Multi-Objective Control-Relevant 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 received considerable interest in recent years, and demand modeling to supply forecasts for these policies is an important component of an effective solution to this problem. Drawing from the problem of control-relevant identification, we present an approach for demand modeling based on data that relies on a control-relevant prefilter to tailor the emphasis of the fit to the intended purpose of the model, which is to provide forecast signals to a tactical inventory management policy based on Model Predictive Control. Integrating the demand modeling and inventory control problems offers the opportunity to obtain reduced-order models that exhibit superior performance, with potentially lower user effort relative to traditional "open-loop" methods. A systematic approach to generating these prefilters is presented and the benefits resulting from their use are demonstrated on a representative production/inventory system case study. A multi-objective formulation is developed that allows the user to emphasize minimizing inventory variance, minimizing starts variance, or their combination.

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1 Introduction

Efficient supply chain management has become a significant imperative for many modern-day enterprises. Properly characterizing and predicting demand plays a significant role in achieving high performance from supply chain management systems. The presence of error in a demand forecast will adversely affect decision-making in a supply chain. Inaccurate market research, customer order changes, out-of-date information, and misreading product/business cycles may have a negative effect on the profitability of a supply chain dependent corporation. While eliminating all sources of error from a demand forecast is impossible, it may be possible to mitigate its detrimental effects. Therefore, it is important to understand the effects of forecast error on a supply chain decision policy.

Control-oriented approaches have been recently proposed to deal with the inventory management problems inherent in supply chains (Tzafestas *et al.*, 1997; Dejonckheere *et al.*, 2002; Perea-López *et al.*, 2003; Braun *et al.*, 2003; Seferlis and Giannelos, 2004; Wang *et al.*, 2004; Schwartz *et al.*, 2006). In these approaches, demand is treated as an exogenous "disturbance" signal that must be properly "rejected" by a sensibly-designed control system. However, an understanding of how a demand forecast should be properly developed for the sake of this class of supply chain management policies has not been examined. This paper attempts to gain a broader understanding of disturbance/demand modeling and the effects of forecast error on a Model Predictive Control (MPC)-based tactical decision policy. The relationship between demand forecast error and changes in inventory and starts are examined for a control-oriented tactical decision policy in a single node of the manufacturing process. Understanding this relationship represents one step towards a fundamental understanding that will allow planning personnel to deal with inherently erroneous forecasts in an educated manner.

To accomplish this goal, we will draw from ideas in control-relevant identification (Rivera *et al.*, 1992). The result is a systematic framework for conducting control-relevant demand modeling in the case of a standard production/inventory system. However, these ideas can be generalized to larger topologies. Results from a case study will show that the use of the framework not only improves the performance of the supply chain, but also enables planners to reduce the complexity of customer demand models.

Section 2 begins with a discussion of the modeling of a production/inventory system using a fluid analogy and the development of a model-based inventory controller relying on Model Predictive Control. In Section 3, the closed-loop transfer functions describing forecast error are developed and the effect of erroneous forecasts is studied in both the time and frequency domains. A procedure for performing control-relevant demand modeling is presented. Section 4 is a case study involving the use of an MPC scheme to manage a production/inventory system. Section 5 highlights the important conclusions that can be drawn from the analysis in this paper.

2 System and Controller

2.1 Inventory Control Fluid Analogy

A single node of a manufacturing supply chain can be modeled using a fluid analogy. The factory is represented as a pipe with a particular throughput time θ and yield K. The inventory is represented as a tank containing fluid. The dynamics relating fluid level (net stock, $y(t)$) to inlet pipe flux (fab starts, $u(t)$) and outlet pipe flux ($d(t)$, composed of the forecasted customer demand, $d_F(t-\theta_F)$, plus unforecasted

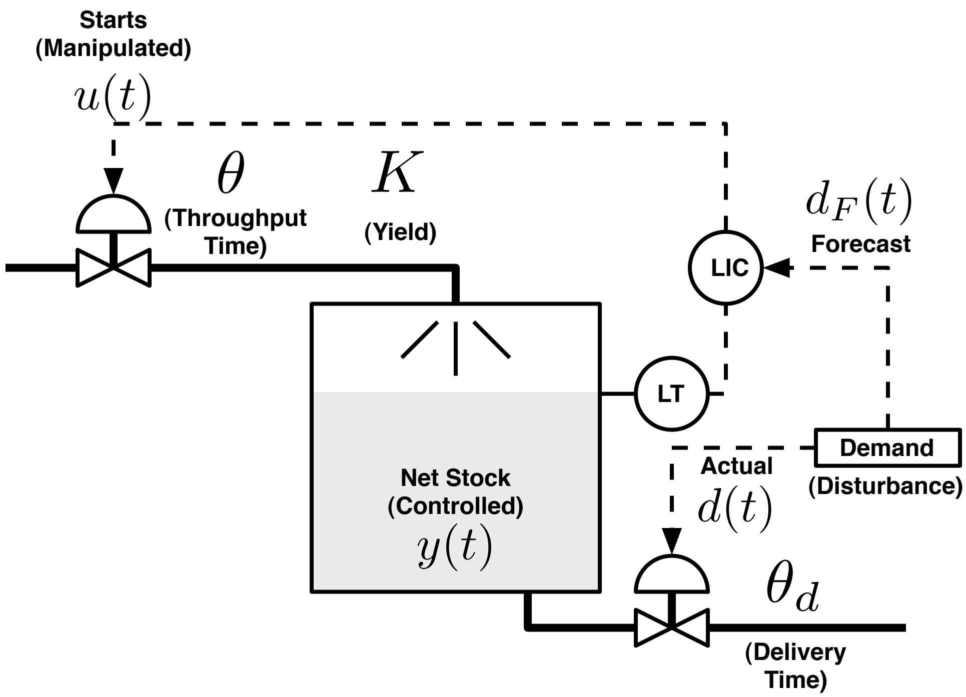


Figure 1: Fluid analogy: a single manufacturing node represented as a system of pipes and a tank.

customer demand, $d_U(t)$) is represented in (1). Note that θ_F is the forecast horizon. The underlying dynamical system has delayed, integrating dynamics according to

$$y(t) = \frac{Kz^{-\theta}\,u(t)}{1-z^{-1}} - \frac{z^{-\theta_F}\,d_F(t)}{1-z^{-1}} - \frac{d_U(t)}{1-z^{-1}} \tag{1}$$

The operational goal of the system is to meet customer demand while maintaining the inventory level at a specified target. This can be accomplished by adjusting the factory starts. An anticipated (forecasted) demand signal can be used for feedforward compensation in this regard.

