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A modeling framework for designing and evaluating curbside traffic management policies at Dallas-Fort Worth International Airport

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A R T I C L E I N F O

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A B S T R A C T

Emerging mobility technologies are changing the transportation system landscape. This is especially evident at airports, such as the Dallas-Fort Worth International Airport (DFW). Without careful analysis, these changes could lead to inefficient and costly airport operations. This paper presents a modeling framework that integrates travel mode encoding, demand projection, and microsimulation to enable airports to develop, simulate, and evaluate curbside traffic managements policies and measure their impact. The framework is utilized to analyze several traffic scenarios and policies for DFW: a baseline scenario which represents DFW traffic pattern as observed in 2018 and projected to 2045, a transit network company (TNC) electrification policy, a TNC queuing policy, a policy that increased transit ridership, a bus-only policy which considers the use of only buses inside DFW, an autonomous vehicle (AV) policy which investigates the impact of autonomous vehicle (AV) adoption on airport operations, and an example COVID-19 scenario which models the impact of the COVID19 pandemic. The simulations' results demonstrate that: increasing the DFW transit ridership postpones the need for airport curbside expansion the most; encouraging shared-mobility with the bus-only policy produces the most savings in curbside congestion delays; automation and electrification for all passenger vehicle trips to/from DFW generates the most saving in fuel consumption and emissions; and uncontrolled AV adoption incurs the highest increase in fuel consumption, delay, and emissions and could require immediate airport capacity extension. Without policy intervention or investment in additional infrastructure capacity, these results predict the current operations would face significant congestion on high demand days starting as early as 2028. While derived in close partnership with DFW, the methodology presented here can be generalized to any airport.

1. Introduction

Given these evolving trends and disruptions, airports need tools and methodologies that can enable them to design, model, and evaluate traffic management policies in order to adapt and operate their complex transportation networks while avoiding increased

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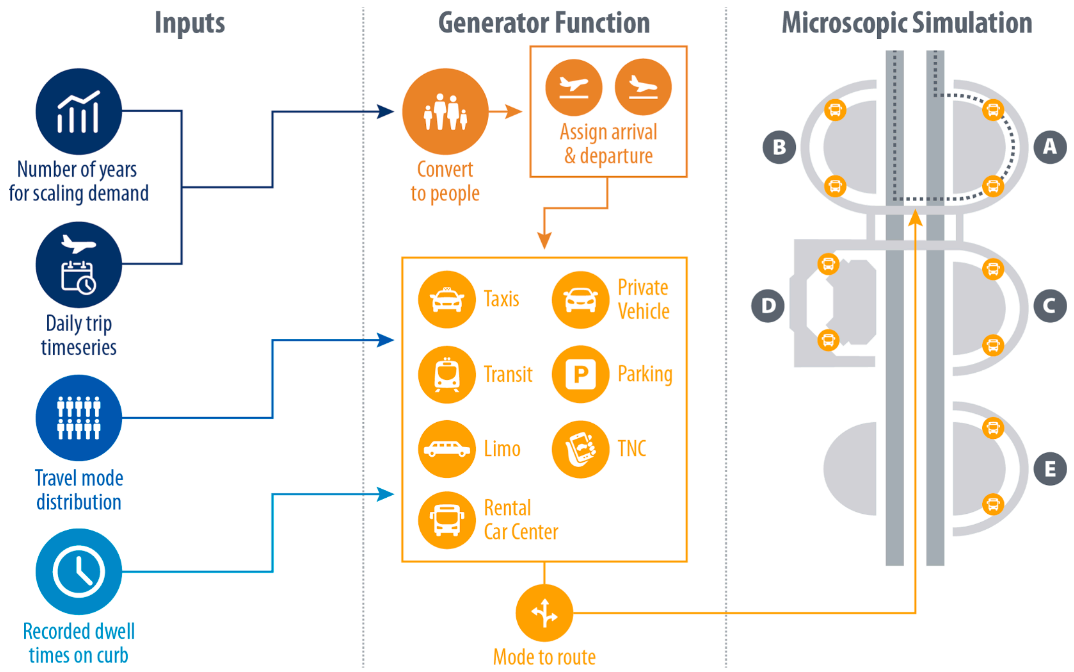


Fig. 1. Modeling framework.

operational inefficiencies, costs, and energy consumption. To conduct research to address this need, we initiated a committed partnership with the Dallas-Fort Worth International Airport (DFW) as part of the US Department of Energy Athena Project (Athena project: Wisdom to guide mobility transformations at us ports, 655 http://athena-mobility.org, accessed:, 2018). DFW is the United States' (US) first carbon–neutral airport, the US' second largest airport by land, and the fourth busiest airport in the world by aircraft movement. It is positioned halfway between the Dallas and Fort Worth cities, an urban area featuring the greatest population growth in the US (Census Bureau, 2018) as recently as 2017.

2. Related works

Most research on airport traffic management focuses on controlling air-side traffic (operations) to minimize aircraft congestion on runways (Simaiakis et al., 2014; Daniel, 2011; Czerny, 2010; Brueckner, 2002; Madas and Zografos, 2010). Research that concentrates on curbside or ground access are mostly qualitative in nature and describe legislation and ground traffic management policies, such as encouraging the use of public transit, without actual modeling and evaluation of these measures (Budd et al., 2014; Ison et al., 2014; Ison et al., 2007; Hamzawi, 1992; Gosling, 1997; Budd et al., 2011). The latest Federal Aviation Association (FAA) report on curbside and terminal roadways operations outlined policies for improved ground access operation, including relocating pedestrian crosswalks, providing alternative pick-up/drop-off areas, and reducing curbside speed limits, without assessing the effectiveness of these strategies (A. C. R. Program, U. S. F. A. Administration, L. F. Associates, 2010).

There has also been some research to explore the impact of travel mode shifts on airport ground traffic, which tends to focus on factors that influence airports' travel access modes (Jou et al., 2011; Tam et al., 2010; Tam et al., 2011; Tsamboulas et al., 2012; Ison et al., 2008; Akar, 2013). These efforts typically center on designing curbside simulation models that represent airport traffic patterns (Harris et al., 2017; Duncan and Johnson, 2020; Kimley-Horn, accessed:2019-07-09 (2019).; B. Hargrove,xxxx; Fellendorf and Vortisch, 2010) or evaluate the performance of specific travel modes, such as taxi (Yazici et al., 2016; Yazici et al., 2013) or transit (Malandri et al., 2017). Most recently, there has been growing interest in investigating the impact of TNCs on airports' curbside congestion and ground access (Bock, xxxx; Mandle and Box, 2017; Wadud, 2020; Davol, 2017; Hermawan and Regan, 2018; C. Leiner, xxxx). There is also limited research on the future impact of AVs on airport planning and operation (Wang and Zhang, 2019).

In contrast, our research focuses on developing a modeling and simulation framework that integrates travel mode encoding, traffic management, and microscopic traffic simulation to enable airports like DFW to optimally operate in the face of current and possible future disruptions. The framework can represent current and future changes in travel modes, including TNCs, emerging modes like AVs, and curbside traffic management policies; it can then convert them into simulations to evaluate their impact on congestion, fuel consumption, and emissions. The framework also enables researchers to project the travel mode choices and traffic management policies in the future to represent possible future scenarios and effects. We utilize the Simulation of Urban Mobility traffic simulator (SUMO) (Behrisch et al., 2011), an open-source simulator which ensures that our framework can be extended to other airports or scenarios. These simulations were calibrated using ground-truth speed data to validate their results. Our framework also enables running many SUMO simulations simultaneously on high-performance computing (HPC) resources, which provide enough

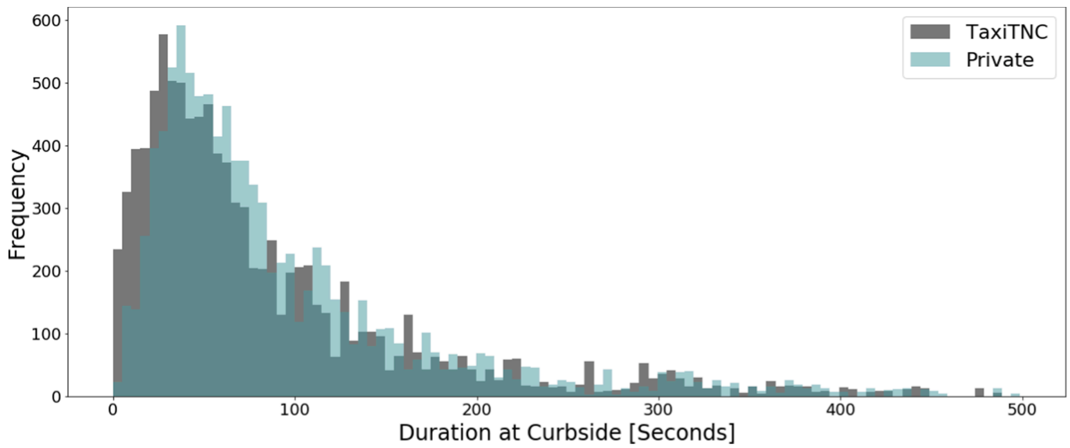


Fig. 2. Curbside dwell time distribution.

