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A Hybrid Agent-Based Simulation and Optimization Approach for Statewide Truck Parking Capacity Expansion

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Abstract

Truck parking shortages are a critical concern for both the trucking industry and truck drivers in the USA. To tackle growing shortages, parking capacity expansions are needed. This paper presents a hybrid agent-based simulation and optimization approach to model truck movements and driver behaviors to determine feasible locations for truck parking facility capacity expansions across a state. The simulation model considers the driving limit and rest requirements of hours-of-service regulations set forth by the federal regulations. By leveraging observed historical truck GPS data, agent profiles are created, capturing truck trip origins, necessary stops, trip destinations, and parking behaviors. The simulation model estimates parking facility utilization over time by identifying where, when, and how long truck drivers rest. The estimated parking usage data is then fed into a maximal coverage capacitated multiple facility location optimization with multiple service model to deduce capacity expansion locations given budgetary restrictions. Ultimately the model recommends where and how many parking spaces to add to accomplish a certain level of parking overcrowding. The simulation and optimization approaches are finally integrated into a map-based, user adaptable decision support tool.

Keywords: Truck Parking; Agent-Based Simulation; Maximal Coverage Problem; Hours of Service Regulations

1. Introduction

Truck parking shortages are a major bottleneck for the trucking industry in the USA. Industry surveys rank truck parking as the fifth most important issue for the trucking industry and the third most important issue for truck drivers

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in their professional lives [1]. Federally mandated truck parking studies reveal that the majority of states (36 states, i.e., 72%) reported parking shortages and more than 75% of truck drivers reported experiencing problems finding safe and adequate parking, while 90% reported struggling to find parking during night hours [2].

Federally mandated hours-of-service (HOS) regulations limit when and how long a truck driver is allowed to drive by restricting the driving and on-duty time [3]. On-duty time includes all time a truck driver works including on-duty driving (period of time a driver is behind the wheel) or on-duty not driving (period of time spent doing any non-driving works, e.g., loading and unloading tasks). Off-duty time includes all time spent on activities other than any work including rest breaks. Specifically, HOS regulations (1) limit the driving window to 14 consecutive hours (*daily limit*), after which drivers may not drive their truck until they take 10 or more hours of off-duty time; (2) limit the driving time to a maximum of 11 hours within the 14-hour driving window; (3) stipulate a maximum of 60/70 hours of on-duty in 7/8 days (*weekly limit*) that can be restarted by 34 consecutive hours of off-duty time; and (4) require a minimum of 30 minutes of off-duty after 8 hours of on-duty.

Fiscally constrained state transportation agencies must prioritize infrastructure capacity expansion projects to address parking overcrowding [4, 5]. Current capacity improvement projects follow a simple approach of adding capacity to the most overcrowded parking facilities. This overlooks the interconnectedness of truck parking facilities considering that smaller and distributed capacity increments could provide a lower cost solution with larger impacts. This paper presents a hybrid agent-based simulation and optimization approach to serve as a policy development and decision support tool to guide strategic investment in statewide truck parking infrastructure. The tool features a map-enabled (e.g., Geographical Information System, GIS) application to capture truck parking and rest patterns. The simulation output feeds an optimization problem to find facility expansion projects that address the most overcrowded facilities, considering a user-specified budget.

2. Methods

A handful of prior studies applied agent-based simulation in freight transportation modeling to simulate (i) touring patterns of commercial trucks (e.g., [6, 7]) and (ii) freight market and firm-level decision making processes (e.g., [8, 9]) to explore route choice behavior and forecast freight movements. Simulation-based approaches that focused on truck parking are limited to assessing the impacts of infrastructure policies (e.g., land-use changes) on truck parking (e.g., [10]). The role of HOS regulations in parking demand have been overlooked in the current freight models. HOS modeling approaches largely focused on the impact of HOS regulation changes in trucking fleet operations (e.g., [11]), often by greatly simplifying truck parking behaviors and challenges. This paper addresses a methodological gap in estimating parking demand under HOS regulations. The methods applied in the study involve two sequential steps: simulation and optimization (Figure 1). In the simulation step, truck driver movements and parking decisions are modeled, so that hourly parking facility usage is estimated under a set of HOS rules and existing facility locations and capacities. Then bundles of capacity improvement decisions depicting where and how many spaces to add at new or existing facilities under a specified budget are determined in the optimization step.