2.2 Model Predictive Control

Model Predictive Control (MPC) (García *et al.*, 1989; Camacho and Bordons, 1999) stands for a family of methods that select control actions based on on-line optimization of an objective function. In MPC, a system model and current and historical measurements of the process are used to predict the system behavior at future time instants. A control-relevant objective function is then optimized to calculate a sequence of future control moves that satisfy system constraints. The first predicted control move is implemented and at the next sampling time the calculations are repeated using updated system states; this is referred to as a Moving or Receding Horizon strategy. Fig. 2 is a useful visualization of the MPC approach. The demand signal, which dictates the shipment of product to the customer, consists of two components: 1) actual demand (which is only fully known as it occurs) and 2) forecasted demand, which is provided to the planning function by a separate organization. As shown in Fig. 2, a demand forecast signal is used in the moving horizon calculation to anticipate future system behavior, which plays a significant role in the use of MPC for supply chain applications.

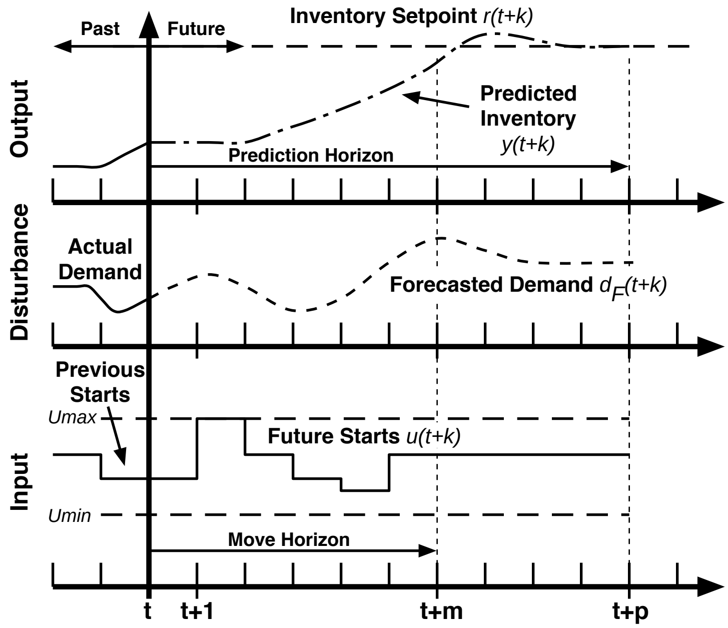


Figure 2: Receding horizon representation of Model Predictive Control.

The Model Predictive Control strategy relies on a state-space form of Eqn. 1 to make predictions of the future output (inventory level) and adjust the input (factory starts) according to the current state of the system and a forecast of future disturbances (customer demand). This is captured in Eqn. 2 and Fig. 3,

$$\begin{aligned} x(t+1) &= A\,x(t) + B_u\,u(t) + B_d\,d(t) \\ y(t) &= C\,x(t) + D_u\,u(t) + D_d\,d(t) \end{aligned} \tag{2}$$

where y, u, and d are as defined previously, $x(t)$ is the state vector and A, B_u, B_d, D_u, and D_d represent constant-valued matrices.

There is significant flexibility in the form of the objective function that can be used in MPC. The formulation considered in this paper is to minimize the following:

$$\min_{\Delta u(k|k)\ldots\Delta u(k+m-1|k)} J$$

$$J = \sum_{\ell=1}^{p} Q_e(\hat{y}(k+\ell|k) - r(k+\ell))^2 + \sum_{\ell=1}^{m} Q_{\Delta u}(\Delta u(k+\ell-1|k))^2 \tag{3}$$

subject to constraints on inventory capacity ($0 \leq y(t) \leq y_{max}$), factory inflow capacity ($0 \leq u(t) \leq u_{max}$), and changes in the quantity of factory starts ($\Delta u_{min} \leq \Delta u \leq \Delta u_{max}$). The objective function is a multi-objective expression that addresses the main operational objectives in the supply chain. For an MPC problem with an objective function per (3), relying on linear discrete-time state-space models to describe the dynamics, and subject to linear inequality constraints, a numerical solution is achieved via a quadratic program.

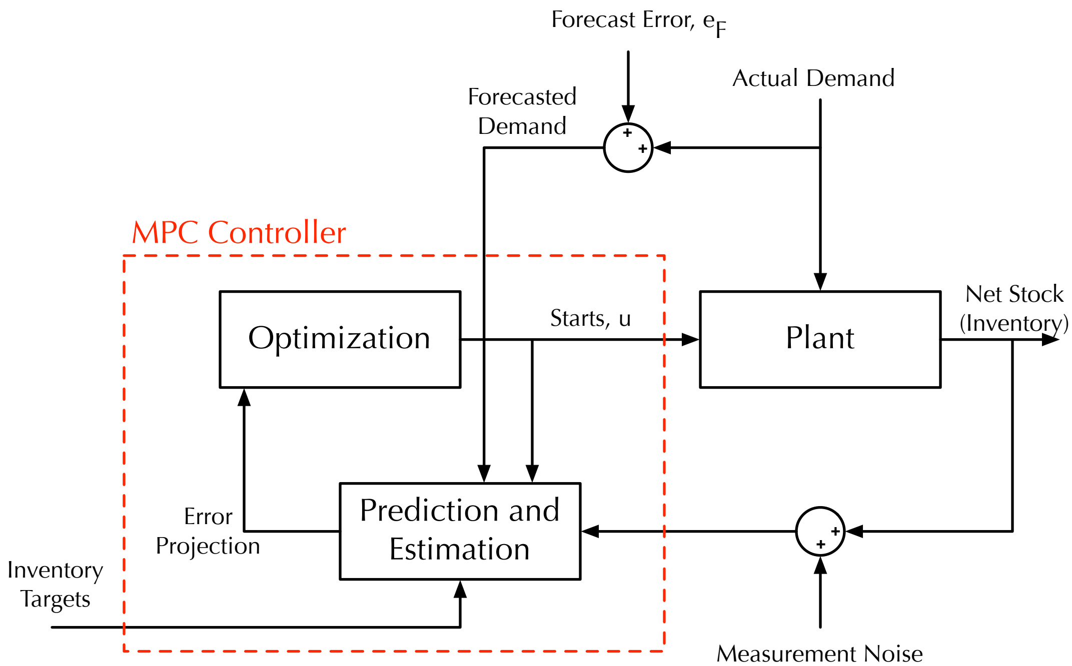


Figure 3: Block diagram schematic of Model Predictive Control, highlighting the introduction of forecast error, e_F.

