Optimal Fleet Size And Mix For A Rental Car Company

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ABSTRACT

In this paper, a linear programming model for optimizing the fleet size and mix for a rental car company is developed and solved. Rental car companies depend on their fleet of vehicles for generating the entirety of their income. Additionally, the investments required are typically very significant due to the high cost of vehicles. Consequently, the composition of the fleet could significantly affect the company's profitability and sustainability in a volatile demand environment. Determining the optimal fleet size and mix has been the focus of research in particular in revenue and yield management and VRP streams. However, most models focused on cost minimization without taking into account the resale value of vehicles once retired from the fleet. This paper addresses the problem from a return maximization perspective while taking into account resale values of vehicles. Sensitivity analysis is carried out to gain further insight into the problem and enable the model to support the company's management in refining the strategic plan.

Keywords: Optimal Fleet Mix; Fleet Composition; Linear Programming; Yield Management

INTRODUCTION

For most rental car companies, having the right vehicle at the right time and place will determine, not only their profitability, but also their survival and sustainability. Decisions made at various levels of the company (strategic, tactical and operational) will undoubtedly steer the company closer or further towards that objective. However, the strategic problem of determining the fleet size and mix remains the most impactful due to the magnitude of the investments made and the fact that all tactical and operational decisions would be of little value if the strategic choices are faulty (Pasha, Hoff, & Hvattum, 2016).

Major research contributions have been made in the past few decades in addressing the problem of fleet size and mix (FSM). The models spanned deterministic and stochastic environments, as well as single or multi-modal fleet planning decisions. Research into FSM has naturally combined elements of the problem with the classical VRP and yield management problems. This is quite reasonable given the strong inter-dependence among FSM, fleet deployment, and fleet inventory control (Baykasoglu, Subulan, Tasan, & Dudakli, 2019).

The literature in the FSM problem is quite extensive despite an apparent shortage in applications addressing rental car companies. The review of such literature can be classified into whether the environment considered is deterministic or stochastic; in addition to whether the planning horizon is single or multi-period. Furthermore, the majority of the literature surveyed used cost minimization as the main objective of the optimization (Martins, Nunes, Joao, & Ferreira, 2019). Other factors have also been considered such as quality of service, but rarely profit or revenue maximization.

Within the deterministic, single mode context, (Wu, Hartman, & Wilson, 2005) developed an integrated model for fleet sizing in the truck-rental industry. Using a time-space network, a two-phase solution approach comprising Bender's decomposition and Lagrangian relaxation was devised. (Lee, Kim, Kang, & Kim, 2008) applied a heuristic using Tabu search and set partitioning to a FSM problem coupled with vehicle routing decisions. (Loxton & Lin, 2011) constructed a FSM problem with one or multiple types of vehicles proposing a cost minimization algorithm based on dynamic programming and the golden-section method. A similar approach was followed by (Liu & Lu, 2012) who developed a hybrid heuristic method that incorporated the vehicle type information into the model. (Jabali, Gendreau, & Laporte, 2012) proposed a continuous approximation (CA) model on a circular grid to minimize the total cost of the FSM. Building on this work, (Nourinejad & Roorda, 2017) determined the optimal fleet to minimize total cost using CA on a rectangular grid. A variation of the problem that included a mix of new and old reusable items was introduced by (Gonzalez & Epstein, 2015) to maximize the expected present value of the fleet. A more integrated view of the problem was studied by (Konur & Geunes, 2019) whereby districting, fleet composition and inventory planning were simultaneously taken into account. The authors formulated a mixed integer nonlinear program that was solved using a column generation based heuristic approach.

