A robust inventory management in dynamic supply chains using an adaptive model-free control

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Abstract

As a complex and nonlinear systems characterized by inherent delays, supply chains call for more robust and efficient strategies for their dynamic management. Given the inherent modeling challenges that often fail to capture their dynamic behavior, this paper examines the application of model-free control, as introduced by Fliess and Join, to address supply chain management (SCM) issues. The proposed control framework integrates the principles of model-free control, further enriched by recent advancements in time series analysis for delay compensation and customer demand forecasting. The primary objective, in addition to ensuring effective supply chain control, is to mitigate the intriguing bullwhip effect, where the system model is assumed unknown, and the delay is constant yet unknown. To substantiate this approach's effectiveness, we present several convincing computer simulations using real-world examples and compare the results with the internal model control strategy.

keyword:
Supply chain management, inventory control, model-free control, time series, forecasting, algebraic techniques, bullwhip effect.

1 Introduction

Coined in 1980s-1990s, Supply Chain Management (SCM), as defined by [(Ivanov, et al., 2012)], [(Bozath and Handfield, 2016)], refers to the management of the flow of services and goods. It also encompasses a set of strategies deployed to efficiently integrate all the actors within the supply chain, including suppliers, manufacturers, distributors, and retailers [(Aghezzaf, et al., 2011)].

The primary objective is to guarantee the precise production and timely distribution of goods in the correct quantities and locations, all aimed at minimizing system-wide costs while maintaining a high level of service. Within the framework of SCM, decisions are typically categorized into three main domains: strategic, tactical, and operational planning [(Simchi-Levi, D et al., 1999)]. It's important to note, however, that many decision policies found in the literature rely on the use of heuristics or mathematical programming techniques to simplify the representation of real processes [(Perakis et al., 2010)]. This poses a significant obstacle that hinders companies from competing on a broader scale.

The modern complexity of supply chains, coupled with the constant imperative of increasing revenues, reducing costs, and enhancing customer satisfaction, within the backdrop of a globalized economy and fierce competition among companies, underscores the need for enhanced management practices where rigorous strategies can assume a pivotal role [(Sarimveis et al., 2008)]. It's

worth noting that despite the wealth of existing literature, it is not surprising that the study, modeling, and control of supply chains remain a thriving area of interest and discussion within the research community. Numerous comprehensive works and in-depth analyses posit that enhancing and dynamically optimizing management significantly heighten the competitiveness and profitability of supply chain systems [(Schwartz and Rivera, 2010)]. Although it is unconventional in the field of control engineering [(Schwartz and Rivera, 2014)], several tools stemming from control and systems theory have demonstrated their ability to handle the problem of dynamic SCM, where uncertainties, delays, and lack of information are among the most critical components to consider.

Numerous studies have concentrated on inventory management within production-inventory systems, encompassing both control and modeling aspects. The primary objective is to maintain the inventory levels at each node of the studied supply chain at desired levels while fulfilling customer demands by ordering products from the upstream echelons.

Model analysis allows companies to evaluate the agility of their organizations and anticipate their responses to the dynamics of an increasingly innovative and competitive environment. Consequently, models are extensively utilized due to their lower costs compared to employing real physical systems, provided they offer an adequate representation of reality. Numerous approaches to supply chain models have been developed, and classifications may vary depending on the authors. Min and Zhou [(Min et al., 2002)] classify quantitative models into four main categories: deterministic models (analytical models with one or more single or multi-criteria objective functions), stochastic models (analytical models in a stochastic environment, including dynamic programming and optimal control theory), hybrid models (which combine deterministic and stochastic aspects, often through simulation), and IT-driven models (which rely on information technologies). According to Beamon [(Beamon, 1998)], quantitative models can be categorized into four groups: deterministic models (where all parameters are known), stochastic models (where at least one parameter is unknown but follows a probabilistic distribution), economic game theoretic models, and simulation-based models that assess the performance of various supply chain strategies [(Sarimveis et al., 2008)]. Riddalls, Bennett, et al. [(Riddalls et al., 2000)] discuss four analytical methods, including continuous-time differential equations, discrete-time differential equations, discrete-event systems, and operations research methods. In this paper, the mathematical model used for simulation purposes is based on continuous-time differential equations.

From a control-based perspective, classical control theory initially introduced tools like the widely-used PID controllers [(Wikner, 1994)], in which the delay was approximated by a transfer function, the degree of which depends on the system's operation [(White, 1999)]. The application of a multi-echelon supply chain approach without considering production lead time has been proposed in [(Rodríguez et al., 2009)], aims to maintain inventory levels at their optimal values and synchronize the incoming and outgoing flows at each node to effectively meet market demand in a timely manner. Advanced control approaches, such as sliding mode control, internal model control, and flatness-based control, have been developed [(Schwartz and Rivera, 2010)], [(Ignaciuk and Bartoszewicz, 2012)], [(Koussaila et., al 2016a)], [(Koussaila et al., (2016b)]. Model predictive control (MPC) represents one of the most popular approaches to supply chain management and inventory control. It has the advantage of using current and historical measurements of the process to predict the system behavior at future time. Based on the predicted horizon and the objective function optimization an optimal control action that satisfies the systems constraints is then calculated. The MPC control was investigated for a single production-inventory system and for a multi-echelon supply chain using centralized or decentralized approach in [(Braun et al., 2003)], [(Kempf, 2004)], [(Wang et al., 2004)], [(Schwartz et al., 2006)], [(Wang, Rivera, and Kempf, 2007)], [(Schwartz and Rivera, 2010)], [(Schwartz and Rivera, 2014)]

and [(Fu et al., 2014)]. The excellent papers of [(Sarimveis et al., 2008)], [(Subramanian et al., 2013)], provide a deep review of the applied to dynamic supply chains management modeling and control approaches (See also e.g., [(Clarck and Scarf, 1960)], [(Salcedo et al., 2013)], [(Fu et al., 2014)], [(Kempf, 2004)], [(Wang et al., 2004)] and the references therein).

It's important to note that the majority of control approaches developed thus far are model-based strategies. However, as supply chain systems grow in complexity, modeling them becomes increasingly challenging, making it difficult to capture all of their dynamic phenomena.

The approach this research advocates is to develop decision policies based on a control oriented formulation where the need of any supply chain model become useless. It might be one of the very few publications that are combine recent advances in time series and model-free control in the frame of SMC. Preliminary results using model-free control are already proposed in [(Koussaila et al., 2019)], [(Nyakam and Abouaïssa, 2022b)], [(Nkayam Hachour and Abouaïssa, (2022)], [(Nyakam and Abouaïssa, 2022a)].

The mathematical model describing the study is replaced by the so-called ultra-local model, valid only over a short period and continuously updated. Delay compensation and demand forecasting rely on the new advances in time series techniques using the theorem of Cartier and Perrin in term of nonstandard analysis.

The remainder of the paper is organized as follows. The problem statement and objective are presented in Section 2. Section 3 briefly recalls the main principle of model-free control (MFC) and the corresponding intelligent controllers. Tools for delay compensation and demand forecasting are reviewed in section 4. Section 5 explains the combination of these two main tools to design the so-called adaptive model-free control (AMFC) and its application to the real problem of semiconductors manufacturing. Comparative studies with a so-called internal model control (IMC) based on performance indices and dynamic analysis appear summarized in Section 6. Finally, Section 7 provides major conclusions and discussion for further work.

2 Problem statement and objective

2.1 System description

Consider a serial, single-product supply chain structure with three echelons ($\eta = 3$), which is similar to the benchmark model used in semiconductor manufacturing, [(Schwartz et al., 2006)],[(Schwartz and Rivera, 201

The system depicted in Fig.1 consists of three ($n = 3$) logistic nodes[1]: Fabrication/test (N_1), Assembly/test (N_2) and finished product (N_3) nodes (See e.g., [(Wang et al., 2004)], [(Schwartz et al., 2006)], [(Schwartz and Rivera, 2010)], for more details about this supply chain system).

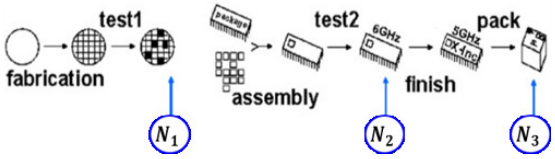

Figure 1: Three-echelon semiconductors manufacturing [(Wang et al., 2004)]

The equivalent fluid representation for a representative three-echelon semiconductor manufacturing supply chain is depicted in Fig. 2.

