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A multi-layer demand-responsive logistics control methodology for alleviating the bullwhip effect of supply chains

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Abstract

This paper presents a multi-layer demand-responsive logistics control strategy for alleviating, effectively and efficiently, the bullwhip effect of a supply chain. Utilizing stochastic optimal control methodology, the proposed method estimates the time-varying demand-oriented logistics system states, which originate directly and indirectly downstream to the targeted member of a supply chain, and associate these estimated demands with estimates of different time-varying weights under the goal of systematically optimizing the logistical performance of chain members. In addition, an experimental design is conducted where the proposed method is evaluated with the two specified criteria. Numerical results indicate that the proposed method permits alleviating, to a great extent, the bullwhip effect in comparison with the existing logistics management strategies. Furthermore, the methodology presented in this study is expected to help address issues regarding the uncertainty and complexity of the distortion of demand-related information existing broadly among supply chain members for an efficient supply chain coordination.

Keywords: Supply chain management; Logistics; The bullwhip effect; Stochastic optimal control

1. Introduction

The bullwhip effect remains to be a critical issue in the area of supply chain management. As illustrated in the literature (Lee et al., 1997; Metters, 1997; Simchi-Levi et al., 2000), a small variance in the demands of the downstream end-customers may cause dramatic variance in the procurement volumes of upstream suppliers via the bullwhip effect under the condition that the distortions of demand-related information exist among the members of a supply chain. As a consequence, the systematic profitability of

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a supply chain is seriously affected. Correspondingly, the functional coordination of a supply chain may no longer exist due to such inappropriate interactions of supply-demand information flows between chain members.

As can be deduced from the previous statement, the distortion of demand information can be viewed as a major factor in the formation of the bullwhip effect because of three related phenomena: (1) bias demand information from the downstream chain members, (2) delayed information transferring, and (3) unsuitable logistical operations responding to the downstream demands. Similar viewpoints can also be found in the previous literature (Simchi-Levi et al., 2000; Chopra and Meindl, 2001). Herein, bias demand information may result either from the increase in demand variability in the end-customer market including price and demand fluctuations or from the estimation errors of downstream-chain-member demands. Delayed information transfer among chain members influences the efficiency of the inter-member information sharing, and more seriously, magnifies the induced effect on the deviation of the demands estimated by suppliers from the real end-customer demands. Furthermore, inappropriate logistics operational strategies including demand forecasting based on the orders, and batch ordering from the direct-downstream chain member also accelerate the formation of the bullwhip effect.

Improvement in forecasting customer demands appears to be an alternative measure for alleviating the bullwhip effect. According to Bowersox and Closs (1996), for the purpose of coordinating logistics activities, accurate forecasts of customer demands may help to proactively allocate resources rather than reacting directly to the needs with expensive changes in inventory. McGinnis and Kohn (1990) also urge that demand forecasting should be further emphasized in the evolution of advanced logistics management.

Nevertheless, there exist some limitations of published demand forecasting methods in dealing with chain-based customer demands. Some typical cases in the previous literature are illustrated as follows. Time series-based techniques, well-known statistical methods, have been widely employed in the traditional area of demand forecasting, and diverse related approaches including moving average, exponential smoothing, extended smoothing, and adaptive smoothing are proposed for short-term forecasting. Given the short-term stable relationships of time-varying demand patterns in sequential time intervals, Kahn (1987) proposed a demand forecasting model utilizing an autoregressive moving average approach. Following Kahn's approach, Xu et al. (2001) further investigated several alternatives to improve supply chain coordination. Similar applications of time series-based approaches have also be reported by Chen et al. (2000). Despite the convenience of utilization of time-series techniques in characterizing the changes of demand patterns under the condition of stable external environments, the capability of the published techniques appears limited to forecast the demands of the direct-downstream chain member, corresponding to the direct orders. In addition, the risk of bias prediction still remains in time-series techniques particularly under conditions of unstable changes in external environments. An analytical hierarchy process (AHP) based approach proposed by Korpela and Tuominen (1996) is elaborately used to forecast the aggregate growth rate of customer demand in the market area. Although they claimed that the proposed AHP-based method permits avoiding some problems inherent in classical demand forecasting techniques, the inter-member relationships of a supply chain are not taken into account in this method.

Furthermore, recent advances in information and communication technologies coupled with various time-based logistics control strategies such as continuous replenishment planning (CRP), and quick response (QR) may be noteworthy for their potentials in addressing the bullwhip effect, there still exists a lack of logistics control techniques in systematically coordinating demand information of chain members for solving problems induced by the bullwhip effect, effectively and efficiently. As pointed out by Metters (1997), most of the early research was devoted to explaining and analyzing the existence of the bullwhip rather than finding the remedy of the effect. In addition, Kahn (1987) claimed that ignorance of changes in end-customer behavior is the major cause of the bullwhip effect, and it remains in the area of supply chain management (SCM). Similar argument can also be found in Naish (1994), which argues that if foreknowledge of demand changes is incorporated, the bullwhip effect may disappear.

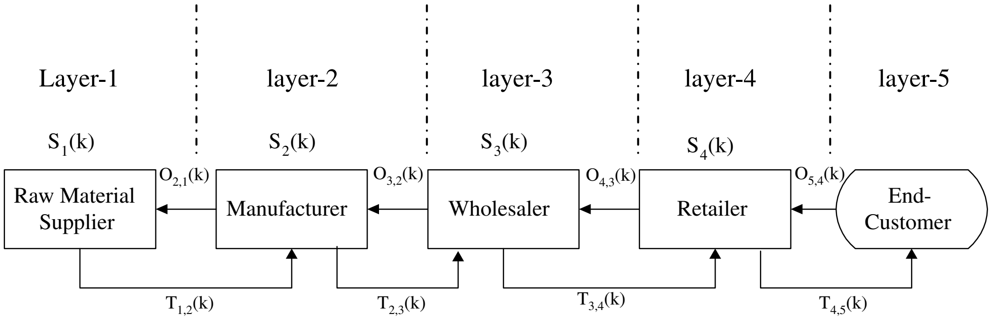

Fig. 1. Illustration of the logistics system scope investigated in this study.

