Model-Free Control Policies for Inventory Management in Supply Chain*

Danielle Nyakam Nya[1] and Hassane Abouaissa[1]

Abstract— In the frame of supply chain networks, several approaches stemming from control theory seem to be more adapted to deal with dynamic inventory management. Nevertheless, the used methods, until today, are model-based control strategies where supply chain models play a major role. Due to the increasing complexity of such systems, the modeling of supply chains becomes more difficult and fails to capture all the dynamic behavior of the supply chain networks. This paper proposes as an alternative to these approaches a model-free control method and its corresponding intelligent controllers for inventory control in supply chain. Several concrete numerical simulations and comparative studies mainly with the internal model control show the efficiency of the approach and promising future of the obtained results even in the presence of various disturbances.

I. INTRODUCTION

Supply chain systems represent a set of meshed and complex networks of facilities which includes several entities like suppliers, manufacturers, distributors, retailers that perform the functions of procurement of raw materials, transformation of these raw materials into intermediate and finished products and distribution of finished products to customers [22]. Recalling that in supply chain, efficient dynamic management often leads to the coordination of supply chain operation to optimize the use of its resources to obtain lower production, inventory, location, and transportation cost and compete on a global scale. Notice that several research issues and gaps are quoted by [14] in the frame of supply chains:

- Writing down a reliable mathematical model of supply chain becomes more difficult.
- These difficulties are amplified by the high fluctuating disturbances and perturbations which need to be treated in order to ensure stability and robustness of the supply chains.

These shortcomings motivate the work presented in this paper and open new perspectives and challenges for future work.

Since the last half century, rigorous framework for analyzing the dynamics of supply chains and the research of the efficient decisions become of utmost importance in order to improve substantially the performance of such systems. In this context, control theory provides a solid background for building such framework and several approaches from control engineering have been applied and tested [4],[28].

Mainly, control theory and concept play an important role in the improvement of the dynamic management of information flow and inventory in supply chain systems. Within the control framework, several tools and applied control techniques have been developed which vary from classical PID controllers to more sophisticated control strategies. The PID controllers have been proposed by [29] where the delay in production-inventory system was approximated by a transfer function which degree depends on the system functioning and recently applied in [21] on multi-echelon supply chain without considering the lead time on production in order to keep the inventory level of each elements at a desired value which is considered as the optimal one which satisfies the requirements of customers in timely and most effective way and to synchronize theirs incoming and outgoing flows. Following the same goal [18], [19], have developed a control strategy based on the differential flatness concept. Optimal control and dynamic programming methods aim to optimize an objective function that describes the performance of the system were applied by [5] and [13]. Another interesting approach rests on the application of Internal Model Control (IMC) based on H_2-optimal tracking set point, unmeasured and measured disturbance (demand) rejection. These controllers allow successfully to deal with tactical decision making as demonstrated in [25] and [26]. The same control strategy enriched by an identification method was proposed by [11] for the inventory control and the estimation of the lead time. The model predictive control (MPC) represents one of the most popular approaches that is widely employed in the field of supply chain management. MPC has the advantage that the future values of the system's outputs, are predicted using a dynamic model of the process, and historical and current measurements. Based on the predicted horizon and the objective function optimization, an optimal control action that satisfies the systems constraints is then calculated. Such approach has been investigated for a single production-inventory system and for a multi-echelon supply chain using centralized or decentralized approach in [3], [10], [17], [27]. Notice that most of the cited above control approaches are model-based ones. Therefore, controlling such systems requires reliable mathematical models.

In the field of modeling, various approaches have been developed and can be subdivided into four categories: stochastic models where at least one parameter is unknown but follows a probabilistic distribution, deterministic models where all parameters are known, economic game theoretic models and models based on simulation, which evaluate the performance of various supply chains strategies. Nevertheless,

unavoidable dead (lead) times or throughput times, result from phenomena like transport and production, as well as the bullwhip effect, make the supply chain modeling a difficult task which impacts the quality of the control strategy, [11], [12], [23]. Generally and as stated in [8], writing down a "goof model", where constraints and perturbations might be severe, is quite beyond our reach especially if online calibration ought to be performed. In addition, the used model needs the identification of several parameters to assess a particular control strategy which is also true in the supply chain systems [15].

