

# Pricing and Manufacturing Decisions When Demand Is a Function of Prices in Multiple Periods

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In most deterministic manufacturing decision models, demand is either known or induced by pricing decisions in the period that the demand is experienced. However, in more realistic market scenarios consumers make purchase decisions with respect to price, not only in the current period, but also in past and future periods. We model a joint manufacturing/pricing decision problem, accounting for that portion of demand realized in each period that is induced by the interaction of pricing decisions in the current period and in previous periods. We formulate a mathematical programming model and develop solution techniques. We identify structural properties of our models and develop closed-form solutions and effective heuristics for various special cases of our models. Finally, we conduct extensive computational experiments to quantify the effectiveness of our heuristics and to develop managerial insights.

*Subject classifications:* inventory/production: uncertainty, deterministic; planning horizons; operating characteristics; marketing: pricing.

*Area of review:* Manufacturing, Service, and Supply Chain Operations.

*History:* Received February 2004; revisions received July 2005, October 2006; accepted November 2006. Published online in *Articles in Advance* August 27, 2007.

## 1. Introduction

In recent years, as manufacturing and supply chains have become more and more efficient, the conflict between production planning and marketing has become more apparent. For example, in recent discussions with the manager of a bread production plant associated with a major supermarket chain, the manager indicated to us that the most significant factor leading to increased inventory levels and decreased efficiency in his plant is the unpredictability of demand *due to promotional and pricing decisions made by the marketing group*.

As a result, there is a growing research literature focusing on joint marketing decision making and production planning. Its objective is to develop approaches that avoid conflicting marketing and operations planning decisions by integrating marketing/pricing decisions and manufacturing decisions to jointly achieve a common objective. A variety of aspects of joint pricing and manufacturing models have been analyzed in the operations management and marketing literature. The models vary from constant demand, EOQ-like frameworks, to nonstationary discrete and continuous-time frameworks. Some models allow no replenishment during a price planning horizon (appropriate for perishable or fashion goods), while others consider models which allow production or inventory replenishment over time. The

models also differ in assumptions on demand and consumer behavior.

A considerable body of work has been developed that considers joint pricing and production models of perishable or seasonal goods—typically referred to as *revenue management*—traditionally applied to the airline, hotel, and car rental industries, and similar techniques (such as mark-down pricing) have been adopted for perishable or seasonal products. Lazear (1986), Gallego and van Ryzin (1994, 1997), Bitran and Mondschein (1997), Subrahmanyam and Shoemaker (1996), Aviv and Pazgal (2005), and Elmaghraby et al. (2006) consider revenue management problems related to our models, and the area is surveyed in review papers by McGill and van Ryzin (1999), Petruzzi and Dada (1999), Bitran and Caldenty (2003), and the textbook by Talluri and van Ryzin (2004). Federgruen and Heching (1999) and Chen and Simchi-Levi (2004a, b) consider period review stochastic production-pricing models, and Eliashberg and Steinberg (1993), Elmaghraby and Keskinocak (2003), Yano and Gilbert (2004), and Chan et al. (2004) provide comprehensive surveys of research milestones and future opportunities for joint production-pricing problems.

To the best of our knowledge, the earliest paper in which price and production quantity are both decision variables

is by Whitin (1955), who extends the basic EOQ model to include a revenue term, and finds the optimal price and lot size using a calculus-based approach. Kunreuther and Richard (1971) propose the same model, and compare decentralized decision making to centralized decision making. Abad (1988) extends Whitin's model to include all-unit quantity discounts, and proposes an iterative algorithm that is guaranteed to converge to the global optimal price and lot size. He applies his model to linear and constant price elastic demand curves and presents a numerical study which compares the decentralized solution to the centralized one, similar to Kunreuther and Richard (1971). Due to the nonconcavity of the profit term in EOQ-type analysis, a global solution may require exhaustive enumeration of local optima. Lee (1993) applies a geometric programming framework to extend pricing the EOQ model to the continuous quantity discount case, and obtains a globally optimal solution to problems under the constant-price elastic demand curve assumption. Kim and Lee (1998) consider a pricing EOQ model where capacity can be expanded or reduced at a cost.

There is also a set of papers that considers the joint production and pricing problem as an optimal control problem. Among these, Stokey (1979) considers the problem faced by a monopolist whose marginal cost of production is decreasing over time. Pekelman (1974), Thompson et al. (1984) and Feichtinger and Hartl (1985) analyze optimal control problems that consider convex production cost with linear and nonlinear demand functions and obtain various planning-horizon results. Cohen (1977) considers an EOQ model with exponentially decaying inventory where demand is a deterministic function of price. Rajan et al. (1992) study the same model with dynamic pricing during the planning horizon and Abad (1996) extends the results obtained by Rajan et al. (1992) to the case in which partial backlogging is allowed.

For the deterministic discrete-time production framework, the trend has been to extend Wagner and Whitin's (1958) model to include price at each period as a decision variable. Under the assumption that the demand in a given period is independent of the prices offered in the adjacent periods and that there is no capacity constraint, Thomas (1970) develops an approach to calculate optimal price and production schedule for each of the  $T$  periods and obtains planning horizon results that extend the results of Wagner and Whitin (1958). Kunreuther and Schrage (1973) and Gilbert (1999) consider the special case of constant pricing. Chan et al. (2000) analyze the capacitated discrete-time problem without setup costs and extend the greedy resource allocation algorithm of Federgruen and Groenevelt (1986) to their model. Deng and Yano (2006) consider both capacity and setup costs in their discrete-time problem and show that introduction of prices into the capacitated lot-sizing problem does not change the fundamental structure of the optimal production decisions characterized by Florian and Klein (1971). Charnsirisakskul et al. (2006) consider a joint

pricing and scheduling problem when the firm can predict the demand as a function of price.

Virtually all this research considers demand at each period to be a function of price in that period and independent of price in other periods. In many cases, customers may consider making a purchase for several periods, so that demand in a period is a function of both price in that period and prices in other periods. Our model explicitly considers these intertemporal demand-price interactions so that realized demand in each period is dependent on realized demands in previous periods as well as past and current prices. Specifically, in each period a potential pool of customers enters the market and these customers remain in the system for more than one period. Some of the customers entering the system in a given period who cannot afford the product in that period have the patience to wait until the price drops to a level they can afford. We first consider a firm's problem facing customers who purchase the product during the first period in which the price falls below their reservation price, then later extend the result to the case with consumers who are aware of a future price pattern during their tenure and buy at the period when their utility is maximized.

Several papers are closely related to our research. In papers by Sorger (1988), Kopalle et al. (1996), Fibich et al. (2003), and Popescu and Wu (2007), authors consider demand models in the dynamic pricing setting, where past prices affect the current demand via reference price formation mechanisms. Their goal is to identify the properties of the optimal pricing path under various assumptions on the functional form of reference price effects on current demand. Bersanko and Winston (1990) consider a markdown pricing mechanism of a monopolist facing a fixed number of customers during a planning horizon. They model a finite horizon problem where customers who do not purchase in each period remain in the market and they identify the properties of optimal markdown pricing sequences when all customers are strategic or myopic. Our paper is most closely related to Conlisk et al. (1984) and Sobel (1991), which consider a durable good monopolist in a market where a stationary cohort of new customers arrives in each period and no customer leaves the market before purchasing the good. After introducing our model in the next section, we compare it to the models in these papers.

In the next section, we introduce our model, in which demand is allowed to remain in the system for more than one period. We also introduce our results and algorithms. Subsequent sections detail these results and the associated proofs and describe our computational analysis.

## 2. Model and Main Results

We consider a deterministic discrete time  $T$  period finite horizon capacitated production model. For each period, decision variables  $p_t$  and  $x_t$ ,  $t = 1, 2, \dots, T$ , represent

pricing and production decisions, respectively. Production capacity, per unit production cost, and per unit holding cost can vary from period to period, and are represented by  $Q_t$ ,  $c_t$ , and  $h_t$ ,  $t = 1, 2, \dots, T$ . Demand in each period is a function of price, as we discuss in detail below.

Our model captures, in a relatively stylized and tractable way, the impact of pricing decisions in one period on demand in others. We are motivated by our own experience when purchasing items like cars or computers, where we have in the past first decided on a budget and then waited for the price to fall within our budget. This concept does not only apply to expensive goods, however. Some of the authors of this paper wear Jockey brand undershirts, and were also motivated by their experience purchasing this product. Jockey has semiannual sales each year, in which all prices are discounted 25%. One author, the big spender, upon noticing that his undershirts could do with replacing, heads to the local department store and stocks up. Another author, the thrifty one, waits some period of time up to six months and stocks up at 25% off. Readers also may be familiar with the Barilla SpA (A) case, which describes issues faced by the Barilla Pasta company, including Barilla’s customers’ tendencies to increase purchase levels of dry pasta during promotional periods and decrease purchase levels at other times (see Hammond 1994).

To model this behavior, we divide demand in each period  $t$  into *current demand* and *residual demand*. Current demand is that demand generated by customers who enter the system at that period (for example, the big spender in the undershirt example). Residual demand is that portion of demand resulting from customers who entered the system in previous periods, but who have not yet made a purchase (for example, the thrifty author in the period in which Jockey underwear is on sale).

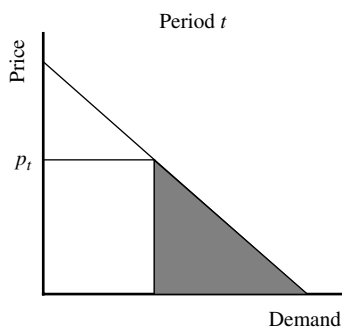
We model current demand in period  $t$  using a standard linear price-demand curve:

$$D_t(p_t) = d_t^o - s_t p_t,$$

where  $d_t^o$  is the maximum demand,  $s_t$  is the price-demand sensitivity, and

$$p_t \leq \frac{d_t^o}{s_t}.$$

**Figure 1.** The price-demand curve (one period).



In Figure 1, we illustrate this simple demand curve. Note that for a particular price  $p_t$ , there is a subset of customers (represented by the shaded portion of the diagram) who would have purchased if the price were lower (in other words, if the price was at or below their reservation price), and who are thus potentially part of the residual demand in future periods.

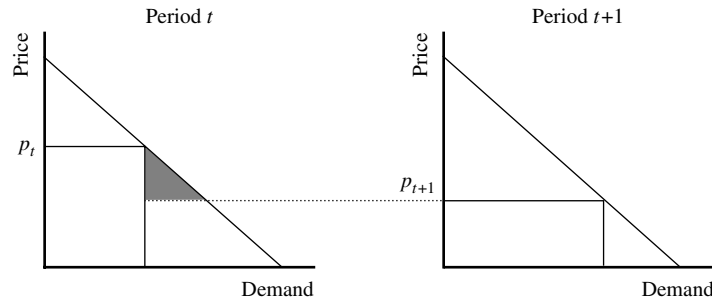
Indeed, in Figure 2 we begin to illustrate the concept of residual demand. The curve on the left represents the current demand curve in period  $t$ , as in Figure 1. The curve on the right represents the current demand curve in period  $t + 1$ . Assume that we have set the price in period  $t + 1$ ,  $p_{t+1}$ , to be lower than the price in period  $t$ ,  $p_t$ . The shaded region on the left represents residual demand from period  $t$  realized in period  $t + 1$ —these are customers who found the price too high in period  $t$ , but low enough to make purchases in period  $t + 1$ . We define *potential* residual demand from period  $t$  to mean demand arriving at period  $t$  that can be realized in periods after  $t$  if prices are far enough below  $p_t$ .

