Measuring Bullwhip Effect in a Single Echelon Supply Chain Using Fuzzy Approach

Ying Xie and Li Zhou

Abstract—**This paper studies the well-established automatic pipeline feedback compensated inventory and order-based production control system (APIOBPCS) for a single echelon supply chain, in which the uncertain demand is modelled using the fuzzy numbers. The bullwhip effect is therefore measured as the possibility variance amplification in replenishment orders. It has been found that the bullwhip effect measured using fuzzy approach has similar features as the one measured using probability theories, and the sharper the fuzzy demand forecast, the smaller the bullwhip effect**.

Index Terms—**Bullwhip effect, fuzzy numbers, supply chain.**

I. Introduction

The bullwhip effect describes a phenomenon where even a small change in customer demand imposed on the front of the supply chain (SC) can be translated into wider and wider swings in demand experienced by the members further back in the SC [1], and it has been researched by the academic since 1958 [2]. There is also much empirical evidence in industries for the bullwhip effect, such as the demand fluctuations in the Procter &Gamble [3] and order variations in Hewlett-Packard [1].

The research on bullwhip became popular since 1997[4], ranging from identifying the causes of bullwhip effects to finding the approaches to reduce them. Beer game, a simulation game was used to demonstrate how the distorted information in a SC results in bullwhip effect [5]. The sources of the bullwhip effect were identified as [1]: demand forecast updating, demand signal processing, rationing and shortage gaming, order batching and price variations. Accordingly, the various approaches are identified to reduce bullwhip effect, including the order information sharing, demand forecasting [6], [7], inventory management [8], and ordering policies [9]. Technically, control theories [10], [11], [12], statistical techniques [1], simulation models [13], fuzzy approaches [14], [15] and soft computing methods [16] had been applied to reduce or even eliminate the bullwhip effect.

The Automatic Pipeline Inventory and Order Based Production Control System (APIOPBCS) [10] is a representative control theory based model developed in the continuous time domain to analyse and reduce bullwhip effect by setting particular controller values [12], changing SC strategies [17], [18], or the ordering policies [19]. Disney modified the APIOBPCS to be a discrete time model and extended it to the vendor managed inventory scenarios [20]. The management insights gained from both the continuous and discrete time APIOPBCS models are similar [21], so either can be used for practical purpose.

From the perspective of the fuzzy approaches, references [13], [14] showed that if the facilities in the SC share information and agree on better fuzzy estimates on future sales for the upcoming period then the bullwhip effect can be significantly reduced. Reference [22] simulated the bullwhip effect in a fuzzy environment using fuzzy time series model, and developed an agent-based system to reduce bullwhip effect. It is shown that the agent-based system is superior to the previous analytical methods in terms of discovering the best available ordering policies. The fuzzy logic controller is applied to reduce the demand information distortion, therefore to improve demand forecast and reduce the bullwhip effect [16].

Although fuzzy approaches have been applied to reduce the bullwhip effect, the majority of research measure the bullwhip effect through the simulation models, and the closed-form variance amplification expression is not derived for the bullwhip effect in the fuzzy environment. This paper is to adopt the APIOPBCS system and the generalised order-up-to (OUT) policy, but implement a fuzzy estimate on the demand imposed on the model, and quantify the bullwhip effect as the variance amplification using the possibility variances rather than the probability variances. The features of the bullwhip effect measured by the fuzzy approaches are to be compared with the bullwhip effect measured by the probabilities distributions.

The paper is organized as follows. In Section II, he APIOBPCS system and the generalised OUT policy are briefly introduced. Modelling demand uncertainties using the fuzzy numbers and measuring the bullwhip effect using possibility variances are discussed in Section III. Finally, the conclusions and directions for future work are presented.

II. The Apiobpcs Model for a Single Echelon Supply Chain

This paper considers a single echelon serial SC encompassing a production unit and an inventory where the production output is stored (Fig.1). The SC is linked with an external environment with customer demand imposed on the inventory, from one side, and a material supplier to supply the production unit, from the other side.