2.1. Simulation approach

Agent-based simulation is used because of its unique ability to model complex systems consisting of independent components (agents) living in a dynamic environment and performing actions over time. The simulation is developed in NetLogo, an open-source multi-agent programmable environment. NetLogo is chosen to promote cost-free adoption by state agencies, and for its capabilities to smoothly integrate into databases, GIS, and other programming languages, like R. In NetLogo, there are four types of agents that can follow instructions: turtles, patches, links, and observer. Turtles are agents that move in a two-dimensional world that is divided into a grid of patches. Patches and turtles have coordinate attributes. A patch's coordinates are integers while a turtle's coordinates can only have decimals, meaning a turtle can have a position anywhere within its patch. Links connect turtles to make networks and graphs while the observer gives instructions to other agents, for instance, an observer can make new turtles. In our simulation, trucks, parking facilities, and transportation network nodes are programmed as turtles. By treating trucks, parking facilities, and the transportation network as turtles, we are able to update their attributes at each time tick (e.g., simulation step) to then make decisions regarding their next movement/action. Static attributes of truck agents include entry location in the map and entry time while dynamic attributes include location and driving and rest hours accrued. For parking facility agents, static attributes include parking location and type (e.g., facility with services like restrooms and fuel vs. no service) while dynamic attributes include parking availability, i.e., number of parking spaces available at a particular point of time. For example, in each time tick, a truck agent may continue to rest or drive depending on their HOS status (e.g., remaining driving time) in the prior time tick. Similarly, for parking facilities, at each time tick, the usage is updated so that the truck agents can interact with the parking facility agent when deciding if they can park at the facility in the current or next time tick.

Attributes such as HOS history, point of entry along the network, and origin-destination of each trip for truck agents are estimated from historical GPS data. Attributes such as time of day usage patterns, capacity, and static location for parking facility agents are estimated from the statewide truck parking facility inventory. Transportation network nodes (intersections between network links) are gathered from road network geospatial data provided by the state transportation agency and represent all interstates, highways, and local roads. Using the road network geospatial data, NetLogo link agents are created by connecting node agents according to their geospatial connections. NetLogo links connect the various pieces of the network and interact with the truck agents so that the trucks can enter into the state, travel along, and exit the state boundary following logical paths along the road network. We define entry and exit links for truck agents based on historical truck volume data on those links. The patches in our model are the Arkansas state boundaries.

Truck agent behaviours include decisions on when, where, and for how long to drive and/or rest are derived from HOS rules and distributions fitting historical driving behaviour data. The study focuses on long-haul truck drivers (multi-state, multi-day driving) seeking overnight parking. Using observed historical truck GPS data, truck agents are assigned a seven-day driving profile, representing their driving, on-duty (both on-duty driving and on-duty not driving), and off-duty durations. Anonymous truck GPS data is used to generate truck activity patterns of truck agents in the simulation. Each GPS data record contains a unique, but anonymous, truck identification number (ID), anonymous driver identification number, timestamp, latitude and longitude coordinates (e.g., pings), point-speed, and driving status (e.g., on-duty, off-duty, sleeper berth, etc.). This data was processed to build seven day driving histories the specific rest and drive times. The driving histories are assigned to truck agents which reference the histories to determine the agent's next move, e.g., drive, park, etc. Two types of off-duty breaks are defined: (1) long off-duty, any off-duty break of 10 or more consecutive hours, (2) short off-duty, any off-duty break that are more than 30 minutes but less than 10 hours. Then, truck agents navigate from a preassigned origin to a preassigned destination, making decisions to rest (choose an off-duty status) or continue to drive or work (choose an on-duty status) based on HOS adherence behaviour and predefined probability distributions for length of duty and rest statuses.