Now, we consider a three-period example, and suppose that prices are ordered so that  $p_{t+2} < p_t < p_{t+1}$ . We illustrate this example in Figure 3. In this example, no potential residual demand from period  $t$  was realized in period  $t + 1$  because  $p_t < p_{t+1}$ . However, residual demands from periods  $t$  and  $t + 1$  are realized in period  $t + 2$  and illustrated with shaded regions in Figure 3.

We further generalize this concept of current and residual demand modeling with two parameters. Potential residual demand from period  $t$  does not stay in the system forever; we define parameter  $K$  to represent the number of periods that potential demand remains in the system, so that  $K = 0$  represents the model with no residual demand, and  $K$  is at least 2 in Figure 3. Also, not all of the unmet potential demand in period  $t$  remains in the system for  $K$  time units—we define  $\alpha_k^t$ ,  $k = 0, 1, \dots, K$ , to represent the proportion of customers who will wait for at least  $k$  periods when they join the system at period  $t$  such that  $1 = \alpha_0^t \geq \alpha_1^t \geq \alpha_2^t \dots \geq \alpha_K^t \geq \alpha_{K+1}^t = 0$  for all  $t$ .

There are several limitations to this model. One reasonable critique is that it assumes that consumers are not aware of impending price decreases. Indeed, this model is intended to represent situations in which customers place a high value on a good’s availability, and tend to buy it as soon as their budget constraints (i.e., reservation prices) are met. In §7, we briefly consider the situation in which customers are aware of pricing patterns, and in many cases the actual situation may lie between these extremes. Another reasonable critique is our use of linear demand curves; however, this assumption helps us develop models that are amenable to analysis, and helps generate insight which we believe will apply in more complex situations. Also, we note that although our model does not explicitly capture the change in consumers’ price sensitivity due to markups and markdowns in prior periods in the same way that typically price/promotion models in the marketing literature

**Figure 2.** The price-demand curve (two periods).



do, our model is consistent with these models in spirit. Weak demand periods will follow a discount period, and discounts generate revenue from consumers who will not buy at the usual price levels.

Within our framework, we identify several useful properties of the optimal solution and develop algorithms to find good (sometimes optimal) solutions for models with capacity constraints. We believe that our model, while clearly stylized, captures many of the important complexities that exist in real-world dynamic pricing and production problems.

To formally define demand at period  $t$ , we first define  $r_t^k$  to represent the portion of demand in period  $t$  originating from period  $t - k$ :

$$r_t^k = \begin{cases} d_t^o - s_t p_t & \text{if } k = 0, \\ \alpha_k^{t-k} s_{t-k} \left[ \min_{i \in \{1, \dots, k\}} p_{t-i} - p_t \right]^+ & \text{if } 1 \leq k \leq K. \end{cases} \quad (2.1)$$

We introduce a minimization operator to select the minimum price between periods  $t - k$  and  $t - 1$  because this gives the leftover residual demand after observing the actual prices from periods  $t - k$  to  $t - 1$ . Hence,  $\alpha_k^{t-k}$  of this leftover residual demand consists of the customers whose reservation prices have not exceeded the product price from period  $t - k$  to  $t - 1$ .

Next, we can write demand at period  $t$  in terms of  $r_t^k$ s as  $d_t = \sum_{k=0}^{\min\{t, K\}} r_t^k$ . With this demand formulation, we consider the following discrete-time multiperiod production system where at each period we decide both price of the product,  $p_t$ , and the production quantity of the product,  $x_t$ .

**Model 2**

$$\max_{p_t, x_t, I_t, d_t, r_t^k} \sum_{t=1}^T p_t d_t - \sum_{t=1}^T c_t x_t - \sum_{t=1}^T h_t I_t \quad (2a)$$

$$\text{s.t. } x_t + I_{t-1} = d_t + I_t, \quad t = 1, 2, \dots, T, \quad t_0 = 0, \quad (2b)$$

$$x_t \leq Q_t, \quad t = 1, 2, \dots, T, \quad (2c)$$

$$d_t = \sum_{k=0}^K r_t^k, \quad t = 1, 2, \dots, T, \quad (2d)$$

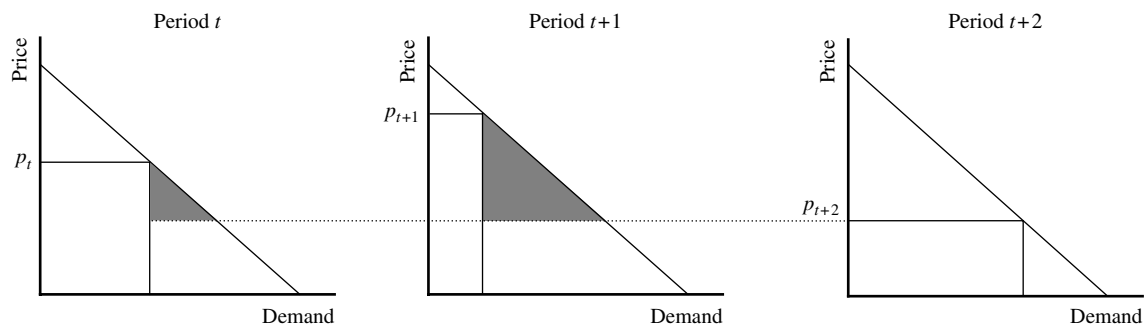
$$0 \leq p_t \leq d_t^o / s_t, \quad t = 1, 2, \dots, T, \quad (2e)$$

$$r_t^k = \begin{cases} d_t^o - s_t p_t & \text{if } k = 0, \\ \alpha_k^{t-k} s_{t-k} \left[ \min_{i \in \{1, \dots, k\}} p_{t-i} - p_t \right]^+ & \text{if } 1 \leq k \leq \min(K, t - 1), \end{cases} \quad (2f)$$

$$x_t \geq 0, \quad I_t \geq 0, \quad t = 1, 2, \dots, T. \quad (2g)$$

Our objective is to maximize the net profit (2a) subject to inventory balance (2b), production capacity (2c), and demand realization constraints (2d)–(2f). In addition to the parameters and constraints defined earlier,  $I_t$ ,  $t = 1, 2, \dots$ , represents the inventory at the end of period  $t$ . To express constraints (2f) as a set of linear constraints, we introduce additional variables,  $m_t^k$  to keep track of the minimum price value observed between periods  $t - k$  and  $t - 1$  and binary variables,  $y_t^k$  to indicate whether there is residual demand from period  $t - k$  realized in period  $t$  (i.e.,  $y_t^k = 1$  if  $r_t^k > 0$

**Figure 3.** The price-demand curve (three periods).



and zero otherwise). Using  $y_t^k$  and  $m_t^k$ , we rewrite constraints (2f) as follows:

$$0 \leq m_t^k \leq p_u \quad \text{for } u = t - k \dots t - 1, \quad (3a)$$

$$0 \leq r_t^k \leq \alpha_k^{t-k} s_{t-k} (m_t^k - p_t) + (1 - y_t^k) \cdot d_{t-k}^o, \quad (3b)$$

$$r_t^k \leq y_t^k \cdot d_{t-k}^o \quad \text{for } t = 2 \dots T; K = 1 \dots \min\{t - 1, K\}, \quad (3c)$$

$$r_t^0 \geq 0, \quad (3d)$$

$$r_t^0 \leq d_t^0 - s_t p_t \quad \text{for } t = 1 \dots T. \quad (3e)$$

It is easy to see that the objective function of Model 2 is neither convex nor concave in general. Note that residual demand is materialized only when past and current prices satisfy a set of conditions, so that the functional form of the objective function changes depending on the relative order of the pricing plan  $(p_1, p_2, \dots, p_T)$ . To demonstrate the difficulty posed by this, consider an instance of a two-period problem with identical demand for each period,  $\alpha_0^1 = \alpha_0^2 = 1$ ,  $\alpha_1^1 = \alpha$ , unlimited capacity, zero holding cost, and zero production cost. This problem is written as:

$$\begin{aligned} &\text{maximize } R(p_1, p_2) = p_1 d_1(p_1) + p_2 d_2(p_1, p_2) \\ &\text{s.t. } d_1 = d^o - s p_1, \\ &\quad d_2 = (d^o - s p_2) + (\alpha s [p_1 - p_2]^+), \\ &\quad 0 \leq p_1 \leq d^o / s, \\ &\quad 0 \leq p_2 \leq d^o / s. \end{aligned}$$

Substituting expressions for  $d_1$  and  $d_2$  into the objective function reveals that the objective function depends on the relative magnitude of  $p_1$  and  $p_2$ :

$$R(p_1, p_2) = p_1(d^o - s p_1) + p_2(d^o - s p_2) + \begin{cases} 0 & \text{if } p_1 \leq p_2, \\ \alpha s (p_1 - p_2) p_2 & \text{if } p_1 > p_2. \end{cases} \quad (4)$$

In general, in Model 2 the revenue generated from residual demands depends not only on the current price, but also on the relative order of prices offered for the last  $K$  periods, which makes the objective function nonconcave over the feasible region of prices. Typically, such problems are difficult to solve, and an efficient algorithm that finds a global optimal solution does not exist. Below, we characterize the structure of the optimal solution to Model 2. Now, consider Model 2 with the addition of a series of constraints that enforce an ordering of prices. For example, if  $T = 3$ , these constraints may require  $p_3 \geq p_1 \geq p_2$ , or some other ordering. We call these constraints *fixed-ordering constraints*, label them  $\Gamma$ , and prove in online Appendix A (an electronic companion to this paper is available as part of the online version that can be found at <http://or.journal.informs.org/>) that for any such set of constraints  $\Gamma$ —that is, for any fixed ordering of prices—the

following result holds:

**THEOREM 1.** *Model 2, together with the addition of a set of fixed-ordering constraints, is a concave optimization problem.*

To simplify the discussion, we call this mathematical program with the addition of constraints  $\Gamma$  Model 2- $\Gamma$  with optimal objective function value  $Z_T^*$ . In §3, we develop a simple algorithm that enumerates possible orderings to solve Model 2, and then use this algorithm to complete a series of computational experiments to assess the effectiveness of our heuristics and to generate managerial insights.

In addition, to develop theoretical insights, as well as efficient optimization algorithms and heuristics, we focus on a variety of special cases of this model. In general, these are cases in which some combination of the following restrictions apply: capacity may be unlimited rather than restricted; residual demand may be limited to one period in the system (that is,  $K = 1$ ); and the model parameters (i.e., demand curves, inventory holding and production costs, proportion of unsatisfied customers who choose to wait, and capacities) may be stationary rather than time varying. We present an algorithm that, although exponential in its complexity, allows us to solve relatively small instances of the original Model 2 presented above, and then move on to special cases of Model 2 to develop solutions and algorithms.

We focus first on the most basic special case of Model 2, the *one-period interaction problem* (that is, the problem with  $K = 1$ ) with stationary parameters and unlimited capacity. For clarity, we refer to this as Model 2- $(K = 1, Q = \infty)$  with stationary parameters. Surprisingly, in this case we can develop a closed-form expression for the optimal pricing policy. In particular, in §4, we develop closed-form expressions for five prices  $p^{\text{high}}$ ,  $p^{\text{low}}$ ,  $p^{\text{3-high}}$ ,  $p^{\text{3-medium}}$ , and  $p^{\text{3-low}}$  and prove:

**THEOREM 2.** *For any uncapacitated one-period interaction problem with stationary parameters, the following policy is optimal:*

- (1)  $(p_1, p_2, \dots, p_{T-1}, p_T) = (p^{\text{high}}, p^{\text{low}}, \dots, p^{\text{high}}, p^{\text{low}})$  when  $T$  is even;
- (2)  $(p_1, p_2, \dots, p_{T-2}, p_{T-1}, p_T) = (p^{\text{high}}, p^{\text{low}}, \dots, p^{\text{high}}, p^{\text{low}}, p^{\text{3-high}}, p^{\text{3-medium}}, p^{\text{3-low}})$  when  $T$  is odd.

