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Adaptive fuzzy vendor managed inventory control for mitigating the Bullwhip effect in supply chains

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ABSTRACT

This paper proposes an adaptive fuzzy control application to support a vendor managed inventory (VMI). The methodology applies fuzzy control to generate an adaptive smoothing constant in the forecast method, production and delivery plan to eliminate, for example, the rationing and gaming or the Houlihan effect and the order batching effect or the Burbidge effects and finally the Bullwhip effect. The results show that the adaptive fuzzy VMI control surpasses fuzzy VMI control and traditional VMI in terms of mitigating the Bullwhip effect and lower delivery overshoots and backorders. This paper also guides management in allocating inventory by coordinating suppliers and buyers to ensure minimum inventory levels across a supply chain. Adaptive fuzzy VMI control is the main contribution of this paper.

1. Introduction

The Bullwhip effect is an observed phenomenon whereby a small change in the demand from end customer results in large variations as it goes upstream. Kaipia et al. (2002) identify two sources for the Bullwhip effect: (1) the supplier delivery lead time (actual replenishment cycle) is far longer than the order fulfillment cycle (the buyer production and delivery lead times); and (2) the inventory level of the supplier is higher than the normal requirement of average inventory levels to cover short delivery lead times and high service levels. These two problems cause a supply chain to generate more capacity to the production system and to increase the safety stock, which inevitably leads to unrealistic deliveries, an effect known as the Houlihan effect (Kaipia et al., 2002). Higher production capacity raises the level of production ordering and inventory response (Holweg and Bicheno, 2002), which inevitably requires higher order batching than the actual demand. This phenomenon is also known as the Burbidge Effect (Burbidge, 1991). Consequently, higher levels of production ordering and inventory response causes the sales forces to issue incentives. The incentives attract customers to order more than they actually require (Chen et al., 1998, 2000; O'Donell et al., 2006). Thus, the Bullwhip effect starts moving from downstream to upstream.

The importance of mitigating the Bullwhip effect in the supply chains has been well recognized. Dejonckheere et al. (2003) focus on providing demand information through the forecast methods as a necessary decision for managers (Zhang, 2004). Forrester (1961) and Sterman (1989) show that the absence of demand visibility and the existence of information distortion are sources of excess delays which require supplier and buyer coordination to share the demand information (Holweg and Bicheno, 2002). This coordination improves the quality of demand information and further minimizes the variability of the lead time (Croson and Donohue, 2003; Chatfield et al., 2004). The deficiencies in information sharing and information quality lead to inefficiencies, such as excessive inventories, quality problems, higher raw material costs, overtime expenses, shipping costs, poor customer service and missed production schedules (O'Donell et al., 2006). The mitigation of the Bullwhip effect is also conducive to production and inventory control in that it coordinates production systems and channel reduction so as to reduce lead times (Van Ackere et al., 1993). The key technical challenges of mitigating the Bullwhip effect can be observed as follows.

1.1. Technical challenges

1.1.1. Quality of demand information

The Bullwhip effect can be mitigated by reducing the inventory variance (Dejonckheere et al., 2002, 2003) which is achieved through a non-smoothed demand pattern (Dejonckheere et al., 2004) or a smoothed demand pattern (Yu et al., 2002; Disney and Towill, 2003a) in the forecast method. Disney and Towill (2003b) provide a resolution of these two contradictory approaches by introducing a lean and an agile supply chain as options

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Nomenclature

α	smoothing constant used in forecast, inventory and delivery adjustment
α_a	the fuzzy weight interval of "very low"
α_b	the fuzzy weight interval of "low"
α_c	the fuzzy weight interval of "medium"
α_d	the fuzzy weight interval of "high"
α_e	the fuzzy weight interval of "very high"
α_f	forecasting constant used in exponential smoothing forecast $\alpha_f = 1/(1+T_f)$
α_i	smoothing constant used in inventory response $\alpha_i = 1/(1+T_i)$
α_W	smoothing constant used in WIP inventory response $\alpha_W = 1/(1+T_W)$
α_q	smoothing constant used in order response $\alpha_q = 1/(1+T_q)$
α^*	the final smoothing constant
B	the magnitude of the Bullwhip effect
$BO(t)$	backorders at time t
C_{crisp}	crisp numbers for comparison or ranking purposes
δ	demand change
D	demand
$D(t)$	demand at time t
Δ	set of $\Delta \in (\varepsilon, \delta, \Omega)$
$\varepsilon_n(t)$	forecast error $\varepsilon_n(t) = D(t) - F(t)$
F	Fischer distribution
$f(\alpha)$	the fuzzy membership weight
$f(\alpha_a)$	the fuzzy membership weight of "very low"
$f(\alpha_b)$	the fuzzy membership weight of "low"
$f(\alpha_c)$	the fuzzy membership weight of "medium"
$f(\alpha_d)$	the fuzzy membership weight of "high"
$f(\alpha_e)$	the fuzzy membership weight of "very high"
$f(\alpha)_{LE}$	the fuzzy membership weight of "Lower Expectation"
$f(\alpha)_{MA}$	the fuzzy membership weight of "Most Acceptable"
$f(\alpha)_{HE}$	the fuzzy membership weight of "Higher Expectation"
F	demand forecast
$F(t)$	demand forecast at time t
Φ_W	the difference between $WIP_n(t)$ and demand $D(t)$
Φ_i	the difference between $I_n(t)$ and $D(t)$
Φ_q	the difference between $q_n(t)$ and $D(t)$, Φ_q
$\Delta I_n(t)$	the required change of product inventory at stage n at time t
$I_n(t)$	product inventory at stage n and time t
K	production capacity
K_n	production capacity at stage n
λ	mean value of demand
L	replenishment time
L_d	delivery lead time
L_p	production lead time
$\mu_n(t)$	production rate at time t at stage n
n	stage or echelon of the supply chain
Ω	offset that is a set of $\Omega \in (\Phi_W, \Phi_i, \Phi_q)$
OUT	order-up-to
P-value	The significance value of F distribution
$\sigma(t)$	demand volatility at time t
T_f	average age of exponential smoothing forecast
T_i	time to adjust for product inventory
T_w	time to adjust for WIP inventory
T_q	time to adjust for order
VMI	vendor managed inventory
V_{out}	order variability at stage n
V_{in}	demand variability at stage n
WIP	work-in-progress
$WIP_n(t+L_{d(n)})$	work-in-progress at time $t+L_d$ at stage n
$\Delta WIP_n(t)$	the required change of work-in-progress at stage n at time t

to set the gain on exponential forecasting. However, either lean or agile parameter setting always gives a considerable order up to (OUT) response overshoot, which potentially generates the Bullwhip effect at longer upstream lead times.

