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Inventory Control Heuristic for a Perishable Item under Stochastic Demand and Restricted Batch Size

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***Abstract*— This paper considers a type of inventory problem that deals with perishable item. The problem, which the authors believe has its main application in quick-service systems, such as fast food restaurants and similar systems, assumes that the item has a fixed lifetime and fixed lead time. The production of the item uses limited-capacity equipment that prepares the item in batches. Inventory review is done periodically. Demand for the item exhibits seasonal fluctuations throughout the planning horizon, and shortage results in lost sales. Unsold items exceeding allowed shelf life are set aside for disposal. Two heuristics were developed in order to identify the number of batches to be prepared at the start of each period. Cost considerations include setup costs, shortage cost, and excess cost. As part of the research, the heuristics were tested using real instances from an actual system. The approach is found to be successful in finding satisfactory solutions for the realistic target cases and specified metrics.**

Keywords— perishable items, heuristics, stochastic inventory model

1. INTRODUCTION

Managing perishable items is a reality for different companies, particularly those in the food, pharmaceutical goods, and even in consumer goods sectors. Items such as blood, medicines, bread, fruits and vegetables, dairy products, and meat products must be consumed within their respective expiration dates to ensure freshness of the item and safety of the consumer.

The food industry is the prime example of a sector that needs to contend with items with limited shelf life. Most food items deteriorate through time, and expired items, ideally, should not reach customers.

Canned goods usually last for months or even years, while some processed meat items take a couple of months before expiration. The same is true for most dairy products. Bread and vegetables are good only for a couple of days. Meanwhile, cooked food should be consumed immediately, preferably within hours after their preparation. This study tackles items offered in quick-service systems, such as fast-food restaurants and similar systems that have products with relatively short lifespan. Perishability, while it adds complexity to inventory decisions, should be properly considered in the analysis.

The paper is organized as follows: Section 2 provides the definition of the problem to characterize the nature of the system being tackled. Research studies addressing related problems are discussed in Section 3. In Section 4, the proposed heuristics are presented. Sections 5 discusses the simulated results for an actual industry application. Lastly, the final section concludes the paper with a brief summary of the research.

2. PROBLEM DEFINITION

This paper studies the problem of determining the production size, i.e., number of units to produce, given the age of the available units and the availability of the units being produced at the time of the decision, to maximize profit.

In the system discussed in this paper, the produced units deteriorate within a short period of time after those units are produced. Given this, the system considers specific "product lifetime" for the produced units. The goal of the system is to have a structured way of determining how many units to produce given strict implementation of considering expired units, i.e., units that have reached a time beyond "product lifetime". Furthermore, this system does not allow backlogs. When a demand is not fulfilled immediately, it translates to stockout. Accordingly, in addition to setup cost, this production control seeks primarily to balance the cost of stockout and cost of item wastage due to expiration. The first-come, first-served policy in the consumption of the units is also used.

The problem likewise considers demand of the product to exhibit fluctuation through time which can be as short as a day. The planning horizon, therefore, is divided into discrete time periods with different demand estimates. Periodic inventory tracking is assumed in this problem.

In the system considered, which can be a quick service restaurant or similar system, inventory review is continuous. To approximate this, time intervals corresponding to discrete time periods should be small. As a rule of thumb, individual average demand estimates during each time period should not exceed equipment capacity. Otherwise, it is suggested to further shorten the initially-chosen time interval. Furthermore, in this system, it is advised that the lifetime of the item should encompass at least two time periods.

Units of the product are packed in batches of the same quantity; hence a complete batch must be produced each time. A production run requires the use of equipment that can accommodate a limited number of batches. Regardless of the number of batches in a run, the equipment runs for a finite duration of time. It is assumed that the system generally has enough equipment units should it decide to meet all demand. Once a production run is initiated on an equipment, whether it is running at full capacity or not, it cannot be interrupted for further addition of batches to maximize the capacity. Thus, preemption of a production run is not allowed. Nevertheless, one of the remaining pieces of equipment available may be used to start a new batch.

Given the above problem description, the following problem parameters are defined.

