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Journal:	*International Journal of Production Research*
Manuscript ID:	TPRS-2005-IJPR-0348.R1
Manuscript Type:	Original Manuscript
Date Submitted by the Author:	20-Jan-2006
Complete List of Authors:	Xiong, Guangyu; University of Vaasa, Logistics Systems Research Group, Industrial management Helo, Petri
Keywords:	INVENTORY MANAGEMENT, SUPPLY CHAIN MANAGEMENT
Keywords (user):	Demand fluctuation

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Submitted to International Journal of Production Research.

Word count: 5915.

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Abstract:

This paper develops a fuzzy inventory model to counteract the demand fluctuation in supply demand networks, which combines fuzzy logic controller with (s, S) policy based on EOQ (Economic Order Quantity) model. Following a literature review and a discussion of counteractions to the bullwhip effect and the obstruction of general counteraction in supply demand networks, a multi-echelon fuzzy inventory model in supply demand networks is proposed. A simulation model with one-echelon and two-echelon supply demand network is built and tested for (s, S) policy based on the classical EOQ (Economic Order Quantity) model and the proposed fuzzy inventory model. Based on the simulation, results of the relevance performance are presented and discussed, which show that the proposed multi-echelon fuzzy inventory model provides not only a cost-effective management of inventory (e.g. lower inventory levels and cost) in market uncertainty, but also another effective alternative for counteracting demand fluctuation. In particular, the proposed multi-echelon fuzzy inventory model shows benefit in counteracting demand fluctuation in multi-echelon supply demand networks. Finally, some conclusions and suggestions for further research works are presented.

Keywords: Supply Demand networks (SDN); Fuzzy Logic Control (FLC); Demand fluctuation; Inventory management; Bullwhip effect

1. Introduction

Since the late 1950s it has been known that internal structures used in multi-echelon systems may create oscillations in demand (Forrester, 1958). The bullwhip effect is emphasized especially in longer supply chains and companies operating in the multi-echelon upstream - for instance, raw material suppliers. Along with the supply chain shifting to supply demand networks (SDN), counteracting demand fluctuation from the bullwhip effect is becoming more important in SDN. This paper presents an evaluation of a cost-effective fuzzy inventory model to counteract the bullwhip effect in customer demand-driven SDN. A connection between order process and the demand fluctuation will be presented in a fuzzy inventory model, which provides an effective alternative for counteracting demand fluctuation and a cost-effective managing of inventory in SDN. The paper is structured as follows: firstly, the demand fluctuations in SDN are addressed; next a brief literature review is presented. Then, in accordance with the literature review, counteractions to demand fluctuation are pointed out. Counteracting demand fluctuations with a cost-effective fuzzy inventory controller in SDN is described, and the relevant results from the fuzzy inventory model using fuzzy logic control (FLC) in the case study are presented. Finally, a discussion based on the simulation results is presented.

2. Demand fluctuations in inventory management

2.1. Brief literature review

As one of the inputs of inventory management in SDN, customer demand plays a key role in achieving effective inventory management. However, demand fluctuations from the bullwhip effect vary significantly between industries. Several scholars (Lee, 1997, 2000; Disney 2003; Fisher 1961, 1997; Burbidge 1984; Towill 1991, 1994, 1999, 2003) have worked with the bullwhip effect and the demand fluctuation that it results in.

According to prevailing opinion, Lee et al (1997a) have identified four basic determinant reasons for the bullwhip effect:

- Quality of the forecast and its update frequency
- Re-order frequency and re-order batch size (order quantity)
- Special price schemes, leading to speculative buying
- Expectation of shortage, leading to protective buying

The demand fluctuations are hard to monitor and control. Based on studies (Lee 1997, 2000; McCullen & Saw 2001; Donovan 2002; Huang 2003; Li 2004), the following list gives related counteractions for these causes of the bullwhip effect:

- Information sharing: including point of sale data (POS), EDI, computer aided ordering (CAO).
- Channel alignment: including vendor managed inventory (VMI), direct sales, outsourcing, and consolidation.
- Operational efficiency: including lead-time reduction, set-up time reduction and ABC approach.

Most recent research has focused on how to avoid and eliminate demand fluctuations by an information sharing strategy. Huang et al. (2003) have researched the impacts of sharing information on the supply chain dynamics, and have reviewed recent representative papers since 1996. Their review shows that the benefits of information sharing are significant, especially in counteracting the bullwhip effect. However, this may not be beneficial to some supply chain entities owing to the high adoption cost of joining an inter-organizational information system, and unreliable and imprecise information. In this case, the company must consider more effective counteractions to demand fluctuation. Warburton (2004) proposed analytical solutions that agree with numerical integrations and previous control theory results. These depend on the exact expressions being derived for the retailer's orders to the manufacturer. But these exact expressions are normally difficult or even impossible to build within an entire supply chain. The approach is quite general, but limited: applicable to a wide variety of inventory management for several different reasons.

Some research studies applied fuzzy sets theory in managing inventory strategies. Carlsson and Fuller (2001) proposed a fuzzy logic approach to reduce the bullwhip effect, and their fuzzy logic model is based on numerous theorems, processes of demand signal processing, and is used in the paper industry. Petrovic et al. (1999) developed a supply chain fuzzy model to determine the order quantities for each inventory in the supply chain in the presence of uncertainties. According to the obtained order-up-to levels for all sites, a simulation approach was developed to evaluate the performance of the entire SC. Later, Petrovic et al. (2001) considered fuzzy lead-times in the SC simulation model developed in their previous research. However, their fuzzy SC model was still isolated and cannot be used to evaluate the entire SC directly. Giannoccaro et al. (2003) proposed a SC inventory policy using a periodical review policy based on the concept of fuzzy echelon stock. However, as Wang (2005) says, Petrovic's model could not estimate the influences of inventory policy (e.g. order-up-to level) determined at an upstream site on downstream sites, although the external supplier's reliability was considered in their model. Thus, Petrovic's fuzzy model could not directly evaluate the performances of an entire supply chain and Giannoccaro's model did not consider material lead-times and the supplier's reliability and could not estimate the effects of supply delay from an upstream site on downstream sites. Similarly, Giannoccaro's fuzzy model could not evaluate the performances of an entire supply chain directly.