Table 1
Sample daily timeseries of trips.

time	parking	pass-through	A	B	C	D	E
00:00:00	15.0	33.0	43	24	48	28	3
00:30:00	23.0	21.0	25	14	27	13	2
01:00:00	15.0	15.0	13	7	14	7	1

computational power and memory to run thousands of simulations in parallel to explore many what-if scenarios.

We used the modeling framework to investigate the following traffic/curbside regulation policies and scenarios:

- **Baseline**: represents the "business-as-usual" traffic patterns at DFW, where airport passengers' travel modes choices are as observed in 2018 and projected out to 2045.
- **TNC**: represents curbside traffic management measures focused on TNC vehicles: a policy scenario focused on a certain proportion of TNC vehicles being electrified (TNC electrification policy) and a scenario centered on implementing a new pickup process at the curb (TNC queuing policy).
- **Increased Transit**: represents a traffic management policy that increases use of DART and TRA transit lines, owned by Dallas and Fort Worth cities respectively, to decrease congestion in the central terminal area.
- **Bus-Only**: a traffic control measure that only allows airport shuttle buses and transit buses to operate inside the airport or to access the curb.
- **Autonomous Vehicles**: models a shift towards electric AVs and the shift's impact.
- **COVID-19**: an example scenario that represents the 2020 dramatic reduction in air travel due to the COVID-19 pandemic and simulates the shifts in travel mode choices due to COVID-19.

The remainder of the paper is organized as follows: section 3 presents the developed modeling framework, section 4 details the above-mentioned scenarios and policies and also presents their simulation results, and finally, section 5 concludes the paper.

3. Methodology

Our modeling framework, depicted in Fig. 1, has two main components: a **generator function** that encodes travel modes and trips and converts them into SUMO demand files and a **simulation module** that combines demand files with network files for simulation.

3.1. Inputs to the generator function

As shown in Fig. 1, the generator function inputs are a daily timeseries of trips going to/from DFW; a travel mode distribution, which is an array of percentages per travel mode; the number of years, which determines by how many years to scale the input demand to represent future scenarios; and a dwell time distribution in Fig. 2, which determines how long vehicles stop at terminals to drop off or pick up passengers. The daily trip timeseries are derived from a previously developed DFW demand predictive model (Lunacek et al., 2020). This model predicts the number of trips to/from DFW for every 30 min in a 24-hour period. We further differentiate these trips by airport destination/origin; that is, the model predicts the number of trips going to each terminal (A,B,C,D, and E), those going to parking lots (parking), and those just passing through the airport (pass-through). The pass-through trips are from vehicles who only traverse the airport on their way to another part of the Dallas/Fort Worth metropolitan area, since DFW sits between the Dallas and Fort Worth cities. The distributions of each column were determined by flight data and data from DFW control plazas, which are ticketing gates located at the north and south ends of the DFW boundaries that regulate vehicles entering and exiting the airport. Table 1 is a sample of trip distributions by terminal for the *generator function*. For more details regarding trip distribution, refer to (Lunacek et al., 2020).

The dwell times, shown in Fig. 2, are the amounts of time that vehicles stop at terminal curbs to pick up or drop off passengers. They were calculated by randomly sampling from an empirical distribution from a study they conducted in 2018, in which they recorded curbside stops for passenger unloading and loading.

3.2. Generator function Sub-modules

The generator function is comprised of several sub-modules that represent different modes, including TNC, taxi, limo, private, transit, parking, and car rentals, as outlined in Fig. 1. The *TNC mode sub-module* encodes travel using ride-hailing services and then generates routes that begin from the control plazas, travel to a terminal curbside for passenger drop-off/pick up, stop for some time, and then depart through one of the airport gates. The *taxi and limo sub-modules* represent the taxi and limo travel modes respectively, which are similar to TNC behavior except for the curbside levels where they stop to drop off passengers. The *private sub-module* creates trips that go from the control plazas to the terminals for drop-off or pickup stops and leave the airport through the control plazas. The *private sub-module* models travel by personal cars, where passengers are picked up/dropped off by family, friends, or business associates. These trips' routes are identical to TNC behavior except for a longer stop on the terminal curbs (refer to Fig. 2). The stop time for the private, TNC, limo, and taxi trips were derived from the dwell time distribution shown in Fig. 2.

The *parking sub-module* models represent trips entering the airport that are going to the various parking areas or leaving the airport from the various parking facilities. The *transit sub-module* represents travel using the airport transit train located within terminal B. Transit passengers are not simulated since they do not affect road traffic other than decreasing the total demand. We also have a *bus sub-module* to represent bus routes, as specified by DFW operations, that move passengers from parking lots and between airport terminals and a *rental sub-module* that encodes the behavior of passengers who rent cars to travel to/from the airport by picking up or dropping off cars at the rental car center (RAC). Trips to the RAC are represented by buses on fixed routes to/from the RAC to/from different terminals. Per the DFW operations team, most top story curb space is dedicated to private vehicles and TNCs, while the bottom story curb area is designated for buses, other service vehicles, limos, and taxis.

As we increase vehicle demand, we need a way to estimate the number of people utilizing the airport so that we can apply different mode choices and still have results that relate to the same demand. Using our demand model (Lunacek et al., 2020), we first converted the demand based on the current mode choice into a passenger count by using a static factor of 1.7 passengers-per-vehicle parameter. While there are several characteristics that could impact this, such as business vs. leisure travel or personal vs. TNC drop-off, we did not have this level of information in our vehicle data in order to extract a more precise estimate. We convert trips to number of people to conserve the DFW demand level even as we vary travel mode choices. The passengers are divided up by arrival, departure, and later on, by travel mode following the input mode distribution. For simplicity, we assume that 50% of passengers are arriving at DFW and 50% are departing, since we lack the supporting data to justify a different arrival-departure allocation. The number of people is then converted back into number of vehicles with the 1.7 passengers-per-vehicle ratio.

3.3. Microscopic simulation

For each vehicle, we build an appropriate SUMO route, following the behavior of the corresponding travel mode as described above. These vehicle routes are then aggregated into a SUMO trip file for simulation. In addition, we also built trips for airport operation shuttles within DFW. These shuttles are used for employee transport, by driving airport employees from/to their parking lots to/from different terminals and other airport offices. There are also inter-terminal shuttles that go from terminal to terminal, allowing passengers to transfer between airport terminals without needing to walk. These shuttle trips generated background traffic used for all the simulated scenarios.

A SUMO microscopic simulation takes as input a DFW road network, a trip file, and various parameters for generating simulation outputs, including congestion measures (ex: road density, delay, and speed), fuel consumption, and emission outputs. We also wrote software to enable running many SUMO simulations in parallel on the Eagle HPC system at the National Renewable Energy Laboratory (NREL, Eagle, , 2019). HPC allowed us to simultaneously run simulations for all the different policies and for many distinct years for faster results and analysis.

3.4. Simulation calibration

To ensure valid simulation results, we calibrated our simulations to match ground-truth speed data. In our case, the available ground-truth data were link-level speeds gathered from the TomTom historic area analysis API (Bv, 2020). TomTom is a provider of traffic data, including anonymous probe count and hourly historic speed aggregates mapped to network links. This historic data was gathered for a DFW bounded latitude/longitude query. We collected historic hourly speed from TomTom for the simulated DFW network, shown in Fig. 3, for three representative days considered for policy evaluation: a low demand day (September-2–2018), a medium demand day (March-16–2018), and a high demand day (June-11 2018).

