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USING DISCRETE EVENT SIMULATION TO ANALYZE PRICING STRATEGIES FOR SAME-LOCATION CAR RENTALS

Abdullah A. Alabdulkarim

Mechanical and Industrial Engineering Department
Majmaah University
College of Engineering Building
Majmaah, 11952, SAUDI ARABIA

Ibrahim M. Al-Harkan

Department of Industrial Engineering
King Saud University
College of Engineering Building
Riyadh, 4545, SAUDI ARABIA

David Goldsman

H. Milton Stewart School of Industrial and Systems Engineering
Georgia Institute of Technology
Atlanta, GA 30332, USA

ABSTRACT

The car rental business is a multi-billion-dollar industry with ever-increasing competitiveness. Car rental companies must adapt dynamic pricing strategies to maximize revenues and operational efficiency. The aim of this study is to understand what pricing strategies work best for rental companies so as to achieve higher revenue for same-location pick-up and drop-off of rentals. With this goal in mind, we have modified a simulation model from a previous study to incorporate the logic for the current analysis. The analysis has been conducted with realistic customer demand inputs and a design of experiments consisting of 195 scenarios. The results show that with our improved pricing strategy, it is possible to increase revenues by more than 20 percent.

1 INTRODUCTION

The car rental industry is becoming more and more important in today's society. For instance, in 2015, in just the United States alone, the sector's revenue totaled $27.11 billion, representing a growth rate of 4% over the previous year. Moreover, the average car rental fleet growth rate stands at 5% (Auto Rental News 2015); this rate has held steady since 2010 and is forecasted to continue into the future (Oliveira et al. 2017).

Large car rental companies typically run their operations using similar business processes in this fiercely competitive industry. But despite the sector's positive economic growth prospects, the operations of car rental companies are risky and complex, especially because of the substantial overhead associated with the companies' large vehicle fleets. Thus, companies are constantly striving to enhance their operational efficiency. Unfortunately, the complex nature of such a large network of vehicles and stations makes it difficult for management to analyze and improve efficiency. One of the main factors increasing the complexity of such networks is the presence of significant and unexpected fluctuations in the demand for pick-up and drop-off locations of the cars. This issue makes it difficult for companies to guarantee the availability of their cars, even for customers having advance reservations. To address this potential problem, all major companies offer their customers incentives such as upgrades in case the desired car class the customer reserved is unavailable at the time of pick-up, and discounts for same-location pick-ups and drop-offs. These offers may seem necessary in order for car rental companies to maintain customers' satisfaction and loyalty. However, it is also important to understand the potential second-order effects of the incentives. For instance, upgrades may cause losses to the company due to missed opportunities of sales for higher classes; and same-location discounts may result in loss of revenue or unanticipated shortages at other stations. In any case, we have found that simulation is an extremely useful tool for analyzing and effectively enhancing this type of system with a view to increasing its efficiency, and ultimately improving it.

To increase the operational profitability and availability of each class of cars at each rental location, companies employ different pricing strategies to deal with and adjust the demand. In this paper, we develop a generic simulation tool that can be used to analyze a large car rental network. We then apply this tool on a realistic case study that embodies a minimum of 15 locations and five car classes. The paper aims to gain a better understanding of the effects of different pricing policies for each car class on the turnover (rental revenue) obtained within this complex operation. Furthermore, the tool can be used to analyze the effects on turnover of diverse strategies such as offering upgrades in case of unavailability and discounts for same-location pick-up and drop-off of rentals; we will concentrate on the latter incentive here.

Our simulation tool enables car rental companies to input their historical data into the system and analyze the effects of different pricing policies for each car class for their specific operations. This will ultimately allow the companies to better understand their operations, so as to increase their operational efficiency and the availability of cars at each location while maintaining high customer satisfaction levels.

The remainder of the paper is organized as follows. Section 2 presents additional background and motivation, as well as a literature review. Section 3 describes the methodologies used to develop the generic simulation tool, and then gives a detailed description of the features of the application. Section 4 presents a case study used to demonstrate our simulation tool and discusses the results. Section 5 concludes the paper. Some of the material in this paper is derived directly from Alabdulkarim (2018).