In this work, a new way is followed which is based on the recently introduced setting of "Model-Free Control, (MFC)" and its related intelligent controllers. The first attempt with a preliminary study was proposed in [20] and provides a solid basis for the future work in the field management of supply chain.

This paper is organized as follow. Section II provides a mathematical description of production-inventory system of supply chain used for simulation purposes and presents the design of multi-degree of freedom internal model control (IMC) for the comparative studies. Section III recalls the main principles of model-free control. Section IV, presents an application of MFC and IMC one to a semiconductor manufacturing supply chain borrowed for comparative study from [25]. Finally, some concluding remarks and discussions are provided in Section V.

II. DYNAMIC MODELING AND CONTROL OF PRODUCTION-INVENTORY SYSTEM

A. Mathematical modeling of production-inventory system

Without loss of generality, consider, for numerical simulations purposes, the production-inventory system borrowed from [25] and depicted in Fig.1.
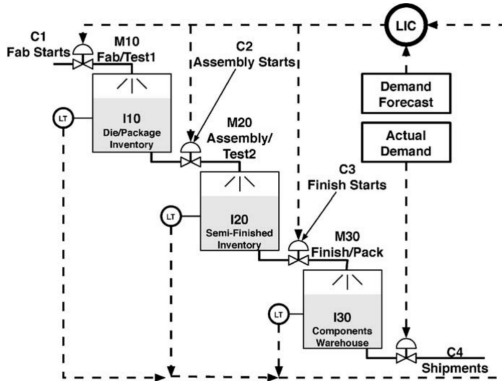

Fig. 1. Fluid representation of a three-echelon supply chain of semiconductor manufacturing [23].

A fluid representation of a three-nodes (or three echelons) semiconductor manufacturing supply chain is consisting of one fabrication/test1, one assembly/test2 and one finish node. C_1, C_2, C_3 and C_4 are control points respectively fabrication starts, assembly starts, finish starts and shipment.

Here the manufacturing nodes M_{10}, M_{20} and M_{30} (Fab/test1, Assembly/test2 and Finish/Pack) are represented

as "pipes" with a particular throughput time θ_i and yield K_i. While the warehouse nodes or inventory storage I_{10}, I_{20} and I_{30} (Die[1]/Package inventory, Semi-finished inventory and components warehouse) are represented as "tanks". Material in these pipes and tanks correspond to Work-in-Progress (WIP) and inventory with a transportation time (or delivery time) θ_d, respectively.

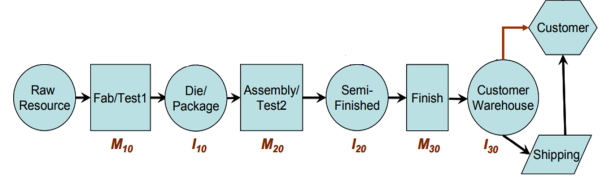The corresponding manufacturing process network is given in Fig. 2.

Fig. 2. Manufacturing Process Network [24].

The output of a factory is stored in a warehouse where it awaits shipments to customers. Thus, the supply chain is modeled as a serial process where each node orders goods to its immediate supplier. In this way, each echelon may obtain enough goods to supply the orders of its immediate customer of the chain [11].

Application of the mass conservation principle to the system leads to a differential equation relating net stock in each echelon (material inventory, $y_i(t)$) to factory starts (input pipe flow, $u_i(t)$) and customer demand (output tank flow, $d_i(t)$) which is represented by (1):

$$\frac{dy_i}{dt} = K_i u_i(t - \theta_i) - d_i(t) \tag{1}$$

Based on (1), it is possible to maintain inventory level ($y_i(t)$) in node i at a desired set point ($y_{d,i}$) by manipulating the factory starts $u_i(t)$ (control action). Customer demand ($d_i(t)$) is considered as the sum of the forecasted demand (d_{F_i}), known a forecast horizon θ_{F_i} days ahead of time and unforecasted demand (d_{U_i}) as shown below:

$$d_i(t) = u_{i+1}(t) = d_{F_i}(t - \theta_{F_i}) + d_{U_i}(t) \tag{2}$$

The overall dynamical system is then defined by (3):

$$\frac{dy_i}{dt} = K_i u_i(t - \theta_i) - d_{F_i}(t - \theta_{F_i}) - d_{U_i}(t) \tag{3}$$

In Laplace domain (3) becomes:

$$Y_i(s) = p_i(s)U_i(s) - p_{d_{1_i}} p_{d_2} d_{F_i}(s) - p_{d_2} d_{U_i}(s) \tag{4}$$

where:

$$\begin{cases} p_i(s) = \frac{K_i e^{-\theta_i s}}{s} \\ p_{d_{1_i}}(s) = e^{-\theta_{F_i} s} \\ p_{d_2}(s) = \frac{1}{s} \end{cases} \tag{5}$$

Equation (4) is the nominal model for production-inventory system control oriented tactical decision policies ([23], [25], [26]), considered in this paper.

