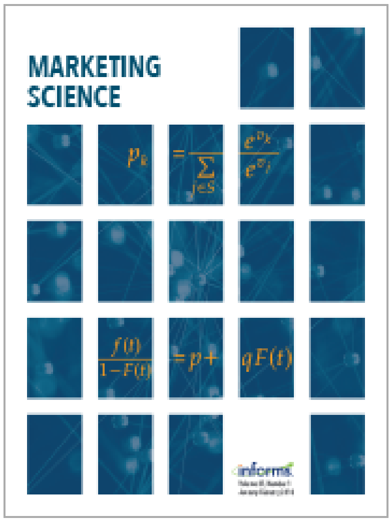

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Practice Prize Paper—PIN Optimal Distribution of Auction Vehicles System: Applying Price Forecasting, Elasticity Estimation, and Genetic Algorithms to Used-Vehicle Distribution

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Practice Prize Paper

PIN Optimal Distribution of Auction Vehicles System: Applying Price Forecasting, Elasticity Estimation, and Genetic Algorithms to Used-Vehicle Distribution

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In addition to retailing new vehicles, automotive manufacturers in the United States sell millions of vehicles through leasing and to fleet customers every year. The majority of these vehicles are returned to the automotive manufacturers at the end of the contracted term and must be "remarketed." In 2007, about 10 million used vehicles were sold at more than 400 auctions in the United States. Large consigners face decisions every day about when, where, and at what price to offer these vehicles, which has significant financial implications for their profitability.

To address the challenges of the distribution process, *Power Information Network* (*PIN*), a division of J.D. Power and Associates, developed the PIN Optimal Distribution of Auction Vehicles System (ODAV), an automated decision optimization system that helps remarketers maximize profits through the most advantageous distribution of their auction vehicles. At the core of the system is a combination of three models that determine the distribution of the vehicles on a daily basis: a nearest neighbor linear regression model for short-term auction price forecasting; an autoregressive integrated moving average time-series analysis model for volume-price elasticity; and a genetic algorithm optimizer for vehicle distribution.

Since its launch in 2003, PIN has been providing ODAV services on a daily basis, and to date, more than two million vehicles have been distributed through this system. In this paper, we will describe the PIN ODAV System, its implementation, and the business impact by using as an example the experience with our largest client, Chrysler Group LLC.

Key words: used vehicle; auction price; distribution; forecasting; optimization
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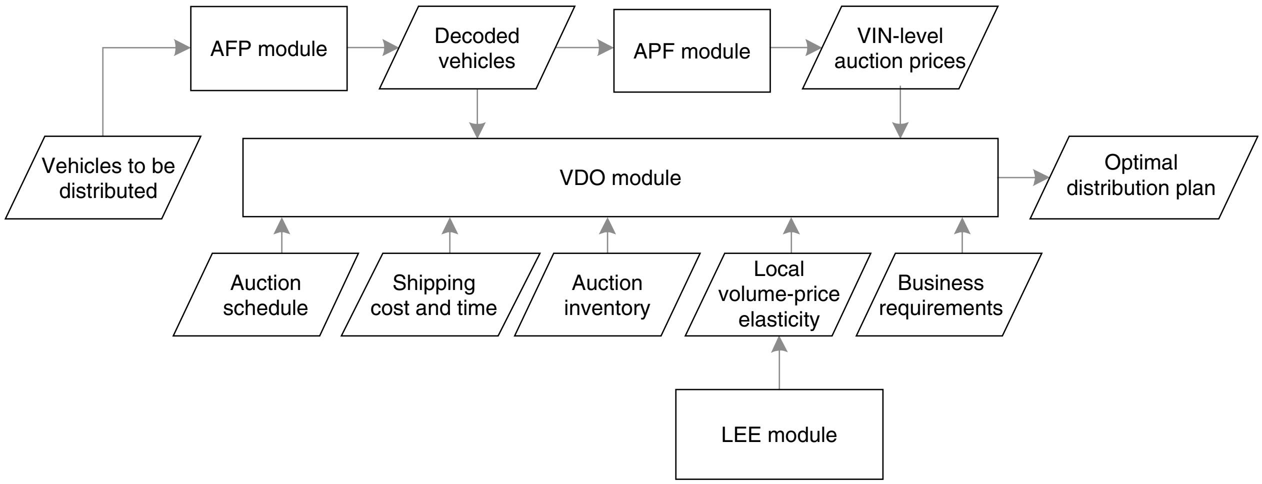
Background

