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Chassis Leasing and Selection Policy for Port Operations

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Abstract. Port cargo drayage operations manage the over-the-road transport of shipping containers that arrive and depart on ocean-going container vessels at a port terminal. While on land, containers are placed on wheeled chassis until they return to the port facility. The acquisition and management of these chassis are significant operational challenges. We address a particular operating environment where chassis may be engaged either as daily rental or via a committed long-term lease at lower cost. We present and describe the implementation of a solution methodology that addresses the two decision problems that arise with this dual sourcing approach: (1) the optimal fleet size for leased chassis and (2) a real-time decision policy for selecting between rental and leased chassis as containers arrive. As we demonstrate, our solution represents an integrated approach that combines descriptive, predictive, and prescriptive analytics, and exhibits a novel interplay of optimization, simulation, and predictive modeling. We conclude with an analysis of the financial benefit that has been achieved and a discussion of the applicability of our methodology to other problem settings.

History: This paper has been refereed. This paper has been accepted for the *INFORMS Journal on Applied Analytics* Special Section on the Innovative Applications in Analytics Award.

Keywords: port drayage operations • fleet sizing • simulation • stochastic optimization • logistic regression

Introduction

The United States imports over $2 trillion worth of foreign products annually with the majority of goods arriving via ocean-going container ships. In 2017, approximately 7 million containers entered U.S. ports. Approximately 40% of international container freight is transloaded into domestic containers or trailers at cross-dock facilities. Although transloading introduces additional costs in time and labor, these costs are more than offset by operational requirements and improved supply chain efficiency. When these international containers are on land, they are placed on wheeled chassis, moved to a transloading facility for unloading, returned empty to a staging area, and then placed on an outbound ship. Transloading facilities may be located within the port facility or a considerable distance inland.

Historically, the chassis used at port facilities have been owned and provided by ocean carriers, leaving no opportunity for the dray operator (i.e., trucking company) to make decisions regarding chassis selection. In recent years, following a trend that started in Europe, ocean carriers have divested their interest in chassis and there has been an almost complete transition to chassis leasing companies. The largest of these, DCLI, operates 216,000 units. Chassis are generally rented from these providers on a daily as-needed basis; however, longer-term commitments are possible in some markets. Long-term leases offer lower per-day costs and the ability to directly manage availability and proactively keep equipment in good working order.

Schneider National has determined that an analytics-driven policy that combines long-term leasing with daily rental leads to significant cost savings while improving both service and reliability. We present and implement a solution methodology that addresses the two decision problems that arise for a port drayage transportation provider when this dual sourcing option is available: (1) the optimal fleet size for leased chassis and (2) a real-time decision policy for selecting between rental and leased chassis as containers are received. We solve the first decision problem using a stochastic programming approach that begins with Monte Carlo generation of scenarios corresponding to possible realizations of future order arrivals and then solves an integer program (IP) to find an optimal fleet size. The novel aspect of our solution is to address the second decision problem by using the explicit choices provided by the IP to develop and train a predictive model that guides individual chassis selection choices in ongoing operations.

Related Work

A comprehensive review of the application of operations research—primarily, optimization and simulation models—to container terminal operations can be found in the work of Stahlbock and Voß (2008). The authors cover a wide range of applications, including equipment and systems choices, workforce scheduling, ship loading (berth allocation), ship unloading (stowage planning), stacking of unloaded containers, dockside automated guided vehicle systems, and inland transportation planning; however, they do not address portside chassis planning or management. Dragovic et al. (2017) provide a comprehensive overview of the literature related to the use of simulation modeling for container terminals. The simulation models that they cover focus on discrete-event modeling of overall facility operations but do not directly consider chassis usage. A comprehensive simulation model described by Cimpeanu et al. (2017) gives an approach to integrating unloading functionality with infrastructure units and maintenance scheduling. However, this model addresses operations at a facility where only bulk materials are processed and provides no insight with respect to containers and chassis.

A paper by Ng and Talley (2017) does focus on the planning of multiple chassis pools, modeling chassis inventory as a periodic Markov chain with the daily inventory positions as states and the transitions reflective of the probabilities of a chassis pickup, chassis return, or chassis repositioning. Their research addresses changes to chassis management and ownership that motivated the problem at Schneider, although the researchers considered only the ownership and management of the chassis pools of outside parties rather than those of the carrier. They also observe that requiring chassis to be returned to a remote location will increase carrier costs that must be borne by someone. In contrast to Ng and Talley (2017), a U.S. Department of Transportation (DOT)-funded simulation study by Chassiakos et al. (2017) demonstrates that the use of off-terminal chassis processing facilities at the ports of Los Angeles and Long Beach can significantly reduce congestion-induced travel time. They do not address alternative chassis acquisition policies.