- L_1 is the fixed lead time of a production run, $L_1 \geq 1$.
- L_2 is the fixed lifetime of the item before it expires, $L_2 \geq 1$.
- r is the fixed number of discrete business periods when customers arrive to demand the item.
- $T = L_1 + r$ is the number of discrete periods included in the planning horizon. The first L_1 periods correspond to initial production system operating periods when there is still no customer demand but the production system may opt to prepare initial batches. The demand for the first L_1 periods

is 0. The last r periods pertain to the periods where the system is open for operations (customer demand).
- m is the fixed item batch size.
- n is the maximum number of batches that can be produced in one equipment. Hence, a production run has a capacity of mn units.
- D_t is the nonnegative discrete random variable representing the demand for period t, $1 \leq t \leq T$. Let $f(d_t)$ be the probability mass function of the said variable. As mentioned, demand during the first L_1 periods is 0. This study assumes that D_t is Poisson distributed with an average of $\bar{d}_t$ units for time period t.
- p is the selling price of an item.
- c_1 is the fixed setup cost of initiating a production run.
- c_2 is the unit cost of an item. Assuming no additional disposal cost, c_2 is also the excess cost due to an expired item. Meanwhile, $p - c_2$ represents the lost margin per unit whenever there is a shortage.

It is emphasized that holding cost – a typical component of the total cost in inventory management problems – is missing in the analysis. In this case, holding cost is immaterial to the analysis since planning horizon is very short and is in the magnitude of 1 operating day.

The objective of the problem is to maximize total expected profit, which is revenue less production setup and unit production costs. The decision to be made is the number of batches to be produced at the start of period t, k_t^*, given the age of available items and the expected availability of items currently being produced during the time of decision.

3. REVIEW OF RELATED LITERATURE

There are several ways how different research works on perishable items may be classified. Kouki et. al. [1] classified works with fixed lifetime based on how the research treats the following problem parameters: (a) whether inventory tracking is continuous or periodic, (b) if lead time is zero, non-zero constant, or continuously distributed, and (c) the included cost components in the problem.

Under continuous review, an early study by Weiss [2] discussed an (r, S) policy for a problem with zero lead time and Poisson demand. Related works with different demand distributions are tackled by Lian and Liu [3] and Liu and Lian [4]. Various (r, S) policies were also proposed in the works by Kalpakan and Sapna [5], Liu and Yang [6], and Kalpakam and Shanthi [7] when there is an exponential lead time and lifetimes, enabling a Markovian analysis.

Still under continuous review, Chiu [8], Kouki et al [1], Berk and Grler [9], and Khouki et al [10] employed the (r, Q) policy in addressing various problems involving perishable items.

An inherent limitation of these continuous review models is that they assume that demand distribution is stationary for the whole planning horizon, barring possible fluctuations due to seasonality of demand.

Wagner and Whitin [11] employed dynamic programming in a heavily-cited work that tackled dynamic lot sizing given non-stationary deterministic demand under a periodic review scheme. Since then, extensions of the approach enable its application to scenarios tackling backlogging, capacity constraints, and stochastic demand with a variety of cost components involved. The use of DP, however, for perishable items is first invoked by Nahmias [12] whose work focused on an item with a lifetime of two time periods.

Other studies utilizing periodic review include works that combine DP and simulation [13, 14]. In [13], Haijema, et. al. applied the approach to a blood platelet problem that exhibits periodicity. The said application is further extended in [14] to consider effects of the irregularity occurring during holiday breaks. Minner and Transchel [15] proposed an inventory control system with positive lead time when service level constraints are imposed.

When the non-stationary probabilistic nature of demand is considered, stochastic DP may be employed to find the optimal solution. However, the state space of the problem becomes too large for practical use.

Alcoba et. al. [16] proposed a heuristic for a similar problem based on the application of Silver's heuristic [17] for perishable items. When there is no available supply to meet immediate demand, the study assumes a backorder situation as opposed to stockouts modelled in this research. Their paper also assumes no batch size restriction.

A study by authors Broekmeulen and van Donselaar [18] presented a heuristic applied to perishable grocery items addressing a related case with inventory review not necessarily done at all time periods. Their heuristic finds a dynamic reorder level assuming static safety stock for all periods and considering possible withdrawal of item due to expiration. However, [18] does not consider fixed ordering cost, which is an important component of the total cost in the present problem.

Meanwhile, Pauls-Worm, et. al. [19] proposed a deterministic mixed integer linear program as an approximation to the stochastic case under additional service level requirements.

In summary, it can be said that a number of research works have tackled related problems involving perishable items. However, considering the exact cost components and other problem characteristics (e.g., restrictions in batch size and stockouts as opposed to backlogs), it seems that none perfectly fits to the problem at hand. Furthermore, this paper presents an application of inventory control model that considers product expiration in the system such as a quick-service restaurant.