Carlsson and Fuller (2000) give the name 'overshoot' to the result of non-stationary demand which raises the non-stationary ordering up to the required quantity of the product for meeting the current demand, which is starting the Bullwhip effect at longer delivery lead times, and furthermore, motivates the Houlihan effect. Fuzzy logic is then applied to find the accurate demand forecast (Zarandi et al., 2008) and OUT level in the distribution supply chains (Wang and Shu, 2005; Petrovic et al., 2008), by developing adaptive fuzzy forecasts to learn about the demand changes (Petrovic et al., 2006; Balan et al., 2009) and to replenish the inventory appropriately by using an adaptive replenishment rule (Petrovic and Petrovic, 2001). In addition, fuzzy forecasts with a learning mechanism is applied by combining the customer and expert forecasts to predict future demand and establish the confidence associated with each of the forecasts (Petrovic et al., 2006). The technical challenge here is to provide higher quality information about the demand by analyzing multiple criteria (demand changes, forecast error, inventory availability, etc.) so as to minimize the overshoot of the OUT level response (Carlsson and Fuller, 2000, 2002; Balan et al., 2009).

1.1.2. Production and distribution coordination

Poor quality demand information leads to poor production and distribution performance. Some contributions withstand this deficiency by proposing a two-level coordinated inventory control within an integrative supply chain to reduce the ambiguity in fuzzy demands (Yu et al., 2002; Xie et al., 2004). Lin et al. (2010) apply fuzzy arithmetic operations in a VMI supply chain with fuzzy demands. The application pays attention to the ordering process and controlling the buyer's target inventory level. Some of the previous contributions (i.e., Petrovic and Petrovic, 2001; Giannoccaro et al., 2003; Zarandi et al., 2008); Aliev et al. (2007) have applied fuzzy control in the distribution chain. Aliev et al. (2007) optimize the fuzzy aggregate planning of production and distribution by holding the inventory in the distribution units without allowing an inventory allocation in the production units. The contributions pointed out above mention that there are close links between production and distribution which demands the co-ordination of production and distribution operations in supply chain systems. Inventory allocation covers not only the production and distribution planning, but also production systems and paradigms, such as making to order, assembling to order or making to stock (Wikner et al., 2007; Sheu, 2005). It is possible to mitigate the Bullwhip effect by cutting down the number of stockholding points and satisfying customer demands through different production systems.

1.1.3. Supplier buyer coordination

Poor quality demand information motivates either the supplier or the buyer to behave opportunistically. This situation resembles a two-stage Stackelberg game in fuzzy demands (Xie et al., 2004). The central demands forecast system (McCullen and Towill, 2000), as first mover, issues information about the demands forecast to the supply chain (Chen et al., 1998). The buyer and the supplier, acting as the second movers, after analyzing the acts of the first mover can play according to either a cooperative or a non -cooperative strategy. The technical challenge here is to provide an optimal response to maximize the second mover benefits. In a decentralized supply chain, information sharing promises an optimal response to demand forecasts (Croson and Donohue, 2003). Thus, information sharing should be available in each supply chain facility to minimize the imprecision of the demand information (Kumar et al., 2004; Chan and Kumar, 2007).

1.2. Strategy for a solution

While coordinating the production and distribution provides a viable solution to reduce the imprecision of the demand signal and to minimize inventory investment (Thonemann, 2002), autonomy among facilities must be maintained to attract the coordination of supplier and buyer. Maintaining autonomous coordination assumes that the customer demand information which is imposed on the end-product inventory is unknown to other facilities in the supply chain. The suppliers have to have autonomy to decide how much to deliver, based on their delivery capacity and how much to produce, based on their production capacity. Thus, at each stage within a supply chain, the facilities for processing work-in-process (WIP) and raw materials receive a centralized demand forecast of what the customer will want in order to properly plan the delivery time and quantities, the inventory adjustment time, the OUT level, and the demand response time (Towill and Disney, 2003; Wikner et al., 2007).

In the context of non-stationary demand, the demand forecast errors at all stages are modeled as a fuzzy set (Petrovic et al., 2006). A fuzzy set is applied by considering that the supply chain dynamics are nonlinear (i.e., the production response is based not only on the offset values between the actual demand and a demand forecast, but also the current production rate), in which fuzzy control seems to be an interesting alternative. Previous genetic algorithm based on the fuzzy VMI control (Lin et al., 2010) look to the optimum non-adaptive fuzzy VMI parameters for controlling nonlinear supply chain dynamics at a certain desired service level. However, it is often difficult in practice to assess service levels for an external customer. Managers seem comfortable with the notion of a 100% service level for some ranges of demand; if the demand exceeds the production capacity and available stock, they will have shortages, unless they can backorder the demand to the next period. Adaptive fuzzy VMI control can always provide 100% service levels by adaptively responding to the demand changes according to production capacity, available stock and shortages.

The rest of the paper proceeds as follows. Section 2 reviews the literature on the fuzzy logic in VMI. Section 3 focuses on the features of supply chain simulation, mainly aiming at mitigating the Bullwhip effect and allocating safety stock and it concludes by applying the VMI to mitigate the Bullwhip effect and the loss of sales by minimizing the safety inventory. Section 4 simulates the supply chain model in the previous section. Section 5 analyses the results of the simulation and finally Sections 6 and 7 suggest some managerial implications and draw a conclusion and future research directions.

2. Related work

The application of fuzzy sets to coordinated supply chains is divided into five areas, namely, inventory management, vendor selecting, transport planning, the planning of production distribution and the planning of procurement, production and distribution (Peidro et al., 2009). Mitigating the Bullwhip effect is the focus area of inventory management (Carlsson and Fuller, 2000). Selecting vendors optimally provides more demand-responsive supply chain in terms of quality, service and cost (Kumar et al., 2004; Chan and Kumar, 2007; Amid et al., 2006, 2009). Minimizing transportation cost is an application of fuzzy sets in transportation problems (Chanas and Kuchta, 1998; Jimenez and Verdegay, 1999). Furthermore, Sakawa et al. (2001) extend the previous application of fuzzy set to a transportation problem to a fuzzy transportation and production problem. Liang (2008) optimizes the production-distribution planning decisions by finding the production, inventory and distribution levels at minimum total cost and total delivery times. Torabi and Hassini (2009) exclude the procurement and distribution lead times from procurement, production and distribution planning. The contributions pointed out above assume that supply chains are non-autonomous and fully integrated with a single decision-maker (Peidro et al., 2009; Chanas and Kuchta, 1998; Jimenez and Verdegay, 1999).