In view of the aforementioned issues relevant to the bullwhip effect, this study presents a multi-layer demand-responsive logistics control approach, which serves not only to address the issues relevant to distortion of demand information in a supply chain cited previously but also to improve the supply chain coordination. The architecture of the proposed method is constructed on the basis of the principles of stochastic optimal control methodology, together with the Kalman filtering technology. Three major procedures including (1) specification of state variables, (2) formulation of a stochastic demand-oriented control system, and (3) development of a recursive decision-making support algorithm, are involved in developing the proposed methodology.

The rest of this paper is organized as follows. In Section 2, we specify the state variables of a multi-layer demand-responsive logistics system as well as the investigated system scope. In Section 3, the proposed logistics system is formulated as a discrete-time nonlinear stochastic system to characterize the time-varying relationships of the specified state variables. Section 4 describes a recursive stochastic optimal control algorithm serving to determine the control strategies, and update the estimates of state variables of the proposed logistics system. Numerical studies are presented in Section 5 to demonstrate the potential advantages of the proposed method. Concluding remarks are summarized in Section 6.

2. System specification

The system investigated in this study is presented in Fig. 1, which represents a 5-layer supply chain typically including members of raw material suppliers, manufacturers, wholesalers, retailers, and end-customers. The inter-member and intra-member logistical operations relationships of such a typical 5-layer supply chain, in reality, can be characterized with four types of time-varying logistics operations status, including: (1) the order from the downstream chain member, (2) the procurement to the upstream chain member, (3) inventory, and (4) the distribution amount to the downstream chain member. Herein, the status of order and procurement exhibits inter-member demand-oriented informative flows in a supply chain; in contrast, inventory and distribution indicate the conditions of intra-member and inter-member physical flows, respectively. Given a chain member in layer-i of the specified 5-layer supply chain, the in-bound and outbound logistics operations of the given chain member i can be characterized with: (1) the time-varying inventory amount in a given time interval [1] $k(S_i(k))$, (2) the time-varying procurement to the upstream chain member of layer "$i-1$" at the beginning of time interval $k(O_{i,i-1}(k))$, (3) the time-varying

[1] In this study, a given time interval k is defined as a given period of time in $[k, k+1)$, where the length of each time interval is set to be the maximum of the disaggregate lead times in the multi-layer logistics control system.

order amount from the downstream chain member of layer $i+1$ at the beginning of time interval $k(O_{i+1,i}(k))$, and (4) the time-varying distribution amount to the downstream chain member in time interval $k(T_{i,i+1}(k))$. Note that the aforementioned four types of time-varying logistics-related activities apply to any chain member of a supply chain, excluding the raw-material supplier and the end-customer in which the activities of procurement to the upstream member and the order from the downstream member, respectively, do not exist.

Next, the hypothesis that the logistics operations of any given chain member in the specified 5-layer supply chain can be influenced primarily by the deviation in multi-layer demand information is postulated as shown in Fig. 2, and herein, the demand-oriented deviation can be caused either by the variance of time-varying demand relative to the average of the previous demands or by the biasness of demand forecasting. Compared to inter-member relationships demonstrated in traditional SCM-related areas, the presented hypothesis exhibits a distinctive feature that the time-varying logistics operations status of a given chain member in a given layer i can be influenced not only by the order from the direct-downstream chain member $(O_{i+1,i}(k))$ but also by the members in farther downstream layers (e.g., $O_{i+2,i+1}(k)$ and $O_{i+3,i+2}(k)$), and the time-varying magnitude of the downstream demand-deviation effect is herein represented by $w_{j,i}(k)$, as can be seen in Fig. 2. As a result, any given chain member may need to take such an effect into account in the operations of logistics-related activities including the procurement to the upstream chain member and the distribution to the downstream chain member in the specified multi-layer supply chain system in order to alleviate the downstream demand-oriented impact.

According to the aforementioned conceptual framework shown in Fig. 2, three groups of decision variables are specified to characterize the operations of the specified multi-layer logistics system: (1) basic state variables, (2) measurement variables, and (3) control variables. Herein, the specified decision variables are regarded as the critical elements which are involved in modeling the proposed stochastic system. Their definitions are given in the following.

Basic state variables are referred to as the critical informative elements of the specified system that can be used to derive other time-varying system states characterizing logistics operations of chain members in the given supply chain, and correspondingly, they play the key role in determining the performance of the proposed 5-layer supply chain. In this study, one type of basic state variable is specified: $O_{i+1,i}(k)$ which represents the time-varying order amount from the chain member of the direct-downstream layer $i+1$ to a

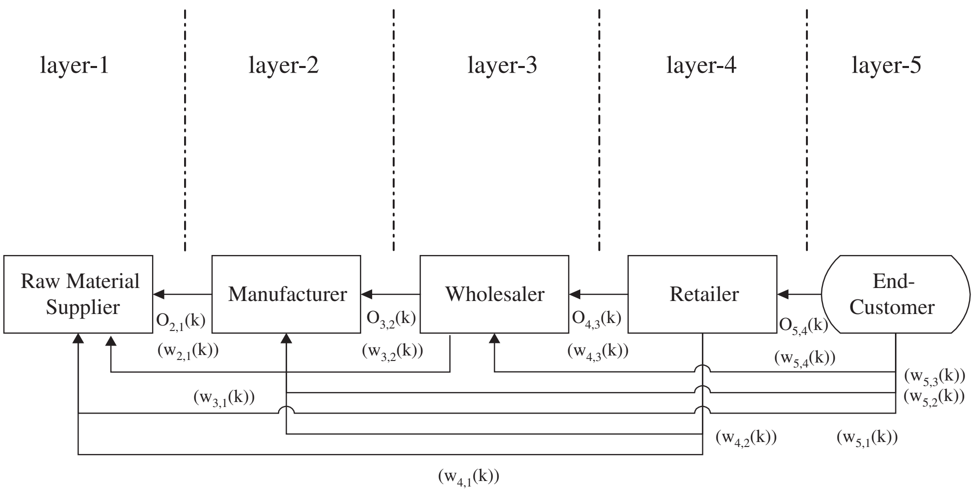

Fig. 2. Illustration of the multi-layer demand-oriented effect in a given 5-layer supply chain.

given chain member of layer i at the beginning of time interval k. Therefore, there are four basic state variables existing in the aforementioned 5-layer supply chain system, namely $O_{2,1}(k)$, $O_{3,2}(k)$, $O_{4,3}(k)$, and $O_{5,4}(k)$, respectively.