The following notations are used in the paper:

t : index of discrete time period within T, $t = 1, 2,\ldots$;

D_t: uncertain demand rate in period t, and modelled using fuzzy numbers,

$\widehat{D}_t$: demand rate forecast for time interval t, and modelled using fuzzy numbers;

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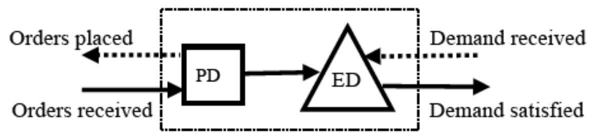
T_p: physical lead time, including the delivery and production lead time, $T_p \geq 0$ and is assumed to be integers;



PD –production unit, ED –end-product inventory

Fig. 1. A single echelon serial SC

WIP_t: the WIP level in period t, equals to goods on order or on manufacturing but not yet received by the end-product inventory;
NS_t: net stock in period t, refers to the inventory on hand minus any backlog;
O_t: order quantity to be placed in period t;
S_t: the order-up-to level in period t;
I_t: the existing inventory level in period t;

The APIOBPCS model is analysed, but the demand signal and demand forecast to APIOBPCS are modelled using fuzzy numbers. In the planning period, the events happen in the same order described by [23], which is adopted by [10] and [12] for the timing of events in the APIOBPCS model.

The inventory is received and demand is satisfied throughout the planning period t,

1) At the beginning of the planning period t, the goods ordered $T_p + 1$ periods ago arrive at the end-product inventory; the WIP level WIP_t is reduced; the net stock NS_t is increased (Note: the lead time T_p is increased by one to ensure the correct order of events in discrete time domain, e.g., even if $T_p = 0$, the orders will be received until the next planning period);
2) next, the demand $\mathrm{D_t}$ is realised and inventory level $\mathrm{NS_t}$ is reduced;
3) lastly, at the end of the planning period t, the order quantity $\mathrm{O(t)}$ is placed using the OUT policy and based on the current inventory level $\mathrm{I_t}$, in order to achieve the order-up-to level $\mathrm{S_t}$.

The new WIP, NS_t, the order-up-to level S_t are updated every period, to cover the demand over the lead time period $T_p + 1$, and the demand is forecasted to be $\widehat{D}_t$ from period $t+1$ to $t + T_p + 1$, so:

$$S_t = \widehat{D}_t \cdot (T_p + 1) \tag{1}$$

After the event i), the WIP level becomes:

$$WIP_t = WIP_{t-1} + O_{t-1} - O_{t-T_p-1} \tag{2}$$

After the event ii), the net stock is:

$$NS_t = NS_{t-1} + O_{t-T_p-1} - D_t \tag{3}$$

So the existing inventory level $\mathrm{I_t}$ is obtained as:

$$I_t = WIP_t + NS_t \tag{4}$$

To achieve the order-up-to level $\mathrm{S_t}$, the order quantity to be placed is:

$$O_t = S_t - I_t = \left(1 + T_p\right) \cdot \widehat{D}_t - WIP_t - NS_t$$
$$= \widehat{D}_t + \overbrace{(0 - NS_t)}^{NS\ error} + \overbrace{(T_p \cdot \widehat{D}_t - WIP_t)}^{WIP\ error} \tag{5}$$

In the format above, the order-up-to level S_t is updated every period and is an estimate of the demand over the lead time period:

$$S_t = (1 + T_p) \cdot \widehat{D}_t \tag{6}$$

According to (5), the order quantity O_t also equals to the sum of the demand forecast, the error between the target net stock (equals to 0 in this analysis) and existing net stock, and the error between the target WIP (equals to $T_p \cdot \widehat{D}_t$) and current WIP, and this is called the classical OUT policy in which both the errors are fully taken into account to adjust the order quantity, or called the full adjustment strategy [12].

Reference [24] altered the above OUT system by using a proportional controller $\frac{1}{T_i}$, i.e., taking into account a fraction of the net stock error and WIP error, and it is demonstrated that the $\frac{1}{T_i}$ is beneficial for the system robustness. The order quantity is then changed to:

$$O_t = \widehat{D}_t - \frac{1}{T_i} \cdot NS_t + \frac{1}{T_i} \cdot \left(T_p \cdot \widehat{D}_t - WIP_t\right) \tag{7}$$

The system above is called generalised OUT policy.