Applying fuzzy sets to the coordinated and autonomous supply chains are challenging since the facilities in a supply chains (i.e., downstream, intermediate and upstream) do not need to share their operations data (production capacity, delivery capacity, material order and maximum allowable inventory level). Indeed, the facilities are required to satisfy the demands of the end customer. In most contexts, this option seems realistic, since each facility can optimize its own goal. VMI is then widely applied, not only to provide more accurate forecasting, but also to provide better logistics control by implementing high integrity demand information throughout a supply chains (McCullen and Towill, 2000). Moreover, fuzzy sets are introduced to avoid imprecise deliveries, orders and demands within supply chains and they outperform traditional VMI in terms of Bullwhip effect and inventory reductions (Lin et al., 2010).

The Bullwhip effect can be modeled as a nonlinear dynamic system which receives inputs from offset values between actual demands and demand forecasts, available stocks and OUT level, where the relationships between inputs are not linear. Previous non-fuzzy VMI control models use linear dynamic control systems to mitigate the Bullwhip effect by assuming that the supply chain dynamic depends solely on a step input of non-stationary demand changes (Disney and Towill, 2003b; Dejonckheere et al., 2002, 2003). Previous fuzzy VMI controls use a linear relationship between the fuzzy service level and fuzzy responsiveness that does not depend on demand changes and forecast errors (Lin et al., 2010). The proposed adaptive fuzzy VMI control increases the coordination of supplier and buyer in terms of the complexity and reliability of the VMI control.

3. Adaptive fuzzy VMI control

We observe a supply chain with a number of the stockholding points typical of a single-item inventory system, namely, the retailer, downstream, intermediate stream and upstream (see Fig. 1). For stage n, the replenishment time, L_n, which comprises production lead times $L_{p(n)}$ and delivery lead times $L_{d(n)}$ is given by:

$$L_n = L_{p_{(n)}} + L_{d_{(n)}}. \tag{1}$$

We assume that the demand process is non-stationary and stochastic, that the OUT level, production and inventory control policy is adaptive and fuzzy and that any demand not satisfied by the inventory is backordered. Adaptive fuzzy control is used because the demand can differ across periods and the delivery rate will need to change or adapt over time along with demand. In all periods, it must be enough to cover the demand over the upcoming L_n. Below, we describe in more detail the forecast model, production and distribution planning to control inventories and present an analysis of the model. We introduce additional assumptions as needed.

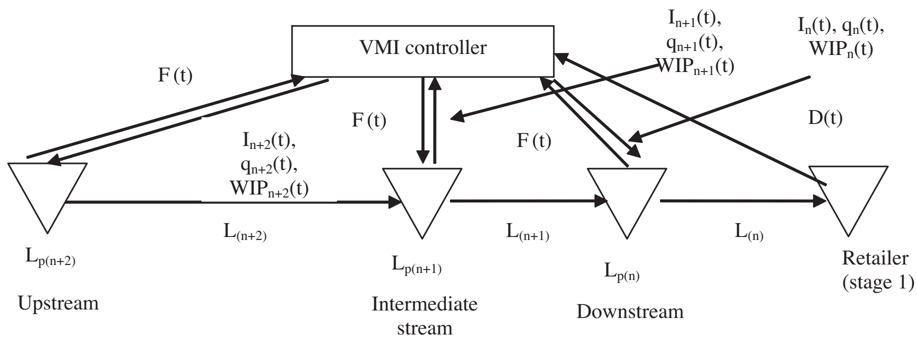

Fig. 1. Overview of VMI scenario (Adapted from Disney and Towill, 2003a).

In presenting the adaptive fuzzy VMI control, the basic concept of VMI can be summarized as in Fig. 1.

In Section 3.1, the downstream forecasts daily the demands for the next day on a daily basis by smoothing the pattern of previous demand. The reason for taking daily forecasts is that it is possible in the middle of the running week for an order to come from the retailers; thus, if the manufacturer does not revise the production plan, then the it will lead to lost sales. With this strategy, the backorders are minimized.

3.1. Forecasting

We use exponential smoothing to estimate future demand. The reason has its roots in the ARIMA-based demand process model (Box et al., 1994; Graves, 1999), in which the forecast demand $F(t)$ at time t and its mean value λ are defined as follows (Graves, 1999):

$$F(1) = \lambda + \varepsilon(t), \tag{2}$$

$$F(t+1) = (1-\alpha_f)F(t) + \alpha_f.D(t) + \varepsilon(t), \tag{3}$$

$$\varepsilon(t) = D(t) - F(t).$$

Eq. (2) shows that the demand forecast, $F(1)$, at time $t = 1$ depends on the mean value of customer demands, λ,and random noise term $\varepsilon(t)$of the time series random variable which represents the forecast error (Graves, 1999). Eq. (3) shows that at the smoothing constant of the forecast method $\alpha_f = 0$, the future demand forecast, $F(t+1)$, depends on the current demand forecast, $F(t)$ and $\varepsilon(t)$. As a result, the demand represents only the stationary process, i.i.d., and normally distributed with the mean value $\lambda$and variance σ^2.Thus the condition which represents the demand process is not serially correlated. When $0 < \alpha_f < 1$, the demand process is a non-stationary process (Graves, 1999) by considering that $F(t+1)$ depends more and more on the most recent realization of demand $D(t)$, as the value of α_f grows (Graves, 1999). When $\alpha_f = 1$, Eq. (3) shows that $F(t+1)$depends on the most recent demand $D(t)$ plus $\varepsilon(t)$.In this case, if the demand process starts at λ, then the demand forecast evolves with each additional successive period, whereby each successive change in the $\varepsilon(t)$is drawn independently from a probability distribution with mean zero and the demand process resembles a random walk (Nelson, 1973). The covariances for the time series of demand and order require the optimum inventory response which is elaborated in Section 3.2.

3.2. Inventory control policy

We assume that in each period t, the observed demand $D(t)$ from period t is used by the adaptive fuzzy VMI control to issue the demand forecast from period t to $t+1$ or $F(t+1)$, determine $\mu_n(t)$ for filling the product inventory in each period $t + L_p(_n)$ and to fill the demand from the product inventory according to $q_n(t)$in each period $t + L_d(_n)$. Any demand that cannot be met from the inventory is backordered. We can formulate the inventory balance equations as shown by the following relations:

$$I_n(t + L_{p(n)}) = I_n(t + L_{p(n)} - 1) + \Delta I_n(t + L_{p(n)}), \tag{4}$$

$$WIP_n(t + L_{d(n)}) = WIP_n(t + L_{d(n)} - 1) + \Delta WIP_n(t + L_{d(n)}), \tag{5}$$

where $I_n(t + L_{p(n)} - 1)$ denotes the stage n on-hand product inventory (or backorders) at the end of period $t + L_{p(n)} - 1$ and $WIP_n(t + L_{d(n)} - 1)$ denotes the stage n WIP inventory at the end of period $t + L_{d(n)} - 1$. The second components are used to adjust the stock level of the product and WIP inventories to accommodate the demand changes, which changes the mean lead time demand so that the adjustment will cover the demand rate at stage n at time t. The WIP inventory comprises the WIP and pipeline (raw material) inventories.