2 LITERATURE REVIEW

This section provides background material pertinent to the car rental industry, a discussion of different potential simulation modeling approaches, and some brief motivation on the suitability of discrete event simulation for the current work.

2.1 Background

Oliveira et al. (2017) review fleet and revenue management of car rentals. In light of the fact that there is only limited literature in the area, they propose research directions for fleet management of car rentals and noted a few problems that need to be fixed, e.g., the determination of the fleet sizes and the mix of types of vehicles (car classes) at each station. Fink and Reiners (2006) propose a realistic approach to the fleet size and mix problem and present a practical, implementable model to tackle various real-world issues that considers such issues as multi-periods, a country-wide network, and car groups with partial substitutability.

Yang et al. (2008), using Pachon et al. (2006) as a basis, review the car rental logistics problem and suggest various interesting future research guidelines, along with a focus on the vehicle-reservation task. The authors compare several specific issues with those faced by the airline industry and claim that some of these problems are applicable in both industries. However, there are significant idiosyncrasies related to the car rental business that require a more-detailed analysis of the sector, and there may be enough growth potential in this area to justify a more-elaborate approach to the proposed frameworks.

Incentives such as vehicle upgrades and same-station pick-up / drop-off discounts are no longer merely essential for the business; they are also necessary for proper model optimization formulation as well. For example, if there is no substitution allowed between car types, the model can be subdivided by class of vehicle, and the optimization complexity is considerably decreased; this is why some papers only consider the simplest one-car type with no upgrades (Li and Tao 2010; Haensel et al. 2012;You and Hsieh 2014). Nevertheless, a number of realistic models do consider various upgrading strategies. The choice of strategies is a trade-off in itself, since higher upgrade flexibility could result in potential short-term revenue losses vs. the potential advantages of better fleet utilization, higher customer satisfaction, and enhanced long-term revenue. The same can be said for pick-up / drop-off flexibility.

Since it is now possible to gather rental prices and other vehicle information in real time with rate-updating techniques via the internet (Oliveira et al. 2017), pricing is becoming more dynamic, substantially less complicated, and faster. With regard to this topic, Bitran and Caldentey (2003) review the principle pricing models in revenue management and highlight their significance within the context of capacity and inventory decision-making. They make the reasonable claim that prices are efficient variables to be used by managers for the purpose of controlling demand. Şen (2013) confirms that the use of dynamic pricing strategies may have an extensive effect on companies' revenues, even if certain dynamic heuristics are used to determine prices. Those papers emphasize the influence and benefits of this practice, which seemed at the time to be missing in the revenue management literature; this was specifically due to the techniques' inherent computational problems.

Simulation is of course a standard tool used to mimic complex operations in the presence of randomness. But, surprisingly, simulation has rarely been used in the car rental literature. To this end, we have developed a generic discrete event simulation (DES) tool to better understand and analyze such a complex car rental operating system. Although our tool is generic, we investigate a specific industrial case study to address the effects of allowing / encouraging same-location car pick-ups and drop-offs. In particular, our aim is to determine what pricing strategies work best for car rental companies so that they can achieve higher revenue arising from such same-location actions.

2.2 Different Modeling Approaches

Various mathematical modeling approaches from the fields of operations research and industrial engineering – including queueing theory, mathematical programming, and heuristic strategies – have been employed as analytical tools for a range of real-world applications. Unfortunately, these classical approaches sometimes suffer from several issues. For instance, the use of queueing theory for analytical models is often problematic when it comes to explaining the specific service mechanisms in use, the complexity of the system design, the nature of the queueing discipline, or a combination of these factors when one encounters a complication queueing network.

Simulation is one of the most widely used techniques for better understanding and analyzing complicated operations systems (Pannirselvam et al. 1999). According to Robinson (2004), simulation is "experimentation with a simplified imitation of an operations system as it progresses through time for the purpose of better understanding and enhancing that system." DES is simply a subcategory of simulation in which the simulation update mechanism and associated states progress through sequential events ordered by time. Sterman (2000) describes the complementary approach of System Dynamics (SD) as a specific form of continuous simulation, which uses a set of stocks and flows to represent a system. SD is applied at a strategic level where fewer operational details are required (Borshchev and Filippov 2004). If a system needs to be modeled in great detail, DES is often more suitable than SD, especially if individual items must be traced within the system (Robinson 2004). This is because SD is regarded as a bit more abstract and does not capture the detail of individual transactions (Sterman 2000). Agent-based simulation (ABS) has emerged as another popular simulation modeling approach. In ABS, a complex system is represented via a collection of agents, which are programmed to follow a few (often simple) behavioral rules (Shannon 1975). Consequently, ABS is oftentimes employed in social behavior modeling; but in the current paper, where process modeling is the dominant characteristic, we shall stick to DES as the most appropriate technique.

