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ORIGINAL ARTICLE

# Optimization of total inventory cost and order fill rate in a supply chain using PSO

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**Abstract** This paper proposes a method to optimize both the total cost and order fill rates in a supply chain using the particle swarm optimization (PSO) method. This method automatically adjusts the initial inventory levels of all tiers involved in a supply chain by considering information quality level (IQL), which is determined by the degree of availability of lead time history data. Analyses of variance are used to examine if there are any effects of IQL on the total cost and order fill rates. The results show that the proposed method finds better solutions which provide a lower inventory level while maintaining higher order fill rates than when PSO is not applied.

**Keywords** Information quality level · Initial inventory · Initial conditions · Particle swarm optimization

## 1 Introduction

Supply chain management (SCM) is well known as the management of the processes to minimize the total cost and to satisfy the customer service level required through a supply chain. SCM is also described as the systematic method to manage all participants in a supply chain, including suppliers, manufacturers, distributors, and retailers for delivering the right amount of the right product to the right place at the right time [1]. A supply chain may have problems about the order process, the lead time, the batch order, the shortage, the price fluctuations, and the sales [2]. These problems may cause the bullwhip effect [3]. Lee et al. [2] explained that "the bullwhip effect or whiplash effect refers to the phenomenon where orders to the supplier tend to have larger variance than sales to the buyer (i.e., demand distortion), and the distortion propagates upstream in an amplified form (i.e., variance amplification)."

One of the most effective ways to solve the bullwhip effect is to share information across participants involved in a supply chain [4, 5]. Chatfield et al. [4] claimed that the bullwhip effect may be more intensified by a violent fluctuation in the order information from the downstream when a participant fully trusts the information. Based on this claim, it can be inferred that the information quality level from the downstream is important to control the bullwhip effect. However, to the authors' knowledge, no previous studies have considered the information quality level to control the bullwhip effect.

The earlier studies have been concentrated on the effectiveness of information sharing, demand forecasting methods in the bullwhip effect [6–11], rather than the strategies to reduce the total cost or increase customer satisfaction by improving the performance of the whole supply chain [12, 13]. Lau et al. [8] studied that the inventory in a supply chain influences the total cost by comparing the superiority among inventory strategies. However, they did not consider the initial inventory level needed for a better operational management. The initial inventory level may not greatly affect a supply chain if the supply chain has been stably operated for a long-term period. However, few manufacturers wants to produce limited types of consumable electronic goods for a long period, because the demand pattern for consumable electronic goods nowadays has shown radical fluctuation [14]. The manufacturer should carefully observe a change in the demand pattern even for a short-term period and timely change the type of consumable electronic products in order to better keep up with the customer demand pattern and to achieve market competitiveness. Consequently, the supply chain model for a short-term period is affected by the initial inventory level.

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Park [5, 12, 13] compared the total inventory cost using the supply chain model suggested by Strozzi et al. [15] and Thomson et al. [16], as shown in Fig. 1.

Park [5, 12, 13] investigated if there is a change in the total inventory cost of each of five supply chain cases, where their initial inventory levels are differently set. For case 1, the initial backlog for each tier is 0, the initial inventory is 12, and the values of other state variables are 4 [15]. For case 2, the values of all state variables are set to 0. For case 3, the initial inventory for each tier is 12, and the values of other state variables are set to 0. For case 4, the initial inventory for each tier is 12, and the values of other state variables are set to 8. For case 5, the values of all state variables are set to 12. The simulation results show that the total inventory cost varies by the initial condition for each supply chain with the total inventory cost of Case 2 being the highest where the initial inventory level for each tier is zero. Thus, as initial inventory level could affect the efficiency of a supply chain, it is necessary to carefully consider the initial condition when building a supply chain model (Fig. 2).

In this paper, we suggest a method using particle swarm optimization (PSO) for optimizing both the total inventory cost and order fill rates while reflecting the information quality level as well as automatically changing the initial inventory condition for each tier.

We explain the motivation and the objective of this research in Section 1 and the characteristics of the suggested model in Section 2. In Section 3, we present an optimal model for the supply chain. The model is simulated, and the result is analyzed in Section 4. In Section 5, we conclude this study and describe the further work.

## 2 Properties of the proposed model

The main aims of this research are to consider the information quality level between tiers in a supply chain and to optimize the initial condition affecting the supply chain. For this purpose, we have made assumptions and definitions as below.

First, we assume that products are produced for a short-term period to reflect the change in market conditions due to the fluctuation in customer demand patterns. Under the short-term period condition, the performance of the supply chain may be affected by the initial condition. As shown in Fig. 3, the initial condition can have a substantial effect on the inventory level for each tier. Since the bullwhip effect depends on the initial condition and affects the total inventory cost in the whole supply chain, it is necessary to optimize the initial inventory condition [5, 12, 13].