Furthermore, we show that if  $p^*$  represents the optimal noninteraction price for this model (that is, the price that maximizes the profit from the demand originated and realized at period  $t$ ), then  $p^{\text{high}}$ ,  $p^{\text{3-high}}$ , and  $p^{\text{3-medium}}$  are all greater than  $p^*$ , and  $p^{\text{low}}$  and  $p^{\text{3-low}}$  are both less than  $p^*$ .

These results imply that a periodic pricing strategy that skims off high-valued customers in the first period and serves many of the low-valued customers in the following period is optimal for the infinite horizon one-period interaction problem. This is conceptually similar to some of the results in the intertemporal price discrimination models cited in the introduction to this paper. Under this high-low

pricing strategy, it is optimal to price higher than the non-interaction price ( $p^*$ ) in the first period with the intention of absorbing surplus from high-valued customers, and then price lower than  $p^*$  in the next period to absorb surplus from low-valued customers before some of them exit the market.

Returning to our Jockey undershirt example, these results support the strategy of that firm, which manages to extract additional money from the big spending coauthor of this paper, while still selling undershirts to the thrifty coauthor. Of course, many firms, including most famously Wal-Mart, have adopted everyday low price (EDLP) strategies, that appear to contradict these results. In the concluding section of this paper, we address this apparent contradiction.

Next, we identify the following property of solutions to our general Model 2 and use this property to determine optimal solutions for some special cases and to develop heuristic algorithms for others. First, we define:

**DEFINITION 1 (PRICING PLAN).** Let  $\mathbf{p} = (p_1, p_2, \dots, p_t)$  be a vector of prices that is a feasible solution to Model 2. We call  $\mathbf{p}$  a *pricing plan*.

Now, define a length  $K$  subplan of this plan as follows:  $PS(t, K) = (p_{t+1}, \dots, p_{\min(t+K, T)})$ . Note that this is either a length  $K$  subsequence of prices (when  $t < T - K$ ), or a sequence that reaches from time  $t + 1$  until the end of the horizon (when  $t \geq T - K$ ). It is easy to see that demand can be decomposed as follows:

**PROPERTY 1 (PRICE/DEMAND DECOMPOSITION PROPERTY).** For any pricing plan in Model 2, if in a length  $K$  subplan  $PS(t, K)$ ,  $\min(p_{t+1}, \dots, p_{\min(t+K, T)}) \geq p_t$ , then there will be no residual demand from periods 1 through  $t$  impacting demands in any periods  $t + 1, \dots, T$ .

**PROOF.** Recall that for the  $K$ -period demand interaction case, the customers in the system at period  $t$  are those whose reservation prices have not exceeded the price at period  $t$ ,  $p_t$ . Therefore, if the manufacturer prices its product higher than  $p_t$  for the next  $K$  periods, then the residual customers coming from periods  $t - K$  to  $t$  will not be able to observe a price that is less than their reservation price, and hence will be forced to leave the system. Therefore, if  $\min(p_{t+1}, \dots, p_{\min(t+K, T)}) \geq p_t$  for any  $t$ , then customers in the system at time  $t$  whose demand is not satisfied by time  $t$  will never have their demand satisfied.  $\square$

Given this property, we define:

**DEFINITION 2 (REGENERATION POINT).** Period  $t$  where  $2 \leq t \leq T$  is referred to as a *regeneration point* if  $\min(p_t, \dots, p_{\min(t+K-1, T)}) \geq p_{t-1}$ .

Furthermore, we assume that the first period of the planning horizon is a regeneration point, and we define dummy period  $T + 1$  to be another regeneration point.

**DEFINITION 3 (PRICING SEQUENCE).** Let  $S_{uv}$  represent a subset of a pricing plan  $\mathbf{p}$  that includes the components of  $\mathbf{p}$  for all periods between the two consecutive regeneration points  $u$  and  $v$ , i.e.,

$$S_{uv} = \{p_i, i = u, \dots, v - 1 \mid u \text{ and } v \text{ are regeneration points}\},$$

where  $1 \leq u \leq v \leq T + 1$ . Then, we call  $S_{uv}$  a *pricing sequence*.

If a pricing plan involves  $n$  regeneration points, then the plan can be decomposed into  $n - 1$  pricing sequences. Also note that there must be at least one pricing sequence, which can be the entire pricing plan, and that we define a minimal length pricing sequence to be a pricing sequence that cannot be decomposed into smaller pricing sequences.

Given these definitions, we consider the *one-period interaction problem with time-varying parameters and unlimited capacity*, that is, Model 2- $(K = 1, Q = \infty)$  with time-varying parameters. By characterizing the structure of the optimal solution to this problem, we are able to develop a polynomial time algorithm to optimally solve it. In particular, we observe that for the one-period interaction case, the regeneration point conditions become equivalent to price markups. In other words, if  $p_{t-1} \leq p_t$ , then a regeneration point is said to occur at period  $t$ . This simple characterization of the regeneration points leads to an important observation about the structure of pricing sequences in this case:

**LEMMA 1.** For the one-period interaction case, prices in any minimal length pricing sequence are nonincreasing.

**PROOF.** Price levels in a minimal length pricing sequence cannot increase, otherwise it would be decomposed into further subsequences which contradicts the minimality of the sequence.  $\square$

Based on this lemma, in §4.2 we develop a shortest-path-based optimal algorithm that optimizes over all possible sets of regeneration points.

Unfortunately, when  $K > 1$ , a result analogous to Lemma 1 does not hold. Consider, for example, the following three-period interaction problem with stationary parameters (that is,  $T = 7, K = 3$  and  $\alpha'_k = 1, D_t = 30 - p_t, h_t = 0, c_t = 0$  for all  $t = 1, \dots, 7$ ). The optimal pricing plan ( $\mathbf{p} = [26.8, 23.6, 18.9, 12.0, 24.5, 18.5, 9.8]$ ) consists of two nonincreasing pricing subplans: (26, 8, 23.6, 18.9, 12.0) and (24.5, 18.5, 9.8). Unfortunately, period 5 is not a regeneration point because customers originating from period 4 purchase the product at period 7. The problem therefore cannot be decomposed into two subproblems, and a sequence of decreasing prices does not coincide with a minimal length price sequence. Thus, the characterization of the optimal price for this problem is in general a formidable task.

However, by focusing on nonincreasing pricing sequences, and using the insight we developed while creating the algorithm and closed-form solution discussed above,

in §5 we are able to develop very effective heuristics for the general Model 2. In fact, for the  $K$ -period interaction problem with stationary parameters, unlimited capacity, and nonincreasing pricing sequences, we develop a closed-form expression for optimal pricing. For the general Model 2, we develop a shortest-path-based heuristic and show that our heuristic proves to be quite effective in computational study.

As we mentioned in the introductory section, our paper is most closely related to Conlisk et al. (1984) and Sobel (1991), which consider a durable good monopolist in a market where a stationary cohort of new customers arrives in each period and no customer leaves the market before purchasing the good. All customers are strategic (thus, they buy in the period in which their utility is maximized), but customers differ in their willingness to pay—the reservation prices of high-type and low-type customers are  $V_1$  and  $V_2$  ( $V_1 > V_2$ ), respectively. Under this setting, the authors show that a cyclical pricing policy such that the firm sells only to high-type customers in most periods, but offers a mark-down (at the end of each cycle) to capture the low-type customers, is a subgame perfect equilibrium.

Our models and results differ from these in several important ways. We allow new customers to enter into the system in each period, but customers will consider buying the good only for a finite number of periods. This assumption plays a crucial role on the length of an optimal pricing sequence and the prices within the sequence. In particular, when  $K = 1$  with stationary parameters, we also show that a two-period pricing sequence maximizes the firm’s average profit regardless of the spread of reservation prices and that prices are fluctuating around the optimal noninteraction price (i.e., the price which maximizes the profit from the demand originated and realized in the same period). In Conlisk et al. (1984) and Sobel (1991), customers never leave the market until they purchase the good, and thus all customers eventually buy the good. However, the length of an optimal pricing sequence depends on the spread of the reservation prices, and the prices within a sequence are always above (if the proportion of high-type customers is small) or below (if the proportion of high-type customers is large) the optimal noninteraction price. Furthermore, in contrast to previous models, we develop solution techniques for situations in which demand and problem parameters are nonstationary during the planning horizon, which allows us to model situations in which the customers become more (less) price sensitive, and in which the production cost decreases (increases) over time. Finally, we consider both limited and unlimited capacity to investigate how capacity impacts the efficacy of the dynamic pricing strategies. In addition, one focus of this paper is on developing effective solution techniques for these models (closed form or optimal when possible, heuristic when appropriate) so that the impact of intertemporal demand interaction and dynamic pricing can be tested under a variety of conditions.

The remainder of this paper is structured as follows. In §3, we present the algorithm that results from Theorem 1. In §4, we develop the optimal closed-form expression for the one-period interaction problem with stationary parameters and unlimited capacity, and the optimal algorithm for the general one-period interaction problem with unlimited capacity. In §5, we use the insight generated in §§3 and 4 to develop effective heuristics for versions of Model 2. In §6, we present results of computational testing, where we investigate the effectiveness of heuristics for the model, and explore the impact of residual demand on production and pricing decisions. Finally, in §7, we discuss an alternate model and conclude.

### 3. Optimal Algorithm for Model 2

Recall that Theorem 1 states that Model 2, with the addition of a set  $\Gamma$  of fixed-ordering constraints (that is, Model 2- $\Gamma$ ), is a concave optimization problem. In this section, we use this result to develop an algorithm for the problem.

Because the problem is reduced to an ordinary concave optimization problem under any realization of fixed-ordering constraints  $\Gamma$ , one approach to solve the original problem is to solve Model 2- $\Gamma$  for all  $\Gamma$ .

**COROLLARY 1.** *Let  $\Gamma$  be a set of fixed-ordering constraints determined by each fixed ordering of prices. The optimal pricing and manufacturing plan for Model 2 (i.e., the general  $K$ -period interaction problem) can be found by solving  $P_\Gamma$  for all  $\Gamma$ .*

**ALGORITHM.**

*Step 1.* Let  $Z_{best} = 0$ .

*Step 2.* For each  $\Gamma$

Solve Model 2- $\Gamma$  to get the optimal objective function value  $Z_\Gamma^*$

If  $Z_\Gamma^* > Z_{best}$ , then update  $Z_{best} = Z_\Gamma^*$

*Step 3.*  $Z^* = Z_{best}$ .

Although the algorithm is guaranteed to find the optimal solution for small problems, the number of possible fixed orderings grows exponentially in  $T$ . Thus, we are motivated to investigate some structural properties of the optimal solution as well as special cases to design more efficient algorithms. We first start with the one-period interaction problem with unlimited capacity, then use the insights generated in this analysis to solve more complex cases of the problem.

### 4. Optimal Solutions for the One-Period Interaction Problem with Unlimited Capacity

We first focus on a special case: the one-period interaction problem with unlimited capacity. For clarity, we call this Model 2- $(K = 1, Q = \infty)$ . For notational simplicity, we let  $\alpha_t^l = \alpha_t$  for all  $t = 1, \dots, T$ . Note that  $\alpha_k^l = 0$  for  $k > 1$ . In

the one-period interaction problem, up to  $100\alpha_i\%$  of unsatisfied new demand in each period can be satisfied in the next period if the price is sufficiently low. For this special case of our model, we are able to efficiently determine the optimal solution. In particular, we can explicitly solve the problem with stationary parameters, and give a closed-form expression for optimal prices. With time-varying parameters, we develop a shortest-path-based algorithm that determines an optimal pricing plan in polynomial time.

