The Implementation of an Apartment Dynamic Pricing System

Abstract

Revenue Management (RM) has been successfully employed by diverse industries to utilize vast data warehouses to forecast demand and supply and price products to maximize profits. However, the apartment industry represents a new frontier for RM. This industry shares many characteristics with the hotel industry, but presents new challenges such as extremely long lengths of stay and relatively small transaction density. The objective of this paper is to introduce the implementation of an apartment dynamic pricing system with particular emphasis on setting optimal rental rates for new leases. Optimal rental rates are recommended as weekly rates based on unit type and lease term for a finite horizon of future weeks. This paper studies the characteristics of apartment firms and discusses similarities and differences between the apartment and hotel industries from an RM point of view. It then provides an overview of an apartment dynamic pricing system, followed by a detailed description of its modules. Finally, it concludes with a summary of benefits.

INTRODUCTION

Everyday apartment operators have to set the rental rates for new and renewal leases. New leases are the agreements between the apartment and the prospective tenants. They are signed for the apartment units which are either vacant or to be vacant shortly. Renewal leases, on the other hand, are the agreements between the apartment and the current residents whose leases are expiring. They are signed for the apartment units which are being occupied.

In traditional apartment management, rents are often set with the objectives of achieving market share, maintaining occupancy rate or gaining investment return. Rents are often determined based on such factors as the physical characteristics of a property, current vacancy, market condition, competitive influence, and so on. In addition, the experience of managing personnel has also played an important role. There is a variety of literature addressing traditional methodologies of apartment rent setting. Sirmans and Benjamin (1991) performed an extensive literature review. For instance, Pagliari and Webb (1996) built a regression model to set rental rates based on rent concessions and occupancy rates. Among the existing literature, to our knowledge, no effort has ever been made to set rates to maximize total revenue growth.

The use of revenue management (RM) has emerged as an alternative methodology in apartment industry. It helps set the optimal rental rates in order to achieve maximum revenue gain for the apartment firms. An apartment revenue management system (RMS) is an application of RM principles to the apartment industry. It provides an automated approach to setting optimal rental rates in a systematic and informed manner. A vast array of service industries has successfully developed proprietary RMSs, but the apartment industry represents a new frontier for RM. The sophistication of an apartment RMS varies with its capabilities, which range from setting optimal rents for new and renewal leases to evaluating the system's performance. Unlike the travel and hospitality industries, very few papers related to apartment RMSs can be found in the existing literature. Davidoff and Small (2003) provide an overview of the apartment RM concept by comparing the hotel and apartment industries, suggest steps that apartment firms need to take to implement an RMS, and predict the future of apartment RMS software products.

The objective of this paper is to describe the implementation of an apartment dynamic pricing system with particular emphasis on setting optimal rental rates for new leases. This system has been helping several leading apartment operators offer prospective tenants a menu of rent options for the last six years. It sets the optimal rents everyday, which are presented in the form of unit type, move-in week and lease term.

Apartment industry has its own unique features and proprietary laws. Unlike traditional hotel and airline industries, apartment customers can not be explicitly differentiated or segmented at the time when their requests are being made. This is partially due to the Fair Housing Act law, which essentially requires that two people being offered the same product (e.g. unit type, move-in date and lease term) at the same time must be quoted the same rates. This legal restriction makes traditional market segmentation approaches inappropriate in apartment industry. Apartment customers can only be differentiated by their purchase behavior such as the desired times of year for move-in and lease terms. This will implicitly distinguish customers by the quote rate at which they are willing to pay. In other words, this system manipulates rent as the only variable to encourage or discourage demand. Specifically, three factors that influence the rent are considered in the system: the capacity of the apartment, the demand arriving process and the competitor influence.

The remainder of this paper is organized as follows: It starts with a study on the characteristics of apartment-rental firms from an RM point of view. Since apartment-rental firms are in many ways similar to hotel firms, this study is performed through a comparison of the similarities and differences between the two industries. It then outlines the system, followed by a detailed description on the individual modules of the system. Finally, it concludes with a summary of benefits of using the system.