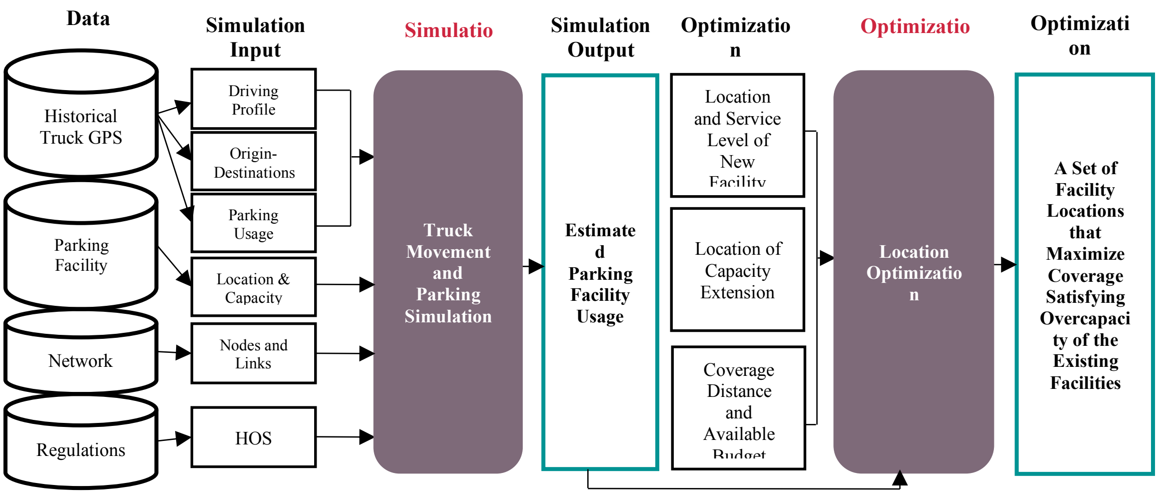


Fig. 1. Research framework

Origins and destinations for truck agents can include locations in and out of the state. For in-state locations, truck agents are initiated in either on-duty driving on roads or off-duty (resting) status in parking facilities. The number of truck agents initiated at in-state locations is derived from truck positions observed from historical GPS data at midnight, the start of the simulation time period. For out-of-state locations, truck agents are initiated at key state border crossings in the on-duty driving status, at rates estimated from the historical GPS data. The number of in-state truck agents on each link and the agents entering the state in each hour and link are static values, pre-set in the simulation. Each driver is uniformly at random assigned a seven-day profile gathered from the historical GPS, drawn from the population of profiles for the day of the week and hour of the day in which the truck agent is initiated. Based on the assigned profile, the simulation determines the length of time for a truck agent to continue on the same duty status. Time remaining for a given status is based on HOS rules to determine the permissible time remaining for the status and a fitted probability distribution to determine how long the truck agent will spend in the duty status, or equivalently how many simulation time ticks. The simulation time tick can be set by the user and represents the temporal resolution of the simulation.

The historical truck GPS data which contained position, timestamp, and duty-status, is used to fit frequency distributions that represent the length (time) a driver spent under each duty status. The fitted distribution for the length (time) of on-duty (not driving) status is a Weibull distribution with shape and scale parameters of 1.19 and 0.22, respectively. The short off-duty (30-minute rest) status has a gamma distribution with shape and scale parameters of 0.96 and 0.61, respectively. It is observed that the length of a long off-duty (10+ hour rest) status had a minimum bound of 8 hours, so the distribution representing the long off-duty status is scaled to begin with 8 hours. The distribution fitted to the long-off duty is then gamma with shape and scale parameters of 1 and 4.81, respectively.

Two types of truck agents exist in the simulation to account for HOS and parking adherence. These are labelled 'risk-takers' and 'risk-averse' agents. The risk characteristic determines when a driver starts looking for parking relative to upcoming duty-status change and whether the driver will choose to park illegally. In this setting, risk-averse drivers start searching for parking earlier than risk-takers. When a parking facility reaches capacity (overcrowding), risk-taking drivers may park on nearby ramps or shoulders while risk-averse drivers will continue to seek legal parking at a downstream facility.

Parking facility agents are initialized with non-zero usage based on historical truck GPS data as observed at the midnight start time of the simulation. The simulation allows a user to input the percentage of risk-averse drivers (to reflect compliance and enforcement policies), HOS daily driving hour limits (to reflect changes to HOS policy), and locations and capacities of existing and future facilities (to reflect investments in capacity expansion). Thus, along with the GIS-enabled simulation to show truck movements and facility usage, the hybrid model is flexible enough to serve as a policy and decision support tool.

2.2. Optimization approach

The optimization step provides the maximal demand coverage by expanding existing or building new parking facilities with multiple service levels while explicitly considering a level of overcrowding, a maximum available budget, and a maximum distance between candidate facilities (supply) and overcrowded existing facilities (demand) locations. The maximum coverage problem has an extensive research base in the optimization and transportation communities. We refer the reader to [12] and [13] that reviewed various versions of this problem for further study. The notation is as follows.