Extending the deterministic model to the multi-period case, (Salhi, Wassan, & Hajarat, 2013) formulated a FSMVRP problem with backhauls as an ILP. Optimal solutions for small instances were generated, while a set partitioning problem-based heuristic was proposed for the general case. A more explicit multi-period model was proposed by (Mardaneh, Lin, & Loxton, 2015) to determine the optimal fleet mix and the corresponding vehicle routes at minimal cost. The formulated MILP was solved via a decomposition heuristic that optimizes the vehicle routes at the first stage, then the corresponding optimal fleet mix was determined using dynamic programming and golden section search heuristics. Incorporating a sell option, (Du, Brunner, & Kolisch, 2016) generated a multi-period fleet investment schedule that minimizes fleet composition cost. A variant of the FSMVRP that incorporated backhauls where delivery and pick-up customers are served from a central depot was studied by (Belloso, Juan, & Faulin, 2017). The authors proposed an algorithm that uses several biased-randomized processes to select the vehicle type, then sorting the savings list and defining the least costly number of routes. (Borthen, Lonnechen, Wang, Fagerholt, & Vidal, 2018) adapted the hybrid genetic search with adaptive diversity control algorithm developed by (Vidal , Crainic, Gendreau, Lahrichi, & Rei, 2012) to solve an offshore supply vessel planning problem where voyages may span multiple time periods.

Research directed to the FSM problem in the stochastic case remained limited due to its complexity. The majority of the literature presented heuristic solution approaches to the problem. For instance, a stochastic fleet composition problem was proposed by (Loxton, Kok, & Teo, 2012) to minimize the operating cost of a new vehicle fleet. The problem was solved using a heuristic comprised of an algorithm that combined dynamic programming and golden section method. Pasha et al. (2016) presented simple heuristics incorporating tabu search to determine the optimal fleet composition. The uncertainty in the demand was simply represented by varying demand levels during the planning horizon. A simulation-based optimization approach was adopted by (Turan, Elsawah, & Ryan, 2020) to solve a strategic fleet renewal problem under uncertainty. The simulation-based approach that uses a genetic algorithm was used to search effectively for an optimal solution among a large set of feasible renewable strategies.

The fleet mix and composition problem I address in this paper diverges from the existing literature on two important factors: the objective function used, and the nature of the business to which the model is applied. Firstly, and as evident from the literature review above, most research used a cost minimization objective. This is warranted due to the fact that the primary objective of the vehicles is not revenue generation, but rather a cost to me minimized within a bigger VRP problem. Secondly, the car rental business depends on the fleet for revenue generation. In fact, the fleet is the primary revenue generator for this type of firms. Additionally, the value of the service provided depends greatly on the fleet mix and composition when it comes to rental rates or customer satisfaction.

PROBLEM STATEMENT AND MODEL DEVELOPMENT

Rental car companies depend on the fleet of vehicles to generate most of their income. The decision on the fleet size and mix is strategic and vital to the company's long-term success and sustainability. Constrained by a limited investment budget, the company must decide on the optimal fleet composition that will maximize its payoff during a predetermined planning horizon. There are different types and models of vehicles with different purchasing, leasing and maintenance costs, and different rental rates. While the lease cost for the vehicles remains constant, the rental rates and the resale value for the various types of vehicles decrease over time as the vehicle ages. On the other hand, the maintenance costs increase over the usability life of the vehicle. The problem is further complicated by the uncertain nature of the demand and by the fact that a sale realization occurs solely when both the demand arises, and the vehicle is available simultaneously. The objective is to determine the optimal fleet size and mix to maximize the company's returns over a predetermined planning horizon. As mentioned earlier, this is different from the majority of the literature which focused on cost minimization. The primary constraints are the budget, the storage (parking) space, the ceiling on the financing amount, and the minimum and maximum number of vehicles of each type set by the company. The decision on the minimum and maximum numbers are dependent on the company's business level strategy. In particular, for a broad differentiation strategy, the company will choose to keep vehicles that would cover the majority of the demand categories (market segments).