3 Control-Relevant Demand Modeling

3.1 Frequency-Domain Analysis of the Effects of Forecast Error on Control Performance

Typically, system identification models are generated by minimizing the one-step ahead prediction error (Ljung, 1999). This classical approach does not take into consideration the end use of the model, such as when the goal of the model is to support a control-oriented decision policy. In particular, we are interested in understanding how forecast error affects the performance of the closed-loop system. It is our contention in this paper that such systems are most responsive to forecast error within a certain frequency bandwidth. Subsequently, the performance of the control system can be improved by utilizing demand models that are most accurate within the frequency band of interest, resulting in the potential for arriving at better demand models with less effort, which has important practical implications.

Given that unconstrained MPC is a linear control system and that linearity is assumed for the production/inventory system, the frequency response of the closed-loop system can be adequately characterized via nonparametric methods. Fig. 4 shows some representative results of the time-domain inventory and starts responses to a forecast error impulse, which can be visualized schematically with Fig 3. The controller anticipates the increased future demand and increases starts accordingly. When no demand change is realized, starts are reduced to return the inventory level to the setpoint. These responses can be captured as Finite Impulse Response models, from which frequency responses are generated. Fig. 5 shows the corresponding amplitude ratios of the MPC closed-loop system for the net stock and starts changes, respectively.

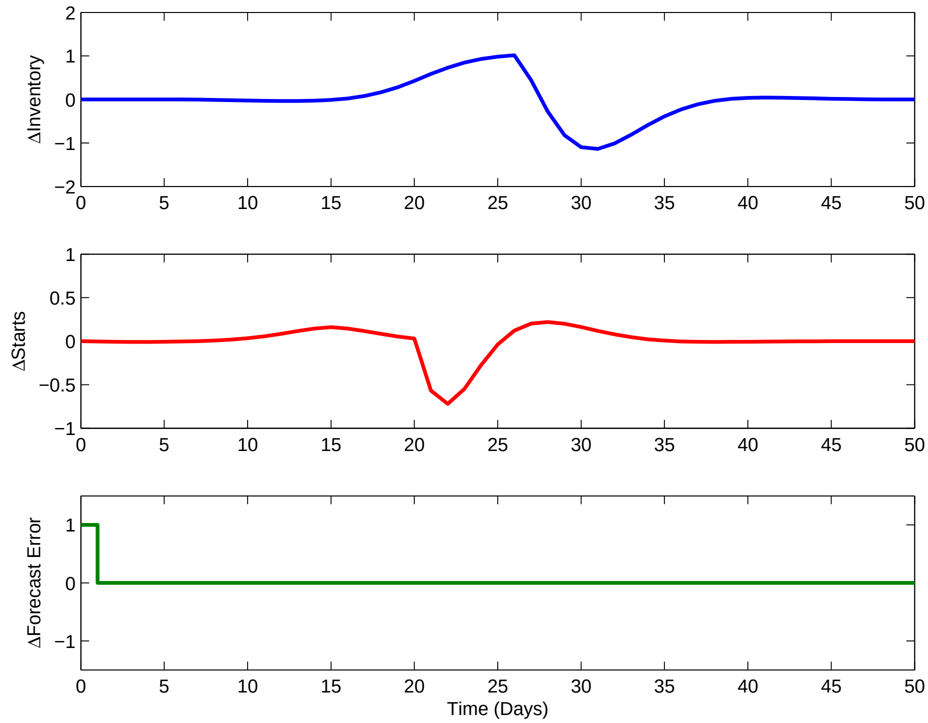


Figure 4: Supply chain control system response to a unit forecast error pulse. Throughput time: $\theta = 5$ days, prediction horizon: p and $\theta_F = 20$ days, move horizon: $m = 10$ days, move suppression: $Q_{\Delta u} = 5$, control error weight: $Q_e = 1$.

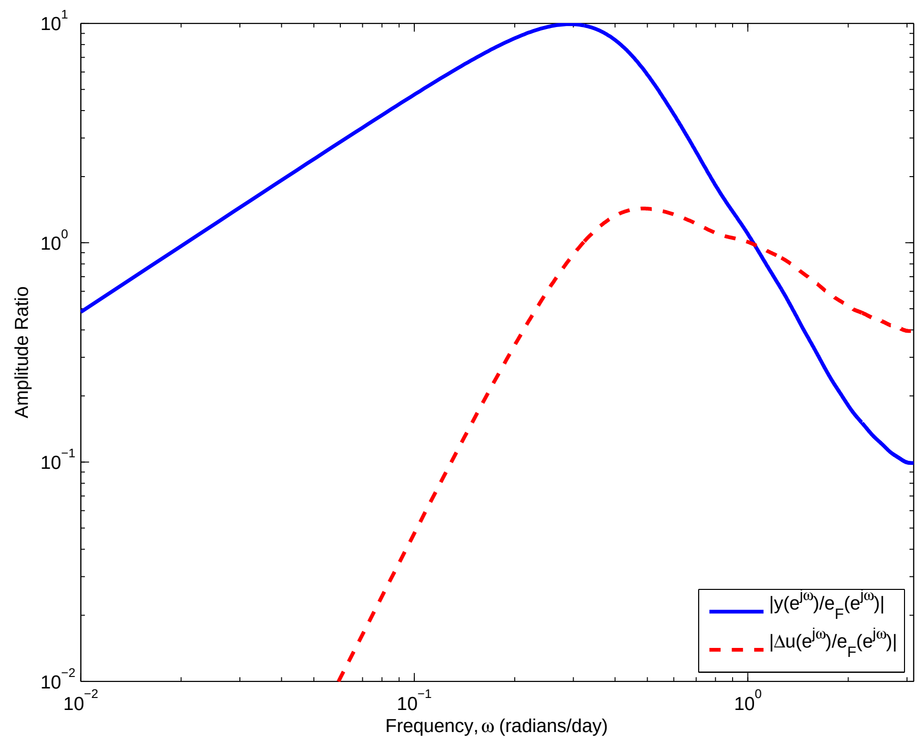


Figure 5: Amplitude ratio of the inventory and starts change response to forecast error ($\frac{y(e^{j\omega})}{e_F(e^{j\omega})}$ and $\frac{\Delta u(e^{j\omega})}{e_F(e^{j\omega})}$, respectively) for the model and controller parameters per Fig. 4.