T	Total number of ticks during simulation
L	Set of distinct geographic facility locations
k	Type of candidate facilities where, $k = 1$ (Build no service), 2 (Build partial service), 3 (Build full service), 4 (Expansion)
U_k	Set of candidate facilities of type k
I	Set of all candidate facilities, $I = \bigcup_{k=1}^{4} U_k$
ℓ_i	The geographic location of candidate facility i for $i \in I$
J	Set of all existing facilities
d_{jt}	Amount of demand overcrowding for existing parking facility $j \in J$ at time t
q_i	Capacity of candidate facility $i \in I$
f_i	Cost of building or expanding facility $i \in I$
d_j	Amount of overcrowding for existing facilities $j \in J$
c_{ij}	Distance between candidate facility $i \in I$ and existing facility $j \in J$
B	Available budget
D	Maximum distance an overcrowded truck will travel to a new facility

y_i	Binary decision variable that takes value 1 if facility $i \in I$ is created or expanded and 0 otherwise
x_{ij}	Decision variable representing the fraction of overcrowding of facility $j \in J$ satisfied by facility $i \in I$
z_{ij}	Binary decision variable representing whether overcrowding of facility $j \in J$ is satisfied by facility $i \in I$

Using the information from a complete run of the simulation, we set values for the parameters of the optimization model. First, the maximum overcrowding level at each facility $j \in J$, is calculated and set to d_j using Equation (1).

$$d_j = \max_{t=1,\dots,T}(0, d_{jt} - q_j) \tag{1}$$

If no overcrowding occurs at an existing facility d_j equals 0, otherwise Equation (1) returns the maximum number of trucks seeking parking above the capacity of each facility. Overcrowding at existing facilities, d_j, is interpreted as the demand to be supplied by adding capacity to existing facilities or building new facilities. The candidate facilities are classified into four different sets U_1, U_2 , U_3, and U_4. New facilities are U_1, U_2 , and U_3 with no, partial, and full-service levels, respectively. Service levels include amenities such as restrooms, fuel, and dining. It is noted that each new facility can have at most one of the three service levels. The existing facilities with the capability of expansion are classified into set U_4. The optimization model is then as follows.

$$\text{Maximize } \frac{\sum_{i \in I}\sum_{j \in J} d_j x_{ij}}{\sum_{j \in J} d_j} \tag{2}$$

Subject to:

$$\sum_{i \in I} f_i y_i \leq B \tag{3}$$
$$\sum_{i \in I} x_{ij} \leq 1 \qquad \forall j \in J \tag{4}$$
$$\sum_{j \in J} d_j x_{ij} \leq q_i y_i \qquad \forall i \in I \tag{5}$$
$$z_{ij} c_{ij} \leq D y_i \qquad \forall i \in I,\ \forall j \in J \tag{6}$$
$$x_{ij} \leq z_{ij} \qquad \forall i \in I,\ \forall j \in J \tag{7}$$
$$\sum_{i \in I:\, \ell_i = \bar{l}} y_i \leq 1 \qquad \forall \bar{l} \in L \tag{8}$$
$$x_{ij} \in [0,1],\ z_{ij} \in \{0,1\} \qquad \forall i \in I,\ \forall j \in J \ \text{ and } y_i \in \{0,1\} \qquad \forall i \in I \tag{9}$$

Equation (2) is the objective function where we seek to maximize the percentage of overcrowding demand satisfied at a new or expanded facility. In Constraint (3), we ensure that the cost of building new facilities and expanding existing facilities is less than or equal to the available budget. In Constraint (4), we enforce that the fraction of overcrowding demand at each existing facility that is satisfied at a new or expanded facilities is less than or equal to 100%. In Constraint (5), we ensure that the overcrowding demand satisfied by a candidate facility's is less than or equal to its (new or expanded) capacity if it is built. In Constraint (6), we enforce that each candidate facility can only satisfy overcrowding demand within a predefined maximum distance or radius, *D,* of the existing facility. In Constraint (7), we link the continuous and binary variables indicating if overcrowding demand is satisfied by a candidate facility. In Constraint (8), we enforce that each new facility can be built with at most one of the three levels of services: no service, partial service, or full service. We define the type, lower-bounds, and upper-bounds of decision variables in Constraint (9).