CHARACTERISTICS OF APARTMENT-RENTAL FIRMS

On the surface, the apartment industry shares many characteristics with the hotel industry. Since the hotel industry has been successfully employing RM techniques for a number of years, it would be of great benefit if the apartment industry can simply adapt existing RM techniques from the hotel industry. In this section, we study the characteristics of apartment-rental firms by noting the similarities and differences between the apartment and hotel sectors from an RM viewpoint.

It is obvious that both apartment and hotel industries share the following characteristics:

- *Perishable Products*. Both offer rooms with multiple types as products for customers to stay in for a certain length of time. These products are perishable in the sense that occupied units have certain value (rental income) until the moment they become vacant. After that point, they are worthless until they are occupied again.
- *Constrained Supply*. Both face supply constraints. In other words, both have a relatively fixed capacity with diverse room types. When demand exceeds current inventory, it would be almost impossible to replenish extra inventory in a short period of time to meet the demand. This kind of situation, however, creates an opportunity for market segmentation, and a price structure that attracts more customers who are higher on the “willingness to pay” spectrum.
- *Advance Consumption Decisions*. Consumers routinely reserve the product before they use it.
- *Censored Demand Observations*. Both demand processes are stochastic, and observations are likely to be censored or constrained due to product availability and/or pricing constraints.

While it might not be obvious, the apartment industry distinguishes itself with its own unique features:

- *Longer Lengths of Stay*. The most obvious difference between hotel and apartment-rental firms is that apartments have extremely long length of stay. Hotel guests usually stay just days, while apartment residents typically stay for months. A hotel RMS can create pricing strategies to dynamically control a guest's length of stay. Doing so enables a hotel to avoid losing a week-long customer because it already sold too many one-night stays. An apartment-rental firm can also vary lease terms to maximize value, but not to the same degree as hotels, due to the inherent characteristic of the lower volume of transactions. In addition, the characteristic of a long life-cycle of product consumption in the apartment industry has added extra modeling complexity. For example, an apartment RMS has to take into account the diverse likelihoods of customer behavior, such as early termination of leases, due to its longer-length-of-stay characteristic. On the contrary, a hotel RMS often focuses on customer behaviors prior to product consumption because of the relatively short average length of stay.
- *Fewer Transactions.* In contrast to the hotel industry, an apartment-rental firm has less traffic and thus fewer transactions. For every hundred transactions that an apartment firm has, a hotel may have thousands. An RMS is a statistically based system. The more data we have, the more accurate the system will be. In the implementation of any RMS, the transaction data are often aggregated into certain levels on which the data share a set of common attributes. When the number of levels increases, the amount of data in each level would decrease. This kind of situation with sparse data will prevent us from obtaining accurate estimates. This problem is also known as the "curse of dimensionality" (Härdle, 1990).
- *No Repeat Customers.* An apartment firm rarely sees the same resident move back in again once he/she moves out. In contrast, it is common for a hotel to see repeat customers. In order to better accommodate these customers, the concept of customer relationship management has been proposed to integrate with the existing RMS in some hotel firms (Noone, *et al.*, 2003).
- *More Renewals.* Hotel firms rarely have "renewals". Most of their guests stay for the exact number of days as they have planned before. It is uncommon for them to "extend" or "renew" to stay extra nights. However, it is very common for apartment tenants to extend their stays. Apartment customers often make monthly payments for a period of time and then decide whether to re-commit for another term at the same or different rate.
- *More Risky Decisions.* With typical hotel transactions usually being a length of stay no more than one week, each transaction only represents a very small fraction of a hotel's total annual inventory. In contrast, a typical apartment lease often represents a length of stay for months. It ties up a much larger portion of the firm's total annual inventory. In addition, in the apartment universe, the initial lease price influences the subsequent rate and probability of a renewal. Therefore, each apartment transaction is more important and more risky than a typical hotel transaction.
- *No Group Booking*. Group booking is very rare for apartment firms, but it happens often with hotel firms when conferences are held or groups of

vacationers arrive. A hotel RMS has to integrate some group optimization functionality to decide if it is profitable to accept a group booking or not.