---

[1]A die, in the context of integrated circuits, is a small block of semiconducting material on which a given functional circuit is fabricated.

Notice that $p_i(s)$ is a pure delay that is often very difficult to order. This is why in the IMC controllers used in the literature for the control of this system have been improved by adding robustness filters (see [25] for example).

Either for the inventory levels $y_i(t)$, or for the control actions $u_i(t)$, physical constraints must be taking into account:

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

The set of the above equations constitute the basis of the development of the Multi-degree of freedom feedback-feedforward IMC to the control of production-inventory system. Such control strategy will be compared with the proposed model-free control approach.

B. IMC control of supply chains

The multi-degree of freedom feedback-feedforward IMC controller structure as depicted in fig. (3), contains three independent controllers that are used for three different objectives based on the H_2-optimal minimization hence the designation as three-degree-of-freedom (3DoF) (See e.g., [26] for more explanation and details).
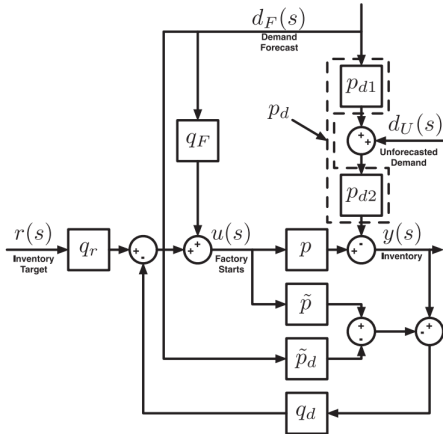

Fig. 3. Three-degree-of-freedom combined feedback-feedforward internal model control structure [23]

IMC(3DoF) contains three controllers that minimizes the average error magnitude. Such controllers will lead to violent reactions from manipulated variables. In order to attenuate these effects, the obtained result are enriched with low-pass filters for robust stability and performance.

- Set-point tracking controller q_r: the controller guarantees no offset for step set-point changes in the control system. The mode allows the controller to adjust safety stock inventory targets to any user-desired level.

$$q_r(s) = \frac{s}{K} \frac{1}{(\lambda_r s + 1)^{n_r}} \quad (7)$$

- Measured disturbance rejection q_F: the controller is designed using H_2 optimization and performs a feed-forward action relying on the known demand θ_F days ahead.

$$q_F(s) = q_F'(s) f_F(s) \quad (8)$$

where $q_F'(s)$ consists of:

$$q_F'(s) = \begin{cases} \frac{e^{-(\theta_F - \theta_d - \theta)s}}{K} & \text{when } \theta_F \geq \theta_d + \theta \\ \frac{(\theta + \theta_d - \theta_F)s + 1}{K} & \text{when } \theta_d + \theta > \theta_F \end{cases} \quad (9)$$

Where θ_F is the forecast horizon, the factory throughput time θ and delivery time θ_d. It is augmented with generalized type-2 filter $f_F(s)$

$$f_F(s) = \frac{(n_F \lambda_F s + 1)}{(\lambda_F s + 1)^{n_F}} \quad (10)$$

- Unmeasured disturbance rejection q_d: this controller takes into account the unforecasted demand in the feedback designed for ramp disturbance changes, with a generalized type-2 filter guaranteeing no offset for both ramp disturbances and asymptotically step [25] given by

$$q_d(s) = \frac{s(\theta s + 1)}{K} \frac{n_d \lambda_d s + 1}{(\lambda_d s + 1)^{n_d}} \quad (11)$$

Each controller is required to be stable and proper, thus imposing the restriction that all values of the user adjustable parameters be positive ($\lambda_d > 0$, $\lambda_F > 0$, $\lambda_r > 0$) and that the filter order is chosen to ensure transfer function properness ($n_r \geq 1$, $n_d \geq 3$, $n_F \geq 3$).

