Excel Based Monte Carlo Simulation for the (Q,r) Inventory Control Model

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Received: Dec 20, 2021; **Revised:** May 09, 2022; **Accepted:** May 11, 2022

Abstract

In supply chain management, inventory plays a key role to deal with demand and supply uncertainty aiming to guarantee a smooth flow of materials and products along the chain. This paper focuses on determining the suitable values of *Q* and *r* in the (*Q,r*) inventory control policy model when it was applied to the situation of nonstationary but known to be empirically discretely distributed of product demands and lead times. The total cost (*TC*) and service level (*SL*) were used to measure the policy performance using an Excel-based Monte Carlo Simulation (MCS) approach with a set of actual historical demand data from an automotive tire service store. Results from the MCS indicated that the (*Q,r*) model could lead to 12.36% lower *TC* with 2.31% higher *SL*, on average, when the *Q* and *r* values were determined based on empirical discrete distribution compared to that of normal distribution. Therefore, the empirical discrete distribution of demand and lead time should be utilized in a situation where the assumption of normal and other traditional distributions is invalid.

Keywords: Inventory Control Policy, Empirical Discrete Demand Distribution, Excel based Monte Carlo Simulation, Automotive Tires

1. Introduction

As a member of the supply chain, a retailer buys products from upstream members and sells them to its customers at a certain retail price. The difference between the retail price and cost that includes unit operations cost marks the profit per unit. To increase the profit and to maintain, perhaps to gain, competitive advantage, the retailer must try to reduce the cost of its operations related to holding of such products while maintaining customer service [1 – 2]. Thus, adopting an appropriate inventory control policy to match the variation of customer demands, then, has become vital and challenged for the retailer [2–4]. This decision is, commonly, a part of inventory management strategy.

Numerous evidences from both practices and researches [5] have indicated that difficulty in selecting the suitable inventory control policy directly relates to variation, especially for the circumstance with unknown and nonstationary demand [6–9]. This is true for the situation of the automotive tire service store who orders tires from manufacturers or wholesalers in advance, stores them at a warehouse until they are sold to customers. It is clear that the exact customer demands are not foreknown and normally are not constant over time [10].

Most continuous review of inventory control policies, decisions on the order quantity (*Q*) and the reorder point (r) are needed for each product to meet customer requirements with reasonable cost. The customer service level (*SL*) is usually set as the target to achieve with minimum (or at reasonable) total cost (*TC*) [2],[8–12]. Thus, *SL* and *TC* are generally used as the main indexes to evaluate the performance of an inventory policy and are significantly affected by the parameters *Q* and *r*. The appropriate values of *Q* and *r* closely relate to the behavior of demands and lead times. Therefore, it is important to statistically understand the demand and lead time behaviors which can be pointed out when sufficient historical data is available. Much of the research about inventory control policies have assumed that demands are normally distributed with a known mean (μ) and standard deviation (σ) [8],[13–14]. Some recently applied researchers have extended their analysis to Poisson [9] and Exponential of demand distribution [15] with constant lead time. However, some historical demand patterns do not statistically match any of the traditional distributions while the ordering lead times are not always constant [10]. Therefore, the empirical distribution should be assumed in the evaluation of an inventory control policy.

This paper considers the situation of nonstationary but known to be empirically discretely distributed of product demands and lead times, focusing on determining the suitable values of *Q* and r for the (*Q, r*) model. The *TC* and *SL* of the model are determined using the Excel-based Monte Carlo Simulation (MCS) approach with a set of actual historical demand data from an automotive tire service.

2. Backgrounds

This section is separated into 2 subtopics. The main performance indexes of inventory control policy are discussed in Section 2.1. A brief literature review related to the problem scenario is discussed in Section 2.2.

To discuss mathematical models related to inventory control concepts throughout this paper, the following notations are defined.