Second, in the current study, the information quality level is about how much information from the downstream is available to each upstream tier, rather than whether or not information is shared across the supply chain [4]. Earlier studies [7, 8] which tested a supply chain model under two different conditions—with and without sharing end-customer information—showed that the bullwhip effect decreases when the end-customer information gets across to upstream.

Third, PSO, one of meta-heuristic methods, will be used as an optimization methodology in order to allow for the information quality level and the initial inventory condition. It uses primitive and simple mathematical operators and is known to be highly efficient in memory requirement and running speed [17, 18]. In addition, it shows superiority to genetic algorithm (GA) in some application areas [19].

## 3 Supply chain optimization model

We use the Strozzi et al. [15] model to simulate a supply chain that consists of a factory, a distributor, a wholesaler, and a retailer (Fig. 1). The decision variables used in this study are illustrated as follows:

$FED_t$ The expected demand of a factory at time $t$
$DED_t$ The expected demand of a distributor at time $t$

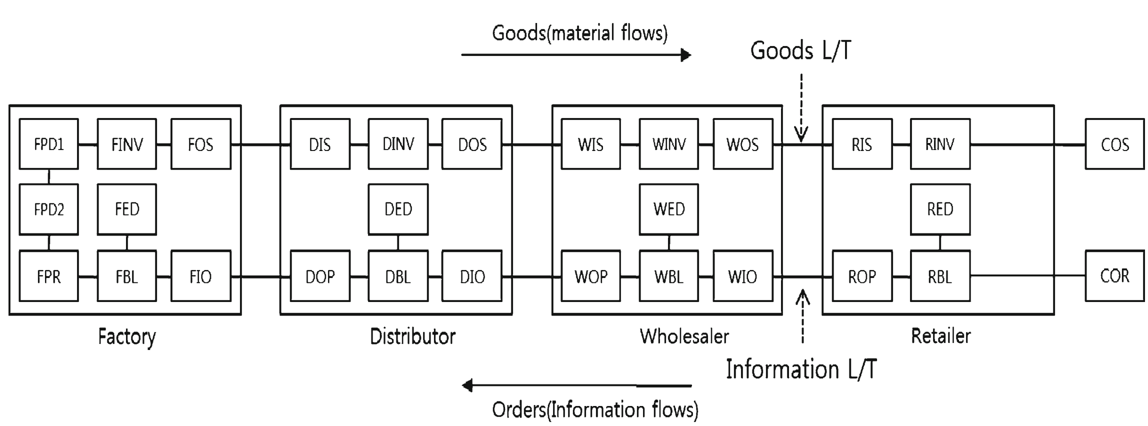



**Fig. 1** Supply chain model [15, 16]

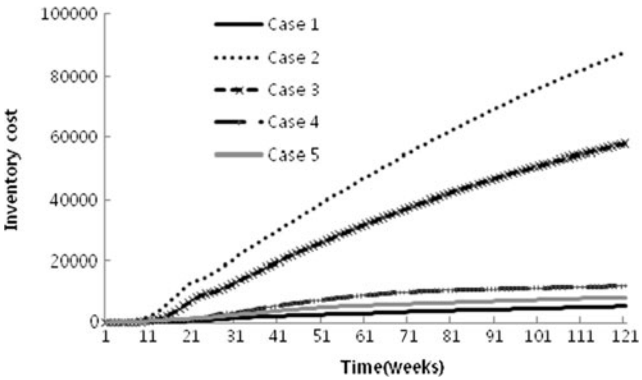
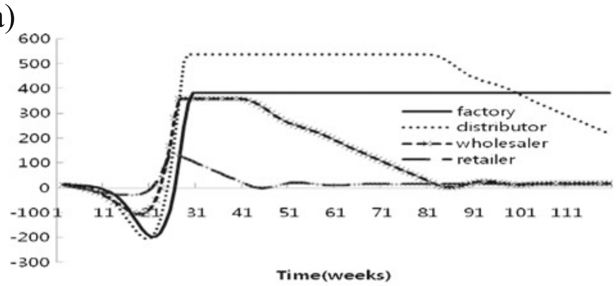



