Journal of Zhejiang University-SCIENCE C (Computers & Electronics)
ISSN 1869-1951 (Print); ISSN 1869-196X (Online)
www.zju.edu.cn/jzus; www.springerlink.com
E-mail: jzus@zju.edu.cn

Model predictive control with an on-line identification model of a supply chain unit*

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Received May 11, 2009; Revision accepted Oct. 19, 2009; Crosschecked Mar. 29, 2010

Abstract: A model predictive controller was designed in this study for a single supply chain unit. A demand model was described using an autoregressive integrated moving average (ARIMA) model, one that is identified on-line to forecast the future demand. Feedback was used to modify the demand prediction, and profit was chosen as the control objective. To imitate reality, the purchase price was assumed to be a piecewise linear form, whereby the control objective became a nonlinear problem. In addition, a genetic algorithm was introduced to solve the problem. Constraints were put on the predictive inventory to control the inventory fluctuation, that is, the bullwhip effect was controllable. The model predictive control (MPC) method was compared with the order-up-to-level (OUL) method in simulations. The results revealed that using the MPC method can result in more profit and make the bullwhip effect controllable.

Key words: Supply chain, Model predictive control, On-line identification, Optimization with constraint, Piecewise linear price
doi:10.1631/jzus.C0910270 **Document code:** A **CLC number:** TP29; C939

1 Introduction

A supply chain is defined as an integrated process wherein a number of various business entities (i.e., suppliers, manufacturers, distributors, and retailers) work together in an effort to: (1) acquire raw materials; (2) convert these raw materials into specified final products; and, (3) deliver these final products to retailers (Beamon, 1998). During the past few years, increasing interest has been attracted by application of control algorithms, especially model predictive control (MPC) to the supply chain management (SCM) (Min and Zhou, 2002; Sarimveis *et al*., 2008). The ordering can be adjusted according to the future demands that the MPC predicts. Lin *et al*. (2004) applied *z*-transform to the SCM, and converted the SCM into a discrete transfer function model. They finally designed a proportional-integral (PI) controller and analyzed the stability of the system. With the determined control structure, SCM can be extended to the frequency domain and be applied to some classic control analysis methods. But the SCM is not exactly the same as the classic control system, and it comprises a series of units such as plants, warehouse, retailers, etc, with each unit having its own economic objective. While the demand is stochastic, a determined model may not reflect this characteristic sufficiently. Perea-López *et al*. (2003) proposed an SCM model from raw material suppliers to consumers based on various reasonable hypotheses, and analyzed each unit on the supply chain, putting forward an overall objective function for the MPC. Wang *et al*. (2007) and Wang and Rivera (2008) focused on the semiconductor manufacturing SCM, and designed filers in the MPC based on the characteristics of the semiconductor manufacturing process. Beyond this research considering SCM with a holistic objective, others have focused on the decentralized objectives of the units in the supply chain (SC). Lin *et al*. (2005),

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* Project supported by the National Natural Science Foundation of China (Nos. 60804023, 60934007, and 60974007), and the National Basic Research Program (973) of China (No. 2009CB320603)

for example, compared the PI control method and the minimum variance controller (MVC) for a single unit of the SC, and concluded that the MVC method could readily restrain the bullwhip effect.

The whole SCM is, as stated, driven by the stochastic demand. In general, the demand is analyzed as a time series. Box *et al*. (1978) introduced the time series in detail. The demand was described therein as a series of white noise filtered by an autoregressive integrated moving average (ARIMA) model. The ARIMA model was determined by the past experience (Erdogdu, 2007; Niu *et al*., 2007). But the variety of demand is so complicated that one fixed model may not forecast the demand very well. Motivated by research on the adaptive disturbance prediction about process engineering (Ohshima *et al*., 1995; Pannocchia and Rawlings, 2003; Han *et al*., 2008), we adopted an on-line disturbance model identification. At each control step, a new demand model is identified to predict the future demand.

An optimal objective function of the MPC method should reflect the relationship between the manipulated variables and the controlled variables. Due to the inheritance of the MPC algorithm (Morari and Lee, 1999; Maciejowski, 2002), an objective function usually has a quadratic form (Lin *et al*., 2005; Wang *et al*., 2007), and the objective is to maintain the inventory and minimize the change of order. However, each unit in the SC aims at a maximal profit. The quadratic objective which seeks a stable process may not simultaneously achieve a maximal profit. Therefore, some researchers have taken the economic objective (usually linear) as the objective of the MPC (Perea- López *et al*., 2003; Seferlis and Giannelos, 2004). Since the inventory may fluctuate tempestuously in this way, the bullwhip effect may be readily identified.