A 2015 study commissioned by the Federal Maritime Commission (2015), which addresses U.S. port congestion, calls particular attention to chassis availability and related issues. The study notes that "Restrictions in today's chassis business models seem to be limiting motor carriers' ability to choose the chassis provider even when they are footing the bill, a restriction which leaves the daily rental charges subject to less competitive pressure" (p. 27). The study also references a report in the magazine *American Shipper* indicating that 13% of port chassis are inoperable at any given time. This analysis is corroborated by Knatz (2017) who investigates the pressure for changes in "port governance, strategic decision-making and government policy in the United States" (p. 67). They document increased cost and congestion associated with chassis shortages and lack of focus on maintenance to keep chassis in good working order. A key aspect of our solution is to provide a data-driven way to make a commitment to long-term lease chassis as a way to minimize high daily rental charges and ensure high availability of a significant portion of the chassis fleet.

A pair of articles in the *Journal of Commerce* (Bonney and Mongelluzzo 2014; Mongelluzzo 2015) corroborate the findings of the Federal Maritime Commission (2015) and provide additional business perspectives on the critical chassis issues faced by U.S. ports. Mongelluzzo (2015) recounts a "chassis summit" in which inefficiencies and additional costs due to chassis shortages and unavailability due to poor maintenance and tracking are discussed. Bonney and Mongelluzzo (2014) discuss several chassis pool models that were under evaluation at the three largest U.S. ports.

An interesting analysis by Hartman and Clott (2014) posits a noncooperative game with asymmetric information between a carrier and a shipper who owns the chassis. They assume that many shipper-owned chassis are in such poor condition that the costs of inspection, maintenance, and failure risk are significant relative to the available revenue, causing drivers to make daily decisions about where to obtain a chassis. The authors formulate the decision in a Bayesian framework with carriers using their past experience as a basis for future decisions. They describe a game in which the carrier decides whether to bring a chassis (acquired from another source), based on a belief regarding the shipper's willingness to provide one. They conclude that "rationally she will use Bayes' theorem on conditional probabilities. Truckers are not necessarily Bayesians, but they do learn from experience, and the model may be sufficiently close to reality" (p. 55). Although the authors discuss trucker–shipper interactions related to chassis, they do not address chassis pool sizes or different chassis cost models.

Zak et al. (2006) provide an extensive review of solution methods for fleet sizing problems (FSPs) over the past 30 years and make the distinction between these and the fleet composition problem (FCP), which considers a mix of heterogeneous assets with differing characteristics. Our problem falls clearly in the FCP space. Golden et al. (1984) illustrate an approach to the mixed-fleet problem wherein the asset types have different costs and load-carrying attributes (e.g., capacities). As in all other instances of FCP that we have identified, the complicating problem characteristics of routes and schedules have led to the use of heuristics combined with large mixed-integer linear programs (MILPs). Our problem is different in that (1) there is no routing problem, (2) scheduling is somewhat simpler, and (3) assets differ only with respect to cost.

Many instances of combining simulation with optimization appear in the literature. Glover et al. (1996) describe the use of optimization models to generate parameters for subsequent simulation models. Marques et al. (2014) and Mendoza et al. (1991) apply this approach to forest-product production systems. Another well-known example of the interaction of optimization and simulation is approximate dynamic programming. This technique applies optimization to solve assignment problems as intermediate steps at the nodes of a large-scale network simulation. Simao et al. (2009) describe this technology and its application to tactical planning problems in freight transportation networks. In reviewing literature specific to port operations and more generally relating to the combined use of simulation and optimization, we have not encountered any approaches that are substantially similar to the approach that we have taken.

Solution Approach

Our solution approach begins with an analysis of the problem inputs derived from 1 year of order-arrival history. The relevant data are the sequence of order arrivals (i.e., allocation of chassis to container), noted by customer, and the corresponding container dwell time (from pickup to return to ship). These historical data are used to develop, validate, and estimate the business value of our approach; however, the system as implemented will use forecasts of incoming orders (i.e., containers requiring chassis) to generate the data corresponding to the history data that were used in the development phase. As we describe below, we generate a collection of scenarios using Monte Carlo simulation; these scenarios represent possible realizations of the orders that will arrive over a forward-looking horizon corresponding to a lease commitment period. We then apply an integer programming optimization to each realization and record both the optimal leased chassis pool size and individual selection choices determined by the optimization. Note that this amounts to solving the online problem as though we have perfect knowledge of the future. Because the annual number of container arrivals is manageable (currently about 10,000 orders with a growth projection of about 100%), we are able to solve these optimizations very quickly.

Using these selections as data points to train a predictive model, we develop business rules that provide the decision criteria to recommend specific chassis selections in ongoing port drayage operations. To develop this predictive model, we note that the following daily information is available in both the simulation runs and the operating (real-world) system:

- Number of orders arriving each day
- Estimated dwell time for each order
- Number of leased chassis available at the beginning of the day
- Number of quick-turn orders (allowing chassis reuse within the same day)

Our predictive model, a combination of a decision tree and a logistic regression, gives us a business rule that we can apply to various problem instances to estimate the expected total chassis cost relative to forecasted demand.

Data Analysis

Our initial data analysis is based on one complete year of recent history. The data relevant to the model include the arrival times (and chassis allocation) of all individual containers and the corresponding release of chassis when containers are returned to the port facility. The container dwell time is defined as the time interval between these paired events. Figure 1 plots the weekly order arrivals in the historical data set, and Figure 2 shows a histogram of the dwell times. Our data show a correlation of –0.015 between dwell times and arrival times; therefore, we conclude that they are uncorrelated. This allows us to simplify the simulation process.

