Computers and Chemical Engineering 79 (2015) 59–69

Contents lists available at ScienceDirect

Computers and Chemical Engineering

journal homepage: www.elsevier.com/locate/compchemeng

A time scale-bridging approach for integrating production scheduling and process control☆

Juan Du[a], Jungup Park[a], Iiro Harjunkoski[b], Michael Baldea[a,*]

[a] McKetta Department of Chemical Engineering, The University of Texas at Austin, 200 East Dean Keeton St., Stop C0400, Austin, TX 78712, USA
[b] ABB AG Corporate Research, Wallstadter Str. 59, 68526 Ladenburg, Germany

ARTICLE INFO

Article history:
Received 6 June 2014
Received in revised form 10 February 2015
Accepted 24 April 2015
Available online 2 May 2015

Keywords:
Production scheduling
Nonlinear control
Integrated scheduling and control

ABSTRACT

In this paper, we propose a novel framework for integrating scheduling and nonlinear control of continuous processes. We introduce the time scale-bridging model (SBM) as an explicit, low-order representation of the closed-loop input–output dynamics of the process. The SBM then represents the process dynamics in a scheduling framework geared towards calculating the optimal time-varying setpoint vector for the process control system. The proposed framework accounts for process dynamics at the scheduling stage, while maintaining closed-loop stability and disturbance rejection properties via feedback control during the production cycle. Using two case studies, a CSTR and a polymerization reactor, we show that SBM-based scheduling has significant computational advantages compared to existing integrated scheduling and control formulations. Moreover, we show that the economic performance of our framework is comparable to that of existing approaches when a perfect process model is available, with the added benefit of superior robustness to plant-model mismatch.

1. Introduction

Competitive pressure from increasingly global market forces has heightened emphasis on improving the integration and coordination of decision-making across all the layers of the chemical supply chain. Advances in numerical optimization algorithms and the accessibility of computing power have led to significant developments in enterprise-wide decision making, already leading to substantial economic benefits for chemical process operations (Grossmann, 2005).

Scheduling and control are two essential functions in the decision-making hierarchy of the chemical supply chain (Fig. 1), dealing with the common goal of maximizing profit from operations by setting production targets based on demand and, respectively, ensuring that the targets are met in the presence of process disturbances and operational uncertainty. It is thus anticipated that integrating scheduling and control can result in improved process economics, particularly in industries such as polymer and metal production, wastewater treatment and power generation (Engell and Harjunkoski, 2012), as well as in managing energy storage systems (Touretzky and Baldea, 2014). Integrating scheduling and control should also be facilitated by their common mathematical basis: they both rely on mathematical models to forecast process performance, and make use of optimization calculations to determine the process settings and inputs that provide the best (economic) outcome.

Yet, in spite of these encouraging facts, the development of a robust and computationally tractable integrated scheduling and control framework remains an open problem. Early publications (Shobrys and White, 2002) have identified, amongst others, the "organizational silos" that result from the fact that scheduling and control are carried out by different divisions of a company, with seemingly different goals and performance metrics, as one of the causes for the failure of integrating scheduling and control in industry. This remained the case a decade later, as confirmed by Engell and Harjunkoski (2012), who have also emphasized the need to strengthen collaboration between academic researchers working independently in the two areas.

The other cause is, however, technical, and is related to the vastly different time horizons that scheduling and control must account for: these range from hours to days for scheduling, and minutes to hours for control (Fig. 1). A solution integrating the two functions must therefore combine the long time horizon of the scheduling formulation as well as the frequent (closed-loop) execution of the control system. Furthermore, the integrated solution must be capable of coping with the discrete decisions that are inherently part of

☆ A preliminary version of these results was submitted for presentation at ESCAPE 24, Budapest, Hungary.

* Corresponding author. Tel.: +1 512 471 1281.
E-mail address: mbaldea@che.utexas.edu (M. Baldea).

http://dx.doi.org/10.1016/j.compchemeng.2015.04.026
0098-1354/

Nomenclature

Sets

i	$i = 1, \ldots, N_p$	products
s	$s = 1, \ldots, N_s$	slots
f	$f = 1, \ldots, N_{fe}$	finite elements
c	$c = 1, \ldots, N_{cp}$	collocation points

Parameters

N_p	number of products
N_s	number of slots
N_{fe}	number of finite elements
N_{cp}	number of collocation points
$\bar{f}$	number of finite elements for convergence tolerance
δ_i	demand of product i
π_i	price of product i
$c_{storage,i}$	inventory cost of product i
q_i	production rate for product i
$t^{p^{\max}}$	upper bound for processing time for product
ω^{max}	upper bound for the total quantity of product
y_i^j	desired steady state value of process output j for product i
x_i^j	desired value of process state j for product i
$\tau_{j,k}$	time constants for closed-loop response of process output j
W	matrix of Radau quadrature weights
ε^j	tolerance for discrepancy between state x^j and its desired steady-state value