We assume that it is possible to set an initial inventory level $I_n(0)$ and that $F(t) = \lambda$ for $t \leqslant 0$ and furthermore $F(t) \geqslant 0$. We also assume that the lead time to replenish the inventory is known and that any unmet demand is backordered (i.e., there are capacity constraints, K). Each stage is expected to provide 100% service for all demands.

We propose the following rule to perform VMI control:

$$\mu_n(t) = \min[K_n, F(t+1) + \Delta I_n(t) + \Delta WIP_n(t)], \tag{6}$$

$$q_n(t) = \min\left(I_{(n)}(t), F(t+1) + \frac{(D(t) - q_n(t - L_{d(n)}))L_{d(n)}}{T_q}\right), \tag{7}$$

$$\Delta I_n(t) = \frac{(\mu_n(t)^* L_{p(n)}) - (q_n(t)^* L_{d(n)})}{T_i}, \tag{8}$$

$$\Delta WIP_n(t) = \frac{WIP_n(t) - \left(\mu_n(t)^* L_{p_{(n)}}\right)}{T_w}. \tag{9}$$

Eq. (6) represents the production decision in stage n at time t for meeting the forecast demand $F(t+1)$ at time $t+1$ and is limited by the capacity constraint K_n at stage n (the first and second components). The third and fourth components are adjustments to recover the product and component inventories due to the error expressed as $\varepsilon_n(t) = D(t) - F_n(t)$. However, we need to adjust product inventory $\Delta I_n(t)$ and WIP inventory $\Delta WIP_n(t)$ at time $t+1$ whenever $D(t+1) \neq D(t)$ to control the whole inventory by considering the demand changes from t to $t+1$. Inserting Eqs. (7)–(9) into Eq. (6), we have

$$\mu_n(t) = \min\left[K, \frac{F(t+1) - \frac{(q_n(t)^* L_{d(n)})}{T_i} + \frac{I_{WIP(n)}(t)}{T_W}}{1 - L_{p(n)}\left(\frac{T_W - T_i}{T_W T_i}\right)}\right]. \tag{10}$$

In the case of $D(t+1) \neq D(t)$, Eq. (7) is used to make the $q_n(t)$ decision to replenish the demand for the period t and to mitigate the Houlihan effect by dispatching the product according to actual demand $D(t)$ at time t. The OUT decision is also constrained by stock availability as the first component of Eq. (7). The third component of Eq. (7) is used to adjust the delivery rate by minimizing the effect of the previous period over– $q_n(t)$ level $(D(t-1) - q_n(t-1))^-$ or under– $q_n(t)$ level $(D(t-1) - q_n(t-1))^+$. Time to adjust the $q_n(t)$ level T_q (Disney and Towill, 2003a,b, 2004; Towill and Disney, 2003; Dejonckheere et al., 2002, 2003, 2004; Wikner et al., 2007) is used to guarantee market product availability by considering the nature of the demand, where $T_q \approx \infty$ for the stationary demand and the delivery rate depends solely on the demand rate variation. Finally, since Eqs. (6) and (7) are independent, they can mitigate the Burbidge effect by decoupling the production and delivery batch size.

In addition to Eqs. (6) and (7), the product inventory adjustment rate T_i (Eq. (8)) and the WIP inventory adjustment rate T_W (Eq. (9)) are given to fill up the product inventory at time t. The second component represents the delivery rates to stage $n+1$ at time t. In Eq. (9), $WIP_n(t)$ denotes the work-in-process inventory at the end of period t. The first component represents additional material from the material inventory at time t and the last component represents the withdrawal rates for producing the product at stage-n at time t. Eq. (9) suggests that the WIP production facilities will process immediately any available raw materials. However, the application of VMI makes it possible to dispatch raw materials from upstream to downstream by sharing demand information. Thus, excess delivery can be avoided.

In posing the delivery policy in Eq. (7), we allow $\Delta I_{(n)}(t)$ and $\Delta WIP_{(n)}(t)$ in Eqs. (8) and (9) to be negative. This change is realistic in most contexts. Rather, Eqs. (7) and (8) seem reasonable for the case of non-stationary demand in providing the best response to demand without creating excessive stock. The quality of the response depends on the time needed to adjust demand forecasts T_f, T_i, T_W and T_q, which are directly related to the transient behaviour of the stockholding points and deliveries (Towill, 1996) to minimize backorder $BO(t)$ and inventory variance at time t as a VMI performance measure. To explore this relationship further, we employ the commonly used relationship between the smoothing constant $\alpha \in (\alpha_f, \alpha_i, \alpha_W, \alpha_q)$ and T_i, T_W and T_q (Dejonckheere et al., 2003):

$$\alpha_f = \frac{1}{1+T_f}; \quad \alpha_i = \frac{1}{1+T_i}; \quad \alpha_W = \frac{1}{1+T_W}; \quad \alpha_q = \frac{1}{1+T_q}. \tag{11}$$

$$BO(t) = \max(D(t) - q_n(t), 0) \tag{12}$$

The smoothing constant in Eq. (11), however, has a drawback. For instance, Dejonckheere et al. (2003) assume that α depends solely on demand changes, δ. However, a supply chains should consider the forecast error ε, as well as Φ_W, the difference between $WIP_n(t)$ and demand $D(t)$, the difference Φ_i between $I_n(t)$ and $D(t)$, and the difference Φ_q between $q_n(t)$ and $D(t)$, as offsets $\Omega \in (\Phi_W, \Phi_i, \Phi_q)$ for adjusting the value of α. This paper proposes fuzzy control to deal with those inputs, $\Delta \in (\varepsilon, \delta, \Omega)$, due to its appropriateness for handling nonlinear dynamic systems.

3.3. Fuzzy controller to counteract non-stationary demand

A fuzzy control uses the fuzzy number A, which is a fuzzy set of the real line with a normal, fuzzy (convex) and continuous membership function of bounded support (Carlsson and Fuller, 2000). A fuzzy set represents an uncertainty in the human cognitive processes which accepts noisy, imprecise input if it increases in complexity (Zadeh, 1975). Thus, we recognize the most commonly used fuzzy membership functions such as straight lines, trapezoids, haversine, exponential and finally triangular as representations of weighting factors to determine their influence on the fuzzy output sets of the final output conclusion. We define the linguistic scale in the matrix in Column 1, Table 1, to represent the level categories of demand change, δ, in Column 2, Table 1.