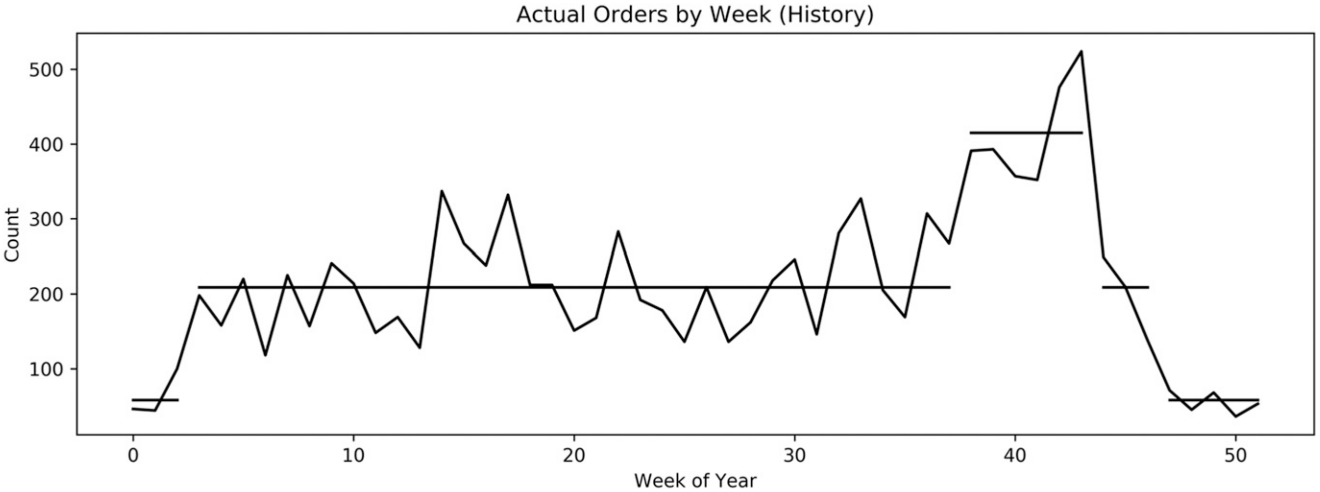
To facilitate modeling of the operational reuse of individual chassis within a single day (because this history was not maintained), we segmented the 52-week history period into 728 half-day periods. In our model, we assume a chassis is available for reuse in the period following its release from a previous order. This approach captures the notion that a leased chassis returned in the morning can be redeployed in the afternoon.

Based on analysis of the arrival data and discussions with business experts, we determined that the order arrival rate could be appropriately modeled as three distinct regimes: a post-holiday low season running from Calendar Week 48 (the beginning of December) through Week 3 of the new year; generally moderate demand for most of the year, Weeks 4–38 and 44–47; and the busy season running from Calendar Week 39 (mid-September) through Week 44 (early November) driven by holiday-season demand. Using the above seasonal groupings, we fitted the weekly arrival totals as truncated normal distributions with input parameters (Table 1).

We also noted that the overall day-of-week distribution for arrivals did not vary significantly across our seasons. Table 2 shows these percentages. Operations personnel confirmed this observation.

We used these historical data to develop, validate, and quantify our solution approach. In our business implementation, we replaced the history with a forward forecast of demand over the horizon of the chassis commitment under consideration. We were able to rerun the model to determine whether the leased chassis pool

Figure 1. Actual Order Arrivals from History



Note. Horizontal lines show the mean weekly total across indicated ranges.

Figure 2. Histogram Depicting the Distribution of Historical Container Dwell Times