Aimed at the weakness of the above models, which could not evaluate the performances of an entire supply chain directly, Wang and Shu (2005) developed a fuzzy decision model to evaluate supply chain performances and select suitable inventory strategies. In their model, a genetic algorithm approach was developed to determine the order-up-to levels of all fill rate of the finished product fulfilling the target at the same time. However, Wang's (2005) fuzzy decision model does not involve the performances of the bullwhip effect and inventory sensitivities caused by demand fluctuation, even though the model has evaluated most supply chain performances. This study is different from the above models and is aimed at their weakness, developing a fuzzy inventory model which also uses a periodical review policy ((s, S) policy) similar to Giannoccaro's model in this respect, but the model here is based on multi-echelon fuzzy logic controllers with each echelon of a multi-echelon SDN, which can be applied to an information sharing case and non- information sharing case in SDN. The proposed model can also directly evaluate the performances of each echelon in an entire supply demand network, including the related performance with costs and inventory levels, and related performance with demand fluctuation and bullwhip effect, which is different from Wang and Petrovic's model. The proposed model decides the order time using a periodical review policy - (s, S) policy, and then determines the order quantity of each echelon using fuzzy logic controller in each echelon.

This study not only works to generally counteract the bullwhip effect, but also concentrates on the available model for the company in practice (in the iron and steel industry). As the major previous objective of this model was to be cost-effective, the model's benefits in terms of order quantity and inventory cost were investigated, so this paper will only set out to explore the benefits of counteracting demand fluctuations with the cost–effective inventory model, and the objectives are to investigate how the fuzzy inventory model counteracts demand fluctuations, evaluates and improves inventory performance without complicated demand signal processing.

3. Managing demand fluctuation using fuzzy inventory controller

3.1 Obstruction of general counteraction in traditional industry

Most modern inventory management systems cannot completely stop demand fluctuations when inventory management from the supply chain shifts to SDN. This is because, according to the inventory model, the demand as input (*D*) is based on several terms; and can be constructed from the historical demand term, as follows:

Customer demand forecast (*D*) = Historical demand + Effect of information+ Demand fluctuations + Error

The first term, *historical demand*, is used for any inventory model and could be collected earlier. Because historical demand analysis is an important task, this capability analyzes historical demand data for each product and identifies the appropriate "demand classes" such as seasonal, non-seasonal, erratic and lumpy. These problems will partly concern the second term, *effect of information*, which connects to two important factors: (1) using the right information, and (2) using the right forecasting model. The bullwhip effect has a negative effect on the first factor and it also causes the third term, daily/weekly *demand fluctuations*. The fourth term is random *error* that is difficult to avoid. Companies make their demand forecasting systems partly according to historical demand; companies also find that the accuracy improvements for demand forecasting begin to deteriorate over time. The reason is that during the implementation of the forecasting system from the above, demand patterns for products are analyzed and parameters are configured, but demand patterns change over time. Hence the reaction of demand forecasting systems always delays the actual demand fluctuations. And even if they detect a pattern change, how do they know whether it is a permanent change or a temporary demand fluctuation by classical inventory order policy? According to the classical inventory models, most EOQ-type models, including (s, S) policy, just consider the first term, historical demand, even though some models consider the probability density function (PDF) of demand, which partly considers the effect of information. Information sharing strategy can produce the right information. Inventory management could also counteract these demand fluctuations in terms of demand with its advanced control model. The fuzzy inventory model proposed here can smooth the fluctuations caused by uncertainty, resulting in slower change to demand fluctuations compared with the classical inventory model. This study will not focus on how information sharing works, since there are a number of publications already devoted to this. Instead, this paper will analyze how the proposed fuzzy inventory model counteracts demand fluctuations.

The literature review has mentioned that there are some researchers who have been interested in using fuzzy sets theory to cope with demand fluctuations in recent years (Wang, 2005; Giannoccaro, 2003; Petrovic 1999, 2001; Carlsson, 2001). In particular, the fuzzy inventory model in this paper can be applied either in a cooperative network or as a competitive model; it can also directly evaluate the related performance with demand fluctuation and bullwhip effect, but it does not need complicated processes.

3.2 Fuzzy inventory model copes with demand fluctuations in SDN

The fuzzy controller based on fuzzy sets theory is an appropriate solution for unclear signals, like demand fluctuations in SDN. This case study, based on an iron and steel company, attempts to illustrate the ability of the proposed fuzzy model to counteract demand fluctuations. More specifically, the four exercises conducted here include:

- Effective ways of counteraction from related literature, e.g. information sharing
- Impact of fuzzy control on multi-echelon inventory management
- Sensitivity of the fuzzy inventory model to demand fluctuations
- Bullwhip effect of the fuzzy inventory model

First, information sharing is applied as far as possible to the company. In detail, for the case company in the iron and steel industry, the BF-ironmaker and BOF-steelmaker can share the same consumption data for their production planning and inventory management. This is reasonable in heavy industry, e.g. an iron and steel company. The case study compared the classical inventory model ((s, S) policy) with the proposed fuzzy inventory model in terms of an information sharing case and non- information sharing case.