III. MODEL-FREE CONTROL AND THE CORRESPONDING INTELLIGENT CONTROLLERS

A. Phenomenological model

Model-free control (MFC) is a novel approach to nonlinear control stemming from M. Fliess et al., [6], (See e.g. [7] for a thorough presentation). In model-free control, there is no need of physical model but the control designer exposes a merely numerical model which involves no many parameters that are estimated thanks to the algebraic methods, online during operation of the system. The feedback control law is build and tuned by the numerical model and is thus updated at each sample time. Notice that since its introduction, several successful concrete applications in different fields have been developed, [1], [2], [8], [9].

The MFC concept rests on the following principle. The *complex* mathematical model which describe the input/output behavior of the system, is replaced by a *phenomenological model* called also an *ultra-local model* given by (12):

$$y^{(v)}(t) = F(t) + \alpha u_{mfc}(t) \quad (12)$$

where:

- $y^{(v)}(t)$ and $u_{mfc}(t)$ are respectively the derivative of order $v \geq 1$ of controlled output $y(t)$ and input. v may always be chosen 1 or 2 (see [7], [8]).
- $\alpha \in \mathbb{R}$, is chosen such that $y^{(v)}(t)$ and $\alpha u_{mfc}(t)$ are of the same magnitude.
- F is estimated by algebraic techniques as developed in [8]. Using values of the output y and the input $u_{mfc}(t)$ at any sample time we calculate F. The time-varying quantity F which is continuously updated, subsumes not only the unmodeled dynamics, but also all the unknown disturbances.

B. Intelligent controllers

Assume that F is estimated (See e.g., Fig.4 for the general principle of MFC) and close the loop with the following controller (13):
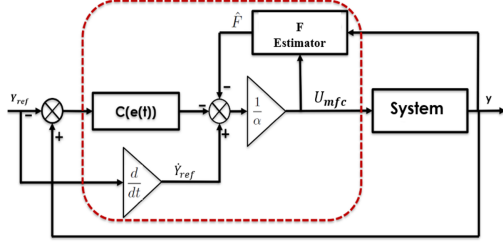

Fig. 4.   General Model-free control principle

$$u_{mfc} = \frac{1}{\alpha} \left(-F(t) + y_{ref}^{(v)}(t) + C(e(t)) \right) \qquad (13)$$

where $e(t) = y(t) - y_{ref}(t)$ is the tracking error and $C(e(t))$ is a function of the error. It is chosen such as $y^v + C(e(t))$ is stable.

$$C(e(t)) = K_P e(t) + K_I \int e(t) + K_D \frac{de(t)}{dt} \qquad (14)$$

Where K_P, K_I and K_D are tuning gains and y_{ref} is the reference trajectory.

Under a weak integrability condition, $F(t)$ is approximated by a constant function (noted $\hat{F}$) in a short interval of time $[t-T,t]$ where T is the estimation horizon. This interval becomes $[0,T]$ by sliding window, with $\sigma \in [0,T]$, σ the time variable.

For the studied supply chain system, the used ultra-local model (12) is considered with $v = 1$ ($K_I = K_D = 0$), which leads to the so-called *intelligent Proportional* controller or (*iP*). Combining Equations (12) and (13) yields:

$$\dot{e}(t) + K_P e(t) = 0 \qquad (15)$$

where $F(t)$ does not appear anymore. Thus $lim_{t \to \infty} e(t) = 0$ if $K_P > 0$. This local stability property proves that the tuning of K_p is straightforward. This is a major difference with the classic gain tuning for PIs and PIDs (see, e.g. [16] and references therein).