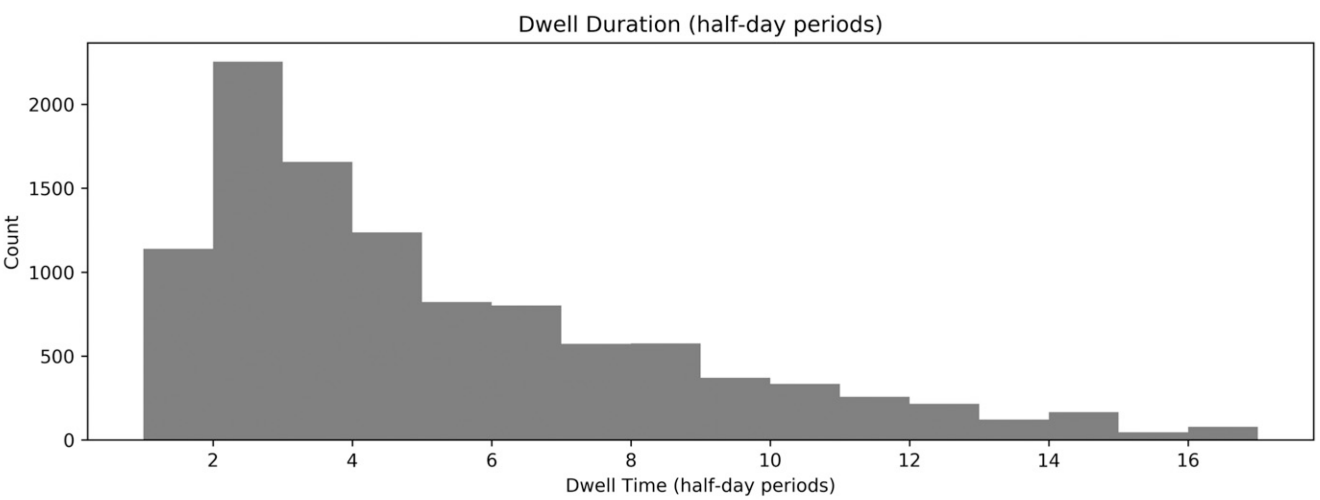


Table 1. Truncated Normal Parameters for the Three Seasonal Regimes

	Seasonal Parameters	Weekly Order Arrivals		
	Week Range	Mean	Std Dev	Range
Regime				
Busy	39–44	415	63	352–524
Low	1–3 and 48–52	58	19	36–100
Moderate	4–38 and 45–47	209	59	118–337

Table 2. Distribution of Order Arrivals by Day of Week

Dow	Orders	Percent
Monday	2,123	20%
Tuesday	2,272	21%
Wednesday	2,097	19%
Thursday	1,717	16%
Friday	2,096	19%
Saturday	590	5%
Sunday	0	0%
	10,895	100%

size or selection rule adjustment was warranted. The activity would normally be triggered by (1) a new or adjusted customer contract or (2) a change in demand forecasts. The model could also be run to provide input to the pricing process for a new contract.

Simulation and Optimization

Using the derived truncated normal distributions above and an empirical distribution for dwell times, we generated 100 simulated realizations of order arrivals and dwell times, each with a duration of 1 year (the contract period commitment for leased chassis) using a half-day period as the unit of measure.

For any given simulated realization, we can formulate and solve an explicit integer programming model that provides the optimal selection of chassis type, rented or leased, for each order and the corresponding size of the leased chassis pool needed to support these selections. The data inputs for this problem include the daily chassis rental cost and the annual cost for leased chassis, and explicit set of orders with arrival and dwell times. To reasonably model the effective reuse of leased chassis, we model time in half-day increments and assume that returning leased chassis are available for reassignment in the following half-day, either the morning-to-afternoon or afternoon-to-next-morning period. In the appendix, we give the mathematical formulation for this problem.

Figure 3 tracks the usage of leased and rental chassis over the course of a representative optimization run. One can clearly see the relationship between leased chassis pool engagement and rental chassis use. In the optimal solution, the cost of an additional leased chassis is balanced by the incremental savings of a corresponding reduction of rental chassis.

Using the simulation approach described above, we generate a large number of scenarios, each consisting of sequences of container arrival times with corresponding dwell times. We then provided each realization as a separate problem to this optimization model together with the business-provided cost data—$19 per day daily chassis rental and $2,972 per year leased chassis cost. The total processing time per simulation to tabulate the incidence matrix and solve the optimization problem is less than 20 seconds running on an Intel i5, 64-bit, 2-core, 2.33-GHz processor. Figure 4 plots the realized number of orders and optimal fleet size for each of 100 optimized simulations. The optimization applied to the actual historical data is denoted by "x."

For any given simulation/optimization run, we can also observe the robustness of the leased chassis pool-size decision. To do this, we rerun the math programming model, adding a constraint to fix the leased pool size at a nonoptimal value, to obtain a new total cost while still optimizing individual selections. Figure 5 depicts the total chassis cost (lease plus rental) as the fleet size is forced to vary from the optimal value (indicated by "x") for a representative scenario.

Figure 3. Mix of Leased and Rental Chassis Over Time for a Representative Optimization Run