Fig. 3 displays the road segments simulated and calibrated using the built-in module from SUMO (G. A. C. (DLR), Simulation/

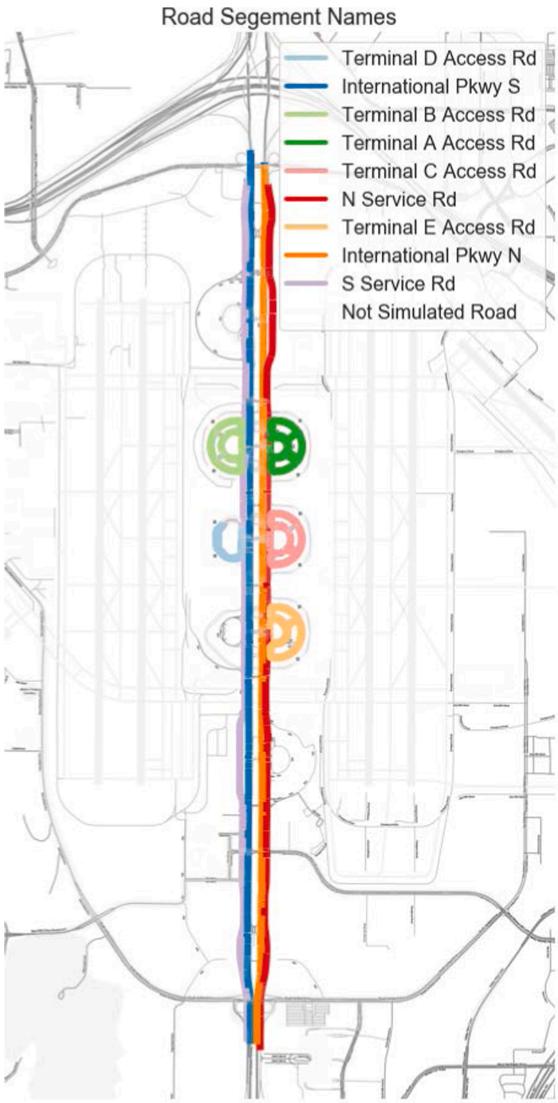


Fig. 3. DFW road segments simulated and calibrated.

calibrator, https://sumo.dlr.de/docs/ 755 Simulation/Calibrator.html (July 2020). The road names are derived from the TomTom network and represent the street name you would find if you were driving around DFW. The SUMO calibrator tunes the car driving behavior based on link level speeds throughout the network. We first adjust the sigma parameter in SUMO's car-following model for every simulated vehicle. Sigma controls the overall perfection/imperfection of vehicle behavior in the simulation and is represented as an increase or decrease to driver responsiveness. In other words, vehicles with lower sigmas have more perfect behavior and are able to react more quickly (via quicker acceleration/deceleration) to an evolving situation, thus avoiding traffic bottlenecks or congestion. Higher sigmas refer to slower reactions (i.e. slower acceleration/deceleration) which tend to lead to more traffic congestion. During calibration we set sigma to zero, representing perfect driving, to allow vehicles to freely and quickly adapt to the varying speed calibrators.

As shown in Fig. 4, the built-in SUMO calibrator's mean absolute percentage error (MAPE) varied by road name but overall was relatively low, with the lowest average MAPE being at 4.7 percent and the highest being 18.9 percent error. We calculated the error of all three days for calibration and found all days had similar MAPE results, with the most error contained on the North Service Road and least on the Terminal E Access Road. We also noticed the highest error occurred where the speed limits differed from the TomTom free-flow speeds. The TomTom free-flow speeds were calculated by observing all three days and then by using the 95th percentile speed of each link. These free-flow speeds were then used to tune the speed limits on the SUMO network. This tuned network was finally used to show the error compared to the results from the SUMO calibrator. Fig. 5 compares the performance of the calibration using built-in calibrator vs. the simulation that uses a DFW network with speed limits adjusted to the TomTom free-flow speeds. The results suggest that the tuned network had less error than the calibrator, demonstrating that the calibrator mainly focused on correcting the link

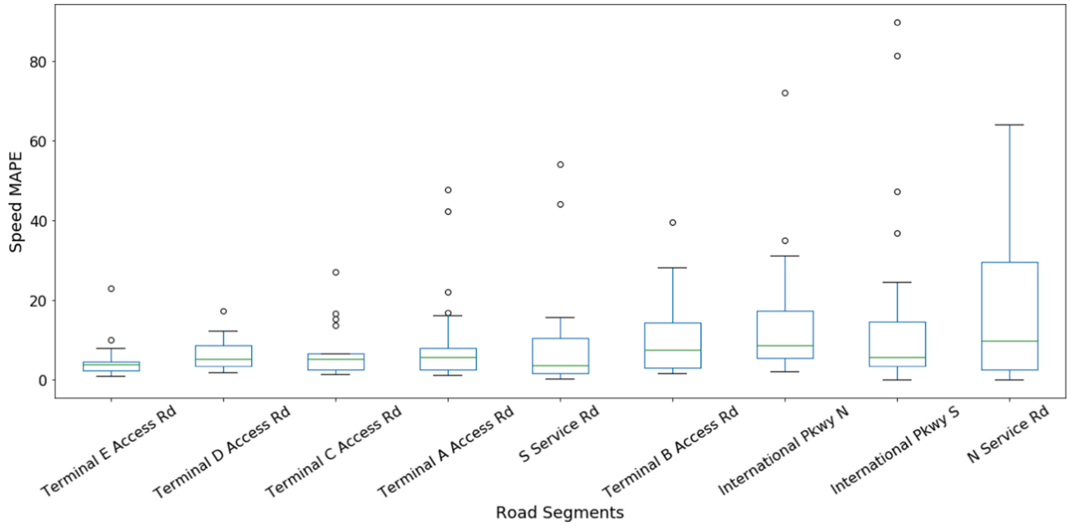


Fig. 4. Mean absolute percentage error of calibrated speeds for medium day.

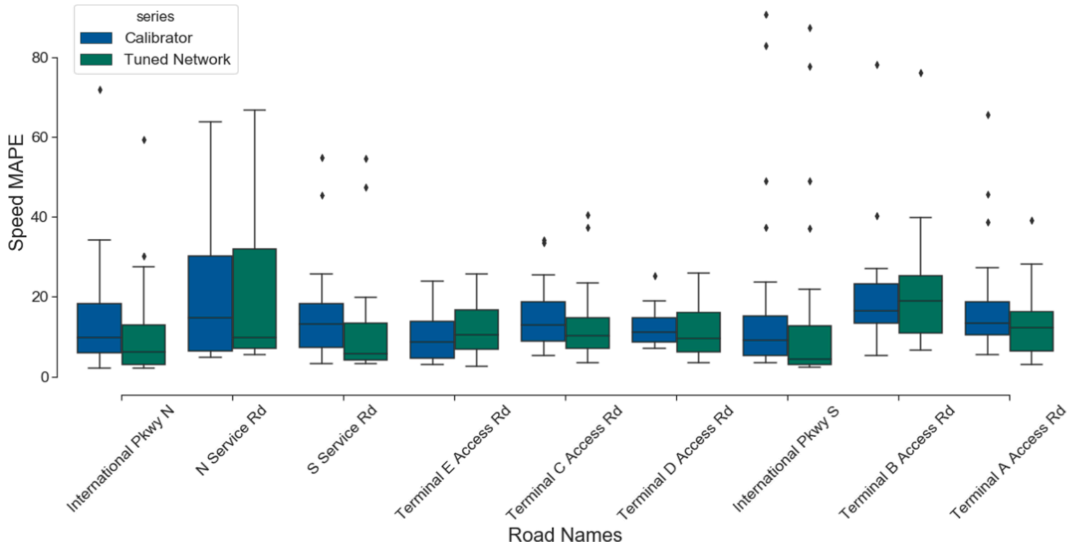


Fig. 5. Mean absolute percentage error of built-in SUMO calibrator vs. the tuned network.

speed limits. We then used this validated network for all the simulation scenarios.

A challenge of our calibration work was how to propagate this calibrated behavior to the simulation of future scenarios where we did not have observation data. To this end, we used the TomTom speed to estimate the actual free-flow or maximum speed per link and adjusted our simulation parameters so that the vehicles could not drive beyond the maximum speed observed by TomTom. Our reasoning was that since the future scenarios have higher demand than the base case scenarios, their simulated maximum speeds per link should not exceed those of 2017–2018 days since these have lower demand.

4. Traffic policy description and simulation results

In our simulation experiments, we considered three representative demand days in 2018 as starting points for DFW simulations: a low demand day with 39,152 trips (September 2, 2018), a medium demand day with 58,231 trips (March 16, 2018), and a high demand day with 73,306 trips (June 11, 2018). These three demand days were selected from a 365-day demand data set generated from our previously developed DFW demand model (Lunacek et al., 2020) that represent daily DFW demand from October 1, 2017 to September 30, 2018. Instead of considering just one average demand day, these three demand scenarios allow us to effectively evaluate the impact of mode shifts and curbside traffic management polices by considering a range of traffic levels at DFW. We then project out these days to 2045 with 3% yearly demand growth-rate as estimated by the DFW planning team. We ended our simulation in year 2045

Table 2
Travel mode distribution per scenario/policy.