As an illustration of multi-echelon inventory management control structure, a SDN (Figure 1 (a)) with supplier-materials supplier (in this case, a raw materials plant) is modelled, which supplies two downstream plants under exogenous stochastic customer demand. An additional raw materials supplier and the end customer are included for completeness.

'[Insert Figure1 about here]'

From a stage perspective, there are two levels in the supply network hierarchy: the material supplier (material plant in this case) and factory (in this case: BF (Blast Furnace) and BOF (Basic Oxygen Furnace)). From a channel perspective, there are two supply chain channels, A and B. For example, the raw material plant sends materials to (BF1), which is in the supplier-tier stage and in chain A. BF1 also sends its product (iron) to company 3 (BOF1, factory echelon, chain A), which makes the production process (BOF) and sends it to the final customer (including downstream factory/customers). The customer also has the choice of using chain B, which is composed of company 2 (supplier echelon, chain B) and company 4 (factory echelon, chain B). Using this model, the counteracting demand fluctuations can be discussed.

Firstly, information sharing could be used in the model for counteracting demand fluctuations. Theoretically, information sharing through coordination and collaboration is available when the partners have their common benefits from SDN, e.g. cooperative network. Secondly, in contrast, there are a number of companies using the traditional arm's-length model-competitive relationship. It advocates minimizing dependence on suppliers and maximizing bargaining power (Porter, 1998). In the case of competitive networks, information sharing is difficult; however the fuzzy inventory model is also an alternative to counteracting demand fluctuations for each echelon besides reducing the inventory level and costs in either a cooperative network or competitive network. Therefore, the cooperative network permits integrated information sharing for the inventory manager on demand input with an integrated fuzzy inventory model. For competitive networks, when information sharing is not easy, it is possible to use the distributed fuzzy inventory models for each echelon's inventory management. In the latter network model, a fuzzy controller for inventory management in each connection can be built, between 1-2, 2-3 and 3-4. When using information sharing in the case company in the iron and steel industry, it has a fuzzy inventory for just 2 connections: 1-2 and 3-4 (Figure 2 (b)).

The fuzzy inventory model will take into consideration the fuzzy logic controller together with classical (s, S) policy. In this model, the (s, S) policy will decide when an order needs to be placed, and the fuzzy controller will evaluate the order quantity. The fuzzification occurs when an order is placed.

'[Insert Figure2 about here]'

With this model, the order is

$$S\ (i+1) = f\ (S\ (i), D\ (i), Q\ (i), L) \qquad (1)$$

Where

$S\ (i)$ = ending inventory (Order-up-to level) at period i

$D\ (i)$ = demand at period i

$Q\ (i)$ = order quantity of at period i

L = lead-time

In detail, the lead-time L is considered; hence the inventory is given by:

$$Inventory\ (i+1)=Inventory(i) - Demand(i+1)+Orderquantity(i\text{-}lead\text{-}time) \qquad (2)$$

The model should always check if the forecast inventory will be below s, the rule of (s, S) policy is as follows:

$$\begin{cases} finv(i-1) < s, & order\,(Q\,(i) \neq 0) \\ finv(i-1) \geq s, & don't\,order\,(Q\,(i) = 0) \end{cases}$$

$$finv\ (i-1) = S(i)-(L\times Davg) + \sum_{k=i}^{i+(L-1)} Q\,(k) \qquad (3)$$

Where

s = reorder point

fin= forecast inventory

$s = Davg \times L + SS$

Where

$Davg$ = average demand (day/week/month)

SS = safety stock.

When considering L, the inventory balance equation is then given by:

$$S(i+1) = S(i) - D(i+1) + Q(i-L) \quad (4)$$

$$Q(i) = (s - S(i)) + D(i)$$

$$0 < SS < s;\ L,\ S(i) \geq 0$$

The part for fuzzy controller of each echelon should consider fuzzy rules, fuzzy operator´s MF (membership functions), and defuzzifications. Here this study extends fuzzy inventory control in SDN from the previous work (single- echelon fuzzy model).

To extend fuzzy inventory control in SDN, shown in Figure 3, for the demand, inventory level and order in each echelon, each universe of discourse should be assumed to be different, as $U_{d\text{-}nb}$ (universe of discourse of demand), $U_{i\text{-}nb}$ (universe of discourse of inventory), and $U_{o\text{-}nb}$(universe of discourse of order). They can be restricted by:

$$U_{d-nb} \in (0, X_{d-nb}),\ U_{i-nb} \in (SS_{nb}, X_{i-nb}),\ U_{o-nb} \in (0, X_{o-nb})$$

Where

nb =number of each fuzzy model in each echelon.