Besides selling more than two million new vehicles annually to dealers and fleet customers, Chrysler Group LLC sells several hundred thousand used vehicles each year through auctions. The main sources of these used vehicles are lease returns, repossessions, and fleet returns from daily rental companies. Maximizing the profit of auction sales is financially critical for Chrysler because the auction profits (auction proceeds less remarketing costs) directly impact the profitability of current operations, as well as the ability to support future sales. If the auction profits are higher than the predicted residual values for the off-lease vehicles or the contracted buyback prices for the fleet return vehicles, Chrysler will improve profitability and be able to provide more attractive leasing and financing at a lower cost. In the event of a loss, Chrysler will have to offset the difference between booked and actual revenue of the past sales, which, in turn, will increase the cost of funding for future sales.

However, achieving high auction profits is a very complex challenge because of the unique characteristics of used vehicles, the vehicle return process, and the used-vehicle market, in general. First, no two used vehicles are alike. Depending on model year, mileage, condition, equipment, etc., the price and rate of depreciation among vehicles of the same make and model can vary by thousands of dollars. Second, because there are no fixed prices for auction vehicles, the supply and demand of vehicles at an auction determine the participating dealer's bidding behavior, which, in turn, determines auction prices. Third, the demand for certain types of vehicles shows strong regional and seasonal differences. For example, four-wheel-drive

Figure 1 Vehicle Distribution Optimization Process



(4WD) is virtually a "must-have" feature on sport utility vehicles (SUVs) in the northern part of the country; however, the demand for 4WD vehicles in the southern part of the country is low. The difference in auction price between the two regions can be as great as $2,000. Finally, the supply and demand of used vehicles, in general, can vary significantly by region and season. For example, the majority of rental-return vehicles are concentrated in the tourist and business centers, such as Florida and California, and rental companies typically defleet large numbers of vehicles after Labor Day when the summer travel season concludes, greatly exceeding the demand in those two markets at that time. In summary, the distribution of used vehicles involves a great deal of complexity and risk that needs to be handled every day.

In the case of Chrysler, the remarketing department needs to make a decision about the distribution of up to 3,000 units per day, six days per week, moving vehicles from 20 distribution centers to 24 auction locations across the country in time for weekly auction sales. In 2007, Chrysler sold 345,000 rental-return vehicles and lease-return vehicles, which is equivalent to 16% of its 2007 new vehicle sales.

The PIN ODAV System and Its Objective Function

The Power Information Network (PIN) Optimal Distribution of Auction Vehicles (ODAV) System is an automated decision support system designed to identify the optimal distribution of auction vehicles to maximize auction profits.

Figure 1 illustrates the process. When the file of vehicles to be distributed is ready at the file transfer protocol server of a client, the automatic file processing (AFP) module retrieves the vehicle information and decodes the vehicles via the Vehicle Identification Number (VIN) decoder and the sales code decoder. Data of the decoded vehicles are fed both to the vehicle distribution optimization (VDO) module for optimization and to the auction price forecasting (APF) module for auction price forecasting. The APF module also processes the sales history file. The sales records are used in the APF module and the local volume-price elasticity estimation (LEE) module as the sales history data set. The forecasted VIN-level prices at all auctions—along with auction schedule, shipping cost and time, current auction inventory, local volume-price elasticity coefficients, and business requirements—are also input for the VDO module. The output of the VDO module is an optimal shipping plan to maximize the overall net profit for these vehicles.

To achieve optimal distribution, the system must consider the following factors simultaneously:

(1) Vehicle price differences among the auctions included in a network;

(2) The seasonal changes of auction prices in a period of four weeks (the typical time between the vehicle distribution and auction sales);

(3) The current inventory levels at auctions;

(4) The volume impact on auction prices based on proposed vehicle shipment;

(5) The shipping cost and time;

(6) The time-related asset carrying costs of vehicles (interest cost and daily penalty for late payment);

(7) Various business constraints, such as truckload building and shipping route restrictions.

The objective function of the PIN ODAV System is defined in Equation (1). The solution that maximizes the objective function under business constraints is considered the optimal distribution plan.

$$\Pi = \sum_{v=1}^{N} (P_v^a + \Delta P_v^a - T_v^a) - \sum_{r=1}^{R} S_r, \tag{1}$$

where

$\Pi =$ The net auction profit of distributing N vehicles;
$P_v^a =$ The forecasted auction price for a vehicle v at an auction a;
$\Delta P_v^a =$ The auction price adjustment for a vehicle v at an auction a because of vehicle shipment;
$T_v^a =$ The time-related asset carrying cost for a vehicle v distributed to an auction a;
$S_r =$ The shipping cost for a route r. The summation is over the all routes R of the day.

