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A control-relevant approach to demand modeling for supply chain management☆

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ABSTRACT

The development of control-oriented decision policies for inventory management in supply chains has drawn considerable interest in recent years. Modeling demand to supply forecasts is an important component of an effective solution to this problem. Drawing from the problem of control-relevant parameter estimation, this paper presents an approach for demand modeling in a production-inventory system that relies on a specialized weight to tailor the emphasis of the fit to the intended purpose of the model, which is to provide forecasts to inventory management policies based on internal model control or model predictive control. A systematic approach to generate this weight function (implemented using data prefilters in the time domain) is presented and the benefits demonstrated on a series of representative case studies. The multi-objective formulation developed in this work allows the user to emphasize minimizing inventory variance, minimizing starts variance, or their combination, as dictated by operational and enterprise goals.

1. Introduction

Among the wealth of contributions made by Manfred Morari to the field of control engineering include examining issues relating to the interplay between control design and modeling (Morari and Zafiriou, 1989). Many years' ago the corresponding author had the privilege to work under Professor Morari in researching this problem in the context of PID control design using internal model control (IMC) (Rivera et al., 1986) and model reduction for control purposes in general (Rivera and Morari, 1987, 1990, 1992). We are more than pleased to present this work on demand modeling in supply chains as an extension of Manfred Morari's outstanding legacy.

Supply chain management represents a fascinating though unconventional problem domain in control engineering. Control-oriented approaches have been proposed to address the inventory management problems inherent in supply chains (Schwartz et al., 2006; Sarimveis et al., 2008). The production-inventory system represents a unit level of a supply chain whose study can shed many insights. Schwartz and Rivera (2010) have shown that an effective decision policy for this problem is a combined feedback–feedforward control structure which can be developed using either IMC or Model Predictive Control (MPC)-based formulations. In these approaches, demand (or more specifically, change in demand) is treated as an exogenous "disturbance" signal that must be properly "rejected" by a sensibly designed control system. Schwartz and Rivera (2010) show that accurate modeling and prediction of demand serves an important role in obtaining good control performance and meeting operational goals. However, a fundamental understanding of how demand models and forecasts should be estimated for the sake of control-oriented supply chain management policies has not been properly examined.

Accurately modeling customer demand has presented a challenge to the business community for many decades. The earliest approaches to demand modeling included polynomial extrapolation and identifying periodic variations such as seasonal or daily effects (Lewis, 1997). The use of time-series analysis to identify trends in demand signals is well treated in the literature (Pankratz, 1991; Box et al., 1994). These approaches seek to minimize the error between a prediction and actual demand in a least-squares sense. In this paper we extend these ideas by introducing the idea of

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developing a *control-relevant* model for customer demand, in essence a dynamical systems model that is tailored to the decision policy used for inventory control.

The presence of error in a demand forecast will adversely affect decision-making in a supply chain. While eliminating all sources of error from demand forecasts is impossible, it may be possible to mitigate their detrimental effects. The requirements for inventory control can be used to specify the frequency bands over which an adequate model fit is necessary. Specifically, if information about the end use of the forecasting model can be incorporated in the parameter estimation stage, it is then possible to obtain model that have improved accuracy over the relevant frequency bands. This goal philosophically parallels the objectives of the control-relevant parameter estimation problem (Rivera and Morari, 1987; Rivera et al., 1992) which was primarily developed for estimating the plant models for feedback-only control.

Drawing from control-relevant parameter estimation principles, this paper examines the relationship between demand forecast error and changes in inventory and starts for control-oriented decision policies in a production-inventory system. The demand modeling issues considered in this paper are approached in two distinct ways. First, we present a control-relevant model reduction problem for an Internal Model Control-based decision policy. In this problem formulation we assume that the true, full-order continuous-time demand model is available (or its frequency response) but it must be reduced to a more manageable, parsimonious structure. The full-order demand model may have been the result of prior modeling efforts, or an accurate frequency response has been generated from data using identification approaches such as the empirical transfer function estimate (ETFE) or high-order AutoRegressive with eXternal input (ARX) estimation (Ljung, 1999). In the second problem formulation, a control-relevant demand modeling framework meaningful for a Model Predictive Control (MPC) based decision policy is developed. In this case a discrete-time demand model is estimated directly from data using classical prediction-error models from system identification. Here a control-relevant filter is applied to input and output forecast data to obtain a restricted complexity demand model that is tailored to supply chain objectives. Three detailed numerical examples drawing on conventional problems in production-inventory systems (as described in Schwartz and Rivera, 2010) are presented in support of these two problem formulations.