Policy Name	Private (%)	TNC (%)	Taxi (%)	Parking (%)	Car Rental (%)	Transit (%)	Limo (%)
Baseline	30.9	25.5	2.7	25	14.4	0.5	1
TNC Electrification	30.9	25.5	2.7	25	14.4	0.5	1
TNC Pin Code Pickup	30.9	25.5	2.7	25	14.4	0.5	1
Increased Transit	26.1	20.4	2.7	19.9	14.4	15.5	1
Bus-Only Policy	0	0	0	62.6	36.1	1.3	0
AV High Penetration	50.6	45.2	2.7	0	0	0.5	1
Controlled AV Adoption	30.9	25.5	2.7	25	14.4	0.5	1

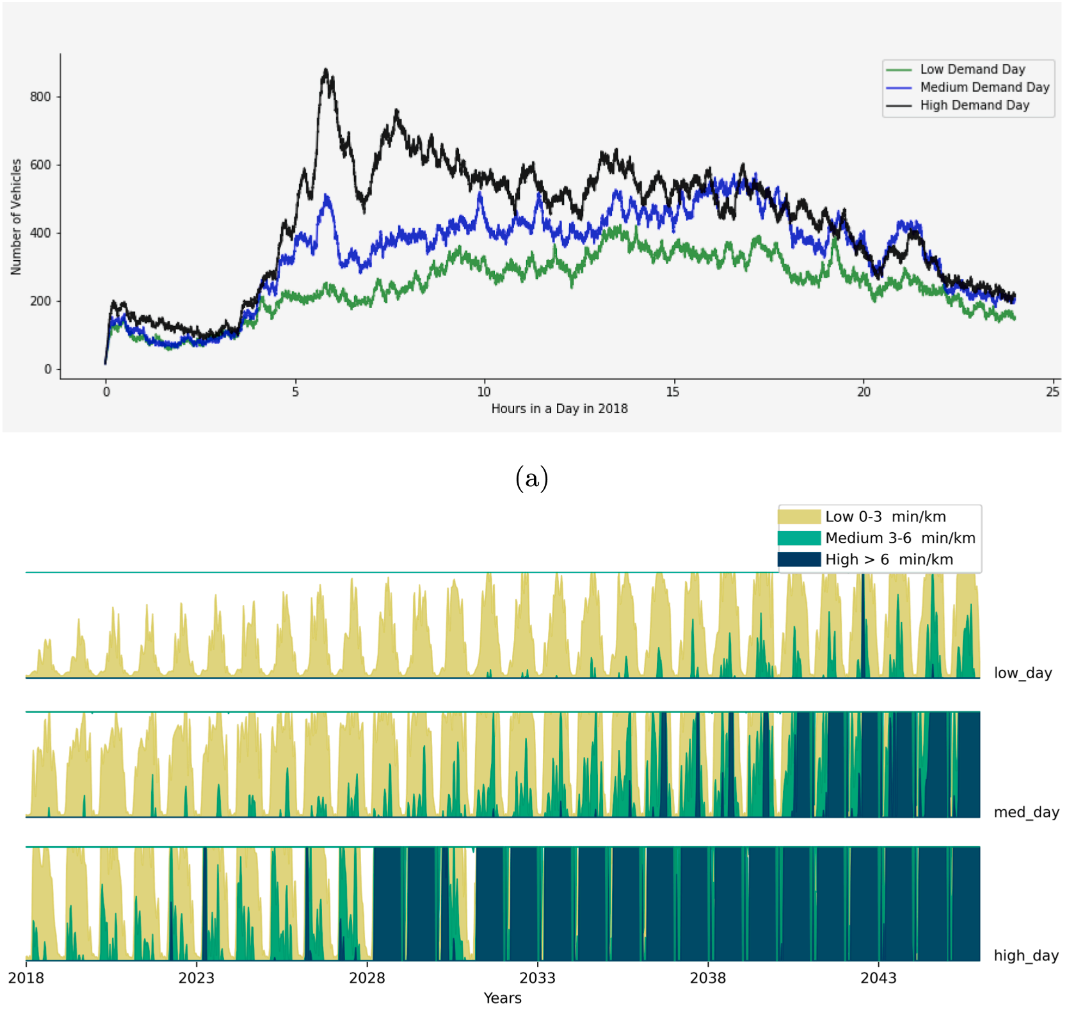
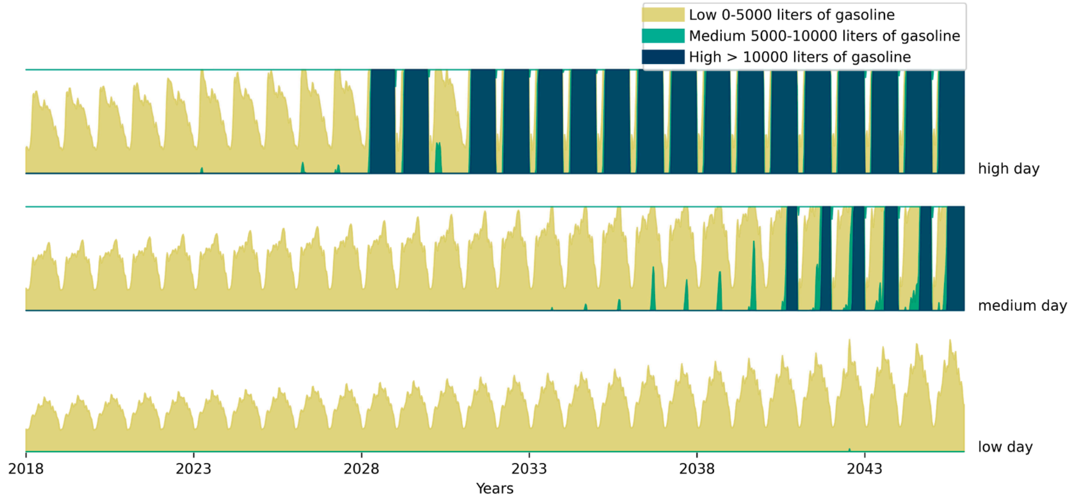


Fig. 6. (a) Baseline number of vehicles per time of day (b) baseline delay per time of day projected to 2045.

since this is the last year in the current DFW planning phase. We understand that the growth rate might vary in the future, especially due to the impact of COVID-19. In this work, we focus on using the current projection as estimated by DFW and evaluate the impact given different traffic management policies. However, the 255 framework allows us to vary the growth rate if needed.

4.1. Baseline scenario

The baseline scenario simulates the "business-as-usual" traffic pattern at DFW as seen in the DFW demand and travel mode choices observed in 2017–2018 and projected to 2045. The first row in Table 2 represents DFW travel mode percent distribution in 2018



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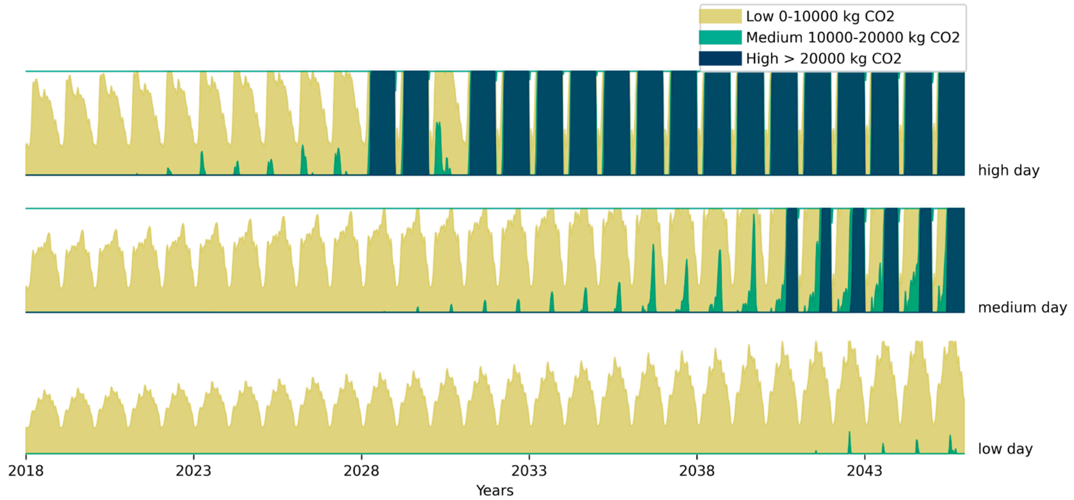