To find out the relationship between $O(t)$ and $D(t)$ and $\widehat{D}(t)$, the z-transform is performed on (2)-(7):

$$NS(z) = \frac{1}{1-z^{-1}} \cdot \left[O(z) \cdot z^{-(T_p+1)} - D(z)\right] \tag{8}$$

$$WIP(z) = \frac{1}{1-z^{-1}} \cdot \left[z^{-1} \cdot O(z) - z^{-(T_p+1)} \cdot O(z)\right] \tag{9}$$

$$DWIP(z) = T_p \cdot \widehat{D}(z) \tag{10}$$

$$O(z) = \widehat{D}(z) - \frac{1}{T_i} NS(z) + \frac{1}{T_i} \cdot [DWIP(z) - WIP(z)] \tag{11}$$

Substituting (8)-(10) to (11), it yields:

$$[T_i + (1 - T_i) \cdot z^{-1}] \cdot O(z) = \left(T_i + T_p\right) \cdot \left[\widehat{D}(z) - z^{-1} \cdot \right.$$
$$Dz{+}Dz \tag{12}$$

Transferring (12) to the time domain using inverse z-transform,

$$T_i \cdot O_t + (1 - T_i) \cdot O_{t-1} = \left(T_i + T_p\right) \cdot (\widehat{D}_t - \widehat{D}_{t-1}) + D_t \tag{13}$$

III. Measuring Bullwhip Effect using Fuzzy Approach

A. Model Uncertain Demand Using Fuzzy Numbers

Uncertain demand encountered in the SC problem has been traditionally modeled using the standard concepts of random variables and probability distributions that are constructed based on the historical information recorded in the past. However, if it is to estimate the demand for a new product, the historical data will not be available, and the estimation can only be based on the subjective beliefs of individuals. During the last few decades limitations of probability theory as the only means for dealing with uncertainty have been recognised [25]. The application of fuzzy sets theory has proved to be very fruitful in areas where intuition and judgment play a significant role [26].

The single echelon SC considered in this paper operates in uncertain environments where there is uncertainty in customer demand and demand forecast along the SCs. It is assumed that there is no evidence on demand recorded in the past, or there is lack of evidence available or lack of confidence in evidence. For these reasons, the application of standard random or probability concepts to modelling of demand appears unsuitable. So the uncertainty in demand is estimated by a practitioner based on his/her assumed level of experience and judgement, and expressed by linguistic terms, such as "demand is about d products every period but not lower than $d-\delta$ and not higher than $d+\delta$". Such linguistic terms can be represented using the concept of fuzzy numbers, and in this research, the uncertain demand D_t is modelled using a symmetric triangle fuzzy number $D_t(d,\delta)$, $\delta \geq 0$, as given in Fig. 2. It has been shown that fuzzy set theory provides an appropriate framework for treating uncertainties inherent in SCs and their environments [27].

The demand forecast $\widehat{D}_t$ is also modelled using a triangle fuzzy number $\widehat{D}_t(\bar{d},\beta)$, $\beta \geq 0$, as shown in Fig. 3, where the $\bar{d}$ is the average demand estimated subjectively and is a real number, and β is estimated subjectively too.

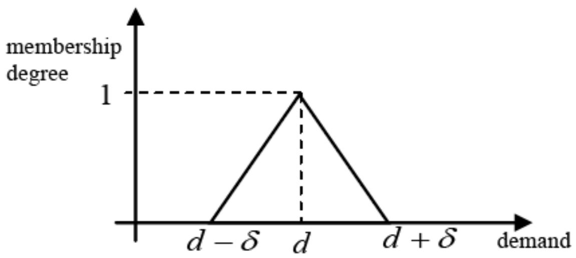


Fig. 2. Fuzzy demand D_t

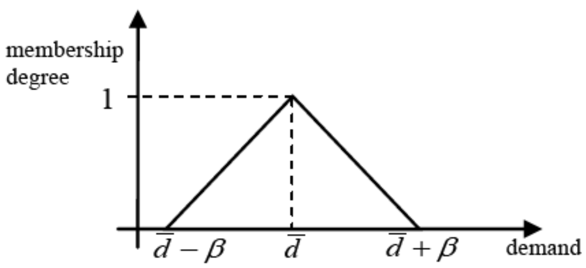


Fig. 3. Fuzzy demand forecast $\widehat{D}_t$

B. Measuring the Bullwhip Using Fuzzy Possibilitic Variance

According to reference [28], the possibilistic variance of a symmetric triangle fuzzy number A is defined as:

$$Var(A) = \frac{1}{2}\int_0^1 \alpha \cdot (A^2(\alpha) - A^1(\alpha))^2 d\alpha \tag{14}$$

where the α-cut of A is $A^\alpha = [A^1(\alpha),\ A^2(\alpha)]$.