#### 4.1. Model 2- $(K = 1, Q = \infty)$ with Stationary Parameters

Consider the lone-period interaction uncapacitated problem with stationary parameters (that is,  $s_t = s$ ,  $d_t^o = d^o$ ,  $\alpha_t = \alpha$ ,  $c_t = c$ ,  $h_t = h$  for  $t = 1, \dots, T$ ). In other words, the variable production cost, holding cost, proportion of customers that choose to wait for one more period, and new customer demand are the same for all periods. Recall that in Theorem 2, we discussed the optimal pricing plan for this problem. In fact, the optimal pricing plan consists of  $T/2$  2-period optimal pricing sequences when  $T$  is even and  $(T - 3)/2$  2-period optimal pricing sequences and one 3-period optimal pricing sequence when  $T$  is odd. Note that it suffices to consider only a sequence of decreasing prices as a candidate for an optimal pricing sequence. This follows immediately from Lemma 1, in which we argue that regeneration points coincide with periods with price markups. Limiting our attention exclusively to a sequence of decreasing prices, we characterize an  $n$ -period optimal pricing sequence that maximizes the profit for  $n$  periods in Lemma 2. In Theorem 3, we then show that repeating the 2-period optimal pricing sequence maximizes the average profit; therefore, it is optimal when  $T$  is even. All that remains is to deal with the case when  $T$  is odd—we address this detail in online Appendix F.

To determine the  $n$ -period optimal pricing sequence, let  $\mathbf{p}_n$  be a  $1 \times n$  vector of decreasing prices (i.e.,  $p_1 \geq p_2 \geq \dots \geq p_n$ ) and  $f_n(\mathbf{p}_n)$  be the firm's profit for  $n$  periods under pricing sequence  $\mathbf{p}_n$ :

$$\begin{aligned} f_n(\mathbf{p}_n) &= f_n(p_1, p_2, \dots, p_n) \\ &= \sum_{t=1}^n (p_t - c)(d^o - sp_t) \\ &\quad + \alpha \sum_{t=2}^n s(p_t - c)(p_{t-1} - p_t). \end{aligned} \tag{5}$$

When  $n = 1$ , finding the optimal price that maximizes  $f_1(p_1) = (p_1 - c)(d^o - sp_1)$  is trivially given by

$$p^* = \frac{d^o + sc}{2s}. \tag{6}$$

We call  $p^*$  the optimal noninteraction price because there will be no demand interaction if  $p^*$  is repeated. If the optimal noninteraction price is repeated for  $n$  periods, the firm's

profit is simply

$$\begin{aligned} f_n^{NI}(p^*, p^*, \dots, p^*) &= \sum_{t=1}^n (p^* - c)(d^o - sp^*) \\ &= -ncd^o + \sum_{t=1}^n ((d^o + sc)p^* - s(p^*)^2) \\ &= n \frac{(d^o - sc)^2}{4s}. \end{aligned} \tag{7}$$

However, in general, the noninteraction price is not optimal, so we derive an expression for an optimal  $n$ -period pricing sequence. To do this, first let

$$\begin{aligned} \Delta f_n(\mathbf{p}_n) &= \Delta f_n(p_1, p_2, \dots, p_n) \\ &= \frac{f_n(p_1, p_2, \dots, p_n) - f_n^{NI}(p^*, p^*, \dots, p^*)}{n} \end{aligned}$$

be the average profit increase per period under  $\mathbf{p}_n$  over  $(p^*, p^*, \dots, p^*)$ . It is clear that a vector of prices that maximizes  $f_n(\mathbf{p}_n)$  also maximizes  $\Delta f_n(\mathbf{p}_n)$ . That is, if  $\bar{\mathbf{p}}_n = (\bar{p}_1, \bar{p}_2, \dots, \bar{p}_n)$  maximizes  $f_n(\mathbf{p}_n)$ , then

$$\begin{aligned} \Delta f_n(\bar{\mathbf{p}}_n) &= \frac{f_n(\bar{p}_1, \dots, \bar{p}_n) - f_n^{NI}(p^*, \dots, p^*)}{n} \\ &\geq \frac{f_n(p_1, \dots, p_n) - f_n^{NI}(p^*, \dots, p^*)}{n} = \Delta f_n(\mathbf{p}_n) \end{aligned}$$

for all decreasing prices  $\mathbf{p}_n$ ; therefore,  $\bar{\mathbf{p}}_n$  defines an  $n$ -period optimal pricing sequence. In online Appendix C, we prove that:

LEMMA 2. An  $n$ -period optimal pricing sequence  $\bar{\mathbf{p}}_n$  is given by

$$\bar{p}_i = p^*(1 + \delta_i^*(n)), \quad i = 1 \dots n, \tag{8}$$

where

$$\begin{aligned} \delta_0^*(n) &= 1 - \frac{c}{p^*} \quad \text{and} \\ \delta_i^*(n) &= \frac{\beta_{n-i}(n)\delta_{i-1}^*(n) - \delta_0^*(n)}{\beta_{n-i+1}(n)}, \quad i = 1 \dots n, \end{aligned} \tag{9}$$

and

$$\begin{aligned} \beta_0(n) &= 1, \quad \beta_1(n) = 2 + \frac{2}{\alpha}, \quad \text{and} \\ \beta_i(n) &= \begin{cases} \left(2 + \frac{2}{\alpha}\right)\beta_{i-1}(n) - \beta_{i-2}(n) & \text{for } i = 2 \dots n-1, \\ \frac{2}{\alpha}\beta_{i-1}(n) - \beta_{i-2}(n) & \text{for } i = n. \end{cases} \end{aligned} \tag{10}$$

The average profit increase under the  $n$ -period optimal pricing sequence (over noninteraction pricing) is

$$\Delta f_n^* = \frac{sp^{*2}\alpha}{n} \left[ \frac{a}{2} (\delta_1^*(n) - \delta_n^*(n)) \right].$$



We use  $\Delta f_n$  instead of  $f_n(\mathbf{p}_n)$  to determine the length of the optimal price sequence that leads to the greatest average profit increase. Note that if an  $n$ -period optimal pricing sequence is used, then the increase in the average profit depends only on the difference between the price distortion (from the noninteraction price  $p^*$ ) in the first period (i.e.,  $\delta_1^*(n)$ ) and the price distortion in the last period (i.e.,  $\delta_n^*(n)$ ) in the price sequence. We analyze the average profit increases with respect to the length of the price sequence,  $n$ , by characterizing the behavior of  $\delta_1^*(n)$  and  $\delta_n^*(n)$  in  $n$ , and then show that the 2-period optimal pricing sequence indeed maximizes the average profit increase. We prove this key result by developing an upper bound on the average profit increase under an  $n$ -period optimal pricing sequence for all  $n$ . Using several technical lemmas proved in online Appendix D, we characterize the asymptotic properties for both  $\delta_1^*(n)$  and  $\delta_n^*(n)$ , and use these results in online Appendix E to prove the following theorem:

**THEOREM 3.** *The optimal 2-period pricing sequence maximizes the average profit increases for the one-period interaction uncapacitated problem with stationary parameters.*

Theorem 3 implies that a periodic pricing strategy that skims off high-valued customers in the first period and serves many of the low-valued customers in the following period is optimal for the infinite horizon one-period interaction problem. Under this high-low pricing strategy, it is optimal to price higher than the noninteraction price ( $p^*$ ) in the first period with the intention of absorbing surplus from high-valued customers, and then price lower than  $p^*$  in the next period to absorb surplus from low-valued customers before some of them exit the market. That is,

$$\begin{aligned} p^{\text{high}} &= p^* + (p^* - c) \left[ \frac{\alpha(\alpha + 2)}{4\alpha + 4 - \alpha^2} \right] \geq p^*, \\ p^{\text{low}} &= p^* + (p^* - c) \left[ \frac{\alpha(\alpha - 2)}{4\alpha + 4 - \alpha^2} \right] \leq p^*, \end{aligned} \quad (11)$$

where  $p^*$ ,  $c$ , and  $\alpha$  denote, respectively, the optimal noninteraction price, the unit production cost, and the portion of unsatisfied customers transferred from the previous period. Note that both inequalities become strict when  $\alpha > 0$ .

Although a cyclic pricing pattern is conceptually similar to the results in intertemporal price discrimination models of Sobel (1991) and Conlisk et al. (1984), there are several key differences. In particular, the fact that customers remain in the market for a finite number of periods plays a crucial role in the length of an optimal pricing sequence and prices within the sequence. First, as we discussed previously, the spread of reservation prices between high-valuation and low-valuation customers affects the length of an optimal pricing sequence in their models. In our model, the effect that customers will stay one more period ( $K = 1$ ) results in a 2-period pricing sequence regardless of the spread of reservation price. Second, in their models, customers never

leave the market until they purchase the product; thus, the seller always finds it optimal to sell to all customers. But, depending on the proportion of high-type customers in a cohort, the prices in an optimal pricing sequence can be either always above or below the optimal noninteraction price. On the other hand, customers in our model will leave the market after one period, thus, the nonsale price  $p^{\text{high}}$  is always higher than the optimal noninteraction price to skim off the top and the markdown price  $p^{\text{low}}$  is always less than the optimal noninteraction price to sell to customers with low reservation price. Even when the seller follows an optimal pricing sequence, not all customers are served.

In a finite horizon problem, repeating this high-low pricing strategy is optimal when  $T$  is even. On the other hand, such a strategy would be cut short when  $T$  is odd, so a small modification of the pricing strategy is required. Indeed, when  $T$  is odd, a strategy that consists of 2-period optimal pricing sequences for  $T - 3$  periods and a 3-period optimal price sequence for the last three periods is optimal, as we show below. When a 3-period optimal pricing sequence is used, it is interesting to note that prices offered in the first two periods are higher than  $p^*$ , while the price in the third period is lower than  $p^*$  to sell to customers with low reservation prices. It is easy to verify that

$$\begin{aligned} p^{3\text{-high}} &= p^* + (p^* - c) \left[ \frac{\alpha(\alpha^2 + 4\alpha + 2)}{2\alpha^2 + 8\alpha + 4 - \alpha^3} \right] \geq p^*, \\ p^{3\text{-med}} &= p^* + (p^* - c) \left[ \frac{\alpha^3}{2\alpha^2 + 8\alpha + 4 - \alpha^3} \right] \geq p^*, \\ p^{3\text{-low}} &= p^* + (p^* - c) \left[ \frac{\alpha(\alpha^2 - 2\alpha - 2)}{2\alpha^2 + 8\alpha + 4 - \alpha^3} \right] \leq p^*. \end{aligned}$$

Finally, in online Appendix F, we complete the proof of Theorem 2 by addressing the odd horizon length case.

#### 4.2. Model 2- ( $K = 1, Q = \infty$ ) with Time-Varying Parameters

In contrast to the case with stationary parameters, no closed-form solution exists for time-varying parameters. Instead, we develop an efficient algorithm to determine the optimal pricing plan using Lemma 1. Recall that the regeneration point conditions are equivalent to price markups in the one-period interaction price. That is, if the price in any period  $t$  is greater than or equal to the price charged in the previous period, period  $t$  is a regeneration point and the original problem can be decomposed into two subproblems (one up to period  $t - 1$  and the other from period  $t$ ). Every pricing sequence between two regeneration points must be monotonically decreasing and we develop a shortest-path-based algorithm using this observation.