- *No Over-Booking*. Over-booking is a well-studied and widely used technique to assure the maximum utilization of inventory in hotel and airline RM industries. The applicability of this technique is critically built on a specific business practice: the separation of a reservation from a particular room or seat. For instance, when a guest books a hotel room, he will not be assigned a room number until he checks in. However, this kind of practice does not prevail in the majority of apartment firms. When prospective residents make a reservation, they are typically given the unit numbers that they will move into later. This kind of situation makes it difficult for an apartment firm to adapt the over-booking technique. Luckily, no-shows or cancellations happen less frequently in apartment industry, in which over-booking becomes less critical.
- *No Walk-ins*. In the hotel industry, a significant number of customers often walk in and check into rooms on the same day. This walk-in situation has added complexity to demand forecasting. In order to get accurate demand prediction, a hotel RMS often updates demand forecasting more frequently. Apartment firms rarely have walk-in customers. This allows for less frequency to perform demand forecasting.
- *Concessions*. Apartments may offer "concessions" as incentives to attract and retain customers. Typically, there are two kinds of concessions: upfront and recurring. Upfront concessions are offered when the customers sign new leases, such as "free rent for the first month." Recurring concessions are amortized evenly over the entire period of stay after customers have moved in, such as "$50 off each month." In the implementation of an apartment RMS, often the "base effective rents," which are the net rents without amenities and concessions, are considered.

This examination shows that apartment-rental firms lack the characteristics of over-booking, group booking, repeat customers and walk-ins that hotel firms have; but it would be deceptive to conclude that it is easier to implement an apartment RMS than a hotel RMS. The distinct features of a low volume of transactions, long lengths of stay, and extended decisions during consumption in the apartment industry present new challenges to traditional RM methodologies used in hotels and other industries.

To our knowledge, very few papers in the literature deal with the issue of these features. Lieberman (2004) points out the similar issue of a low volume of transactions in "non-traditional" RM industries, such as commercial real estate and self-storage, which have started to explore RM opportunities.

MODULES

The levels of demand, inventory and market in the apartment sector vary over time, and managers are forced to act or react by dynamically adjusting rental rates as uncertainty reveals itself. This system described here is thus modeled to forecast demand, inventory and market changes over a finite planning horizon, and to apply an estimation of price elasticity of demand to explore the opportunity to optimally set rental rates.

Specifically, this dynamic pricing system formulates and solves a mathematical programming problem in an attempt to optimally balance demand and inventory while taking into account the market situation. This system can be regarded as the stochastic version of "dynamic price model with multiple products" with an extension to market competition (Bitran and Caldentey, 2003).

The system consists of seven interdependent modules: Data Aggregator, Statistics Updater, Supply Forecaster, Demand Forecaster, Reference Rent Calculator, Rent Optimizer, and Rent Recommender. It can be operated in a user-defined frequency, typically being in daily batch run or on demand. Figure 1 illustrates the relationships among these seven modules.

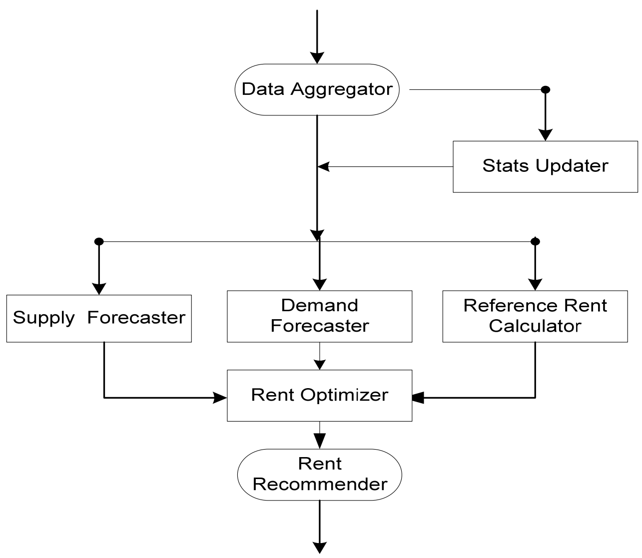

Figure 1. Module Relationships

In this section, we describe the functionality of each individual module. We begin our description with the Data Aggregator module.