$X_{d\text{-}nb}$ = 2× average weekly demand in nbth echelon

$X_{i\text{-}nb}$ = re-order point in nbth echelon

$X_{o\text{-}nb}$ = 2× average ordering quantity in nbth echelon

SS_{nb} = safety stock in *nb*th echelon

$X_{d\text{-}nb}$ is for the demand of *nb*th echelon, $X_{i\text{-}nb}$ is for the inventory of *nb*th echelon and $X_{o\text{-}nb}$ is for the order of *nb*th echelon. Theoretically, for multi-echelon inventory management, the fluctuations will be less and less from the end partner to the beginning partner with a multi-echelon fuzzy inventory controller for each echelon. Basically, companies should consider avoiding multi-echelon demand forecast updates first, and then build a multi-echelon fuzzy inventory model in each echelon. Therefore, the fuzzy control model (Figure 2) in a multi-echelon fuzzy model is given by:

MEF = Multi-echelon fuzzy model ($F._{inv\text{-}1}$, $F._{inv\text{-}2}$… $F._{inv\text{-}nb}$…) = f{[F ($Rule_{-1}$, MF_{-1}, Inference-1, Def_{-1})], [F ($Rule_{-2}$, MF_{-2}, $Inference_{-2}$, Def_{-2})]… [F ($Rule_{-nb}$, MF_{-nb}, $Inference_{-nb}$, Def_{-nb})] …}

Where

MEF = multi-echelon fuzzy model

f = MEF is the function of the each fuzzy controller in each echelon inventory

$F._{inv\text{-}nb}$ = fuzzy model in *nb*th echelon

= F ($Rule_{-nb}$, MF_{-nb}, $Inference_{-nb}$, Def_{-nb})

$Rule_{-nb}$ = fuzzy rules in *nb*th echelon

MF_{-nb} = membership function in *nb*th echelon

$Inference_{-nb}$ = fuzzy inference in *nb*th echelon

Def_{-nb} = defuzzification in *nb*th echelon

4. Simulation results from the case study

A simulation was conducted to measure the sensitivity of the inventory model of the proposed fuzzy model and classical (s, S) policy. Since previous studies have investigated the benefits with cost, inventory level and order quantity, an objective for this experiment was to measure the counteraction to demand fluctuation. The sensitivity of inventory and bullwhip to demand fluctuations were conducted on a one and two-echelon inventory model.

The case study is based on an iron and steel company. Its raw materials flow and information flow are illustrated in Figures 3 and 4. The simulation models use a one echelon model (Figure 4 (a)) and two echelon model (Figure 4 (b)). In the one echelon model, the node between BF and raw materials plant share the end customer data as the demand information. The model is executed with the input data and the output. Several kinds of participants are defined for the purpose of explanation: the BF process, raw materials plant, and supplier. The BF process is the consumer, who places orders for feeding, then uses feeding for the iron production. They are the downstream participants of the supply chain. The supplier is the most upstream participant of the supply chain. The supplier supplies iron ore, etc to the raw materials plant, but does not receive any supplies. The raw materials plant is the intermediate participant in the supply chain. The raw material plant both places orders from the supplier and delivers orders to feed the BF process.

To investigate the multi-echelon fuzzy inventory model to counteract demand fluctuation in SDN, an inventory model with a two echelon fuzzy model in the case study was also built when the two inventory node cannot have information sharing. In this model (Figure 4(b)), the first level controller is next to the end customer (in the case study: BOF), and the second level controller BF and raw materials inventory are near to the supplier (in the case study: raw materials plant). The demand for the first inventory controller is from the end customer, and the demand for the second inventory controller is from the order of the first inventory controller (Figure 4 (b)).

4.1 Experimental design

The simulation model tested both the classical and fuzzy model. The simulation design considered data that was based on demand data from a one-year period from an iron and steel company. MatLab's Statistics Toolbox is used to return the different random seed at the values in x (52 weeks). According to historical data from the iron and steel industry, heavy white noise was added as demand fluctuations to each node in order to demonstrate the counteraction of the inventory model to demand fluctuations and the sensitivity of the model to heavy fluctuated demand.

In the inventory model, the cost structure is the same as the normal EOQ model; however, the order quantity was evaluated by the fuzzy controller. This experiment focused solely on the fuzzy inventory model to demand fluctuations caused by the bullwhip effect.

'[Insert Figure3 about here]'

'[Insert Figure4 about here]'

A commonly used methodology exists for measuring the extent of the bullwhip effect in a supply chain. The variation of demand at a certain echelon in the chain is described as the standard deviation of the demand divided by the average demand during a certain time interval. This is calculated for both incoming and outgoing demand at the echelon – and the demand at any two points in the chain. The extent of the bullwhip effect is the quotient of the coefficient of variation of demand generated by this (these) echelon(s) and the coefficient of variation of demand received by this echelon:

Bullwhip (ω) = $\frac{c_{out}}{c_{in}}$

Where

$$c_{in} = \frac{Std\_D_{in}(t, t+T)}{Mean\_D_{in}(t, t+T)}$$

$$c_{out} = \frac{Std\_D_{out}(t, t+T)}{Mean\_D_{out}(t, t+T)}$$

D_{in} and D_{out} are the incoming and outgoing demands during the time interval (t, $t+T$); *Std_* and *Mean_* are the standard deviation and mean of the demand, respectively. In the fuzzy inventory supply chain with 2 echelons (Fig 4 (b)), each echelon consists of inventory, order and demand, distinguishing between demand coming from the next downstream echelon (D_{in_1}) and demand going out to the next upstream echelon (D_{out_1}). Demand upstream (D_{in_2}) is usually affected by placing orders from the downstream (D_{out_1}). Using $c_{out}|_{Order}$ to express c_{out} that is the function of order; and $c_{in}|_{Demand}$ is the function of demand. All bullwhip will be calculated in each echelon for one and two echelon inventory systems by classical (s, S) policy and fuzzy model in the case study.

Besides bullwhip measurement, the performance measures of interest are listed as follows:

- Annual inventory levels (*AAI*): annual average inventory of the items, which is the mean of the inventory levels.
- Fuzzy improvement of inventory level (*AAIP*): percentage of decrease for *AAI* using the fuzzy approach from (s, S) policy. $AAIP = \frac{AAI_{(s,S)} - AAI_{Fuzzy}}{AAI_{Fuzzy}}$.