The three key modules of the system (APF, LEE, and VDO) work together to solve Equation (1). In the following sections, we will briefly describe each module.

The APF Module and Nearest Neighbor Linear Regression

To solve Equation (1), we first need to forecast the auction price P_v^a at all auctions in the short term for each used vehicle to be distributed. Short term is defined as within the next four weeks, a typical time range for vehicle shipping and sale preparation. The auction price depends on a variety of independent variables that can be grouped into the categories in Equation (2).

$$P = \{\text{B, A, E, U, L, T}\}, \tag{2}$$

where

The vehicle brand category B = {segment, make, model, model year};
The vehicle attribute category A = {trim level, series, engine, transmission, drive type, body style, and doors};
The vehicle equipment category E = {leather seating, sunroof, entertainment system, color, etc.};
The vehicle usage category U = {age, mileage, condition};
The location category L = {auction location and region};
The auction time category T = {auction time, depreciation, seasonality}.

The following linear regression (LR) model is developed to estimate the impacts of the above independent variables:

$$P = a + \sum_{i=1}^{I} \alpha_i x_i + \sum_{j=1}^{J} \beta_j m_j + \sum_{k=1}^{K} \gamma_k t_k + \lambda n + \varepsilon, \tag{3}$$

where

P: Auction price;
a: The intercept of the LR;
I: The number of independent variables in the adjustments;
x_i: The ith independent variable of category B, A, E, or L in Equation (2);
α_i: LR coefficient for ith independent variable;
β_j: Mileage adjustment in a mileage band;
m_j: Mileage per age year in a mileage band;
J: Total mileage band number;
γ_k: Vehicle depreciation rate of an age band in price percentage;
t_k: Vehicle age in an age band;
K: Total age band number;
λ: The calendar month adjustments for seasonality;
n: $\{1, 2, \ldots, 11\}$, the calendar month dummy variable;
ε: The random error term.

Because some of the independent variables, such as color and region, have interactions, a composite variable for color and region is used. To model the nonlinearity of mileage and age, these are broken into different bands. The impact of each band is estimated. We use five mileage bands for all vehicles. However, the boundaries of the bands are dependent on vehicle model and model year. We use three age bands, with the first for the nearly new vehicles and third for the older (>8 years old) vehicles to account for different depreciation rates. Market factors such as gasoline price and new-vehicle incentives also affect the auction price. However, we cannot include them in the model because they are usually published one month later, which is too late for short-term price forecasting. Instead, we use a nearest neighbor filter (NNF) to capture the effect of market factors as much as possible.

At the earlier modeling stage, we created a linear regression model with all independent variables and tried to estimate the coefficients based on the entire sales history. However, we found two issues with this approach: (1) The model is not responsive enough to the current market changes, especially in light of missing some of the market factors; and (2) we ran into sample size issues for certain variables, such as unusual exterior colors. We designed a nearest neighbor linear regression (NNLR) scheme to overcome these issues. In the NNLR, the price of a used vehicle is estimated in the following steps:

Step 1. Estimate LR coefficients for age, mileage, condition, month dummy, auction location, exterior color, and region at the segment level, using multiple years of sales history data. Vehicle segment, such as SUV, is a class of vehicles with distinct characteristics. We assume vehicle price behaves similarly to the variation of the above inputs within the same segment. The coefficients are estimated periodically and stored in a database for daily use.

Step 2. Estimate coefficients of vehicle optional equipment to auction price at the segment level, using multiple years of sales history data. If the coefficient of a type of optional equipment cannot be reliably estimated from sales history, the coefficient is calculated using the manufacturer's suggested retail price and the segment depreciation curve. These coefficients are estimated periodically and the results are stored in a database for daily use.

