), compressor recycle valve (closed), stripper steam valve (closed) and agitator speed (maximum). Ricker (1996) provided detailed physical interpretations why these constraints are active at the optimum.

Above control requirements consume 9 degrees of freedom (DOF) for plant operation. For the remaining unconstrained 3 DOF, Ricker (1996) chose to control the