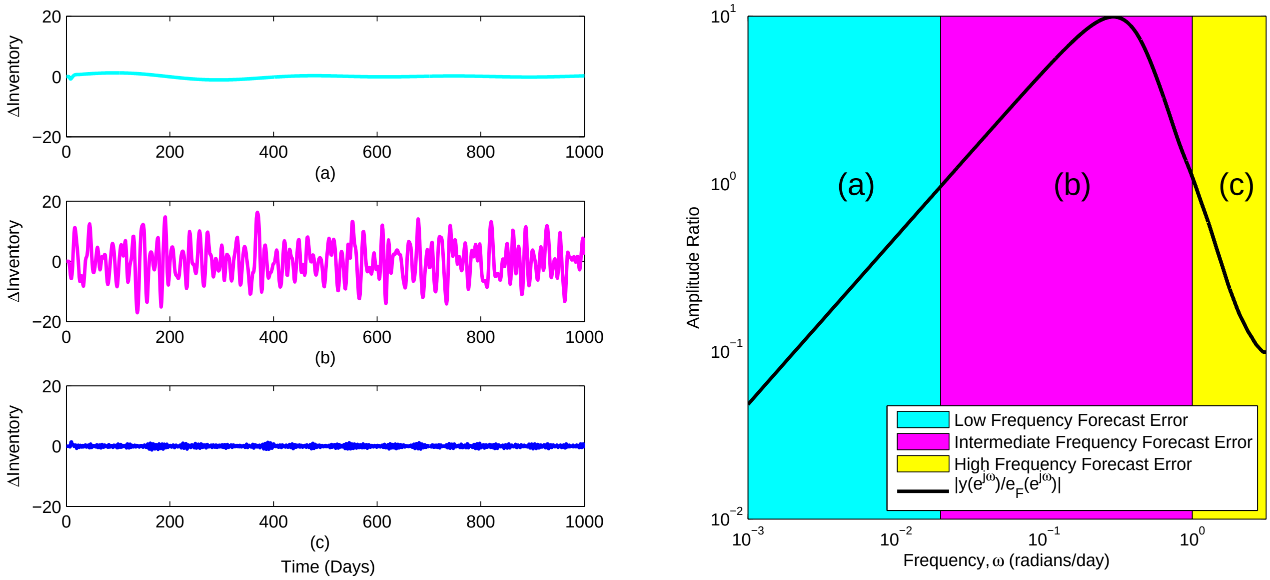


Figure 6: Inventory response of the closed-loop production/inventory system to low frequency (a), intermediate frequency (b), and high frequency forecast error (c).

Fig. 5 shows that the response of the MPC decision policy to forecast error is characterized by notch filters, where high and low frequencies are attenuated, and only forecast error in an intermediate bandwidth is amplified. The size of this bandwidth is determined by controller tuning, and for the case of starts changes the bandwidth of emphasis lies at higher frequencies than for inventory. The filtering effect is illustrated in the time-domain in Fig. 6 where bandlimited forecast error signals with unity variance are introduced. Forecast error in the intermediate bandwidth causes the most change in the inventory, and it is in this bandwidth that a high degree of goodness-of-fit in the demand model is desired.

3.2 Control-Relevant Modeling

Since the MPC decision policy amplifies forecast error only in a limited frequency bandwidth, it is desirable to systematically take advantage of the reduced bandwidth over which demand modeling accuracy is necessary. Therefore, the goal is to emphasize the frequencies of interest when generating a model. Prefiltering represents an important design variable for emphasizing the goodness-of-fit in system identification (Ljung, 1999; Rivera *et al.*, 1992). Assume that true demand is described by a stationary process $p_d(z)$ driven by the input signal $u_d(t)$ plus some unforecasted component $H(z)a(t)$.

$$d(t) = p_d(z)u_d(t) + H(z)a(t) \tag{4}$$

For the purposes of this analysis, the input signal $u_d(t)$ is known; in a univariate case this signal can be reconstructed using a two-stage approach (Stoica and Moses, 1997). In practical applications, the input signal could represent variables that influence demand such as interest rates, seasonal changes, and per capita income. Our goal is to find a demand model $\tilde{p}_d(z)$ that describes the true process $p_d(z)$. For the purposes of this analysis the demand is defined as the sum of the contributions from the transfer function $\tilde{p}_d(z)$ and a noise model $\tilde{p}_e(z)$.

$$d(t) = \tilde{p}_d(z)u_d(t) + \tilde{p}_e e(t) \tag{5}$$

The forecast error, $e_F(t)$ is defined as the difference between the actual and forecasted customer demand, as shown in Eqn. 6.

$$e_F(t) = d(t) - \tilde{d}(t) = d(t) - \tilde{p}_d(z)u_d(t) = \tilde{p}_e e(t) \tag{6}$$

$e(t)$ is the one-step ahead prediction error; if $\tilde{p}_e = 1$ then $e(t) = e_F(t)$. The system identification problem then involves minimizing the squared sum of the filtered one-step ahead prediction error, where $L(z)$ is the prefilter,

$$\min_{\tilde{p}_d} V = \min_{\tilde{p}_d} \sum_{t=1}^{N} [L(z)e(t)]^2 = \min_{\tilde{p}_d} \sum_{t=1}^{N} e_L^2(t) \tag{7}$$

and the filtered prediction error is comprised of:

$$e_L(t) = \frac{L(z)}{\tilde{p}_e(z)} \left[(p_d(z) - \tilde{p}_d(z))\, u_d(t) + H(z)a(t) \right] = \frac{L(z)}{\tilde{p}_e(z)} e_F(t) \tag{8}$$

The application of Parseval's theorem allows an analysis of the problem in the frequency domain.

$$\lim_{N\to\infty} \frac{1}{N} \sum_{t=1}^{N} e_L^2(t) = \frac{1}{2\pi} \int_{-\pi}^{\pi} \left| \frac{L(e^{j\omega})}{\tilde{p}_e(e^{j\omega})} \right|^2 \Phi_{e_F}(\omega) d\omega \tag{9}$$

where

$$\Phi_{e_F}(\omega) = \left| p_d(e^{j\omega}) - \tilde{p}_d(e^{j\omega}) \right|^2 \Phi_{u_d}(\omega) + \left| H(e^{j\omega}) \right|^2 \Phi_a(\omega) \tag{10}$$

From Eqn. 9 we know that we can use $L(z)$ to provide user-defined emphasis, although it is important to note that the noise model $\tilde{p}_e(z)$ will also act to emphasize certain frequency regimes. The user choice of an Output Error structure results in $\tilde{p}_e(z) = 1$, eliminating the bias introduced by the noise model.

Our goal is to obtain estimates $\tilde{p}_d(z)$ of the true demand process $p_d(z)$ with emphasis in the frequencies of interest defined by the control-relevant prefilter $L(z)$. Emphasis can be applied for the purpose of either decreasing inventory deviations from a setpoint $r(t)$, starts variance, or some weighted combination of both. First, the time-domain relationships and corresponding power spectra for the control error and factory starts change signals are defined: as

$$\begin{aligned}
e_c(t) &= y(t) - r(t) = L_{e_c}(z)e_F(t) && (11)\\
\Delta u(t) &= (1 - z^{-1})u(t) = L_{\Delta u}(z)e_F(t) && (12)\\
\Phi_{e_c}(\omega) &= |L_{e_c}(e^{j\omega})|^2 \Phi_{e_F}(\omega) && (13)\\
\Phi_{\Delta u}(\omega) &= |L_{\Delta u}(e^{j\omega})|^2 \Phi_{e_F}(\omega) && (14)
\end{aligned}$$

where $L_{e_c}(z)$ and $L_{\Delta u}(z)$ are the transfer functions relating forecast error to inventory deviations and starts changes, obtained using the nonparametric approach described previously. $\Phi_{e_c}(\omega)$ and $\Phi_{\Delta u}(\omega)$ are their corresponding power spectra.

