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Heuristic Approach to Inventory Control with Advance Capacity Information

Marko Jakšič[1, 2], Borut Rusjan[1]

[1]University of Ljubljana, Faculty of Economics, Ljubljana, Slovenia, Kardeljeva ploščad 17, Ljubljana
marko.jaksic@ef.uni-lj.si, borut.rusjan@ef.uni-lj.si,
[2]School of Industrial Engineering, Eindhoven University of Technology, The Netherlands

There is a growing trend of information sharing within modern supply chains. This trend is mainly stimulated by recent developments in information technology and the increasing awareness that accurate and timely information helps firms cope with volatile and uncertain business conditions. We model a periodic-review, single-item, capacitated stochastic inventory system, where a supply chain member has the ability to obtain advance capacity information ('ACI') about future supply capacity availability. ACI is used to reduce the uncertainty of future supply and thus enables the decision-maker to make better ordering decisions. We develop an easily applicable heuristic based on insights gained from an analysis of the optimal policy. In a numerical study we quantify the benefits of ACI and compare the performance of the proposed heuristic with the optimal performance. We illustrate the conditions in which the procedure is working well and comment on its practical applicability.

Keywords: Operational research, inventory, stochastic models, advance capacity information, heuristic

1 Introduction

In a realistic supply chain setting a common modeling assumption of sure deliveries of an exact quantity ordered may not be appropriate. Several factors in a production/inventory environment, such as variations in the workforce level (e.g. due to holiday leave), unexpected machine breakdowns and maintenance, changing the supplier's capacity allocation to their customers etc., affect the available supply capacity and correspondingly cause uncertainty in the supply process. Anticipating possible future supply shortages allows a decision-maker to make timely ordering decisions which result in either building up stock to prevent future stockouts or reducing the stock when future supply conditions might be favorable. Thus, system costs can be reduced by carrying less safety stock while still achieving the same level of performance. These benefits should encourage the supply chain parties to formalize their cooperation to enable the requisite information exchange by either implementing necessary information sharing concepts like the Electronic Data Interchange ('EDI') and Enterprise Resource Planning ('ERP') or using formal supply contracts. We may argue that extra information is always beneficial, but further thought has to be put into investigating in which situations the benefits of information exchange are substantial and when it is only marginally useful.

In this paper, we explore the benefits of using available advance capacity information ('ACI') about future uncertain supply capacity to improve inventory control mechanisms and reduce relevant inventory costs. The assumption is that a supplier has some insight into near future supply capacity variations (the extent of the capacity that they can delegate to a particular retailer for instance), while for more distant future periods the capacity dynamics are uncertain. Thus, the supplier can communicate this information to the retailer and help the retailer reduce supply uncertainty (Figure 1). However, the simultaneous treatment of demand uncertainty and supply uncertainty proves to be too complex to establish simple and easily applicable inventory control policies. Bush and Cooper (1998) and Buxey (1993) indicate that firms facing these conditions tend to have no formal planning mechanism.

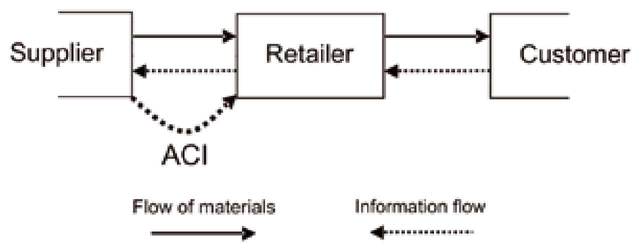

Figure 1: Supply chain with ACI sharing.

The aim of this paper is to build a practical and reasonably accurate heuristic procedure that captures the important problem characteristics mentioned. The heuristic is developed based on insights gained from a study of the optimal policy behavior by Jakšič et al. (2008). They show that the optimal ordering policy is a base stock policy characterized by a single base stock level, which is a function of deterministic ACI that is available for a limited number of future periods.

However, they stress that the complexity of the underlying optimal dynamic programming procedure prevents an analysis of real-life situations. This problem will be addressed in this paper by considering an approximate approach to determine the parameters of the inventory policy.