**Fig. 2** Effects of different initial inventory conditions on the total inventory cost of a supply chain

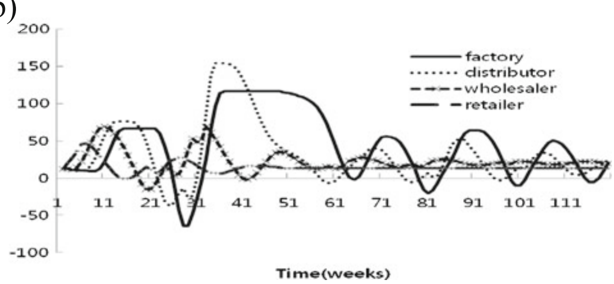
| | |
|---|---|
| $WED_t$ | The expected demand of a wholesaler at time $t$ |
| $RED_t$ | The expected demand of a retailer at time $t$ |
| $FOS_t$ | The outgoing shipment of a factory at time $t$ |
| $DOS_t$ | The outgoing shipment of a distributor at time $t$ |
| $WOS_t$ | The outgoing shipment of a wholesaler at time $t$ |
| $ROS_t$ | The outgoing shipment of a retailer at time $t$ |
| $FIO_t$ | The incoming order of a factory at time $t$ |
| $DIO_t$ | The incoming order of a distributor at time $t$ |
| $WIO_t$ | The incoming order of a wholesaler at time $t$ |
| $RIO_t$ | The incoming order of a retailer at time $t$ |
| $DIS_t$ | The incoming shipment of a distributor at time $t$ |
| $WIS_t$ | The incoming shipment of a wholesaler at time $t$ |
| $RIS_t$ | The incoming shipment of a retailer at time $t$ |

(a)




The bullwhip effect depending on the initial inventory conditions for Case 3

(b)




The bullwhip effect depending on the initial inventory conditions for Case 5

**Fig. 3** Bullwhip effects influenced by initial inventory conditions

| | |
|---|---|
| $COR_t$ | The order of a customer at time $t$ |
| $FPR_t$ | The production of a factory at time $t$ |
| $DOP_t$ | The order placed by a distributor at time $t$ |
| $WOP_t$ | The order placed by a wholesaler at time $t$ |
| $ROP_t$ | The order placed by a retailer at time $t$ |
| $FBL_t$ | The backlog of a factory at time $t$ |
| $DBL_t$ | The backlog of a distributor at time $t$ |
| $WBL_t$ | The backlog of a wholesaler at time $t$ |
| $RBL_t$ | The backlog of a retailer at time $t$ |
| $FINV_t$ | The inventory of a factory at time $t$ |
| $DINV_t$ | The inventory of a distributor at time $t$ |
| $WINV_t$ | The inventory of a wholesaler at time $t$ |
| $RINV_t$ | The inventory of a retailer at time $t$ |
| $FPD1_t$ | The production and moving delay of a factory at time $t$ |
| $FPD2_t$ | The production delay of a factory at time $t$ |
| $COR_t$ | The customer order rate at time $t$ |
| $\theta$ | The parameter of expectation rate |

It is assumed that the end-customer demand is stochastic, rather than deterministic, and can be modeled using the autoregressive AR(1) model of $D_t=\mu+\rho D_{t-1}+\varepsilon_t$, $|\rho|<1$, where $D_t$ is the demand at time $t$, $\mu$ is a nonnegative constant, $\rho$ is the first-order autocorrelation coefficient, and $\varepsilon_t$ is the error term following the normal distribution with the mean of 0 and the variance of $\sigma^2$. The AR($p$) model is a type of random process that is used to model various natural phenomena with the order of $p$ [20]. It predicts customer demand based on past data. In this paper, the order $p$ is set to 1. The expected demand for each tier is estimated by adding the order from the downstream and the expected demand for the downstream. The expected demand for each tier is calculated by $ED_t=\theta \cdot IO_{t-1}+(1-\theta)\cdot ED_{t-1}$, where $ED_t$ and $ED_{t-1}$ are the expected demand at time $t$ and $t-1$, respectively, and $IO_{t-1}$ is the order at time $t$. $\theta(0\leq\theta\leq1)$ is a parameter that controls the rate at which expectations are updated. $\theta=0$ describes the stationary expectation, and $\theta=1$ explains a situation in which the immediately preceding value of received orders is used as an estimate of future demand. As the $\theta$ increases, the order from the downstream becomes more important, while the expected demand that involves uncertainty becomes less important.

It is assumed that the lead time is 1 week for each tier, and the lead time for a factory is 3 weeks considering the delivery of raw materials. It is supposed that the production capacity is infinite, and there is a place for inventory at each tier. It is assumed that the order cannot be canceled and the remaining inventory cannot be returned. The total inventory cost is calculated using the following equation:

$$\sum\nolimits_{t=1}^{n}\left(\mathrm{BLC}\cdot\left(\sum\nolimits_{i=1}^{m}\mathrm{BL}_{t,i}\right)+\mathrm{HIC}\cdot\left(\sum\nolimits_{i=1}^{m}\mathrm{INV}_{t,i}\right)\right) \quad (1)$$

The total cost is estimated by adding the backlog cost (BLC) and the inventory holding cost (HIC). The backlog cost would be estimated higher than the inventory holding cost because the backlog cost includes loss of sale chance and credibility. In expression (1), $\mathrm{BL}_{t,i}$ is the backlog for tier $i$ at time $t$, and $\mathrm{INV}_{t,i}$ is the inventory for tier $i$ at time $t$.