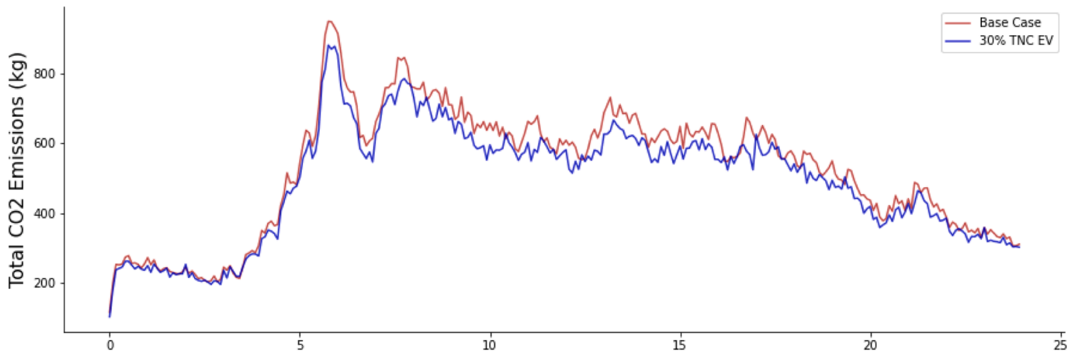
(b)

Fig. 7. (a) Baseline fuel consumption per time of day of the three representative demand days projected out to 2045 (b) baseline emissions per time of day of the three representative demand days projected out to 2045.

obtained from the 2015 DFW Originating Passenger Survey (U. C. Inc., Summary of results and findings -, 2015). The baseline scenario fixes these mode distributions, while growing the demand yearly from 2018 to 2045. The travel modes are converted in SUMO simulations using the generator function, as described above. This scenario allows the investigation of the evolution of congestion, fuel consumption, and emissions at DFW if the current travel mode distribution and traffic management measures were to persist until 2045. representative days, illustrating a daily peak between 6am and 9am, and Fig. 6 (b) shows the change in Fig. 6 (a) illustrates zoomed-in daily number of vehicles in the DFW network in 2018 for the three traffic delay projected out to 2045 using horizon plots [1]. Fig. 7 shows the variation in fuel consumption and CO_2 emissions of the three representative days projected out to 2045. We simulated the buses as diesel vehicles and converted their diesel fuel consumption into equivalent gasoline (1 gasoline liter = 1.155 × 1 diesel liter (DOE/EERE, xxxx) to allow for uniform fuel units. The projected figures show that at some point in future, the volume, fuel consumption, and emissions over the whole network increase dramatically from one year to the next. *This corresponds to the tipping point when the traffic demand reaches the airport capacity, and vehicles are stuck in the simulation and unable to avoid gridlock*. For the high demand day, the spikes of standstill-level congestion seem to waver once reached. In the years 2028 to 2032, we think the number of

[1] Throughout this paper, we sometimes show results using a horizon graph, which is a more compressed visualization of a traditional timeseries plot. Essentially it divides the timeseries, which is plotted as an area chart, vertically and overlays sections such that larger values will have more overlays and will therefore appear darker. This makes it easy to see where the timeseries values are higher without losing the detail of the lower sections.

Fig. 8. Time of day delay distribution per curb for high demand day projected out to 2045.



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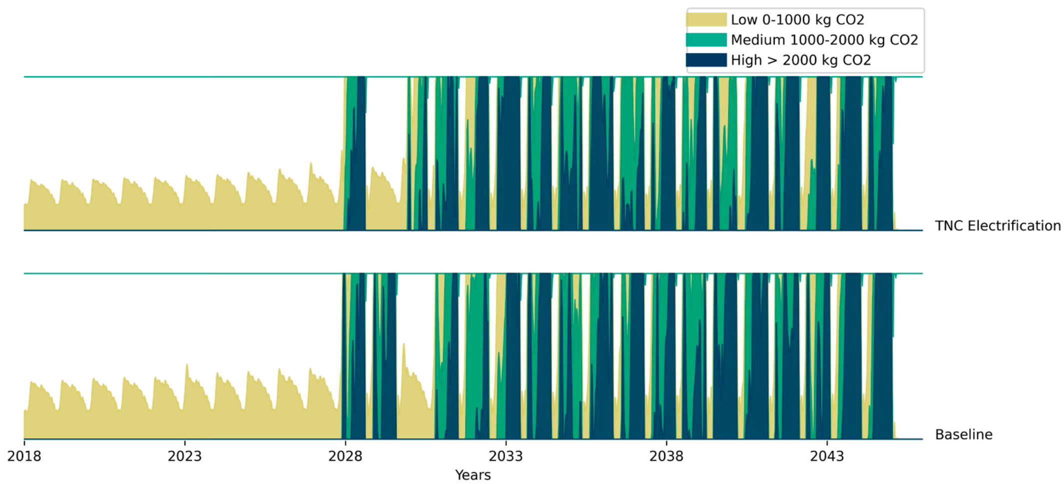


(b)

Fig. 9. (a) Time of day CO_2 emission for baseline vs. 30% TNC EVs in 2018 for high demand day (b) time of day CO_2 emission for baseline vs. 30% TNC EVs for high demand day projected to 2045.

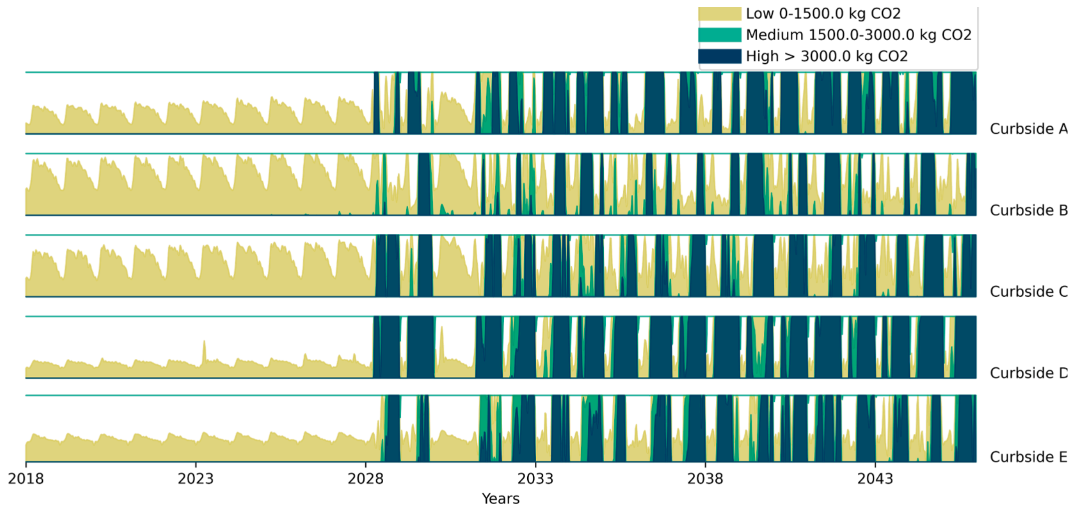


Fig. 10. Time of day CO_2 emission per curb for high demand day projected out to 2045.

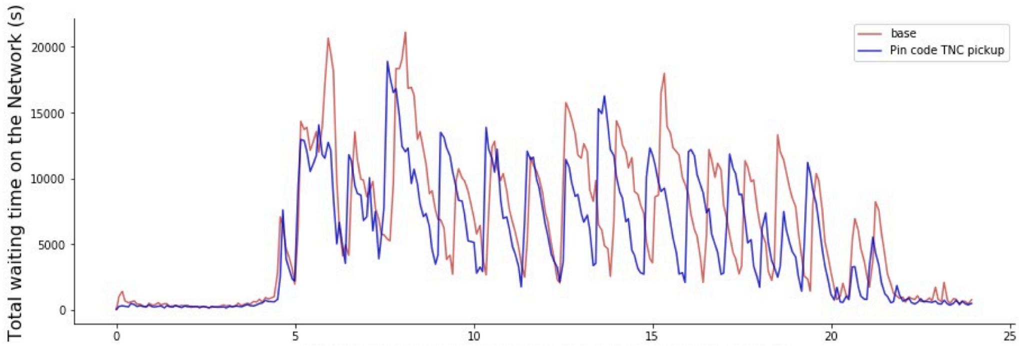
vehicles circle around the tipping point, which may or may not be reached due to random fluctuations in the timing of vehicles on the network. When gridlock occurs, the simulation becomes overwhelmed and unstable, thus producing somewhat irregular outputs. That is, we observed that the simulation parameters were not well calibrated to handle highly congested scenarios, but instead produced almost random behavior and outputs for very high volume scenarios. This is also influenced by the built-in randomness in the SUMO traffic model, including the randomness in loading vehicles and in vehicle dynamics (G. A. C. (DLR), others., Simulation/randomness, https://sumo.dlr.de/ docs/Simulation/Randomness.html, accessed:, 2019). The three cases get to this saturation point during different years: the low demand day never grows beyond the airport capacity, the medium day reaches airport capacity in 2040, while the high day reaches the tipping point in 2028. This result demonstrates the significance of considering different demand level scenarios when making operation or planning decisions for the airport, as some decisions might be effective for low and medium scenario but not for high demand days and vice-versa.