This paper begins with some background on the use of process control ideas for supply chain management; a brief overview of the fluid analogy and IMC and MPC as decision policies for inventory management is presented in Section 2. Section 3 shows how control-relevant demand model reduction can be applied through frequency-weighted curvefitting. Section 4 extends the work to the discrete-time domain by performing control-relevant system identification using prefiltering. The paper ends with conclusions presented in Section 5.

2. Supply chain management background

2.1. Fluid analogy for production-inventory systems

A fluid analogy for a standard single-product production-inventory system, the simplest unit in a supply chain, is shown in Fig. 1. Fluid analogies represent meaningful descriptions of supply chains associated with high volume manufacturing problems at sufficiently long time scales (for instance, in daily or weekly decision-making). This applies to discrete-parts manufacturing problems such as semiconductor manufacturing (Braun et al., 2003; Wang and Rivera, 2008). The output of a factory is stored in a warehouse where it awaits shipments to customers (retailers, distributors, etc.). The warehouse serves as a buffer in the presence of stochastic, uncertain customer demand and factory output.

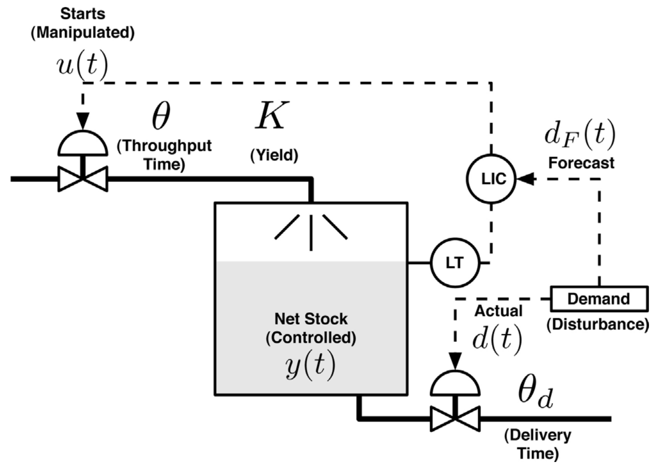

Fig. 1. Fluid analogy for a classical production-inventory system.

The factory is modeled as a pipe with a particular throughput time θ and yield K. Inventory is modeled as material (fluid) in a tank. Delivery from the warehouse is modeled as a pipe with a transportation time θ_d. Customer demand is treated as a disturbance signal at the tank outlet, which contrasts with traditional level control problems where the outflow is manipulated to control the fluid level subject to disturbances at the inflow (Ogunnaike and Ray, 1994; Seborg et al., 2004). Applying the principle of conservation of mass to this system leads to a differential equation relating net stock (material inventory, $y(t)$) to factory starts (input pipe flow, $u(t)$) and customer demand (output tank flow, $d(t)$) which is represented by the following equation:

$$\frac{dy}{dt} = Ku(t-\theta) - d(t) \tag{1}$$

Based on (1) it is possible to derive feedback-only decision policies that manipulate factory starts to maintain inventory level at a designated setpoint. However, if knowledge of future customer demand is available, it is advantageous to use feedforward compensation. Customer demand $d(t)$ is treated as a disturbance signal at the tank outlet, and consists of the sum of forecasted demand ($d_F(t)$, known θ_F days ahead of time), forecast error $d_F^e(t)$, and unforecasted demand $d_U(t)$, as shown below:

$$d(t) = \underbrace{d_F(t-\theta_F) + d_F^e(t-\theta_F)}_{d_F^{ideal}(t-\theta_F)} + d_U(t) \tag{2}$$

$d_F^{ideal}(t) = d_F(t) + d_F^e(t)$ represents the ideal forecast signal. The demand forecast d_F is generated from a demand model $\tilde{P}_f(s)$

$$d_F(s) = \tilde{P}_f(s) f_i(s) \tag{3}$$

which is a function of a disturbance input f_i. f_i represents any measurement signal that can be used as an input to predict future demand, for example, an economic indicator. The demand forecast error d_F^e represents a signal that should be minimized according to some criterion,

$$d_F^e(s) = d_F^{ideal}(s) - d_F(s) = E_f(s) f_i(s) \tag{4}$$

with $E_f = P_f - \tilde{P}_f$ representing the demand modeling error that we hope to reduce in a control-relevant manner. The dynamical system