In this study, we focused on a single unit of the SCM, and put forward an MPC algorithm based on the demand model which was identified at each control step. The MPC algorithm made a compromise between the profit and bullwhip effect.

2 Model description

Based on the assumption that an upstream unit can always satisfy the unit discussed, two models should be considered: the inventory model to maintain the balance of material and information, and the demand model to forecast the future demand.

2.1 Inventory model

To simplify, let the unit have a form of a distributor or retailer. The revenue comes from the downstream unit. The cost comprises the purchase from the upstream unit and the stock. It is assumed here that there is no other cost in the unit. The profit comes from the difference between revenue and cost. Let $I(t)$ be the inventory of the unit at an instant time t, $M_{in}(t)$ be the incoming material amount, and $M_{out}(t)$ be the material amount that the unit can offer to the downstream unit. Then the inventory balance can be derived:

$$I(t+1)=I(t)+M_{in}(t)-M_{out}(t). \tag{1}$$

Let O_{in} be the order that the unit applies to its upstream unit, and O_{out} be the order of demands from its downstream unit. If one assumes that there is always enough stock in the upstream unit, and that the demand is stochastic, the relationship of the unit with the upstream unit can be expressed as

$$M_{in}(t+L)=O_{in}(t), \tag{2}$$

where L is the delay time between the order and the material. And the relationship of the unit with the downstream unit is

$$M_{out}(t)=\begin{cases} O_{out}(t), \text{ if } I(t)+M_{in}(t)\geq O_{out}(t), \\ I(t)+M_{in}(t), \text{ if } I(t)+M_{in}(t)< O_{out}(t), \end{cases} \tag{3}$$

which can be regarded as a hard constraint. The unit can do its best to satisfy the downstream unit, but if there is insufficient stock for the demand, it can offer all of its stock only to the downstream unit (the inventory cannot be negative).

Let P_{in} be the purchase price, P_{out} the price for the downstream unit, and P_{stock} the stock price. To imitate a real market process, we assume that P_{in} varies with the order amount and has a piecewise relationship with the order amount. Let C_{pur} be the cost of purchase and it can be expressed as

$$C_{\text{pur}}(t) = \begin{cases} P_1 O_{\text{in}}(t), \text{ if } 0 < O_{\text{in}}(t) \le O_1, \\ P_1 O_1 + P_2 \left(O_{\text{in}}(t) - O_1\right), \text{ if } O_1 < O_{\text{in}}(t) \le O_2, \\ \vdots \\ \sum_{i=1}^{n-1} P_i O_i + P_n \left(O_{\text{in}}(t) - O_{n-1}\right), \text{ if } O_{n-1} < O_{\text{in}}(t) \le O_n, \end{cases} \tag{4}$$

where P_i are the values of purchase price P_{in} according to different orderings, and O_i are the bounds of ordering.

Let $R(t)$ be the revenue which is a product of P_{out} and $O_{\text{out}}(t)$. This can be expressed by Eq. (5). We assume that P_{out} is always a constant.

$$R(t)=P_{\text{out}}O_{\text{out}}(t). \tag{5}$$

Let C_{stock} be the stock cost, and assume that P_{stock} has a linear relationship with the amount of stock. Then C_{stock} can be expressed as

$$C_{\text{stock}}(t)=P_{\text{stock}}I(t). \tag{6}$$

Therefore, the profit of the unit at an instant time t is

$$J_{\text{profit}}(t)=R(t)-C_{\text{pur}}(t)-C_{\text{stock}}(t). \tag{7}$$

The objective for one single unit in the SC is usually the maximal profit, while satisfaction of the downstream unit should also be considered simultaneously. One finds that $O_{\text{in}}(t)$ is the only manipulate variable and $O_{\text{out}}(t)$ is a stochastic disturbance. In order to achieve the objective, a demand model for forecasting $O_{\text{out}}(t)$ should next be considered.