3.3.1. Fuzzy inference systems

The Mamdani (1977) and Sugeno (1985) fuzzy inference systems are the two best known in developing a fuzzy model. The output of the system is generally defuzzified, resulting in fuzzy sets. These fuzzy sets are combined using an aggregation operator, from the consequent on each rule of the output. A single if-then rule is written as IF "X" is A AND "Y" is B, THEN "Z" is C, where A and B are the linguistic scales of Δ and C is the linguistic scale of α which is represented as the fuzzy set on the ranges in Table 1.

The fuzzy control rules are based on the experience of supply chain managers. The relationship between Δ and α is summarized in Table 2. For instance, the actual meaning of Table 2 should be that if ε in period $t-1$ is very low and δ is very low, then α for the forecast method is medium, and so on.

Fig. 2 exhibits the fuzzy inference systems in Table 2, as follows:

Fig. 2 shows the inference systems for the forecast error and demand change where the vertical axis represents the membership weight, $f(\alpha)$, and the horizontal line represents the value of the $\Delta \in (\varepsilon, \delta, \Omega)$ in the linguistic scale.

Table 1
Membership function.

Linguistic scale	Inputs $\Delta \in (\varepsilon, \delta, \Omega)$	Triangular fuzzy number of smoothing constant (α)
Very high	$75\% \leqslant \Delta \leqslant \infty$	0.5;1;1
High	$74\% \geqslant \Delta \geqslant 51\%$	0.25;0.75;1
Medium	$50\% \geqslant \Delta \geqslant 26\%$	0.25;0.5;0.75
Low	$25\% \geqslant \Delta \geqslant 5\%$	0;0.25;0.75
Very low	$\Delta \leqslant 4\%$	0;0;0.5

Δ: forecast error, demand change, the difference between demand and order rate, the difference between WIP inventory and demand and the difference between product inventory and demand (adapted from Mamdani, 1977).

Table 2
Rules for membership function. *Source:* Adapted from Mamdani (1977).

		Demand forecast error ε and offsets Ω				
		Very high	High	Medium	Low	Very low
Demand changes δ	Very low	Very low	Very low	Low	Low	Medium
	Low	Very low	Low	Low	Medium	High
	Medium	Low	Low	Medium	High	High
	High	Low	Medium	High	High	Very high
	Very high	Medium	High	High	Very high	Very high

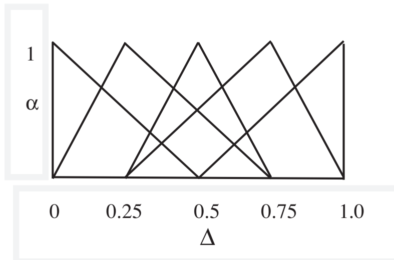

Fig. 2. Fuzzy inference systems of smoothing constant α for inputs Δ.

3.3.2. Defuzzification

Defuzzification is applied to quantify the result of the fuzzy logic. The most popular defuzzification is the centroid calculation, known as the centre of gravity of area defuzzification. The others are the bisector, the mean of maximum, the largest of maximum and the smallest of maximum (Liu, 2008). In Column 3, Table 1, the leftmost number is called the Lower Expectation (i.e., "LE"), the middle number the Most Acceptable (i.e., "MA") and rightmost number the Higher Expectation (i.e., "HE"). As a general defuzzification procedure, we need to change these weights into crisp numbers C_{crisp} for comparison or ranking purposes, as follows:

$$\alpha = C_{crisp} = 1 - \frac{f(\alpha)_{LE} + 2f(\alpha)_{MA} + f(\alpha)_{HE}}{4}. \tag{13}$$

In order to accommodate the fuzziness of the response against forecasting error, we need to map Eq. (13) into Fig. 2 so as to give several membership function degrees, as follows:

$$\text{Very low}: f(\alpha_a) = \frac{0.5 - \alpha_a}{0.5}; \quad 0 \leqslant \alpha_a \leqslant 0.5, \tag{14}$$

$$\text{Low}: f(\alpha_b) = \frac{\alpha_b}{0.25}, 0 \leqslant \alpha_b \leqslant 0.25;$$
$$f(\alpha_b) = \frac{0.75 - \alpha_b}{0.5}, \quad 0.25 \leqslant \alpha_b \leqslant 0.75, \tag{15}$$

$$\text{Medium}: f(\alpha_c) = \frac{\alpha_c - 0.25}{0.25}, \quad 0.25 \leqslant \alpha_c \leqslant 0.5;$$
$$f(\alpha_c) = \frac{0.75 - \alpha_c}{0.25}, \quad 0.5 \leqslant \alpha_c \leqslant 0.75, \tag{16}$$

$$\text{High}: f(\alpha_d) = \frac{\alpha_d - 0.25}{0.5}, \quad 0.25 \leqslant \alpha_d \leqslant 0.75;$$
$$f(\alpha_d) = \frac{1 - \alpha_d}{0.25}, 0.75 \leqslant \alpha_d \leqslant 1, \tag{17}$$

$$\text{Very high}: f(\alpha_e) = \frac{\alpha_e - 0.5}{0.5}; \quad 0.5 \leqslant \alpha_e \leqslant 1.0. \tag{18}$$

The following step is the identification of the final smoothing constant, α^*, by finding the membership function of αfrom Eqs. (14)–(18), we can find the final smoothing constant, α^*. Fig. 2 shows that almost all the values on axis (α^*) have more than one membership function, $f_C(\alpha^*) \in (A, B)$. Thus, we use a common rule for the membership function $f_C(\alpha)$ problem, which is formulated as

$$f_C(\alpha^*) = \min\{\mu_A(\alpha^*), \mu_B(\alpha^*)\}; \quad \text{for} A \cap B. \tag{19}$$

The reason for using Eq. (19) is that we want to accommodate the largest fuzzy set contained in two Δ intersection areas of fuzzy membership weight (see Fig. 2). We do not allow any trade-off between $\mu_A(\alpha^*)$ and $\mu_B(\alpha^*)$, so long as $\mu_A(\alpha^*) > \mu_B(\alpha^*)$,

$$\alpha^*_{fuzzy} = f_C(\alpha^*) \cdot \alpha^* \tag{20}$$

for $\{\alpha_a, \alpha_i, \alpha_W, \alpha_q\} \in \alpha^*_{fuzzy}$. Thus, we can use the results of Eqs. (19) and (20) to get the supply chain responsiveness in terms of T_i, T_W and T_q as

$$T_i = \frac{1 - \alpha_i}{\alpha_i}; T_W = \frac{1 - \alpha_W}{\alpha_W}, T_q = \frac{1 - \alpha_q}{\alpha_q}. \tag{21}$$

The response time for demand forecast T_f is not calculated, since α_f is used directly in Eq. (3) for forecasting the next end customer demand.