A measurement variable corresponds to the observable physical amount associated with a given logistics-related activity, which dominates the performance of the proposed multi-layer logistics system, and determines the time-varying status of basic state variables. Herein, one type of measurement variable $S_i(k)$ is specified, which is defined as the time-varying inventory amount of the given chain member of layer i observed in time interval k. In the given 5-layer supply chain system, there are totally four measurement variables, including $S_1(k)$, $S_2(k)$, $S_3(k)$, and $S_4(k)$.

Control variables determine the magnitude of the downstream demand-oriented deviation effect on the logistics operations of a given chain member in the system, and herein, one type of control variable is proposed: $w_{j,i}(k)$ which represents the time-varying magnitude of the effect oriented from the short-term changes in the time-varying order amount associated with the chain member of a given downstream layer j on the logistics operations of a given upstream chain member of layer-i in a given time interval k. The value of $w_{j,i}(k)$ changes with time, and is determined in each time interval during the process of the proposed multi-layer demand-responsive logistics control approach for each given chain member of layer i in response to the time-varying downstream demand-oriented deviation effect in the specified multi-layer logistics system. As can be seen in Fig. 2, there are a total of ten control variables in this system.

Utilizing the aforementioned specified variables, we further propose an aggregate demand effect variable ($\Psi_i(k)$) associated with the chain member in a given layer i in a given time interval k, and $\Psi_i(k)$ is denoted by

$$\Psi_i(k) = \sum_{j=i+1}^{J} w_{j,i}(k) \times \left[O_{j,j-1}(k) - \left(\sum_{\varepsilon=1}^{\widetilde{K}} O_{j,j-1}(k-\varepsilon) \right) \Big/ \widetilde{K} \right], \tag{1}$$

where J represents the number of layers in a given supply chain, which is equal to 5 in the proposed framework; ε is a time-lag index; and $\widetilde{K}$ represents the total number of time lags pre-set for identifying the deviation between the time-varying downstream demand and the associated average demand in the previous given time intervals. Herein, $\Psi_i(k)$ is introduced to serve the specified multi-layer logistics system in order to achieve the following systematical equilibrium condition:

$$\Psi_i(k) = T_{i-2,i-1}(k+1) + \widetilde{S}_{i-1} - O_{i,i-1}(k), \tag{2}$$

where $O_{i,i-1}(k)$ is referred to as the time-varying procurement amount from the given chain member in layer i to the chain member in the direct upstream layer $i-1$ at the beginning of time interval k; $T_{i-2,i-1}(k+1)$ corresponds to the time-varying distribution amount from the chain member of layer $i-2$ to the chain member of layer $i-1$ at the beginning of the next time interval $k+1$; $\widetilde{S}_{i-1}$ represents the pre-set safety stock amount associated with the chain member of layer $i-1$, and can be further expressed as

$$\widetilde{S}_{i-1} = \delta_{i-1}^{\alpha} \times \sigma_{i-1} \times \sqrt{\bar{u}_{i-1}}, \tag{3}$$

where δ_{i-1}^{α} is a constant associated with the given service level α of the chain member of layer $i-1$, which ensures that the stockout probability of the chain member of layer $i-1$ during the lead time is exactly $1-\alpha$; σ_{i-1} represents the standard deviation of daily demand faced by the chain member of layer $i-1$; and $\bar{u}_{i-1}$ is the average lead time associated with the chain member of layer $i-1$. Accordingly, under the aforementioned systematical equilibrium condition, the physical amount in terms of the net inventory associated with the chain member of layer $i-1$ must ideally satisfy the informative demand originated from the downstream chain member of layer i in any time intervals in the specified multi-layer logistics system.

3. Model formulation

In this study, the following two assumptions are postulated to facilitate the formulation of the proposed stochastic model.

(1) The activity of procurement associated with the chain member of any given layer is triggered at the beginning of any given time interval.
(2) The lead time associated with the chain member of any given layer is not greater than the length of a given time interval. Correspondingly, the issue of the order crossing a time interval is assumed not to exist in the presumed QR environment. In addition, as diverse marketing theories emerge, more and more distribution channel researchers and business decision makers believe the philosophy—"the customer is the king," leading to the existing demand-driven marketing environment. As such, our intention is focused on multi-layer demand-responsive logistics control, which can also make the corresponding assumption more agreeable. Accordingly, it is inducible that the time-varying procurement amount from a given chain member i to its upstream chain member $i-1$ is consistent with the distribution amount from the upstream chain member $i-1$ to the given chain member i in any given time interval (i.e., $O_{i,i-1}(k) = T_{i-1,i}(k)$).

Based on these assumptions, we formulate the operations of the proposed time-varying 5-layer supply chain system as a discrete-time nonlinear stochastic optimal control problem employing the specified decision variables as well as the fundamentals of stochastic optimal control approaches. The entire stochastic system is characterized primarily with three groups of time-varying equations including (1) state equations, (2) measurement equations, and (3) boundary constraints. These equations are denoted respectively as follows.

3.1. State equations

The state equations denote the time-varying relationships between the next-time-interval and the current-time-interval basic state variables, namely the procurement/order variables, in the specified logistics system, assuming that these time-varying state variables follow Gaussian–Markov processes. Correspondingly, these state variables are assumed to possess the Markovian properties preferably in the deterministic environment; however, they may be affected in practice by noise terms which follow, to a certain extent, Gaussian processes that contribute to a stochastic system. Therefore, we formulate the generalized form of the time-varying state equations as

$$\mathbf{O}(k+1) = \mathbf{F}[o(k), w(k), k] + \mathbf{L}[o(k), w(k), k]\mathbf{U}(k), \tag{4}$$

where $\mathbf{O}(k+1)$ is a $(J-1)\times 1$ time-varying vector of basic state variables in the given time interval $k+1$, and in the proposed model, $\mathbf{O}(k+1)$ primarily contains the time-varying procurement variables associated with specific chain members excluding the raw supplier (i.e., the chain member of layer-1); $\mathbf{F}[o(k), w(k), k]$ represents a $(J-1)\times 1$ time-varying vector of basic state variables in terms of the downstream orders ($o(k)$) and the control variables ($w(k)$) in the given time interval k; $\mathbf{L}[o(k), w(k), k]$ is a $(J-1)\times(J-1)$ diagonal noise-coupling matrix which is dependent on basic state variables ($o(k)$) as well as the control variables ($w(k)$); and $\mathbf{U}(k)$ corresponds to a $(J-1)\times 1$ state-independent zero-mean white noise vector, which involves elements following zero-mean Gaussian processes. The proposed state equations exhibit the nature of the specified stochastic system that if $\mathbf{L}[o(k), w(k), k]$ and $\mathbf{U}(k)$ do not exist, the prior predictions of procurements associated with chain members ($\mathbf{O}(k+1)$) will depend merely on the multi-layer order-related information in the given supply chain ($\mathbf{F}[o(k), w(k), k]$). However, there exist such internal and external factors as the variation in lead time and the deviation of demand prediction error which may influence the prior prediction of procurement to a certain extent, and thus, the aforementioned state-independent noise and noise-coupling terms, i.e., $\mathbf{U}(k)$ and $\mathbf{L}[o(k), w(k), k]$, respectively, are involved.