Data Aggregator

The Data Aggregator is the critical link between legacy property management systems and the RMS. It defines and builds the basic data elements that will be used by other modules. A data element is the most discrete and controllable unit that the system will deal with. It is characterized by three dimensions: Unit Category, Lease Term Category, and Move-In Week.

Unit Category is defined as the collection of apartment units with a common property-specific attribute such as the number of bedrooms.

Lease Term Category is defined as the bucket of lease terms, which is similar to the length of stay in a hotel RMS. It is also property-specific. For instance, we can define three lease term categories: short, medium and long. Short may contain the lease terms of 1 to 3 months, medium terms of 4 to 9 months, and long terms of 10+ months.

Move-In Week is defined as the “week” when a prospective resident would move in. The meaning of week is not necessarily a calendar week. For example, Move-In Week could be defined as the days from Thursday to Wednesday. Furthermore, it can also be characterized by Week Type and Month Type attributes. A Week Type can be defined as the beginning, middle, or end of a month, respectively. It is analogous to the day of week commonly used in a hotel RMS. In a similar manner, a Month Type can be defined accordingly.

Based on the three data dimensions defined above, transaction data from an apartment’s property management system will be fetched and aggregated periodically. The system takes into account a number of transaction types such as move-ins, move-outs, notice-to-move-outs, guest cards, leases, etc. These transaction data will be used in the calculation of demand forecast, supply forecast and business statistics. Two kinds of transaction data are described: guest cards and leases.

A guest card transaction records what a prospective tenant prefers. Guest card information may include the desired move-in and move-out dates, the preferred unit type, the monthly rents and concessions offered, and so on. A guest card is said to be realized when the prospect signs a lease and becomes a tenant. A realized guest card is always tied to a particular apartment unit. On the other hand, a guest card is said to be unrealized when the prospect does not sign a lease. Any unrealized guest card is not associated with any particular apartment unit.

A lease transaction represents a realized guest card and records the action of a resident. A lease transaction contains information such as the apartment unit number that the resident leases, the actual move-in and move-out dates, the number of months of the lease term, and so forth. A lease transaction always associates the resident with a specific, dedicated unit.

A wide variety of information can be derived from the aggregated transactions, including the numbers of guest cards, move-ins, move-outs, early terminations, available units, and so on.

Statistics Updater

The Statistics Updater module estimates a number of business statistics based on the aggregated historical data. Each of the statistics is estimated in the appropriate dimensions of aggregation such as Unit Category, Lease Term Category, Week Type, and Month Type. These statistics are used for two purposes. One is to provide an informed description of how business has been recently, the other is to feed the statistics produced by the module into the subsequent modules.

The business statistics estimated by the module include:

- Demand and Rent Seasonality, which depict the effects of different seasons on demand and rent. Apartment reservation data commonly exhibits a high degree of seasonality. For instance, demand during the summer season usually appears higher than other seasons in the northern markets.
- Demand Average, which represents the estimates of the average de-seasonalized demand by removing seasonal factors.
- Booking Pace Curve, which characterizes the pace at which demand arrives during the booking horizon by days left prior to a move-in week.
- Early Terminations, which estimates the number of leases that might be terminated early.
- Renewal Fraction, which approximates the fraction of expiring leases which are likely to be renewed.
- Average Lease Term, which describes the averages length of lease terms.

In estimating each of these statistics, observation data are pooled in a proprietary approach in an attempt to circumvent the data sparseness issue. It is worthwhile to address the issues of demand unconstraining.