2.3 Suitability of Discrete Event Simulation

From the above remarks, we see that research in car rental settings has turned up unique issues compared to other similar sectors such as the airline industry. The DES approach is a technique that can capture the dynamic behavior of car rental operating systems, e.g., arrivals of customers, choices of destinations, etc. In this paper, we develop a novel generic DES tool that includes several branches of a car rental network and different car classes to better understand such a system; and we concentrate on the effects of various pricing strategies for car rental companies so that they can achieve higher revenue arising from same-location pick-ups and drop-offs (cf. Alabdukarim 2018, which discusses the consequences of upgrades in the presence of shortages within rental classes). We also present an industrial case to assess our simulation tool in a practical setting and to address different scenarios involving same-location pick-ups and drop-offs.

3 METHODOLOGY

This section concerns our simulation software tool. Section 3.1 discusses how we established the tool's requirements, Section 3.2 details its high-level capabilities, and Section 3.3 provides a description of the application's features.

3.1 Simulation Tool Requirements

In order to build a generic DES tool for evaluating complex car rental operations, we first needed to establish a set of tool requirements, in particular, with respect to the necessary inputs and outputs. We undertook several semi-structured interviews (see, for instance, King 1994) with academics and practitioners to establish such a requirements list. Five interviews were carried out with experts from academia and industry having backgrounds in simulation, operations management, and/or the car rental space. The interviews were conducted mostly face-to-face, although some telephone correspondence took place in certain cases. The interviews were carried out consecutively over three months, and they were concluded when the received responses added no new requirements to the tool.

3.2 Generic DES Tool Capabilities

The generic DES tool for our car rental system is an ExtendSim (2018) application, which we feel incorporates adequate flexibility and can be tuned to any car rental system of arbitrary size. The software was selected due to its robustness and ease of use. The DES tool has no practical limitation on the number of locations and car classes (categories) in the system. It has a simple interface, which users with no simulation background can easily use via an Excel spreadsheet. The tool can work in three different modes:

- Reading car rental data from Excel and generating demand accordingly;
- Creating car rental data based on random distributions for
    - Customer arrival times,
    - Rental durations (and drop-off times),
    - Differences in times between reservations and rental starts,
    - Customer types (walk-in or by reservation),
    - Percentages of customers requesting each car category,
    - Pick-up location preference percentages, and
    - Drop-off location preference percentages; and
- Reading car rental data entered from Excel and generating random additional car rental data.

In addition, the DES tool can facilitate various types of operational rules that the rental enterprise can try out, e.g., the number of upgrade levels to be offered to customers if the car class they asked for is unavailable at the pick-up time, or different decisions involving same-location pick-up / drop-off actions. Operational rule selections are as easy as clicking appropriate buttons in the main user interface. Moreover, the user can also decide on the precision (desired standard errors) of the estimated mean values of the turnover; and then the simulation model runs replications until the relative error for the calculated mean of the turnover is less than the value entered by the user.

3.3 DES Tool Description

The following subsections serve as a mini-manual on how to use our generic DES tool for complex car rental operations, along the way describing the inputs of the simulation model.

3.3.1 Interface

Surprisingly few people in the car rental industry are familiar with the use of simulation software packages. To allow practitioners to easily use our tool, we developed an internal interface for data entry. The interface is composed of four sections – the buttons on the left side, the simulation model at the center, the main inputs at the bottom left, and the results at the bottom right corner, as depicted in Figure 1 and as explained in detail in the following subsections. We first describe the various buttons and their functionalities.