And the addition and multiplication by a scalar of the two fuzzy numbers A and B are defined in (19):

$$Var\ (\rho \cdot A + \varphi \cdot B) = \rho^2 \cdot Var(A) + \varphi^2 \cdot Var(B) + 2|\rho \cdot \varphi| Cov(A,B) \tag{15}$$

The covariance of the two fuzzy numbers are defined as:

$$Cov(A,B) = \frac{1}{2}\int_0^1 \alpha \cdot \left(A^2(\alpha) - A^1(\alpha)\right) \cdot (B^2(\alpha) - B^1(\alpha)) d\alpha \tag{16}$$

The α-cut of D_t is defined as:

$$[D_t]^\alpha = [D_t^1(\alpha), D_t^2(\alpha)] = [d - \delta(1-\alpha), d + \delta(1-\alpha)] \tag{17}$$

Using (14), the possibilistic variance of D_t is calculated as:

$$Var(D_t) = \frac{1}{2}\int_0^1 \alpha \cdot (D_t^2(\alpha) - D_t^1(\alpha))^2 d\alpha \tag{18}$$

After integration, the variance of D_t is obtained as:

$$Var(D_t) = \frac{\delta^2}{6} \tag{19}$$

And the possibilistic variance of $\widehat{D}_t$ is:

$$Var(\widehat{D}_t) = \frac{\beta^2}{6} \tag{20}$$

Under the classical OUT policy, the T_i is set to be 1, so the (13) becomes:

$$O_t = (1+T_p)(\widehat{D}_t - \widehat{D}_{t-1}) + D_t \tag{21}$$

Using (15), the possibilistic variance of O_t is calculated as:

$$Var(O_t) = \left(1+T_p\right)^2 Var\left(\widehat{D}_t - \widehat{D}_{t-1}\right) + Var(D_t) + 2 \cdot \left|1+T_p\right| \cdot Cov[(\widehat{D}_t - \widehat{D}_{t-1}), D_t] \tag{22}$$

The α-cut of $\widehat{D}_t$ is defined as $[\widehat{D}_t]^\alpha = [\bar{d} - \beta(1-\alpha), \bar{d} + \beta(1-\alpha)]$, and the α-cut of $\widehat{D}_{t-1}$ is also defined as $[\widehat{D}_{t-1}]^\alpha = [\bar{d} - \beta(1-\alpha), \bar{d} + \beta(1-\alpha)]$, so using the sum operation between the α-cuts of the two fuzzy numbers:

$$[\widehat{D}_t - \widehat{D}_{t-1}]^\alpha$$

$$= [\bar{d} - \beta(1-\alpha) - (\bar{d} + \beta(1-\alpha)), \bar{d} + \beta(1-\alpha) - (\bar{d} - \beta(1-\alpha))]$$

$$= [-2\beta(1-\alpha), 2\beta(1-\alpha)] \tag{23}$$

Using (15), the possibility variance of $\widehat{D}_t - \widehat{D}_{t-1}$ is obtained as:

$$Var\left(\widehat{D}_t - \widehat{D}_{t-1}\right) = \frac{1}{2}\int_0^1 16\alpha\beta^2 (1-\alpha)^2 d\alpha = \frac{2\beta^2}{3} \tag{24}$$

The covariance between $\widehat{\mathrm{D}}_{\mathrm{t}} - \widehat{\mathrm{D}}_{\mathrm{t-1}}$ and $\mathrm{D_t}$ is calculated using (16) as:

$$Cov\left[\left(\widehat{D}_t - \widehat{D}_{t-1}\right), D_t\right] = \frac{1}{2}\int_0^1 \alpha \cdot 4\beta\,(1-\alpha)\cdot 2\delta(1-\alpha)d\alpha = \frac{\delta\beta}{3} \quad (25)$$

Substituting (19), (24) and (25) to (22), it yields:

$$\mathrm{Var}(\mathrm{O_t}) = \frac{2\left(1+\mathrm{T_p}\right)^2 \cdot \beta^2}{3} + \frac{\delta^2}{6} + \frac{2(1+\mathrm{T_p})\cdot\delta\beta}{3} \quad (26)$$

In the discrete time domain, the lead time $\mathrm{T_p} \geq 0$, so

$$Var[O_t] > Var[D_t] = \frac{\delta^2}{6}$$

And the bullwhip effect is measured as:

$$Bullwhip(O_t) = \frac{Var[O_t]}{Var[D_t]} = 1 + \frac{4\left(1+T_p\right)^2 \cdot \beta^2}{\delta^2} + \frac{4(1+T_p)\cdot\beta}{3\delta} \quad (27)$$