4. DESCRIPTIONS OF THE HEURISTICS

Two heuristics are proposed to solve the given problem. One is simple enough to be implemented in the target area of application with the provision of guide sheets. The other one, on the other hand, will require a computer to execute some calculations. These heuristics are labelled Heuristic A and Heuristic B, respectively.

A key feature of Heuristic A is the identification of the run size appropriate for the demand of the time interval the batch is expected to cover.

To be able to do that, the profit function is constructed as a function of average demand λ. Expected profit, E(P), is the difference of expected revenue, E(R), and expected cost, E(C). The formula of the E(P) is given below assuming Poisson demand rate λ during the interval and a production run size of km, k = 0, 1, 2, … n:

$$E(P(k,\lambda)) = p\sum_{d=0}^{km} d\frac{e^{-\lambda}\lambda^d}{d!} - c_1 J_k - c_2 km,$$

where J_k is a binary indicator pertaining to whether there is an actual production (J = 1 if k > 0) or not (J = 0 if k = 0).

The first term of the formula corresponds to the E(R), while the next ones are the fixed setup and unit production costs, deducted from the revenue. This is related to the regular newsvendor problem with an additional fixed setup cost. E(P), as a function of both k and λ, is illustrated in Figure 1 below for a case where m = 8, p = 70, c_1 = 30 and c_2 = 40.

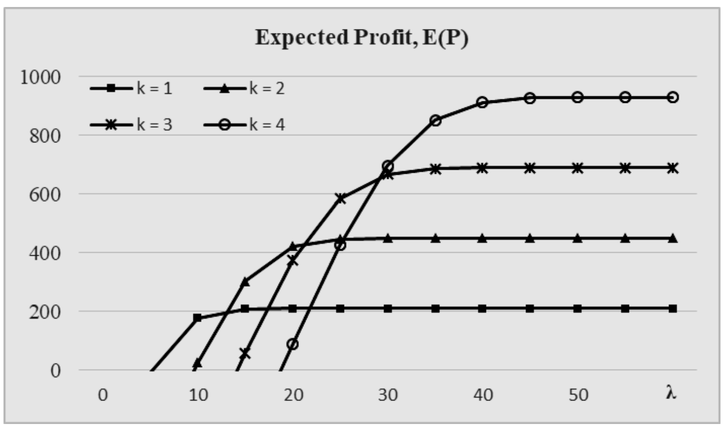

Figure 1. Sample expected profit curves

Let λ_k be the value of λ where E(P(k, λ)) = max { 0, E(P(k-1, λ))}, k = 1, 2, …, n. The critical "breakeven" demand rates, λ_k, can be estimated from the graph. As an alternative, a non-linear program may be formulated. This program can be handled easily by any competent optimization software. For the given case above, the values are λ_1 = 5.14, λ_2 = 12.88, λ_3 = 21.05, and λ_4 = 29.19. To illustrate, a batch that is expected to protect a time interval with an average Poisson demand of, for example, 15.2 units should have a size of km = 2*8 = 16 since $\lambda_2 \leq 15.2 < \lambda_3$. Since some values of k will always generate negative profit, λ_k may not always exist for all k. The variable λ_{min} is used to denote the minimum demand rate that will result in a break-even profit.

Further definitions are made before the pseudocode of Heuristic A is introduced:

- $\mathbf{I}_t = [i_t^1, i_t^2, \ldots, i_t^{L1+L2-1}]$ is a ($L_1 + L_2 - 1$)-dimensional vector representing the inventory position at the start of time t. Elements $i_t^1, i_t^2, \ldots, i_t^{L1-1}$ represent incoming units due to arrive at the start of period t + L_1 - 1, t + L_1 - 2, …, t + 2, t + 1, while elements i_t^{L1}, i_t^{L2}, …, $i_t^{L1+L2-1}$ correspond to available units with remaining shelf lives L_2, L_2 – 1, …, 1 time periods, respectively.

- $\hat{\lambda}(\mathbf{I}_t)$ is the estimated demand covered by the lifetime of a new batch produced at the start of time t given initial inventory of $\mathbf{I}_t$.
- $\hat{g}_{t'}(\mathbf{I}_t)$ is the estimated ending inventory for time period t' – prior to setting aside items that reach their lifetime at the end of t' – assuming no production is made at time t onwards, where t' > t.

The pseudocode of the Heuristic A is now presented.