C. Estimation of F

In Laplace domain, (12) with $v = 1$ becomes:

$$sY(s) - y(0) = \frac{\hat{F}}{s} + \alpha U_{mfc}(s) \qquad (16)$$

Deriving both sides of (16) with respect to s in order to eliminate the initial condition $y(0)$:

$$\frac{\hat{F}}{s^2} = -Y(s) - s\frac{dY(s)}{ds} + \alpha \frac{dU_{mfc}(s)}{ds} \qquad (17)$$

The application of the inverse Laplace transform on the interval $\sigma \in [0,T]$, with $\frac{d^k}{ds^k}$, $k \geq 1$ equivalent to $(-t)^k$ in time domain and s^k equivalent to $\frac{d^k}{dt^k}$, yields:

$$\sigma \hat{F} = -y(\sigma) + \left(\frac{d}{d\sigma} \sigma y(\sigma) \right) - \sigma \alpha u_{mfc}(\sigma) \qquad (18)$$

And finally, by evaluating (18) in T, we have:

$$T\hat{F} = -y(T) + \left(\frac{dy(\sigma)}{d\sigma} \sigma + y(\sigma) \right)(T) - \alpha T u_{mfc}(T) \qquad (19)$$

We have $\hat{F}$:

$$\hat{F} = \frac{1}{T} \left[-y(T) + \left(\frac{dy(\sigma)}{d\sigma} \sigma + y(\sigma) \right)(T) - \alpha T u_{mfc}(T) \right] \qquad (20)$$

The estimation of F may be achieved via other methods as in [16].

IV. APPLICATION TO INVENTORY CONTROL OF SEMICONDUCTOR SUPPLY CHAIN

A. Application of multi-degree of freedom IMC

From the general structure depicted in Fig. 3, each node is controlled by (7). Measured and unmeasured disturbance rejection are ensured by (8)–(10).

B. Application of model-free control

For implementation, it is strongly advisable to discretize (20) and filter $\hat{F}$ using a classic second filter [9]. Then the MFC (*iP*) for each node is given by (21) with a term $u_{i,nom}$ that improves its robustness.

$$u_{i,mfc} = \frac{1}{\alpha_i} \left(-\hat{F}_i(t) - \dot{y}_{i,ref}(t) + C_i(e(t)) \right) + u_{i,nom} \qquad (21)$$

$$u_{i,nom} = \frac{1}{K_i} \left(\frac{dy_{i,ref}^*}{dt} + d_i^*(t) \right) \qquad \begin{cases} y_{i,ref}^* = y_{i,ref} \\ d_i^*(t) = d_{F_i}(t - \theta_{F_i^*}) \\ \theta_{F_i^*} = \theta_{F_i} - \theta_i \end{cases}$$

$$(22) \qquad\qquad (23)$$

C. Case study

The considered case study is a three-echelons semiconductor manufacturing supply chain borrowed from [25]. The goal is to keep inventory level y_i to its desired value $y_{d,i}$, while the customer demand is the sum of unforecasted demand $d_U(t)$ and the forecasted demand ($d_{F_i}(t)$, known θ_{F_i} days ahead of time), must be satisfied respecting physical constraints given by (6). The numerical values of different parameters used in this paper are summarized in table I.

TABLE I

NUMERICAL VALUES

Echelons	$y_{d,i}$	$u_{i,max}$	$u_{i,min}$	K_{P_i}	θ_{F_i}	θ_i	K_i
Echelon1	1000	200	0	0.24	7	1	0.99
Echelon2	900	400	0	0.25	6	2	0.98
Echelon3	800	200	0	0.1	5	3	0.99

$y_{i,0} = 0$, $\alpha_i = 100$, $n_{r_i} = 2$, $n_{d_i} = 3$, $n_{F_i} = 3$, $\lambda_{r_i} = 2$, $\lambda_{F_i} = 2$, $\lambda_{d_i} = 4$ and $\theta_{d_i} = 0$.

In addition: $y_{d,i}$ in MT: Mega tonnes; $u_{i,max}$ and $u_{i,min}$ in MT/days; θ_{F_i}, θ_{d_i} and θ_i in 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.

D. Numerical results

Fig. 5 represents the total demand of customer $d_3(t)$. At day $t = 60$ days, a customer demand step change from 0 to 100 MT/day is introduced (forecasted demand $d_{F_3}(t)$ known $\theta_{F_3} = 5$ days ahead of time) and at day $t = 100$ days, the demand signal becomes stochastic (unforecasted demand $d_{U_3}(t)$).
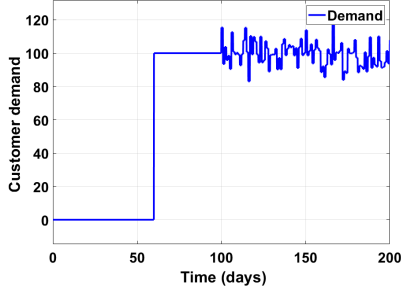