A supply chain planner may choose to reduce either depending on the cost of inventory deviation, stockout, or changing a factory setup. In essence, it is desirable to meet the following control objective

$$\min_{\tilde{p}_d, \tilde{p}_e} \left[\int_0^\infty (1-\gamma) e_c^2(t) dt + \lambda \int_0^\infty \gamma \Delta u^2(t) dt \right] \tag{15}$$

where γ is used as a weight to emphasize either inventory deviation from setpoint ($\gamma = 0$) or factory starts variance ($\gamma = 1$). The user-adjustable parameter λ is used to keep the variances of the two signals equivalent.

Rearranging Eqn. 15 and applying Parseval's theorem results in Eqn. 16, which allows for the analysis to be conducted in the frequency domain. The amplitude ratios represented by L_{e_c} and $L_{\Delta u}$ correspond to those shown in Figure 5.

$$\min_{\tilde{p}_d,\tilde{p}_e}\left[(1-\gamma)\frac{1}{2\pi}\int_{-\pi}^{\pi}\Phi_{e_c}(\omega)d\omega+\gamma\lambda\frac{1}{2\pi}\int_{-\pi}^{\pi}\Phi_{\Delta u}(\omega)d\omega\right] \tag{16}$$

Comparing Eqn. 16 with Eqn. 9 leads to the following relationship.

$$\frac{|L(e^{j\omega})|^2}{|\tilde{p}_e(e^{j\omega})|^2}\Phi_{e_F}(\omega)=(1-\gamma)|L_{e_c}(e^{j\omega})|^2\Phi_{e_F}(\omega)+\gamma\lambda|L_{\Delta u}(e^{j\omega})|^2\Phi_{e_F}(\omega) \tag{17}$$

By assuming an output error model structure ($\tilde{p}_e=1$), the control-relevant prefilter $L(z)$ can be reduced to the following form.

$$|L(e^{j\omega})|^2=(1-\gamma)|L_{e_c}(e^{j\omega})|^2+\gamma\lambda|L_{\Delta u}(e^{j\omega})|^2 \tag{18}$$

A curve fitting procedure is then used to obtain an Infinite Impulse Response filter that matches the amplitude ratio of the control-relevant prefilter. A standard curve fitting algorithm for rational discrete-time transfer functions can be used for this purpose, such as the output-error minimizing algorithm as implemented in the MATLAB® function `invfreqz`.

4 Case Studies

4.1 Representative Case Study

A representative production/inventory system with an MPC-based tactical decision policy will be used to quantify the benefits achieved through the use of control-relevant demand modeling. The case study involves the single node shown in Fig. 1 where the throughput time of the factory (θ) is 5 days, the yield is unity, the forecast horizon (θ_F, which is also the MPC prediction horizon p) is 20 days, the MPC move optimization horizon (m) is 10 days, and MPC weights for penalizing starts changes and inventory deviation ($Q_{\Delta u}$ and Q_e) are 5 and 1, respectively. A data set was generated from the true demand process $p_d(z)$ subject to a white noise input in $u_d(t)$.

$$d(t) = \frac{1+z^{-1}+z^{-2}}{1-0.4z^{-1}+0.5z^{-2}}u_d(t) \tag{19}$$

In all analyses shown in this paper, the value of the parameter λ will be defined as the ratio of the maximum squared amplitude ratio values of the control error and starts change transfer functions

$$\lambda = \frac{\sup_\omega |L_{e_c}|^2}{\sup_\omega |L_{\Delta u}|^2} \tag{20}$$

For the MPC production/inventory problem described the value of λ is approximately 48.

Figure 7 shows the inventory and factory responses that result when OE-[1 2 1] models of the form

$$\hat{d}(t) = \frac{b_1+\cdots+b_{n_b}z^{-n_b+1}}{1+\cdots+f_{n_f}z^{-n_f}}u(t-1)+e(t) \tag{21}$$

are obtained from either unfiltered or control-relevant filtered data. The data is tabulated in Table 1. Note the substantial reduction in inventory variance compared to the case of no filtering for the simulation where $\gamma = 0$, however starts variance increases by a factor of four. When $\gamma = 1$ there is a reduction in starts variance, but inventory variance remains high. Figure 7(d) shows the result for $\gamma = 0.3$, where both the inventory and starts variances are substantially reduced relative to the case where no filtering is applied. Also note that starts variance is nearly equivalent to the $\gamma = 1$ case, but inventory variance is reduced by 40%.

Fig. 8 shows the minimum (or best case) inventory (a) and starts variance (b) that occur when estimating demand models of varying complexity ($1 \leq n_b \leq 10$ and $0 \leq n_f \leq 10$). The number of OE parameters is defined as the sum of n_b and n_f. Low order models (up to five parameters) obtained from prefiltered data provide superior performance relative to the classical unfiltered approach. The use of the user-adjustable parameter γ allows a supply chain planner to reduce inventory or starts variance. It is interesting to note that when γ is set to an intermediate value, one can achieve a substantial reduction in inventory variance with only a small corresponding increase in starts variance. This is shown in the case where $\gamma = 0.1$ and $n_b + n_f = 3$, the inventory variance is comparable for the $\gamma = 0$ case, but starts variance is dramatically lower. Conversely, a dramatic reduction in starts variance can be attained at the price of increased inventory variance. This is demonstrated in the case where $\gamma = 0.3$ and $n_b + n_f = 5$. Starts variance for both filters is approximately 3, but the use of the mixed objective filter allows the inventory variance to be reduced from 80 to 50.