Box 1: Pseudocode of Heuristic A

```
Expected Output: production run size k_t* to be
     initiated at the start of time t.
1. for (t = 1; t ≤ T; t++)
2.      update I_t
3.      compute λ̂(I_t) and ĝ_{t+L1}(I_t)
4.      if (λ̂(I_t) ≥ λ_min) and (ĝ_{t+L1}(I_t) = 0) then
5.           k_t* = argmax 1 ≤ k ≤ n {E(P(k, λ̂(I_t)))}
6.      else
7.           k_t* = 0
8. end
```

Line 2 of the heuristic takes note the demand and production in the previous period to ensure that the beginning inventory of the current period is accurate. Line 3, meanwhile, estimates the average demand to be covered by any new batch produced at time t, which will become available at the start of period t + L_1, and the ending inventory for time period t + L_1.

An estimate of $\hat{g}_{t+L_1}(\mathbf{I}_t)$ is made. Note that time t + L_1 is the time when a batch produced at the start of time t becomes available. It is a simple non-exact approximation as it assumes that future demand will just be the average demand for that time period.

For brevity of exposition, without loss of generality, the computation of $\mathbf{I}_{t+1}$ from $\mathbf{I}_t$ is illustrated for a case where L_1 = 3 and L_2 = 4. Note that $\mathbf{I}_t = [i_t^1, i_t^2, i_t^3, i_t^4, i_t^5, i_t^6]$ and $\mathbf{I}_{t+1} = [i_{t+1}^1, i_{t+1}^2, i_{t+1}^3, i_{t+1}^4, i_{t+1}^5, i_{t+1}^6]$.

The following cases may apply, assuming no production at time t.

- If $\bar{d}_t \le i_t^6$, $\mathbf{I}_{t+1} = [0, i_t^1, i_t^2, i_t^3, i_t^4, i_t^5]$.
- If $i_t^6 < \bar{d}_t \le i_t^5 + i_t^6$, $\mathbf{I}_{t+1} = [0, i_t^1, i_t^2, i_t^3, i_t^4, i_t^5 + i_t^6 - \bar{d}_t]$.
- If $i_t^5 + i_t^6 < \bar{d}_t \le i_t^4 + i_t^5 + i_t^6$, $\mathbf{I}_{t+1} = [0, i_t^1, i_t^2, i_t^3, i_t^4 + i_t^5 + i_t^6 - \bar{d}_t, 0]$.
- If $i_t^4 + i_t^5 + i_t^6 < \bar{d}_t \le i_t^3 + i_t^4 + i_t^5 + i_t^6$, $\mathbf{I}_{t+1} = [0, i_t^1, i_t^2, i_t^3 + i_t^4 + i_t^5 + i_t^6 - \bar{d}_t, 0, 0]$.
- If $\bar{d}_t > i_t^3 + i_t^4 + i_t^5 + i_t^6$, $\mathbf{I}_{t+1} = [0, i_t^1, i_t^2, 0, 0, 0]$.

Figure 2 illustrates sample computations for the same L_1 and L_2 values.

Time t	Inventory Position at start of t i_t^1	i_t^2	i_t^3	i_t^4	i_t^5	i_t^6	Demand $\bar{d}_t$
5	0	4	0	8	0	4	3.8
6	0	0	4	0	8	0	4.1
7	0	0	0	4	0	3.9	8.2
8	0	0	0	0	0	0	3.7

For $i_6^5 = 8$, 4.1 is used to meet demand, while 3.9 is carried to next period

To meet demand for period 7, both i_7^4 and i_7^6 are used. There is a stockout of 0.3 unit. No remaining unit is carried to the next period.

For $i_5^6 = 4$, 3.8 is used to meet demand, while the rest (0.2) is outdated.

Figure 2. Sample $\mathbf{I}_{t+1}$ computations

These computations are made iteratively until $\mathbf{I}_{t+L1}$, which represents the inventory position at the start of time t + L_1. Using the notation $x^+ = \max(0, x)$, the formula of $\hat{g}_{t+L_1}(\boldsymbol{I}_t)$ is now presented.

$$\hat{g}_{t+L_1}(\boldsymbol{I}_t) = \left(\sum_{u=1}^{L1+L2-1} i_{t+L1}^u - \bar{d}_{t+L1} \right)^+$$

To estimate $\hat{\lambda}(\mathbf{I}_t)$, the computations of inventory positions until time t + L_1 + L_2 are continued. The approximation is given by the sum of average demand when the batch becomes available until its lifetime less the amount expected to be covered by previous batches with consideration of possible outdating. The formula of $\hat{\lambda}(\boldsymbol{I}_t)$ is given by:

$$\hat{\lambda}(\boldsymbol{I}_t) = \sum_{v=t+L1}^{t+L1+L2-1} \left(\bar{d}_v - \sum_{u=1}^{L1+L2-1} i_v^u \right)^+$$

Lines 4 to 7 point out that the heuristic will suggest a production if demand to be protected during lifetime of a new batch exceeds the breakeven demand rate λ_{min} and when expected ending inventory for the period t + L_1 if no new batch is produced is 0.