3. Results and Discussions

The model is applied to the state of Arkansas in the US. The simulation model used historical truck GPS data provided by a national trucking firm to define truck agent profiles of weekly driving histories and parking facility usage initialization. The road network used in the study is gathered from the routable network used by the state transportation agency in their existing travel demand model. Existing parking facility locations are gathered from the state transportation agency's overnight truck parking study which is an observational study of parking facility usage.

Reasonableness checks of the parking usage pattern results by time of day, day of week, and location show agreement with parking usage data from historical truck GPS records. Further, rates of HOS violations and illegal parking also show agreement with national statistics reported by federal agencies that set, regulate, and enforce HOS rules. The GIS-enabled simulation allows the model to be implemented as an effective decision support tool.

3.1. Existing truck parking facility usage patterns

This section describes the results of 10 repeated runs of the simulation under the following user-specified parameters and inputs: (i) HOS daily driving limit of 11 hours, e.g., current HOS regulation, (ii) Assumed highway speed limit of 70 mph, (iii) Percent of risk-taking drivers is 20% to reflect nationally reported HOS and parking compliance rates, (iv) 168 existing facilities, and (v) 42 possible new facility locations. The share of risk-taking drivers is selected based on historical parking behaviour data, garnered from processing of truck GPS data. The goal of this analysis is to demonstrate the effect of randomness in agent behaviour and resulting parking facility usage.

In total, there are 168 existing parking facilities accounting for 6,887 truck parking spaces (total capacity), and 42 new facilities with maximum possible capacity of 3,160 spaces. Facility expansion costs for no service facilities range from $800,000 to $1.1 million USD depending on the size of the facility. The full-service facilities cost ranges from $11 million to $14 million USD.

Applying the simulation under the above-mentioned criteria shows that on average overcrowding (more than 100% use of capacity) occurs at 26 of the 168 facilities with many significant overcrowding issues along the major interstates. On average, across all facilities, usage is approximately 33% of total capacity. Although this seemingly shows provision of adequate capacity, overcrowding at popular facilities (i.e., along major interstate highways I-30 and I-40) is observed. Comparing the ability of the simulation to match observed parking facility usage, the simulation results are compared to truck GPS data for the overnight peak parking period (10PM to 6PM). Overall, the Mean Absolute Error (MAE) is 14.98% usage, e.g., the average absolute difference between the simulation estimates of facility usage and the usage measured from the truck GPS sample. On average, 55 (40%) of the 138 parking facilities have Absolute Error (AE) below 4% usage, and the median absolute error is 5.41% usage.

3.2. Capacity improvements with a user-defined budget

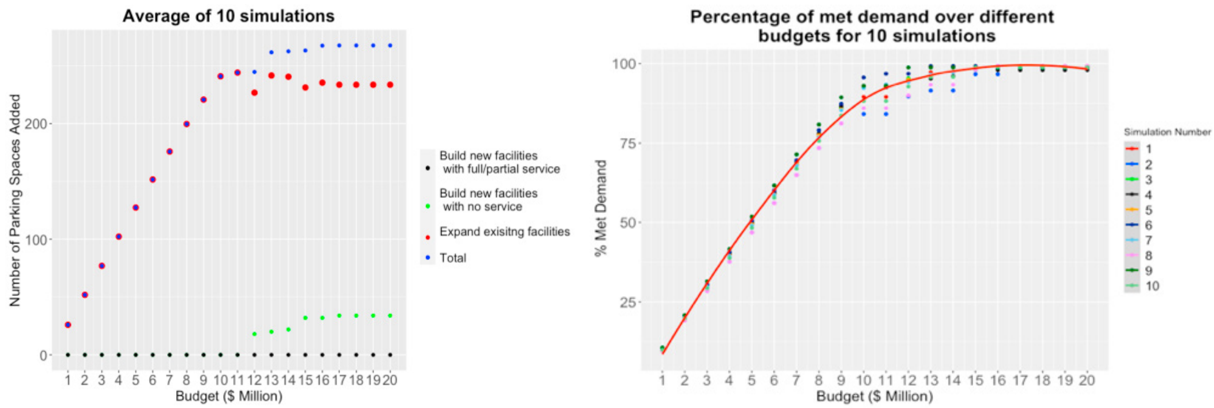
From the simulation output, the usage rate for facilities operating over capacity is used as input to the optimization model. First, the model considers any facility to be over capacity if the usage ratio is above 1.0, e.g., more than 100% of its capacity is used. This can occur as truck agents can choose to park illegally along the exit/entrance ramps leading to the parking facility, in which case the illegal parking is attributed to the nearest legal parking area. Second, the model identifies candidate facilities that could potentially serve the unmet overcrowding demand at the existing facilities. Candidate facilities are those within a specified search radius (or maximum coverage distance) of the overcrowded facility. The maximum coverage distance between candidate facilities and overcrowded existing facilities is set to 40 miles or approximately 30 to 60 minutes of drive time. From the list of possible candidate locations, considering the set of all candidate locations (e.g., the candidates for each overcrowded existing facility) the model seeks to select a subset of the candidate locations such that their total improvement/building cost does not exceed the budget while maximizing the amount of overcrowding demand that can be satisfied by the selected facilities (existing or new). For existing facilities, capacity expansions consider the purchase cost of available land surrounding the existing facility, site preparation (e.g., grading, tree removal), and the cost of paving and striping to get additional spaces. For new facilities, possible locations are selected by the research team from the list of available commercial locations reported by the state's economic development agency. The candidate sites must be zoned commercial or industrial, be large enough to accommodate a reasonable truck parking lot and its related services, and be located close to the interstate.