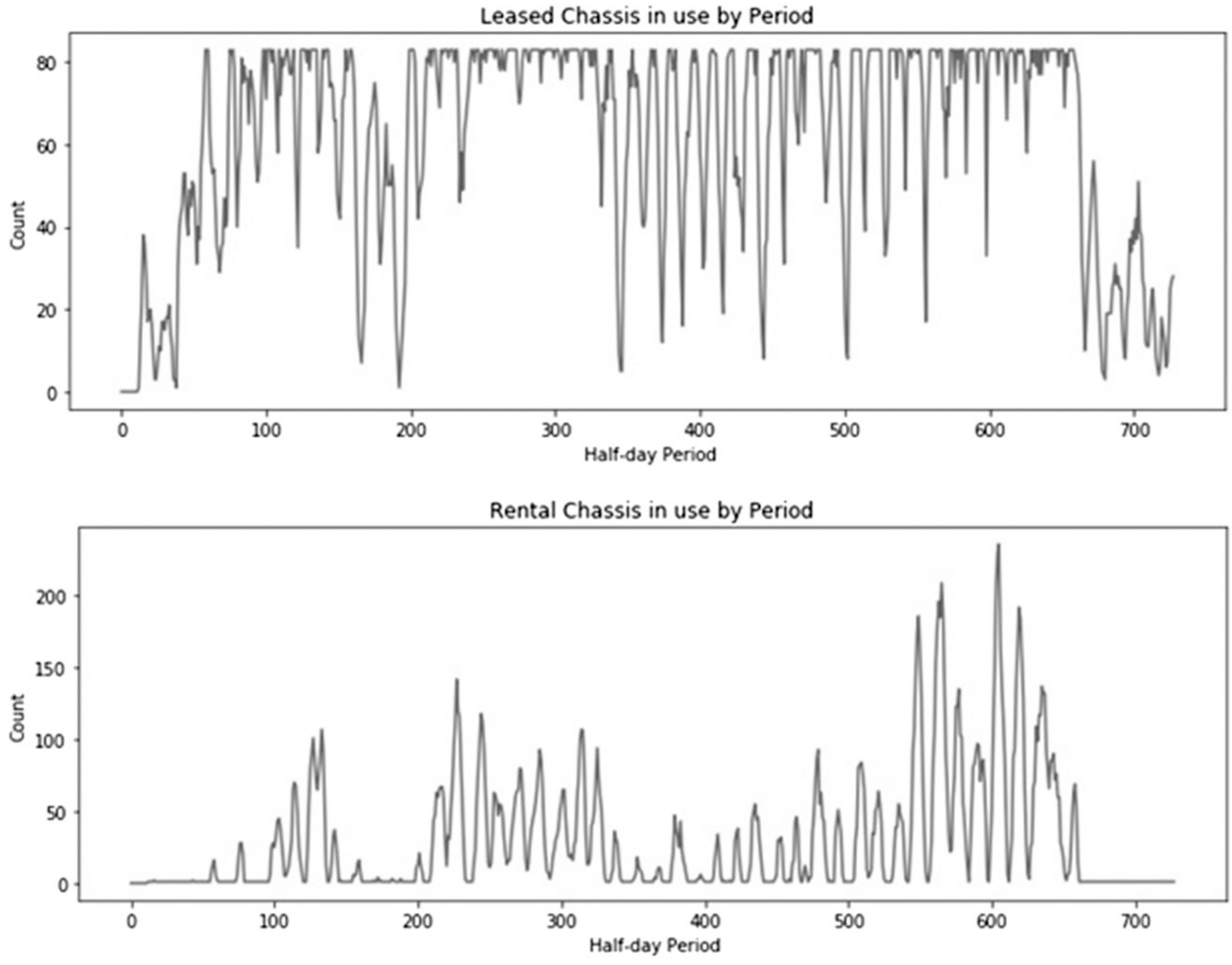
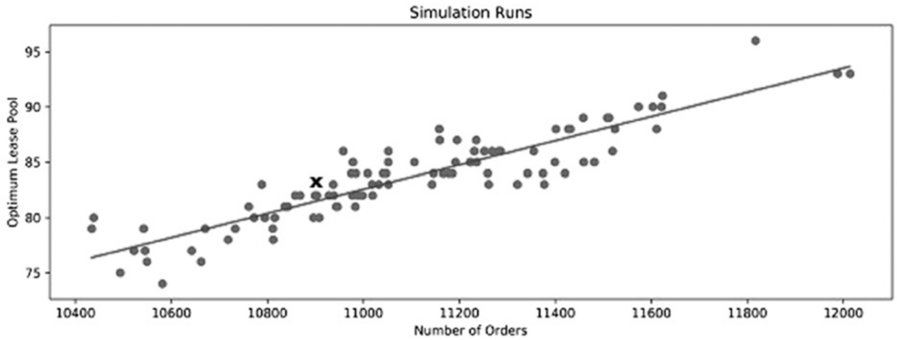
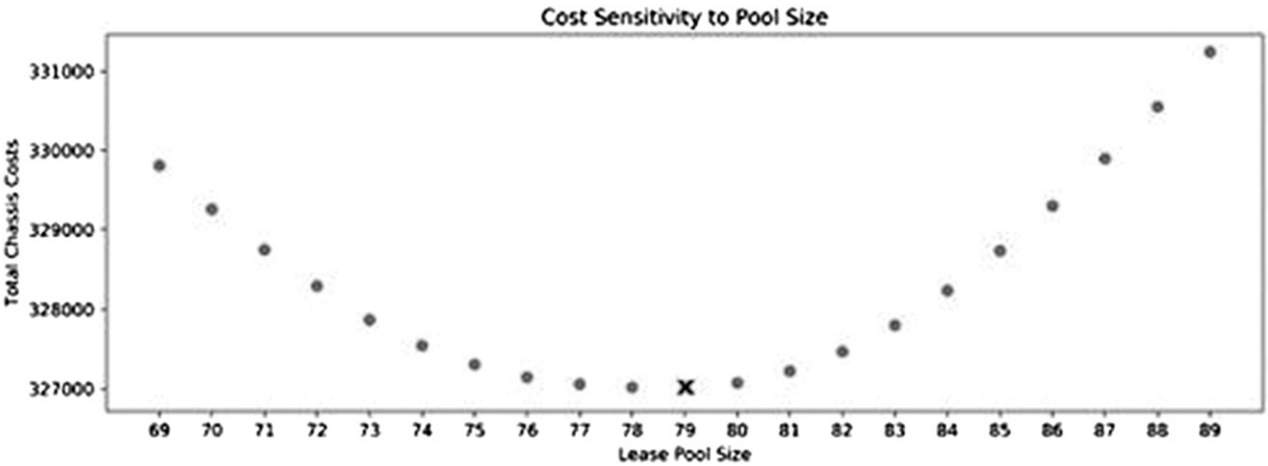


Figure 4. Optimal Fleet Size and Number of Orders for a Collection of Simulation Runs



Note. "x" denotes the optimization model applied to actual history.