Without loss of generality, we consider a problem satisfying a nonspeculative production condition  $c_t \leq c_{t-1} + h_{t-1}$ ,  $t = 1, \dots, T$ , because any arbitrary problem instance can be reformulated as an equivalent problem satisfying the condition. With unlimited capacity and the nonspeculative

condition, there is no incentive to carry inventory, i.e.,  $I_t = 0$  for all periods and the production quantity equals demand realized in each period ( $x_t = d_t$ ,  $t = 1, \dots, T$ ). Then, Model 2 for  $K = 1$  can be simplified as follows:

**Model 2-( $K = 1, Q = \infty$ ) with Time-Varying Parameters**

$$\begin{aligned} \max_{p_t, d_t, r_t^k} \quad & \sum_{t=1}^T p_t(d_t - c_t) \\ \text{s.t.} \quad & d_t = r_t^0 + r_t^1, \\ & 0 \leq p_t \leq d_t^0/s_t, \\ & r_t^k = \begin{cases} d_t^0 - s_t p_t & \text{if } k = 0, \\ \alpha_{t-1} s_{t-1} [p_{t-1} - p_t]^+ & \text{if } k = 1. \end{cases} \end{aligned} \tag{12}$$

After substituting for  $d_t$  and rewriting the objective function, we get

$$\begin{aligned} \max_{0 \leq p_t \leq d_t^0/s_t, t=1, \dots, T} \quad & \left[ \sum_{t=1}^T (p_t - c_t)(d_t^0 - s_t p_t) \right. \\ & \left. + \sum_{t=2}^T (p_t - c_t) \alpha_{t-1} s_{t-1} [p_{t-1} - p_t]^+ \right]. \end{aligned} \tag{13}$$

The concavity of (13), together with Lemma 1, enables us to decompose the problem into several independent sub-problems, each of which starts at a regeneration point and contains a monotonically decreasing pricing sequence. Let  $R = \{t_1 = 1, t_2, \dots, t_n = T + 1\}$  be the set of regeneration periods. Then, Equation (13) can be rewritten as the sum of  $n - 1$  independent maximization problems:

$$\begin{aligned} \max_{0 \leq p_t \leq d_t^0/s_t, t=1, \dots, T} \quad & \sum_{i=1}^{n-1} \sum_{t=t_i}^{t_{i+1}-1} \left[ (p_t - c_t)(d_t^0 - s_t p_t) \right. \\ & \left. + \sum_{t=i+1}^{n-1} \alpha_{t-1} s_{t-1} [p_{t-1} - p_t]^+ \right] \end{aligned} \tag{14}$$

subject to  $t_1 = 1, t_2, \dots, t_n = T + 1$ , are regeneration points.

This suggests that finding the optimal pricing plan is equivalent to finding the optimal set of regeneration points and solving the pricing problem for each subsequence independently; and this, in turn, suggests a shortest-path-based algorithm for this problem (see Figure 4).

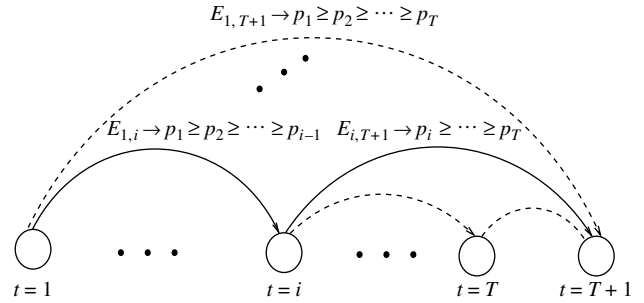
**ALGORITHM.**

Step 1. Calculate  $E_{(i,j)}$  for  $1 \leq i < j \leq T + 1$  as follows:

$$\begin{aligned} E_{(i,j)} = - \max_{\{p_t\}_{t=i}^{j-1}} \quad & \left[ \sum_{t=i}^{j-1} [(p_t - c_t)(d_t^0 - s_t p_t)] \right. \\ & \left. + \sum_{t=i+1}^{j-1} [\alpha_{t-1} s_{t-1} (p_t - c_t)(p_{t-1} - p_t)] \right] \\ \text{s.t.} \quad & p_i \geq \dots \geq p_{j-1}, \\ & 0 \leq p_t \leq d_t^0/s_t \quad \text{for all } t = i, \dots, j - 1, \end{aligned} \tag{15}$$

and let  $(p_t)_i^{j-1} = (p_i, p_{i+1}, \dots, p_{j-1})$  be the prices determined in  $E_{(i,j)}$ .

**Figure 4.** The shortest path that goes through the optimal set of regeneration points.



Step 2. Construct a complete graph  $G_T$  with nodes  $t = 1, 2, 3, \dots, T + 1$  and weights on arc  $(i, j)$  defined as  $E_{(i,j)}$ .

Step 3. Solve the shortest-path problem on the graph  $G_T$  from node 1 to  $T + 1$ .

Let  $(t_1 = 1, t_2, t_3, \dots, t_{n-1}, t_n = T + 1)$  be the shortest path from node 1 to  $T + 1$ . Then, the  $t_i$ s are regeneration points, the optimal pricing plan is

$$\{p_t^*\}_{t=1}^T = \{(p_t)_{t_1}^{t_2-1}, (p_t)_{t_2}^{t_3-1}, \dots, (p_t)_{t_{n-1}}^{T+1}\},$$

and the optimal production plan is

$$\{x_t^*\}_{t=1}^T = \{(d_t)_{t_1}^{t_2-1}, (d_t)_{t_2}^{t_3-1}, \dots, (d_t)_{t_{n-1}}^{T+1}\}.$$

Step 1 of the algorithm requires maximization of a concave quadratic objective function with linear inequalities for each  $(i, j)$ , where  $1 \leq i < j \leq T + 1$ , which is globally solvable in polynomial time by interior point methods. Let  $T_C$  be the time complexity of solving one concave quadratic program. Then, in Step 2 of the algorithm, constructing a complete graph requires  $O(T^2 T_C)$ . Because the time complexity of solving a shortest-path algorithm on a complete graph is  $O(T^2)$ , the overall complexity of the algorithm is  $O(T^2 T_C)$ .

We now show that the algorithm above finds the optimal pricing plan by finding the optimal set of regeneration points. Note that  $-E_{(t_i, t_{i+1})}$  is the maximum profit that can be generated from period  $t_i$  and period  $t_{i+1} - 1$  when any profit from residual demand realized in period  $t_i$  is ignored. Let  $(p_t)_{t=i}^{t_{i+1}-1}$  and  $(x_t)_{t=i}^{t_{i+1}-1}$  be a sequence of decreasing prices and corresponding production quantities which determine  $E_{(t_i, t_{i+1})}$ . Suppose that two arcs,  $(t_i, t_{i+1})$  and  $(t_{i+1}, t_{i+2})$ , are on the shortest path, but  $t_{i+1}$  is not a regeneration point, i.e.,  $p_{t_{i+1}-1} \geq p_{t_{i+1}} \geq p_{t_{i+1}+1} \geq \dots \geq p_{t_{i+2}-1}$ . From the definition of  $E_{(i,j)}$ ,  $E_{(t_i, t_{i+2})}$  is no greater than  $E_{(t_i, t_{i+1})} + E_{(t_{i+1}, t_{i+2})}$ , and this contradicts the fact that both arcs are on the shortest path. Therefore, the shortest path will only consist of paths connecting regeneration points, so that the algorithm determines the optimal set of regeneration points as well as the optimal pricing and production plan.

### 5. Heuristic Pricing Policies for K-Period Interaction

Building on our analysis of the one-period interaction model, we consider the  $K$ -period interaction case, in which some portion of demand can remain in the system up to  $K$  periods. Although this problem can be decomposed as in the single-period interaction case, a pricing sequence for the  $K$ -period problem is not necessarily a monotonically nonincreasing sequence; therefore, regeneration points do not necessarily coincide with price markups. This means that solving for a nondecreasing sequence of prices which maximizes the profit for  $n$  periods does not generate an  $n$ -period optimal pricing sequence.

Because of this, we focus on an intuitive and efficient pricing scheme based on the result of the one-period interaction model. In particular, we develop heuristic pricing policies consisting of nonincreasing sequences of prices.

#### 5.1. Closed-Form Expression for Unlimited Capacity and Stationary Parameters (Model 2-( $Q = \infty$ ))

As in the one-period interaction case, we start with a  $K$ -period interaction model with stationary parameters, and no capacity limitation. In addition, we assume that a constant fraction of unsatisfied customers will wait in the market up to  $K$  periods (i.e.,  $\alpha_k^t = \alpha$  for all  $k = 1, \dots, K$ ,  $t = 1, \dots, T$ ). Note that because all parameters are assumed to be stationary, nonanticipation constraints hold for all periods (i.e.,  $c_{t+1} \leq c_t + h_t$ ,  $t = 1, \dots, T - 1$ ), so that there is no incentive to carry inventory in any period. As a result, demand realized in each period,  $d_t$ , must be equal to the production quantity in the same period,  $x_t$ . After substituting  $x_t = d_t$  into Model 2, we obtain the following objective function for the  $K$ -period interaction case:

$$f(\mathbf{p}) = \sum_{t=1}^T (p_t - c_t)(d^0 - sp_t) + \sum_{t=2}^T \sum_{k=1}^{\min(t-1, K)} \alpha s(p_t - c) \cdot [p_{m(t, k)} - p_t] I_{p_{m(t, k)} \geq p_t} \tag{16}$$

In general, a  $K$ -period interaction problem cannot be decomposed by decreasing pricing sequences. However, for long enough time horizons, it makes sense that decreasing pricing sequences will perform reasonably well. Consider an  $n$ -period sequence of decreasing prices and a pricing plan that repeats this  $n$ -period sequence (i.e., an  $n$ -period cyclic pricing plan such that  $p_{j+n} = p_j$ ,  $h = 1, \dots, n - 1$ , and  $j \geq 0$ ). When  $T$  is sufficiently large and a multiple of  $n$ , no residual demand will be realized between two periods in different cycles. In this case, the only demand interactions realized are the ones caused by decreasing prices within an  $n$ -period sequence of decreasing prices. Thus, we are motivated to find a nonincreasing sequence of prices which maximizes the average profit contribution under the assumption that the same sequence will be

repeated in a pricing plan. Therefore, the profit from an  $n$ -period sequence of decreasing prices can be expressed as

$$f_n(\mathbf{p}) = \sum_{t=1}^n (p_t - c)(d^0 - sp_t) + \sum_{t=2}^n \min(t - 1, K) \alpha s(p_t - c)(p_{t-1} - p_t). \tag{17}$$

Following our single-period interaction result, we give a closed-form expression for the optimal nonincreasing sequences of length  $n$  which maximizes Equation (17).