For the proposed model, the demand is aggregated over the planning horizon. This is a common practice for strategic decision making (Du et al., 2016). The current purchasing prices and the lease rates of the vehicles are known with certainty. However, the rental rates, the maintenance costs and the resale values are uncertain. The latter costs are estimated based on a fixed decreasing pattern for the rental rates and the resale values, and a fixed increasing pattern for the maintenance costs. The following notation is introduced and used throughout the manuscript for *I* vehicle models and *J* types:

x_{ij}: number of vehicles of model i, type j
M: Maximum number of vehicles
P_{ij}: Purchasing price of vehicle model i, type j
D_{ij}: Downpayment for vehicle model i, type j
R_{ij}: Resale value of vehicle model i,type j
r_{ij}: estimated rental return from vehicle model i, type j
l_{ij}: lease cost of vehicle model i, type j
m_{ij}: maintenance cost of vehicles model i, type j

The return maximization linear programming model to maximize the net return over the planning horizon thus becomes:

$$Max \sum_{i=1}^{I} \sum_{j=1}^{j} x_{ij}(R_{ij} + r_{ij} - P_{ij} - l_{ij} - m_{ij})$$

$s.t.$

$$\sum_{i=1}^{I} \sum_{j=1}^{J} x_{ij} D_{ij} \leq B$$

$$\sum_{i=1}^{I} \sum_{j=1}^{J} x_{ij} P_{ij} \leq F$$

$$\sum_{i=1}^{I} \sum_{j=1}^{J} x_{ij} \leq M$$

$$x_{ij} \leq max_{ij}$$
$$x_{ij} \geq min_{ij}$$
$$x_{ij} \geq 0;$$

Where B is the initial available budget, $min_{ij}$and $max_{ij}$are the minimum and maximum of each type of vehicle. Additionally, due to parking space limitations, the total number of vehicles could not exceed M. Furthermore, the second constraint refers to the maximum amount that could be financed through financial institutions.

CASE STUDY

The model is applied to the case of a rental car company in the Sultanate of Oman. The company prefers to use one vehicle brand (Toyota in this case) due to its reputation of durability and reliability, and for the maintenance team efficiency. Additionally, the company's management initial business level strategy is that of broad differentiation, i.e., having a minimum number of vehicles to cater to most demand segments in the Omani market., the minimum is set for the model and not the type (different variations of the same model are assumed similar). A maximum is set for the higher range vehicles as these are costlier and the corresponding demand is assumed to be limited. The resale value of the car is a function of its original price, typically a vehicle loses 10% of its value for each year of service. This percentage is slightly higher for the higher-end vehicles though, as these tend to lose value faster in the first few years of operation. The rental rates also drop by about 10% after each year of usage. The starting rates have been determined by considering the median rates for similar cars in the market.

The lease cost is a fixed percentage of the initial vehicle price, typically with an APR of around 3% to 5% depending on the lease duration. In the case at hand, the duration of the lease is taken as the planning horizon of five years. The maintenance cost is dependent on the age and the frequency of usage of the vehicle. To simplify the exposition, the initial maintenance cost is assumed to average 5% of the vehicle price and increases at 10% annually. The demand for rental cars is highly volatile and seasonal in Oman. With Oman's strategic initiative to promote tourism, the demand is expected to increase. However, the recurring geo-political tensions in the region tend to have a negative effect on the growth and stability of the demand. Nonetheless, and for ease of exposition, the demand is aggregated and estimated as a percentage of days a vehicle is used during the planning horizon. Different models and types have different usage percentages, with higher-end vehicles having a lower usage ratio. For this reason and due to the limitation on the parking space available at the company's facility, the maximum number of vehicles is initially set at 20, with the management willing to consider a bigger lot, or multiple lots, if deemed economically attractive.

SOLUTION PROCEDURE AND RESULTS ANALYSIS

The above formulated model could be solved with requiring integer decision variables. This would render the problem a mixed integer program and would unnecessarily increase the solution burden. The choice of a linear programming formulation allows for an insightful sensitivity analysis given the strategic nature of the problem where many of the management decisions can still be modified if they are deemed scientifically sound. The linear program is solved with the data provided in Table A.1 (appendix A) using an Opensolver ® freeware run on Excel ® 2016. The initial results are summarized in the following table (Table 1).