Demand Seasonality, Demand Average, and Booking Pace Curve statistics all use the data of unconstrained demand. Data censoring is commonly seen in RM. For example, Liu, *et al.* (2002) list three censoring constraints: capacity limitation, stay controls, and rate controls. There are a variety of papers that address the issue of demand unconstraining. Talluri and Van Ryzin (2004) review some parametric and non-parametric approaches to correcting censored demands.

Although demand unconstraining has become an important process in RM practice, no rigorous definition of unconstrained demand has been given in the literature. Unconstrained demand is often described as the "true" demand that would be satisfied if there were no censoring limitations *within a rate class*. However, under the context of dynamic pricing RM, this description seems inappropriate, because no specific rate classes are defined and used.

Therefore, to meet our needs, we define unconstrained demand as the demand for the reference rent that would be realized if there were no capacity limitation. In other words, unconstrained demand would be observed when inventory were available and the offered rate happened to be the same as reference rent. Reference rent is defined here as the "economic value" of an apartment unit in the marketplace, which is often perceived from the viewpoint of an apartment operator. It is analogous to the concept of "rack rate" in the hotel industry. The actual rental rates offered are often optimized around the reference rents.

Denote $d\ (t,r)$ as the unconstrained demand for the reference rent r at time t. Given the definition of unconstrained demand above, it would be easy to identify a censored demand if the reference rent were known. In reality, however, the reference rent is unknown. We use $\hat{r}$ to denote its estimate. In the "Reference Rent Calculator" section below, we describe how to estimate the value of $\hat{r}$. In addition, denote p as the offered rate at time t, which is observable and known. An estimator for unconstrained demand $d\ (t,r)$ can be expressed as follows

$$\hat{d}\ (t,\hat{r}) = \hat{D}(t,p)\ G(\hat{r},p)$$

where $\hat{D}(t,p)$ represents the estimate of unconstrained demand for the offered rent p, which is only censored by the capacity limitation. $G(\hat{r},p)$ is the estimate of the price elasticity effect, comparing the offered rent p with the estimate of reference rent $\hat{r}$.

Note that although the estimation of $\hat{d}\ (t,\hat{r})$ involves the use of the published rate p, we expect that a good estimate of $\hat{d}\ (t,\hat{r})$ should be invariant of the value of p used. In addition, $\hat{D}(t,p)$ and $G(\hat{r},p)$ should be non-increasing and non-decreasing, respectively, when p increases for a fixed $\hat{r}$.

The estimation of $\hat{D}(t,p)$ can adapt some existing unconstraining approaches such as the expectation maximization method (Dempster, *et al*. 1997). The estimation of $G(\hat{r},p)$, on the other hand, relies on the underlying assumption of elasticity model. When elasticity $\beta(<0)$ is assumed to be constant, one approach to estimate $G(\hat{r},p)$ can be formulated as

$$G(\hat{r},p) = 1 - \beta\left(1 - \frac{\hat{r}}{p}\right)$$

It can be easily seen that $G(\hat{r},p) = 1$ when $p = \hat{r}$; $G(\hat{r},p) > 1$ when $p > \hat{r}$; and $G(\hat{r},p) < 1$ when $p < \hat{r}$. In addition, it can be shown that this function of $G(\hat{r},p)$ is increasing with respect to p as expected.

Figure 2 illustrates an example of price elasticity factor. Assume that the value of elasticity β was -8, and the value of reference rent estimator $\hat{r}$ was fixed as $1000. Consistent with the above argument, the factors of $G(\hat{r},p)$ is increasing as the rent of p increases.