Step 3. The coefficients of market-sensitive independent variables in categories B and A are estimated daily. However, we only use the sales history data of vehicles that are in the nearest neighbor of the vehicle to be priced, rather than the entire sales history data. A vehicle is regarded as a near neighbor of the vehicle to be priced if it (1) shares the same make, model, model year, drive type, and body style; and (2) was sold within the most recent three months at the same auction for which the vehicle is to be priced. We first apply a NNF to the sales history data to select the vehicles that are in the nearest neighbor of the vehicle to be priced. After adjusting the sales price of each vehicle in the nearest neighbor data set for different independent variables described in Steps 1 and 2, we run another LR model to estimate the coefficients for variables in category A. The variables in category B are eliminated by using NNF, because all vehicles in the nearest neighbor share the same segment, make, model, and model year. A minimum of 50 vehicles is required for the estimation; otherwise, various fallback schemes are used to increase the sample size. These schemes expand the data set from vehicles of the same model and model year at an auction in the past three months to the same segment and all model-year vehicles at all auctions in the past six months, with appropriate adjustments of different models, model years, locations, and sales months. In the rare case when there are not enough data available, default values are assigned for the coefficients. These default values are based on empirical study.

Step 4. With all the coefficients, we can now estimate the auction prices in the next four weeks for all vehicles in the nearest neighbor by adjusting the actual auction prices for the differences in their values of independent variables and the values of the vehicle to be priced.

Step 5. The final forecast price is the weighted average of the estimated prices of individual vehicles in the nearest neighbor data set. We usually use 50%, 30%, and 20% for vehicles sold one month earlier, two months earlier, and three months earlier, respectively.

The most significant advantage of applying the NNF to the sales history data prior to the regression is that it results in a model that is very responsive to local market changes that are otherwise very difficult or impossible to capture. The NNF also increases the computing efficiency of the daily price forecasting by reducing both the sample size and the independent variables in the model. The LR model is chosen because of its robustness, efficiency, and clear explanation of impacts of independent variables. These are the desirable properties for both the daily production and for client consultations.

Because consigners must sell vehicles as quickly as possible after they arrive at an auction location, the supply—or inventory level—has direct impact on auction prices. If more vehicles are offered than there is a demand for, the consigners must reduce the prices to sell them. Conversely, if the demand is higher than the supply, the auction prices will increase. We do not include the inventory level as an independent variable in our pricing model, but rather include it instead in the optimization stage as a price adjustment, because of the fact that the distribution will change the inventory level. We forecast the auction price based on normal auction sales volume, then adjust forecasted price to the degree of deviation from normal sales volume by local volume-price elasticity (the topic of the next section). In our NNLR with elasticity adjustment, there is no feedback from auction prices to sales volume because it is not a common practice in auto auctions to sell vehicles at a fixed-price target. Therefore, the issue of endogeneity that often exists in naturally occurring data does not apply in our case.

The LEE Module and ARIMA Procedure

The auction price P_v^a is a forecast based on the normal sales volume at an auction. However, after we distribute vehicles to the auctions, we introduce an auction supply change that, in turn, causes an auction price change ΔP_v^a for a given market demand. We define the local volume-price elasticity coefficient, or simply elasticity, as Equation (4).

$$\varepsilon = \frac{dP^a/P^a}{dV^a/V^a} = \frac{d\log(P^a)}{d\log(V^a)}, \tag{4}$$

where

$P^a =$ The average auction price at an auction a for a vehicle type, and

$V^a =$ The auction sales volume at an auction a for a vehicle type.

Here, a specific vehicle type is defined as a combination of vehicle make, model, drive type, and body style. Equation (4) is the inverse of the traditional elasticity definition in economics and marketing science, in which demand is stimulated by manipulating price (Hall and Lieberman 2001). At auto auctions, the supply drives the auction price. We estimate elasticity ε weekly from the most recent two years of sales history data by creating two time series: (1) the average sales volume at a given auction, and (2) the average sales price at the same auction after controlling for vehicle differences in mileage, condition, equipment level, and age. The autoregressive integrated moving average (ARIMA) scheme (SAS Institute 1999), based on the Box and Jenkins (1976) model, is used to estimate the interaction, or the elasticity ε, of the two time series in the form of Equation (5):

$$\ln(P_t) = \mu + \varepsilon \ln(V_t) + \frac{\theta(B)}{\phi(B)} a_t. \tag{5}$$

In this equation, P_t is the auction price, V_t is the sales volume, μ is the intercept, a_t is the independent disturbance, $\theta(B)$ is the moving average operator, and $\phi(B)$ is the autoregressive operator. The model for each vehicle type is calibrated each month.