Therefore, $Bullwhip(O_t) = \frac{Var[O_t]}{Var[D_t]} > 1$, i.e., the bullwhip exists, and has the following features:

- Reducing β reduces the variance of order quantity $Var(O_t)$, therefore reduces the bullwhip. It means the bullwhip gets smaller when the fuzzy demand forecast gets sharper, in other words, the more certain the demand forecast, the less the variance of the demand forecast, and the less the bullwhip effect. However, this might deteriorate the customer service level, and the effect on the customer service level will be investigated in the future research.
- When $\beta = 0$, the forecast becomes a crisp value $\widehat{D}_t = \widehat{D}_t\left(\bar{d}, 0\right) = \bar{d}$, and is a long term average demand. In this case, $Var(\widehat{D}_t) = 0$, and $Bullwhip(O_t) = 1$. This is the same result as the one obtained in [12], i.e., the bullwhip effect generated by the classical OUT policy equals to 1 using average demand as a forecaster. The forecast produces no possibilistic variance ($Var(\widehat{D}_t)$=0), but the bullwhip still exists due to the forecasting mechanism, order delay and inventory feedback loops in the OUT system, as explained and proved in [12].
- Reducing δ reduces the variance of order quantity $Var(O_t)$, but increases the bullwhip, that is because $Var(D_t)$ decreases and $Var(\widehat{D}_t)$ remains unchanged. To maintain the bullwhip ratio, the demand forecast should be adjusted in the same ratio as the demand, i.e., changing β using the same ratio as δ.
- Decreasing T_p reduces the variance of order quantity $Var(O_t)$, and reduces the bullwhip. The shorter the lead time, the less the bullwhip effect.
- When $T_p = 0$, $Bullwhip(O_t) = 1 + \frac{4\beta^2}{\delta^2} + \frac{4\beta}{3\delta}$ >1. It means setting the lead time to be zero does not eliminate the bullwhip effect due to the forecasting mechanism and inventory feedback loops in the OUT system.

IV. Conclusion

In this paper, the bullwhip effect arising from a single echelon SC is measured using a fuzzy approach. The uncertainties in customer demand and demand forecast are expressed by linguistic expressions and modelled by the symmetrical triangle fuzzy numbers. The possibility variance is calculated for the order quantity, and the bullwhip effect is obtained as the ratio between the possibility variances of the order quantity and the demand. The similar features have been identified compared with the bullwhip effect measured by the probability variance:

- the bullwhip effect is reduced when the fuzzy demand forecast gets sharper (more accurate)
- the bullwhip effect equals to 1 when the forecast is a long term average value.
- The shorter the lead time, the less the bullwhip effect. But the bullwhip effect still exists even when there is no lead time (lead time is zero) due to the forecasting mechanism and inventory feedback loops in the OUT system.

The simulation model will be developed in the future work to verify the bullwhip effect obtained in this research, and the customer service level will be considered when updating the fuzzy demand forecast. Fuzzy logic controllers will be built into the APIOBPCS model, and the effects on the bullwhip effect will be investigated.

References

[1] H. L. Lee, V. Padmanabhan, and S. Whang, "Information distortion in a supply chain: The bullwhip effect," *Management Science*, vol. 43, pp. 546–558, 1997.

[2] J. W. Forrester, "Industrial dynamics: a major breakthrough for decision makers," *Harvard Business Review*, vol. 36, no. 4, pp. 37-66, 1958.

[3] R.W.Schmenner, "Looking ahead by looking back: Swift, even flow in the history of manufacturing," *Production and Operations Managment*, vol. 10, no. 1, pp.87-95, 2001.

[4] H. L. Lee, V. Padmanabhan, and S. Whang, "The bullwhip effect in supply chains", *Sloan Management Review*, pp. 93-102, 1997.

[5] J. D. Sterman, "Modeling managerial behaviour: misperceptions of feedback in a dynamic decision making experiment," *Management Science*, vol. 35, no. 3, pp. 321-339, 1989.

[6] F. Chen, Z. Drezner, J. K. Ryan, and D. Simchi-Levi, "Quantifying the bullwhip effect in a simple supply chain: the impact of forecasting, lead times and information", *Management Science*, vol. 46, no.3, pp. 436-443, March 2000.

[7] G. Li, S. Wang, H. Yan, and G.Yu, "Information transformation in a Supply Chain," *Computers and Operations Research*, vol. 32, pp. 707–725, 2005.

[8] I. Dhahri and H. Chabchoub, "Nonlinear goal programming models quantifying the bullwhip effect in supply chain based on ARIMA parameters," *European Journal of Operational Research*, vol. 177, pp. 1800-1810, 2007.