One of the general inventory replenishment strategies is the order-up-to-level including the order point–order quantity ($s$, $Q$) system, the order point–order-up-to-level ($s$, $S$) system, the periodic review–order-up-to-level ($R$, $S$) system, and ($R$, $s$, $S$) system [21]. In this study, we use the periodic review–order-up-to-level ($R$, $S$) for the inventory replenishment, and the inventory is estimated every $R$ period and the order quantity will be Max $(0, S-\mathrm{INV}_{t,i})$.

We consider two information quality levels (IQL) as follows:

IQL A: Each tier retains the order history of the downstream, and can use the average ($\overline{D}$ ) and standard deviation ($s_{\mathrm{D}}$) of demand. It knows the average lead time ($\overline{L}$ ), but there is no lead time history data available. The order-up-to-level, $S$, is expressed as follows ([4; 22]:

$$S = \overline{X} + z s_x \tag{2}$$

where,

$$\overline{X} = \left(\overline{L} + R\right)\overline{D} \tag{3}$$

$$S_X = S_{\mathrm{D}} \cdot \sqrt{\left(\overline{L} + R\right)} \tag{4}$$

$\overline{X}$ and $s_X$ are the average and standard deviation of demand during lead time, respectively. $\overline{\mathrm{D}}$ and $$ SD $$ are, respectively, the average and standard deviation of demand from the downstream.

IQL B: A tier retains the order history from the downstream. It, therefore, can use the average ($\overline{D}$ ) and variance ($V_{\mathrm{D}}$) of demand. It also has the lead time history data with an upstream tier, and can use the average ($\overline{L}$ ) and standard deviation ($s_{\mathrm{L}}$) of lead time. The standard deviation of the demand during lead time can be expressed as follows:

$$s_{\mathrm{X}} = V_{\mathrm{D}} \cdot \sqrt{\left(\overline{L} + R\right)} + \overline{D} \cdot s_{\mathrm{L}} \tag{5}$$

The optimal supply chain process suggested in this study is depicted in Fig. 4.

In Fig. 4, the input information in the supply chain includes initial inventory, the expected demand for each tier, lead time, and information quality level. Using this input information, the values of the objective functions with the decision variables are determined. From the supply chain model, we get the values of performance measures under a given condition rather than an optimal value.

The optimal model can get the objective value using the PSO, and the objective values generate a set of Pareto front candidates. This paper uses the concept of non-dominated solution explained as Pareto front because it is impossible to get the optimal solutions which satisfy all the objectives simultaneously. A solution is called a non-dominated solution if it is not dominated by other solutions among all candidate solutions. The Pareto front is composed of a set of all non-dominated solutions. The simulation ends when termination conditions (e.g., the total simulation period) are met.

PSO, introduced by Eberhart and Kennedy [23], is based on the social behavior pattern of a biological group such as a flock of birds or a school of fish, whereas GA imitates a natural evolutionary process. In the PSO method, a decision variable is regarded as a particle, and the population of decision variables is considered as a swarm [23–25].

In the PSO method, the decision variable $X_n^{(t+1)}$ of the population in a swarm of $N$ particles has the velocity determining the location of the next generation. $X_n^{(t+1)}$ is