LEMMA 3. Among all sequences of decreasing prices of length  $n$ , the following sequence maximizes Equation (17) in the  $K$ -period interaction case:

$$p_i = p^*(1 + \delta_i), \quad i = 1 \dots n, \tag{18}$$

where  $\delta_i$ ,  $i = 1, \dots, n$ , satisfies the following recursive relationship. Define  $a = (1 - c/p^*)$ . For  $n \leq K + 1$ ,

$$\delta_i = \begin{cases} 1, & i = 0, \\ (i - 1) \frac{\beta_{n-i}}{\beta_{n-i+1}} \delta_{i-1} - a * \frac{(n - 1)!}{(i - 1)!} \frac{n - 1}{\beta_{n-i+1}} \\ + a * \frac{\sum_{j=i}^{n-1} ((j - 1)! / (i - 1)!) \beta_{n-j}}{\beta_{n-i+1}}, & i = 1 \dots n - 1, \\ \frac{(n - 1)\beta_0}{\beta_1} \delta_{i-1} - \frac{a}{\beta_1} (n - 1), & i = n, \end{cases} \tag{19}$$

$$\beta_i = \begin{cases} 1, & i = 0, \\ \beta_1 = 2(n - 1 + \alpha^{-1}), & i = 1, \\ 2(n - i + \alpha^{-1})\beta_{i-1} - (n - i + 1)^2 \beta_{i-2}, & i = 2 \dots n. \end{cases} \tag{20}$$

For  $n > K + 1$ ,

$$\delta_i = \begin{cases} 1, & i = 0, \\ (i - 1) \frac{\beta_{n-i}}{\beta_{n-i+1}} \delta_{i-1} - a * \frac{K!}{(i - 1)!} \frac{K^{n-K}}{\beta_{n-i+1}} \\ + a * \frac{\sum_{j=i}^K ((j - 1)! / (i - 1)!) \beta_{n-j}}{\beta_{n-i+1}}, & i = 1 \dots K, \\ \frac{K\beta_{n-i}}{\beta_{n-i+1}} \delta_{i-1} - \frac{a}{\beta_{n-i+1}} K^{n-i+1}, & i = K + 1 \dots n, \end{cases} \tag{21}$$

$$\beta_i = \begin{cases} 1, & i = 0, \\ 2(K + \alpha^{-1}), & i = 1, \\ 2(K + \alpha^{-1})\beta_{i-1} - (K)^2 \beta_{i-2}, & i = 2 \dots n - K, \\ 2(n - i + \alpha^{-1})\beta_{i-1} - (n - i + 1)^2 \beta_{i-2}, & i = n - K + 1, \dots, n. \end{cases} \tag{22}$$

As in the one-period interaction case, all  $\beta_i$ s and  $\delta_i$ s are functions of sequence length  $n$  (i.e.,  $\beta_i(n)$  and  $\delta_i(n)$ ), but we suppress this dependence for ease of exposition. The proof is in online Appendix G.

**5.2. Capacity Constraints and Time-Varying Parameters (Model 2)**

To find a heuristic solution for the most general Model 2 based on the results and intuition developed in prior sections, we focus on nonincreasing pricing sequences, extend the optimal algorithm from §5.1 to the  $K$ -interaction period problem, and then develop a linear program to deal with capacity constraints.

**HEURISTIC ALGORITHM.**

*Step 1.* Let  $P^h = \{P_t^h\}_{t=1}^T$  be the pricing plan found by solving the following shortest-path problem:

(a) Calculate  $E_{(i,j)}$  for  $1 \leq i < j \leq T + 1$  as follows:

$$E_{(i,j)} = - \max_{\{x_t, I_t, p_t\}_{t=i}^{j-1}} \left[ \sum_{t=i}^{j-1} [p_t(d_t^o - s_t p_t)] + \sum_{t=i+1}^{j-1} \sum_{k=1}^{\min(t-1, K)} \alpha_k^{t-k} s_{t-k} \cdot [p_t(p_{t-1} - p_t)] - \sum_{t=i}^{j-1} c_t x_t - \sum_{t=i}^{j-1} h_t I_t \right]$$

s.t.  $I_{t-1} + x_t = I_t + [d_t^o - s_t p_t]$   
 $+ \sum_{k=1}^{\min(t-1, K)} \alpha_k^{t-k} s_{t-k} (p_{t-1} - p_t)$   
 $\forall t = i, \dots, j - 1,$   
 $p_t \leq d_t^o / s_t \quad \forall t = i, \dots, j - 1,$   
 $p_t \geq p_{t+1} \quad \forall t = i, \dots, j - 2,$   
 $x_t \leq Q_t \quad \forall t = i, \dots, j - 1,$   
 $x_t, I_t, p_t \geq 0 \quad \forall t = i, \dots, j - 1,$   
 $I_{i-1} = 0,$

and let  $(P_t^h)^j = (p_i^h, p_{i+1}^h, \dots, p_{j-1}^h)$  be the prices determined in  $E_{(t_1, t_2)}$ .

(b) Construct a complete graph  $G_T$  with nodes  $t = 1, 2, 3, \dots, T + 1$  and weights on arc  $(t_1, t_2)$  defined as  $E_{(t_1, t_2)}$ .

(c) Solve the shortest-path problem on the graph  $G_T$  from node  $t = 1$  to  $t = T + 1$ . Let  $(t_1 = 1, t_2, t_3, \dots, t_{n-1}, t_n = T + 1)$  be the shortest path from node  $t_1 = 1$  to  $t_n = T + 1$ . Then, construct a pricing plan

$$\{P_t^h\}_{t=1}^T = \{(P_t^h)_{t_1}^{t_2}, (P_t^h)_{t_2}^{t_3}, \dots, (P_t^h)_{t_{n-1}}^{T+1}\}.$$

*Step 2.* Calculate the demand,  $D_t^h$ , for each period generated by the heuristic pricing sequence as follows:

$$D_t^h = \begin{cases} [d_t^o - s_t P_t^h] & \text{if } t = 1, \\ [d_t^o - s_t P_t^h] + \sum_{k=1}^{\min\{t-1, K\}} \alpha_k^{t-k} s_{t-k} \cdot \left[ \min_{i \in \{1, \dots, k\}} P_{t-i}^h - P_t^h \right]^+ & \text{if } 2 \leq t \leq T. \end{cases} \quad (23)$$

*Step 3.* Solve the following linear program to determine optimal allocation of capacity:

$$\max_{\{x_t, d_t, I_t\}_{t=1}^T} \sum_{t=1}^T P_t^h d_t - \sum_{t=1}^T c_t x_t - \sum_{t=1}^T h_t I_t \quad (24a)$$

$$\text{s.t. } x_t + I_{t-1} = d_t + I_t, \quad (24b)$$

$$x_t \leq Q_t,$$

$$d_t \leq D_t^h,$$

$$x_t, d_t, I_t \geq 0 \quad \forall t = 1, \dots, T.$$

In Step 1(a) of the algorithm, we define a concave quadratic function,  $E_{(i,j)}$ , to approximate the profit accrued between  $i$  and  $j - 1$ . The first term in  $E_{(i,j)}$  is the revenue from the demand originated and realized in the same period, the second term represents the revenue from the residual demand, and the third and fourth terms are production and inventory costs. We find  $(p_i, \dots, p_{j-1})$  which maximizes  $E_{(i,j)}$  under the following constraints: initial inventory and inventory balance constraints, nonnegative demand constraints ( $p_t \leq d_t^o / s_t$ ), fixed-ordering constraints, and capacity constraints. We also assume that all variables are nonnegative.

Step 1(a) of the algorithm requires maximization of a concave quadratic objective function with linear inequalities for each  $(i, j)$ , where  $1 \leq i < j \leq T + 1$ , which is globally solvable in polynomial time. Let  $T_C$  be the time complexity of solving one concave quadratic program. Then, in Step 1(b) of the algorithm, constructing a complete graph requires  $O(T^2 T_C)$ . Because time complexity of solving a shortest-path algorithm on a complete graph is  $O(T^2)$ , the overall complexity of Step 1 of the heuristic algorithm is  $O(T^2 T_C)$ .

Note that for the problem with time-varying parameters, nonanticipative costs, and no capacity constraints, this algorithm without Step 3 finds the best solution among solutions with nonincreasing pricing sequences. Step 3 transforms this solution into a feasible solution for the capacity-constrained problem. In §6, we test the performance of this heuristic.

**6. Computational Study**

We conducted a computational study to develop insights into the impact of demand interaction on profit and manufacturing decisions, as well as the effectiveness of our heuristics. We created 972 problem instances by varying problem parameters and demand assumptions and tested three different policies: the optimal pricing/manufacturing policy that explicitly takes demand interactions into account, our proposed heuristic policy, and a myopic policy that ignores demand interactions (that is, assuming  $K = 0$ ) and follows a pricing schedule determined by a myopic algorithm.

### 6.1. Design of the Computational Study

We first consider a 6-period planning horizon ( $T=6$ ) and created a set of experiments by varying several model parameters and demand patterns.

**Demand Curve Scenarios.** We examine four scenarios for demand variations: stationary, increasing, decreasing, and seasonal demand. We consider a standard demand curve,  $D_t(p_t) = d_t^0 - s_t p_t$ , where  $d_t^0$  and  $s_t$  are, respectively, demand at zero price and sensitivity of demand to price variations. Depending on the demand scenario, we vary  $d_t^0$  in different ways, while keeping  $p_t^0$  constant. This corresponds to a series of linear demand curves whose intersection with the demand axis is changing in three different fashions (seasonal, increasing, and decreasing) around the standard demand curve, while intersection with price axis is constant throughout the periods. For computational study, we use  $D_q(p_t) = 30 - p_t$  as our standard demand price curve. The actual demand curves for each scenario follow (see Figure (5)):

(1) Stationary demand curve scenario:  $D_1(p_1) = D_2(p_2) = D_3(p_3) = D_4(p_4) = D_5(p_5) = D_6(p_6) = 30 - p$ .

(2) Increasing demand curve scenario:  $D_1(p_1) = 15 - \frac{5}{10} p_1$ ;  $D_2(p_2) = 21 - \frac{7}{10} p_2$ ;  $D_3(p_3) = 27 - \frac{9}{10} p_3$ ;  $D_4(p_4) = 33 - \frac{11}{10} p_4$ ;  $D_5(p_5) = 39 - \frac{13}{10} p_5$ ;  $D_6(p_6) = 45 - \frac{15}{10} p_6$ .

(3) Decreasing demand curve scenario:  $D_1(p_1) = 45 - \frac{15}{10} p_1$ ;  $D_2(p_2) = 39 - \frac{13}{10} p_2$ ;  $D_3(p_3) = 33 - \frac{11}{10} p_3$ ;  $D_4(p_4) = 27 - \frac{9}{10} p_4$ ;  $D_5(p_5) = 21 - \frac{7}{10} p_5$ ;  $D_6(p_6) = 15 - \frac{5}{10} p_6$ .

(4) Seasonal demand curve scenario:  $D_1(p_1) = 15 - \frac{5}{10} p_1$ ;  $D_2(p_2) = 30 - p_2$ ;  $D_3(p_3) = 45 - \frac{15}{10} p_3$ ;  $D_4(p_4) = 45 - \frac{15}{10} p_4$ ;  $D_5(p_5) = 30 - p_5$ ;  $D_6(p_6) = 15 - \frac{5}{10} p_6$ .

**Interaction Levels.** ( $K = 1, 2, 3$ ).

**Capacity Levels.** We keep capacity constant over the planning horizon, although at different levels. Those levels

are defined loosely as uncapacitated, mildly capacitated, and strictly capacitated. Because we use  $D_q(p_t) = 30 - p_t$  as the base demand curve, the optimal noninteraction price when  $c = 0$  is  $p^* = 15$  and the demand at  $p^* = 15$  is  $D_q(p^*) = 15$ . We set capacity levels first at infinity (uncapacitated case), then at 15 (mildly capacitated case), and finally at 5 (strictly capacitated case). For the demand curves given above, these values are calculated as follows:

- (1) No capacity constraint: for this range of parameters, no capacity is equivalent to the case where capacity is 100.
- (2) Medium capacity constraint: capacity = 15.
- (3) Tight capacity constraint: capacity = 5.

**Production Costs.** Low production cost ( $c = 0$ ), medium production cost ( $c = 5$ ), and high production cost ( $c = 10$ ). We assume that production cost is constant over the planning horizon.