In the state equations, $\mathbf{O}(k+1)$, $\mathbf{F}[o(k), w(k), k]$, $\mathbf{L}[o(k), w(k), k]$, and $\mathbf{U}(k)$ can be further expressed as:

$$\mathbf{O}(k+1) = \begin{bmatrix} O_{2,1}(k+1) \\ O_{3,2}(k+1) \\ O_{4,3}(k+1) \\ O_{5,4}(k+1) \end{bmatrix}, \tag{5}$$

$$\mathbf{F}[o(k), w(k), k] = \begin{bmatrix} O_{2,1}(k) + \Psi_2(k) \\ O_{3,2}(k) + \Psi_3(k) \\ O_{4,3}(k) + \Psi_4(k) \\ O_{5,4}(k) \end{bmatrix}. \tag{6}$$

With the notation of the equilibrium demand variable shown in Eqs. (1) and (6) can be rewritten as

$$\mathbf{F}[o(k), w(k), k] = \begin{bmatrix} O_{2,1}(k) + \sum_{j=3}^{5} w_{j,2}(k) \times \left[O_{j,j-1}(k) - \left(\sum_{\varepsilon=1}^{\widetilde{K}} O_{j,j-1}(k-\varepsilon) \right) \Big/ \widetilde{K} \right] \\ O_{3,2}(k) + \sum_{j=4}^{5} w_{j,3}(k) \times \left[O_{j,j-1}(k) - \left(\sum_{\varepsilon=1}^{\widetilde{K}} O_{j,j-1}(k-\varepsilon) \right) \Big/ \widetilde{K} \right] \\ O_{4,3}(k) + \left\{ w_{5,4}(k) \times \left[O_{5,4}(k) - \left(\sum_{\varepsilon=1}^{\widetilde{K}} O_{5,4}(k-\varepsilon) \right) \Big/ \widetilde{K} \right] \right\} \\ O_{5,4}(k) \end{bmatrix}, \tag{7}$$

$$\mathbf{L}[o(k), w(k), k] = \mathbf{Dia} \begin{bmatrix} w_{2,1}(k) \times [O_{2,1}(k) - O_{3,2}(k)]/t_k \\ w_{3,2}(k) \times [O_{3,2}(k) - O_{4,3}(k)]/t_k \\ w_{4,3}(k) \times [O_{4,3}(k) - O_{5,4}(k)]/t_k \\ w_{5,4}(k) \times [O_{5,4}(k) - D_5(k)]/t_k \end{bmatrix}, \tag{8}$$

$$\mathbf{U}(k) = \begin{bmatrix} u_2(k) - \bar{u}_2 \\ u_3(k) - \bar{u}_3 \\ u_4(k) - \bar{u}_4 \\ \ell_5(k) - \bar{\ell}_5 \end{bmatrix}, \tag{9}$$

where t_k is denoted as the length of any given time interval k; $D_5(k)$ shown in Eq. (8) represents the time-varying demand of layer 5 (i.e., the time-varying demand in the end-customer market) in any given time interval; $u_i(k)$ and $\bar{u}_i$, shown in Eq. (9), correspond to the time-varying lead time associated with the given chain member of layer i in a given time interval k and the associated average lead time, respectively; $\ell_5(k)$ and $\bar{\ell}_5$, shown in Eq. (9), represent the time-varying length of the product life cycle in a given time interval k and the average length of the product life cycle, respectively. Note that the order amount from the chain member of layer 5 to that of layer 4 ($O_{5,4}(k)$) does not need to be exactly the same as $D_5(k)$, but can be a certain proportion of $D_5(k)$ in a given time interval. That is, the chain members of layer 4 in other competitive supply chains may share the rest of the end-customer demand (i.e., $D_5(k) - O_{5,4}(k)$) in the given time interval.

3.2. Measurement equations

The measurement equations represent the time-varying relationships between the measurement variables and the basic state variables. In the proposed multi-layer demand-responsive logistics control approach they are employed to update the prior predictions of the basic state variables through the proposed stochastic optimal control algorithm which is depicted in the following section. Therein, the generalized form of the measurement equations is given by

$$\mathbf{Z}(k) = \mathbf{H}[o(k), w(k), k] + \mathbf{V}(k), \tag{10}$$

where $\mathbf{Z}(k)$ is a $(J-1) \times 1$ time-varying inventory vector in which each element represents the measured inventory amount associated with the chain member of a given layer i in time interval k (i.e., $S_i(k)$ for $i = 1, 2, 4$) excluding that of layer 5 ($S_5(k)$); $\mathbf{H}[o(k), w(k), k]$ is a $(J-1) \times 1$ time-varying vector which expresses the relationships between the measured inventories and the basic state variables; and $\mathbf{V}(k)$ is a $(J-1) \times 1$ zero-mean white noise vector, which involves the state-independent zero-mean Gaussian error terms ($v_1(k)$, $v_2(k)$, $v_3(k)$, and $v_4(k)$) of the measured inventory associated with the chain members of layers 1, 2, 3, and 4 in a given time interval k. Herein, $\mathbf{Z}(k)$, $\mathbf{H}[o(k), w(k), k]$, and $\mathbf{V}(k)$ are given, respectively, by:

$$\mathbf{Z}(k) = \begin{bmatrix} S_1(k) \\ S_2(k) \\ S_3(k) \\ S_4(k) \end{bmatrix}, \tag{11}$$

$$\mathbf{H}[o(k), w(k), k] = \begin{bmatrix} T_{0,1}(k) + S_1(k-1) - T_{1,2}(k) \\ T_{1,2}(k) + S_2(k-1) - T_{2,3}(k) \\ T_{2,3}(k) + S_3(k-1) - T_{3,4}(k) \\ T_{3,4}(k) + S_4(k-1) - T_{4,5}(k) \end{bmatrix}. \tag{12}$$