We now briefly review the relevant research literature. The practical importance of the effect of limited capacity has generated considerable interest in the research community. Extending the results of the classical uncapacitated inventory control, the capacitated manufacturing/supply setting was first addressed by Federgruen and Zipkin (1986). They proved the optimality of the modified base stock policy for a fixed capacity constraint and stationary demand. Kapuscinski and Tayur (1998) assume stochastic seasonal demand where they again show the optimality of a modified base-stock policy. The anticipation of future demand, due to its periodic nature, causes a corresponding increase or decrease in the base stock level. A line of research assumes stochastic capacity (Ciarralo et al., 1994; Güllü et al., 1999; Iida, 2002), within which Ciarralo et al. (1994) show that the optimal policy remains a base stock policy where the optimal base stock level is increased to account for possible capacity shortfalls in future periods. They extend this work by introducing the notion of extended myopic policies and show these policies are optimal if the decision-maker considers appropriately defined review periods. The optimality or near-optimality of myopic policies in a non-stationary demand environment was explored by Morton and Pentico (1995) and later extended with the inclusion of fixed or stochastic capacity by Bollapragada et al. (2004), Khang and Fujiwara (2000), and Metters (1998). Metters (1997) presents a heuristic constructed utilizing an analytical approximation for optimal policy. In developing heuristics, researchers have generally resorted to an approximate analysis of the optimal policies and a close inspection of the behavior of myopic policies.

The remainder of the paper is organized as follows. In Section 2 we present a model incorporating ACI and its dynamic programming formulation as the basis for an optimal solution. In Section 3 we consider an alternative approach to solving the presented inventory problem by developing a heuristic procedure. Section 4 provides the results of a numerical study in which we assess the accuracy of the proposed heuristic and outline relevant managerial insights about the settings in which it should be applied. Finally, we summarize our findings in Section 5.

2 Model formulation

In this section, we describe in detail the ACI model developed in Jakšič et al. (2008). We introduce the notation and present the optimality equations. The model under consideration assumes periodic-review, stochastic demand, stochastic limited supply with a fixed nonnegative supply lead time, finite planning horizon inventory control system. However, the manager is able to obtain ACI on the available supply capacity for orders placed in the future and use it to make better ordering decisions. We introduce parameter n, which represents the length of the ACI horizon, that is, how far in advance the available supply capacity information is revealed. We assume ACI z^+_{t+n} is revealed in each period t for the supply capacity that will be realized in period $t+n$. The model assumes perfect ACI, meaning that we know the exact upper limit on supply capacities limiting orders placed in the current and following n periods.

Presuming that unmet demand is fully backlogged, the goal is to find an optimal policy that minimizes the relevant costs, that is inventory holding costs and backorder costs. Hence, we assume a zero fixed cost inventory system. The model presented is quite general in the sense we do not make any assumptions about the nature of the demand and supply process, with both being assumed to be stochastic non-stationary and with known distributions in each time period, however, independent from period to period. The major notation is summarized in Table 1 and some other notation is introduced later as required.

Table 1: Summary of notation

T	:	number of periods in the planning horizon
L	:	constant nonnegative supply lead time, where $L=0$, for "zero lead time" case
n	:	advance supply information parameter, $n \geq 0$
h	:	inventory holding cost per unit per period
b	:	backorder cost per unit per period
x_t	:	inventory position at time t before ordering
y_t	:	inventory position at time t after ordering
$\hat{x}_t$	:	net inventory at the beginning of period t
z_t	:	order size at time t
c_t	:	lack of capacity in period t
a_t	:	anticipatory stock required in period t
D_t	:	random demand in period t
d_t	:	actual demand in period t
Z^+_t	:	random available supply capacity at time t
z^+_t	:	actual available supply capacity at time t, for which ACI was revealed at time $t-n$

We assume the following sequence of events. (1) At the start of the period t, the manager reviews x_t and ACI z^+_{t+n} for supply capacity in period $t+n$ is received, limiting order z_{t+n} (Figure 2). (2) The ordering decision z_t is made and correspondingly the inventory position is raised to $y_t = x_t + z_t$. (3) The quantity ordered in period $t-L$ is received. (4) At the end of the period demand d_t is observed and satisfied through on-hand inventory; otherwise it is backordered. Inventory holding/backorder costs are incurred based on the end-of-period net inventory.

Due to positive supply lead time, each order remains in the pipeline stock for L periods. We can therefore express the inventory position before ordering x_t as the sum of the net inventory and pipeline stock.

$$x_t = \hat{x}_t + \sum_{s=t-L}^{t-1} z_s . \quad (1)$$

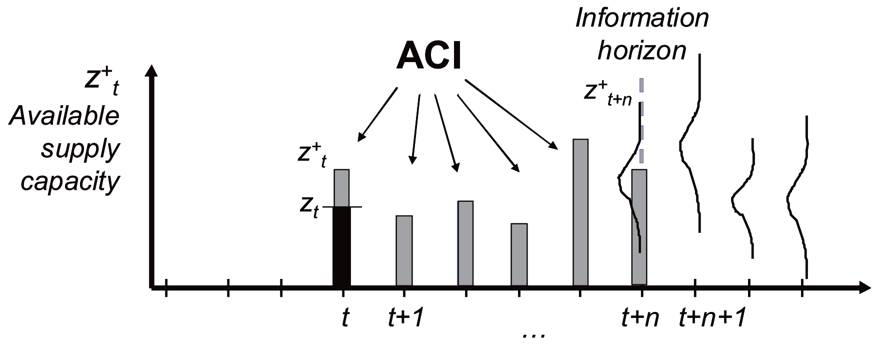

Figure 2: Advance capacity information updating.