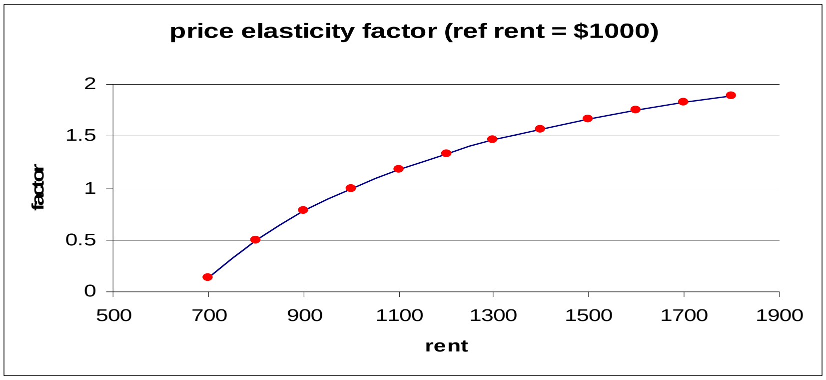

Figure 2. Price Elasticity Factor

Demand Forecaster

The Demand Forecaster module predicts the remaining unconstrained demand for a finite planning horizon, which will be fed into the Rent Optimizer module. A remaining unconstrained demand forecast represents the level of demand that will arrive at the reference rent, disregarding the constraint of inventory availability. An important virtue of demand is based on the assumption that customers making reservations may identify themselves by three quantities: the booking day, the length of stay and the move-in week.

It is well known that forecasting accuracy will significantly impact the profits of the RM industry. Research on the appropriate RM forecasting techniques has thus received extensive attention from both academic and industrial researchers; but most of the published papers are related to hotel and other RM industries. As the time of this writing, no literature on forecasting modeling has been found for the apartment industry. The inherent problem of data sparseness in the apartment RM industry presents challenges to finding the appropriate RM forecasting techniques.

A heuristic forecasting model is used to predict the unconstrained remaining demand on the level of Unit Category, Lease Term Category, and Move-in Week. The basic assumption underlying this model is that a similar pace of historical demand would be followed. This modeling procedure is similar to the methodology of pick-up forecasting strategy (Talluri and van Ryzin, 2004), but is formulated in top-down manner. The idea behind the pick-up method is to predict incremental bookings over short intervals of time prior to service based on recent booking activity, and then aggregate these increments to obtain a forecast of total demand to come. On the contrary, our method estimates the total demand and then disaggregates the remaining demand based on related statistics.

Supply Forecaster

The Supply Forecaster module predicts the numbers of units available for lease for a finite horizon of future weeks. This module does not take into account an over-booking strategy as in the hotel industry. Specifically, the weekly inventory for a given future week is equal to the number of capacity minus the number of units to be occupied, plus the number of units to be vacant.

The units to be occupied represent those units that will be dwelled by both current residents and prospective tenants. The prospective residents here consist of either new leases to be signed or renewal leases to be extended. The number of renewal leases is estimated by applying the statistics of renewal fraction to the number of expiring leases from current or future residents. The units to be vacant, on the other hand, denote any occupied units that might become available due to any early termination of leases.

Reference Rent Calculator

The Reference Rent Calculator is a module to estimate reference rents. From an apartment RM aspect, setting reference rents establishes the base threshold around which optimal rental rates will be determined. In other words, optimal rents will be derived from reference rents as the result of balancing demand and supply under the objective of maximizing revenue growth.

In actual implementation, the reference rents for the current day are estimated on the level of Unit Category and Lease Term Category, which will be projected into future Move-in Weeks by using the rent seasonality statistic. A number of methodologies can be used to estimate the reference rents. One method can be to use surveys along with expert judgment, but this approach tends to be subjective, costly and biased. An alternative is to utilize a rule-based approach. This method utilizes a set of business rules based on the values of some specific indicators. The indicators are selected to better reflect the reality of a property and its competitive influences. The use of indicators breaks the limitation of a traditional RMS to rely on internal data only. Two main indicators are described as follows:

- Market Composite, which reflects current market pricing. Estimating market composite involves identifying the “right” competitors, shopping their current rates, positioning their rates, and weighing their relative importance. This indicator enables an apartment firm to understand and respond to customer behavior in an informed manner.
- Leasing Velocity, which gauges the speed that exposed units are being leased. For instance, if the value of leasing velocity is too high, i.e., the exposed units are being leased too fast, it is reasonable to suspect that the price being offered may be too low.

It is worthwhile to emphasize that the consideration of leasing velocity is helpful. Market composite merely reflects the external market changes. By only taking into account this indicator, we are unable to justify the estimated reference rents, especially when the estimation of market composite is skewed.