t	Subperiod in a planning time
T	Planning horizon
C_o	Ordering cost (baht/unit)
C_c	Carrying cost (baht/unit/period)
C_s	Shortage cost (baht/unit)
C_{EX}	Expediting cost in (baht/time)
D_t	Product demand for *t*
$\bar{d}$	Average demand
L_t	Ordering lead time *t*
$\bar{L}$	Average ordering lead time
Q	Order quantity
Q*	Optimal order quantity
r	Reorder point
A_t	Available inventory for *t*
SS	Safety Stock
SL	Customer service level
SL_{tg}	Target customer service level
TC	Total cost
SD_t	Satisfied product demand for *t*
Z_t	1 if an order is placed at the end of *t* or 0 otherwise
$I_{avg,t}$	Average inventory for *t*
$I_{int,t}$	Inventory at the beginning of *t*
$I_{end,t}$	Inventory at the end of *t*
$I_{s,t}$	Shortage units for *t*
I_t^*	Dummy inventory at the end of *t*
CC_t	Carrying cost incurred for *t*
OC_t	Ordering cost incurred for *t*
SC_t	Shortage cost incurred for *t*
$f(D_{t,i})$	Probability mass function of D_t
$F_t(A_t)$	Cumulative distribution function of A_t
$E(D_t)$	Expected value of D_t
OR_t	Order received at the beginning of *t*
AV_t	Order arrival time for order placed at the end of *t*

The dummy inventory at the end of period *t*, (I_t^*), is determined using $I_{end,t}$ +$Q.Z_t$ to prevent reordering if the preceding order has not arrived.

2.1 Performance Indexes

The main reason to employ an inventory strategy is to meet customer demand, especially in a retail operation [1–2],[16]. However, the demand is usually not known for certainty. Thus, it is not always possible to hold exactly the amount of product demanded. In practice, with selected inventory control policy the additional amount of inventory, called safety stocks (*SS*), is kept on hand to increase the ability to meet the product demand in a timely, efficient manner. The higher expected *SL* requires a higher inventory level and, thus, higher inventory costs.

The actual *SL* of any product, as shown in Equation (1), is the ratio between the total satisfying demand and the total demand for the entire controlling period (denotes by T) [2],[9].

$$SL = \frac{\sum_{t=1}^{T} SD_t}{\sum_{t=1}^{T} D_t} \quad (1)$$

The target (or planned) customer service level (SL_{tg}) may be set at the beginning of the controlling horizon. The demand for the product for subperiod t is a random variable. SL_{tg} is simply the probability of demand for subperiod t (D_t) being less than or equal to the available inventory for the same period (A_t). For period t, the probability is given by the cumulative distribution function $F_t(A_t)$, which can be expressed in Equation (2).

$$SL_{tg,t} = F_t(A_t) = P[D_t \leq A_t] \quad (2)$$

Where P represents the probability of the term in the bracket. The expected service level for the entire planning horizon can be expressed as $\prod_{t=1}^{T} F_T(A_t)$. Obviously, at is a function of the order quantity *Q* and reorder point *r*. In practice, shortage cost may occur when the condition in Equation (2) is violated for some t's which would pull the overall *SL* down and damage the image of a company (or a retailer). Numerically, the shortage cost is added to the total inventory management cost to better enumerate the situation and it is given in Equation (3).

$$TC = \sum_{t=1}^{T} \left(Z_t C_o + I_{avg,t}.C_c + C_s \right) \quad (3)$$

$I_{avg,t}$ can be calculated from $(I_{int,t} + I_{end,t}) / 2$. The value of C_s may vary depending on how the shortage situation is handled. Assuming that there is no other constraints, the inventory control policy should be selected and implemented in order to maximize the *SL* with the minimum *TC* or to minimize the *TC* with acceptable target *SL*, regardless of demand distribution.

2.2 Literature Review

Some books [1–2],[16], and many research papers described the importance and details of inventory management. The recent versions tended to emphasize more on the supply chain [1],[3],[10]. Bedworth and Bailey [16] explained the principle of *EOQ* and how it can be implemented with a variety of inventory control policies under deterministic assumptions. They also have suggested how to use safety stock in dealing with stochastic conditions with an underlying normal probability of demand and lead time. Applications can be found in [17–19]. Similar background can be found in Russell and Taylor III [1] with more emphasis on supply chain management. Lila [2] provided detail regarding how to set up Excel spreadsheet for inventory control using the Monte Carlo Simulation approach. Implementation and adaptation of such technique can be seen in numbers of application researches, [8–10],[12],[14],[20], for example. All of them tried to determine the appropriate inventory control policies with uncertain demands. Silsat and Lila [8] applied to the case of consumable items that their demands did not dependent on finished products and are highly fluctuated. Mahitpan, Lila, and Kunadilok [9] and Pengsawat [12] applied to spare parts for maintenance of critical equipment. Smmutranukul and Phanvijitsiri [10] compared performance between the (*Q, r*) and (*T, S, s*) models for a tire service store while Leepaitoon, and Bunterngchit [20] studied similar cases but demands were generated based on the maximum, minimum and average of historical data. Ruanghiranwanich and Lila [14] used the MCS to find a suitable order quantity of parts for electronic products. Some other researches about inventory management have utilized high-level simulation programs to study the performance of inventory policies with uncertain demands [6–7],[11],[19]. Abuizam [6] studied the periodic inventory model using Parasade@RISK simulation. Cholodowicz and Orlowski [7] considered inventory policy for perishable products that have Weibull demand distribution using System Dynamics. Limbuan and Lila [11] used ARENA to simulate the (*Q, r*) and the (*T, S, s*) models for uncertain but low demands for spare parts. These researches resulted in a saving of 7–25% of inventory management cost compared to the before-studied policies through numerical cases.