- Fuzzy improvement for cost (*FP*): percentage of decrease for annual cost (*CTU*) using the fuzzy model from (s, S) policy from EOQ model.

$$FP=\frac{CTU_{(s,S)}-CTU_{Fuzzy}}{CTU_{Fuzzy}}$$

- *Std_D* = Standard deviation of demand
- *Std_Q* = Standard deviation of order quantity
- *Std_S* = Standard deviation of inventory level
- *Sensi* = Sensitivity of inventory to demand fluctuations. *Sensi*= $\frac{Std\_S-Std\_D}{Std\_D}$
- Bullwhip (ω) = ω= $\frac{c_{out}}{c_{in}}=\frac{c_{out}|_{Order}}{c_{in}|_{Demand}}$
- Bullwhip (ω_1) = first echelon bullwhip ω_1= $\frac{c_{out\_1}}{c_{in\_1}}=\frac{c_{out\_1}|_{order1}}{c_{in\_1}|_{Demand1}}$
- Bullwhip (ω_2) = second echelon bullwhip ω_2= $\frac{c_{out\_2}}{c_{in\_2}}=\frac{c_{out\_2}|_{order2}}{c_{in\_2}|_{Demand2}}=\frac{c_{out\_2}|_{order2}}{c_{in\_2}|_{order1}}$
- Bullwhip (ω_t) = final (second) order to end customer (first bullwhip)

$$\omega_t=\frac{c_{out\_2}|_{order2}}{c_{in\_2}|_{Demand1}}$$

4.2 Simulation results and discussion

To analyse the behaviour in different uncertainty environments, different percentages of noise were added to demand fluctuation as demand input in the model from 30% to 70% as shown in Tables 1- 3 in the one echelon and two echelon inventory models. Table 1 shows that the one echelon fuzzy controller in the inventory model has a higher counteracting ability to demand fluctuations (lower bullwhip) and much better (lower) sensitivity of inventory to the demand fluctuations than the classical model; and some results, also shown in Figure 5, demonstrate the inventory level in the fuzzy model is more stable, fluctuating over fluctuated demand, compared to the classical model. Table 4 also shows *Std_Q* by fuzzy model is higher than the classical model; the reason is that its frequency of order is much less than the classical model for the same planning period; it also results sometimes in the single order quantity being higher than the classical model.

‘[Insert Table1 about here]’

‘[Insert Table2 about here]’

‘[Insert Table3 about here]’

However, the total annual cost and inventory level (See Figure 5) are much better with the fuzzy model, as both *AAIP* (%) and *FP* (%) show positive. It is obvious that the fuzzy inventory model with fuzzy controller not only has higher counteraction to demand fluctuations, but also lower inventory cost and inventory level. The presented fuzzy inventory model demonstrates the lower sensitivity of inventory level to demand fluctuation and better ability of counteraction to the bullwhip effect, mostly in areas that contain the annual cost, inventory level, order times, emergent-order times and service level, the benefits of which with the fuzzy model have been investigated in previous research.

‘[Insert Figure 5 about here]’

‘[Insert Figure 6 about here]’

For the two echelon fuzzy inventory model, Tables 2 and 3 give the performance measures of sensitivity of inventory level and bullwhip for each echelon, and Figures 6, 7 and 8 demonstrate the response of the inventory levels and order quantities for each echelon. Figure 6 shows the one echelon fuzzy model has superiority in sensitivity of inventory level. Since one aim is evaluating the counteracting demand fluctuation of the multi-echelon fuzzy inventory model, Table 2 only shows the sensitivity of the two echelon fuzzy model, so that each echelon's sensitivity can be compared. In detail, the first fuzzy controller in the inventory model has much higher sensitivity in different grade fluctuation to demand fluctuations than the second fuzzy controller (Fuzzy2). That means the demand fluctuations impacting on fluctuated inventory level become weaker through the 2 echelon fuzzy inventory controller in SDN. Figures 7 and 8 also show the same superiority in the fuzzy model. Table 3 shows the measures of the bullwhip effect in each echelon for the two echelon inventory model. It is obvious that the bullwhip effect of each echelon and the total bullwhip of the upstream supplier to downstream - the end customer- is much lower with the fuzzy inventory model. Figures 7 and 8 show that orders with the fuzzy model have more stable fluctuations than the classical model. These results correspond with the discussion that the demand fluctuations will be much less when networks cross multi-echelon fuzzy inventory controllers (Fuzzy1 and Fuzzy2).

'[Insert Figure7 about here]'

'[Insert Figure8 about here]'

5. Conclusions and further research

This paper evaluates the application of a cost-effective fuzzy inventory model to counteract demand fluctuation. The difference from previous research found in the literature is that the fuzzy inventory model presented here can counteract demand fluctuation without numerous theorems and heavy and complicated processes, and also directly evaluate the performances of each echelon's bullwhip effect and sensitivity of the inventory level in an entire supply demand network. Based on the simulation results in the case study, the paper shows that this fuzzy inventory control model yields benefits from the features in fuzzy logic control and better sensitivity of inventory level and lower bullwhip effect and demand fluctuations in both one and two echelon fuzzy inventory model cases. In addition to the model being cost-effective, the results show that it also has the ability of higher counteraction to bullwhip, while also satisfying the needs for lower inventory level and ability to decrease inventory cost.