According to the postulated assumptions and Eq. (1), using the specified decision variables, Eq. (12) can be rewritten as

$$\mathbf{H}[o(k), w(k), k] = \begin{bmatrix} \Psi_1(k-1) + S_1(k-1) - O_{2,1}(k) \\ O_{2,1}(k) + S_2(k-1) - O_{3,2}(k) \\ O_{3,2}(k) + S_3(k-1) - O_{4,3}(k) \\ O_{4,3}(k) + S_4(k-1) - O_{5,4}(k) \end{bmatrix}, \tag{13}$$

$$\mathbf{V}(k) = \begin{bmatrix} v_1(k) \\ v_2(k) \\ v_3(k) \\ v_4(k) \end{bmatrix}. \tag{14}$$

3.3. Boundary constraints

In order to yield feasible solutions of decision variables efficiently in the proposed multi-layer demand-responsive logistics operations, the estimates of basic state variables ($O_{i,i-1}(k)$) should be subjected to the limitation of time-varying allowable storage amount in specific layers.

$$0 \leqslant O_{i,i-1}(k) \leqslant \left[S_i^{\max} - S_i(k-1) + \frac{\sum_{\varepsilon=1}^{\widetilde{K}} O_{i+1,i}(k-\varepsilon)}{\widetilde{K}} \right] \quad \text{for } i = 2, 3, 4, 5. \tag{15}$$

4. Algorithm development

The proposed stochastic optimal control-based algorithm serves to minimize the demand-deviation impact on the operations of the specified multi-layer logistics system in a given time period, and correspondingly, to alleviate such an effect with the goal of systematical equilibrium, as depicted in Eq. (2). Therefore, the objective function (ξ) can be represented as:

$$\xi = \min E\left\{ \sum_{k=0}^{N} [\mathbf{O}(k) - \mathbf{O}^*(k)]^{\mathrm{T}} \mathbf{R}_1(k)[\mathbf{O}(k) - \mathbf{O}^*(k)] + [\mathbf{W}(k) - \mathbf{W}^*(k)]^{\mathrm{T}} \mathbf{R}_2(k)[\mathbf{W}(k) - \mathbf{W}^*(k)] \right\}, \tag{16}$$

where $\mathbf{R}_1(k)$ and $\mathbf{R}_2(k)$ represent the $(J-1)\times(J-1)$ and $\left[\sum_{i=1}^{J}(J-i)\right]\times\left[\sum_{i=1}^{J}(J-i)\right]$ time-varying diagonal, positive-definite weighting matrix associated with the estimation vector of the basic state variables ($\mathbf{O}(k)$), and that of the control variables ($\mathbf{W}(k)$), respectively; N corresponds to the total number of time intervals in terms of the logistics control period, and is pre-determined in the study; $\mathbf{O}^*(k)$ and $\mathbf{W}^*(k)$ are the time-varying target vectors associated with $\mathbf{O}(k)$ and $\mathbf{W}(k)$, respectively. Herein, each element in $\mathbf{O}^*(k)$ represents the ideal value of a given basic state variable that contributes to the systematical equilibrium condition. Similar explication is applied to the elements of $\mathbf{W}^*(k)$. Accordingly, the aforementioned objective function serves the purpose of minimizing the operational cost in the process of approaching to systematical equilibrium.

To perform the functionality of multi-layer demand-responsive logistics control, a stochastic optimal control-based algorithm is developed where the extended Kalman technology is employed to update the estimates of decision variables in each time interval. Note that Kalman filtering techniques have been investigated for a couple of decades, and applied successfully in many areas such as spacecraft navigation, target tracking, trajectory determination (Stengel, 1986; Santina et al., 1994) as well as transportation (Busch, 1987; Cremer, 1987; Sheu, 1999, 2002). An extended Kalman filter is adapted from a basic Kalman filter, particularly for the state estimation of nonlinear stochastic systems. Using an extended Kalman filter, the estimates of the current-time-interval basic state variables ($\mathbf{O}(k)$) as well as control variables ($\mathbf{W}(k)$) are updated with the objective function shown in Eq. (16), and then, used as the basis for estimating the next-time-interval decision variables. Moreover, other physical measurements including the inbound distribution amount ($T_{i-1,i}(k)$) and the outbound distribution amount ($T_{i,i+1}(k)$) associated with a given chain member i in each layer, are derived in each time interval in the control process. The entire control logic is presented in Fig. 3, and corresponding computational procedures are summarized below.

Step 0: Initialize decision variables. Given $k=0$, decision variables including (1) the vector of basic state variables $\mathbf{O}(0|0)$, (2) the initialized inventory measurements $\mathbf{Z}(0)$, (3) the control variable vector $\mathbf{W}(0|0)$, (4) the covariance matrix of the basic state estimation error $\Phi(0|0)$, and (5) the weighting matrix $\mathbf{R}_1(0)$ are initialized.

Step 1: Input time-varying end-customer demand data and measured multi-layer inventories. Let the time-varying demand of the end-customer market ($D_5(k)$) in each given time interval be known, and let the measured inventories ($S_1(k)$, $S_2(k)$, $S_3(k)$, and $S_4(k)$) associated with the chain members of layers 1, 2, 3, and 4 be the input in time interval k.