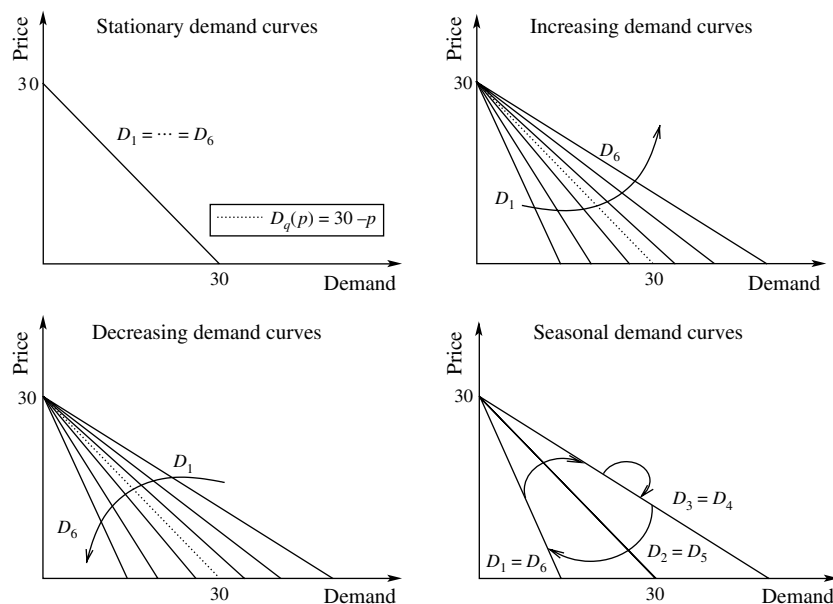
**Inventory Holding Costs.** Low inventory holding cost ( $h = 1$ ), medium inventory holding cost ( $h = 2$ ), and high inventory holding cost ( $h = 10$ ). We assume that the holding cost is constant over the planning horizon.

**Customer Waiting Proportions.**  $\alpha_k^t = \alpha^k$  for all  $t = 1, \dots, T$  and  $k = 1, \dots, K$ , where  $\alpha = 1$  (high), 0.5 (medium), and 0.2 (low).

### 6.2. Analysis

For our analysis, we solve each problem instance using three different policies: the optimal policy, our heuristic, and a myopic policy. Let  $\Pi^{\text{OPT}}$ ,  $\Pi^H$ , and  $\Pi^M$  be profits generated by the optimal, heuristic, and myopic algorithms, respectively. To compare how the optimal policy (or the heuristic policy) fares with the myopic policy, we use the percentage improvement in profit over myopic pricing

**Figure 5.** The price-demand curves for each scenario.



as follows. Note that even when the policy is determined myopically, the profit is determined assuming that there is demand interaction in the underlying system:

$$\Delta_{\text{OPT}} = \frac{\Pi^{\text{OPT}} - \Pi^M}{\Pi^M} * 100,$$

$$\Delta_{\text{HEU}} = \frac{\Pi^H - \Pi^M}{\Pi^M} * 100.$$

Note that  $\Delta_{\text{OPT}} - \Delta_{\text{HEU}}$  represents a gap between an optimal policy and a heuristic.

We found an optimal policy using Theorem 1 and the algorithm described in Corollary 1. This algorithm enumerates all possible orderings of price sequences and solves a concave maximization problem for each ordering. Because an optimization problem with a quadratic and concave objective function and a set of linear constraints is polynomially solvable with complexity of  $O(T_C)$ , the complexity of the optimal algorithm is  $O(T!T_C)$ . On the other hand, the complexity of our heuristic algorithm based on the shortest-path computation is  $O(T^2T_C)$ , and the complexity of a myopic algorithm is simply  $O(T_C)$ .

Under the myopic algorithm, we first solve the pricing model as if no demand interaction exists, then determine the demand realization (assuming demand interaction) generated by the myopic pricing solution. Finally, we solve an LP to determine the final production decisions.

**MYOPIC ALGORITHM.**

Step 1. Let  $\mathbf{p}^m = \{\mathbf{P}_t^m\}_{t=1}^T$  be the pricing plan found by solving the following concave maximization problem:

$$M_T = \max_{\{p_t, x_t, I_t\}_{t=1}^T} \left[ \sum_{t=1}^T [p_t(d_t^o - s_t p_t)] - \sum_{t=1}^T c_t x_t - \sum_{t=1}^T h_t I_t \right]$$

s.t.  $I_{t-1} + x_t = I_t + [d_t^o - s_t p_t] \quad \forall t = 1, \dots, T,$   
 $p_t \leq d_t^o / s_t \quad \forall t = 1, \dots, T,$   
 $x_t \leq Q_t \quad \forall t = 1, \dots, T,$   
 $x_t, I_t, p_t \geq 0 \quad \forall t = 1, \dots, T.$

Step 2. Calculate the demand,  $D_t^m$ , for each period generated by the myopic pricing sequence as follows:

$$D_t^m = \begin{cases} [d_t^o - s_t P_t^m] & \text{if } t = 1, \\ [d_t^o - s_t P_t^m] + \sum_{k=1}^{\min\{t-1, K\}} \alpha_k^{t-k} s_{t-k} & \text{if } 2 \leq t \leq T. \end{cases}$$

Step 3. Solve the following linear program to determine optimal allocation of capacity:

$$\Pi^M = \max_{\{x_t, d_t, I_t\}_{t=1}^T} \sum_{t=1}^T P_t^m d_t - \sum_{t=1}^T c_t x_t - \sum_{t=1}^T h_t I_t$$

s.t.  $x_t + I_{t-1} = d_t + I_t,$   
 $x_t \leq Q_t,$   
 $d_t \leq D_t^m,$   
 $x_t, d_t, I_t \geq 0 \quad \forall t = 1, \dots, T.$

We used the CPLEX(R) solver running on an Intel(R) Pentium(R) 4 Mobile CPU 1.60 GHz computer with 512 MB RAM and 30 GB HDD to conduct the computational study.

**6.2.1. The Impact of Parameters on Optimal Policy.**

We present the results of our numerical study in Tables 1–4. We first examine how each problem parameter affects the benefit of accounting for demand interaction when making pricing and production plans. To this end, we compute  $\Delta_{\text{OPT}}$  for various scenarios and observed the following.

- On average, the gain from using the optimal policy ( $\Delta_{\text{OPT}}$ ) is quite significant. The average gain of the optimal policy is 6.73%. There are many instances where the gain is 20% or more. On average, the gain from the optimal policy ( $\Delta_{\text{OPT}}$ ) decreases as the capacity becomes more constrained. This is intuitive because when capacity is tight, the firm can only sell to customers with high reservation prices anyway. When the firm has excess capacity, on the other hand, the

**Table 1.**  $\Delta_{\text{OPT}}$  and  $\Delta_{\text{HEU}}$  w.r.t. various capacity and interaction levels (i.e.,  $K$ -values).

Capacity	Interaction level	$\Delta_{\text{OPT}}$ (%)				$\Delta_{\text{HEU}}$ (%)			
		Mean	Min	Max	SD	Mean	Min	Max	SD
UnCap	1-period	6.53	0.71	15.95	5.77	6.53	0.71	15.95	5.77
	2-period	10.99	1.19	26.96	9.69	10.99	1.19	26.96	9.69
	3-period	13.73	1.40	35.56	12.26	13.62	1.40	35.56	12.31
MedCap	1-period	4.65	0.15	14.36	4.21	4.57	-0.21	14.36	4.21
	2-period	7.69	0.15	23.08	6.79	7.59	-0.05	23.08	6.78
	3-period	9.48	0.15	31.53	8.47	9.34	-0.02	31.53	8.45
TightCap	1-period	1.83	0.00	6.79	1.89	1.71	-0.69	6.79	1.92
	2-period	2.65	0.00	10.05	2.68	2.57	-0.69	10.05	2.73
	3-period	3.04	0.00	11.52	3.06	2.94	-0.69	11.52	3.09

Note. UnCap/MedCap/TightCap: no capacity/medium capacity/tight capacity.

**Table 2.**  $\Delta_{OPT}$  and  $\Delta_{HEU}$  w.r.t. various capacity and the proportion of customers who stay in the market (i.e.,  $\alpha$  values).

Capacity	$\alpha$	$\Delta_{OPT}$ (%)				$\Delta_{HEU}$ (%)			
		Mean	Min	Max	SD	Mean	Min	Max	SD
UnCap	High	22.77	12.68	35.56	7.23	22.77	12.68	35.56	7.23
	Medium	6.99	3.77	11.43	2.32	6.90	3.77	11.43	2.25
	Low	1.50	0.71	2.81	0.61	1.48	0.71	2.81	0.60
MedCap	High	14.97	2.97	31.53	6.39	14.81	2.97	31.53	6.41
	Medium	5.47	0.93	12.00	2.83	5.36	0.92	12.00	2.84
	Low	1.40	0.15	5.71	1.00	1.33	-0.21	5.71	1.00
TightCap	High	3.80	0.00	11.52	3.09	3.73	0.00	11.52	3.11
	Medium	2.38	0.00	8.16	2.44	2.28	-0.63	8.16	2.49
	Low	1.33	0.00	4.90	1.53	1.22	-0.69	4.90	1.55

**Table 3.**  $\Delta_{OPT}$  and  $\Delta_{HEU}$  w.r.t. various capacity and inventory holding-cost parameters.

Capacity	Inv. holding cost	$\Delta_{OPT}$ (%)				$\Delta_{HEU}$ (%)			
		Mean	Min	Max	SD	Mean	Min	Max	SD
UnCap	Low	10.42	0.71	35.56	10.07	10.38	0.71	35.56	10.08
	Medium	10.42	0.71	35.56	10.07	10.38	0.71	35.56	10.08
	High	10.42	0.71	35.56	10.07	10.38	0.71	35.56	10.08
MedCap	Low	8.04	0.35	31.53	7.49	7.83	-0.18	31.53	7.48
	Medium	7.23	0.15	31.21	6.86	7.14	-0.21	31.21	6.84
	High	6.55	0.19	31.21	6.58	6.53	0.19	31.21	6.57
TightCap	Low	2.77	0.00	11.52	2.56	2.58	-0.69	11.52	2.67
	Medium	2.46	0.00	10.97	2.58	2.35	-0.40	10.97	2.60
	High	2.28	0.00	10.87	2.75	2.28	0.00	10.87	2.75

**Table 4.**  $\Delta_{OPT}$  and  $\Delta_{HEU}$  w.r.t. various capacity and production cost parameters.

Capacity	Production cost	$\Delta_{OPT}$ (%)				$\Delta_{HEU}$ (%)			
		Mean	Min	Max	SD	Mean	Min	Max	SD
UnCap	Low	10.42	0.71	35.56	10.07	10.38	0.71	35.56	10.08
	Medium	10.42	0.71	35.56	10.07	10.38	0.71	35.56	10.08
	High	10.42	0.71	35.56	10.07	10.38	0.71	35.56	10.08
MedCap	Low	6.46	0.15	24.85	6.04	6.28	-0.21	24.85	6.04
	Medium	6.67	0.35	26.79	6.32	6.58	0.23	26.79	6.27
	High	8.70	0.52	31.53	8.26	8.64	0.52	31.53	8.23
TightCap	Low	1.90	0.00	6.77	1.91	1.82	-0.41	6.77	1.94
	Medium	2.39	0.00	8.53	2.40	2.30	-0.52	8.53	2.44
	High	3.23	0.00	11.52	3.25	3.10	-0.69	11.52	3.30

**Table 5.** Relative frequency table of  $\Delta_{OPT} - \Delta_{HEU}$ .

	[0-0.05%] <sup>1</sup>	(0.05-0.10%]	(0.10-0.20%]	(0.20-0.40%]	(0.40-0.80%]	(0.80-1.60%]	(1.60-3.20%]
$N^2$	758	31	50	61	60	10	2
$F^3$ (%)	77.98	3.19	5.14	6.28	6.17	1.03	0.21

<sup>1</sup>Class Intervals for  $\Delta_{OPT} - \Delta_{HEU}$ .