Based on the reviews, it is obvious that the simulation technique is an appropriate tool for use in studying inventory control policies with stochastic conditions. To overcome the burden of buying specific simulation programs (normally with high cost) and learning how to use them, Excel is a convenient choice since it is most certainly available with any computer.

3. Inventory Control Concepts

Inventory refers to items or products that are kept to satisfy the future demands that are random variables [2]. Holding insufficient inventory may lower the *SL* while having too large inventory incurs costs. An appropriate inventory control policy can help to minimize the costs while meeting acceptable *SL*. The basic parameters needed are order size, reorder point and safety stock.

With known and constant demand, no shortage and instantaneous assumptions, the optimal order quantity is determined using Equation (4).

$$Q^* = \sqrt{\frac{2.\sum D_t.C_o}{C_c}} \tag{4}$$

The quantity Q^* is enough to fulfill the constant demand for $Q^*/\bar{d}$ Periods and minimizes the total cost. In this case *TC* in Equation (3) can simply be written as shown in Equation (5).

$$TC = \frac{C_o.\sum D_t}{Q^*} + C_c.I_{avg} \tag{5}$$

The amount Q^* is reordered when the inventory level is less than or equal to the reorder point *r*, that can be set using Equation (6).

$$r = \bar{d}.L \tag{6}$$

If the lead time is also constant, the time between each order is placed, remains the same.

In reality, the deterministic condition about demand and lead time are usually not true. Thus, *SS* is enacted to deal with the stochastics conditions. This requires an analysis of statistical behaviors for both demands and lead times through historical data. In the case that demand and lead time are normally distributed, *SS* could be calculated using several equations explained in [1],[2],[5],[16]. However, the focus of this paper is on the case of an empirical discrete demand. In any period, D_t can take any value in position i^{th} in a discrete random variable having $f_t(D_{t,i})$ as its probability mass function (*PMF*) as depicted in **Table 1**. $D_{tm,i}$ represents the mid-point of each class *i*. For subperiod *t*, D_t can be classified into classes, *i* starts from 1 and increases upward. Each class *i* has probability of occurrence of $f(D_{t,i})$. The actual demand value ($D_{t,i}$) is assumed to be discretely uniformly distributed between the lower ($LD_{t,i}$) and upper ($UD_{t,i}$) bounds of each class *i*.

Table 1 Probability mass function of Dt

$Class_i$	$D_{tm,i}$	$LD_{t,i}$	$UD_{t,i}$	$f(D_{t,i})$
1	D_{tm1}	$LD_{t,1}$	$UD_{t,1}$	$f(D_{t,1})$
2	D_{tm2}	$LD_{t,2}$	$UD_{t,2}$	$f(D_{t,2})$
…	…	…	…	…
u	D_{tm3}	$LD_{t,u}$	$UD_{t,u}$	$f(D_{t,u})$
u+1	$D_{tm,u+1}$	$LD_{t,u+1}$	$UD_{t,u+1}$	$f(D_{t,u+1})$
…		…	…	…

Thus, in any subperiod, holding inventory greater than or equal to $E(D_{tm})$, statistically, corresponding to ≥0.5 or 50% *SL*. The variable A_t in Equation (2) also represents the reorder point *r* to reach the SL_{tg}. Based on this relationship, the *r* is then derived and can be expressed in Equation (7).

$$r = E(D_t) + \sum_{i=1}^{u} f_t(D_{ti}) \qquad (7)$$

The term $\sum_{i=1}^{u} f_t(D_{t,i})$ is the cumulative probability function of D_t with values ranging from class $i = 1$ to class $i = u$ that enable *r* satisfies the SL_{tg}. Thus, it also represents the *SS*.