An extreme example is to assume that all competitors were making an irrational decision by dramatically dropping their rents. The corresponding market composites would become small, which could thus produce low reference rents. However, when considering the performance of leasing velocity, if we see that units are already being leased too fast, we might not want to follow our competitors to decrease the reference rents. That is, we now have an additional indicator to validate the rationality of this rate descreases.

The addition of leasing velocity is in essence an attempt to fine-tune the estimation of reference rents. It protects us from the abnormal changes of outside world. Furthermore, we will see that leasing velocity also complements the restrictive capability of Rent Optimizer in the next section.

Rent Optimizer

The Rent Optimizer module calculates optimized rents, from which the optimal rental rates will be derived in the Rent Recommender module.

This module formulates a revenue optimization problem. It attempts to set optimal rental rates around projected reference rents by balancing demand and supply forecasts. A crucial element embedded in the module is the use of price elasticity. Denote $\hat{r}$ as the estimate of reference rent, and $\hat{d}$ its corresponding unconstrained demand. When elasticity $\beta(<0)$ is assumed to be constant, the optimized rent p^* and its corresponding demand d^* will satisfy the following relationship

$$p^* = \Delta(\hat{r}, \hat{d}, d^*, \beta) + \left(1 - \frac{1}{\beta}\right)\hat{r}$$

where $\Delta(\hat{r}, \hat{d}, d^*, \beta)$ represents some monetary decrease, which is a monotonically decreasing function of d^*. In particular, $\Delta(\hat{r}, \hat{d}, d^*, \beta)$ tends to be zero as $d^* \to 0$, and $\Delta(\hat{r}, \hat{d}, d^*, \beta)$ tends to be $-\infty$ as $d^* \to +\infty$.

The range that optimized rents can vary is limited by the values of elasticity. It can be shown that the upper bound of optimal rents in the above model is $(1 - 1/\beta)\hat{r}$. According to this relationship, when the reference rents are set too low, the optimized rents cannot be adjusted as high as desired by this Rent Optimizer module. In other words, the use of elasticity requires that reference rents be appropriately estimated. For the example in the above section, it can be seen that the addition of leasing velocity does indeed help improve estimating reference rents, which will thus enhance optimized rent setting.

Rent Recommender

The optimized rates computed from the Rent Optimizer module are in the aggregation level of Unit Category, Lease Term Category, and Move-in Week. In actual leasing operations, however, prospective customers are offered optimal rates in the form of Unit Type, Lease Term and Move-in Week. The Rent Recommender module recommends optimal rents by disaggregating optimized rents.

Note that different pricing requirements on the distribution of optimal rates across unit types and lease terms can result in different disaggregating procedures. For example, one common pricing policy specifies that the optimal rates should be distributed in inverse proportional to the lengths of lease terms. That is, the longer the lease term is, the cheaper the optimal rent should be.

CONCLUSION

This paper describes the implementation of an apartment dynamic pricing system with particular emphasis on setting optimal rental rates for new leases.

As a conclusion, four benefits of using this system are summarized as follows

- Revenue maximization. Very few companies do not pursue revenue maximization as their ultimate goals. The objective of this system is consistent with those of apartment operators. This system has been successfully used in production environments by several leading apartment operators for six years. An average of a 3 percent revenue increase has been reported by these apartment operators.
- Profiting opportunity exploration. As described in this paper, this system takes into account market condition and competitor influence. During the high demand periods, this system will leverage higher base effective rents as anticipated. During the low demand season, on the other hand, this system will proactively identify the softening market, and react with the proper rent recommendation.
- Corporate process improvement. The forecasting capability of this system will help the apartment operators better understand the market. This enables apartment managers to foresee market change early, and make the right decisions. In particular, the use of this system will minimize the interfering from human beings, especially at the time when the contradicting outcomes are predicted from the apartment managers with different levels of experience.
- Disciplined pricing process. Embedded with the corporate pricing strategy, this system will allow apartment operators to make consistent decisions everyday.

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