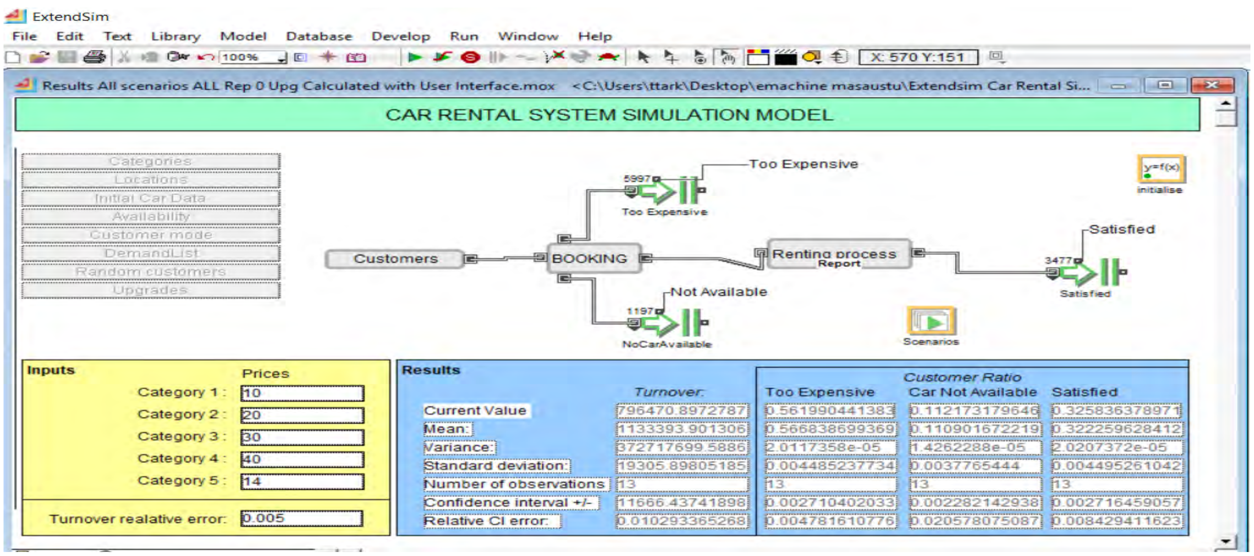

Figure 1: Car rental system simulation model interface.

3.3.2 Categories Button

We use the categories button to define the car classes (categories) in the system. The user can define as many classes as desired. When the user clicks on this button, a pop-up menu appears. Here, the user inputs the class name and price of each category. The percentage column is effective only in the mode when the demand data are created randomly and represents the percentage of customers requesting each car class. “MaxPrice” represents the distribution and mean for the budget of customers asking for that car class. The class prices can instead be entered via the main user interface screen without clicking any buttons.

To add new car classes, the user can simply right click anywhere in the table and choose the “Append Rows” option. A window will pop up asking how many rows (car classes) will need to be appended to the table. The user can add as many car classes as desired and input the values for all the columns in the appended rows. If the user wishes to reduce the number of car classes, he selects the row(s) to be deleted by left clicking on the record # values of the relevant row(s). Then, it is necessary to right click and select the “delete selected rows” option.

3.3.3 Locations Button

Here the pick-up and drop-off locations in the system are defined. Users can add as many locations as they need to and delete existing locations, in a manner similar to that described in the previous subsection. Pick-up and Return Probability columns are required only for the random demand generation mode.

3.3.4 Initial Car Data Button

The initial car data button is where the data regarding the numbers of cars available for each car class at each location at the beginning of the simulation are entered. Initially, as a crude default, there are five cars available at each location for each category.

3.3.5 Availability Button

The table that pops up when this button is clicked reports the availability of each car class at each location over different timeframes. This table is constantly and automatically updated during the simulation run as new reservations and car hires are made; no values need to be manually entered in this table.

3.3.6 Customer Mode Button and Arrival Distribution

The customer mode button is where the user can choose one of three modes of the simulation run: “List,” “Random,” and “List and Random.” When the List mode is chosen, the simulation will only read the data entered in the demand data section and generate customers accordingly. Under the Random mode, the simulation will create customers based on the distribution and parameters entered regarding the arrival rate, customer class preference, rental duration, time between booking request and pick-up, drop-off location, and pick-up location. When both options are selected, the simulation will create customers, both from the demand data entered and randomly according to the parameters for the above-mentioned criteria.