Fig. 8 shows the distribution of the traffic delay per curb for high demand days. Similar to the number of vehicles, delay is used as a measure of congestion. The curb delay measures were normalized to a unit of length to ensure consistent comparison among the terminal curbs since the terminals had different curbside length. We observe that the terminal curbs also reach saturation in 2028 for high demand scenarios, which is similar to the aggregate network behavior for high demand day.

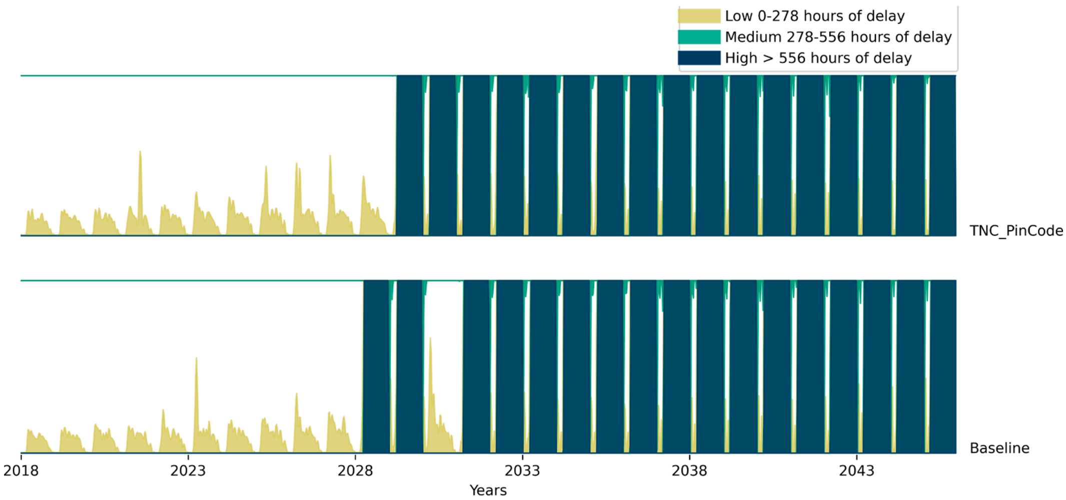
4.2. TNC: Electrification

Recently, electric vehicle (EV) use has been growing in Texas. EV, including Plug-in electric vehicle (PEV) and battery electric vehicle (BEV), sales more than doubled from 5,419 in 2017 to 11,764 units in 2018 in the Texas market (evadoption.com, Ev market share by state, https://evadoption. com/ev-market-share/ev-market-share-state/, accessed:, 2019). One of the most important benefits of EVs are lower fuel costs and greenhouse emissions compared to gasoline or diesel vehicles. In this scenario, we considered a policy that incentivizes the electrification of a portion of the TNC vehicles. Using the modeling framework and travel mode distribution as indicated in Table 2, we generated vehicle trips using the baseline travel mode distribution and the TNC sub-module to define some TNC vehicles to be EVs. We considered multiple TNC what-if scenarios with different portions of EVs to see the effectiveness of the various cases. These scenarios were then translated into SUMO demand files for simulations. In simulation, each EV is equipped with a battery device with adjustable emission levels (G. A. C. (DLR), Sumo models/electric, https://sumo.dlr.de/docs/ Models/Electric.html, accessed:, 2020). In this work, we consider the EVs as zero-emission vehicles and do not consider any other carbon footprint produced by the manufacture of the EVs and their batteries.

We first simulated a scenario where 30% TNC vehicles were EVs. As expected, Fig. 9 shows that this 30% TNC EV scenario has lower emissions compared to the baseline scenario (high demand day) with only gasoline vehicles. The average difference in emission between the two scenarios is about 7.3% for the first 10 years before the simulation reaches its maximum capacity. The reason why we cannot see as much as a 30% difference is that TNC vehicles only comprise 25.5% of the total trips to/from the airport. The horizon graph in Fig. 10 shows the distributions of CO_2 emission of curbside areas. This graph indicates that Curbside D reaches saturation first compared to other curbs. We can notice this occurrence across other simulation scenarios. A plausible cause is that Curbside D has the least curb space compared to other terminals. This makes it more susceptible to traffic congestion compared to other terminals. We also considered other TNC EV percentages, including 10%, 20%, …, 100%. We measure total CO_2 emission and total fuel consumption of the TNC vehicles for the three representative days of passenger demand: low, medium, and high demand days. As expected, we observed that the TNC vehicles' emissions and fuel consumption decreased almost linearly as the EV portion increases for every case. Based on this result, airports may be able to make significant reductions in emissions and meet energy cost targets by making policies that encourage TNC drivers to use EVs.



(a)



(b)

Fig. 11. (a) Time of day delay for high demand day in 2018 for TNC pin code vs. baseline (b) time of day delay for TNC pin code pickup scenario for high demand day projected to 2045.

4.3. TNC queuing policy

This TNC policy aims to streamline the curbside pickup process of TNC passengers, using the baseline's mode choice distribution (refer to Table 2). Currently at DFW, TNC drivers are matched with passengers when trip requests are accepted, and passengers are instructed to get ready for the pickup in a specified area at the curb (Uber.com, Ride to dallas fort worth international airport (dfw), https: //www.uber.com/global/en/airports/dfw/ (July 2020). This process causes pickup difficulty for some drivers in two scenarios: (1) when the curb is congested, passengers can have trouble recognizing the vehicles that are coming to pick them up, increasing TNC vehicles' dwell times and (2) when passengers mistakenly selected the wrong pick up area, the drivers have to loop around in the airport until they find the location of their passengers which induces extra traffic. The TNC pick up policy we explore is called a pin code functionality. It imitates a traditional taxi line that dedicates a waiting area for passengers. Instead of being matched with a passenger during the trip request stage, TNC vehicles arrive at the pickup location as a fleet and serve the passenger on a first come first serve basis. When the passenger enters the vehicle, the driver and the passenger exchange pin codes, which facilitate the driver-passenger matching. Theoretically, this process should eliminate confusion at the pickup stage and streamline curbside TNC movements. This is a practice that has been experimented with by Chicago Midway International Airport (CMIA) (C. M. I. , 2021-02-09 (2019).).

In the SUMO model, the baseline pickup process was implemented by randomly assigning the curbside dwell time according to a predefined distribution obtained from the DFW staff (refer to Fig. 2). The pickup difficulty was simulated by having 15% of the TNC vehicles temporarily stop at a wrong waiting area for a short period of time and then go to the right pickup location to serve their passengers. Using the generator function, the pin code pickup (Pin Code TNC) process was implemented by fixing the dwell time of all vehicles to 30 s.

Fig. 11(a) shows the comparison of the total waiting time in the network for the baseline and pin code pick up process. This comparison shows that the pin code pickup process significantly reduces the waiting time during high demand hours and it postpones reaching the airport capacity by one year (Figure 370 11(b)). The benefit of this policy is the greatest during high demand hours. For

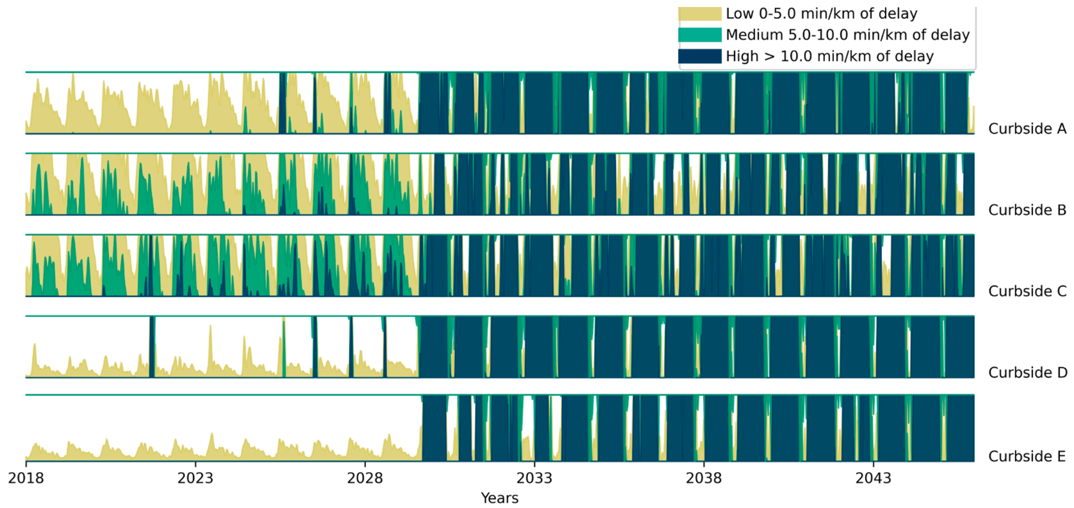


Fig. 12. Time of day delay distribution per curb for high demand day projected to 2045.

low demand time periods, the waiting time improvement of this policy is minimal, which is why in some cases during low-demand hours, the waiting time of the pin code pickup scenario appears to be longer than the base scenario. In 2018 for the high volume day, pin code pickup helps save 143 gallons of gas per day (0.87% reduction), and that number increases to 206 gallons of gas per day ten years later (1.19% reduction). Similarly, the pin code pickup process also delays saturation of terminal curbs by one year as shown in Fig. 12.