Table 1. Optimal Fleet Composition

Vehicle Model	Optimal number
Toyota Corolla 2019	3
Toyota Land Cruiser 2019	1
Toyota Fortuner 2019	1
Toyota Hilux 2019	1
Toyota FJ Cruiser 2019	1
Toyota Camry 2019	3
Toyota Sequoia 2019	0
Toyota Aurion 2019	0
Toyota Avanza 2019	0
Toyota Coaster 2019	2
Toyota Hiace 2019	2
Toyota Innova 2019	0
Toyota Land Cruiser Pick Up 2019	1
Toyota Land Cruiser Prado 2019	1
Toyota Previa 2019	0
Toyota Prius 2019	0
Toyota Rav4 2019	2
Toyota Yaris 2019	2

The above results correspond to an initial budget of 50,000 OMR, a finance ceiling of 500,000 OMR and a 20-slot parking limit. The maximum expected return is 594,024 OMR with a total fleet size of 20 vehicles. This immediately points to the fact that the main binding constraint is the parking space limit set at 20. A further inspection of the sensitivity analysis report provides the evidence: the shadow price of the parking constraint is the only positive value. All other binding constraints have negative shadow prices. This is quite counter intuitive as one would expect that, in a return maximization case, the higher the number of vehicles, the more return that is generated. The other recurring observation is that the top type of each model has been selected for all models except the Hiace model. A quick look at the data indicates that the lowest priced type of this particular model has the highest rental fare per day. This could be a data error, but it could simply be a manifestation of supply versus demand as this type is the most popular among customers.

By relaxing the parking space limit, the financing ceiling constraint becomes binding with a positive shadow price of 6.2 OMR. This provides us a priority ranking of the key constraints: budget, finance ceiling and parking space limit. With the current minimum number of vehicles required, the lowest feasible financing amount is 200,000 OMR. It is noteworthy that the parking space limit is due to the availability of commercial space. However, if it is deemed economically desirable, the company might consider having multiple storage locations for the vehicles as opposed to a central parking facility.

CONCLUSION AND FUTURE RESEARCH

In this paper, a fleet composition linear programming model was developed and solved. The key features of the model are its ability to incorporate a number of industry-specific constraints such as treating the vehicles as the primary revenue generators as opposed to being a cost within a bigger VRP problem. Additionally, the resale value, the maintenance and lease costs are taken into consideration to provide the management with a clearer perspective relative to their strategic priorities. The sensitivity analysis indicated that the parking space available for storage of the vehicles represents the primary constraint, followed by the finance amount ceiling.

The model assumes a deterministic aggregate demand, which is quite common in strategic planning (Turan et al., 2020). However, the uncertainty is taken into account in the form of a fixed percentage of usage of the vehicles within a given period of time. Additionally, the return is calculated without the fixed operating costs (staff salaries, facility rental and operating costs, management cost, etc.), and thus the return calculated may provide an upper limit on what the return on the investment would be if the management is considering other investment alternatives within the same domain, such as a logistics services offering. Consequently, future research will address these limitations by including additional costs incurred in the business model, as well as considering the uncertainty in the demand explicitly. Another venue that will be investigated is the translation of the strategic plan for the fleet composition to more tactical and operational plans, in particular if the company opts for multiple parking and vehicle storage locations.