The lead time is often easier to manage as it does not vary in a wide range [9],[10]. The probability mass function L_t can be defined using discrete probability as shown in **Table 2**.

Table 2 Probability mass function of L_t

L_t	$f(L_t)$
1	$f(L_1)$
2	$f(L_2)$
…	…
L	$f(L_L)$

In this paper, performance indexes (*SL* and *TC*) of the *(Q, r)* model was investigated if it was implemented as the control policy at a retailer for an automotive tire service where demand and lead time are empirically discrete random variables. The concept of the (*Q,r*) model is the quantity *Q* is ordered and is reordered once the inventory depletes to the level of *r* or lower. The process repeats for the entire planning horizon.

The investigation was performed through the Monte Carlo Simulation on Microsoft Excel. The development of such simulation model is explained in Section 4.

4. Excel Based Monte Carlo Simulation

Monte Carlo (MC) is a technique to generate random variables of interest from a known behavior [2]. Subsequently, such variables can be used in the logic of a simulation model or a system to evaluate its performance. This type of model is often referred to as the Monte Carlo Simulation (MCS) [2]. This paper built the MCS on Microsoft Excel Spreadsheet to simulate the performance of the (*Q,r*) model. The MCS for *T* periods was constructed for individual tire model having TC and SL as performance indexes, the logical concepts and their corresponding Excel formula are explained in section 4.3.

4.1 Input Parameters

In **Fig. 1**, the main inputs for the MCS model consist of the following.

1) All cost parameters including Co, Cc, and Cs,

beginning inventory, CEX and SLtg. These parameters were placed on the top left, above the Logic model.

2) The starting values of Q and r which were determined using Equations (4) and (7), respectively.

3) Distributions of demand and lead time in the form of empirical discrete probability tables.

4.2 Generation of Random Variables

The demand (D_t) and the lead time (L_t) are the main random variables. With the discrete form for D_t as shown in **Table 1**, the value was generated using a nested *VLOOKUP()* function that performs the following 2 steps;

1) Select the class *i* based on the given discrete probability function.
2) The value of D_t, was generated based on a discrete uniform distribution between the $LD_{t,i}$ and the $UD_{t,i}$. The generated values must be rounded to the nearest whole number if the demand are integers.

Similarly, but easier, the L_t was generated using a *VLOOKUP()* function based on its probability mass function when the order was placed.

4.3 Logic of the Model

Logics of the MCS can be described as follow;

1) Generated the pseudorandom numbers (rn_t) for all *t*'s using a *rand()* function.
2) Generate D_t using the nested *VLOOKUP()* function from its *PMF*, for all *t*'s.
3) For *t*=1,
   a. Set $I_{int,1}$ = beginning inventory ($I_{int,0}$), and $I_{int,t}$ = $I_{end,t-1}$ for the remaining periods.
   b. *Set* $OR_1 = 0$, indicating a starting period.
4) Set $A_t = I_{int,t} + OR_t$ for all *t*'s
5) Set $SD_t = Min(D_t, A_t)$ for all *t*'s
6) Set $I_{end,t} = A_t - SD_t$ for all *t*'s
7) Set $Z_t = 1$, if $I_{end,t} + Q.Z_t \leq r$ or 0 otherwise.
8) If $Z_t = 1$, generate L_t using VLOOKUP function from its PMF, or 0 otherwise, for all *t*'s
9) Set $AV_t = t + 1 + L_t$, if $L_t \neq 0$ or 0 otherwise.
10) For t > 1 to T,
    a. Set OR_t = countif(range from 1 to t, t)*Q
    b. Set $I_t^* = I_{t-1}^* - SD_t + Q$, if $Z_{t-1} = 1$ or $I_t^* = I_{t-1}^*$ SD_t otherwise.
11) Costs calculation,
    a. $CC_t = C_c. I_{avg,t}$
    b. $OC_t = C_o. Z_t$
    c. $SC_t = C_{EX} + C_s.(D_t - A_t)$, *if* $D_t - A_t > 0$ or 0 otherwise.

The concept used in calculating shortage cost was based on actual practice that the owner would always seek available products from a nearby store when he/she did not have what the customer wanted. Therefore, the expediting cost (C_{EX}) would occur along with loss of some profit which refers to as C_s.