[1]Generalization to multi-echelons, multi-nodes, multi-products supply chain is straightforward.

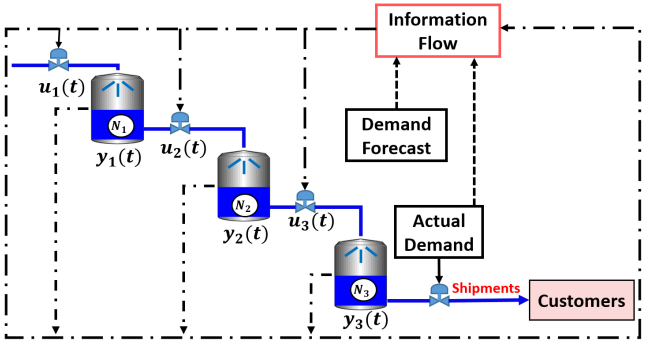

Figure 2: Fluid representation for a representative three-echelon supply chain

There are three control points: $u_1(t)$ for fabrication starts; $u_2(t)$ for assembly starts and $u_3(t)$ for finished starts. After each control operation the product is stored in N_1, N_2 and N_3, respectively.

Applying a straightforward conservation principle, a model analogous to this delay system can be formulated as follows:

$$\dot{y}_i(t) = \zeta_i u_i(t - \theta_i) - d_i(t), \qquad t \geq \theta_i \tag{1}$$

where, the output variable $y_i(t)$ $(i = 1, ..., n)$, represents the material inventory level; $u_i(t)$ is the factory starts (the input pipe flow, control variable); $d_i(t)$ is the total customer demand. The yield parameter $\zeta_i \neq 0$ and the throughput time θ_i may be known or not.

Equation (1) shows that the considered supply chain represents a typical example of delay systems, (See e.g., [(Koussaila et al., 2019)] for mathematical explanations about the difficulty to control such infinite-dimensional system and the clear illustration of the so-called "bullwhip effect"). The customer demand $d_i(t)$ in (1) is the sum of two quantities: a forecasted demand $d_{F_i}(t)$, knowns θ_{F_i} days ahead of time, and unforecasted demand $d_{U_i}(t)$:

$$d_i(t) = d_{F_i}(t - \theta_i) + d_{U_i}(t) \tag{2}$$

The overall dynamical system can be expressed as follows:

$$\dot{y}_i(t) = \zeta_i u_i(t - \theta_i) - d_{F_i}(t - \theta_i) - d_{U_i}(t) \tag{3}$$

Equation (3) represents the nominal model for production-inventory system control oriented tactical decisions policies. Based on this equation it is possible to derive feedback-only decision policies that manipulate factory starts $u_i(t)$ to maintain inventory level $y_i(t)$ at a desired setpoint $y_{d,i}(t)$.

The system disturbance $d_i(t)$ corresponds to the flow of products leaving the storage at any time t due to the customer demand. The input of the system $u_i(t)$ represents the order to produce and deliver the flow of products. Fig. 3, outlines the different components of the model. Table 1 summarizes all variable definitions and notations.

Application of the model (3) to the studied semiconductors manufacturing supply chain of three echelons leads to:

$$\begin{cases} \dot{y}_3(t) = \zeta_3 u_3(t - \theta_3) - d_3(t) \\ \dot{y}_2(t) = \zeta_2 u_2(t - \theta_2) - d_2(t) \\ \dot{y}_1(t) = \zeta_1 u_1(t - \theta_1) - d_1(t) \end{cases} \tag{4}$$

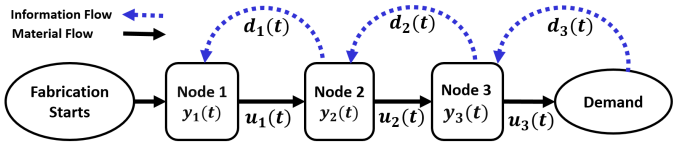

Figure 3: Definition of states, control variables, and outputs

Table 1: Definitions of variable and notation

Variables	Symbol description	Variable type
$u_1(t)$	Starts of Fab/Test1 node	Manip var.
$u_2(t)$	Starts of Assembly/Test2 node	Manip var.
$u_3(t)$	Starts of Finish/Pack node	Manip var.
$y_1(t)$	Starts of Fab/Test1 node	Measured var.
$y_2(t)$	Starts of Assembly/Test2 node	Measured var.
$y_3(t)$	Starts of Finish/Pack node	Measured var.
$d_3(t)$	Customer demand	Measured disturbance
θ_1	Throughput time of Fab/Test1 node	Model para.
θ_2	Throughput time of Assembly/Test2 node	Model para.
θ_3	Throughput time of Finish/Pack node	Model para.
ζ_1	Yield of of Fab/Test1 node	Model para.
ζ_2	Yield of of Assembly/Test2 node	Model para.
ζ_3	Yield of Finish/Pack node	Model para.

Given the interconnection between nodes, the customer demands in each node i are defined as follows:

$$\begin{cases} d_3(t) = d_{F_3}(t-\theta_3) + d_{U_3}(t) \\ d_2(t) = u_3(t) = d_{F_2}(t-\theta_{F_2}) + d_{U_2}(t) \\ d_1(t) = u_2(t) = d_{F_1}(t-\theta_{F_1}) + d_{U_1}(t) \end{cases} \tag{5}$$

Remark 2.1. *The customer demands are considered as disturbances. This contrasts with traditional level control problems where the outflow is manipulated in order to control the fluid level subject to disturbances at the inflow [(Schwartz and Rivera, 2014)].*

2.2 Constraints and objective

The considered problem consists on a basic logistic processes, where the time-delayed system with a constant lead time θ_i is subject to physical limitations. The maximal and minimum production rates of each node i are denoted by $u_{i,max}$ and $u_{i,min}$ respectively. Maximum and minimum inventory capacities are $y_{i,max}$ and $y_{i,min}$. The controller should be designed in such a way that, for all $t \geq 0$ the system, while adhering to the physical limitations of (6), must effectively compensate for the various delays and be capable of attenuating the variability and uncertainties in demand, notably addressing the "bullwhip effect".

$$\begin{cases} y_{i,min} \leq y_i(t) \leq y_{i,max} \\ u_{i,min} \leq u_i(t) \leq u_{i,max} \end{cases} \tag{6}$$

3 Model-free control: an overview

3.1 Main principle

The complexity of studying and managing supply chains is compounded by the challenge of describing all the dynamic phenomena in such a meshed network. Here, we adopt an alternative approach, replacing the more or less complex model of the supply chain with the so-called "ultra-local" model derived from model-free control theory.

Model-free control (MFC) is an approach to linear and nonlinear systems control introduced by Fliess and Join a few years ago [(Fliess and Join, 2009)]. While Model-Free Control (MFC) is a relatively recent concept in modern control theory, its practical successes in several domains are indisputably attributed to the straightforward gain tuning and remarkable robustness of its corresponding intelligent controllers (See, e.g., [(Abouaïssa, Fliess and Join, 2017)], [(Abouaïssa, and S. Chouraqui, 2019)], [(Afsi, et al., 2018)], [(Barth, et al., 2020)], [(Bara, et al., 2018)], [(Bekcheva et al., 2018)], [(Coşkun and İtik, 2023)] [(Hong et al., 2011)], [(Menhour et al., 2018)], [(Telsang et al., 2018)], [(Ismail et al., 2021)], [(Scherer et al., 2023)], [(Yaseri, 2023)], [(Ziane et al., 2022)] and the reference therein). Fig. 4 provides non-exhaustive statistics of works based on such theory.