After elasticity ε is determined, the auction price elasticity adjustment ΔP_v^a can be calculated by

$$\Delta P_v^a = \varepsilon \frac{V^a - \overline{V}^a}{\overline{V}^a} P_v^a, \tag{6}$$

where

V^a = The auction inventory at an auction a for a vehicle type after distribution, and
$\overline{V}^a$ = The average sales volume at an auction a for a vehicle type.

The VDO Module and the Generic Algorithm

The objective function (Equation (1)) represents an NP-hard combinatorial problem. The function itself is nonlinear and complicated. Because the elasticity price adjustment ΔP_v^a depends on the vehicle distribution, it introduces the nonlinearity to the objective function. The asset-carrying cost term T_v^a in Equation (1) accounts for the interest rate charge of the fund or the daily penalty fee for late payment to the rental companies. Although this term can be readily calculated by the daily charge and days to the next auction, it introduces discontinuity to the objective function. Because auction sales usually occur weekly or biweekly, if a shipment is not delivered in time for the next auction, it must be held one or two extra weeks until the following auction. The shipping cost term S_r is another term that causes complexity in the objective function. The shipping rate is based on full truckloads of eight vehicles. Therefore, the per-vehicle shipping rate changes based on how many vehicles are loaded on a truck. The shipping rate reaches the minimum per vehicle when a truck is fully loaded. The changing shipping rate per vehicle creates a "sawtooth" landscape in the optimization search space or numerous local optima. Therefore, there are no theoretical solutions to the objective function (Ausiello et al. 1999). Among various approximation methods, we chose the genetic algorithm (GA) not only because of its robustness to generate a better solution and efficiency of optimal search, but also because of its flexibility and relative ease to implement business constraints.

In the ODAV GA implementation, a genome is defined as a collection of classes of vehicles to be distributed. One of the class variables is the vehicle destination. Therefore, a genome represents a distribution plan. The objective function is the net profit defined in Equation (1). The fitness of the genome is defined as the net profit adjusted by soft constraint satisfaction factors. A fixed number of genomes form a population. Five specially designed genetic operators are used to create new generations of the population: selection operator, mutation operator, crossover operator, switch operator, and block move operator. A traditional GA is used to perform the optimal search. It starts by randomly assigning available auction destinations to each gene of a genome in the population. Next, the population is evolved by the generic operators described above. The fitness of each new genome is then calculated. If the convergence criterion is satisfied, the GA search is terminated and the results are output. Otherwise, the evolution continues. In the ODAV GA search, the convergence criterion is that the changes of fitness of the healthiest genome in the population are within a predefined range in consecutive generations.

The optimal auction vehicle distribution plan has to meet all business requirements. We implemented them as hard or soft constraints in the GA optimizer as follows:

- Hard constraints *must* be satisfied, e.g., closing a shipping route. The information on all available routes is stored in a database table for the optimal search. When a route is closed, its corresponding entry is removed from the table, eliminating the route from the optimal search space.
- It is encouraged, but not required, that soft constraints be satisfied, e.g., meeting auction-suggested target volume. The fitness of a genome is penalized by how far the inventory after shipment to an auction deviates from the target volume.

The hard and soft constraints give us the ability to handle a variety of business requirements in the distribution optimization, such as auction volume support, promotion sales support, and cost control. However, the constraints cause difficulties for the GA process to converge to the global optimum. To increase the efficiency and accuracy of the solution, the following three techniques are used in the algorithm to accelerate the convergence:

(1) *Using the decoder for shipping route constraints*—The most common operation in GA operators is to

sample an available auction based on a uniform probability density function. That sampled auction becomes a new destination for a vehicle. If the route from the distribution center to the sampled auction is closed, that auction is rejected and a new one is sampled. To avoid wasting time in selecting an unavailable destination that is later rejected, we dynamically create an available destination array for each distribution center and only sample the available auction destinations. The decoder technique increases the solution efficiency by providing information on how to build a solution (Michalewicz 1999).

(2) *Sorting vehicles by distribution center and vehicle line before optimization*—Both the schema theorem and building block hypothesis suggest that a GA seeks near-optimal performance through the juxtaposition of short, low-order, high-performance schemata (Goldberg 1989). Therefore the performance of a GA depends on the arrangement of the genes in a genome. To control shipping costs, a distribution center typically distributes vehicles to the nearby auctions. In addition, a shipment from a distribution center to an auction typically consists of vehicles from the same vehicle line. If we sort the vehicle by distribution center and vehicle line, and then arrange the genes in a genome accordingly, there is a greater chance of creating those short building blocks in the optimal search.