<sup>2</sup>Number of cases where  $\Delta_{OPT} - \Delta_{HEU} \in$  class interval.

<sup>3</sup>Percentage of cases where  $\Delta_{OPT} - \Delta_{HEU} \in$  class interval.

**Table 6.**  $\Delta_{HEU}$  w.r.t. various demand scenarios, planning horizons, and capacity values.

Demand curve scenarios	Capacity	Planning horizon							
		$T = 6$				$T = 12$			
		Descriptive statistics of $\Delta_{HEU}$				Descriptive statistics of $\Delta_{HEU}$			
		Mean	Min	Max	SD	Mean	Min	Max	SD
Stationary	UnCap	9.76	0.84	27.09	9.28	10.14	0.84	30.14	9.81
	MedCap	6.85	0.35	22.95	6.42	6.96	0.35	24.85	6.54
	TightCap	0.49	0.00	3.37	0.82	0.48	0.00	3.33	0.81
Increasing	UnCap	8.48	0.71	23.42	8.05	9.08	0.74	26.71	8.75
	MedCap	4.24	-0.21	15.91	4.48	4.69	-0.17	19.38	4.86
	TightCap	0.15	-0.69	2.69	0.70	0.32	-0.56	3.10	0.79
Decreasing	UnCap	11.66	0.99	33.66	11.09	11.41	0.95	33.83	10.93
	MedCap	9.15	0.99	31.53	8.34	8.38	0.94	27.17	7.27
	TightCap	4.83	1.07	11.52	2.54	3.88	0.76	10.00	2.24
Seasonal	UnCap	11.62	0.90	35.56	11.24	10.67	0.87	31.81	10.27
	MedCap	8.43	0.35	28.11	7.15	7.50	0.03	27.07	6.95
	TightCap	4.15	1.10	8.34	1.81	3.39	0.65	8.15	1.74

optimal policy improves the profit by selling to residual demand.

- We also notice that  $\Delta_{OPT}$  increases as the demand interaction level (represented by  $K$ ) increases (Table 1). As the demand interaction level increases, the size of residual demand also increases, thus the firm’s profit from selling to residual demand also increases. Similarly,  $\Delta_{OPT}$  increases as the proportion of customers who stay in the market increases (Table 2).

- As expected,  $\Delta_{OPT}$  decreases as holding or production cost increases. Increasing operating cost decreases the range within which intertemporal price discrimination can take place, thus decreasing the benefit of dynamic pricing (Tables 3 and 4).

**6.2.2. Heuristic Performance.** As demonstrated in Tables 1–4, our heuristic policy performs very well. In many cases, our heuristic either coincides with the optimal policy or is very close to the optimal policy. As illustrated in Table 5, in 98.76% of the instances we ran, the gap is within 0.8%. Out of 972 problem instances, the worst case is 3.2%.

Furthermore, the insights we developed by comparing the optimal policy with the myopic policy continue to hold for the heuristic.  $\Delta_{HEU}$  decreases as capacity gets tight (Tables 1–4), increases as demand interaction level ( $K$ ) increases (Table 1), increases as  $\alpha$  increases (Table 2), and decreases as holding cost or production cost increases (Tables 3 and 4).

In a relatively small number of cases, the heuristic algorithm diverges from optimality. These cases are characterized by:

- Tight capacity: the decomposition ignores inventory carryover between subproblems, and this may lead to heuristic errors when capacity is tight.

- High  $K$ : when  $K$  is strictly greater than one, there might be residual demand between two subproblems because nonincreasing sequences do not decompose the problem into subproblems.

Also, for a small number of cases (41 of 972 cases), the performance of the heuristic policy is either equal to or slightly less than that of the myopic algorithm, i.e.,  $\Delta_{HEU} \leq 0$ . As shown in Table 6, the negative values appear only when the capacity is tight and the firm faces increasing demand patterns. Recall that the heuristic algorithm solves a shortest-path problem, and we find the best non-increasing pricing sequence to represent the profit of each arc. However, the increasing demand curve scenario under tight capacity limitations leads to an optimal pricing policy that is increasing in time with no residual demand. Hence, the myopic policy generates more profit by considering only current demand and solving the entire problem without decomposition.

Finally, to evaluate the performance of the heuristic algorithm for different planning horizon lengths, we conducted additional computational experiments with the same set of parameters, except that the length of the horizon  $T = 12$ . Because the complexity of computing the optimal policy grows exponentially with  $T$ , for this case we only compared heuristic and myopic policies.

As Table 6 illustrates, the relative performance of the heuristic algorithm over the myopic algorithm remains significant as the planning horizon increases from  $T = 6$  to  $T = 12$ .

## 7. Extensions, Conclusions, and Further Research

### 7.1. Pricing-Pattern Aware Customers

As we mentioned in the introduction, one reasonable critique of this model is that it assumes that consumers are



not aware of impending price decreases. Thus, this model is intended to capture situations in which customers place a high value on a good's availability, and tend to buy it as soon as their budget constraint (i.e., reservation price) is met. We can alternatively model a situation in which customers are aware of the pricing pattern. In this case, they enter the system and stay for at most  $K$  periods, and actually make a purchase when their discounted utility is maximized. We model utility as the difference between modified price and reservation price, where  $\beta_j \geq 1$  is a factor that we multiply by price in the future to represent the disutility of waiting  $j$  periods. In other words, all of the customers who arrive at time  $t$  and eventually make a purchase will make their purchase at time  $t^*$ , where

$$t^* = \arg \min_{t \leq t+K} \beta_{(t-t)} p_t.$$

Thus, the revenue from demand in period  $t$  is

$$p_{t^*} (d_t^0 - s_t \beta_{(t^*-t)} p_{t^*}).$$

We let  $\tilde{d}_i^j$  represent the demand from customers that arrive in period  $i$  if they make their purchase  $j$  periods in the future, and let  $y_i^j$  be a binary variable that takes on the value of one if the utility from making a purchase  $j$  periods in the future is the maximum utility over periods  $t, t+1, t+2, \dots, \min(t+K, T)$ . Then, this model can be expressed as described below. Once again, we consider a discrete-time multiperiod production system where at each period we decide both price of the product,  $p_t$ , and the production quantity of the product,  $x_t$ . As before, our objective is to maximize the net profit (25a) subject to inventory balance (25b), production capacity (25c), and demand realization constraints (25e)–(25i):

$$\max_{p_t, x_t, I_t, d_t, \tilde{d}_t^j} \sum_{t=1}^T \sum_{j=0}^{\min(K, T-t)} p_{t+j} y_t^j \tilde{d}_t^j - \sum_{t=1}^T c_t x_t - \sum_{t=1}^T h_t I_t \quad (25a)$$

$$\text{s.t. } x_t + I_{t-1} = d_t + I_t, \quad t = 1, 2, \dots, T, \quad t_0 = 0, \quad (25b)$$

$$x_t \leq Q_t, \quad t = 1, 2, \dots, T, \quad (25c)$$

$$d_t = \sum_{j=0}^{\min(K, T-t)} \tilde{d}_{t-j}^j, \quad t = 1, 2, \dots, T, \quad (25d)$$

$$\tilde{d}_t^j = d_t^0 - s_t \beta_j p_{t+j} + (1 - y_t^j) \cdot M \quad t = 1, 2, \dots, T, \quad j = 0, 1, 2, \dots, \min(K, T-t), \quad (25e)$$

$$p_t \leq d_t^0 / s_t, \quad t = 1, 2, \dots, T, \quad (25f)$$

$$\tilde{d}_t^j \geq y_t^j \cdot d_t^0, \quad t = 1, 2, \dots, T, \quad j = 0, 1, 2, \dots, \min(K, T-t), \quad (25g)$$

$$\sum_{j=1}^{\min(K, T-t)} y_t^j = 1, \quad t = 1, 2, \dots, T, \quad (25h)$$

$$y_t^j \in \{0, 1\}, \quad t = 1, 2, \dots, T, \quad j = 0, 1, 2, \dots, \min(K, T-t), \quad (25i)$$

$$x_t, I_t, d_t, p_t \geq 0, \quad t = 1, 2, \dots, T, \quad (25j)$$

$$\tilde{d}_t^j \geq 0, \quad t = 1, 2, \dots, T, \quad j = 0, 1, 2, \dots, \min(K, T-t). \quad (25k)$$

Note that constraints (25e)–(25i) ensure that  $y_t^j$  takes the appropriate value and that  $M$  is a large constant.

Gümüř (2007) develops properties of this model, and an optimal (exponential) algorithm that is similar to the algorithms we have developed for our original model in this paper. However, we observe here that the uncapacitated version of this model with stationary parameters is much simpler to analyze than the equivalent formulation of the original model. Because all newly arriving demand that is met before customers exit the system is met in the same period, a simple contradiction-based argument can be used to prove the following result:

**THEOREM 4.** *For the pricing-aware customer model with unlimited capacity and stationary parameters, each period's price will be identical and equal to the noninteraction price,*

$$p^* = \frac{d^0 + sc}{2s}. \quad (26)$$

Interestingly, although Theorem 4 applies in a more general setting than Theorem 2, Theorems 2 and 4 can conceptually be interpreted as supporting the use of two very different retail pricing strategies. When customers place a high value on a good's availability and tend to buy it as soon as their budget constraint is met, relatively frequent sales can serve to maximize profits, as indicated by Theorem 2. This strategy tends to be employed, for example, by high-end department stores, whose customers may place a high value on the good's availability. Discount stores such as Wal-Mart, however, may employ everyday low-price strategies because their customers are more adequately modeled by the model introduced in this section—they are willing to wait for the lowest possible price.

## 7.2. Conclusions and Future Research

In this paper, we have demonstrated that it can be valuable to model demand interactions in production/pricing models, and we presented several possible ways to model this interaction. We have presented structure, algorithms, and heuristics for our models. Our computational analysis helps to characterize the value of accounting for demand interaction when making pricing and production decisions in various cost and capacity settings.

Our models have a variety of limitations. These are deterministic models, although actual problems will typically be stochastic. In addition, while we assume that all customers in the market follow the pattern of the behavior described

either in our main model or in the model introduced in the previous subsection, we believe that most actual markets have a mixture of customers following the behavior characterized in both models. Nevertheless, we think that the models and results presented in this paper are a good initial step toward capturing the impact of demand interaction in production/pricing models.

Building on our initial framework, we are currently extending these models in several ways. We are working to extend more of our 1-period results to the general  $K$ -period case. We are also considering models with fixed setup costs associated with production orders. Our framework allows us to easily integrate setup costs into the model. We are also working to extend our models to a multiproduct setting where a manufacturer produces more than one product and demand for each product is a function of its own price and the prices of other products.

While our model has focused on the problem of a monopolist, a game-theoretic model where multiple manufacturers compete for the same potential demand is worth investigating. This extension will help us to understand the effect of dynamic pricing as a tool to achieve competitive advantage. Finally, we hope to extend our models to the case of stochastic demand.

## 8. Electronic Companion

An electronic companion to this paper is available as part of the online version that can be found at <http://or.journal.informs.org/>.

## Acknowledgment

This material is based on work supported by the National Science Foundation under grants DMI-0092854 and DMI-0200439.

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