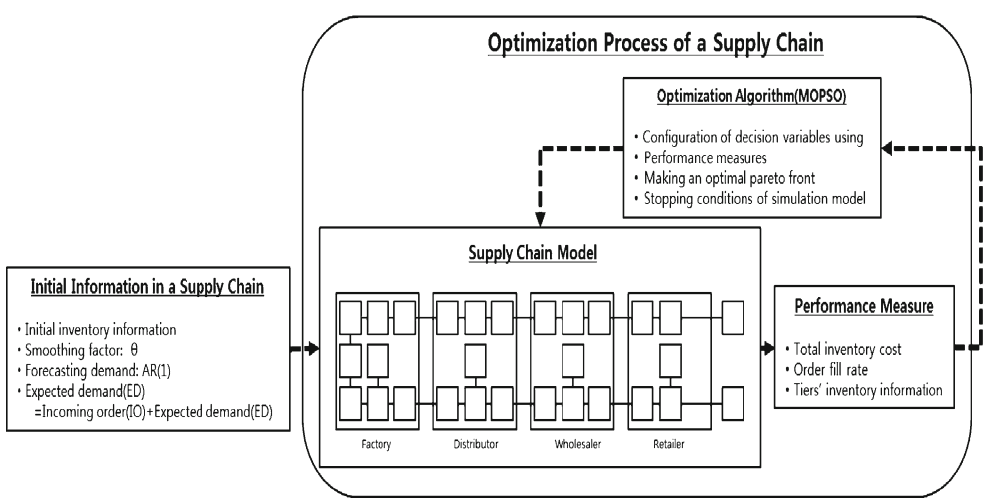



**Fig. 4** The optimal supply chain process

**Table 1** The population of decision variables for the supply chain model using PSO

| FPD2 | FPR | FPD1 | FINV | FBL | FED | FIO | FOS | DOP | DIS | DINV | DBL | DED | DIO | DOS | WOP |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 8 | 8 | 8 | 12 | 0 | 8 | 8 | 8 | 8 | 8 | 12 | 0 | 8 | 8 | 8 | 8 |
| . | . | . | . | . | . | . | . | . | . | . | . | . | . | . | . |
| . | . | . | . | . | . | . | . | . | . | . | . | . | . | . | . |
| . | . | . | . | . | . | . | . | . | . | . | . | . | . | . | . |

| WIS | WINV | WBL | WED | WIO | WOS | ROP | RIS | RINV | RBL | RED | RIO | ROS | COR | $\theta$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 8 | 12 | 0 | 8 | 8 | 8 | 8 | 8 | 12 | 0 | 8 | 8 | 0 | 8 | 0.25 |
| . | . | . | . | . | . | . | . | . | . | . | . | . | . | . |
| . | . | . | . | . | . | . | . | . | . | . | . | . | . | . |
| . | . | . | . | . | . | . | . | . | . | . | . | . | . | . |

the vector value of the $n$th particle of the $t+1$th generation. The location for each particle is estimated as follows [17].

$$X_n^{(t+1)} = X_n^{(t)} + V_n^{(t)} \tag{6}$$

$$Xn^{(t+1)} = Xn^{(t)} + \chi Vn^{(t)} + \varepsilon^{(t)} \tag{7}$$

The expression (6) is generally used for estimating each particle of the $t+1$th generation using the location and velocity of the $t$th generation. $V_n^{(t)}$ is the velocity of the $n$th particle of the $t$th generation. The expression (6) can be replaced with the expression (7) to adjust the location and the velocity of a particle. The expression (7) includes a constriction factor, $\chi$ ($\chi \in [0,1]$), and the velocity of a particle moving to the next generation becomes slow as the value of $\chi$ is near zero. The term of $\varepsilon^{(t)}$ in the expression (7) is a turbulence factor of the $t$th generation, a small stochastic perturbation for searching the decision place to avoid falling into a local optimum and to search for a global optimum. The expression (7) can be modified as the expression (8) including $R^{(t)}$, a special turbulence factor [19, 26].

$$X_n^{(t+1)} = R^{(t)} + X_n^{(t)} \tag{8}$$

In the expression (8), $R^{(t)}$ is used for updating the location of each particle. The turbulence factor is similar in its concept to the mutation operator used in evolutionary algorithm, and the next location is calculated by adding a random value to the current location [19]. The velocity of each particle is estimated as follows:

$$v_{nk}^{(t+1)} = wv_{nk}^{(t)} + c_1 r_1 \left(P_{nk} - x_{nk}^{(t)}\right) + c_2 r_2 \left(G_{nk} - x_{nk}^{(t)}\right) \tag{9}$$

The velocity of each particle, $v_{nk}^{(t+1)}$, is updated considering both the particle optimum, $P_{nk}$, and the global optimum, $G_{nk}$. $v_{nk}^{(t+1)}$ is the velocity of the $k$th component of the $n$th particle of the $t+1$th generation. $P_{nk}$ is the particle optimum which is found by each particle up to the present time, and $G_{nk}$ is the global optimum which is found by population to share information and search the place. $r_1$ and $r_2$ are random variables uniformly distributed on the interval [0, 1], and $c_1$and $c_2$ are acceleration constants adjusting the effect of the particle optimum and the effect of the group optimum.

If the velocity of a particle is too high, it might be necessary to lower its velocity in order to prevent it from being placed out of the valid place. On the other hand, if its velocity is too low, the feasible region is less likely sufficiently searched. $w$ is inertia weight and limits this velocity. A global optimum is more likely found with a large value for $w$, whereas a local optimum is more likely found with a small value for $w$.