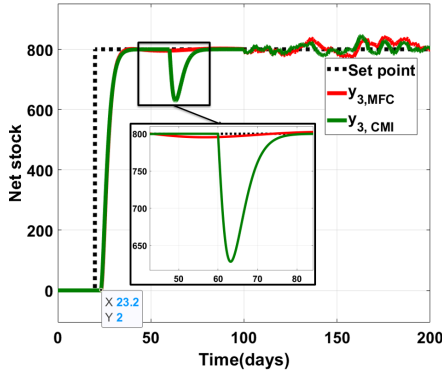Fig. 5.   Customer demand $d_3(t)$

Fig. 6.   Net stock $y_3(t)$ in echelon 3

Fig. 6 shows the net stock $y_3(t)$ with the two controllers in echelon 3. Both MFC and IMC perform equivalently on unforecasted demand changes (unmeasured disturbance rejection $d_{U_3}(t)$, $100 \leq t \leq 200$ days) and set point tracking i.e all controllers converge to the desired value $y_{d,3} = 800$ MT in respect of physical constraints corresponding to their maximal starts factory $u_{3,MFC} = u_{3,IMC} = 158.886 < u_{i,max} = 200$ MT/day and $y_3(t) > 0$ (Fig. 7).

However, differences between the controllers are visible in presence of the fast changing forecasted demand (measured disturbance rejection). At the day $t = 57$ days, the two controllers anticipate the demand change that occurs at day $t = 60$ days, and adjust their factory starts $u_{3,MFC}$ and $u_{3,IMC}$ (see Fig. 7) accordingly.

One can see that the MFC (iP) stands out from IMC (3DoF) by its speed to reach steady state ($u = 105$ Mt/day corresponding to $y_{3,MFC} = y_{3,d} = 800$ MT) while it is at the

time $t = 76$ days that IMC reaches this value. This speed of MFC reduces the transport and delivery delays and mitigate production phenomena like bullwhip effect.

We observe then in Fig. 7 an overshoot $u_{3,IMC} = 132.45$ MT/day at the day $t = 63.2$ which creates an inventory drift $\Delta y = y_{3,d} - y_3 = 800 - 628.3 = 171.7$ MT on safety stock $y_{3,IMC}(t)$.
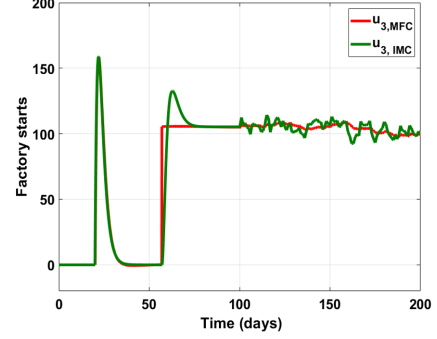

Fig. 7.   Factory start $u_3(t)$ in echelon 3

Considering the demand in echelon 2 given by $d_2(t) = u_3(t)$, the factory start $u_2(t)$, and the net stock $y_2(t)$ are shown in fig. 8.
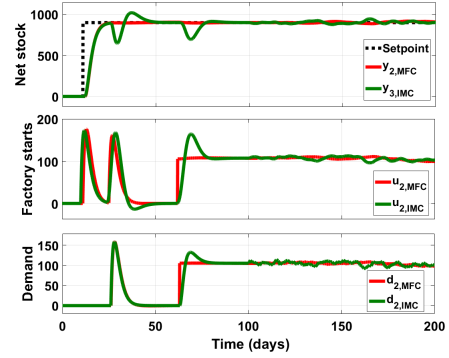

Fig. 8.   Net stock $y_2(t)$, factory start $u_2(t)$ in echelon 2

There is no overshoot in the inventory level with MFC (iP) in node 2 contrary to IMC when it is subjected to demand $d_2(t)$ changes. Overshoots in the inventory response $y_{2,IMC}$ which lead to a large spike in factory starts $u_{2,IMC}$ that is unacceptable for factory managers.

The variability in the ordering patterns increases (see Fig. 7) as we move up into the chain from echelon 3 (customer) to echelon 1 (supplier). This phenomena is call bullwhip effect.