Correspondingly, the inventory position after ordering is

$$y_t = x_t + z_t, \tag{2}$$

where $0 \le z_t \le z_t^+$, where z_t^+ represents the upper bound on the realization of the order z_t that will be delivered L periods later in period $t+L$. Note, that due to perfect ACI, the inventory position y_t reflects the actual quantities that will be delivered at all times. Apart from x_t and the current supply capacity z_t^+, we need to keep track of ACI, $\vec{z}_t^{\,+} = [z_{t+1}^+, z_{t+2}^+, \ldots, z_{t+n}^+]$. The ACI vector consists of available supply capacities potentially limiting the size of orders in future n periods. The state space is thus represented by a $n+2$ -dimensional vector and is updated at the end of period t in the following manner

$$\begin{aligned} x_{t+1} &= x_t + z_t - d_t, \\ \vec{z}_{t+1}^{\,+} &= [z_{t+2}^+, \ldots, z_{t+n}^+, z_{t+n+1}^+]. \end{aligned} \tag{3}$$

Going from period t to period $t+1$, order z_t is placed according to the available supply capacity z_t^+ and demand in period t is realized. Before a new order is placed in period $t+1$, ACI z_{t+n+1}^+ for the order that will be placed in period $t+n+1$ is revealed and the oldest data point z_t^+ is dropped out of the ACI vector and ACI is updated by the new information z_{t+n}^+. Observe that in the case of $n=0$ the ACI affecting the current order is revealed just prior to the moment when the order needs to be placed. Due to a constant non-zero lead time the decision-maker should protect the system against lead time demand, $D_t^L = \sum_{k=t}^{t+L} D_k$, which is demand realized in time interval $(t, t+L)$. Since the current order z_t affects the net inventory at time $t+L$, and no later order does so, it makes sense to reassign the corresponding inventory-backorder cost to period t. Thus, the expected inventory-backorder cost charged to period t is based on the net inventory at the end of the period $t+L$, $\hat{x}_{t+L+1} = y_t - D_t^L$, and we can write it in the following form of a single-period expected cost function $C_t(y_t)$:

$$C_t(y_t) = \alpha^L E_{D_t^L} \hat{C}_{t+L}(y_t - D_t^L), \tag{4}$$

where α is a discount factor. The expectation is with respect to lead time demand D_t^L and the single-period cost function takes the following form, $\hat{C}_{t+L}(\hat{x}_{t+L+1}) = h[\hat{x}_{t+L+1}]^+ + b[\hat{x}_{t+L+1}]^-$.

The minimal expected cost function, optimizing the cost over a finite planning horizon T from time t onward and starting in the initial state $(x_t, \vec{z}_t^{\,+})$, can be written as:

$$f_t(x_t, z_t^+, \vec{z}_t^{\,+}) = \begin{cases} \min\limits_{x_t \le y_t \le x_t + z_t^+} \{C_t(y_t) + \alpha E_{D_t} f_{t+1}(y_t - D_t, z_{t+1}^+, \vec{z}_{t+1}^{\,+})\}, & \text{if } T-n \le t \le T \\ \min\limits_{x_t \le y_t \le x_t + z_t^+} \{C_t(y_t) + \alpha E_{D_t, Z_{t+n}^+} f_{t+1}(y_t - D_t, z_{t+1}^+, \vec{z}_{t+1}^{\,+})\}, & \text{if } 1 \le t \le T-n-1 \end{cases} \tag{5}$$

where $f_{T+1}(\cdot) \equiv 0$. The solution to this dynamic programming formulation minimizes the cost of managing the system for a finite horizon problem with $T-t$ periods remaining until termination. It was shown in Jakšič et al. (2008) that the optimal policy is the modified base stock policy, characterized by a single optimal base stock level $\hat{y}_t(\vec{z}_t^{\,+})$, which determines the optimal level of the inventory position after ordering. The optimal base stock level depends on the future supply availability, that is supply capacities given by the ACI vector $\vec{z}_t^{\,+}$. Optimal policy instructs that we raise the base stock level if we anticipate a possible shortage in supply capacity in the future. We thereby stimulate the inventory build-up to avoid possible backorders which would be a probable consequence of a capacity shortage. On the contrary, the base stock level is decreasing with the higher supply availability revealed by ACI.