According to the design procedure for the fuzzy controller and systematic procedure of implementation in the company presented, the fuzzy inventory model could be appropriately applied in ERP systems and inventory supply chain management if the company can get the relevant data for the each fuzzy controller from each echelon. The model and simulation results make clear that the proposed model is not only based on cooperative networks, and also available for competitive networks, but it also does not need numerous theorems and heavy and complicated processes and can be effectively applied in industry. Further research on inventory control could be extended by:

- Expanding the relative application in different industries in addition to the iron and steel industry.
- Researching a suitable fine-tuned fuzzy control system specific to demand fluctuation control, i.e. find appropriate rules and methods to calculate membership function for the minimization of demand fluctuation. However, this would still need to consider applicability in practice.

Acknowledgements

The authors would like to acknowledge the financial support from the Agile Supply-Demand Networks project (ASDN) from the Finnish Ministry of Transport and Communication, and ABB Corporate Research Centre. The source code for the MatLab software is available from the authors on request.

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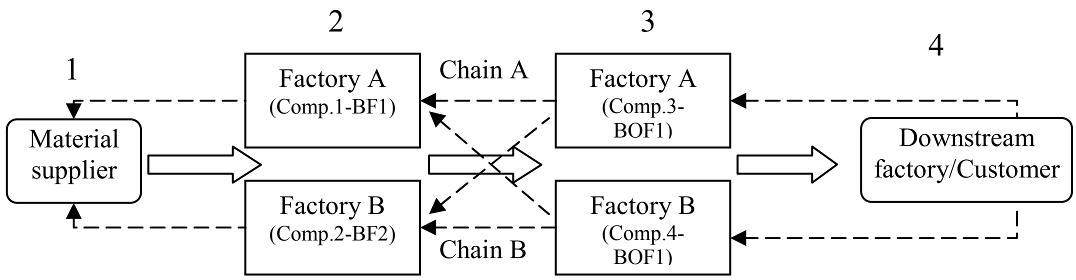
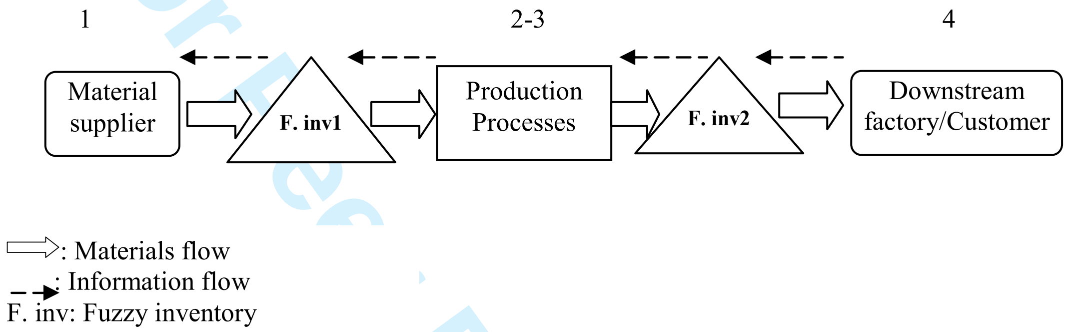


(a) Supply Network Structure Model in Iron & Steel Industry



(b) 2 and 3 with Information Sharing

Figure 1. Supply Network Structure Model in Iron and Steel Industry

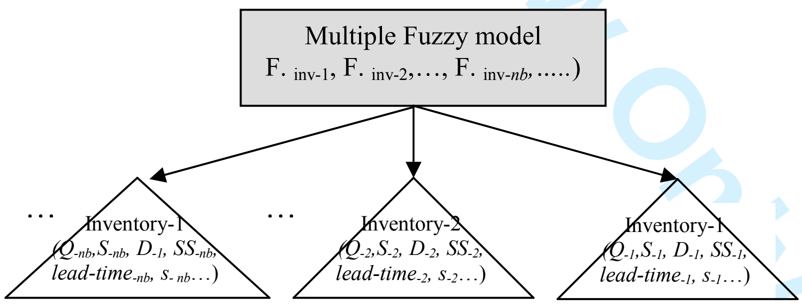


Figure 2. Multi-Echelon Fuzzy Inventory Control in SDN

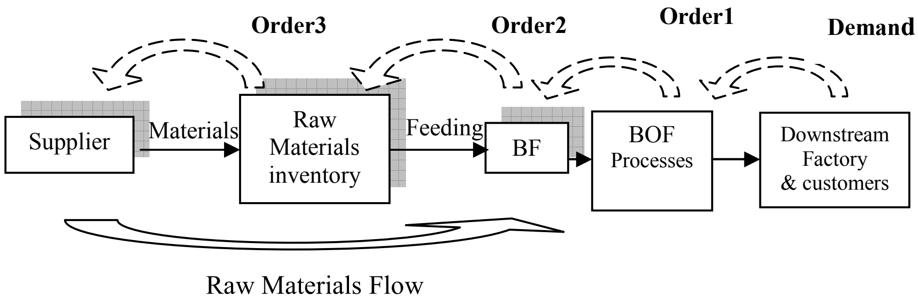
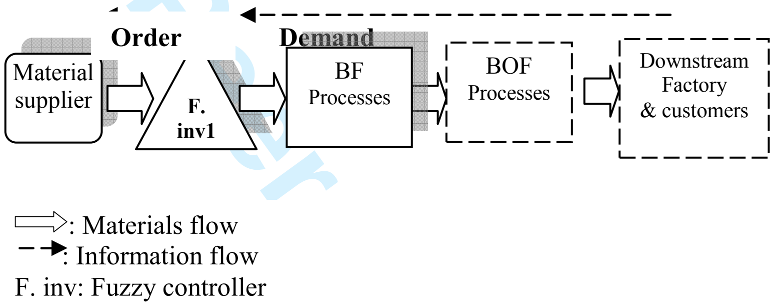
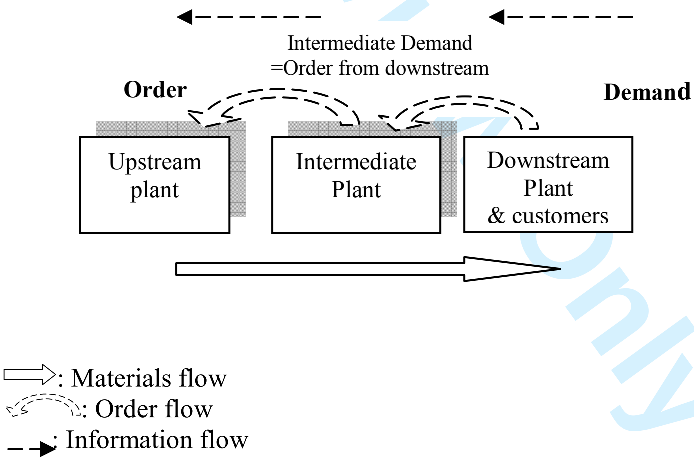