(3) *Turning on truckload penalty at a later stage of the optimal search*—The truckload penalty in the objective function creates a sawtooth-like landscape in the search space and numerous local optima. To avoid the distractions from these discontinuities, the load penalty is turned on only when the optimal search has almost converged.

Implementation

The PIN modeling team started to develop the ODAV System in August 2001. We finished the first system by the end of January 2002 and continued testing and fine-tuning until the end of April 2002.

Chrysler Financial Services (CFS), the financial arm of Chrysler LLC, piloted the PIN ODAV System between May 2002 and August 2002. During the three-month test, daily lease-return vehicles were randomly divided into two equal size sets, one sent to PIN for ODAV System distribution and the other distributed by CFS Remarketing. At the end of the pilot period, the net profits from both distributions were compared. The PIN ODAV System demonstrated a profit lift of $128 per vehicle, for a total net profit lift of more than $300,000.

Today, the PIN ODAV System is fully integrated into the corporate remarketing processes of Chrysler and other clients. Six days a week at 1:00 A.M., the system automatically retrieves information from each client's file server about vehicles to be distributed. The system then forecasts the auction prices of each vehicle at all auctions in the network and generates an optimal distribution plan based on forecasted prices, current inventory levels at auctions, auction sales, available shipping routes, auction schedule, and business constraints. The optimal shipping plan is sent back to each client's file server by 6:00 A.M. that same day. Each client retrieves its shipping plan and sends it to related shipping companies. By 8:00 A.M., the PIN ODAV System Web server is updated for review by each client's management team.

Since 2002, more than two million vehicles have been distributed through the PIN ODAV System. In 2006 alone, PIN helped clients manage more than 580,000 units, representing a total of $6 billion in assets. The PIN ODAV System has proved to be both reliable and efficient, demonstrating a shipping plan on-time delivery rate of 99%.

In addition, the PIN ODAV team provides clients with a full spectrum of support services, including strategic planning, operational metrics tracking, auction performance reporting, and profit lift analysis.

Profit Lift Evaluation

One of the most important metrics used to evaluate the effectiveness of a given distribution is the profit lift. If the PIN ODAV System distributes only part of a client's used-vehicle portfolio, the net profit of the vehicles from ODAV distribution can be compared to the net profit based on other distribution methods, as was done in the Chrysler Financial Services pilot.

This comparison is no longer possible after the full ODAV implementation. For purposes of continuous operational monitoring, PIN has worked with its clients to establish a baseline distribution based on the historical distribution pattern before the application of ODAV. The profit lift is calculated by subtracting auction proceeds and various costs of the baseline distribution from actual ODAV proceeds and costs. We estimate the auction proceeds of the baseline distribution by computing the average actual proceeds of the same type of vehicle at auctions. However, because the auction offerings in the baseline (without ODAV distribution) are different than the actual sales (with ODAV distribution), the baseline proceeds need to be adjusted to the supply changes based on Equation (5).

For example, assume the PIN ODAV System distributes 50 units from a distribution center to auction A and 50 units to auction B. The proceeds from auction A and auction B are $15,000 and $15,500, respectively. Based on the historical distribution pattern, we know that 80% of the vehicles at the distribution center go to auction A and 20% to auction B. Therefore the baseline auction sales volume at auctions A and B are 80 units and 20 units, respectively.

If the elasticity coefficients at both auctions are the same (0.05), the auction proceeds elasticity adjustment at auction A is $\$15{,}000 \times (-0.05) \times (80 - 50)/50 = -\$450$. This tells us to adjust the proceeds at auction A down \$450 from the actual proceeds because of the auction sales volume increase of the baseline (80 units) from the actual sales volume (50 units). Similarly, the proceeds at auction B need to be adjusted up by \$465. The average elasticity adjustment for these 100 units is $(-\$450 \times 80 + 465 \times 20)/100 = -\$267$. The baseline auction proceeds need to be adjusted down \$267. With the actual cost terms, auction proceeds, and auction proceeds adjustments of the baseline, we can readily compute the net profit lift of the ODAV System distribution.

Impact Statement

The PIN ODAV System can transform a company's used-vehicle remarketing process and turn challenging auction market conditions into a competitive advantage.