Each new and existing facility can have a different service level in terms of amenity provision, e.g., showers, fuel, food, and are classified into full service, partial service, and no service facilities. Each service level for each facility has a unique cost that is based on the size of the available land parcel and construction cost estimates for the facility infrastructure. Of the 168 existing facilities, 50 have land area suitable for capacity expansion. There are 42 new locations each of which can be considered for building new parking facilities under three service levels. Thus, there are 126 possibilities for new facilities and, in total, 176 possible expansion sites considering existing and new facilities.

The simulation length is set to 14 days with the tick length equal to 10 minutes. To provide more robust computational tests, 10 simulations are run and stored. The maximum facility usage is fed to the optimization model. For the test experiments, we embedded R within the interface, which utilizes the open-source solver 'rglpk' for solving the optimization problem. Running multiple simulations with a budget of over $20 million show that the optimal objective values do not change, which implies increasing the budget over $20 million does not improve the ability to address overcrowding issues. Hence, a sensitivity analysis is performed for budgets between \$1 million and \$20 million with \$1 million increments. For all 10 simulations, when the available budget is less than \$11 million, no new facility is recommended to be built and instead capacity expansions across multiple existing facilities is recommended. On average, for available budgets {\$12 million, \$13 million, \$14 million}, {\$15 million, \$16 million}, and {\$17 million, \$18 million, \$19 million, \$20 million}, 1, 1.6 and 1.7 new facilities need to be built with no service, respectively. The optimal solution of different budgets does not include any facility with partial and full service.

In Figure 2(a), we display the number of parking spaces added resulting from building new facilities and expanding existing facilities. Because the optimal solution does not require new parking facilities with partial and full service to be built, the number of added parking spaces for these cases is zero. When the available budget increases from \$1 million to \$11 million, the number of added parking spaces resulting from building new and expanding existing facilities steadily increases. On average, 24 spaces will be added for every additional \$1 million. On average, three parking spaces are added when the budget increased from \$10 million to \$11 million. For budgets over \$12 million, the optimal solution shows the tendency to invest in building new facilities with no service, and the average number of added spaces through expanding existing facilities is approximately constant around 235 spaces.

Figure 2(b) shows the percentage of met demand (objective function values) of 10 simulations at different budgets. There is no significant deviation between the optimal values of simulations for each level of budget, e.g., the average standard deviation is 1.51%. Increasing the budget from \$1 million to \$13 million leads to a steadily increasing percentage of met demand from an average of 10.05% to 96.66%. However, the percentage of met demand increases by less than 2% even though the budget increases from \$13 million to \$17 million, essentially tapering off. Increasing the budget over \$17 million does not change the amount of met demand because there are no more options to build new facilities or expand existing facilities within the maximum coverage distance of 40 miles.