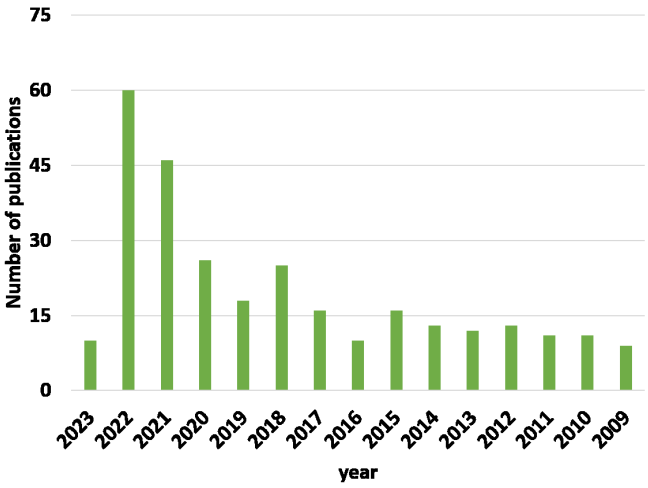

Figure 4: Number of annual publications related to MFC since 2009. The statistical data are based on searching of Scopus

It also explain why it has already been summarized recently many times: [(Abouaïssa et al., 2017)], [(Coşkun and İtik, 2023)], [(Join et al., 2017)]. This leads us to present only the general scheme and the main equations. The main theoretical ideas which are shaping the MFC can be founded in [(Fliess and Join, 2013)]. In brief, under some weak assumptions, the complex mathematical model of the studied system can always be substituted with the so-called *ultra-local model* or *phenomenological model* of the form

$$\mathfrak{y}^{(\nu)}(t) = F(t) + \alpha u(t) \tag{7}$$

where, $\alpha \in \mathbb{R}$ is a parameter chosen by the practitioner such that $\alpha u(t)$ and $\mathfrak{y}^{(\nu)}(t)$ are of the same order magnitude: it does not need to be precisely known. The ultra-local model is only valid during a short time period: it must be continuously updated.

As stated in [(Mounier et al., 2023)], numerous successful applications have demonstrated that a first order ($\nu = 1$) ultra-local model suffices to describe and design the control law for the system, a principle that holds true for our supply chain model.

$$\dot{\mathfrak{y}}(\mathfrak{t}) = F(t) + \alpha u(t) \tag{8}$$

where the data-driven $F(t)$, which subsumes not only the unmodeled dynamics, but also all the unknown disturbances, is estimated at any sample time by algebraic techniques as developed in [(Mboup, Join and Fliess, 2007)], [(Mboup, Join and Fliess, 2009)].

$$\hat{F}(t) = -\frac{6}{\tau^3}\int_{t-\tau}^{t} ((\tau - 2\sigma)\mathfrak{y}(\sigma) + \alpha\sigma(\tau - \sigma)u(\sigma))\, d\sigma \tag{9}$$

Remark 3.1. *The integral in (9), is a low pass filter which may, in practice, be replaced by a simple classical digital filter [(Fliess and Join, 2013)].*

3.2 The corresponding intelligent controllers

The intelligent controllers permit to close the loop as follows for $\nu = 2$ in (7)

$$u(t) = -\frac{\hat{F}(t) - \ddot{\mathfrak{y}}^{\star}(t) + K_P e(t) + K_I \int e + K_D \dot{e}(t)}{\alpha} \tag{10}$$

K_P, K_I and K_D are the usual tuning gains. $e(t) = \mathfrak{y}^{\star}(t) - \mathfrak{y}(t)$ is the tracking error. $\mathfrak{y}^{\star}(t)$ represents the output reference trajectory. $C(e(t)) = K_P e(t) + K_I \int e + K_D \dot{e}(t)$ is a causal function of the error $e(t)$.

Combining Eqs (7) (for $\nu = 2$) and (10) yieds $\dot{e} + K_P e + K_I \int e + K_D \dot{e} = F - \hat{F}$. With a good estimate $\hat{F}$, i.e., if $F - \hat{F} \approx 0$, then $\lim_{t \to +\infty} e(t) \approx 0$, if, and only if $K_P, K_I, K_D > 0$. Figure 5, resumes the main principle of MFC.

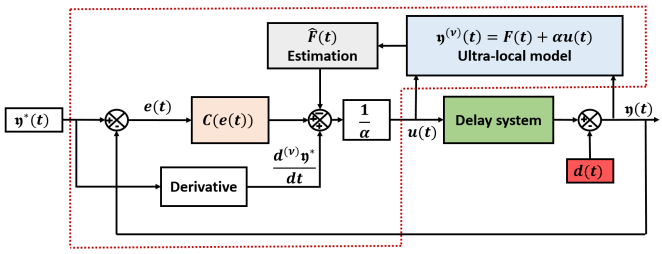

Figure 5: General Model-free control principle

3.3 Ultra-local model with delay

The introduction of delay in (7) leads:

$$\dot{\mathfrak{y}}(t) = \mathfrak{F}(t) + \alpha u(t - \theta) \tag{11}$$

In (11), $\mathfrak{F}(\mathfrak{t})$ plays the same role as $F(t)$ in Eq. (7) and reads

$$\hat{\mathfrak{F}}(t) = -\frac{6}{\tau^3}\int_{t-\tau}^{t} ((\tau - 2\sigma)\mathfrak{y}(\sigma) + \alpha\sigma(\tau - \sigma)u(\sigma - \theta))\, d\sigma \tag{12}$$

Most of the applications use the Smith predictors[(Smith, 1959)] as an efficient tool for delay compensation. As Smith predictor is a model-based, the proposed control approach is enriched by the recent trends in time series for delay compensation and demand forecasting.

4 Time series and prediction

4.1 New viewpoint of time series

Consider a real-valued polynomial Taylor function in τ

$$p(\tau) = \sum_{i=0}^{\infty} p^{(i)}(0)\frac{\tau^i}{i!} \tag{13}$$

where $p_n(\tau) = p(\tau) + \pi(\tau)$ a noisy observation on a finite interval of time from a signal $p(\tau)$ (the denoising signal). The numerical differentiation principle is based on the fact that each signal can be replaced by its truncated Taylor expansion of order N:

$$p(\tau) = \sum_{i=0}^{N} p^{(i)}(0)\frac{\tau^i}{i!} \tag{14}$$

Let us start with the first degree polynomial time function $N = 1$,

$$p(\tau) = p(0) + p^{(1)}(0)\frac{\tau^1}{1!} \tag{15}$$

The main tool allowing the prediction via time series rests on the use of the algebraic methods of derivatives estimate. This is summarized via the parameters estimation ($a_i = p^{(i)}(0)$, for $i = 0, 1$) of $p(\tau) = a_0 + a_1\tau, \quad \tau \geqslant 0, \quad a_0,\ a_1 \in \mathbb{R}$ [(Fliess and Join, 2009b)]. Rewrite (15) in operational calculus $L\{t^{(n)}\} = \frac{n!}{s^{n+1}}$. With respect to the Laplace variable s, $p(\tau)$ reads

$$P(s) = \frac{a_0}{s} + \frac{a_1}{s^2} \tag{16}$$

Simple algebraic manipulations, as well described many times (See e.g., [(Tian et al., 2008)], [(Fliess and Join, 2009b)], [(Koussaila et al., 2019)], [(Mounier et al., 2023)]) allow the obtention of all the unknown parameters a_0 and a_1 as follow:

$$a_0 = 2sP(s) + s^2\frac{dP(s)}{ds} \tag{17}$$

$$a_1 = -s^2P(s) - s^3\frac{dP(s)}{ds} \tag{18}$$

Remark 4.1. *Recall that $\frac{d}{ds}$ corresponds to the multiplication by t, the obtained, in time domain parameters estimate correspond to a set of iterated integrals which are low pass filters attenuating the corrupting noises.*

Remark 4.2. *A quite short time window is sufficient for obtaining accurate values of the parameters a_0 and a_1.*

From the above derivatives estimate, the estimation of the mean, or trend $E(X)(t)$ of a time series $X(t)$ defined according to the theorem of Cartier and Perrin [(Cartier and Perrin, 1995)]:

$$X(t) = E(X)(t) + X_{\text{fluctuation}}(t) \tag{19}$$

where $E(X)(t)$ is quite smooth and it is obtained like a_0 in (17), and $X_{\text{fluctuation}}$ is quickly fluctuating.

4.2 Forecasting via time series

Having the estimation of the mean, or trend $E(X)(t)$, the following forecast $X_{forecast}(t+\Delta T)$, where $\Delta T > 0$ is not too "large" reads

$$X_{forecast}(t+\Delta T) = E(X)(t) + \left[\frac{dE(X)(t)}{dt}\right]_e \Delta T \tag{20}$$

$\left[\frac{dE(X)(t)}{dt}\right]_e$ is estimated like a_1 from (18).

