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Robust decision making for hybrid process supply chain systems via model predictive control

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ABSTRACT

Model predictive control (MPC) is a promising solution for the effective control of process supply chains. This paper presents an optimization-based decision support tool for supply chain management, by means of a robust MPC strategy. The proposed formulation: (i) captures uncertainty in model parameters and demand by stochastic programming, (ii) accommodates hybrid process systems with decisions governed by logical conditions/rulesets, and (iii) addresses multiple supply chain performance metrics including customer service and economics, within an integrated optimization framework. Two mechanisms for uncertainty propagation are presented – an open-loop approach, and an approximate closed-loop strategy. The performance of the robust MPC framework is analyzed through its application to two process supply chain case studies. The proposed approach is shown to provide a substantial reduction in the occurrence of back orders when compared to a nominal MPC implementation.

1. Introduction

A supply chain (SC) is a network of facilities that performs the functions of raw material procurement, raw material transformation into intermediate and finished products and distribution of products to customers, traditionally characterized by a forward flow of material, and a backward flow of information in the form of demand and orders. In a chemical process supply chain (PSC), as in the petrochemical or pharmaceutical industry, manufacturing is a major component (Grossmann, 2012). Reducing working capital and operating costs, while maintaining a high level of customer service are critical for remaining competitive within highly global environments.

Supply chain management (SCM) and supply chain optimization (SCO) are concerned with the efficient coordination and integration of business and operational functions, including strategic supply chain design, purchasing, production, transportation and distribution in order to bring greater net value to the customer, at minimum overall cost. Key drivers toward an increased focus on SCO in the chemical industry include increasingly global markets, reducing costs/inventories, improving responsiveness, and mitigating against uncertainty. There are significant economic incentives to be realized through improved integration between business planning and operational decision making at manufacturing facilities.

Poor SCM can contribute to unwanted instabilities within the network, such as the bullwhip effect, defined as the amplification in demand variability observed when moving up the supply chain from retailers to suppliers. The bullwhip effect was first illustrated through a series of case studies in the seminal work of Forrester (1961), and it has since been acknowledged that this major phenomenon is linked to forecast driven and decentralized decision-making, resulting in poor efficiency (Geary, Disney, & Towill, 2006; Lee, Padmanabhan, & Whang, 1997). Applications for SCM that integrate classical control technology have been motivated by the need for effective approaches to mitigate inefficiencies. These applications generally apply feedback laws for maintaining inventory positions and satisfying demand (e.g. Lalwani, Disney, & Towill, 2006; Perea-López, Grossmann, Ydstie, & Tahmassebi, 2001; Perea, Grossmann, Ydstie, & Tahmassebi, 2000; Towill, 1982). As discussed in Sarimveis, Patrinos, Tarantilis, and Kiranoudis (2008) in their comprehensive review on the application of control theory to SCM, the limitations associated with classical control technology, such as the inability to explicitly consider delays and interactions in the network, can be averted by applying an advanced control method such as model predictive control (MPC). Further advantages of MPC include a feed-forward control capability, an ability to address economics, and considerable flexibility in the underlying optimization formulation.

MPC is a multivariable control method that has found wide application to industrial processes over the past three decades; however, the application of MPC to SCM has been considered more recently. Tzafestas, Kapsiotis, and Kyriannakis (1997) developed a generalized production planning framework utilizing the MPC

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Nomenclature

Indicies/sets

$d \in D$	distribution site
$e, e' \in E$	plant site inventory echelon
$j \in J$	material (chemical)
$ls \in LS$	raw material supplier
$m, m' \in M$	plant site
$ps \in PS$	production scheme
$s \in S$	scenario
$t, t' \in T$	time period (in supply chain model)
$t^* \in T^*$	actual time period
J^P	set of final products
J_m^{PF}	set of products for FPM at plant site m
J_m^{PI}	set of products for IPM at plant site m
J^R	set of raw materials
J_m^{RF}	set of raw materials for FPM at plant site m
J_m^{RI}	set of raw materials for IPM at plant site m
PS_m^I	set of production schemes available at IPM at plant site m
PS_m^F	set of production schemes available at FPM at plant site m

Binary variables

$u_{m,ps,t}^I$	1 if the IPM process unit in plant site m begins a production scheme ps at time period t; and 0 otherwise
$u_{m,ps,t}^F$	1 if the FPM process unit in plant site m begins a production scheme ps at time period t; and 0 otherwise