2.2 Demand model

Box *et al.* (1978) first presented a time series forecasting model: ARIMA model. Erdogdu (2007) used the ARIMA model to forecast the electricity demand of Turkey, and the results showed that the ARIMA model was an effect-forecasting model. Niu and Qian (2007) applied the ARIMA model to the semiconductor demand prediction. Here the demand forecasting model is chosen as

$$O_{\text{out}}(z) = \frac{\Theta(z^{-1})}{\Phi(z^{-1})\Delta^r}\xi(z) + \mu, \tag{8}$$

where $\xi(z)$ is white noise with a mean of zero and unity variance, $\Theta(z^{-1})$ and $\Phi(z^{-1})$ are polynomials of z^{-1}, and Δ^r is an integrated term. If r=0, the demand is stationary; if r>0, the demand is nonstationary because the demand cannot have a fixed mean value. μ is a mean value when demand is stationary, and is a reference value when the demand is nonstationary. Chu (2008) further analyzed the demand, and divided the demand time series into three memory types: long memory, short memory, and no memory. The long memory series corresponds to the integrated term corresponding to Δ^r in Eq. (8), the short memory series corresponding to $\Phi(z^{-1})$ in Eq. (8), while the no memory series is white noise. Based on this approach, one can correct the prediction by feedback and design a model predictive controller based on the demand model. At each control step, one chooses proper orders for $\Theta(z^{-1})$, $\Phi(z^{-1})$, and Δ^r to identify the demand model.

3 Model predictive control with an on-line identification model

Model predictive control (MPC) is a control algorithm that solves a discrete time optimal control problem which maximizes an objective function as it designs the optimal control laws for a system (Camacho and Bordons, 1995). The MPC is considered to be the only advanced control technique that has had a significant and widespread impact on industrial process control, because it is the only generic control technology which can deal routinely with equipment and safety constraints (Maciejowski, 2002). The MPC can be regarded as having three parts: model prediction, feedback correction, and rolling horizon optimization (Maciejowski, 2002; Qian *et al.*, 2007). In process control, the objective is usually to maintain a steady process. Thus, the objective function is usually of a quadratic form to minimize the error from the set point. Including this characteristic, Lin *et al*. (2004) and Wang *et al*. (2007) adopted a method of maintaining the inventory at a certain level, and chose steady inventory as the control objective. The real aim of a single unit, however, is the maximal profit. Maintaining the inventory is simply a means of avoiding stock deficiency. Therefore, we take the maximal profit as the control object, and design an

MPC algorithm based on the demand model, and choose the inventory as the constraints. As the demand dynamic characteristics may be so complex that one fixed model may not forecast very well, we take advantage of the research on on-line identification disturbance model (Ohshima *et al*., 1995; Pannocchia and Rawlings, 2003; Han *et al*., 2008), and identified the demand model at each control step.

3.1 Model prediction

Based on the demand forecast model expressed by Eq. (8), we predict the demand in the future. From Eq. (8), we find that

$$O_{\text{out}}(t)=\sum\nolimits_{i=1}^{n}a_iO_{\text{out}}(t-i)+\sum\nolimits_{j=0}^{m}b_j\xi(t-j)+\mu, \quad (9)$$

where $\sum\nolimits_{i=1}^{n}a_iO_{\text{out}}(t-i)$ is the memory type term determined by $\Phi(z^{-1})\Delta^r$ in Eq. (8), and $\sum\nolimits_{j=0}^{m}b_j\xi(t-j)$ is the no-memory type term determined by $\Theta(z^{-1})$ in Eq. (8). So the prediction is

$$\hat{O}_{\text{out}}(t+P\,|\,t)=\sum\nolimits_{i=P}^{N}a_iO_{\text{out}}(t+P-i) +\sum\nolimits_{i=1}^{P-1}a_i\hat{O}_{\text{out}}(t+P-i\,|\,t)+\sum\nolimits_{j=0}^{m}b_j\xi(t+P-j)+\mu. \quad (10)$$

According to Box *et al.* (1978), $\xi(t+P-j)$ is set to be zero when $P>j$. $\sum\nolimits_{i=P}^{N}a_iO_{\text{out}}(t+P-i)$ is the memory term, $\sum\nolimits_{j=0}^{m}b_j\xi(t+P-j)$ is the no-memory term, and $\sum\nolimits_{i=1}^{P-1}a_i\hat{O}_{\text{out}}(t+P-i\,|\,t)$ is influenced both by the memory term and by the no-memory term. The prediction is mostly determined by the memory term when the prediction horizon is relatively small. But the prediction turns stochastic with a larger prediction horizon, because the no-memory term is stochastic. So unlike the commonly held 'the longer prediction the better' dictum in process control, the prediction horizon should not be too long, while the prediction should be corrected at each control step by feedback.