(a) (b)

Fig. 2. Impact of increasing the budget on (a) the number of parking spaces added (b) the percentage of met demand

Lastly, based on the 200 optimal solutions derived from solving 10 simulation instances over 20 levels of budget, we find two strategic locations for expanding existing facilities and two locations for building new facilities with no service. Interestingly, we observe that the optimal solution of all 200 instances include expanding the same two facilities with 10 and 8 parking spaces added. There are three additional facilities which are included in more than 90% of optimal solutions. The frequency of optimal solutions associated with building new facilities with no service is significantly lower than that of expanding existing facilities. This is reasonable because when the available budget is less than \$12, the optimal solutions do not include building new facilities. The two most preferred new locations are observed in the optimal solutions of 34 and 32 cases out of 200 experiments.

3.3. Impact of HOS on parking demand

In this section, we demonstrate how the results of the simulation and optimization model can be used to assess policy changes regarding the HOS daily driving hour rule. Specifically, we observe the change in the percentage of met parking demand as we increase and decrease the daily driving limit. The default HOS daily driving rule allows a maximum of 11 hours driving in a 14-hour driving window. As seen with the pandemic, HOS can be lifted (daily driving limit increased) to expedite goods movements. Counter to that the daily driving limit may be reduced for safety concerns to encourage drivers to rest more often. Hence, we consider both cases where a 14-hour (the relaxed driving rule) and 8-hour (the restrictive driving rule) driving time are allowed within a 14-hour driving window. We use the average percentage of met demand over 10 simulations when allowed driving time is 11 hours and compare it with the relaxed and restrictive driving hour rules.

Relaxing the 11-hour rule to 14 hours leads to a slight increase (1.5%) in the percentage of met demand as drivers have more time to possibly drive and reach their destinations or search for uncrowded parking facilities. Restricting allows driving from 11 hours to 8 hours significantly reduces the percentage of met demand by 44.3%, on average. The result indicates that if driving time was to be further restricted, more overcrowded parking facilities would occur.

Comparing parking facility overcrowding by driving limit, on average, 205 trucks are unable to find parking under the restricted (8-hour) driving scenario compared to 29 under the current (11-hour) and relaxed scenarios. As shown in Figure 3, with the goal of satisfying 40% of overcrowded facilities, we need to spend $11 million when the driving time is restricted; however, we can reach the 40% target with a $5 million investment when drivers are allowed to drive for 11 hours. To satisfy a higher percentage of met demand when the driving rule is restrictive, the optimal solutions indicate building new facilities with full and partial service as well as building new facilities with no service and expanding existing facilities. Comparatively, if the target is to satisfy 92% of demand, at least a $90 million investment is required. With this, the optimal solution includes building four new facilities with no service (80 spaces added), three new facilities with partial service (120 spaces added), three new facilities with full service (231 spaces added) and expanding 32 existing facilities (265 spaces added).