Figure 3. Inventory Management in Case Study



(a) One echelon fuzzy inventory



(b) Two echelon fuzzy inventory

Figure 4. Multi-Echelon Fuzzy Inventory in Case Study

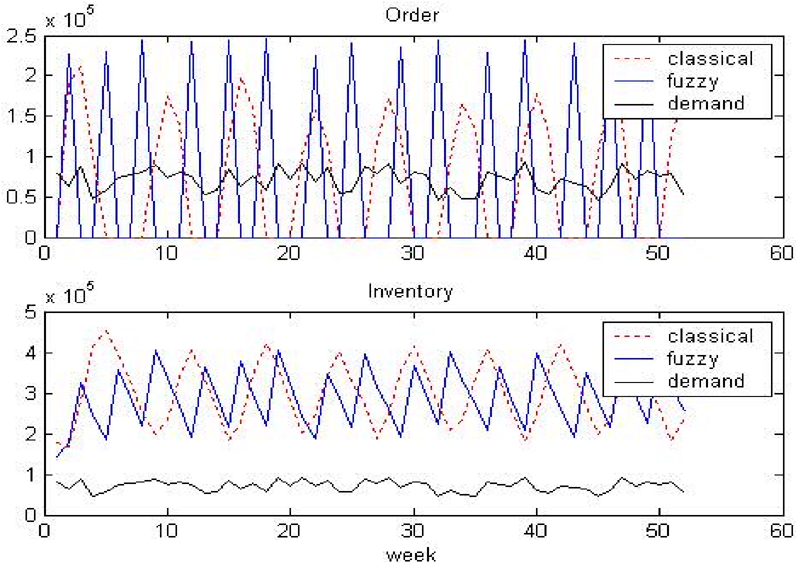


Figure 5. Response of Order and Inventory Level for One Echelon Models to Fluctuated Demand (50% fluctuation)

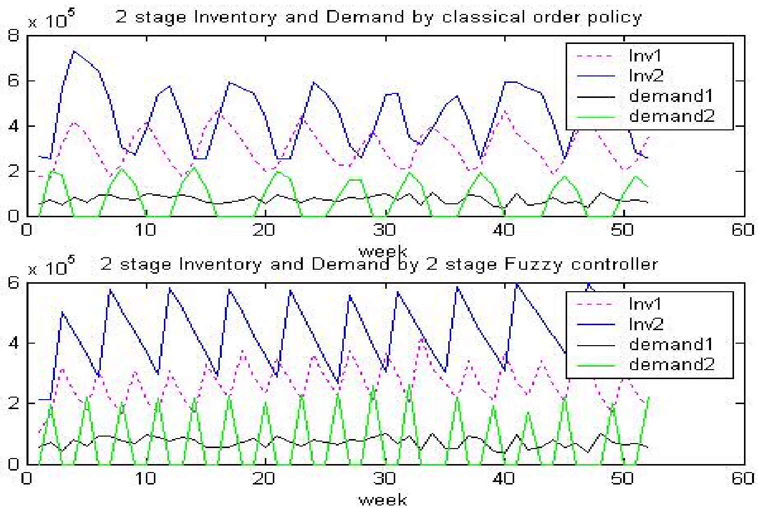


Figure 6. Response of Inventory Level of Two Echelon Model to Fluctuated Demand

(50% fluctuation; Inv1: the first echelon inventory level; Inv2: the second echelon inventory level; demand1: the first echelon demand from end customer; demand2: the second echelon demand from downstream order)

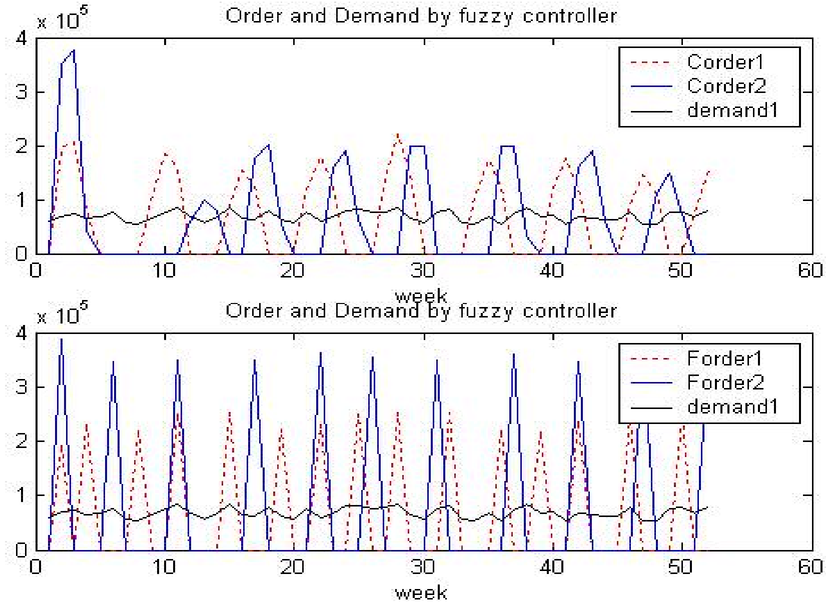


Figure 7. Response of order of the first echelon of two echelon model to fluctuated demand