Given historical demand patterns, expected demand corresponding to the lifetime of a batch produced at a given time can be summarized. Together with the availability of critical demand rates, λ_k's, the said information may help the user apply Heuristic A without heavy computations.

Heuristic B further enhances Heuristic A with the use of additional rules. Here are some additional definitions used in the heuristic.

- t_0 is the minimum value of t', t ≤ t', that satisfies $\hat{g}_{t'+L1}(\mathbf{I}_t) = 0$.
- Z(s, k) is a cost indicator corresponding to a batch of size km produced at time s. It will be used to compare alternative timing and size of production.

The pseudocode of the heuristic is outlined below.

Box 2: Pseudocode of Heuristic B

```
Expected Output: production run size kt* to be
    initiated at the start of time t.
 1.  for (t = 1; t ≤ T; t++)
 2.      update It
 3.      compute λ̂(It) and t0
 4.      if (λ̂(It) ≥ λmin) then
 5.          for (s = t; s ≤ t0; s++)
 6.              ks* = argmax_{1≤k≤n} E(P(k, λ̂(Is)))
 7.          end
 8.          (s*, k*) = argmin_{t≤s≤t0, 1≤k≤ks*} Z(s, k)
 9.          if (s* = t) then
10.              kt* = k*
11.          else
12.              kt* = 0
13.      else
14.          kt* = 0
15.  end
```

In Heuristic A, production is initiated only when its availability corresponds to the expected time period when existing items are depleted. Heuristic B, on the other hand, may opt to produce items in advance to protect the system from possible stockouts since actual demand may exceed average demand.

Line 6 computes the number of batches that will optimize the profit function $E(P(k, \hat{\lambda}(\mathbf{I}_s)))$. Similar with the determination of k_t^* in Heuristic A, k_s^* can be identified by comparing $\hat{\lambda}(\mathbf{I}_s)$ and the critical demand rates λ_k.

Values of $Z(s, k)$ are computed for different values of s and k, where $t \leq s \leq t_0$ and $1 \leq k \leq k_s^*$. Line 8 seeks the values of s and k that will minimize $Z(s, k)$.

The formula of Z(s,k) is presented below.

$$Z(s,k) = (p - c_2)\sum_{d>a}(d-a)\frac{e^{-\lambda_a}{\lambda_a}^d}{d!} + c_2\sum_{d=0}^{km}(km-d)\frac{e^{-\lambda_b}{\lambda_b}^d}{d!} + \frac{b_{k^*,t_0}}{b_{k,s}}c_1$$

The first term of Z(s, k) corresponds to stockout penalty. The values of variables a and λ_a depend on whether $t = t_0$ as shown below.

$$a = \begin{cases} km + \sum_{u=1}^{L_1+L_2-1} i_{t+L_1}^{u}, & t = t_0 \\ \sum_{u=1}^{L_1+L_2-1} i_{t+L_1}^{u}, & t < t_0 \end{cases}$$

$$\lambda_a = \begin{cases} \bar{d}_{t+L_1}, & t = t_0 \\ \sum_{u=t}^{s-1} \bar{d}_{u+L_1}, & t < t_0 \end{cases}$$

If $t = t_0$, stockout penalty is based on the demand for the period when the batch is expected to arrive. This ensures that the batch size will be sufficient to cover for the said demand since no future production can cover this period.

When $t < t_0$, it is implied that the model is checking whether it is beneficial to produce in advance of the estimated depletion of existing units. Stockout is based on the demand during periods $t + L_1$, $t + L_1 + 1, \ldots, s + L_1 - 1$.

The second term of Z(s,k) refers to expected wastage cost of the batch produced, where $\lambda_b = \hat{\lambda}(\mathbf{I}_s)$. The last term estimates a penalty associated to the setup cost. If a batch is produced in advance or if the batch is fewer in size relative to another alternative production plan, this may increase setup cost. To estimate the penalty, variable $b_{k,s}$ is defined as the number of periods starting from t_0 that the batch of size km and produced at time s is expected to last. This is again based on the assumption that the demand for a future period is just the average demand for the period. Variable $b_{k^*,t0}$ is defined similarly for a batch of size $mk^*_{s=t0}$ produced at time t_0.