Continuous variables

$B_{j,d,t}$	quantity of back orders of final product j in distribution site d at time period t
$F_{j,m,d,t}^F$	quantity of final product j shipped from plant site m to distribution site d at time period t
$F_{j,m,t}^{IW}$	quantity of material transferred from intermediate product storage facility to warehouse in plant site m at time period t
$F_{j,e,e',m,m',t}^P$	quantity of material shipped from storage echelon e at plant site m to storage echelon e' at plant site m' in time period t
$F_{j,d,t}^S$	quantity of final product j shipped from distribution site d to fulfil customer demand and back orders at time period t
$I_{j,m,t}^F$	inventory of final product j at warehouse in plant site m at time period t
$I_{j,m,t}^I$	inventory of intermediate product j at intermediate product storage facility in plant site m at time period t
$I_{j,m,t}^R$	inventory of raw material j at raw material storage facility in plant site m at time period t
$I_{j,d,t}^S$	quantity of final product j inventory in distribution site d at time period t
$P_{ps,m,t}^F$	quantity of main raw material which begins to undergo processing to final product in plant site m via scheme ps at time period t
$P_{ps,m,t}^I$	quantity of main raw material which begins to undergo processing to intermediate product in plant site m via scheme ps at time period t
$O_{j,ls,m,t}$	purchase quantity of raw material j to supplier ls from plant site m at time period t

Parameters

β_{ps}^P	process yield of product produced per unit of raw material consumed in production scheme ps
$\gamma_{m,ps}^{M^u}$	maximum batch size for production scheme ps in plant site m
$\gamma_{m,ps}^{M^l}$	minimum batch size for production scheme ps in plant site m
δ_{ps}^M	manufacturing delay for production scheme ps (days)
$\delta_{m,m'}^P$	shipping delay between plant site m and m' (days)
$\delta_{ls,m}^R$	delivery delay of procured material between supplier ls and plant site m (days)
$\delta_{m,d}^S$	shipping delay between plant site m and distribution site d (days)
κ	ratio between weighting parameters (ω_1/ω_2)
$\lambda_{ls,m}^R$	maximum quantity of raw material which can be ordered from supplier ls during a time period
$\lambda_{m,d}^F$	maximum transportation capacity from plant site m to distribution site d during a time period
$\lambda_{m,m'}^P$	maximum transportation capacity from plant site m to m' during a time period
$\mu_{j,ps}$	mass balance coefficient of material j in production scheme ps
ρ_s	probability of the occurrence of scenario s
ω_1	weighting parameter attributed to customer service ($\Im_1$)
ω_2	weighting parameter attributed to operating cost ($\Im_2$)
Ω_m^R	maximum storage capacity of raw material in plant site m
Ω_m^I	maximum storage capacity of intermediate product inventory in plant site m
$\Omega_{j,m}^F$	maximum storage capacity of final product j in plant site m
$\Omega_{j,d}^S$	maximum storage capacity of final product j in distribution site d (units)
$D_{j,d,t}^F$	customer demand of final product j at distribution site d at time period t
ΔT	execution frequency of model predictive controller (days)
n	length of prediction horizon (days)

approach, where decision variables include production, as well as advertising effort to influence sales. Bose and Pekny (2000) investigate the performance of a supply chain system where the demand level is uncertain. A hierarchical approach is proposed, where a forecasting model generates inventory targets (levels) to achieve a desired customer service level, and a scheduling model determines production tasks to achieve inventory targets, in a rolling horizon fashion as in MPC. Seferlis and Giannelos (2004) developed a two-layered control scheme for SCM, where a decentralized PID inventory controller is embedded within a MPC framework that computes shipments and places orders to nodes. Braun, Rivera, Flores, Carlyle, and Kempf (2003) implement a decentralized MPC framework for a supply chain in the semiconductor industry, and investigate control performance under plant model mismatch, and demand forecast error. Wang, Rivera, and Kempf (2007) examine the application of MPC as an integral component of a hierarchical framework for SCM within the semiconductor industry, where key challenges include high stochasticity in demand, and nonlinearity in model parameters. The effect of move suppression parameters, model parameters, and plant capacity on robustness and performance is illustrated through simulation case studies. Wang and Rivera (2008) enhance the prior study by formulating a multiple-degree-of-freedom observer for the systematic tuning