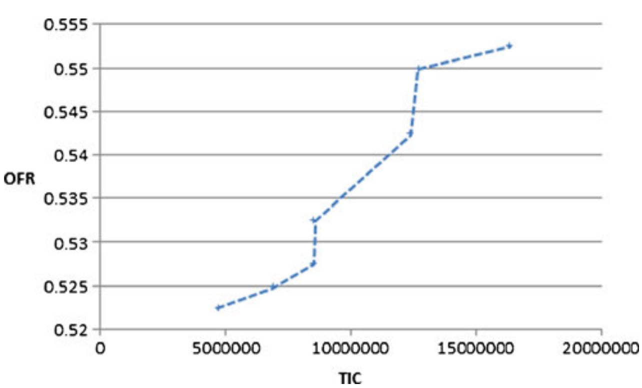



**Fig. 5** Pareto front using IQL A without optimization process

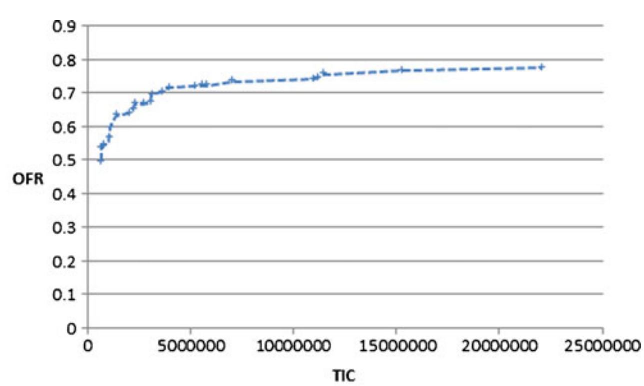



**Fig. 6** Pareto front using IQL A with optimization process

**Table 2** The values of decision variables with and without optimization process

| Decision variable | Without optimization process | With optimization process using IQL A |
|---|---|---|
| $\theta$ | 0.1 | 0.005 |
| COR | 2 | 17 |
| ROS | 13 | 15 |
| RIO | 16 | 16 |
| RED | 15 | 7 |
| RBL | 6 | 13 |
| RINV | 12 | 14 |
| RIS | 13 | 17 |
| ROP | 11 | 8 |
| WOS | 12 | 11 |
| WIO | 7 | 11 |
| WED | 18 | 9 |
| WBL | 11 | 15 |
| WINV | 17 | 12 |
| WIS | 3 | 13 |
| WOP | 16 | 15 |
| DOS | 18 | 8 |
| DIO | 5 | 15 |
| DED | 10 | 19 |
| DBL | 12 | 9 |
| DINV | 12 | 6 |
| DIS | 20 | 16 |
| DOP | 19 | 7 |
| FOS | 14 | 9 |
| FIO | 7 | 11 |
| FED | 13 | 10 |
| FBL | 16 | 10 |
| FINV | 9 | 10 |
| FPD1 | 14 | 15 |
| FPR | 13 | 17 |
| FPD2 | 12 | 10 |

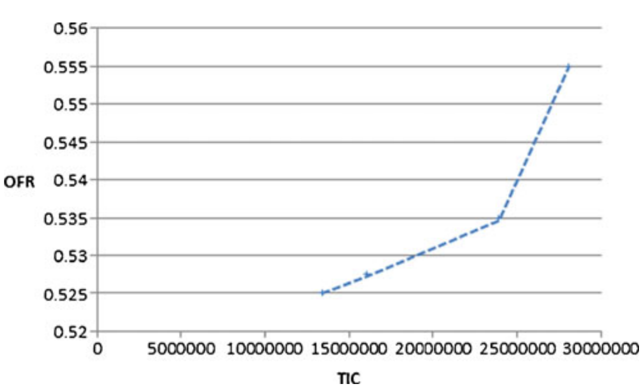



**Fig. 7** Pareto front using IQL B without optimization process

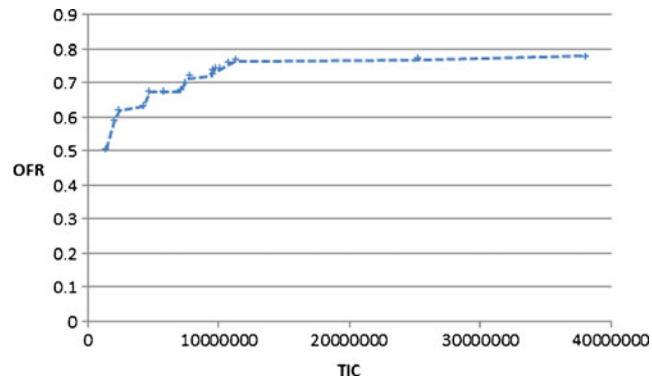



**Fig. 8** Pareto front using IQL B with optimization process

The population of decision variables to perform the PSO method in this study is summarized in Table 1.

The variables in Table 1 are used to calculate the objectives during the optimization process of the PSO method. Those values are randomly chosen or set to 0 when the simulation begins. The initial values are updated as a better solution is found through the optimization process and the generation of Pareto front. Thus, the optimization process is performed with the information summarized in Fig. 4 and Table 1 to minimize the total inventory cost and maximize the order fill rate while considering the information quality level and the initial inventory condition.