AUTHOR BIOGRAPHY

Nasreddine Saadouli earned his Ph.D. in management science from the University of Tennessee, Knoxville, in 2000. He held assistant/associate professor positions at the American University in Dubai, UAE, the Gulf University for Science and Technology in Kuwait, the University of Monastir in Tunisia, and Sohar University in the Sultanate of Oman, where he is currently an Assistant Professor at the Faculty of Business. His research interests include applied optimization techniques, stochastic and dynamic programming, integrated optimization-simulation frameworks, and entrepreneurship and human capital formation. Email: saadouli1971@yahoo.fr

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APPENDIX A

Table 2. Model Data

Vehicle model	Type	Price (OMR)	Resale Value (OMR)	Rental rate / day (OMR)	APR (%)
Toyota Corolla 2019	1.6L SE+	6,300	2520	18.4	4%
	2.0L SE+	6,700	2680	19.3	4%
	1.6L Limited	7,000	2800	20.8	4%
	2.0L Limited	7,500	3000	23.0	4%
Toyota Land Cruiser 2019	4.0L EXR	20,000	8000	53.3	4%
	4.0L Safari	20,000	8000	55.0	4%
	4.6L EXR	21,600	8640	56.3	4%
	4.0L GXR GT	26,900	10760	58.0	4%
	4.6L VXR	28,700	11480	60.0	4%
	4.6L GXR GT	29,000	11600	61.3	4%
	5.7L EXR	31,500	12600	63.0	4%
	5.7L VX.R White Edition	36,000	14400	65.0	4%
	5.7L VXR	36,000	14400	70.0	4%
	VX White Edition	36,000	14400	73.0	4%
Toyota Fortuner 2019	2.7L EXR	11,000	4400	37.0	4%
	4.0L GXR	13,100	5240	39.0	4%
	4.0L VXR	14,700	5880	44.0	4%
Toyota Hilux 2019	2.7L Double Cab GL M/T (4x2)	8,900	3560	35.0	4%
	2.7L Double Cab GLX (4x2)	8,900	3560	38.0	4%
	2.7L Double Cab GLX M/T (4x2)	8,900	3560	40.0	4%
	2.0L Double Cab 4x2	9,300	3720	30.0	4%
	2.0L Double Cab 4x2 (Top Spec)	9,300	3720	32.0	4%
	2.0L Single Cab 4x2	9,300	3720	25.0	4%
	2.0L Single Cab 4x2 (Top Spec)	9,300	3720	27.0	4%
	2.4L Double Cab 4x4	9,300	3720	40.0	4%
	2.4L Double Cab DLS M/T (4x2)	9,300	3720	42.0	4%
	2.7L Double Cab GL (4x4)	9,300	3720	45.0	4%
	2.7L Double Cab GL M/T (4x4)	9,300	3720	47.0	4%
	2.7L Double Cab GLS (4x4)	9,300	3720	49.0	4%
	2.7L Double Cab GLX (4x4)	9,300	3720	50.0	4%
	2.7L Double Cab GLX M/T (4x4)	9,300	3720	52.0	4%
	2.7L Single Cab 4x2	9,300	3720	35.0	4%
	2.7L Single Cab GLX (4x4)	9,300	3720	37.0	4%
	4.0L Double Cab TRD (4x4)	9,300	3720	40.0	4%
	2.4L Double Cab 4x4 (Top Spec)	10,000	4000	45.0	4%
	2.7L Double Cab 4x4	10,200	4080	38.0	4%
Toyota FJ Cruiser 2019	4.0L EXR	11,500	4600	40.0	4%
	4.0L GXR	14,500	5800	42.0	4%
	4.0L VXR	15,500	6200	45.0	4%
	4.0L Extreme	16,500	6600	50.0	4%

(Table 2 continued on next page)

(Table 2 continued)