3 Construction of the heuristic

However, the computational efforts related to establishing the parameters of the optimal policy are cumbersome even for simple problem instances. Practical applicability is therefore severely restricted. This creates an incentive to develop approximate procedures to tackle the problem. In this section we present a modification of existing heuristics for a non-stationary demand, fixed capacity inventory system, known as the *proportional safety stock heuristic* (Metters, 1997). We upgrade this heuristic considerably for the case of our ACI model by accounting for both the effect of the variable capacity and the proposed ACI setting.

To construct the heuristic it is first useful to define the myopic optimal solution to the single-period newsvendor problem:

$$\hat{y}_t^M = \Phi_t^{-1}\left(\frac{b}{b+h}\right), \tag{6}$$

where $\Phi_t(d_t)$ represents the cumulative distribution function of demand in period t. For a single-period problem with stochastic limited capacity Ciarallo et al. (1994) show that the variable capacity does not affect the order policy. The myopic policy of the newsvendor type is optimal, meaning that the decision-maker has no incentive to try to produce more than is dictated by the demand and the costs, and simply has to hope that the capacity is sufficient to produce the optimal amount. However, in multiple period situations one can respond to possible capacity unavailability by building up inventories in advance.

We continue by constructing the illustrative example presented in Figure 3. Consider the base scenario characterized by the following parameters: $T=6, \alpha=0.99, h=1, b=20$, discretized truncated normal demand and supply capacity following a pattern where expected demand is given as $D_{1..6}=(5,5,5,15,5,5)$ and the expected supply capacity as $Z_{1..6}^{+}=(10,10,10,10,10,10)$. The average capacity utilization is 67%; however, there is a significant mismatch between demand and supply capacity from period to period. In particular, period 4 is problematic since the occurrence of a supply capacity shortage is highly likely.

Observe the difference between the optimal base stock levels $\hat{y}_t$, determined by solving , and the myopic optimal levels $\hat{y}_t^M$. The myopic optimal solution $\hat{y}_t^M$ only optimizes an uncapacitated single-period problem. Therefore, the corresponding base stock levels follow changes in mean demand, while the height depends on the relevant cost structure, in our case the ratio between the backorder and inventory holding cost, b/h, through . Optimal base stock levels align with the myopic ones only in some periods, in our case, in periods 1, 5 and 6, and are close in the peak demand period 4; in the rest of the periods, $\hat{y}_t$ lies above $\hat{y}_t^M$. This difference is due to the anticipation of future capacity shortages. The rational reaction is to pre-build stock to prepare in advance. Based on this insight, we can state the following conditions when an inventory buildup is needed and potentially brings considerable benefits to the decision-maker:

- when there is a mismatch between the demand and supply capacity, meaning that there are time periods when the supply capacity is highly utilized or even over-utilized, but there are also periods when capacity utilization is low;
- when we can anticipate a possible mismatch in the future; and
- when we have enough time and excess capacity to build up the inventory to a desired level to avoid backorder accumulation during a capacity shortage.

For an uncapacitated system Veinott (1965) shows that the myopic policy represents near-optimal upper bound to the optimal policy. Since $\hat{y}_t^M$ is near-optimal in the uncapacitated case, the difference between $\hat{y}_t$ and $\hat{y}_t^M$ reflects the need to pre-build inventory by raising the base stock level in the capacitated case. In our example, we see that the pre-build phase for period 4 has started back in period 2, where the heightened $\hat{y}_t$ already reflects the need for inventory accumulation. In the peak period, the nature of the problem is close to a single-period problem thus $\hat{y}_t^M$ represents a good upper bound, but only if there are no anticipated future capacity shortages for at least a few following time periods.

Some anticipation is already possible without knowledge of actual supply capacity realizations in future periods, as we have just shown. For this, knowing the demand and supply capacity distributions is enough. However, we argue that through the use of ACI we can improve inventory control further due to better information about the evolution of the system in near future periods. In Figure 4, we present the same base setting in the case where we have an insight into supply capacity realizations in the next period, $n=1$. We see that, if ACI warns us of a capacity shortage (a low z_{t+1}^{+}), we will respond by increasing the base stock level. This is also