3.2 Feedback correction

Feedback can help to correct the prediction, because the no-memory term increases the uncertainty. One can see that

$$\sum_{i=P}^{N}a_iO_{\text{out}}(t+P-i)=\sum_{i=P+1}^{N}a_iO_{\text{out}}(t+P-i)+a_PO_{\text{out}}(t). \quad (11)$$

The memory term comprises the current and the past values (we use the error between the current value and prediction value of the last moment to improve the prediction). Let

$$\boldsymbol{e}(t)=\boldsymbol{O}_{\text{out}}(t)-\hat{\boldsymbol{O}}_{\text{out}}(t\,|\,t-1), \quad (12)$$

where $\boldsymbol{O}_{\text{out}}(t)$ is the real demand, and $\hat{\boldsymbol{O}}_{\text{out}}(t\,|\,t-1)$ is the prediction demand. We give the error a weight vector $\boldsymbol{H}$ to modify the prediction.

$$\boldsymbol{O}_{\text{cor}}(t)=\hat{\boldsymbol{O}}_{\text{out}}(t)+\boldsymbol{He}(t), \quad (13)$$

where $\hat{\boldsymbol{O}}_{\text{out}}(t)=\begin{bmatrix}O_{\text{out}}(t+1\,|\,t)\\ O_{\text{out}}(t+2\,|\,t)\\ \vdots\\ O_{\text{out}}(t+P\,|\,t)\end{bmatrix}$, and $\boldsymbol{O}_{\text{cor}}(t)$ is the modified prediction.

3.3 The objective

We directly use the predictive maximal profit as the objective exactly as discussed in Eq. (7).

$$J_{\text{profit}}=\sum_{i=1}^{P}R(t+i\,|\,t)-\sum_{i=1}^{P}C_{\text{pur}}(t+i\,|\,t)-\sum_{i=1}^{P}C_{\text{stock}}(t+i\,|\,t), \quad (14)$$

where

$R(t+i\,|\,t)=P_{\text{out}}\hat{O}_{\text{out}}(t+i\,|\,t)$,

$C_{\text{stock}}(t+i|t)=P_{\text{stock}}I(t+i|t)$, $i=1, 2, \ldots, P$,

$$C_{\text{pur}}(t+i\,|\,t)=\begin{cases}P_1\hat{O}_{\text{in}}(t+i\,|\,t), \text{ if } 0<\hat{O}_{\text{in}}(t+i\,|\,t)\le O_1,\\ P_1O_1+P_2(\hat{O}_{\text{in}}(t+i\,|\,t)-\hat{O}_1), \text{ if } O_1<\hat{O}_{\text{in}}(t+i\,|\,t)\le O_2,\\ \vdots\\ \sum_{i=1}^{n-1}P_iO_i+P_n(\hat{O}_{\text{in}}(t+i\,|\,t)-\hat{O}_{n-1}), \text{ if } O_{n-1}<\hat{O}_{\text{in}}(t+i\,|\,t).\end{cases}$$

To avoid acute fluctuation, we take the inventory model as the soft constraint. We set the maximal and the minimal constraints for the predictive inventory. That is

$$I_{\min}<I(t+i|t)<I_{\max},\ i=1, 2, \ldots, P. \quad (15)$$

Because O_{out} is stochastic, the constraint is just for the predictive vectors. But in fact the solution may break the constraint. This constraint can help to weaken the fluctuation. Because C_{pur} is piecewise linear, the objective function is not a standard linear programming question. Therefore, we use an intelligent algorithm such as GA to solve this question.

3.4 On-line demand model identification

We first estimate the order of integrate term $\varDelta^r$, and obtain the ARMA model of Eq. (8),

$$\Delta O_{\text{out}}(z)=\frac{\Theta(z^{-1})}{\Phi(z^{-1})}\xi(z), \quad (16)$$

where $\Delta O_{\text{out}}(z)$ is n-order difference of $O_{\text{out}}(z)$. Eq. (16) can be expressed as

$$\Phi(z^{-1})y(t)=\Theta(z^{-1})\xi(t), \quad (17)$$

where $y(t)=\Delta O_{\text{out}}(z)$, $\Phi(z^{-1})=1+a_1z^{-1}+\ldots+a_{n_a}z^{-n_a}$, $\Theta(z^{-1})=1+c_1z^{-1}+\ldots+c_{n_c}z^{-n_c}$. Then we use the method mentioned in (Han *et al*., 2008), and obtain the estimation of $\Phi(z^{-1})$ and $\Theta(z^{-1})$. The method is expressed as