Step 2: Compute prior prediction in terms of the vector of basic state variables ($\mathbf{O}(k+1|k)$) and the covariance matrix of the state estimation error ($\Phi(k+1|k)$) by:

$$\mathbf{O}(k+1|k) = \mathbf{F}[o(k), w(k), k], \tag{17}$$

$$\Phi(k+1|k) = \mathbf{f}(k)\Phi(k|k)\mathbf{f}^{\mathrm{T}}(k) + \mathbf{L}[o(k), w(k), k]\mathbf{R}_1(k)\mathbf{L}[o(k), w(k), k]^{\mathrm{T}}, \tag{18}$$

where matrix $\mathbf{f}^{\mathrm{T}}(k)$ is the transpose matrix of $\mathbf{f}(k)$ which is given by:

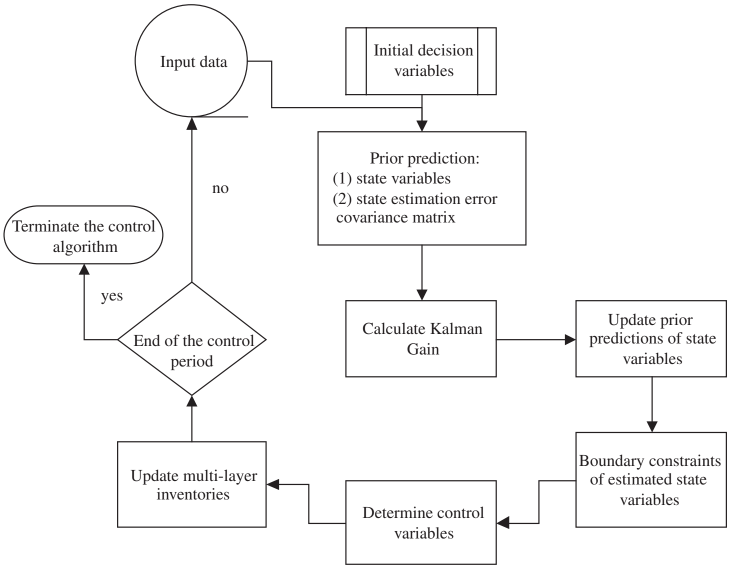

Fig. 3. Diagram of the proposed multi-layer logistics control logic.

$$\mathbf{f}(k) = \left.\frac{\partial \mathbf{F}[o(k), w(k), k]}{\partial \mathbf{O}(k)}\right|_{O(k)=O(k|k)}. \tag{19}$$

Step 3: Calculate the Kalman gain ($\Gamma(k+1)$) by:

$$\Gamma(k+1) = \Phi(k+1|k)\mathbf{h}^{\mathrm{T}}(k+1)[\mathbf{h}(k+1)\Phi(k+1|k)\mathbf{h}^{\mathrm{T}}(k+1) + \mathbf{R}_2(k+1)]^{-1}, \tag{20}$$

where $\mathbf{R}_2(k+1)$ is pre-specified in the algorithm based on the covariance matrix of $\mathbf{V}(k)$ and $\mathbf{h}(k+1)$ is denoted by:

$$\mathbf{h}(k+1) = \frac{\partial \mathbf{H}[o(k+1|k), w(k), k+1]}{\partial \mathbf{O}(k+1|k)}. \tag{21}$$

Step 4: Update the prior prediction in terms of the vector of basic state variables ($\mathbf{O}(k+1|k+1)$) by:

$$\mathbf{O}(k+1|k+1) = \mathbf{O}(k+1|k) + \Gamma(k+1)\Delta\mathbf{Z}(k+1|k), \tag{22}$$

where $\Delta\mathbf{Z}(k+1|k)$ is given by:

$$\Delta\mathbf{Z}(k+1|k) = \mathbf{Z}(k+1) - \mathbf{H}[o(k+1|k), w(k), k+1]. \tag{23}$$

Step 5: Truncate the updated estimates of basic state variables with boundary constraints shown in Eq. (15).

Step 6: Update the covariance matrix of the state estimation error ($\Phi(k+1|k+1)$) as:

$$\Phi(k+1|k+1) = [\mathbf{I} - \Gamma(k+1)\mathbf{h}(k+1)]\Phi(k+1|k). \tag{24}$$

Step 7: Calculate the control-variable vector $\mathbf{W}(k+1)$. According to the principles of stochastic optimal control (Stengel, 1986; Santina et al., 1994), the updated vectors of basic state variables ($\mathbf{O}(k+1|k+1)$) and control variables ($\mathbf{W}(k+1)$) are fed back through the optimal gain matrix $\mathbf{E}(k+1)$ to minimize the pre-specified operational cost function (see Eq. (16)), and $\mathbf{W}(k+1)$ is estimated by:

$$\mathbf{W}(k+1) = -\mathbf{E}(k+1)\mathbf{O}(k+1|k+1) + \boldsymbol{\eta}(k+1). \tag{25}$$

In Eq. (25), $\mathbf{E}(k+1)$ and $\boldsymbol{\eta}(k+1)$ are denoted respectively by:

$$\mathbf{E}(k+1) = [\mathbf{B}^{\mathrm{T}}(k+1)\mathbf{C}(k+2)\mathbf{B}(k+1) + \mathbf{R}_2(k+1)]^{-1}\mathbf{B}^{\mathrm{T}}(k+1)\mathbf{C}(k+2)\mathbf{f}(k+1), \tag{26}$$

$$\begin{aligned}\boldsymbol{\eta}(k+1) = {} & [\mathbf{B}^{\mathrm{T}}(k+1)\mathbf{C}(k+2)\mathbf{B}(k+1) + \mathbf{R}_2(k+1)]^{-1} \\ & \times [\mathbf{B}(k+1)\mathbf{R}_1(k+1)\mathbf{O}^*(k+1) + \mathbf{R}_2(k+1)\mathbf{W}^*(k+1)],\end{aligned} \tag{27}$$

where matrix $\mathbf{C}(k+2)$ should satisfy the Riccati equation as shown below:

$$\mathbf{C}(k+1) = \mathbf{R}_1(k+1) + \mathbf{f}^{\mathrm{T}}(k+1)\mathbf{C}(k+2)\mathbf{f}(k+1) - \mathbf{f}^{\mathrm{T}}(k+1)\mathbf{C}(k+2)\mathbf{B}(k+1)\mathbf{E}(k+1) \tag{28}$$

and matrix $B(k+1)$ can be further expressed as:

$$B(k+1) = \frac{\partial \mathbf{F}[o(k), w(k), k]}{\partial \mathbf{W}(k)}. \tag{29}$$

Step 8: Update the estimated time-varying inventory amount ($S_i(k+1|k+1)$) associated with the chain member in each given layer i at the end of time step $k+1$ as

$$S_i(k+1|k+1) = T_{i-1,i}(k+1) + S_i(k) - T_{i,i+1}(k+1) \quad \text{for } i = 1,2,3,4. \tag{30}$$

According to the assumptions and Eq. (13), Eq. (30) can be rewritten as

$$S_i(k+1|k+1) = O_{i,i-1}(k+1|k+1) + S_i(k) - O_{i+1,i}(k+1|k+1) \quad \text{for } i = 1,2,3,4. \tag{31}$$

Step 9: Check the status of the logistics control routine by conducting the following rules.