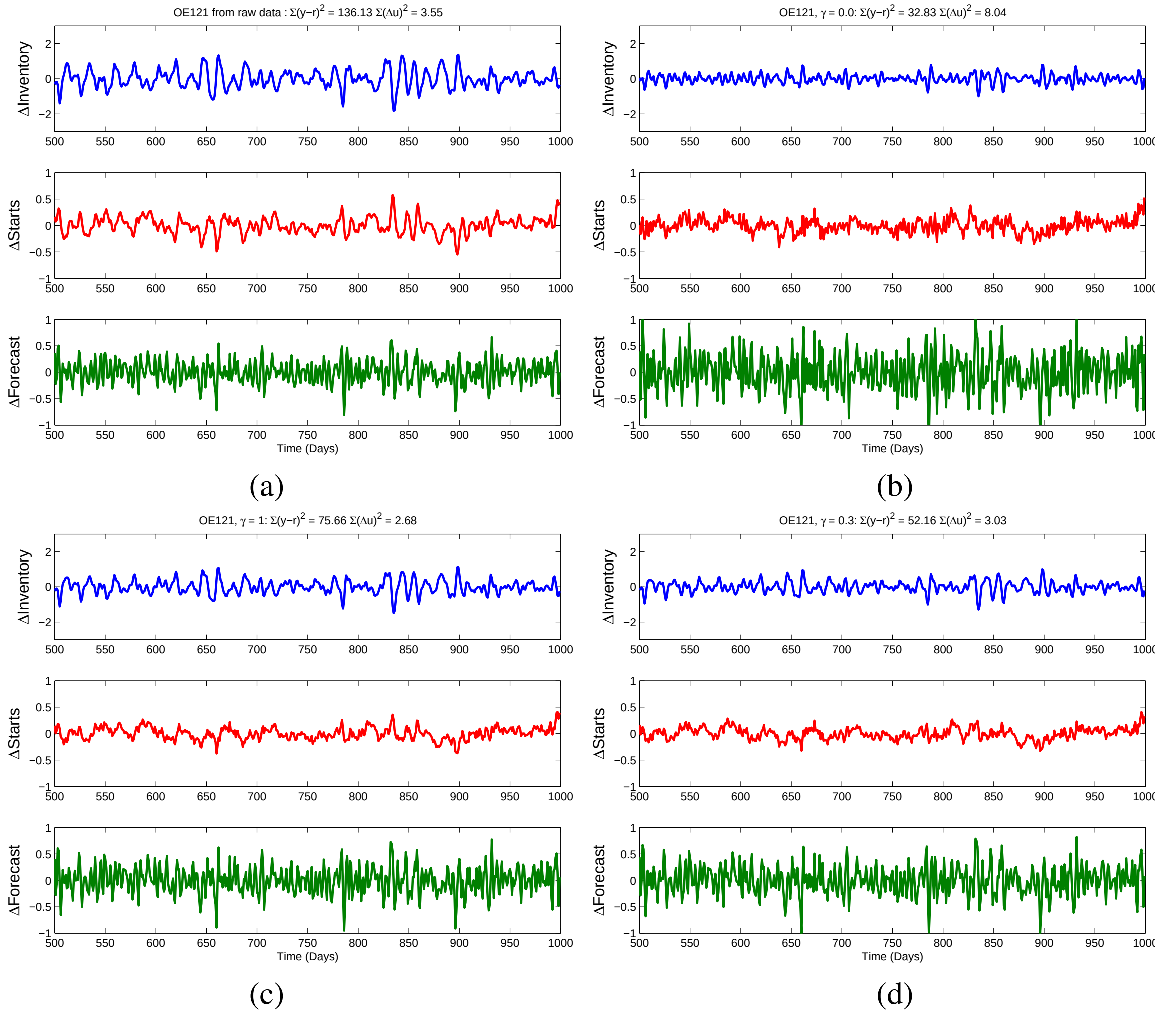
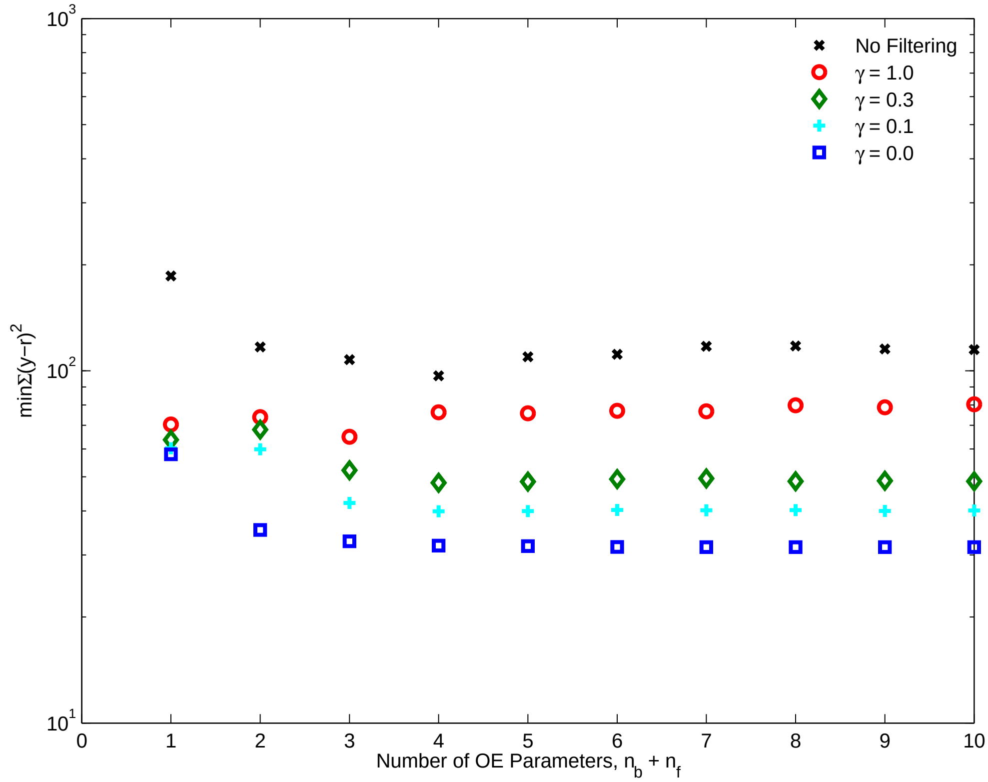