However, in the second echelon, the performance to bullwhip effect mitigation with IMC under this tuning is deteriorated (the increasing of demand $d_1(t) = f(u_2(t)) = 164.8$ MT/day at around the time $t = 76$ days in echelon 1, see Fig. 9)), but the MFC control approach works successfully in the entire supply chain. The same results in echelon 3 are observed in echelon 1, given by Fig. 9.

V. CONCLUSIONS

The proposed in this paper, model-free control approach allows to bypass any dynamic mathematical model for the
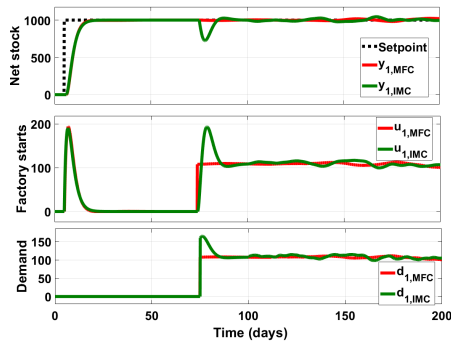
Fig. 9. Net stock $y_1(t)$, Factory start $u_1(t)$ in echelon 1

supply-chain management. It has demonstrated its capability to manage inventory in supply/demand network on a real study case, a three-echelons semi-conductor manufacturing supply chain. The results are discussed with a comparative study which shown that all the controllers are both stable and appropriate for controlling inventory in supply chain but Model-Free Control stands out from Internal Model Control by its speed and its robustness to forecasted demand.

The ideal case for the company is to produce the exact amount needed product by costumers. By using forecast, the net stock can be reduced compared to the net stock obtained without forecast. Then the operating costs for the company are significantly decreased. Then, the effectual solution to this intricate problem is to anticipate the customer's demand at sufficient time before its occurrence. Generally, the existing forecasting methods are approaches that use historical data based on identifying, modeling and extrapolating. Then, we will proposed in the future work, a forecasting method does not need information about the pattern or a model to predict the customer demand.

REFERENCES

[1] H. Abouaissa, M. Fliess, and C. Join. "On ramp metering: Towards a better understanding of ALINEA via model-free control." International Journal of Control, vol. 90, no 5, 2017, pp. 1018-1026.

[2] H. Abouaissa, and S. Chouraqui. "On the control of robot manipulator: A model-free approach." Journal of Computational Science, vol. 31, 2019, pp. 6-16.

[3] M. W. Braun, D. E. Rivera, M. E. Flores, W. M. Carlyle, and K. G. Kempf. "A model predictive control framework for robust management of multi-product, multi-echelon demand networks." Annual Reviews in Control, 27 (2), 2003, pp. 229-245.

[4] H. Carvalho, K. Govindan, S. G. Azevedo, and V. Cruz-Machado. "Modelling green and lean supply chains: An eco-efficiency perspective." Resources, Conservation and Recycling, vol. 120, 2017, pp. 75-87.

[5] A. J. Clark, and H. Scarf. "Optimal policies for a multi-echelon inventory problem." Management science, vol 6,1960, pp. 475–490.

[6] M. Fliess, C. Join, M. Mboup, and H. Sira-Ramìrez. Vers une commande multivariable sans modèle. Proc. Conférence Internationale Francophone d'Automatique "CIFA'06", 2006.

[7] M. Fliess, and C. Join. Model-free control and intelligent PID controllers: towards a possible trivialization of nonlinear control? 15th IFAC Symp. System Identif., Saint-Malo. 2009.

[8] M. Fliess, and C. Join. "Model-free control". International Journal of Control, 86 (12), 2013, pp. 2228–2252.

[9] M. Fliess, and C. Join. "An alternative to proportional-integral and proportional-integral-derivative regulators: Intelligent proportional-derivative regulators." International Journal of Robust and Nonlinear Control, 2021.

[10] D. Fu, C. M. Ionescu, and E. Aghezzaf, and R. De Keyser. "Decentralized and centralized model predictive control to reduce the bullwhip effect in supply chain management." Computers & Industrial Engineering, 73, 2014, pp. 21–31.

[11] C. A. Garcia, A. Ibeas, J. Herrera, R. Vilanova, and J. H. Cuartas. "Inventory control of supply chains: Mitigating the bullwhip effect by centralized and decentralized Internal Model Control approaches." European Journal of Operational Research, vol. 224, no 2, 2013, pp. 261-272.