4. Model validation

Adaptive fuzzy VMI control modelling is validated by observing rationing and gaming or the Houlihan effect, order batching or the Burbidge effect and the Bullwhip effect. In order to consider the space limitation and the similarity of downstream, intermediate stream and upstream, we give only an overview of one stage stockholding unit based on Section 3, as in Fig. 3. The block diagram in Fig. 3 exhibits the demand signal processing by the adaptive fuzzy controller to decide on $\mu_n(t)$ and $q_n(t)$ by changing smoothing constants $\alpha \in (\alpha_f, \alpha_i, \alpha_W, \alpha_q)$ and finally T_i, T_W and T_q.

4.1. Case example

This section shows the way in which the proposed model is applied. A hypothesis can be designed as follows: "If the demand forecast and inventory adjustments are accurate, then economies of scale in transportation costs can be achieved without generating backorders or over-capacity in delivery and production". The Houlihan effect is used to indicate the existence of poor quality demand information and the Burbidge effect to indicate the lack of production and distribution coordination. To this end, a simple two-stage supply chain is considered. The demand process is non-stationary, and it is assumed that the demand at time zero is known as 40 items/day as the base of a random walk calculation. We use a target value of 40 items/day as the sales target even if the actual demand fluctuates according to the sales programme (i.e., quantity discounts or seasonal events). Thus, the successive demand values are generated as follows:

$$D(t) = D(t-1) + \varepsilon.\sigma(t), \tag{22}$$

where $D(t)$ is the new demand value, $D(t-1)$ is the previous value (in our case $D(t-1)$ for $t = 1$ is 40 items/day), ε is a random standard normal value (sampled from a distribution with mean 0 and standard deviation 1) and σ is the volatility of 10 items/day.

4.2. System implementation

In order to illustrate the numerical example, the GoldSim simulation software developed by the GoldSim Technology Group is used. This general-purpose simulator combines system dynamics with some aspects of discrete-event simulation and embeds a dynamic simulation engine within a Monte Carlo simulation framework, which is well-suited for modelling time-dependent conditions or processes. GoldSim also provides an equation editor to apply analytical models to the software.

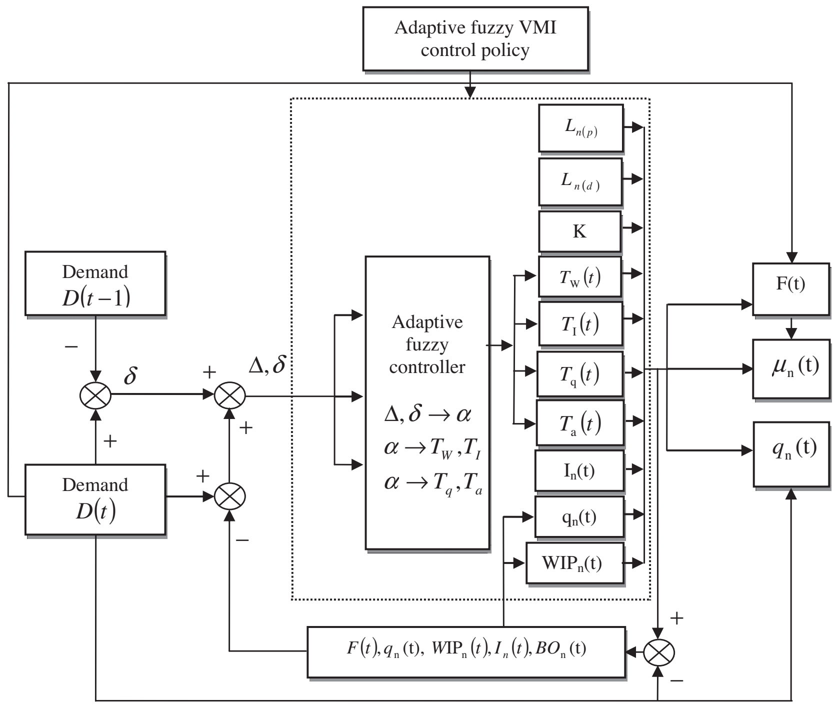

Fig. 3. Block diagram of adaptive fuzzy VMI control.

4.3. Simulation setup

The simulation is run for 1000 days at different $L_{p(n)}$ and $L_{d(n)}$. An ANOVA test is used to test the hypothesis and to detect the existence of the Houlihan and the Burbidge effects. After that, the Bullwhip effect is calculated. With regard to the traditional and the Genetic algorithm (GA)-based fuzzy VMI control policy, which are used as benchmarks, the $q_n(t)$overshoot and inventory-level standard deviation are used to measure supplier and buyer coordination. Finally, the number of backorders is also benchmarked between the fuzzy VMI control and the traditional and GA-based fuzzy VMI control policy, from the fact that the other VMI advantage is to eliminate backorders (Disney and Towill, 2003a).

5. Simulation results and analysis

Qualitative and quantitative analyses are made to observe the Houlihan effect and the Burbidge effect by detecting $q_n(t)$ and $\mu_n(t)$ magnifications and the possibility of applying economies of scale to transportation costs. The Bullwhip effect is calculated to measure the quality of the demand information. At the end of this section, the inventory allocation is analysed to exploit its benefit for managing the coordination between the supplier and buyer.

5.1. The Houlihan effect and the Burbidge effect

Qualitatively, this study adopts ANOVA for detecting the Houlihan and the Burbidge effects during a 1000-day simulation run with different delivery lead times. In Tables 3 and 4, $q_n(t)$ and $\mu_n(t)$ are not statistically different from $D(t)$ at the 5% significant level, with average P-values of 0.43 ($L_d(n) = 2/L_p(n) = 2$) and 0.42 ($L_d(n) = 4/L_p(n) = 2$) for $q_n(t)$ and the P-values are 0.44 for $\mu_n(t)$ ($L_d(n) = 2/L_p(n) = 2$) and 0.41 ($L_d(n) = 4/L_p(n) = 2$) in all stages, with adaptive fuzzy VMI control. The results show that $q_n(t)$ of the adaptive fuzzy VMI control is close to the demands and the Ld does not change significantly due to the magnification of $q_n(t)$.

Fig. 4 supports Tables 3 and 4 by exhibiting the comparison of backorders between an adaptive fuzzy VMI control, GA based fuzzy VMI (Lin et al., 2010) and traditional VMI downstream of them. This implies that L_d does not affect the customer service level. Thus the adaptive fuzzy VMI control gives better production and distribution coordination, in decoupling the production and the delivery batch sizes to meet economies of scale on transportation costs.