5 Adaptive model-free control: an application

5.1 Principle

The ultra-local model (11) of section 3.3 can be rewritten in the form

$$\hat{\dot{\mathfrak{y}}}(t+\theta) = \hat{\mathfrak{F}}(t+\theta) + \alpha u(t) \tag{21}$$

where $\hat{\dot{\mathfrak{y}}}(t+\theta)$ and $\hat{\mathfrak{F}}(t+\theta)$ are the estimate and forecast of $\dot{\mathfrak{y}}(t)$ and $\mathfrak{F}(t)$, respectively. Introduce the corresponding intelligent proportional (iP) controller

$$u(t) = \frac{1}{\alpha}\left(-\hat{\mathfrak{F}}(t+\theta) + \dot{\mathfrak{y}}^\star(t+\theta) - K_P\hat{e}(t+\theta)\right) \tag{22}$$

where $\hat{e}(t+\theta) = \hat{\mathfrak{y}}^\star(t+\theta) - \hat{\mathfrak{y}}(t+\theta)$ is the estimation of the tracking error at time $(t+\theta)$. In order to estimate $\hat{\mathfrak{y}}(t+\theta)$, integrate (21)

$$\hat{\mathfrak{y}}(t+\theta) = \int\left(\hat{\mathfrak{F}}(t+\theta) + \alpha u(t)\right) \tag{23}$$

Notice that the estimation of $\hat{\mathfrak{y}}(t+\theta)$ needs the forecast $\hat{\mathfrak{F}}(t+\theta)$ of $\mathfrak{F}$. The main tool which is used here rests on the new trend in time series presented below [2]. The forecast of $\hat{\mathfrak{F}}$ is obtained via Expressions (12) and (20).

The main issues encountered in the proposed strategy concern the case where the delay is unknown. Therefore, the approach depicted in Fig. 6, introduces a so-called Adaptive Model-Free Control (AMFC). The core of the idea consists to estimate and update the time delay in the system control model.

5.2 Delay estimation

Rewrite the delay ultra-local model (11)

$$\dot{\mathfrak{y}}(t) = \mathfrak{F}(t) + \alpha u(t-\theta) \tag{24}$$

The estimation of the delay θ is achieved according to the following steps:

Step 1: Apply to Eq. (11) the Laplace transforms

$$sY(s) - y_0 = F(s) + \alpha e^{-\theta s}U(s) \tag{25}$$

Using the first-order Padé approximation on the delay term $e^{-\theta s} \approx \frac{-\frac{\theta}{2}s+1}{\frac{\theta}{2}s+1}$, (25) reads:

$$sY(s) - y_0 = F(s) + \alpha\left[\frac{-\frac{\theta}{2}s+1}{\frac{\theta}{2}s+1}\right]U(s) \tag{26}$$

[2] The same approach is very useful for customer's demand forecasting.

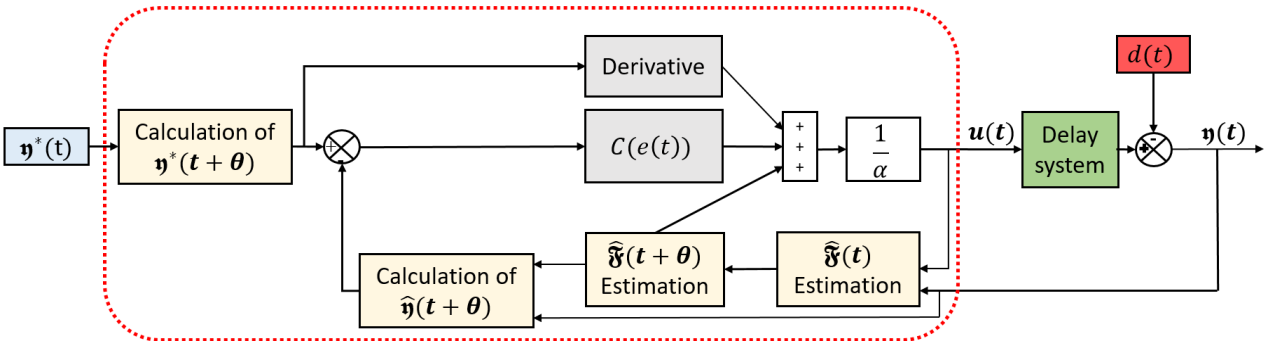

Figure 6: Adaptive model-free control scheme

Step 2: Take the two derivatives of (26) with respect to the complex variable s in order to get rid of the initial conditions y_0

$$\frac{\theta}{2}\left[s^2\frac{d^2Y(s)}{ds^2}+4s\frac{dY(s)}{ds}+2Y(s)+W(s)\right]=R_1(s) \tag{27}$$

$$W(s)=\alpha s\frac{d^2U(s)}{ds^2}+2\alpha\frac{dU(s)}{ds}-2\frac{dF(s)}{ds}-s\frac{d^2F(s)}{ds^2} \tag{28}$$

$$R_1(s)=-s\frac{d^2Y(s)}{ds^2}-2\frac{dY(s)}{ds}+\alpha\frac{d^2u(s)}{ds^2}+\frac{d^2F(s)}{ds^2} \tag{29}$$

Step 3: Finally, multiplying both sides of (27) by s^{-3}, in order to eliminate any non causal term and to avoid differentiation with respect to time

$$\Longrightarrow \theta=2\left(\frac{R_1^*(s)}{R_2^*(s)}\right) \tag{30}$$

$$R_1^*(s)=-s^{-2}\frac{d^2Y(s)}{ds^2}-2s^{-3}\frac{dY(s)}{ds}+s^{-3}\frac{d^2F(s)}{ds^2}+\alpha s^{-3}\frac{d^2U(s)}{ds^2} \tag{31}$$

$$R_2^*(s)=s^{-1}\frac{d^2Y(s)}{ds^2}+4s^{-2}\frac{dY(s)}{ds}+2s^{-3}Y(s)+\alpha s^{-2}\frac{d^2U(s)}{ds^2} + 2\alpha s^{-3}\frac{du(s)}{ds}-2s^{-3}\frac{dF(s)}{ds}-s^{-2}\frac{d^2F(s)}{ds^2} \tag{32}$$

Step 4: Back in the time domain via the inverse Laplace transform on the interval $\sigma\in[0,T]$.[3] Expression (30) becomes:

$$\theta=2\left(\frac{R_1^*(t)}{R_2^*(t)}\right) \tag{33}$$

where $R_1^*(t)$ and $R_2^*(t)$ are the inverse Laplace transform.

[3]Notice that $\frac{d^k}{ds^k}$, $k\geq 1$ is equivalent to $(-t)^k$ in time domain and s^k is equivalent to $\frac{d^k}{dt^k}$.

$$R_1^*(t) = -\int^{(2)} t^2 y(t) - 2\int^{(3)} ty(t) + \int^{(3)} t^2 F(t) + \alpha \int^{(3)} t^2 u(t) \tag{34}$$

$$R_2^*(t) = \int^{(1)} t^2 y(t) + 4\int^{(2)} ty(t) + 2\int^{(3)} y(t) + \alpha \int^{(2)} t^2 u(t) - 2\alpha \int^{(3)} tu(t) - 2\int^{(3)} tF(t) - \int^{(2)} t^2 F(t) \tag{35}$$

As illustration of the aforementioned algebraic technique, assume that for each node $i = [1, 2, 3]$, the delay values are $\theta_i(t) = [0.25, 0.75, 1]$ days. Their estimations are represented in Fig. 7. It is worth noting that the parameter estimation process is fast, resulting in the rapid determination of the exact values of θ_i.