[12] K. Hoberg, R. J. Bradley , and U. W. Thonemann. "Analyzing the effect of the inventory policy on order and inventory variability with linear control theory." European Journal of Operational Research, vol. 176, no 3, 2007, pp. 1620-1642.

[13] D. L. Iglehart. "Optimality of (s, S) policies in the infinite horizon dynamic inventory problem." Management science, 9 (2): 1963, pp. 259–267.

[14] D. Ivanov, and A.Dolgui, and B. Sokolov. "Applicability of optimal control theory to adaptive supply chain planning and scheduling." Annual Reviews in control, vol 36 (1), 2012. pp. 73–84.

[15] C. Join, J. Bernier, S. Mottelet, M. Fliess, S. Rechdaoui-Guérin, and S. Azimi, and V. Rocher. "A simple and efficient feedback control strategy for wastewater denitrification." IFAC-PapersOnLine, 2017. arXiv preprint arXiv:1703.05278.

[16] C. Join, H. Abouaissa, and M. Fliess. "Ramp metering: modeling, simulations and control issues." arXiv preprint arXiv:2111.06610, 2021.

[17] K. G. Kempf. "Control-oriented approaches to supply chain management in semiconductor manufacturing." American Control Conference, 2004. Proceedings of the 2004, 5 : 4563-4576.

[18] H. Koussaila and H. Abouaïssa, G. Goncalves, and T. Hsu. "Real-Time decentralized flatness-based control of dynamic supply chain systems." IEEE - International Conference on Control, Decision and Information Technologies (CoDIT)'16, 2016. pp. 607–612.

[19] H. Koussaila, H. Abouaïssa, G. Goncalves, and T. Hsu. "Nonlinear inventory levels control of dynamic supply chain systems." 3rd International Conference on Green Supply Chain, 2016, London UK.

[20] H. Koussaila, M. Fliess, C. Join and H. Abouaïssa. "Bullwhip effect attenuation in supply chain management via control-theoretic tools and short-term forecasts: A preliminary study with an application to perishable inventories". 6th International Conference on Control, Decision and Information Technologies, CoDIT 2019, Apr 2019, Paris, France.

[21] A. Rodríguez-Angeles, D. América Morales, and A. Sánchez. "Dynamic Analysis and Control of Supply Chain Systems." Supply Chain the Way to Flat Organisation. IntechOpen, 2009.

[22] X. MA, R. Rossi, and T. Archibald. "Stochastic inventory control: A literature review." IFAC-PapersOnLine, vol. 52, no 13, 2019, pp. 1490-1495.

[23] C.Salcedo, A. G. Hernandez, A. I. Vilanova, and J. H. Cuartas. "Inventory control of supply chains: Mitigating the bullwhip effect by centralized and decentralized Internal Model Control approaches." European Journal of Operational Research, vol. 224, no 2, 2013, pp. 261-272.

[24] H. Sarjoughian, D. Huang, G. W. Godding, W. Wang, D. E. Rivera, K. G. Kempf, and H. D. Mittelmann. " Hybrid discrete event simulation with model predictive control for semiconductor supply-chain manufacturing." In IEEE Proceedings of the Winter Simulation Conference, 2005, pp. 11.

[25] J. D. Schwartz, and D. E. Rivera. "A process control approach to tactical inventory management in production-inventory systems." International Journal of Production Economics, 125 (1): 2010, pp.111–124.

[26] J. D. Schwartz, W. Wang, and D. E. Rivera. "Simulation-based optimization of process control policies for inventory management in supply chains." Automatica, vol. 42, no. 8, 2006, pp. 1311-1320.

[27] W. Wang, D. E. Rivera, and K. G. Kempf, and K. D. Smith. "A model predictive control strategy for supply chain management in semiconductor manufacturing under uncertainty." American Control Conference. Proceedings of the 2004, 5 : pp. 4577-4582.

[28] Q. Wang, J. Wu, N. Zha, and Q. Zhu. Inventory control and supply chain management : A green growth perspective. Resources, Conservation and Recycling, vol. 145, 2019, pp. 78-85.

[29] A.S. White. "Management of inventory using control theory." International Journal of Technology Management, 17 (7-8), 1999, pp. 847–860.