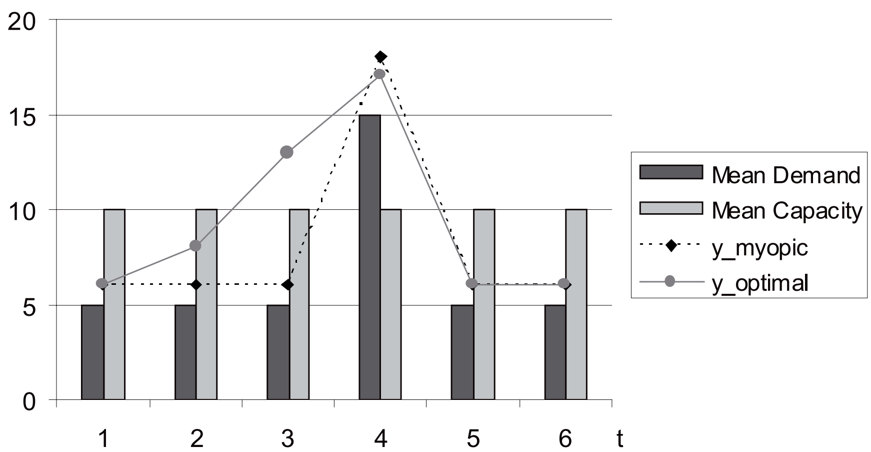

Figure 3: Optimal $\hat{y}_t$ and myopic optimal $\hat{y}_t^M$ base stock levels.

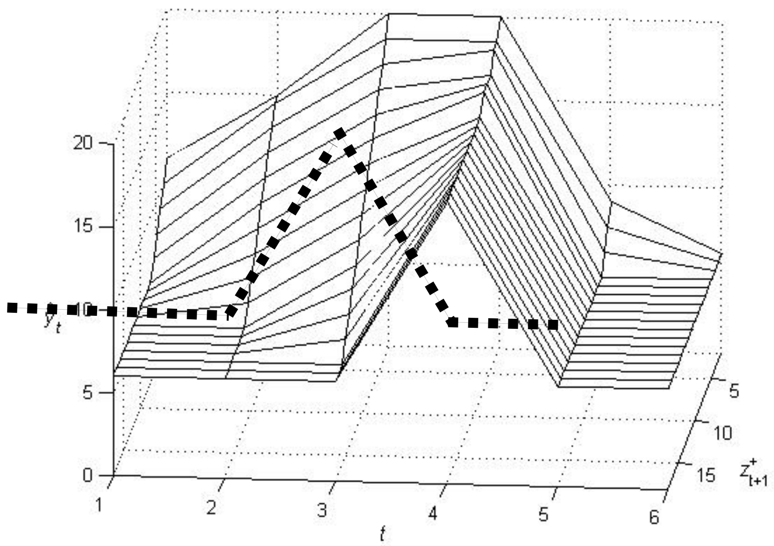

Figure 4: Optimal $\hat{y}_t$ and myopic optimal $\hat{y}_t^M$ base stock levels for the ACI model

the case in the peak period, where $\hat{y}_t$ can exceed $\hat{y}_t^M$, when shortages are announced by ACI in the remaining two periods; although their probability is likely to be very small. A practical interpretation of the above findings can be made for a simple heuristic policy, which instructs the following:

- Set the base stock level at $\hat{y}_t^M$, unless you anticipate a capacity shortage.
- In the case of a shortage the inventory needs to be pre-build and thus the base stock level needs to be increased above $\hat{y}_t^M$ in the pre-build periods.

The determination of the amount of the pre-build inventory needed is based on an evaluation of future mismatches between available capacities (given by ACI for near future periods and the parameters of capacity distributions for distant periods) and the myopic optimal base stock levels. We start by determining the mismatch in supply capacity c_t in period t, where we distinguish two possible cases. First, we look at a mismatch in supply capacity for the case when ACI is already available for that period. In this case, we know the realization of capacity and therefore $c_t(z_t^+)$ is a function of the actual realization of supply capacity z_t^+. In the second case, the supply capacity is not yet revealed so the best we can do is to work with the expected supply capacity, thus, $c_t(E(z_t^+))$. We formulate the mismatch of supply capacity c_t in period t as:

$$\left.\begin{matrix} c_t(z_t^+) \\ c_t(E(z_t^+)) \end{matrix}\right\} = \hat{y}_t^M - \left(\hat{y}_{t-1}^M - E(D_{t-1}) + \left\{\begin{matrix} z_t^+ \\ E(z_t^+) \end{matrix}\right.\right) . \qquad (7)$$

Observe that c_t is determined as the difference between the myopic base stock level $\hat{y}_t^M$ and the ending inventory position y_t (determined from , where $x_t = \hat{y}_{t-1}^M - E(D_{t-1})$), given that all of the supply capacity z_t^+ available in period t was used. A negative c_t corresponds to an excess of supply capacity, and a positive to a lack of capacity in period t. Knowing the potential lack or excess of supply capacity in each period allows us to calculate the amount of inventory build-up required in a particular period. That is the amount of inventory we have to build in advance in period t to cover future supply capacity/demand mismatches. We will denote this inventory as anticipatory $a_{t,n}$ required in period t:

$$a_{t,n=0} = \max\left(a_{t+1,n=0} + c_{t+1}(E(z_{t+1}^+)), 0\right), \quad if\ n = 0,$$
$$a_{t,n}(\vec{z}_{t,n}^{\,+}) = \max\left(a_{t+1,n}(\vec{z}_{t+1,n-1}^{\,+}) + c_{t+1}(z_{t+1}^+), 0\right), \quad if\ n > 0 \qquad (8)$$