For purposes of illustration, the arrivals of customers over the entire rental system (15 locations) are modeled by an exponential distribution with a mean interarrival time of 28.8 minutes. Arrivals are randomly assigned to one of the 15 locations according to the probabilities given in Table 1.

Table 1: Customer arrival probabilities to each pick-up location.

Location Code	Pick-up probability
1	0.0429
2	0.0613
3	0.0919
4	0.0153
5	0.0245
6	0.0306
7	0.0613
8	0.0140
9	0.0208
10	0.0340
11	0.0459
12	0.1532
13	0.1838
14	0.1225
15	0.0980

The drop-off locations also employ empirical distributions (not illustrated here) based on the pick-up location, so that there are also 15 empirical distributions for drop-off locations. On average, 45.4 % of customers drop off the car at their pick-up location.

3.3.7 Demand List

The demand list button allows the user to enter the demand data into the model so as to generate customers. The demand data require the following information in each column:

- Booking date and time
- Pick-up date and time
- Rental duration
- Category (demanded car class)
- Pick-up location
- Return location

The booking time must be at least that of the pick-up time. The difference between the two times represents the delay between the booking request time and the requested pick-up time. If the two values are equal, the customer is regarded as a walk-in customer.

3.3.8 Random Customers Button

This is where the parameters for the randomly generated customers are entered. The values entered in this table are effective only when “Random” or “List and Random” are selected in the Customer Mode option.

3.3.9 Other Parameters Button

This button allows for entry related to miscellaneous functionality. For instance, in the upgrades option, the number of upgrades offered to the customer can be entered, i.e., the number of levels of car classes the customer is allowed to upgrade to. An upgrade is offered to the customer when the car class the customer requested is unavailable at the pick-up time.

4 DES TOOL DEMONSTRATION

We use simulation to assess various pick-up and drop-off incentive strategies. We start in Section 4.1 with a case study description and pose a number of interesting research questions. Section 4.2 gives some brief remarks concerning the base case, against which we will compare any alternative strategies. Section 4.3 describes the experimental design, and Section 4.4 discusses the results.

4.1 Case Study Description and Research Questions

This case study employs an analysis of pricing strategies for same-location rentals using the discrete event simulation model built in ExtendSim AT 9. This line of research is a continuation of the initial study by Alabdulkarim (2018) which was aimed at finding best pricing strategies for each car class as well as the number of upgrades to be offered to customers so as to increase revenues for car rental companies. Our case study is based on the initial study where the model and the data have been updated to incorporate the logic that is required for our current purposes. Our previous findings for the pricing strategies and upgrades offered to customers are incorporated into this study.

There are two types of customers who wish to rent a car, namely, walk-in and reservation customers. Walk-ins arrive at a car rental location where they ask about the availability of the car category they wish to rent, the duration they desire, and the ability to drop the car off at their desired destination. Walk-ins ask for the immediate rental of the car. Reservation customers specify the car class they wish to rent for a starting date and duration in the near future; and they pay or secure the amount for the payment to the rental company at the time of reservation. All demands (walk-in and reservation customers) arriving at the car rental office or via the reservation system include the following information:

- The class of car the customer wants to rent
- The duration of the car rental (in days)
- The maximum amount the customer is willing to pay per day for renting the desired car class
- The location of the start of the rental (pick-up point)
- The location of the end of the rental (drop-off point)

Walk-in customers are unaware of the availability of the cars and their prices before arriving at the rental office. They make their decisions based on the response they receive regarding the availability and price of the cars. Reservation customers entering the reservation system act in a similar fashion regarding car price and availability. If they find an available car within their budget and for the time and duration they require, they then fill in the online form to complete the reservation. In this case study, the customer's budget for a specific car class is determined by assigning an exponential random variate for this value. According to our interviews with the subject matter experts, this distribution reasonably represents the maximum amount a customer is willing to pay for any product or service (though we could of course use any other input distribution as we collect additional data). This feature of the simulation model adds real-life complexity to the system, where the demand for any car class depends (in a random way) on the price of that car class.