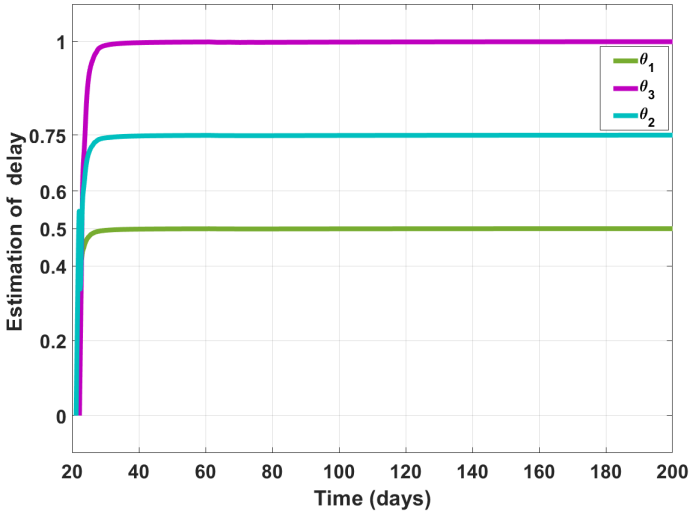

Figure 7: Estimation of delay θ

5.3 Inventory control of semiconductors manufacturing supply chain

The objective of the decision policies is to keep the inventory level $y_i(t)$, $i = [1, 2, 3]$ of the supply chain depicted in Figure 2, at its desired value $y_{d,i}(t)$, while the customer demand (the sum of forecasted and unforecasted, Eq. (2)) must be satisfied and the physical constraints defined in (6), respected.

The control law in each node i of three-echelon semiconductors manufacturing supply chain described by system (4) is given by:

$$u_i(t) = \frac{1}{\alpha_i}\left(-\hat{\mathfrak{F}}_i(t+\theta_i) + \dot{y}_{d,i}(t+\theta_i) - K_{P_i}\hat{e}(t+\theta_i)\right) \tag{36}$$

5.4 Forecasting customer demand

The proposed approach to predict the customer demand is based on algebraic technique describe in the section 4.2. Forecasting the future demand $d_i(t+\theta_i)$ (considered as a disturbance) allows to dictate to shipment flow. Therefore, the algorithm for delay compensation described in section 4.2 is applied and leads:

$$\hat{d}_i(t+\theta_i) = \frac{2\left[\int_{t_o}^{t} (2t - 3\tau)\, d_i(\tau) d\tau\right]}{t^2} \tag{37}$$

6 Simulation results and comparative studies

The application of adaptive model-free control approach is made using the system of semiconductors manufacturing borrowed from [(Schwartz et al., 2006)]. Figure 8, depicts the profil of the considered customer demand $d(t)$.

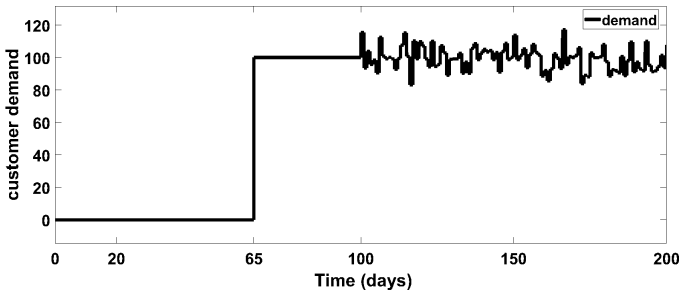

Figure 8: Customer demand $d(t)$

Two regions can be identified. The first one corresponds to the known demand. Indeed, at $t = 65$ days, a customer demand step change from 0 to 100 MT/day is introduced (forecasted demand $d_F(t)$ known $\theta_F = 5$ days ahead of time). At $t = 100$ days, the demand becomes stochastic. This second region describes the unforecasted demand $d_U(t)$. Notice that the orders of products propagate upstream from right to left (the final customer to initial supplier: information flow), and products are shipped downstream in the opposite direction (initial supplier to the final customer: material flow) as illustrated in Figure 9 (See also Figure 3).

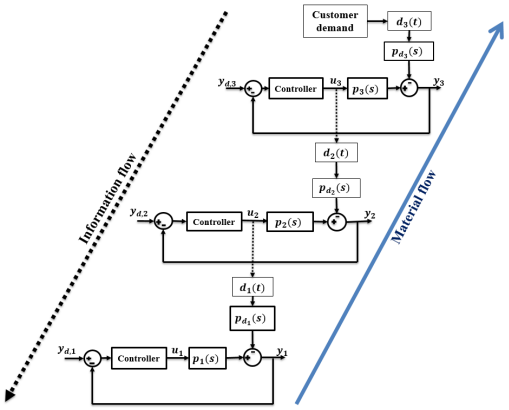

Figure 9: Block diagram of the installation-stock policy

The numerical values of the different parameters are summarized in Table 2.

In addition, the initial values are $y_{i,0} = 0$ in Mega Tonnes (Mt), and $\theta_{d_i} = 0$ in days. $u_{i,max}$ and $u_{i,min}$ are in MT/days. In the way that, each echelon may obtain enough goods (y_i equal to the desired value $y_{d,i}$) to supply the orders of its immediate customer ($d_i(t)$), the information flow must be satisfied and synchronized to production rate $u_i(t)$. Let us emphasize that the AMFC approach is compared to Internal Model Control (IMC) in [(Schwartz et al., 2006)] (See

Table 2: Numerical values

Nodes	$y_{d,i}$	$u_{i,max}$	$u_{i,min}$	θ_{F_i}	θ_i	ζ_i
node 1	1000	200	0	7	1	0.99
node 2	900	200	0	6	2	0.98
node 3	800	200	0	5	3	0.95

also [(Salcedo et al., 2013)]) [4] with the following model parameters, $\lambda_R = 40$, $\lambda_{C_1} = 10$, $\lambda_{C_2} = 2$, $\lambda_{C_3} = 2$, $\lambda_I = 0.1$ and $\lambda_B = 5$. The dynamic analyzes are carried out in comparison with the ideal case named Base 0. Four cases studies are conducted as summarized in Table 3. In addition,

Table 3: Different control policies

Policies	Control laws
Base 0	Ideal case ($y_i(t) = y_{d,i}(t)$ and $u_i(t) = d_i(t)$)
Case 1	Adaptive MFC without Forecasting demand
Case 2	Adaptive MFC with Forecasting demand
Case 3	2DoF IMC without Forecasting demand
Case 4	3DoF IMC with Forecasting demand

two types of analyzes are carried out. The first one concerns the qualitative analysis will the second deals with quantitative analysis.

6.1 Qualitative analysis

The proposed qualitative analysis is conducted in order to study the dynamic response of the three nodes semiconductors manufacturing supply chain subject to the various control laws. The following performances are analyzed:

1. Rise Time (RT): time interval corresponding to the growth from 10% to 90% of its total variation.
2. The maximum value of the production rate $|U_{max}|$. This information will be required for the sizing of flow capacities.
3. Settling time (ST): is the time required for the system to settle within a certain percentage (2% in our case) of the input amplitude.
4. Overshoot (OV): this criterion shows the maximum overshoot on the output signals.
5. Mean Tracking Error (MTE) with $N = T_s * T_f$; T_s is the sampling time.

$$\text{MTE} = \frac{1}{N} \sum_{i=1}^{N} |y_{d,i} - y_i|$$

[4] Future works will provide a deep comparative study with Model Predictive Control (MPC).

Figure 10, shows the evolution of the three levels of the studied systems both for the AMFC approach and for the IMC with two degree of freedom (2DoF) without any customer demand forecasting (case 1 and case 3).

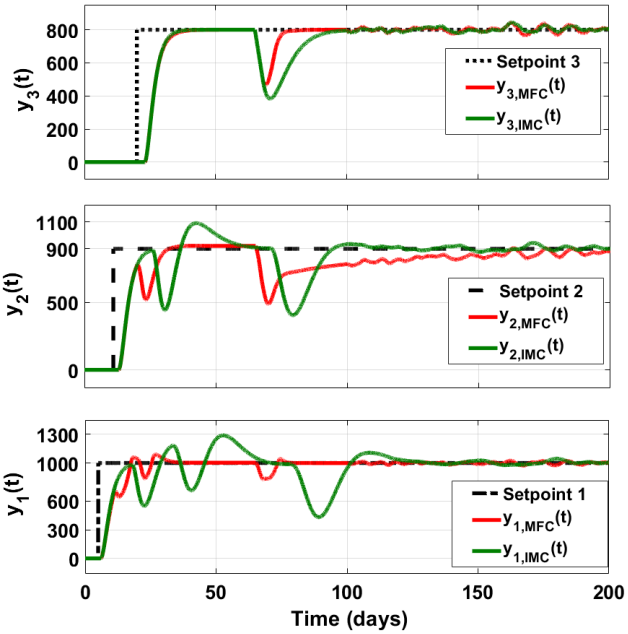

Figure 10: Net stock $y_i(t)$ in the three nodes without demand forecasting with AMFC and IMC

Both of the two controllers converge towards the desired values $y_{d,i}$ (MT) in each node. Consider, for example the level $y_3(t)$ and calculate $I_d = y_3(t) - y_{d,3}(t)$. The first plot of Figure 10, shows that around the interval $t = [65 - 100]$ days, the inventory level presents a negative deficit about of $I_d = 375$ MT for the AMFC approach while the 2DoF IMC one presents a deficit of $I_d = 414.3$ MT. The AMFC strategy anticipates the customer demand change at the day $t = 65$ and promptly adjusts the factory starts accordingly. Contrary to the 2DoF IMC approach which reacts to the customer demand change once it occurs. The same results are observed in the others nodes 1 and 2 (See e.g. the MTE criteria in Table 4, for case 1 and Table 5, for case 3). Given θ_i days of the throughput time in each node this results in a need for high levels of safety stock. In practice this means that the AMFC strategy is less likely to reach a critical inventory level.