## 4 Result analysis

The end-customer demand is explained by AR(1) model with $\rho=-0.6$ and $\mu=100$, and it is assumed that $\varepsilon_t$ follows a normal distribution, with the mean of 0 and the standard deviation of 10 [9, 11]. The range of inventory for each tier is [0, 20], and the range of $\theta$ for demand forecasting is [0, 1]. The population size is set to 200, and the generation is set to 100. It is assumed that there is no lead time for information delivery, and the product lead time follows a normal distribution with the mean of 3 and the standard deviation of

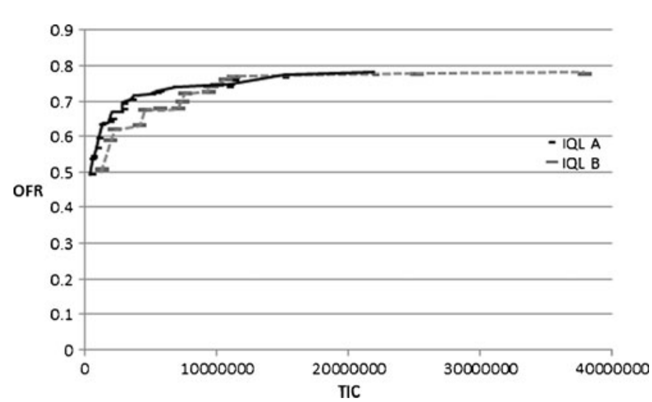



**Fig. 9** The optimization results based on information quality level

**Table 3** ANOVA test result of total inventory cost

| Cause of Variance | Sum of Squares | df | Mean Square | $F$ | Sig. | Pr>$F$ |
|---|---|---|---|---|---|---|
| Treatment | 1.64E+15 | 1 | 1.64E+15 | 46.04803 | 4.2E-11 | 3.864929 |
| Residual | 1.41E+16 | 398 | 3.55E+13 | | | |
| Total | 1.58E+16 | 399 | | | | |

1 [4]. The total simulation period is 800 weeks. The first 200 weeks are regarded as a warm-up period and are removed from the analysis.

The review period, $R$, is 1 week, the service level for order-up-to-level is 95 %, and safety factor, $z$, is 1.65 in ($R$, $S$) inventory replenishment strategy (Chatfield 2004; [22]).

The parameters' values can vary by the applied problems. The parameters' values used in this paper follow Mostaghim and Teich [19] and Julio et al. [17], where it is assumed that $c_1$and $c_2$ are 1, $w$ is 0.4, the constriction factor, $\chi$, is 1, and the turbulence factor, $\varepsilon^{(t)}$, is 0. The initial particle of $X_n$ and velocity of $V_n$ are randomly set within their valid range.

The first experiment is to determine the initial condition with IQL A, offering the demand history and the average lead time from the downstream. Figures 5 and 6 are the total inventory cost and the order fill rate, with and without the application of the PSO optimization process, respectively.

Without the optimization process, the total cost is [4,735, 607, 16,326,540], and the order fill rate is [0.5225, 0.5525]. The mean of total inventory cost is 10,014,216, and the mean of order fill rate is 0.536. The result is depicted in Fig. 5. With the optimization process, the total cost is [590,581, 22,074, 611] and the order fill rate is [0.4950, 0.7775]. The mean of total inventory cost is 4,267,272, and the mean of order fill rate is 0.66. The result is depicted in Fig. 6.

Comparing Figs. 5 and 6, the minimum total inventory cost is 4,735,607 when the optimization process is not considered. But the minimum total inventory cost is decreased to 590,581 when the optimization process is considered. In terms of the mean of the total inventory cost, the improved rate of the optimization process is 57.4 % and it is better than the result without the optimization process. In the perspective of order fill rate, the maximum order fill rate is 0.5525 without the optimal process, but with the optimal process the order fill rate is enhanced up to 0.7775. Thus, the objective is satisfied by moving toward the lower total inventory cost and the higher order fill rate. As shown in Figs. 5 and 6, the ranges of the total inventory cost and order fill rate are larger in the case with the optimization process because the Pareto optimization process generates various solutions by satisfying the multiple objectives.

The values of the decision variables for the minimum total inventory cost without the optimization process and those with the optimization process are summarized in Table 2. As the value of $\theta$ changes, other decision variables also change accordingly during the optimization process.

Next, the simulation model using IQL B is tested considering the optimization process. Figure 7 illustrates the Pareto front without the optimization process, and Fig. 8 depicts the Pareto front with the optimization process.

As shown in Fig. 7, the range of the total inventory cost is [13,379,557, 28,041,558], and the mean is 20,345,131 in the simulation model using IQL B without the optimal process. In the simulation model, the range of the order fill rate is [0.525, 0.555], and the mean is 0.536. With the optimal process, the range of the total inventory cost is [1,306,099, 37,994,506], and the mean is 8,312,250. The range of the order fill rate is [0.505, 0.778], and the mean is 0.685 as shown in Fig. 8. The mean of the total cost with the optimal process is 59 % less than the mean without the optimal process. The mean of the fill rate with the optimal process is also 28 % higher than the mean without the optimal process.