$$y(t)=\boldsymbol{\theta}^{\text{T}}\boldsymbol{\phi}(t)+\xi(t), \quad (18)$$

$$\varepsilon(t)=y(t)-\hat{\boldsymbol{\theta}}^{\text{T}}(t-1)\boldsymbol{\phi}(t), \quad (19)$$

$$\hat{\boldsymbol{\theta}}(t)=\hat{\boldsymbol{\theta}}(t-N)+r(t)R^{-1}(t)\boldsymbol{\phi}_N(t)\varepsilon_N(t), \quad (20)$$

$$R(t)=R(t-1)+r(t)[\boldsymbol{\phi}(t)\boldsymbol{\phi}^{\text{T}}(t)-R(t-1)], \quad (21)$$

$$R(t)=\begin{cases}R(t),\ R(t)>\delta I,\\ R(t)+M\delta(t),\ \text{else},\end{cases} \quad (22)$$

$$\bar{\varepsilon}(t)=\hat{y}(t)-\hat{\boldsymbol{\theta}}^{\text{T}}(t)\boldsymbol{\phi}(t), \quad (23)$$

where $\hat{\boldsymbol{\theta}}$ is the estimation of $\boldsymbol{\theta}$, $\hat{y}$ is the estimation of y, $\boldsymbol{\theta}=[a_1,\cdots,a_{n_a},c_1,\cdots,c_{n_c}]^{\text{T}}$, $\boldsymbol{\phi}(t)=[-y(t-1),\cdots,-y(t-n_a),\xi(t-1),\cdots,\xi(t-n_c)]^{\text{T}}$,
$R(t)=\frac{1}{t}\sum_{k=1}^{t}\boldsymbol{\phi}(k)\boldsymbol{\phi}^{\text{T}}(k)$, $\bar{\varepsilon}(t)=\hat{y}(t|\boldsymbol{\theta})-\hat{\boldsymbol{\theta}}^{\text{T}}\boldsymbol{\phi}(t)$.

4 Case study

Comparisons between the method mentioned above and the order-up-to-level (OUL) control method are presented. The OUL method can be expressed by

$$O_{\text{in}}(t)=I_{\text{sp}}-I(t), \quad (24)$$

where I_{sp} is the set inventory and $I(t)$ is the real inventory. The real demand is generated by

$$O_{\text{out}}(t)=\frac{1+0.7z^{-1}}{1-0.6z^{-1}}\xi(t)+100+\varepsilon, \quad (25)$$

where ε is a random number between −0.1 and 0.1, and the time unit is a day. This means that the demand amount fluctuates around 100. The purchase cost is expressed by

$$C_{\text{pur}}(t)=\begin{cases}10O_{\text{in}}(t),\ 0<O_{\text{in}}(t)\le 100,\\ 1000+8(O_{\text{in}}(t)-100),\ O_{\text{in}}(t)>100.\end{cases} \quad (26)$$

Let P_{stock}=0.7. In order to compare with the OUL method, we assumed that the two methods have the same average inventory, that is

$$I(t)+O_{\text{in}}(t-1)-O_{\text{out}}(t)=(I_{\max}+I_{\min})/2, \quad (27)$$

where the expectations of $I(t)$ and $I(t-1)$ are the same, and the expectation of $O_{\text{out}}(t)$ is 100. Combined with Eq. (16),

$$I_{\text{sp}}=(I_{\max}+I_{\min})/2+100. \quad (28)$$

A simulation corresponding to a demand sequence of 100 days was carried out. We compared the MPC method with the OUL method, adopting different predictive horizons, lists of the maximum inventory (MaI), the minimum inventory (MiI), and average inventories (AI) in the conditions of P_{out}=15 and P_{out}=12 in Table 1 when $I_{\max}$=320, $I_{\min}$=280 and $I_{\max}$=350, $I_{\min}$=250.