Figure 5. Optimal Cost for Various (Forced) Fleet Sizes



Note. "x" corresponds to the optimum fleet size.

We also tested how the optimization solution would vary with changes in the ratio of annual lease cost to the daily rental cost. As one might expect, Figure 6 shows a nearly linear decrease in the optimal lease pool size as the annual lease cost rises.

These analyses combine to support empirically the approach of recommending the mean value of the fleet-size solutions across a collection of replications drawn from distributions that best represent the forecast of order arrivals over a forward period for which a chassis lease commitment decision will be made.

In the Predictive Model section, we describe the process of building a chassis selection decision rule using the specific choices made in the Monte Carlo simulation and optimization steps.

Predictive Model

From the simulation and optimization work, we collected over 100,000 orders (and corresponding optimization solution decisions) from randomly selected instances of simulated order streams, and we determined the following predictor variables corresponding to relevant data available on the day the order (container) arrived and was processed:

- Total daily orders for pickup (Count)
- Number of available leased chassis (Avail)
- Estimated dwell for each order (Dwell)
- Whether the planned chassis drop is morning or afternoon (DL Early)

We then fit a logistic regression with these predictors and the corresponding chassis (leased or rented) selection (from the optimization) as the target. The details of the logistic regression are shown in Figure 7.

For each problem instance, the model yields a score—the probability that a leased chassis was chosen. To test the goodness of fit for this model, we applied the Hosmer–Lemeshow test. Figure 8 shows the results of this test for one of the model training sets.

We propose to use these scores to develop a business rule; however, we first want to know something about the stability of the scores across different scenarios.

Figure 6. How the Optimal Lease Pool Size Decreases as the Lease Cost Increases While Holding Daily Rental Cost Constant

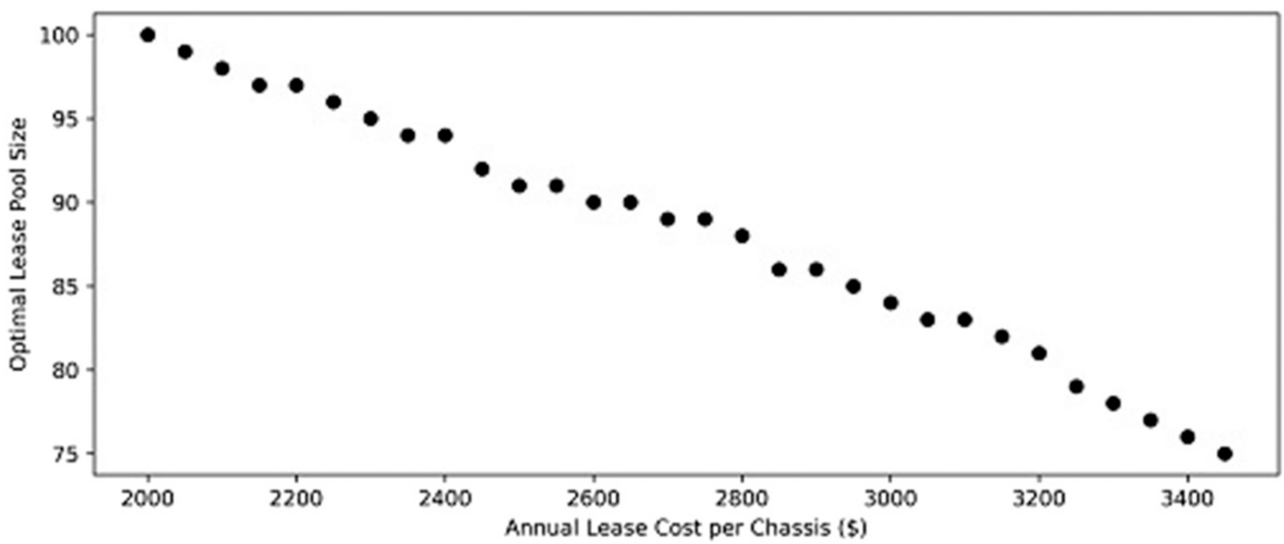


Figure 7. Output of the Logistic Regression Model

```
Call:
glm(formula = Opt ~ Dwell + DLEarly + Avail + CountofOpt, family
= binomial(), data = ords)

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)  1.6336252  0.0289629   56.40   <2e-16 ***
Dwell        0.6155231  0.0048532  126.83   <2e-16 ***
DLEarly     -0.2159459  0.0176484  -12.24   <2e-16 ***
Avail        0.0891214  0.0014419   61.81   <2e-16 ***
CountofOpt  -0.0731835  0.0005896 -124.12   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Note. Model coefficients and p-values indicate the significance of the model parameters.

Figure 8. Results of the Hosmer–Lemeshow Test