(50% fluctuation; Corder1: the first echelon's order by classical order policy; Cdemand1: the first echelon's demand from end customer by classical order policy; Forder1: the first echelon's order by fuzzy controller)

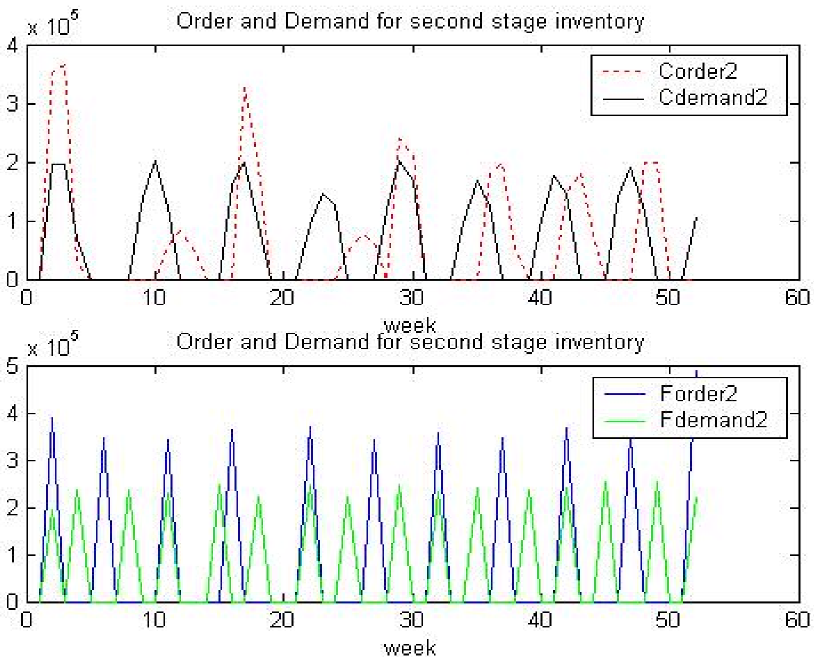


Figure 8. Response of order of the second echelon of two echelon model to fluctuated demand

(50% fluctuation; Corder2: the second echelon's order by classical order policy; Cdemand2: the second echelon's demand from the first echelon's order by classical order policy; Forder2: the second echelon's order by classical fuzzy controller; Fdemand2: the second echelon's demand from the first echelon's order by fuzzy controller)

Fluc.	AAIP	FP	Std_D	Std_S ($\times 10^4$)		Std_Q ($\times 10^4$)		Sensi		Bullwhip(ω)	
(%)	(%)	(%)	($\times 10^4$)	s, S	Fuzzy	s, S	Fuzzy	s, S	Fuzzy	s, S	Fuzzy
30	6.49	10.72	0.62152	7.4445	7.3009	5.7904	2.6706	10.9780	10.7469	9.1023	4.1394
50	7.72	14.50	0.86444	7.2667	7.1636	5.2814	1.4169	7.4062	7.2870	5.9526	1.6291
60	10.06	4.51	1.0449	8.2672	7.3893	6.1658	1.6878	6.9118	6.0716	5.8704	1.5646
70	7.7	5.84	1.1406	8.3783	7.2170	6.3193	1.3781	6.3455	5.3273	5.6802	1.2465
Comp.	positive	positive		higher	lower	lower	higher	higher	lower	higher	lower

Note: Fluc.: Fluctuation, Comp.: Comparison

Table 1: Performance measures of one echelon fuzzy inventory model

Fluc.	Std_D ($\times 10^4$)		Std_S ($\times 10^4$)		Std_Q ($\times 10^4$)		Sensi	
(%)	1st	2nd	1st	2nd	1st	2nd	Fuzzy1	Fuzzy2
30	0.63253	2.3589	4.9297	3.5516	8.1029	4.6440	6.7936	0.5056
50	1.0943	2.4438	3.3663	5.0167	8.2178	4.1501	3.5843	0.3775
60	1.2441	2.1665	5.2181	3.6408	8.2351	4.3465	3.1942	0.6805
70	1.4015	2.4621	5.2140	3.4482	8.3216	4.5733	2.7203	0.4005
Comp.					higher	lower	higher	lower

Table 2: Sensitivity measures of two echelon fuzzy inventory model

Fluc. (%)	Each echelon Bullwhip				Total bullwhip (ω_t)	
	1st (ω_1)		2nd (ω_2)		Classical	Fuzzy
	Classical1	Fuzzy1	Classical2	Fuzzy2		
30	9.4192	3.8868	1.3832	0.5434	17.3701	7.5462
50	5.5207	2.2970	1.2883	0.6962	9.0670	5.4464
60	5.3336	1.8430	1.2824	0.4030	8.7719	2.9673
70	4.7126	1.6509	1.3077	0.3895	7.3410	2.3620
Comp.	higher	lower	higher	lower	higher	lower

Table 3: Bullwhip measures of two echelon inventory model