If the next time interval is at the end of the control period, then stop the control routine. Otherwise, let $k = k+1$, and go to Step 1 to continue the routine.

5. Experimental design

This section describes the major procedures of experimental design conducted for verifying the potential of the proposed logistics control method in terms of alleviating the bullwhip effect between the second layer (i.e., the manufacturer) and the fourth layer (i.e., the retailer) through systematically optimizing the logistics performance in a typical 5-layer supply chain of the manufacturing industry. Evaluation measures were based mainly on the comparison of the output data generated from the proposed method with that measured using a simplified (s, S) ordering strategy for each chain member giving the same patterns of the end-customer demand which follow specific stochastic processes during a given 10-time-interval control period.

The input data acquisition procedure primarily involves two stages: (1) specification of initialized system states, and (2) generation of time-varying end-customer demands and measured inventories via simulation. As noted in *Step 0* of the proposed logistics control algorithm, system states primarily including basic state variables, measurement variables, and control variables should be initialized at the onset of the logistics control period. Moreover, the data sets of time-varying end-customer demand ($D_5(k)$) and the measured inventories associated with chain members of layers 1–4 (i.e., $S_1(k)$, $S_2(k)$, $S_3(k)$, and $S_4(k)$) in each given time interval k, all assuming to follow Gaussian processes, were generated via simulation. Utilizing random numbers, a subroutine which serves to generate Gaussian-based random variables was then executed in the simulation procedure to obtain these time-varying end-customer demands and inventories. Tables 1 and 2 summarize the primary initialized system states and control variables, respectively.

Table 1
Summary of initialized system states

Parameter	Layer-i				
	1 (raw-material supplier)	2 (manufacturer)	3 (wholesaler)	4 (retailer)	5 (end-customer)
Initialized inventory ($S_i(0)$)	1000	1000	1000	1000	*
Initialized order ($O_{i,i-1}(0\|0)$)	*	1300	1200	1100	1000

Table 2
Summary of initialized control variables ($w_{i,j}(0)$)

Layer-"i"	Layer-"j"				
	1	2	3	4	5
1	*	*	*	*	*
2	1.00	*	*	*	*
3	0.75	1.00	*	*	*
4	0.50	0.75	1.00	*	*
5	0.25	0.50	0.75	1.00	*

The output database used for comparison includes the basic state variables estimated via the proposed logistics control algorithm, and the order associated with each chain member yielded utilizing the simplified well-known (s, S) ordering strategy. Given the initialized system states and pre-set parameters, the aforementioned two specific logistics control strategies were executed to obtain time-varying orders during the 10-time-interval period. Herein, we compared the performance of the proposed logistics control approach with that of the given (s, S) ordering strategy utilizing two types of measures defined as follows:

(1) $\mathrm{VR}_{i,5}^{\theta}(k)$ corresponds to the variance of the time-varying procurement amount placed by the chain member of layer i relative to the variance of the time-varying end-customer demand (i.e., the demand of the chain member of layer 5) in a given time interval k under the condition of a given logistics control strategy θ. Herein, $\mathrm{VR}_{i,5}^{\theta}(k)$ is given by

$$\mathrm{VR}_{i,5}^{\theta}(k) = \frac{\mathrm{Var}[O_{i,i-1}^{\theta}(k|k)]}{\mathrm{Var}[O_{5,4}^{\theta}(k|k)]}, \tag{32}$$

where $\mathrm{Var}[O_{i,i-1}^{\theta}(k|k)]$ represents the variance of the estimated procurement amount placed by the chain member of layer i to the chain member of layer $i-1$ in a given time interval k given the logistics control strategy θ; and similarly $\mathrm{Var}[O_{5,4}^{\theta}(k|k)]$ is referred to as the variance of the estimated orders from the end-customer (i.e., the chain member of layer 5) to the retailer (i.e., the chain member of layer 4) in the time interval k given the logistics control strategy θ.

(2) $\overline{\mathrm{VR}}_{i,5}^{\theta}$ is denoted as the average value in terms of $\mathrm{VR}_{i,5}^{\theta}(k)$ estimated during the control period, and is given by

$$\overline{\mathrm{VR}}_{i,5}^{\theta} = \frac{\sum_{k=1}^{N}\sum_{i=1}^{J-1}\mathrm{Var}[O_{i,i-1}^{\theta}(k|k)] \Big/ \mathrm{Var}[O_{5,4}^{\theta}(k|k)]}{[N \times (J-1)]}. \tag{33}$$

Note that as to the aforementioned two types of evaluation measures, $\mathrm{VR}_{i,5}^{\theta}(k)$ can be used to indicate the change in patterns of the relative deviation of the time-varying procurement associated with a given upstream chain member in comparison with that associated with the end customer, and in particular to imply the improvement in the bullwhip effect which can be measured readily by $\mathrm{VR}^{\theta}_{2,5}(k)/\mathrm{VR}^{\theta}_{4,5}(k)$ given the logistics control strategy θ. In contrast with $\mathrm{VR}^{\theta}_{i,5}(k)$, $\overline{\mathrm{VR}}^{\theta}_{i,5}$ evaluates the long-term performance of a given logistics control strategy. The comparison results according to the aforementioned criteria are summarized in Table 3.

Overall, the comparison results shown in Table 3 revealed the significant improvement in reducing the deviation of chain-based orders by implementing the proposed multi-layer demand-responsive logistics control in comparison with the classical (s, S) ordering strategy. Two observations from the analysis are provided to elucidate this generalization. First, the comparative improvements with respect to the two aforementioned measures, $\mathrm{VR}^{\theta}_{i,5}(k)$ and $\overline{\mathrm{VR}}^{\theta}_{i,5}$ are significantly high under the control of the proposed logistics control method. As depicted in Table 3, the measurements associated with the proposed approach are lower than that of the (s, S) ordering strategy, either in the short-term or in the long-term temporal domain, and overall, the relative improvement is up to 64%. Second, the estimates of $\mathrm{VR}^{\theta}_{i,5}(k)$ associated with the proposed method change rather smoothly over time during the control period, implying the stability of the order patterns of chain members, and thus, help to accomplish the goal of systematical equilibrium in the chain-based logistics operational environment. Accordingly, it is inducible that the proposed multi-layer logistics control strategy appears to respond efficiently to the variability of the end-customer demand.