The customers arriving to the car rental system already know the car class they want to rent, which can be represented either in the entered demand data or by the percentage values for each car class in the random demand generation mode. In this case study, the simulation runs with realistic random values for all demand inputs such as the arrival frequency, pick-up location, drop-off location, and rental duration. The initial number of cars available at each location for each car class is set to 5, with 15 car rental branches (locations). The rental fee (turnover) is trivially calculated as the number of rental days multiplied by the price for the desired car category (not necessarily the upgraded class) (Alabdulkarim 2018).

We investigate the effects of certain dynamic pricing strategies for same-location rentals. In addition, the results will be compared to the case where there is no discount for same-location pick-ups / drop-offs and no price increases for different-location rentals. Specifically, we ask:

1. How is revenue affected when discounts are offered for same-location rentals?
2. How is revenue affected when prices are increased for different-location pick-ups and drop-offs?
3. What is the combination of discounts and price increases that provides the highest revenue?
4. How much improvement can be made by adopting the best pricing strategies for same-location rentals?

4.2 Current Baseline

The data inputted into the simulation model portrays realistic behavior for the demands of a car rental system in Saudi Arabia. The demands are created by randomly generated arrivals based on the data collected from certain car rental companies. As discussed earlier, the system under study is composed of 5 car classes in 15 different locations. At the start of the simulation run there are 5 cars for each car class at each location. The demand exhibits great variation throughout the year, and the overall imbalance for pick-up and drop-off locations can be significant. An analysis of the current state of the system has shown that only about 45% of the rentals are returned to the same location – in the United States, for instance, this imbalance figure would be much lower. In any case, as a direct consequence of this imbalance phenomenon in the pick-up and drop-off locations for the different-location rentals, we observed that some locations have excessive car availability whereas other locations often have no availability for certain car classes.

4.3 Experiments

In line with the research questions posed above, in order to understand the best strategy for same-location rentals, it is necessary to understand how the revenue is affected when discounts for the same-location rentals and price increases for different-city rentals are introduced, as well as a when a combination of both the same-location discounts and different-city price increases are introduced. In order to conduct an analysis to answer these questions, we ran a set of 195 experiments involving the two variables: (i) discounts assigned for same-location rentals, and (ii) price increases assigned for different-location rentals.

The main output (response) of the system to be evaluated is the revenue generated. Other outputs of interest are the percentage of customers who are satisfied, the percentage who find no car available to pick up, and the percentage who do not have the necessary budget (too expensive). The demand data covers a 1-year period, so that the simulation length is set to 365 days. The simulation runs replications until the relative error for the estimated mean of revenue is believed to be less than 0.01 of the true mean.

For all scenarios, the base prices of all car classes are set to the mean values for the budget of customers for that class except for the highest car class which is set to a price 10% higher than the mean value of the budget for the customers for that car class. The motivation for such a set-up arises from the findings of the initial study by Alabdulkarim (2018). Therefore, the base daily rental prices of the 5 car classes are set to 10, 20, 30, 40, 55, where the associated mean values of the exponential distributions for the budgets of customers of each car class are 10, 20, 30, 40, 50, respectively. Further, with the findings of the initial study in mind, two car class upgrades are offered to all customers in cases for which the desired class is unavailable at time of pick-up.

When designing our experiments, we wanted to understand the behavior of the response corresponding to wide range of values for the input parameters. Therefore, our experiments have been organized in such a way that the percentage of discount is increased by a step size of 5 percent from 0 to a maximum of 60 percent. For the price increase variable, the step size is assigned manually as follows: 0, 5, 10, 20, 30, 40, 50, 75, 100, 150, 200, 250, 500, 1000.

4.4 Results and Analysis

4.4.1 Discounts Introduced for Same-Location Rentals

In this case the change in the revenue has been analyzed when the discounts are offered to same-location rentals from the base prices discussed in Section 4.3. The results for all the scenarios for this case are presented in Table 2. We see that offering a 5% discount (Scenario 16) for same-location rentals results in the highest revenue – a yield of \$1,404,416, which is 1.6% higher than the scenario with no discount (Scenario 1). It is important to observe that additional discounts result in lower revenue for the company. These results effectively answer, for this particular study, the first research question posed in Section 4.1.