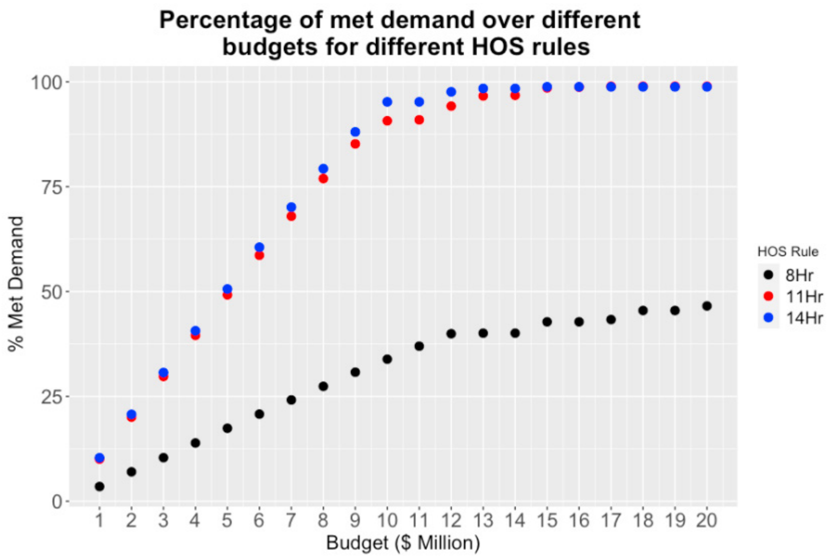


Fig. 3. Impact of changing driving hour rule on the percentage of met demand

4. Conclusions

This research developed an integrated agent-based simulation and optimization tool to prioritize truck parking facility capacity expansion projects at a statewide level. Uniquely, the simulation model considers Hours-of-Service (HOS) daily and weekly cumulative rules and incorporates risk taking behaviors to mimic real-world parking and HOS violation occurrences. The simulation output (parking facility usage by time of day and day of week) is fed to an optimization model to determine infrastructure investment bundles. The location model considers how to best distribute a user-specified budget to address overcrowded facilities while considering different service levels for new facilities, e.g., showers, fuel, food. The model is applied to the State of Arkansas, USA, and results showed alignment of the simulation with observed parking usage patterns and driving behaviors. Further, parking usage patterns and capacity expansions under two extreme HOS daily driving changes are explored, which aligns with our intuitive understanding while quantifying the extent to which reducing the driving limit will increase the demand for parking.

This tool is intended to be used by public transportation agencies, e.g., state and federal departments of transportation, to evaluate truck parking capacity expansions under specified budget scenarios and to serve as a policy evaluation tool. The benefit of the tool is that it allows stakeholders to generate performance metrics (e.g., the percent of met parking demand) under scenarios of varied budget and HOS policy- both variables which are under stakeholder control. Performance based planning such as that embodied by this tool is required for public transportation agencies as it encourages data-driven decision making.

References

[1] American Transportation Research Institute "Critical Issues in the Trucking Industry-2019", *Critical Issues in the Trucking Industry*. Accessed September 3, 2020. ATRI online. https://truckingresearch.org/wp-content/uploads/2019/10/ATRI-Top-Industry-Issues-2019-FINAL.pdf.

[2] Federal Highway Administration. *Jason's Law Truck Parking Survey Results and Comparative Analysis*. Accessed September 4, 2020. https://ops.fhwa.dot.gov/freight/infrastructure/truck_parking/jasons_law/truckparkingsurvey/ch3.htm.

[3] Federal Motor Carrier Safety Administration. *Interstate Truck Driver's Guide to Hours of Service*. Accessed September 3. 2020.https://www.fmcsa.dot.gov/sites/fmcsa.dot.gov/files/docs/Drivers%20Guide%20to%20HOS%202015_508.pdf

[4] Arizona Department of Transportation. "Arizona Truck Parking Study". Accessed September 3, 2020. https://azdot.gov/sites/default/files/2019/08/final-report-arizona-truck-parking-study.pdf

[5] Washington Department of Transportation. The Washington State Truck parking Study. Accessed September 3, 2020. https://www.wsdot.wa.gov/sites/default/files/2014/09/22/TruckParkingStudyfFinal.pdf

[6] Liedtke G. Principles of micro-behavior commodity transport modeling. *Transportation Research Part E: Logistics and Transportation Review*. 2009 Sep 1;45(5):795-809.

[7] Hunt JD, Donnelly R, Abraham JE, Batten C, Freedman J, Hicks J, Costinett PJ, Upton WJ. Design of a statewide land use transport interaction model for Oregon. In Proceedings of the 9th World Conference for Transport Research, Seoul, South Korea 2001 Jul (Vol. 19).

[8] Pourabdollahi Z. *An Agent-based Freight Transportation Modeling Framework* (Doctoral dissertation, University of Illinois at Chicago).

[9] Cavalcante RA, Roorda MJ. Freight market interactions simulation (FREMIS): An agent-based modeling framework. *Procedia Computer Science*. 2013 Jan 1;19:867-73.

[10] Gopalakrishnan R, Alho AR, Sakai T, Hara Y, Cheah L, Ben-Akiva M. Assessing overnight parking infrastructure policies for commercial vehicles in cities using agent-based simulation. *Sustainability*. 2020 Jan;12(7):2673.

[11] Young J. Simulation-based truck fleet analysis to study the impact of federal motor carrier safety administration's 2013 hours of service regulation changes. In 2013 Winter Simulations Conference (WSC) 2013 Dec 8 (pp. 3395-3405). IEEE.

[12] Daskin MS. Network and discrete location: models, algorithms, and applications. John Wiley & Sons; 2011 Feb 14.

[13] Farahani RZ, Asgari N, Heidari N, Hosseininia M, Goh M. Covering problems in facility location: A review. *Computers & Industrial Engineering*. 2012 Feb 1;62(1):368-407.