Figure 11, shows the corresponding time evolution of the factory starts $u_i(t)$. Notice the violation of physical constraints in the case of the IMC approach for $u_1(t)$ and $u_2(t)$. Contrary, the introduction of the compensation in the AMFC (case 1) allows to the inventory targets to be lowered substantially and the starts evolution in response to demand changes to be less abrupt than in the case 3. The noticeable over and undershoots means that orders are not bring satisfied on time.

The amplitude of oscillation observed in Figure 10 and Figure 11 are increased when they move from node 3 to node 1. It shows that 2DoF IMC is not able to cancel or to attenuated the amplification problem. The AMFC shows the same problem but in a lower magnitude then reduces arrival of misleading signals to the fabrication node (node 1). This is a clear illustration of so-called bullwhip effect phenomenon.

Table 4: Performances of Adaptive Model-Free Control (AMFC)

Policies	Case 1			Case 2		
Nodes	Node 1	Node 2	Node 3	Node 1	Node 2	Node 3
RT (day)	9.67	13.76	7.13	6.67	6.67	6.67
ST (day)	189.81	191.10	191.68	17.64	24.64	34.64
OV	0	4.78	4.59	0	0	0
$\|U_{max}\|$	200	200	192.8	193.34	174.04	159.59
MTE	20.81	72.04	16.28	11.7692	4.16	2.91

Table 5: Performances of Internal Model Control (IMC)

Policies	Case 3			Case 4		
Nodes	Node 1	Node 2	Node 3	Node 1	Node 2	Node 3
RT (day)	6.62	6.74	6.84	6.62	6.74	6.84
ST (day)	171.38	167.86	187.18	171.38	167.85	187.2
OV	25.84	20.98	5.04	4.88	12.64	5.04
$\|U_{max}\|$	216.53	179.27	155.28	195.17	169.35	155.28
MTE	90.04	63.09	31.37	15.55	22.79	11.17

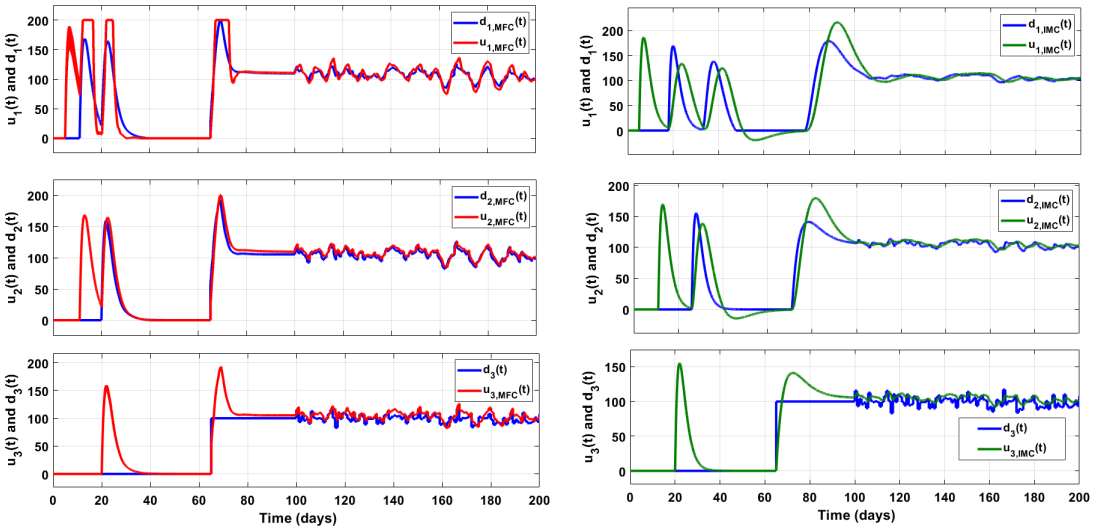

Figure 11: Factory starts $u_i(t)$ and demand $d_i(t)$ in 3 nodes with AMFC and IMC approaches

In order to mitigate the bullwhip effect, forecasting methods, as described before (See e.g., Section 5.4) play an important role in the frame of supply chain management. Using the AMFC policy with this forecasting method (case 2 in Table 3), Figure 12 shows the amelioration of this

strategy compared to the case 1. A significant reduction of the net stock $y_i(t)$ and the maximal value of factory starts $u_i(t)$ (Figure 13) can be observed compared to the case 1 (without customer demand forecasting) while respecting the physical constraints $u_{min} = 0 \leq u(t) \leq u_{max} = 200MT/days$.

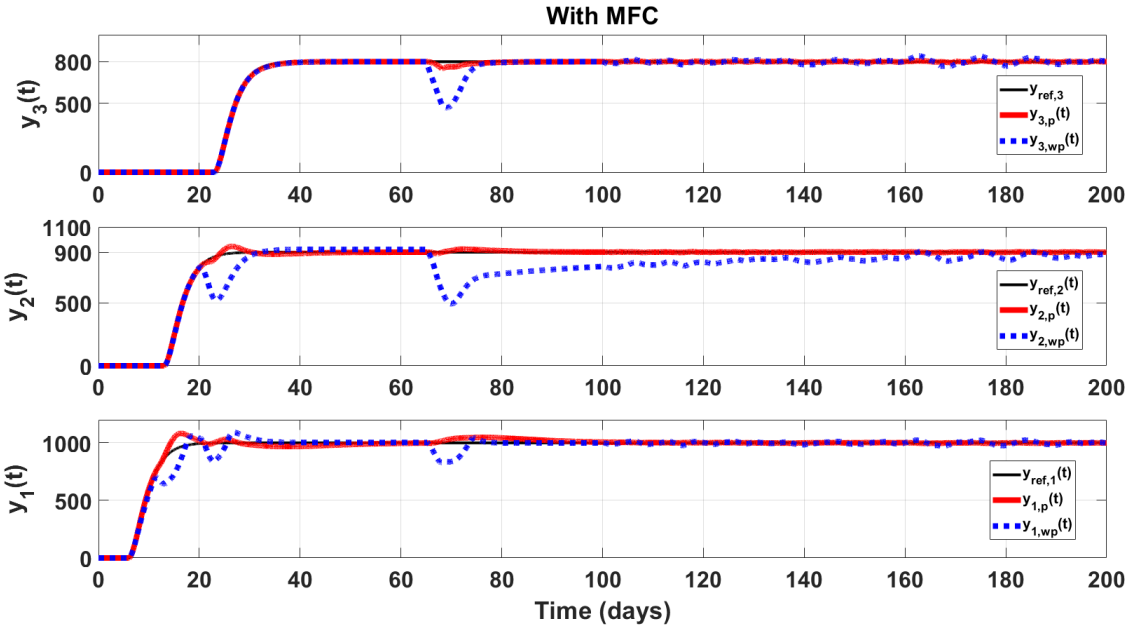

Figure 12: Net stock $y_{i,p}(t)$ evolution for case 2 (red) and case $(y_{i,wp}(t))$ (blue) using Adaptive Model-Free Control

All of the qualitative analyzes reported in the Tables 4 and 5 confirm the superiority of the proposed AMFC strategy with the customer demand forecasting. Notice that the performance with the 2DoF IMC approach (case 3) which does not take advantage of a demand forecasting is lower than the performance considers the fully functional, three degree-of-freedom (3DoF) combined feedback-feedforward control system (case 4) (See e.g. Figure 14).