It can be said that Heuristic B can be practically implemented with the help of a computer that will perform these necessary computations.

5. RESULTS FOR ACTUAL PROBLEM INSTANCES

This study validated the proposed heuristics in sample instances from a system that fits the system descriptions cited in Section 2.0. In the validation, each period is equivalent to 5 mins and the specific problem has the following problem parameters: $L_1 = 5$ (25 mins), $L_2 = 6$ (30 mins), r = 204 (17 hrs), m = 8 units per pack, n = 4 batches per run. Demand patterns for weekday and weekend were separately run. Figure 3 illustrates the expected weekday and weekend demand of a particular item with respect to operating hours in 30-min interval.

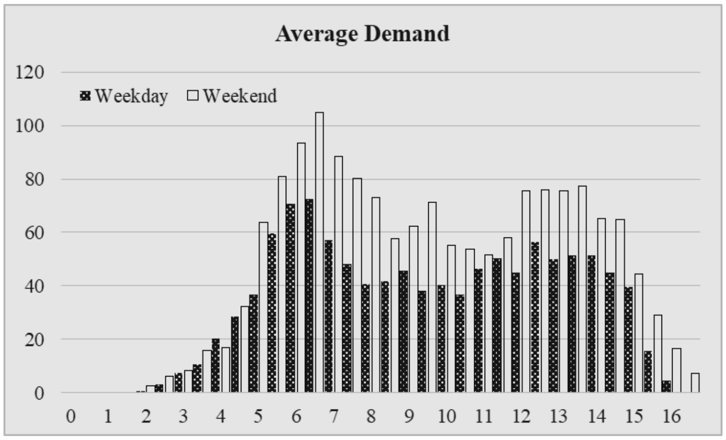

Figure 3. Average demand

For the estimates of price and costs, this study used for this case, p = 70, c_1 = 30 and c_2 = 40. Expected profit is the main performance measure used, while metrics such as shortage and expired item percentages are likewise monitored. Table 1 and Table 2 present the results of 500 simulations for the two test cases using the proposed heuristics. The number of replicates is enough to estimate mean profit with an error of less than 1%.

Table 1. Results for the Weekday Test Case

Metric	Heuristic A	Heuristic B
Ave Revenue	74,505	75,443
Ave Setup Cost	1,130	1,381
Ave Unit Cost	43,822	43,807
Ave Profit	29,553	30,256
% Shortage	4.24 %	2.72 %
% Expired	2.85 %	1.60 %

Table 2. Results for the Weekend Test Case

Metric	Heuristic A	Heuristic B
Ave Revenue	107,952	110,907
Ave Setup Cost	1,594	1,888
Ave Unit Cost	62,412	63,920
Ave Profit	43,946	45,100
% Shortage	3.57 %	1.30 %
% Expired	1.16 %	0.85 %

For the above test cases, it can be said that Heuristic B is superior to Heuristic A. Based on profit figures, Heuristic B improves results of Heuristic A by 2.4% and 2.6% for weekdays and weekends, respectively. Heuristic B is successful as well in significantly improving % shortage and % expired, although this comes with increase in setup costs. Considering however, the simplicity of Heuristic A, its results are deemed satisfactory as well.

To see how figures vary in the simulation, the histograms of % shortage and % expired are presented below, in Figures 4 and 5, for the weekday scenario.