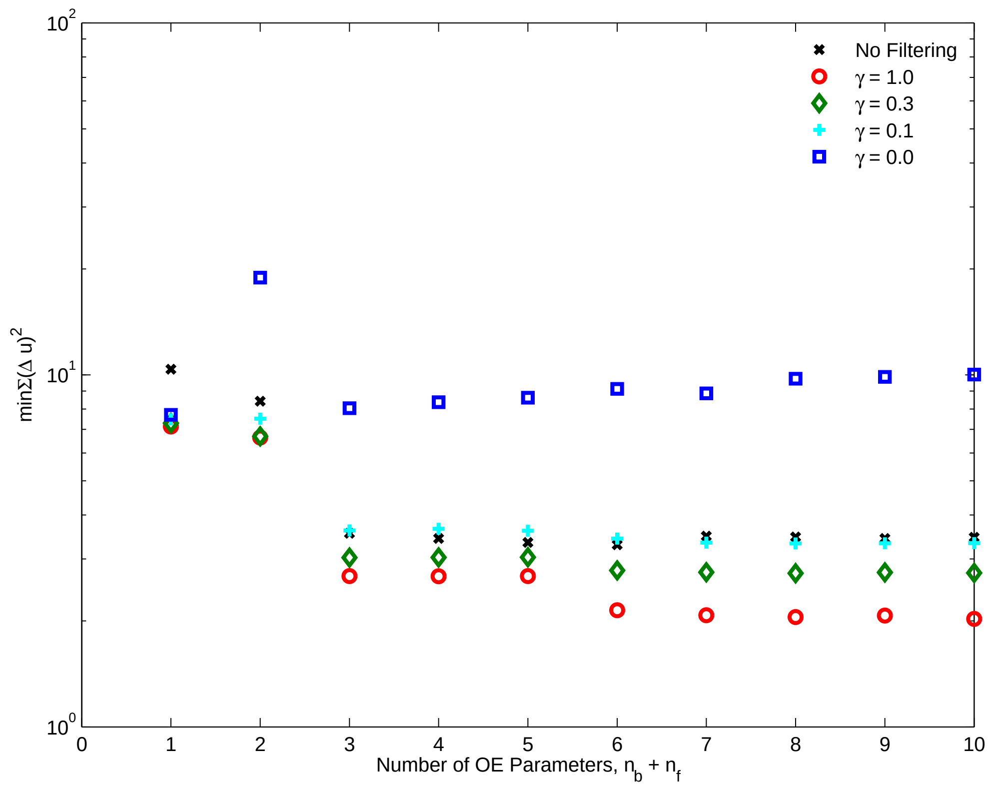
Figure 7: Time series for closed-loop responses of the production/inventory system where the demand forecast is developed from (a) an OE-[1 2 1] fit to unfiltered data, (b) an OE-[1 2 1] fit to control-relevant filtered data ($\gamma = 0.0$), (c) an OE-[1 2 1] fit to control-relevant filtered data ($\gamma = 1.0$), and (d) an OE-[1 2 1] fit to control-relevant filtered data ($\gamma = 0.3$).

Filter Type	$\Sigma(y-r)^2$	$\Sigma(\Delta u)^2$	Time Series
No Filtering	136.1	3.6	Figure 8(a)
$\gamma = 1.0$	75.7	2.7	Figure 8(c)
$\gamma = 0.3$	52.2	3.0	Figure 8(d)
$\gamma = 0.1$	42.1	3.6	not shown
$\gamma = 0.0$	32.8	8.0	Figure 8(b)

Table 1: Results summary of OE121 demand models fit to unfiltered and control-relevant filtered data.



(a)



(b)

Figure 8: Lowest inventory variance (a) and starts variance (b) for a variety of estimated OE demand models. The plot shows the best performance for the group of models defined as having $n_b + n_f$ parameters.

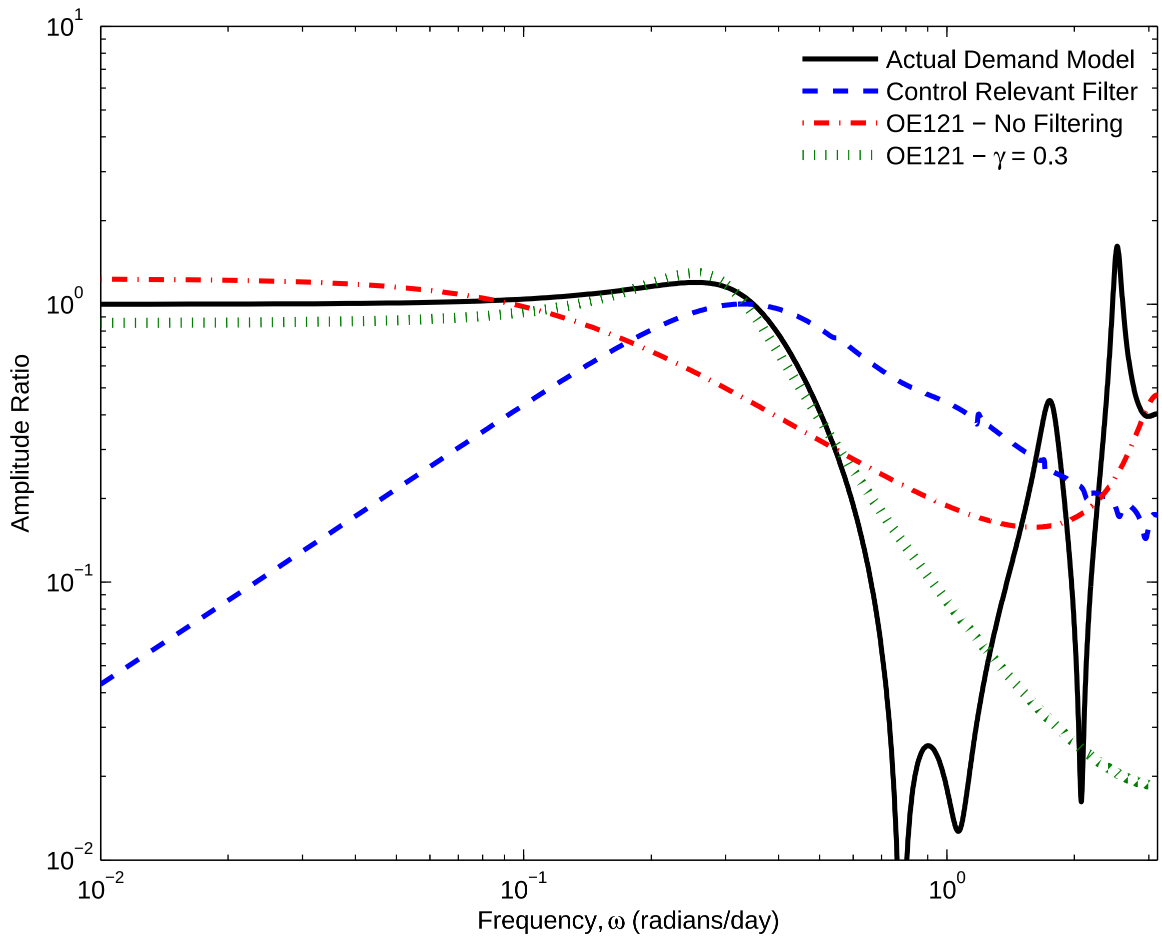
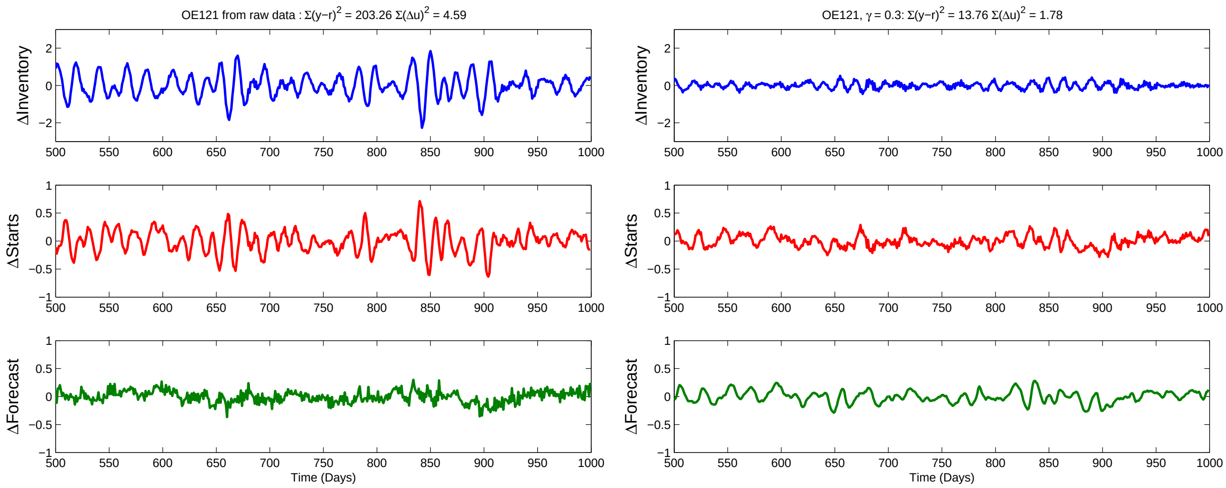