Examining Figure 14 shows that the AMFC has advantages over IMC to improve performance (see case 2 in table 4 and case 4 in table 5), in addition the corresponding control policy $u_i(t)$ represented by Figure 15, are smoother and respect physical limitations than ones generated by 2DoF IMC.

More comprehensive and systematic comparison of the robustness and the bullwhip effect attenuation performances is achieved over the fourth cases. The measurement of the bullwhip effect is usually performed using the expression (38) (See e.g. [(Fu et al., 2014)]).

$$\text{Bullwhip} = \frac{\sigma_s/\mu_s}{\sigma_c/\mu_c} \tag{38}$$

where s, c refer to the orders placed on a supplier and customer demands respectively σ and μ denote the variance and the mean value of the variables.

The obtained results are summarized in Table 6. They demonstrate the flexibility through AMFC to put different emphasizes on bullwhip reduction in different nodes.

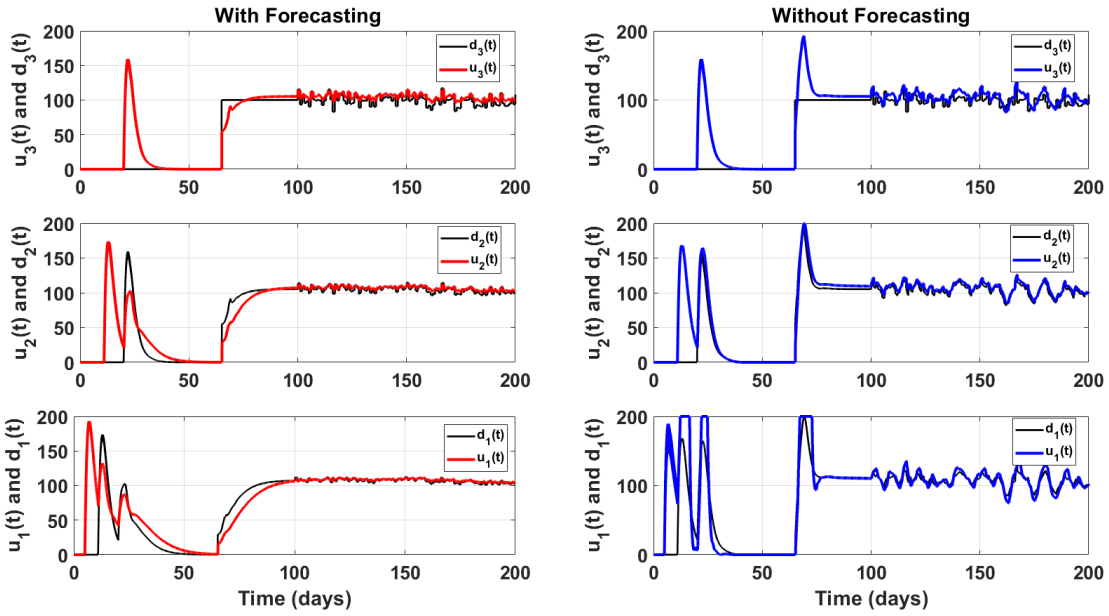

Figure 13: Starts $u_i(t)$ with/without demand forecasted with Adaptive Model-Free Control

Table 6: Bullwhip effect with AMFC and IMC

	Bullwhip Effect (AMFC)		Bullwhip Effect (IMC)	
Nodes	without forecasting	with forecasting	without forecasting	with forecasting
Node 1	1.1572	0.8396	1.0825	1.3241
Node 2	0.9219	0.8329	1.1287	1.0622
Node 3	0.9847	0.9154	0.9727	0.9020

6.2 Quantitative analysis

Quantitative analyses are conducted in term of the profit, the total cost, the customer satisfaction, and the total shipment rate defined below.

1. Profit is determined according to the objective function P_{max} for a planification time T_f (T_f is time considered for the evaluation):

$$P_{max} = R - PC - IC - BC \tag{39}$$

The objective function shown in (39) comprehensively accounts for the production cost, inventory holding cost, back-order penalty, and revenue generation via the parameters σ_R, λ_C, λ_I and λ_B respectively.

- Revenue (R) is the product of the price of an item λ_R by the demand of the final customer $d(t)$ (demand at the end of the supply chain.)

$$R = \sum_{t=0}^{T_f} \lambda_R d(t) \tag{40}$$

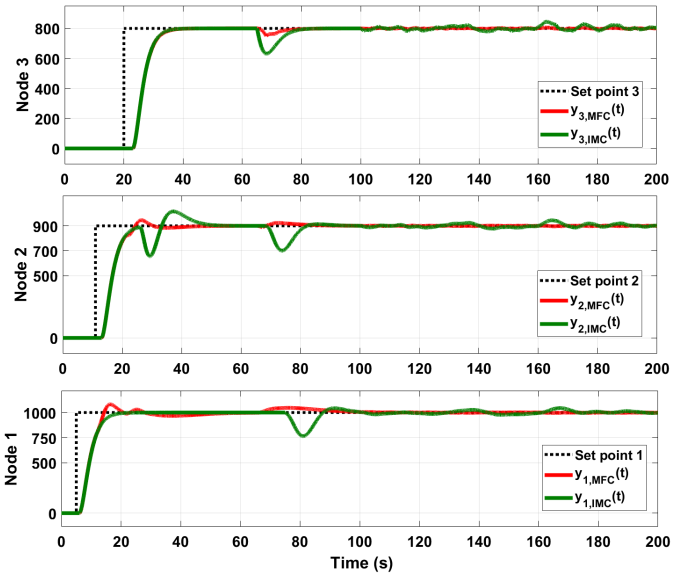

Figure 14: Inventories levels $y_i(t)$ in the three nodes with AMFC with forecasting demand and 3DoF IMC

- The cost of production (PC) is the sum of the cost of producing an item λ_C by the demand $d_i(t)$ (request at each node i $(i = 1, ..., n)$.

$$PC = \sum_{t=0}^{T_f} \sum_{J=1}^{n} \lambda_{C_j} d_j(t) \tag{41}$$

- The inventory storage cost (IC) is the sum of the storage cost per item λ_I (considering that we stock the same product) by the number of items present in available stock $y_i(t)$ (inventory level at each node i $(i = 1, ..., n)$.

$$IC = \sum_{t=0}^{T_f} \sum_{J=1}^{n} \lambda_I y_j(t) \tag{42}$$

- Backorder cost (BC) is the sum of the return cost per item λ_B (if considering the same product) by the number of items returned by the customer $b(t)$.

$$BC = \sum_{t=0}^{T_f} \lambda_B b(t) \tag{43}$$

2. Total Cost (TC): this index measures the average operational cost of the supply chain. This index considers storage and manufacturing costs only. Regarding the inventory costs, each product has a specific storage cost at each node in the distribution channels. The cost function is evaluated as the average cost in the entire period of analysis. Its value is calculated as the mean value of the instantaneous cost function using the mean value theorem

$$TC = \sum_{t=0}^{T_f} \sum_{J=1}^{n} \lambda_I y_j(t) + \sum_{t=0}^{T_f} \sum_{J=1}^{n} \lambda_{C_j} d_j(t) \tag{44}$$

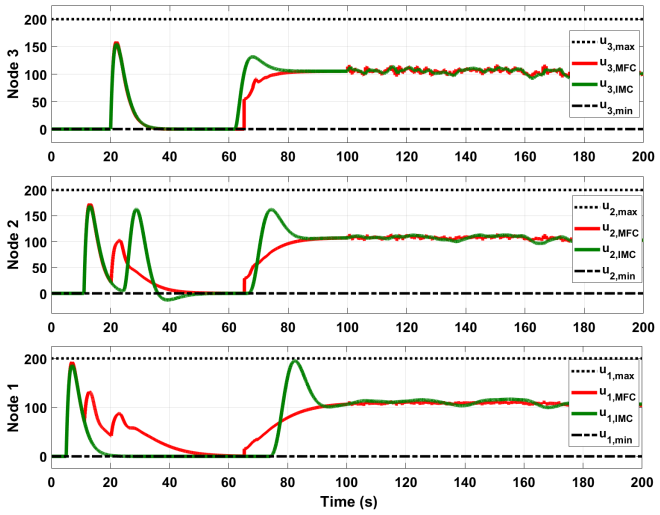

Figure 15: Factory starts $u_i(t)$ in the three nodes with AMFC with forecasting demand and 3DoF IMC

3. Customer Satisfaction Level (CS): this index provides information on the ability of the system to deliver orders on time. The customer satisfaction level is evaluated by comparing the rate of arrival of orders from the customers with the rate of deliveries to them. The difference between these quantities is the amount of orders not satisfied on time. This error is reported as a percentage of the total orders received. This index is evaluated as follows:

$$CS = \left[1 - \sum_{t=0}^{T_f} \left(\frac{d_i(t) - u_i(t)}{di(t)}\right)\right] \times 100 \tag{45}$$

where, $d_i(t)$ $(i = 1, ..., n)$ is the ordering rate to node i from one its customers and $d_{i-1}(t)$ is the material delivery rate from node i to its downstream product node.