4.4 Output Analysis

The *TC* and *SL* could be determined based on the relationship in Equations (3) and (1), respectively. In the MCS, *TC* is simply the summation of CC_t, OC_t and SC_t for all periods t = 1 to T. Similarly, the *SL* is the ratio between the summations of SD_t and D_t for all periods t = 1 to T.

The MCS was verified by comparing its *TC* and *SL* with manual calculation when the known and constant demands and lead times were entered. The result indicated that the MCS model worked properly and can be used for further analysis.

Equations (5) and (7) were utilized to determine the values of *Q* and *r*, respectively. The fact that the aspect of stochastic lead time was not considered in Equations (7), the values of *Q* and *r* were only set as the starting values in the MCS. The *TC* with values of *Q* and r varied from -50% to +100%, with 10% step, from their starting values were run to find the minimum *TC* with acceptable *SL* ($SL \geq SL_{t,g}$). For each combination of *Q* and *r* values, the number of simulation runs was determined according to the criteria that the error (half-width, HW) of 95% confidence interval (CI) of the *TC* must be less than 10% of its mean. After the Q and r values were set to use in the MCS model to investigate the performance of the (*Q, r)* control policy in the interested case.

5. Numerical Case

In this paper, the real historical weekly units sold of the highest demand tire model at an automotive tires retail service located in Chonburi province was collected between 2019 to 2020, along with its order lead times. Statistically, based on the sum of the square of error, at 0.05 significant level, the demand and lead time behaviors did not match with any traditional probability distribution. Therefore, empirically discrete distributions seem to be the best functions and are in **Tables 3 and 4** for demand and lead time, respectively.

From **Table 3**, the average ($E(D_t)$) is 82.85 units and standard deviation (*SD*) of D_t is 47.85 units. Similarly, from **Table 4**, the average ($E(L_t)$) is 1.1 weeks and standard deviation (*SD*) of L_t is 0.3 weeks. Other relevant information of this tire model was collected and is provided in **Table 5**.

Table 3 Distribution of D_t (units/week)

$Class_i$	$D_{tm,i}$	$LD_{t,i}$	$UD_{t,i}$	$f(D_{t,i})$
1	15.150	0.000	30.300	0.08
2	45.451	30.301	60.601	0.27
3	75.752	60.602	90.902	0.37
4	106.053	90.903	121.203	0.13
5	136.354	121.204	151.504	0.02
6	166.655	151.505	181.805	0.06
7	196.956	181.806	212.106	0.08

Table 4 Distribution of Lt (weeks)

L_t	$f(L_t)$
1	0.90
2	0.10

Table 5 Relevant information

Item	value	unit
Unit cost	2850	Baht/unit
C_c	2.39	Baht/unit/week
C_o	2000	Baht/order
C_s	82	Baht/unit

Table 5 Relevant information (*cont.*)

Item	value	unit
C_{EX}	1000	Baht/time
Annual Demand	3779	units
Beginning Inventory	322	units
SL_{tg}	0.85	

According to reasonable management of the store manager, *TC* for the 2019–2020 years were evaluated to be 93,877 baht/year with 1.00 of *SL*. These numbers would be used as a baseline for comparison with the indexes getting from the MCS.

The starting values of *Q* and *r* were calculated to be 297.31 units and 173.85 units, respectively ($E(D_t)$ = 82.85, from class *i* = 1 to *u* = 3, SS = 91 units). The SL_{tg} was set to 0.85 (with r = 173.85 units, according to **Table 3**, this value falls into class 6, thus the SL_{tg} of 0.87 could be expected). The values of *Q* and *r* were rounded to 300 units and 170 units, respectively, and were used to run the experiments by varying *Q* from 150 to 600 and varying *r* from 85 to 340, with 10 runs for each combination which was enough since the half-widths were between 3.78–7.65% for *TC*s, and were between 1.55– 2.29% for *SL*s, for all combinations. The outcomes showed that the minimum *TC* occurred at the combination of *Q* = 330 and *r* = 204 and 221, with *SL* at least 0.945. To confirm the outcome, *r* = 210 was chosen at set to run the MCS to find the optimal *Q*. Results are shown in **Fig. 1**.