Figure 9: Corresponding frequency responses where the demand forecast is developed from an OE-[1 2 1] fit to unfiltered data and an OE-[1 2 1] fit to control-relevant filtered data obtained from the user defined weighting function ($\gamma = 0.3$).

4.2 Case Study with High-Order Demand Model

For this case study, the true demand model (a 10th order Auto Regressive Moving Average model) is characterized by unity gain and significant power at high frequencies. The demand model conforms to an Output Error (OE-[n_b n_f 1]) structure as shown in Eqn. 21. The amplitude ratios of the actual demand model, control-relevant prefilter $L(e^{j\omega})$, and the resulting OE model fits are shown in Figure 9. The lack of emphasis in the unfiltered data causes the OE fit to focus on the high frequency spike at approximately 3 radians per second. The control-relevant filter emphasizes the resonant peak while de-emphasizing the high frequency components of the demand. Consequently, the OE fit to the control-relevant data captures the dynamics of the true demand spectrum where the closed-loop system is most sensitive to forecast error. Fig. 10 shows the time-domain responses obtained when OE-[1 2 1] models are developed from unfiltered and control-relevant filtered data. For this particular low-order model structure the use of the control-relevant prefilter leads to significantly lower inventory and starts variance.



(a) (b)

Figure 10: Time series where the demand forecast is developed from (a) an OE-[1 2 1] fit to unfiltered data ($\Sigma(y-r)^2 = 203$, $\Sigma(\Delta u)^2 = 5$) and (b) an OE-[1 2 1] fit to control-relevant filtered data ($\Sigma(y-r)^2 = 14$, $\Sigma(\Delta u)^2 = 2$) obtained from the user defined weighting function ($\gamma = 0.3$).

5 Conclusions

Demand modeling is a critical problem in supply chain management. An analysis of an MPC-based decision policy associated with inventory control shows that these systems are most responsive to forecast error in an intermediate frequency bandwidth. With this knowledge, historical demand data can be prefiltered to emphasize the frequency regimes where the most accuracy is desired, resulting in improved control system performance. The work also shows that the use of control-relevant prefiltering allows simpler, low-order models to be used. This results in more efficient computation and greater insight into the most relevant characteristics associated with customer demand. The formulation of multi-objective control-relevant filter allows a supply chain planner the flexibility to minimize inventory variance, factory starts variance, or their weighted combination.

Future work will involve extending the analysis to forecasting problems involving Box-Jenkins-style approaches (Box *et al.*, 1994), and multivariable demand modeling problems.

6 Acknowledgements

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References

Box, G. E., G. M. Jenkins and G. C. Reinsel (1994). *Time Series Analysis Forecasting and Control*. Prentice-Hall. Englewood Cliffs, NJ.

Braun, M. W., D. E. Rivera, M. E. Flores, W. M. Carlyle and K. G. Kempf (2003). A Model Predictive Control framework for robust management of multi-product, multi-echolon demand networks. *Annual Reviews in Control* **27**, 229–245.

Camacho, E. F. and C. Bordons (1999). *Model Predictive Control*. Springer-Verlag. London.

Dejonckheere, J., S. M. Disney, M. R. Lambrecht and D. R. Towill (2002). Transfer function analysis of forecasting induced bullwhip in supply chains. *International Journal of Production Economics* **78**, 133–144.

García, C. E., D. M. Prett and M. Morari (1989). Model predictive control: theory and practice-a survey. *Automatica* **25**(3), 335–348.

Ljung, L. (1999). *System Identification: Theory for the User*. Prentice-Hall. Upper Saddle River, New Jersey.

Perea-López, E., B. E. Ydstie and I. E. Grossman (2003). A model predictive control strategy for supply chain optimization. *Computers and Chemical Engineering* **27**, 1201–1218.

Rivera, D. E., J. F. Pollard and C. E. García (1992). Control-relevant prefiltering: A systematic design approach and case study. *IEEE Transactions on Automatic Control* **37**(7), 964–974.

Schwartz, J.D., W. Wang and D. E. Rivera (2006). Simulation-based optimization of model predictive control policies for inventory management in supply chains. *Automatica* **42**(8), 1311–1320.

Seferlis, P. and N. F. Giannelos (2004). A two-layered optimisation-based control strategy for multi-echelon supply chain networks. *Computers and Chemical Engineering* **28**, 799–809.

Stoica, P. and R. Moses (1997). *Introduction to Spectral Analysis*. Prentice-Hall. Upper Saddle River, New Jersey.

Tzafestas, S., G. Kapsiotis and E. Kyriannakis (1997). Model-based predictive control for generalized production planning problems. *Computers in Industry* **34**, 201–210.

Wang, W., D. E. Rivera, K. G. Kempf and K. D. Smith (2004). A model predictive control strategy for supply chain management in semiconductor manufacturing under uncertainty. In: *Proceedings of the American Control Conference*. Boston, MA. pp. 4577–4582.