4. Total shipping rate: this equation is used because qualitatively it reproduce the amplification problem observed in supply chain, or the "bullwhip effect" as reported by companies. This demand amplification has been observed in real systems because in common operations, retailers tend to over order products to ensure a high customer satisfaction level and to satisfy their forecasts of sales. By doing so, retailers "amplify" the original signal of orders coming from the customers and send this "amplified signal" (orders) to the next distribution level. As a result, the amount of orders that arrives to the next level is amplified and the next level receives more orders than the actual orders placed to the system. In turn, a small fluctuation in the demand reflects a small fluctuation in the inventory of the retailer but creates a much larger fluctuation in the inventory levels of the upper distribution nodes.

$$TSR = \frac{D_{out}}{D_{in}} \tag{46}$$

Where D_{out} ans D_{in} are the variance of demand generated by this node and the variance of demand received during a time interval respectively.

The obtained performances measurements for all the policies are reported in Tables 7-9. Table

7, resumes the customers satisfaction with AMFC and IMC in comparison of their ideal cases (case 0).

Table 7: Customer satisfaction with AMFC and IMC

	Node 1		Node 2		Node 3	
Policies	Cust. Sat. 1 (%)		Cust. Sat. 2 (%)		Cust. Sat. 3 (%)	
Base 0	100	$u_2 = d_2$	100	$u3 = d2$	100	d_3
Case 1	104.75	+4	103.46	+3.46	107.369	+7.3.7
Case 2	97.3671	-2.63	98.21	-1.79	103.1283	**+3.13**
Case 3	85.59	-14.40	93.78	-6.22	107.23	+7.23
Case 4	85.143	-14.85	95.03	-4.9715	106.192	**+6.2**

The customer satisfaction is calculated using (45). Table 7, provides information on the ability of the system to deliver orders on time. Therefore, the customer satisfaction level is the percentage of orders delivered on time.

- Comparison between the ideal case (base 0) and the first case (AMFC without forecasting) shows that the the system is not able to attenuate completely the bullwhip effect in different nodes (see Figure. 15 and table 6). The customer satisfaction levels exceed on average to 100%. Therefore, there is a surplus of materials on average in node of about 5%. When the forecasting of demand is used, corresponding to the case 2, the system achieves the highest bullwhip effect reduction then the customer satisfaction level drops up on average in the three nodes to 99.568% in comparison to case 1. Compared to base 0, the customer satisfaction in nodes 1 and 2 is less than 100% created a surplus of +3.13% in node 3.

- Using either case 3 or 4, the customer satisfaction is reduced at least by $14.4 - 4.9\%$ in nodes 1 and 2 compared to base 0. This reduction is the consequences of presence of bullwhip effect (see Fig. 11 and Fig. 15 and table 6) and the fact that design of IMC do not respect physical limitations. In node 3 for case 4 (with forecasting) compared to base 0, the customer satisfaction is more than 100% created a surplus of +6.13%.

Table 8: Cost value against the demand foresting and control AMFC

Policies	Total Cost (10^6\$)	Storage Cost (10^6\$)	Production Cost (10^6\$)
Base 0	36.509	4.9313	31.577
Case 1	39.115	4.7631	34.352
(%)	+12.03%	−3.4099%	+8.7876%
$\text{Profit}_1 = R - TC = 14.4565$ with $CS_{moy} = 105.1960\%$			
Base 0	34.915	4.9313	29.984
Case 2	36.508	4.9393	31.569
(%)	+4.5619%	+0.163%	+5.2854%
$\text{Profit}_2 = 17.173$ with $CS_{moy} = 99.568\%$			

Table 9: Cost value against the demand foresting and IMC

Policies	Total Cost (10^6\$)	Storage Cost (10^6\$)	Production Cost (10^6\$)
Base 0	35.890	4.9313	30.959
Case 3	37.445	4.7804	32.664
(%)	+4.3328%	−3.0584%	+5.5101%
$\text{Profit}_3 = 16.236$ with $CS_{moy} = 95.5352\%$			
Base 0	35.902	4.9313	30.971
Case 4	35.794	4.8989	30.895
(%)	−0.3001%	−0.6563%	−0.2434%
$\text{Profit}_4 = 17.7887$ with $CS_{moy} = 95.4544\%$			

Comparing the results in the tables 8 and 9, one can see the effect of the control policies and the forecasting demand over the total costs, storage cost and production cost of the system. An important finding is that the selection of control policies affects the decisions made by the production and storage facility.

- In case 1 (Adaptive Model-Free Control without the forecasting demand), the total cost production (regarding inventory cost and storage cost at each node) increases by +12.03%, whereas in case 2 (Adaptive Model-Free Control with the forecasting demand), the increase goes up by +4.5619% compared to the ideal case. This extra cost is due to extra production costs. The extra total cost of case 1 implies less profit $\text{Profit}_1 = R - TC = 14.4565 \times 10^6$\$

and high customer satisfaction $CS_{moy} = 105.1960\%$ (See also, node 3 in table 7) compared to case 2 with higher profit $\text{Profit}_2 = 17.173 \times 10^6\$$ with customer satisfaction $CS_{moy} = 99.568\%$. This results obtained by the AMFC policy show that the model is able to reproduce what real systems experience: stability and high customer satisfaction represent an extra cost.

- Something similar happens in the total cost in case 3 or 2 degree-of freedom feedback-only Internal Model Control increase by $+4.3328\%$ compared to base 0 implies high profit $\text{Profit}_3 = 16.236 \times 10^6\$$ but less the mean of customer satisfaction in nodes $CS_{moy} = 95.5352\%$. In case 4 (three degree-of-freedom combined feedback-feedforward Internal Model Control), the mean of customer satisfaction in nodes $CS_{moy} = 95.4544\%$ but profit $\text{Profit}_4 = 17.7887 \times 10^6\$$ is higher than in case 3 because the total cost is reduced -0.03001% compared to base 0.

7 Conclusion

The works presented in this paper demonstrate how to deal with complex supply chain control without going through the tedious modeling stage. Indeed, through an easy and efficient framework, the report introduces an adaptive model-free control strategy to the inventory control problem in the case of three semiconductors' manufacturing supply chain echelons. Here is shown that:

- Each supply chain model (usually approximated by a delay differential equation) can easily replace by an "ultra-local model" continuously updated.
- Instead of using any model-based compensation tool, a forecasting method of algebraic favors can advantageously allow for a delay compensation as well as customer demand prediction.
- The simulation results compared with the 2DoF IMC and 3DoF IMC policies demonstrate the proposed approach's ability to deal with the most intriguing bullwhip effect.
- Quantitative analysis shows the relevance of the adaptive model-free control in profit, total cost, customer satisfaction, and total shipment rate.

Constraints are an essential feature of most real-life control problems, and the ability to address these explicitly in the controller formulation is part of the significant appeal of AMFC. It also provided the foundation for current and future efforts. At the same time, the authors have highlighted controllers' vital role in achieving acceptable performance in the supply chain.

From the managerial viewpoint, let us emphasize that from the analysis of the input and output behavior of a studied system, the supply chain manager can gain visibility of the chain's capacity, productivity and delays, as well as their impact on the overall operation of the chain. The company's decision-makers should then adjust their objectives online according to the policies of the companies that make up the supply chain, enabling them to operate efficiently and achieve the desired performance.

A natural extension of this work is to apply AMFC with the demand forecast using an algebraic approach in controlling multi-products, multi-echelon supply systems with perishable goods and considering the environmental aspect.

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