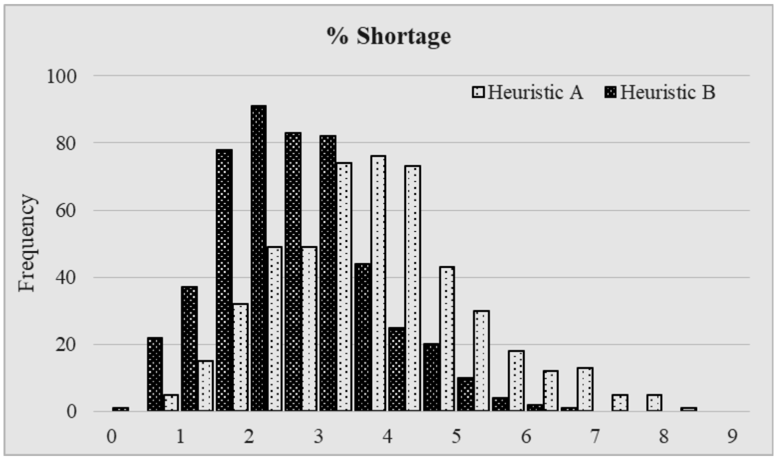

Figure 4. Histogram of % Shortage

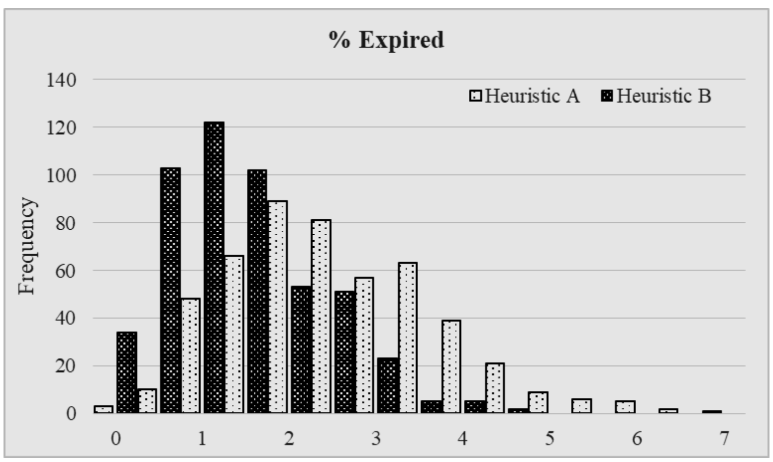

Figure 5. Histogram of % Expired

In both metrics, Heuristic B is better. It is observed also that there are few replicates that result in poor performance, exceeding twice the average figures. While these scenarios cannot be completely eliminated, it is desired to gauge how the values fluctuate to ensure reasonable expectations from the heuristic. Table 3 presents the 90th and 95th percentiles for these two metrics using Heuristic A. Resulting figures for Heuristic B are found in Table 4.

Table 3. Key Metrics using Heuristic A

Percentile	Weekday		Weekend	
	Short	Expired	Short	Expired
90th	6.10 %	4.44 %	5.06 %	1.93 %
95th	6.96 %	4.96 %	5.44 %	2.16 %

Table 4. Key Metrics using Heuristic B

Percentile	Weekday		Weekend	
	Short	Expired	Short	Expired
90th	4.21 %	2.85 %	2.16 %	1.59 %
95th	4.70 %	3.17 %	2.36 %	1.77 %

One should expect that in 10% and 5% of all operating days, the % shortage and % expired exceed the 90th and 95th percentile figures indicated, respectively. These “worst” values, nevertheless, are still within acceptable levels.

Sensitivity analysis was also performed to determine the effect of different price and unit cost combinations to the different metrics. Simulation with 500 replicates each was also employed to come up with the results. Figure 6 presents how changes in these cost parameters affect the proportion of unmet demand using Heuristic A for the weekday scenario. Results for Heuristic B closely follow the same observations found in Heuristic A results.

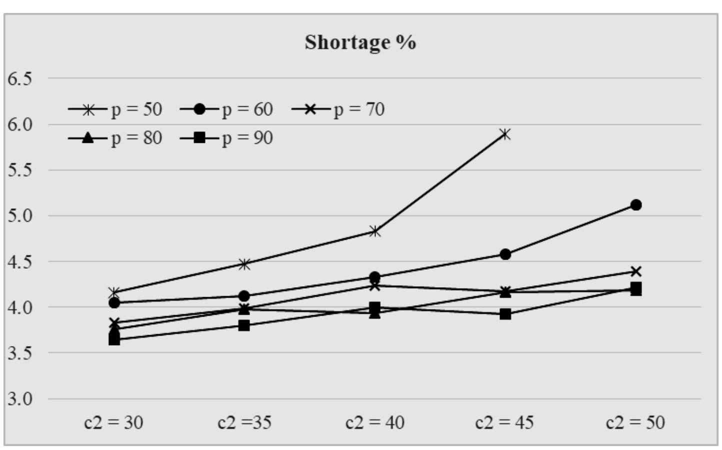

Figure 6. % Shortage for different p and c_2

It can be seen that majority of the points are within 5%. As unit cost increases, cost of shortage is reduced in comparison to cost of excess units. This lets the model to suggest a plan that increases % shortage.