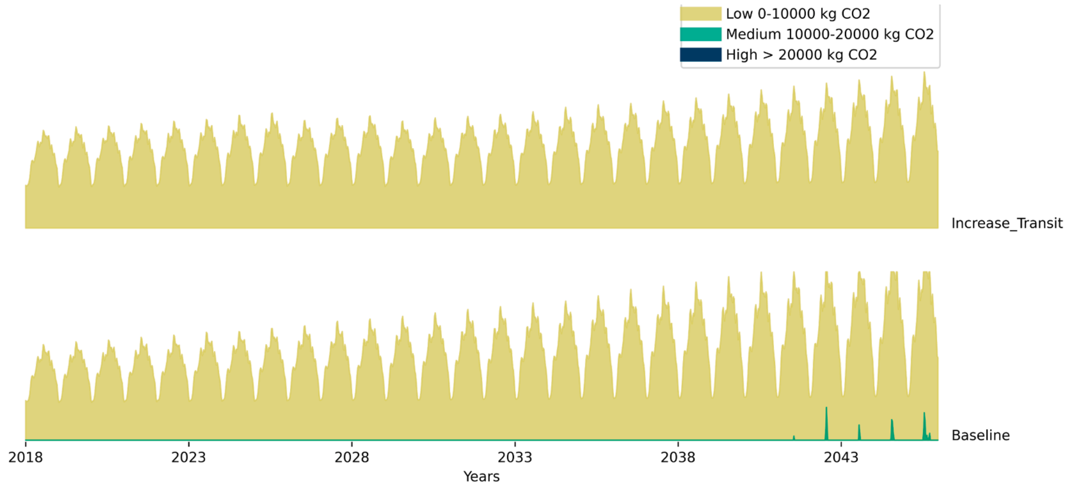
4.4. Increased transit scenario

This scenario examines the effects of increased use of public transit (DFW, Traveling to and from dfw international airport, https://www. dart.org/riding/dfwairport.asp, accessed:, 2019), with the passengers shifting away from private, TNC, and parking modes. Starting from the actual 0.5% transit mode choice, we examined an increase of 5, 10, and 15 percent of transit over the course of the next 25 years. For each 5%, we used the generator function to increase public transit share with 1.6% share diverted from private mode and 1.7% from TNC and parking modes each.

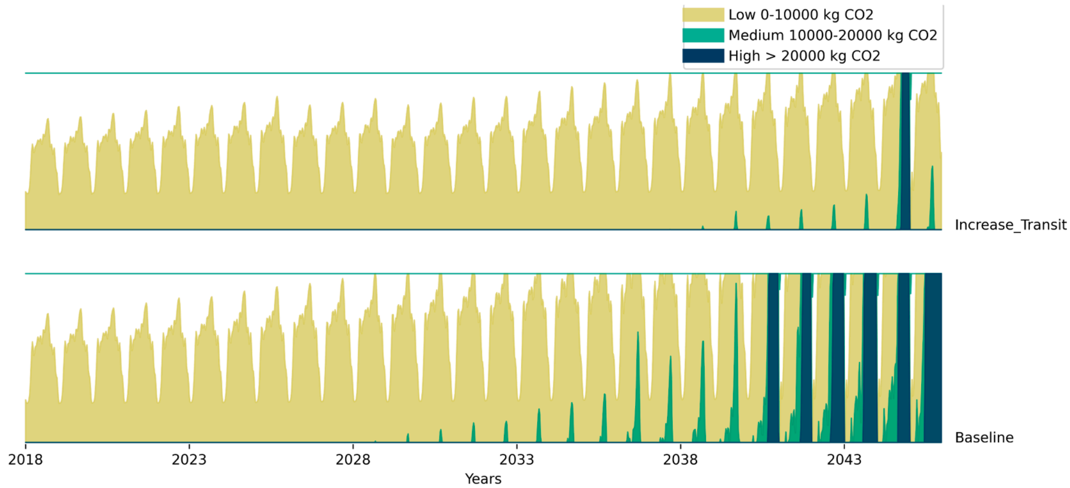
With loads similar to before the COVID-19 pandemic and based on rough approximations of available seats on DART rail lines (DFW, Traveling to and from dfw international airport, https://www. dart.org/riding/dfwairport.asp, accessed:, 2019), existing public transit infrastructure may possibly accommodate 5% of DFW traffic. For this reason and due to a possible lack in return to use of public transit in the wake of the COVID-19 pandemic, the 5 years after 2020 (2021 through 2025) are simulated to have 5% of total trips shifted to public transit, for a total of 5.5% public transit mode choice. Increased advertising of public transit and policy changes, such as female-only rail cars and other safety measures, can increase public transit use actually changing any infrastructure or routing (Budd et al., 2016). To achieve this 5% shift, airports could potentially work with transit agencies to advertise their services and collect a small percentage of fares.

As airport demand grows and if the percent share of public transit choice increases above 5%, current transit options will likely need to be expanded. We utilize this time frame to allow development of increased public transit capacity which will enable higher transit use. In five years, there may be forces for increased use, such as updated or new infrastructure and increased societal pressure for energy efficient transport modes, that may combat with the known obstacle of habit-based mode choice decisions and other down-regulating factors (Budd et al., 2016). In the United Kingdom, due to societal pressure for increased environmental considerations at airports and government policies requiring such consideration, public transport accounts for between 29 and 48% of mode choice to the six airports in London; and there are efforts to increase this share (Budd et al., 2016). Perhaps in the coming years, 15.5% mode share in public transit represents an achievable scenario for DFW. Due to these factors, we estimated a transitional period of 3 years (2026 through 2028) at 10.5% transit usage, followed by 17 years (2029 through 2045) at 15.5% public transit usage. Table 2 shows the resulting travel mode distribution.

With this transit scenario, the network carrying capacity for vehicles will not be reached until 2042. For a conservative scenario where all days are only low or medium demand in a fifty-fifty split, the transit strategy is simulated to prevent 196,185 tons of CO_2 from entering the atmosphere (refer to Fig. 13), as well as 3,247 tons of CO and 193 tons of NO_x emissions. Those three savings amounts are calculated from 2021 to 2039, when the base case medium demand day reaches stop-flow congestion and results may become unstable. Fig. 14 compares the year when gridlock occurs for the base case and transit scenario using vehicles' waiting or idling times. Even if only 20% of days were high demand over the next 25 years and the rest were low demand, the transit strategy would save 13,564 people-years spent idling and over 1 million tons of CO_2 from being emitted. Furthermore, if we only consider years 2021 to 2028 to eliminate unstable simulations due to gridlock, the transit strategy saves 42 people-years of idling and 31,686 lbs of CO_2 in just those 7 years. Fig. 15 indicates that terminal D may be responsible for initiating slowdowns since it hits high congestion levels very



(a)



(b)

Fig. 13. (a) Time of day CO_2 for increased transit vs. baseline for low demand day (b) time of day CO_2 for increased transit vs. baseline for medium demand day.

briefly for the high-demand day simulated in 2041, one year prior to full network congestion, and in 2042, it reaches high congestion earliest in the day. Terminal C is the last to succumb to stop-flow congestion once it starts propagating into the rest of the network on the high demand day simulated in 2042. Shifting towards more transit, starting with 5.5% transit in 2021, followed by 10.5% transit in 2026, and 15.5% transit in 2029 and beyond, will delay standstill congestion by 14 years from 2028 to 2042 and greatly reduce emissions and wait times on the DFW network.

4.5. Buses-Only policy scenario

The buses-only policy scenario looks into the case where only shuttle buses are allowed to stop at the terminals' curbs. Using the generator function, we redistributed the passengers using any types of passenger cars (e.g. self-owned passenger cars, taxi, TNC cars, or limo) to the train, shuttle buses from the remote parking, and shuttle buses from the rental car center proportionally to the current distribution of the use of trains, remote parking shuttle buses, and rental car center shuttle buses. The ratio among the use of trains, remote parking shuttle buses, and rental car center shuttle buses remain the same as the baseline scenario. The passenger trip mode choice for the bus-only scenario 445 is shown in Table 2.