Vehicle model	Type	Price (OMR)	Resale Value (OMR)	Rental rate / day (OMR)	APR (%)
Toyota Camry 2019	2.5L LE STD (204 HP)	9,000	3600	28.0	4%
	2.5L S	9,000	3600	20.8	4%
	2.5L S (178 HP)	9,000	3600	24.5	4%
	2.5L SE (178 HP)	9,000	3600	27.0	4%
	3.5L LTD (298 HP)	9,000	3600	30.0	4%
	3.5L SE (298 HP)	9,000	3600	32.0	4%
	3.5L SE+ (298 HP)	9,000	3600	35.0	4%
	3.5L Sport (298 HP)	9,000	3600	40.0	4%
	2.5L SE	9,700	3880	24.0	4%
	2.5L SE+	10,500	4200	26.0	4%
	2.5L Limited	11,100	4440	30.0	4%
Toyota Sequoia 2019	5.7L SR5 4x2	15,500	6200	45.0	4%
	5.7L Platinum	21,000	8400	50.0	4%
Toyota Aurion 2019	3.5L Sport	11,900	4760	65.0	4%
	3.5L Grande	14,100	5640	55.0	4%
Toyota Avanza 2019	1.5L SE	5,600	2240	45.0	4%
Toyota Coaster 2019	2.7L (23-Seater)	20,900	8360	95.0	4%
	2.7L SWB (20-Seater)	20,900	8360	100.0	4%
	4.2L (23-Seater)	21,500	8600	105.0	4%
Toyota Hiace 2019	3.5L GL STD Roof Panel Van (3-Seater)	8,900	3560	40.0	4%
	2.7L Panel Van High Roof LWB	9,900	3960	35.0	4%
	2.5L Commuter M/T	10,500	4200	35.0	4%
Toyota Innova 2019	2.7L SE	8,500	3400	38.0	4%
	2.7L SE+	10,500	4200	40.0	4%
	2.7L Limited	10,900	4360	42.0	4%
Toyota Land Cruiser Pick Up 2019	4.0L Double Cab	12,500	5000	60.0	4%
	4.0L Hard Top	12,500	5000	55.0	4%
	4.0L Single Cab	12,500	5000	50.0	4%
Toyota Land Cruiser Prado 2019	(3 Door) 2.7L GXR	12,500	5000	44.0	4%
	2.7L EXR	13,100	5240	47.0	4%
	2.7L GXR	14,000	5600	48.0	4%
	2.7L VXR	15,500	6200	49.3	4%
	4.0L EXR	15,900	6360	51.4	4%
	4.0L GXR	17,400	6960	52.7	4%
	4.0L VXL	19,000	7600	54.0	4%
	4.0L VXR	19,500	7800	56.0	4%
Toyota Previa 2019	2.4L S	11,500	4600	60.0	4%
	2.4L SE	13,000	5200	65.0	4%
Toyota Prius 2019	Eco	9,300	3720	12.0	4%
	Iconic	10,200	4080	15.0	4%
Toyota Rav4 2019	2.5L (2WD) EX	9,200	3680	41.0	4%
	2.5L 4WD EXR	10,000	4000	42.5	4%
	2.5L 4WD GX	11,000	4400	44.0	4%
	2.5L (2WD) VX	11,500	4600	45.4	4%
	2.5L 4WD GXR	12,500	5000	47.5	4%
	2.5L 4WD VXR	13,500	5400	48.8	4%
Toyota Yaris 2019	1.3L SE	5,400	2160	13.9	4%
	1.5L SE	5,800	2320	15.4	4%
	1.5L SE+	6,100	2440	18.3	4%

Table 3. Minimum and maximum number of vehicles per model

Vehicle Model	Min	Max
Toyota Corolla 2019	3	N/A
Toyota Land Cruiser 2019	1	5
Toyota Fortuner 2019	1	5
Toyota Hilux 2019	1	5
Toyota FJ Cruiser 2019	1	5
Toyota Camry 2019	3	N/A
Toyota Sequoia 2019	N/A	5
Toyota Aurion 2019	N/A	5
Toyota Avanza 2019	N/A	5
Toyota Coaster 2019	N/A	5
Toyota Hiace 2019	2	5
Toyota Innova 2019	N/A	5
Toyota Land Cruiser Pick Up 2019	1	5
Toyota Land Cruiser Prado 2019	1	5
Toyota Previa 2019	N/A	5
Toyota Prius 2019	N/A	5
Toyota Rav4 2019	2	5
Toyota Yaris 2019	2	N/A

NOTES