```
> hoslem.test(ords$Opt, fitted(logModel), g=10)

        Hosmer and Lemeshow goodness of fit (GOF) test

data:  ords$Opt, fitted(logModel)
X-squared = 376.02, df = 8, p-value < 2.2e-16
```

Note. The small p-value confirms that the model fit is very good.

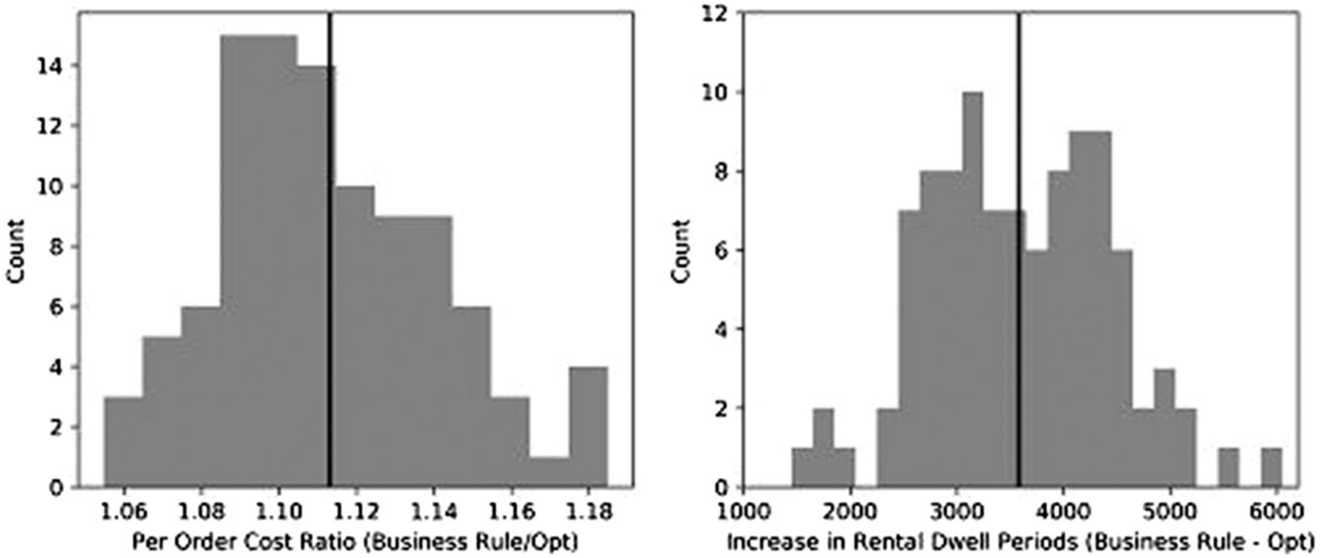
To do this, we aggregate the inputs over a narrow range across all models and measure the average and standard deviation of the scores. In Table 3, we show examples for three aggregations.

Overall, the standard error was under 10%, which suggests that the scoring is consistent across different models. The next step is to derive a selection business rule using the scores. Using a straightforward application of our model results, we define the rule as follows: When an order arrives, we use a rental chassis if no lease chassis are available (quite obviously!); otherwise, we calculate the probability from the regression equation. If the value is greater than 0.5, we select a leased chassis; otherwise, we select a rental chassis. In follow-up simulation runs, we observed that this rule (without knowledge of the future) uses more daily chassis than the optimization (with knowledge of the future) and, as we show in Figure 9, incurs a 31% higher rental cost

Table 3. Standard Error for Three Representative Input Aggregations

DLEarly	Dwell	Orders/Day	Avail Chassis	Avg Score	Std Dev	Num Orders	Std Err
0	1	0 to 5	0 to 5	0.83	0.04	24	4%
0	1	5 to 10	0 to 5	0.80	0.04	134	5%
0	1	5 to 10	5 to 10	0.89	0.03	19	4%

Figure 9. Cost Comparison of Optimization and Business Rule Results for a Representative Simulation Run



and an 11% additional total cost. For our set of 100 simulation runs, we calculated the cost per order for the optimization and business rule approaches.

Given the business tendency (prior to our engineering analysis) to underestimate significantly the best size of the lease pool, we use historical data to estimate that the per-order cost would have been in the range of $50–$55, or approximately 50% higher than the business rule-based cost. The foregoing analysis is based on the application of our approach to representative historical data. Because of company financial disclosure policies, we cannot share current volume and cost data, other than to confirm that the realized savings and benefits are consistent with the amounts calculated from the historical analysis.

Observations and Extensions

We describe an analysis and modeling methodology to develop a defined process that a logistics transportation provider can use to manage chassis activity as part of a port transloading operation. The key results are a recommended number of leased chassis, a way to estimate costs, and a decision rule that can be used in real time to choose between leased and daily rental chassis. Our literature search found several examples of modeling some aspects of port operations, but none was specific to the management of chassis pools. The unique feature of our approach was the use of repeated runs of an optimization model as input to a statistical model. Frequently, one sees a statistical model used as an input to an optimization, but rarely the reverse. While the scale of the problem is more than 10,000 orders per year, the optimization model, an explicit-solution integer program formulation, solves very quickly, consuming only a few seconds per model run. At some times of the year, the demand can be met with only leased chassis, while during high-demand periods additional daily rental chassis are needed. The value of our model is to balance the lower cost of leased chassis with the intermittent usage flexibility of daily rentals. Possible extensions of this model would be any problem with choices between two alternatives with an equivalent quality of service but with different cost; one a long-term cost and the other a short-term commitment.

The defining aspects of our problem suggest other domains of application. These include

- sizing and assignment of a company vehicle fleet for temporary employee use wherein higher-cost short-term commercial car rental is used to augment the company fleet;
- making a long-term commitment to a block of hotel rooms that would incur a cost if unused and would need to be supplemented at a higher rate if excess demand occurred;

- determining a mix of dedicated and flexible machines that can perform the same task wherein the dedicated machines may be idle during low-demand periods and flexible machines would be needed (at a higher cost) to meet excess demand; and
- determining an optimal size of a dedicated freight transportation fleet in the case where spot (variable) capacity is obtainable at higher cost.