Table 3
$q_n(t)$ at different L_d.

System parameter	*F*			P-value		
$q_n(t)$ versus demands	Downstream	Intermediate	Upstream	Downstream	Intermediate	Upstream
$L_d(n) = 2$	0.96	1.03	1.01	0.431	0.431	0.431
$L_d(n) = 4$	0.72	0.924	1.93	0.059	0.279	0.948

Table 4
μn(t) at different L_p.

System parameter	*F*			P-value		
$\mu(t)$ versus demands	Downstream	Intermediate	Upstream	Downstream	Intermediate	Upstream
$L_p(n) = 2$	0.97	0.967	0.981	0.449	0.439	0.431
$L_p(\mathrm{n}) = 4$	0.71	0.891	1.146	0.057	0.321	0.835

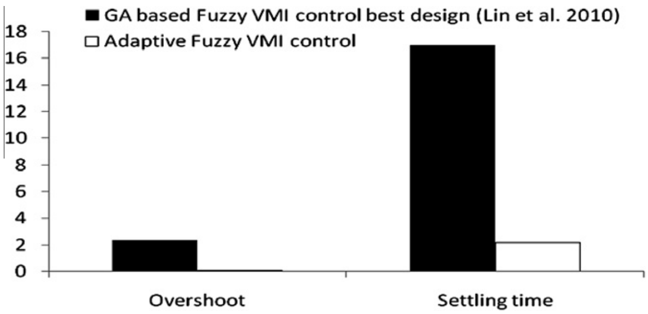

Fig. 4. Step response for GA based fuzzy VMI control and adaptive fuzzy VMI control for $L_p = 2$ and $L_d = 2$ during 1000 days with non-stationary demand process rate average of 40 units per day, with 10 items annual volatility.

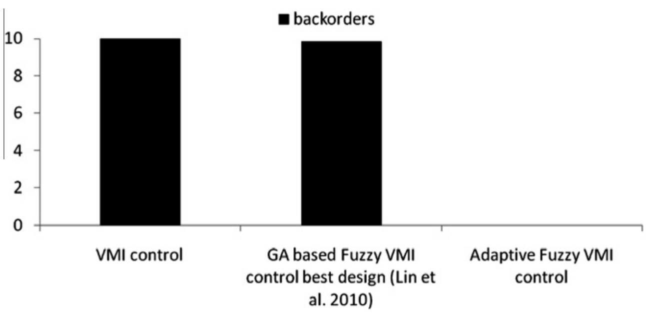

Fig. 5. Maximum backorders during 1000 days with non-stationary demand process rate average of 40 units per day, with 10 items annual volatility.

Quantitatively, Fig. 5 shows the $q_n(t)$ overshoot comparison between the adaptive fuzzy VMI control and the GA based fuzzy VMI downstream. The overshoot is used to measure the Houlihan effect which inevitably leads to unrealistic deliveries. Indeed, Fig. 5 shows that adaptive fuzzy VMI control surpasses other GA-based fuzzy VMI control (Lin et al., 2010) in terms of lower $q_n(t)$ overshoot and shorter $q_n(t)$ settling time, at a step response. Minimum $q_n(t)$ overshoot indicates that the adaptive fuzzy VMI control is capable of mitigating the Houlihan effect. Shorter settling time indicates that the production and the delivery batch sizes are not linearly correlated. A nonlinear relationship between the production batch size and delivery batch size gives an advantage to the mitigation of the Burbidge effect by allowing economies of scale in transportation costs. Thus, the Houlihan and the Burbidge effects are simultaneously mitigated by adaptive fuzzy VMI control and the research hypothesis is accepted.

5.2. Quantification of the Bullwhip effect

$$Bullwhip(B) = \frac{\frac{\sigma_{q_n(t)}(t,t+L_{d(n)})}{q_n(t)(t,t+L_{d(n)})}}{\frac{\sigma_{D(t)}(t,t+L_{d(n)})}{D(t)(t,t+L_{d(n)})}} = \frac{V_{out}}{V_{in}}. \tag{23}$$

There are some contributions that quantify the Bullwhip effect in different ways. Warburton (2004) calculates the relationship between order rate and demand rate without considering the method of estimating the mean and standard deviation of the output demand. Other quantifications, such as Lee et al. (1997) and Chen et al. (1998), calculate the variance ratio (VR) of order quantity and demand in a way which does not take the lead time variance into account. Similarly, Chatfield et al. (2004) also consider VR as the Bullwhip effect metric, which does take into account the effect of stochastic lead times. However, if for instance the supplier would like to optimize the order batching then the variance of the order quantity would always be less than the demand. As a result, the Bullwhip effect is never detected. In addition, it generates a higher level of inventory in the buyer warehouse. Since one of the VMI benefits is to reduce the inventory level of the supply chain, then VR creates a conflict between minimizing the inventory and mitigating the Bullwhip effect.

The Bullwhip effect quantification in Eq. (23) which is calculated in Table 5 Section 5.2 employs the quotient of the demand coefficient of variation (CV) generated in a given supply chain level and the demand CV received by the same level (Fransoo and Wouters, 2000). The CV is appropriate for implementation in the echelon level of the demand. The reason is that most of the demand data in many supply chains are incomplete and not available in the echelon level (Fransoo and Wouters, 2000). Furthermore, the demand data at each echelon is not necessarily equal to the demand data at the product level. As a result, the magnitude of order rate is not necessarily equal to the demand rate. Thus, the ratio between the variability of the order rate and demand rate reflects the capability of the supply chain to respond to the demand. If this principle is applied to the VR then the Bullwhip effect is greatly magnified.

Whereas the Houlihan and the Burbidge effects are mitigated, Table 5 shows that adaptive fuzzy VMI control supports are appropriate for mitigating the Bullwhip effect by sharing the demand information to avoid multiple forecasting at all stages in the supply chain. Table 5 shows that the imprecision of the demand signal is eliminated to such an extent that variation in the delivery lead times has no significant impact on creating demand magnification. This is one more reason to support the mitigation of the Houlihan and the Burbidge effects.

5.3. Inventory allocation across the supply chain

Bullwhip effect mitigation cannot ignore the role of coordination between supplier and buyer. Fig. 6 shows this coordination in terms of the inventory allocation across the supply chain. The Figure shows that the downstream causes higher $I_n(t)$ for the intermediate and the upstream echelons. The reason is that the downstream hedges directly against the demand variability without having the opportunity for dampening the shock. The adaptive fuzzy VMI control helps to decouple the inventories into $I_n(t)$ and $WIP_n(t)$.Thus, $I_n(t)$ covers only the demand variability during the delivery lead times ($I_n(t)$ standard deviation), while the $WIP_n(t)$

Table 5
Bullwhip effect at different L_d and L_p.