Like IQL A case, while various solutions are generated without the optimal process, the Pareto optimization process generates more various and good solutions with the optimal process. The optimization process, also, moves toward the lower total inventory cost and the higher order fill rates.

To validate the effect of information quality level, we will compare the case of IQL A and the case of IQL B. The Pareto front of the total inventory costs and the order fill rate for 200 populations is depicted in Fig. 9.

With IQL A, the range of total inventory cost is [590,580, 22,074,611], and the range of order fill rate is [0.495, 0.7775].

**Table 4** ANOVA test result of order fill rate

| Cause of Variance | Sum of Squares | df | Mean Square | $F$ | Sig. | Pr>$F$ |
|---|---|---|---|---|---|---|
| Treatment | 0.062438 | 1 | 0.062438 | 10.14053 | 0.001565 | 3.864929 |
| Residual | 2.450574 | 398 | 0.006157 | | | |
| Total | 2.513012 | 399 | | | | |

**Table 5** The optimal values of decision variables when total inventory cost and order fill rate are best cases

| Decision variable | IQL A (TIC) | IQL B (OFR) | Decision variable | IQL A (TIC) | IQL B (OFR) |
|---|---|---|---|---|---|
| $\theta$ | 0.005 | 0.001 | DOS | 8 | 8 |
| COR | 17 | 14 | DIO | 15 | 6 |
| ROS | 15 | 14 | DED | 19 | 15 |
| RIO | 16 | 14 | DBL | 9 | 7 |
| RED | 7 | 1 | DINV | 6 | 7 |
| RBL | 13 | 13 | DIS | 16 | 14 |
| RINV | 14 | 4 | DOP | 7 | 9 |
| RIS | 17 | 16 | FOS | 9 | 15 |
| ROP | 8 | 14 | FIO | 11 | 4 |
| WOS | 11 | 7 | FED | 10 | 17 |
| WIO | 11 | 10 | FBL | 10 | 13 |
| WED | 9 | 13 | FINV | 10 | 14 |
| WBL | 15 | 15 | FPD1 | 15 | 11 |
| WINV | 12 | 15 | FPR | 17 | 2 |
| WIS | 13 | 9 | FPD2 | 10 | 15 |
| WOP | 15 | 9 | | | |

The mean of total inventory cost is 4,267,272, and the mean of order fill rate is 0.6601. Using IQL B, the range of total inventory cost is [1,306,099, 37,994,506], and the range of order fill rate is [0.505, 0.778]. The mean of total inventory cost is 8,312,250, and the mean of order fill rate is 0.685.

In this paper, analysis of variance (ANOVA) is used to find whether or not the IQL A and B have an effect on the total inventory cost and order fill rates. The two information levels are compared by ANOVA test for 200 populations. The ANOVA tests are performed at the 0.05 level of significance, and the results are summarized in Tables 3 and 4.

As shown in Table 3, it is clear that there is a significant difference between using IQL A and using IQL B at $\alpha$=0.05 in terms of total inventory cost. Thus, the total inventory cost using IQL A is less than the total inventory cost using IQL B.

As shown in Table 4, there is a significant difference between using IQL A and using IQL B in terms of order fill rate. Consequently, the order fill rate using IQL B is higher than the order fill rate using IQL A.

Table 5 shows that IQL A is good in terms of the total inventory cost, and IQL B is good in terms of order fill rate. The values are determined depending on the condition of objectives, rather than randomly being set to small or large numbers.

Accordingly, the simulation model with the optimization method is better than the model without the optimization method in terms of total inventory cost and order fill rates. In this study, the suggested optimization process finds the optimal initial inventory condition values, reducing the total inventory cost and enhancing order fill rate. Considering information quality level, using IQL A is better than using IQL B in the perspective of the total inventory cost, but using IQL B is better than using IQL A in terms of order fill rate.

## 5 Conclusions and future work

Supply chain is easily affected by the initial inventory condition and the information quality level. Most existing researches have studied how to reduce the bullwhip effect caused by the initial inventory condition in a supply chain, but they do not consider the initial inventory condition and the information quality.

In this study, we suggest a method for optimizing the total inventory cost and the order fill rate by adjusting the initial inventory condition, and reflecting information quality level. We determined the initial inventory condition using the suggested optimization process. The optimization process results in better total inventory cost and order fill rate. That is, the initial inventory condition is determined by the suggested optimization process, decreasing the total inventory cost and improving the order fill rate. In terms of information quality level, the total inventory cost with IQL A is better than the total inventory cost with IQL B, and the order fill rate with IQL B is better than the order fill rate with IQL A.

In this study, we determine the initial inventory condition to optimize the total inventory cost and the order fill rate considering the demand information from the downstream and the lead time information from the upstream. To further generalize the results from this study, it is warranted to investigate the effects of a different information quality level for each tier on the supply chain optimization process.

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