Observe that $a_{t,n}(\vec{z}_{t,n}^{\,+})$ is a function of ACI, if ACI is available ($n > 0$). The anticipatory inventory is calculated recursively from the end of the planning horizon down to the first period. First, the anticipatory inventory for $n = 0$ case is determined and it is then used as the building block to determine the anticipatory inventory for $n = 1$ case. In the same manner we proceed by calculating $a_{t,n}$ for higher n, where $a_{t,n}$ is a function of all currently available ACI. Where excess supply capacity is available, we can use it to build up the anticipatory inventory. If the size of the excess supply capacity accounts for more than the anticipatory inventory needed, we only use up to the amount needed and we therefore limit ourselves to positive values of c_t, by imposing a max function in the above formulation. If current excess supply capacity is not high enough some of the anticipatory inventory needs to be pre-built in earlier periods.

Finally, the heuristic base stock level $\hat{y}_{t,n}^H$ is determined by raising it above the myopic optimal level $\hat{y}_t^M$, for the extent of anticipatory inventory $a_{t,n}$:

$$\hat{y}_{t,n}^H = \hat{y}_t^M + a_{t,n}(\vec{z}_{t,n}^{\,+}) \qquad (9)$$

While with the myopic base stock level we only account for uncertainties in demand, by adding the anticipatory stock we now also account for future capacity shortages. With this the variability in future supply capacity is also taken into consideration. Given the actual supply capacity realization in the current period the ending inventory position may not be raised to the heuristic base stock level $\hat{y}_{t,n}^{H}$. In this case, all of the available capacity is used. In general the heuristic policy behaves in the same way as the optimal policy, where the optimal base stock level $\hat{y}_t$ is replaced by its heuristic counterpart.

4 The value of ACI and heuristic performance

In this section we present a numerical study to assess the value of ACI and the heuristic performance. The results are given in Table 2. Using the same base setting as in the previous section, we now look at the influence of the cost structure and the variability of both the demand and supply capacity on heuristic performance. We vary:

- the coefficient of the variation of demand $CV_D = (0, 0.25, 0.5, 0.7)$ and supply capacity $CV_Z = (0, 0.25, 0.5, 0.7)$, where both CVs do not change through time; and
- the cost structure, by changing the backorder cost $b = (5, 20)$ and keeping the inventory holding cost constant at $h = 1$, thus changing the cost ratio b/h.

We give the following managerial insights about the situations in which ACI considerably improves the inventory cost. The value of ACI is defined as the reduction in cost for the case where ACI is available $n > 0$, relative to the base case with no ACI, $n = 0$. Looking at the results presented in Table 1, we see that cost reductions of 5-15% can be expected and in certain situations they can exceed 20%. Several factors affect the value of ACI and we formulate the following conditions in which inventory costs can be effectively decreased: (1) when there is a mismatch between demand and supply capacity, which can be anticipated through ACI, and there is an opportunity to pre-build inventory in an adequate manner; (2) when uncertainty in future supply capacity is high and ACI is used to lower it effectively; and (3) in the case of high backorder costs, which further emphasizes the importance of avoiding stock-outs. In these circumstances, managers should recognize the importance of ensuring the necessary information exchange with their suppliers. Such relations may bring considerable operational cost savings.

We proceed by establishing the performance of the proposed heuristic. To do this, we give two accuracy measures: the *Absolute error* and the *Relative error*. Both are determined based on a comparison of total inventory costs between the heuristic case and the optimal case, where the first one gives the absolute cost difference and the latter the relative one. Observe that in general the heuristic performance is within or close to 1% of the optimal. However, we can also see that there are some variations for different selections of the parameter settings we have tested. In a completely deterministic scenario (Exp. No. 1), the heuristic manages to reproduce the optimal results. For stochastic scenarios, where cost reduction through ACI is possible, we see that the relative error decreases when we extend the ACI horizon n. This is in line with the intuition which suggests that the heuristic will perform better if the general uncertainty is lower, and the uncertainty in this case is effectively reduced through ACI. This suggests that the proposed heuristic should be applied in the ACI setting in particular. While this can be observed in most of the cases where $b = 20$, it does not hold for some scenarios where $b = 5$. We attribute this to the fact that the heuristic generally puts a stress on assuring enough inventory build-up, which can be suboptimal in the case of a low b/h. In a practical application this might not pose a big problem since one rarely comes across such a low b/h ratio. Also observe also that the heuristic performs well in the case where demand uncertainty, CV_D, is high relative to the capacity uncertainty, CV_{Z^+}, or in the case where both demand and capacity uncertainty are similar. This is due to the heuristic being highly sensitive to demand uncertainty through the use of myopic optimal base stock levels as the simple lower bounds. However, the effect of changing CV_D and CV_{Z^+} is heterogeneous and by itself it does not exhibit any obvious monotonic properties. The heuristic performance is worst for the specific setting of high capacity uncertainty and low ACI availability, particularly the case of $n = 0$, which is due to the fact that the proposed heuristic does not fully account for capacity variability. However, because of the complexity of the underlying model it should be noted here that, for the base case of nonstationary demand and capacity uncertainty, no easily applicable approximation techniques are proposed in the literature apart from more complex and time-consuming algorithms involving simulation and search methods.