	Downstream	Intermediate	Upstream		Downstream	Intermediate	Upstream
$L_d = 1$				$L_d = 3$			
$L_p = 2$	0.98	1.02	1	$L_p = 2$	0.98	1.02	1
$L_p = 3$	0.98	1.02	1	$L_p = 3$	0.98	1.02	1
$L_p = 4$	0.97	1.04	0.99	$L_p = 4$	0.96	1.04	1
$L_d = 2$				$L_d = 4$			
$L_p = 2$	1	1	1	$L_p = 2$	0.99	1.01	1
$L_p = 3$	0.98	1.03	1	$L_p = 3$	0.97	1.03	1
$L_p = 4$	0.97	1.03	0.99	$L_p = 4$	0.97	1.03	1

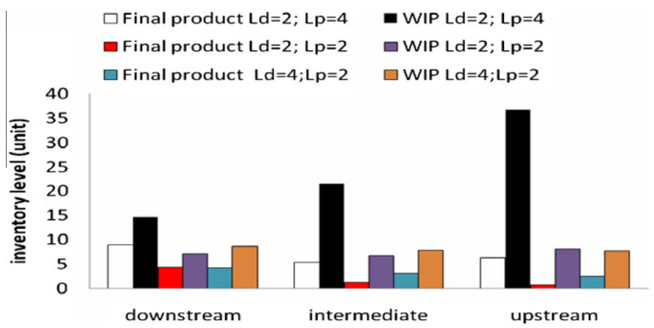

Fig. 6. WIP and product inventory standard deviation in all stages at various L_p and L_d.

covers the remaining demand variability during production lead times ($WIP_n(t)$ standard deviation).

Fig. 6 provides some insight into where we might allocate the $WIP_n(t)$. For example, at a longer $L_{p(n)}$, implementing the adaptive fuzzy VMI control is not advisable, since it creates a Bullwhip effect in the $WIP_n(t)$allocation. The reason is that $\mu_n(t)$ depends on $F(t)$ and $\Delta I_n(t)/\Delta WIP_n(t)$. Conversely, a shorter $L_{p(n)}$ may also reduce the total inventories in both stage n and stage $n+1$. Since $\Delta I_n(t)/\Delta WIP_n(t)$ depends on the production lead time, finding an optimum $L_{p(n)}$ is critical for mitigating the Bullwhip effect. However, adaptive fuzzy VMI control allows longer $L_{d(n)}$ to meet the economic order quantities without creating the Bullwhip effect.

6. Management level decision making

This section focuses on adaptive VMI control against other VMI models in terms of their applicability to a supply chain. We benchmarked two VMIs in detail, as explained below:

- We showed that an adaptive fuzzy smoothing constant surpasses that of a fixed smoothing constant by providing a 100% service level to eliminate backorders in a non-stationary demand process (Fig. 4).
- The adaptive fuzzy VMI control gives a lower inventory standard deviation (Fig. 6) and therefore, requires lower product inventory levels in all stages within the supply chain (Fig. 6) to signify that the magnitude of the backorders depends on the appropriateness of the assigned T_f, T_i, $T_W$and T_q and does not depend on $I_n(t)$ and the $WIP_n(t)$ of the supply chain. Mitigating the Houlihan effect and the Burbidge effect are two additional benefits, ensuring that the magnification of $q_n(t)$ and $\mu_n(t)$ across the supply chain is avoided (Tables 3 and 4) and the Bullwhip effect is mitigated (Table 5). Thus, it is not beneficial to each stage to increase the OUT level, because the downstream does not generate orders to compare against deliveries. Indeed, the upstream cares only about stock availability from the downstream.

Fig. 6 also provides a description of the adaptive fuzzy VMI control capable of eliminating the Burbidge effect by transporting every time period only so as to satisfy the demands of that time period plus backorders (if any). The supply chain often resolves the conflict between reducing the Bullwhip effect and obtaining economies of scale in transportation costs by order batching. However, Fig. 6 shows that the Bullwhip effect is not sensitive to $L_{d(n)}$. Therefore, the supply chain has enough flexibility to dispatch the order as long as there is stock available upstream and the $q_n(t)$ may be different from $\mu_n(t)$. In other words, a longer $L_{d(n)}$ due to economies of scale would not generate a Bullwhip effect.

Adaptive fuzzy VMI control, however, has a drawback: it increases the $WIP_n(t)$ exponentially with a longer $L_p(n)$. This signifies that adaptive fuzzy VMI control is more appropriate in flexible process design, rather than in a dedicated production line. It is shown that at stage n, shorter and longer $L_{p(n)}$ and $L_{d(n)}$ perform almost equally well downstream by requiring a roughly equal safety stock. However, this is not the case upstream.

Fig. 6 suggests sharing the risk due to demand uncertainty, by decoupling inventories into $WIP_n(t)$ and $I_n(t)$. The inventory decoupling supports production and distribution coordination since $WIP_n(t)$ can absorb the demand shocks. However, a shorter $L_p(n)$ is required to avoid the growth of $WIP_n(t)$ along the supply chain. Thus adaptive fuzzy VMI control is advisable for cheaper production costs, since it requires higher production capacity to shorten $L_p(n)$.

7. Concluding remarks

This paper has extended the functionality of the VMI model by developing an adaptive fuzzy smoothing constant. The proposed adaptive fuzzy VMI control has been successfully applied, with bullwhip effect reduction and OUT level information obtained. Moreover, the adaptive smoothing constant is used for searching for optimal parameters in terms of T_f, T_q, T_W, T_I. This study uses a quotient of the order and demand coefficients of variation, which belong to Bullwhip measures and stock and delivery performance to compare the performance of the traditional VMI and GA-based fuzzy VMI (Lin et al., 2010) with adaptive fuzzy VMI control models in different production and delivery lead times. From observing the results, the quality of demand information is improved significantly by eliminating backorders at a lower $q_n(t)$ overshoot and reducing the settling time against the previous GA-based fuzzy VMI (Lin et al., 2010). Thus the performance of the adaptive fuzzy VMI control model is apparently better than that of the previous VMI models (Figs. 4 and 5).

The simulation results show that adaptive fuzzy VMI control model reduces the Bullwhip effect by eliminating the Houlihan effect and the Burbidge effect (Tables 3 and 4). It provides more accurate production and distribution plans in a supply chain by lowering standard deviation from the product inventory level at a proportional inventory allocations (Graves and Willems, 2008; Neale and Willems, 2009).

Further research may investigate a number of remaining issues. The adaptive fuzzy VMI control should optimize production lead time to mitigate the Bullwhip effect in the WIP inventory. The application of the GA in adaptive smoothing may be useful for improving the current results.

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