Binary variable

$z_{i,s}$	product i is manufactured in slot s

Continuous variables

T_c	cycle time
$t^p_{i,s}$	processing time for product i in slot s
t^s_s	start time in slot s
t^e_s	end time in slot s
$\mathbf{x}$	process states
$\mathbf{y}$	process outputs
$\mathbf{u}$	process inputs
τ_s	transition time in slot s
ω_i	amount of product i produced
$\omega_{i,s}$	amount of product i produced in slot s
$x^j_{f,c,s}$	discretized process state j in finite element f at collocation point c in slot s
$t_{f,c,s}$	discretized time in finite element f and collocation point c in slot s

production scheduling. The ensemble of these requirements results in a large scale, stiff optimization problem that poses significant challenges, especially when it must be solved in closed-loop and in real time.

The available literature studies dealing with the "tyranny of scales" (Fish, 2009) that emerges from integrating scheduling and control fall, broadly speaking, into two categories: those that incorporate control considerations into an essentially scheduling-oriented framework, and, conversely, those that extend the formulation of the supervisory control problem to account for scheduling objectives, decisions and constraints (Baldea and Harjunkoski, 2014):

– From the perspective of the hierarchy presented in Fig. 1, the former can be regarded as "top-down" approaches. Several such studies have focused on improving the link between control and scheduling by relating the transition times used in (otherwise static) scheduling calculations to control performance Mahadevan et al. (2002) and to the definition and selection of controller tuning parameters (Chu and You, 2012). Formulating the integrated scheduling and control problem as a large mixed-integer dynamic optimization (MIDO) over the entire production cycle has also been explored. Both sequential (Allgor and Barton, 1999; Chatzidoukas et al., 2003; Nyström et al., 2005; Prata et al., 2008) and simultaneous (Flores-Tlacuahuac and Grossmann, 2006; Mitra et al., 2009; Zhuge and Ierapetritou, 2012) solution approaches have been proposed. The work of Flores-Tlacuahuac and Grossmann (2006) was extended by Zhuge and Ierapetritou (2012) to a closed-loop implementation that provides a rescheduling mechanism.
– "Bottom-up" approaches have focused on including economic and scheduling considerations in the formulation of the supervisory control problem (Kadam and Marquardt, 2007; Engell, 2007, 2009), leading to the emergence of the economic model predictive control (EMPC) paradigm (Engell, 2009; Amrit et al., 2011; Heidarinejad et al., 2012).

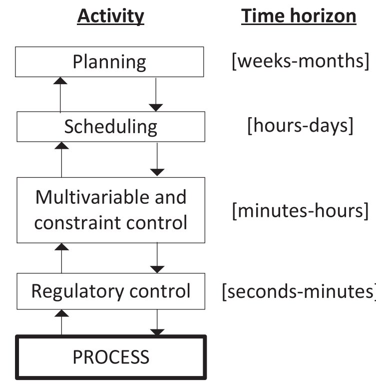

Fig. 1. Hierarchy of decision making in the chemical supply chain (Seborg et al., 2010).

In a different vein, we note the use of MPC-type algorithms for solving scheduling problems (see, e.g., Gallestey et al. (2003), Mestan et al. (2006)). A state-space approach which affords the reformulation of the scheduling problem as a control problem that is amenable to a solution based on model predictive control has been proposed by Subramanian et al. (2012). A multiparametric solution to the state-space scheduling problem has also been investigated by several authors (e.g., Poncet and Stothert (2006), Kopanos and Pistikopoulos (2014)).

For a comprehensive overview of literature studies concerning the integration of production scheduling and process control, we point the reader to the recent study by Baldea and Harjunkoski (2014).

In this paper, we propose a novel approach to integrating scheduling and process control. Our methodology originates in the scale-bridging techniques used in multi-scale modeling and simulation, whereby a low-order representation of the system properties on a faster time horizon and/or more detailed space scale is obtained and embedded in the model at the next higher scale to improve its accuracy and/or predictive abilities while lowering its computational demands. Similarly, we introduce the scale-bridging model (SBM) as an explicit, low-order representation of the closed-loop input-output dynamics of the process, which can be used in scheduling calculations. The paper is organized as follows: the mathematical formulations of the scheduling and control problems are presented in the next section, and existing approaches for