[9] J. Dejonckheere, S. M. Disney, M. R. Lambrecht, and D. R. Towill, "Measuring and avoiding the bullwhip effect: a control theoretic approach," *European Journal of Operational Research*, vol. 47, no. 3, pp. 567-590, 2003.

[10] S. John, M. M. Naim, and D. R. Towill, "Dynamic analysis of a WIP compensated decision support system," *International Journal Manufacturing System Design*, vol.1 no.4, pp.283–297, 1994.

[11] J. Dejonckheere, S. M. Disney, M. R. Lambrecht, and D. R. Towill, "The impact of information enrichment on the Bullwhip effectin supply chains: A control engineering perspective," *European Journal of Operational Research*, vol. 153, pp. 727-750, 2004.

[12] S. M. Disney, I. Farasyn, M. R. Lambrecht, D. R. Towill, and W. Van de Velde, "Taming the bullwhip effect whilst wathcing customer service in a single supply chain echelon," *European Journal of Operaitonal Research*, vol.173, pp.151-172, 2006.

[13] F. Campuzano, J. Mulab, and D. Peidrob, "Fuzzy estimations and system dynamics for improving supply chains," *Fuzzy Sets and Systems*, vol. 161, pp. 1530–1542, 2010.

[14] C. Carlsson and R. Fuller, "Reducing the bullwhip effects by means of intelligent, soft computing methods," in *Proc. the 34th Hawaii International Conference on System Science*, 2001.

[15] G. Y. Xiong and P. Heloa, "An application of cost-effective fuzzy inventory controller to counteract demand fluctuation caused by bullwhip effect," *International Journal of Production Research*, vol.44, no.24, pp.5261-5277, 15 December 2006.

[16] S. Balan, P. Vrat, and P. Kumar, "Information distortion in a supply chain and its mitigation using soft computing approach," *Omega: The International Journal of Management Science* vol. 37 no. 2, pp. 282-299, 2009.

[17] S. M. Disney, M. M. Naim, and D. R. Towill, "Dynamic simulation modelling for lean logistics," *International Journal of Physical Distribution and Logistics Management* , vol. 27, no.3, pp.174–96, 1997.

[18] D. R. Towill and P. McCullen, "The impact of an agile manufacturing programme on supply chain dynamics," *International Journal of Logistics Management* , vol. 10, no.1, pp.83–96, 1999.

[19] S. M. Disney, and D. R. Towill "On the bullwhip and inventory variance produced by an ordering policy," *Omega*, vol. 31, pp. 57–167, 2003.

[20] S. M. Disney, "Application of discrete linear control theory to Vendor Managed Inventory," *PhD thesis*, Cardiff Business School, Cardiff University, UK, 2001.

[21] S. M. Disney, D. R. Towill, and R. D. H. Warburton, "On the equivalence of the control theoretic, differential and difference equation approaches to solving the production and inventory control system design problem," *International Journal of Production Economics*, vol. 101, issue 1, pp. 194-208, 2006.

[22] M. H. Fazel Zarandi, M. Pourakbar, and I. B. Turksen, "A fuzzy agent-based model for reduction of bullwhip effect in supply chain systems," *Expert Systems with Applications*, vol. 34, pp. 1680-1691, 2008.

[23] H. J. Vassian, "Application of discrete variable servo theory to inventory control," *Journal of the Operations Research Society of America*, vol. 3., pp.272-282, 1955.

[24] S.M. Disney, D.R.Towill, 2002. "A discrete linear control theory model to determine the dynamic stability of vendor managed inventory supply chains", *International Journal of Production Research*, vol.40,2002, pp.179−204.

[25] I. B. Turksen and M. Berg, "An expert system prototype for inventory capacity planning: An approximate reasoning approach," *International Journal of Approximate Reasoning*, vol.5, pp. 223-250, 1991.

[26] H. J. Zimmermann, "Fuzzy Set Theory – and Its Applications," Second, Revised Edition, Kluwer Academic Publisher, 1991.

[27] D. Petrovic, R. Roy, and R. Petrovic, "Production supply chain modelling using fuzzy sets," *International Journal of Production Economics*, vol. 599, pp. 443-453, 199.

[28] C. Carlsson and R. Fuller, "On possibilistic mean value and variance of fuzzy numbers", *Fuzzy Sets and Systems*, vol. 22, pp. 315–326, 2001.

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