5 Conclusions

In this paper, we propose a heuristic to evaluate the cost of the ACI inventory model and determine the value of ACI. The heuristic development was motivated by the fact that the optimal analysis of the problem is very tedious, even impossible for larger, real-life problems. Based on the insights gained from analyzing the optimal policy, we first give the relevant managerial insights by showing when ACI can bring considerable inventory cost reductions and describe the important characteristics that had to be addressed when formulating the heuristic. This, in itself, is a valuable result since it helps with building up decision-makers' intuition and helps them address the problem better in a realistic situation. We can conclude that the performance analysis of the proposed heuristic shows that the heuristic works reasonably well in the ACI setting. Especially in the case where ACI is available and the common backorder to inventory holding cost ratio is assumed, the heuristic performance is within 1% of the optimal. We foresee that efforts to establish a superior heuristic may be seriously hampered by the complexity of the underlying problem. For an inventory control policy to be applicable and effective in a practical situation, a certain degree of simplification is needed and finding a good heuristic is a compromise between remain-

Table 2: The value of ACI and heuristic performance

Exp.			b	5	20	5	20	5	20	5	20	5	20
No.	CV_D	CV_Z	n	**Optimal Cost**		Value of ACI (%)		**Heuristic Cost**		Absolute Error		Relative Error (%)	
1	0	0	0	**2.91**	**2.91**	0.00	0.00	**2.91**	**2.91**	0.00	0.00	0.00	0.00
2	0.5	0	0	**21.30**	**30.28**	0.00	0.00	**22.74**	**30.41**	1.43	0.13	6.31	0.42
3	0.25	0.25	0	**13.84**	**20.22**			**13.99**	**21.10**	0.15	0.88	1.07	4.18
			1	**13.13**	**18.47**	5.17	8.66	**13.32**	**19.03**	0.19	0.56	1.46	2.96
			2	**12.83**	**17.41**	7.29	13.91	**13.32**	**17.50**	0.49	0.09	3.67	0.54
			3	**12.77**	**17.06**	7.76	15.60	**13.43**	**17.07**	0.66	0.01	4.94	0.03
			4	**12.76**	**17.02**	7.78	15.83	**13.46**	**17.02**	0.70	0.00	5.17	0.01
4	0.25	0.5	0	**19.96**	**36.85**			**20.20**	**42.12**	0.24	5.27	1.17	12.52
			1	**17.60**	**32.41**	11.85	12.04	**17.63**	**34.26**	0.03	1.85	0.18	5.40
			2	**16.65**	**29.80**	16.59	19.11	**16.90**	**30.78**	0.25	0.98	1.46	3.17
			3	**16.35**	**28.76**	18.10	21.95	**16.85**	**29.34**	0.50	0.58	2.96	1.98
			4	**16.28**	**28.51**	18.47	**22.63**	**16.92**	**28.94**	0.64	0.43	3.80	1.50
5	0.5	0.25	0	**22.91**	**35.40**			**23.68**	**35.42**	0.77	0.02	3.27	0.04
			1	**22.50**	**34.09**	1.79	3.73	**23.31**	**34.19**	0.81	0.10	3.49	0.31
			2	**22.31**	**33.30**	2.62	5.94	**23.40**	**33.32**	1.09	0.02	4.68	0.05
			3	**22.26**	**32.96**	2.81	6.89	**23.56**	**33.02**	1.30	0.06	5.52	0.17
			4	**22.26**	**32.86**	2.82	7.19	**23.60**	**32.99**	1.34	0.13	5.69	0.39
6	0.5	0.5	0	**28.63**	**54.05**			**28.68**	**58.41**	0.05	4.36	0.19	7.47
			1	**27.01**	**51.00**	5.65	5.64	**27.21**	**52.52**	0.20	1.52	0.74	2.90
			2	**26.36**	**49.15**	7.93	9.06	**26.60**	**49.69**	0.24	0.54	0.92	1.08
			3	**26.18**	**48.37**	8.55	10.51	**26.47**	**48.70**	0.29	0.33	1.10	0.68
			4	**26.14**	**48.17**	8.68	10.87	**26.44**	**48.40**	0.30	0.23	1.13	0.47
7	0.7	0.5	0	**38.70**	**76.10**			**39.35**	**78.24**	0.65	2.14	1.66	2.73
			1	**37.44**	**74.09**	3.24	2.64	**38.24**	**74.48**	0.80	0.39	2.08	0.52
			2	**36.94**	**72.83**	4.54	4.31	**38.03**	**73.07**	1.09	0.24	2.87	0.34
			3	**36.81**	**72.24**	4.88	5.07	**37.97**	**72.53**	1.16	0.29	3.05	0.40
			4	**36.78**	**72.09**	4.94	5.27	**37.95**	**72.45**	1.17	0.36	3.08	0.49
8	0.5	0.7	0	**40.73**	**93.43**			**41.31**	**100.23**	0.58	6.80	1.40	6.79
			1	**37.12**	**89.21**	8.86	4.51	**37.32**	**92.11**	0.20	2.90	0.53	3.15
			2	**35.89**	**86.45**	11.88	7.47	**36.35**	**88.10**	0.46	1.65	1.26	1.87
			3	**35.49**	**85.22**	12.87	8.78	**36.27**	**86.04**	0.78	0.82	2.15	0.95
			4	**35.39**	**84.88**	13.12	9.15	**36.25**	**85.44**	0.86	0.56	2.38	0.66
9	0.7	0.7	0	**49.97**	**115.82**			**50.86**	**124.64**	0.89	8.82	1.75	7.08
			1	**47.14**	**112.92**	5.67	2.50	**47.69**	**114.65**	0.55	1.73	1.16	1.51
			2	**46.17**	**110.89**	7.60	4.25	**46.62**	**111.64**	0.45	0.75	0.96	0.67
			3	**45.88**	**109.99**	8.18	5.03	**46.25**	**110.52**	0.37	0.53	0.79	0.48
			4	**45.82**	**109.74**	8.31	5.25	**46.11**	**110.04**	0.29	0.30	0.63	0.27