In general, we would consider problems with the following characteristics:

- a finite set of asset classes that can perform the same tasks but have differing cost and commitment profiles;
- availability of representative data from which to build the arrival and dwell (interval of use) time distributions; and
- no asset swapping once an assignment is made.

Appendix

Here, we describe the optimization model that determines both the optimal number of chassis to be leased in advance for the time period spanned by the collection of orders (i.e., the scenario) specified as the problem input. The solution also provides the optimal selection choice (leased or daily rental chassis) for each individual order.

We begin by converting the arrival and dwell data into an incidence matrix of orders by half-day periods. We define $M(i,p) = 1$ if the order i container requires a chassis in period p and 0 otherwise. The decision variables $x_i = 1$ or 0 indicate whether the container for order i is assigned to a leased or rental chassis. We also introduce derived variables, y_p, to count the number of leased chassis engaged in each period p. While not strictly necessary for the optimization, these values facilitate solution analysis. We now formulate the model as follows:

$$\min \sum_{i\in\mathcal{I}} (1 - x_i) D_i C_R + nC_L, \tag{A.1}$$

subject to

$$\sum_{i\in\mathcal{I}} M(i,p)x_i = y_p, \forall p \in \mathcal{P} \tag{A.2}$$

$$y_p <= n, \forall p \in \mathcal{P}. \tag{A.3}$$

The variables appearing above are defined as follows:

n ≡ total number of chassis to lease,
x_i ≡ indicator of chassis selection, and
y_p ≡ number of leased chassis engaged in period p.

Problem data are defined as follows:

I ≡ index set of orders representing chassis requirements,
P ≡ index set of half-day time periods,
D_i ≡ dwell time (in half-day periods) of order i,
C_R ≡ per-period chassis rental cost,
C_L ≡ per-chassis annual lease cost, and
$M(i,p)$ ≡ the order-period incidence matrix.

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Verification Letter

Randy Justice, Terminal Manager, Schneider National Inc., Savannah, Georgia, and Chicago, Illinois, writes:

"Please consider this letter as verification of the business applicability and value delivered by the article 'Chassis Leasing and Selection Policy for Port Operations,' submitted for the Innovative Applications in Analytics Award by Robert Gremley and Ted Gifford of the Engineering and Advanced Analytics Group at Schneider National.

"We used the results of this engineering analysis study to determine the correct number of chassis needed to serve our customers most adequately at the lowest cost for both us and our customer. Additionally, we used it to gauge the rate we need to bill the customers in order to maximize profits while still being competitive from a pricing standpoint. While the project started primarily under the scope a single customer, we were able to extend it to use on multiple customers.

"The full program is now up and running. With all things being equal compared to not having the leased units, our projected annual cost savings this year will be approximately $365K in chassis costs.

"We have also gained much better insight into how containers turn and dwell at the customer, and how our empty and load returns flow with regards to days of the week and time of the day.

"If I can provide any additional information, do not hesitate to contact me."

Ted Gifford was a distinguished engineer at Schneider National, Inc., where he previously served as vice president of engineering and research. Before joining Schneider, he was a member of the mathematical sciences faculty and an associate dean at the University of Alaska. His various technical leadership and research roles include president of Computer Consultants of Alaska, director of quantitative research at McKinley Capital Management, and senior engineering manager at Symantec Corporation.

Robert Gremley is a senior engineer in the central engineering group at Schneider National, Inc., where has been since 1998. He is currently responsible for projects across a range of areas including equipment management, employee retention and safety, revenue management, and operations planning. He has more than 30 years of professional and consulting experience in logistics, transportation, and supply chain strategy. Before joining Schneider, he worked at A.T. Kearney and Baxter-Travenol. He received his bachelor's and master's degrees in industrial engineering from the University of Illinois in Urbana.