Considering the efficiency of the proposed logistics control method in alleviating the bullwhip effect under different conditions of control periods, further tests of hypotheses with statistical techniques were conducted. Given the pre-determined parameters, we estimated the measures of $\mathrm{VR}^{p}_{i,5}(k)$ in different control-period scenarios, including 5-time-interval, 10-time-interval, 20-time-interval, and 30-time-interval cases utilizing the proposed method. Then, the following hypothesis (H_0) was tested to verify that the bullwhip effect does not remain in any control-period cases under the control of the proposed logistics control method.

$$H_0 : \overline{\mathrm{VR}}^{p}_{2,5} = \overline{\mathrm{VR}}^{p}_{3,5} = \overline{\mathrm{VR}}^{p}_{4,5}. \tag{34}$$

Table 3
Comparison of system performance

Time interval "k"	Layer-"i"					
	2 (manufacturer)		3 (wholesaler)		4 (retailer)	
	$\mathrm{VR}^{p}_{2,5}(k)$	$\mathrm{VR}^{s}_{2,5}(k)$	$\mathrm{VR}^{p}_{3,5}(k)$	$\mathrm{VR}^{s}_{3,5}(k)$	$\mathrm{VR}^{p}_{4,5}(k)$	$\mathrm{VR}^{s}_{4,5}(k)$
1	1.67	2.78	1.72	2.54	0.83	1.89
2	1.21	3.62	0.89	2.09	0.75	1.62
3	0.84	1.97	0.72	3.26	0.74	2.12
4	0.77	2.54	0.93	2.11	0.69	1.63
5	0.54	3.80	0.77	1.98	0.72	2.05
6	0.68	3.31	0.53	1.70	0.80	2.53
7	0.73	2.22	0.69	2.04	0.98	1.44
8	0.62	2.96	0.70	3.62	0.76	1.62
9	0.74	3.74	0.61	2.79	0.80	1.23
10	0.69	3.26	0.54	2.33	0.77	1.98
Average ($\overline{\mathrm{VR}}^{\theta}_{i,5}$)	$\overline{\mathrm{VR}}^{p}_{2,5}$	$\overline{\mathrm{VR}}^{s}_{2,5}$	$\overline{\mathrm{VR}}^{p}_{3,5}$	$\overline{\mathrm{VR}}^{s}_{3,5}$	$\overline{\mathrm{VR}}^{p}_{4,5}$	$\overline{\mathrm{VR}}^{s}_{4,5}$
	0.85	**3.02**	**0.81**	**2.45**	**0.78**	**1.81**

$\mathrm{VR}^{p}_{i,5}(k)$: the time-varying measure generated using the proposed logistics control strategy.
$\mathrm{VR}^{s}_{i,5}(k)$: the time-varying measure generated using the simplified (s, S) logistics control strategy.
$\overline{\mathrm{VR}}^{p}_{i,5}(k)$: the average value of $\mathrm{VR}^{p}_{i,5}(k)$.
$\overline{\mathrm{VR}}^{s}_{i,5}(k)$: the average value of $\mathrm{VR}^{s}_{i,5}(k)$.

Table 4
Results of two-tailed p-value tests

Test scenario	p-value	Significance level	Result
5-time-interval	0.28	0.01	Accepted
10-time-interval	0.33	0.01	Accepted
20-time-interval	0.24	0.01	Accepted
30-time-interval	0.13	0.01	Accepted

Herein, the p-value testing approach, a conventional hypothesis-testing technique, was used in this test scenario. Table 4 summarizes the results of case-by-case two-tailed p-value tests with the level of significance $\alpha = 0.01$.

The p-value test results shown in Table 4 indicate that the aforementioned hypothesis is acceptable. Accordingly, there is no reason to reject the assumption that given patterns of the end-customer demand, there is no difference in terms of the variance of orders among the chain members of layers 2–4 in these tests. Therefore, it implies that the proposed multi-layer demand-responsive logistics control approach appears promising to address the bullwhip effect, efficiently and effectively, in different control-period cases.

6. Concluding remarks

This paper has presented a novel multi-layer demand-responsive logistics control method to address the bullwhip effect, which is a critical issue remaining in the field of supply chain management. Through analyzing the intra-member and inter-member relationships linking with demand-related information flows and physical flows, a conceptual framework is specified to illustrate the potential effect of demand-oriented information deviation on the multi-layer logistics operations of a typical 5-layer supply chain. Utilizing the specified conceptual framework, three groups of decision variables including (1) basic state variables, (2) measurement variables, and (3) control variables are proposed, followed by the formulation of a discrete-time nonlinear stochastic model to characterize the operations of the specified multi-layer logistics system under the condition of demand variability. To accomplish the goal of systematical equilibrium which serves to minimize the chain-based logistics operational cost, a stochastic optimal control based algorithm is developed, in which the extended Kalman technology is employed in aid of updating the estimates of decision variables during the logistics control period.

In addition, experimental design is conducted to illustrate the potential performance of the proposed logistics control method in terms of addressing the issue of bullwhip effect in comparison with a simplified (s, S) ordering strategy. With two specified evaluation measures, the comparison results have revealed the comparative potential of the proposed method in reducing the effect of the variability of the end-customer demand on the logistics operations of the other chain members. The results of hypotheses tests further imply that the proposed multi-layer demand-responsive logistics control approach appears promising to address the bullwhip effect, efficiently and effectively, in diverse control-period cases.

Nevertheless, further tests as well as modifications may be necessary to verify the robustness of the proposed multi-layer demand-responsive logistics control methodology, and its applicability in real cases. Further comparison of the performance of the proposed control method with that of other advanced logistics control approaches can also help to demonstrate the potential advantages of the proposed method. Moreover, efforts on either integrating the proposed control method with other published logistics management strategies such as QR and JIT or extending it for multi-layer multi-member (i.e., multiple chain members in a given layer) cases seem to be necessary. On the basis of the present results, our future research will aim at incorporating advanced ITS-related technologies into the architecture of the proposed method to improve time-based demand-responsive logistical control and management. Moreover, the applicability of the proposed method for QR logistical operations in the e-business environment is also interesting, which warrants further research.

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