4.4.2 Price Increases are Introduced for Different-Location Rentals

We now analyze the changes in revenue when price increases are introduced to different-location rentals compared to the base prices mentioned in Section 4.3. The results for all of the scenarios for this case are presented in Table 3. We observe that, for this particular study, the price increases have more-significant effects on revenue compared to the results of the first case presented in Section 4.4.1. Due to the high imbalance in the demand patterns among each location, it turns out that for this particular experiment, increasing the base prices of all car classes by 150 to 200 percent for rentals with different pick-up and drop-off locations results in the highest revenues. By introducing this policy, the revenue increases by as much as 22.7% (Scenario 10) compared to the base case (Scenario 1).

Table 2: Results (ordered by revenue) when discounts are introduced for same-location rentals.

Scenario	Same-Location Discount	Increase for Different Locations	Revenue	Too Expensive	Unavailable	Satisfied
Baseline 1	0	0	$1,381,945	0.636	0.238	0.126
16	**5**	**0**	**$1,404,416**	**0.629**	**0.241**	**0.130**
31	10	0	$1,395,115	0.620	0.247	0.132
46	15	0	$1,374,876	0.612	0.254	0.134
61	20	0	$1,365,784	0.601	0.262	0.136
76	25	0	$1,346,902	0.592	0.269	0.140
91	30	0	$1,328,862	0.582	0.276	0.142
106	35	0	$1,301,543	0.570	0.285	0.145
121	40	0	$1,288,734	0.560	0.292	0.149
136	45	0	$1,250,919	0.547	0.303	0.150
151	50	0	$1,228,162	0.535	0.310	0.154
166	55	0	$1,182,858	0.521	0.322	0.157
181	60	0	$1,157,840	0.506	0.331	0.162

Table 3: Results when price increases are introduced for different-location rentals.

Scenario	Same-Location Discount	Increase for Different Locations	Revenue	Too Expensive	Unavailable	Satisfied
Baseline 1	0	0	$1,381,945	0.636	0.238	0.126
2	0	5	$1,423,105	0.647	0.228	0.125
3	0	10	$1,461,308	0.657	0.217	0.125
4	0	20	$1,496,372	0.676	0.202	0.122
5	0	30	$1,545,204	0.691	0.187	0.121
6	0	40	$1,572,883	0.707	0.174	0.119
7	0	50	$1,559,218	0.723	0.160	0.116
8	0	75	$1,622,024	0.748	0.139	0.113
9	0	100	$1,670,148	0.770	0.118	0.113
10	**0**	**150**	**$1,695,284**	**0.801**	**0.087**	**0.113**
11	0	200	$1,693,955	0.819	0.067	0.114
12	0	250	$1,650,656	0.832	0.052	0.116
13	0	300	$1,592,085	0.838	0.044	0.118

These results and findings have addressed the second research question from Section 4.1.

4.4.3 Combination of Price Increases and Discounts

We investigate the effects on revenue generation of combining the discounts for same-location rentals with price increases for different-location rentals. Table 4 gives the results for the top-performing scenarios. The "winners" are Scenarios 10 and 11 in which there is no same-location discount offered, but there are instead price increases for different drop-off locations of 150 and 200 percent, respectively, compared to the base prices for all car classes. Note that the calculated revenue of $1,695,284 for Scenario 10 is the same as that found in Section 4.4.2. Since the difference between the revenues for Scenarios 10 and 11 is less than 1%. it is statistically difficult to conclude which scenario is better with 1% relative error (in fact, we can make the same conclusion even for the 3rd-place finisher, Scenario 26). That being said, in order to achieve the greatest revenue, the discount that should be offered for same-location rentals should be between 0 and 5 percent, whereas the price increase that should be introduced to all car classes for rentals with different pick-up and drop-off locations should be between 150 to 200 percent. These results have addressed research questions 3 and 4 from Section 4.1.

Table 4: Top-performing scenarios (ordered by revenue) for combination discount and price increases.