It enables clients to take full advantage of supply and demand dynamics of the auction market in the following five areas:

(1) *Financial results*—In 2006, the ODAV System generated an average profit lift of \$220 per vehicle for all clients. The lift came from a combination of arbitrage opportunities, better balance of supply and demand at auctions, and a profit-driven optimization process. Figure 2 lists the monthly profit lift report of one of our clients in the first half of 2007.

(2) *Operational efficiencies*—The PIN ODAV System frees remarketing managers from daily operational tasks so that they can focus more on tactical and strategic business decisions.

(3) *Improved operating cost*—The ability to ship vehicles daily and match supply with market demand reduces cycle time, which enables clients to take advantage of short-term market changes and reduce inventory carrying costs. Also contributing to operating cost improvement are lower administrative and transportation costs, streamlined remarketing processes, and reduced transportation costs through centralization of transportation decisions and negotiation of corporate (as opposed to local) service contracts.

(4) *Increased transparency*—Rather than relying on intuition and disparate data sources, the PIN ODAV System provides a single, data-driven, decision-making platform that provides the same level accuracy of information to all stakeholders (i.e., auction mangers, transporters, remarketing managers, and financial controllers).

(5) *Improved strategic decision-making capabilities*—The PIN ODAV System allows clients to simulate the distribution of upcoming inventories, changes in distribution strategies, and the effects of alternative distribution plans, which enable informed decision making and a new level of control over the remarketing operation. Clients are in a position to decide how to distribute vehicles, whether to optimize for profit or proceeds, and to evaluate the outcome of their decisions based on their choices.

Transportability

The ODAV System is not only an example of applied science, but it is also a business model. The transportability of ODAV can be viewed in the following three general ways:

(1) *How the combination of multiple models (LR, ARIMA, GA) can solve complex business decisions and provide an operational output*—Much like in other areas such as finance, sales, or production, remarketing includes tactical and operational aspects. ODAV combines models from various research and science disciplines to provide a front-to-end solution for the entire process, rather than just providing one piece of the solution.

(2) *A blueprint for similar business challenges that require the optimization of supply and demand*—ODAV solves the fundamental question, "Where should I sell a specific supply over a specific distribution network in a very short time?" For example, this also applies to the retail process. Today, no efficient process exists

Figure 2 Monthly Profit Lift Report

Sales summary	January 2007	February 2007	March 2007	April 2007	May 2007	June 2007	YTD
Units sold	27,524	26,091	25,601	13,339	10,770	9,633	112,958
ODAV proceed (\$)	13,575	13,647	14,156	14,485	14,906	15,593	
Baseline proceed (\$)	13,502	13,632	14,077	14,415	14,855	15,552	
Proceed lift (\$)	73	15	79	70	51	41	
ODAV shipping cost (\$)	149	156	182	149	112	145	
Baseline shipping cost (\$)	25	24	26	26	23	24	
Shipping cost change (\$)	124	132	156	123	89	121	
Elasticity adjustment (\$)	303	274	407	432	254	229	
Net ODAV lift per unit (\$)	252	157	330	372	215	150	
Total lift (\$)	6,936,048	4,096,287	8,448,330	4,962,108	2,315,550	1,444,950	28,203,273

that connects supplier-specific used vehicle inventory with dealer-specific demand to determine an optimal allocation. PIN is currently in discussions with clients to explore this opportunity as an extension of the ODAV service. Other areas inside and outside the automotive industry are the integration of new product pricing and promotion planning tools with sales and demand planning.

(3) *The successful commercialization of a service based on applied science*—From its initial goal of providing daily shipping plans, ODAV has developed into a remarketing service that includes the monitoring of daily distribution, performance reporting, and remarketing planning support. In 2008, ODAV will generate in excess of $1 million in revenue for J.D. Power and Associates.

Conclusion

The financial gains our clients have realized demonstrate that the PIN ODAV System is an effective solution to the very dynamic used-vehicle auction market. The NNLR model can accurately forecast auction prices for each vehicle by striking a good balance of modeling short-term market variation and long-term market trend. The local volume and price elasticity and its adjustment to the auction price can adequately capture the relationship of local supply and demand. The GA can produce an optimal or near-optimal distribution plan for as many as 4,000 vehicles within the operational time limit of two hours.

The success of the system also relies on the implementation process. We work closely with clients to continuously improve the process to meet their evolving requirements. In addition, we assign each client a dedicated consultant to provide production support.

The system effectively addresses the challenge of auction distribution, which is the final link in the remarketing value chain. We are currently researching extending the ODAV methodology to upstream applications.

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