Meanwhile, Figure 7 illustrates how proportion of excess units reacts in the changes in cost parameters using Heuristic A as applied also to the weekday case.

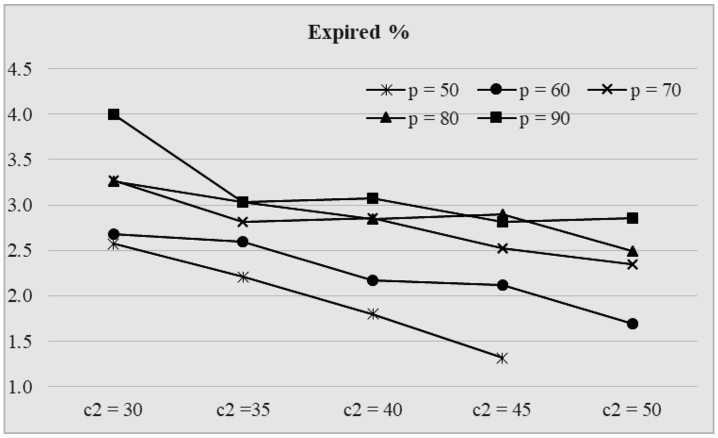

Figure 7. % Expired for different p and c_2

An expected result is observed: as contribution margin narrows, the model generally suggests a plan that yields fewer expired items.

Lastly, expected daily profit is shown for different values of p and c_2 in Figure 8. The general patterns suggested by the results are likewise intuitive.

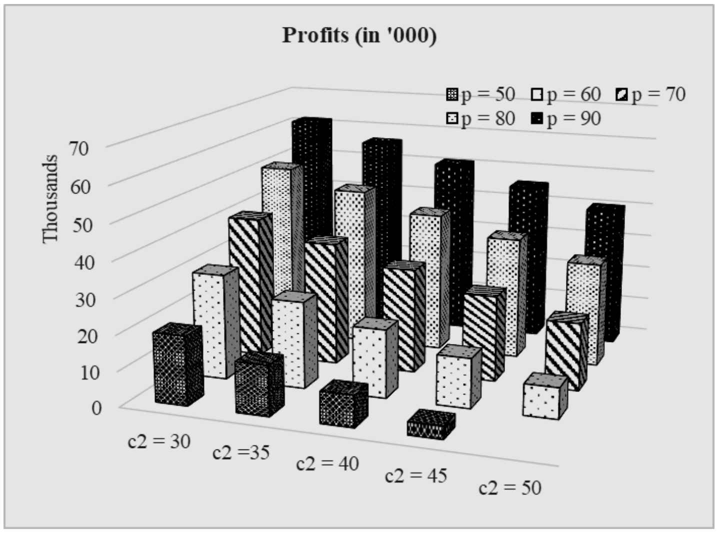

Figure 8. Profit values for different p and c_2

It is noteworthy to mention that most of the 500-replicate simulations of the heuristic for the given actual scenarios, as implemented in a programming language, completed their runs within 30 s.

Finally, an insight related to implementation is that most systems plan on production on a trial-and-error basis. For example, the system from which the actual problem data was obtained used no formal, structured and regular production plan to identify the number of units to produce. In the said system, without the implementation of the disposal of expired items, a total of 257 units exceeded the set lifetime in a three-day observation period. This figure is very significant as it is 43.3% of the total demand of 594 for the observed peak operating hours. Since these expired units are not disposed, it resulted in a very low stockout of 4 units.

The same experienced-based approach, coupled with the strict implementation of disposing expired units, led to stockout and expiration levels of 0.9% and 1.0%, respectively, in one observed period. In another case corresponding to another peak demand time, the figures were 8.1% and 14.6% of total demand, respectively. The latter values are considered unsatisfactory. With the aid of the proposed heuristics, the said numbers may be improved.

6. SUMMARY AND CONCLUSION

This research addressed an inventory problem involving a perishable item with non-zero production lead time. Furthermore, production run quantity is restricted by the allowed batch sizes. The goal is to maximize profit considering setup cost and unit production cost. Two heuristics were developed to identify the number of batches to be produced given the age distribution of available items and estimated future demand.

The simulated results of the application of the proposed heuristic on sample data sets of the system described suggest that the heuristics are capable of producing satisfactory inventory control plans with average proportion of unmet demand and proportion of expired units not exceeding 5% and 3% for the worse of the two test instances tested. Run times of the heuristics are satisfactory as well. Sensitivity analyses made also indicated how the model reacts to changes in problem parameters.

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