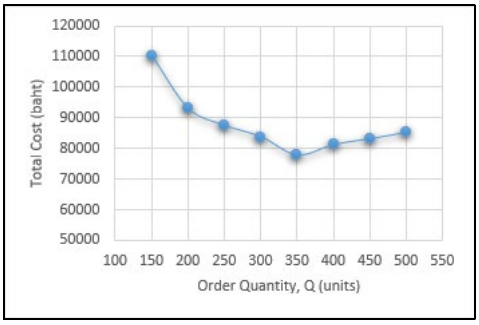

Figure 1 *TC* from *r* = 210 units

From Figure 1, the minimum *TC* could be found with *Q* between 300 to 400 units. The value of *Q* = 350 units and *r* = 210 units were set to run the MCS again for 30 runs. Statistical results of *TC* and *SL* are given in **Table 6**.

Half-widths of both *TC* and *SL* deviate from their means of only 4.68% and 1.03%, respectively. Therefore, results from 30 runs of the MCS were statistically accurate.

Table 6 *TC* and *SL* from the MCS

Statistics	*TC*	*SL*
Mean	77682	0.968
SD	7599	0.022
HW	3638	0.01

The analysis also indicated that if the (*Q,r*) model was implemented, about 17.25% (93,877 - 77,682 = 16,195 baht/year) of the total inventory management cost could be reduced with expected SL dropped from 1.00 to 0.968, or around 3.2% decrement.

Performances of the (*Q,r*) model were also compared based on normal and discrete distributions of demand and lead time. Input parameters that were used in 30 runs of the MCS for the two underlying distributions are provided in **Table 7**.

Table 7 Input parameters for normal and discrete distribution

Parameters	Normal	Discrete
μ (unit/week)	71.69	82.74
σ (unit/week)	46.27	47.77
Q (unit)	300	350
r (unit)	176	210

For normal distribution, the value *Q* from historical demand was 297.32 (rounded to 300) while the value *r* was calculated from $\overline{D}_t.\overline{L_t} + z_{0.85}.SD.\sqrt{\overline{L_t}}$. On the other hand, for discrete distribution, the values *Q* and *r* were the result of the experiments discussed previously. The statistical results are given in **Table 8**.

Table 8 *TC* and *SL* from the MCS between normal and discrete distribution

Statistics	Normal		Discrete	
	TC	*SL*	*TC*	*SL*
Mean	88640	0.946	77682	0.968
SD	13504	0.027	7599	0.022
HW	5043	0.01	3638	0.01

Half-widths for all values of *TC* and *SL* for both distributions were within 6% of their respective means indicating that 30 runs were reasonable accurate.

The means of *TC* and *SL* getting from the use of normal and discrete *Q,r* parameters were compared using 2 unequal variance t-tests. Results, as shown in **Table 9**, strongly indicated that there were differences in both means at 0.05 significant level. The *Q,r* parameters from the discrete distribution return, 10,958 baht/year or 12.36% lower *TC* and 0.022 or 2.31% higher *SL* than that of the normal distribution.

Table 9 Result of t-test of *TC* and *SL* from MCS between normal and discrete distributions

Items	*TC*		*SL*	
	Normal	Discrete	Normal	Discrete
Mean	88640	77682	0.946	0.968
SD	13504	7599	0.027	0.022
Observations	30	30	30	30
Hypothesized	Mean Diff. = 0		Mean Diff. =0	
p value	0.0003		0.0011	

6. Results and Conclusions

This paper aimed to determine the suitable values of *Q* and *r* in the (*Q,r*) inventory control policy model when it was applied to the situation of nonstationary but known to be empirically discretely distributed of product demands and lead times. The product demand for each period (D_t) is defined in the form of an empirically discrete classes while the discrete uniform distribution is assumed to represent the random distribution of demand within a class. The Excel-based Monte Carlo simulation (MCS) approach was described in detail and utilized to evaluate the performance of the model in terms of *TC* and *SL*. Application to the numerical case of a high-demand tire model of an automotive tire service store demonstrated that the MCS can be used to estimate the outcome of the (*Q,r*) model efficiently. Based on the set of historical data used in this case study, result from the MCS also showed that setting of the inventory control parameters with the discrete distribution of demands and lead times of products led to significantly better performance in terms of *TC* and *SL* than that of the normal distribution. Thus, the method proposed should be utilized in a situation that demand and lead time do not seem to be normally distributed or match with other traditional probability distributions. The MCS can also be modified to fit the concept of other similar control policies. However, this paper did not perform the sensitivity analysis of the C_o, C_c, C_{EX}, and C_s parameters as they may influence the performance of such control policies, since they are generally fixed for a specific situation.

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