ing practical and improving accuracy by increasing the complexity. The proposed heuristic could also be tested for other, more specific demand/capacity situations such as where we are dealing with two-point capacity distribution (either zero or full capacity availability).

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Marko Jakšič currently holds a position of a Teaching Assistant at the Faculty of Economics University of Ljubljana. His area of expertise is Operations Management and especially Supply Chain Management, which are the topics he is lecturing on at the bachelor and the master level studies. He has attained his Ph.D. in cooperation with Technische Universiteit Eindhoven, The Netherlands, as a doctoral student at Faculty of Economics and a student at Beta School for Operations Management and Logistics. His research work is focused on quantitative analysis of inventory management strategies in supply chains and as a result he has published several papers in domestic and foreign journals and conferences.

Borut Rusjan attained his Ph.D. at the Faculty of Economics University of Ljubljana in 1998. He is currently employed as an Associate Professor in the Department of Management and Organization, primarily lecturing in the field of Operations and Quality management. He has published a series of papers in domestic and international journals and conferences, where his main research interest lies in strategic view of operations management, quality management and business excellence.

Hevrističen pristop k uravnavanju zalog z informacijo o razpoložljivosti oskrbe

V sodobnih oskrbnih verigah je v zadnjih dveh desetletjih močno prisoten trend izmenjave informacij, ki omogočajo izboljšanje poslovanja posameznih podjetij, kot tudi celotne oskrbne verige. S pomočjo natančnih in pravočasnih informacij, katerih prenos je z nedavnim razvojem informacijskih tehnologij močno olajšan, se podjetja uspešno spopadajo s spremenljivimi in negotovimi pogoji poslovanja. V članku predstavimo model uravnavanja zalog s periodičnim spremljanjem zalog v pogojih neenakomernega stohastičnega povpraševanja z omejeno zmogljivostjo oskrbe, kjer ima člen oskrbne verige dostop do informacije o razpoložljivosti oskrbe. Informacija o razpoložljivosti oskrbe zmanjša negotovost prihodnje oskrbe in omogoči managerju učinkovitejše naročanje. Na podlagi glavnih vpogledov pridobljenih z analizo optimalne politike naročanja razvijemo praktično uporabno hevristično metodo. Z numerično analizo določimo vrednost informacije o razpoložljivosti oskrbe in prepoznamo scenarije, kjer je ta največja. Ob tem na podlagi primerjave med rezultati optimalne politike naročanja in predlagane hevristike izmerimo natančnost le-te in podamo pogoje, ki morajo biti izpolnjeni, da hevristika doseže željeno natančnost.

Ključne besede: Operacijske raziskave, uravnavanje zalog, stohastični modeli, informacija o razpoložljivosti oskrbe, hevristika