Scenario	Same-Location Discount	Increase for Different Locations	Revenue	Too Expensive	Unavailable	Satisfied
10	**0**	**150**	**$1,695,284**	**0.801**	**0.087**	**0.112**
11	**0**	**200**	**$1,693,955**	**0.819**	**0.067**	**0.113**
26	5	200	$1,682,225	0.811	0.070	0.119
25	5	150	$1,678,495	0.792	0.092	0.115
9	0	100	$1,670,148	0.770	0.118	0.113
40	10	150	$1,656,065	0.784	0.097	0.119
12	0	250	$1,650,656	0.832	0.052	0.116
39	10	100	$1,650,611	0.753	0.128	0.119
24	5	100	$1,648,630	0.761	0.124	0.115
55	15	150	$1,639,070	0.775	0.101	0.124
38	10	75	$1,638,642	0.731	0.148	0.121
23	5	75	$1,632,622	0.740	0.143	0.117
27	5	250	$1,627,196	0.823	0.057	0.120
8	0	75	$1,622,024	0.748	0.139	0.113
41	10	200	$1,616,171	0.804	0.074	0.121
54	15	100	$1,614,976	0.744	0.134	0.122
56	15	200	$1,613,601	0.794	0.081	0.125
42	10	250	$1,609,899	0.814	0.061	0.125
53	15	75	$1,603,834	0.722	0.154	0.124

5 CONCLUSIONS

This article is based on an initial study in which pricing strategies for each car class and the number of upgrades were analyzed (Alabdulkarim 2018). The findings of the initial study have been employed herein in order to assign base prices for car classes as well as the number of upgrades to be offered to customers. In the current paper, we have used DES to investigate the effects of dynamic pricing strategies for same-location and different-location rentals in a complex car rental system using. The results of this case study showed that offering rental prices between 150 to 200 percent higher than the base prices for rentals with different pick-up and drop-off locations resulted in the highest revenues. Since this work is based on a realistic demand pattern, the findings could be similar for other car rental companies, perhaps even outside of Saudi Arabia. Of course, each company should conduct its own analysis to identify specific optimal values for dynamic pricing strategies regarding same- and different-location rentals. An important aspect of this research is that it provides an analysis tool (simulation model) for car rental companies to identify these optimal values for their own scenarios.

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AUTHOR BIOGRAPHIES

ABDULLAH A. ALABDULKARIM is an assistant professor in the Mechanical and Industrial Engineering Department at Majmaah University in Saudi Arabia. He currently serves as the Dean of the College of Engineering at Majmaah. He obtained his Ph.D. from Cranfield University in the UK. He received his M.Sc. in Logistics and Optimization from the University of Portsmouth, while his B.Sc. in Industrial Engineering was earned at King Saud University in Saudi Arabia. His research focuses on simulation modeling for the service sector. His background is in the aerospace industry in aviation maintenance and operations, and he worked in several other industries before pursuing his academic career. He can be contacted at a.alabdulkarim@mu.edu.sa.

IBRAHIM M. AL-HARKAN is an associate professor of Industrial Engineering at King Saud University, Saudi Arabia. He holds a B.S. in Industrial Engineering from King Saud University, and an M.S. and Ph.D. in Industrial Engineering from The University of Oklahoma, USA. His specialization areas are in production planning and control, modeling and simulation of industrial and service systems, and applied operations research. Dr. Al-Harkan is one of the founders of the Saudi Industrial Engineering Society (SIES) and is currently the vice president for the society, one of the founders of the Industrial Engineering Council at the Saudi Council of Engineers, and one of the founders of the Saudi chapter of the Institute of Industrial Engineers. He also established the Department of Industrial Engineering in the College of Engineering at King Saud University. Dr. Al-Harkan was the Chairman for the Mechanical Engineering Department for four years, as well as the Chairman for the Industrial Engineering Department for two years. In addition, he was the Dean for Graduate Studies for five years. Dr. Al-Harkan was the Vice Rector Assistant for Graduate Studies and Scientific Research for Knowledge Exchange and Technology Transfer for one year. He was the General Director of the External Joint Supervision Program (EJSP) for ten years. Dr. Al-Harkan is currently the General Director for the Entrepreneurship Institute. He can be contacted at imalhark@ksu.edu.sa.

DAVID GOLDSMAN is a professor in the H. Milton Stewart School of Industrial and Systems Engineering at the Georgia Institute of Technology. His research interests include simulation output analysis, ranking and selection, and healthcare simulation. He was Program Chair of the Winter Simulation Conference in 1995, and a member of the WSC Board of Directors between 2001–2009. He was also a trustee of the WSC Foundation. His e-mail address is sman@gatech.edu, and his Web page is www.isye.gatech.edu/~sman.