Because the purchase price is piecewise linear, fluctuant inventory can take advantage of the characteristic and achieve more profit. Table 1 shows that the inventory of the OUL method is more stable than

Table 1 Inventories of the MPC method (P=1, 2, …, 9) and the OUL method

Method	MaI		MiI		AI	
	I_{max}=320, I_{min}=280	I_{max}=350, I_{min}=250	I_{max}=320, I_{min}=280	I_{max}=350, I_{min}=250	I_{max}=320, I_{min}=280	I_{max}=350, I_{min}=250
MPC						
P=1	302.4	272.1	280.2	302.4	242.1	250.5
P=2	324.8	272.1	299.4	354.8	248.0	298.1
P=3	323.8	276.6	301.2	353.7	245.4	302.5
P=4	323.3	276.6	297.8	353.8	246.6	297.2
P=5	322.9	276.6	295.7	353.1	247.7	291.5
P=6	323.8	276.9	296.9	352.0	247.1	289.9
P=7	324.8	278.6	297.0	352.9	249.0	294.2
P=8	323.4	275.4	296.6	354.6	247.9	295.1
P=9	323.7	272.2	293.5	352.1	246.5	286.5
OUL	304.6	295.9	300.0	304.6	295.9	300.0

MaI: the maximum inventory; MiI: the minimum inventory; AI: average inventory. MPC: model predictive control method; OUL: order-up-to-level method

that of the MPC method, but the inventory of the MPC method can be controlled in a certain range by the constraints which, in turn, make the bullwhip effect controllable. Moreover, using the MPC method can increase the profit more than using the OUL method, as shown in Fig. 1. Because of the piecewise linear price of the purchase, the looser inventory constraints correspond to more profit. We can compromise the inventory constraints and the profit in different situations. P_{out} has a great effect on the profit as well. When P_{out} is relatively high, the profits of the MPC with different predictive horizons differ little from these of the OUL method. For example, when P_{out}=15, I_{max}=320, and I_{min}=280 the maximal profit (P=2) is about 12.31% higher than the minimal profit (OUL). Both methods can receive vastly positive profits. However, when P_{out} is relatively low, P_{out}=15, I_{max}=320, and I_{min}=280, the differences between profits can be enlarged. The maximal profit (P=2) is about 10.8 times the second most minimal profit (P=9). As well, the OUL method receives negative profit. The simulation also indicates that using a relatively short predictive horizon can achieve more profit than using a relatively long predictive horizon. When market competitions become increasingly scorching, and P_{out} becomes lower and lower, choosing an effective policy of ordering and inventory management becomes increasingly important.

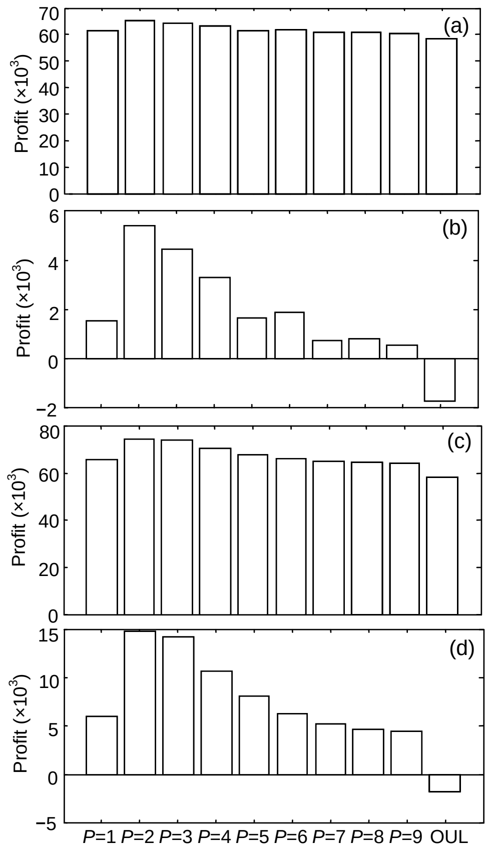

Fig. 1 Profits of the stationary demand
(a) P_{out}=15, I_{max}=320, and I_{min}=280; (b) P_{out}=12, I_{max}=320, and I_{min}=280; (c) P_{out}=15, I_{max}=350, and I_{min}=250; (d) P_{out}=12, I_{max}=350, and I_{min}=250

5 Conclusion

We present an MPC method for a single unit of the supply chain. The demand model is identified on-line. The predictive inventory is used as the constraints for the MPC, which make the inventory fluctuation controllable and allow one to control the bullwhip effect readily. The purchase price is considered piecewise linear, wherein the control objective tune to be a nonlinear programming, which can be solved using the GA algorithm. In the simulations the MPC method was compared with the order-up-to-level (OUL) method, validating that the MPC is an effective method in the supply chain management.

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