We calculated the frequency of the buses so that the bus service rates $\mu_{T,R}$ meet the demand $\lambda_{T,R}$ for terminal T through remote stop R (could be the rental car center or the remote parking). $\lambda_{T,R}$ is determined by the maximum number of the arrival passengers and the departure passengers of the airport per unit time, i.e. $\lambda_{T,R} = \max({\lambda^{arrival}}_{T,R}, {\lambda^{departure}}_{T,R})$. DFW airport uses 43-seat buses. The service rates are calculated by the frequency of the buses, $N_{T,R}$, multiplied by the 70% of the bus capacity, i.e. $\mu_{T,R} = 0.7 \times 43 \times N_{T,R}$. We did not use the capacity times the frequency as the service rate, because the bus service usually needs to maintain a certain headway and

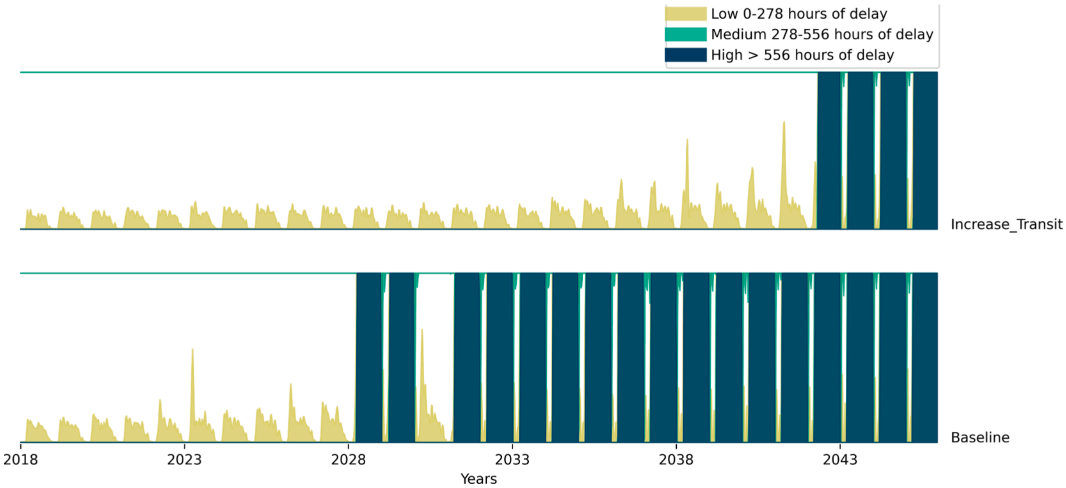


Fig. 14. Baseline scenario vs. transit scenario, time of day delay on a high-demand day: network capacity reached in 2028 for baseline, 2042 for transit.

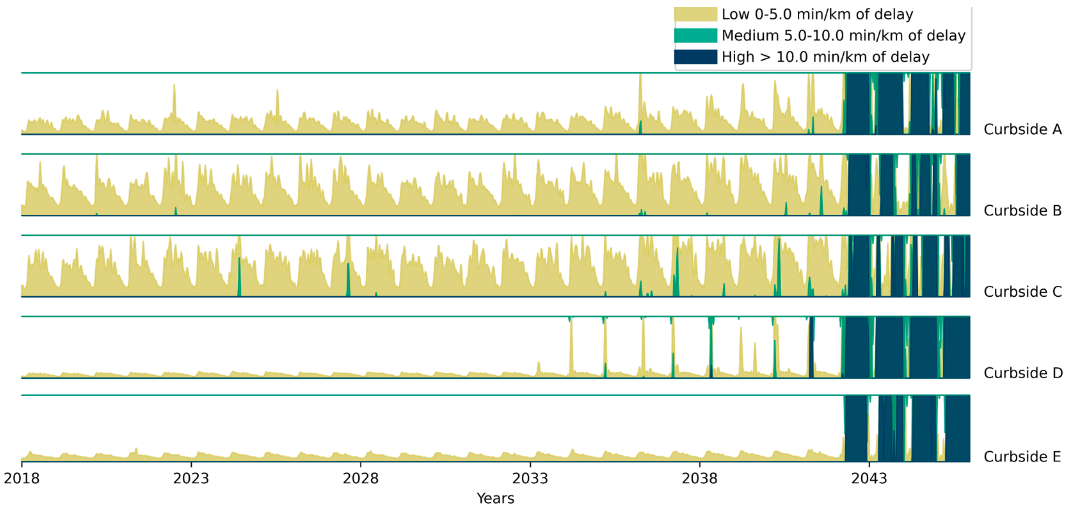


Fig. 15. Traffic delay per time of day distributed by curb for a high-demand day projected to 2045.

buses do not wait to 455 be full before departing.

The number of buses per hour needed between a remote stop R and a terminal T, $N_{T,R}$ can be calculated using Eq. (1).

$$N_{T,R} = \frac{\max(\lambda_{T,R}^{arrival}, \lambda_{T,R}^{departure})}{0.7 \times 43} \tag{1}$$

Since the buses-only scenario only allow buses on the curb, it reduced the congestion and traffic volume significantly and thus reduced the energy consumed. 460 Fig. 16 shows the delay distribution by curbside over the simulated years. The lines over the years look flat because the delays under buses-only scenario are low along the curbside. The delay was not heavily impacted by the volume until saturation.

Fig. 17 shows that the buses-only policy at the terminal curbside can reduce the fuel consumption significantly. The buses-only scenario did not reach airport saturation until 2039 for high demand days, while the base line reached saturation in 2028 in the simulation. The buses-only scenario postponed the need to address infrastructure issues for 11 years.

4.6. Autonomous vehicles

4.6.1. High penetration scenario

One possible effect of high AV penetration in the future is that people may shift from public and shared travel modes due to reduced driving and parking costs of AVs (Harper et al., 2016). Airport passengers may choose to not park their personal cars, but rather have

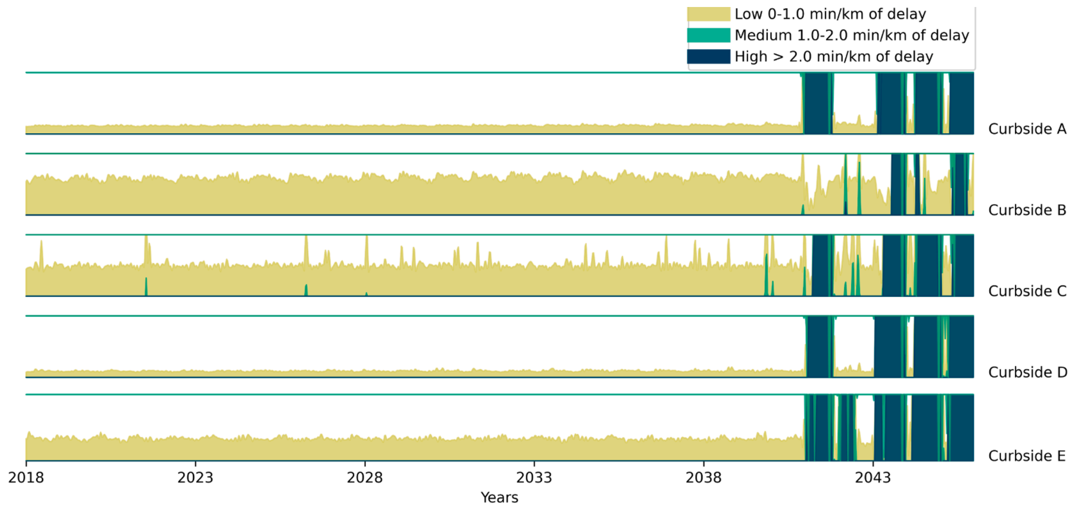


Fig. 16. Time of day delay distribution by curbside for high demand day projected to 2045.

Fig. 17. Time of day fuel consumption of base case and buses-only scenario for high demand day projected to 2045.

their AVs drop them at the airport and drive back autonomously to park at their residences. In this section, we consider this possible future scenario, where the use of AVs will be widespread. To model this scenario, we used the generator function to redistribute passengers from parking and rental travel modes to TNC and private pick-up/drop-off modes. The new percentage allocations can be seen in Table 2. This would be a change that would be largely driven by the possibility of adoption of autonomous vehicles and travelers choosing personal vehicles over shared modes. We also simulated AVs as battery electric vehicles with zero emissions.

Research showed AVs will increase the driving safety due to computers having the ability to reduce mistakes typically made by human drivers (Bock et al., 2016). Hence, we also changed other simulation parameters in SUMO to more accurately describe autonomous vehicles. For all passenger vehicles, we lowered the distance between vehicles, assumed perfect driving, lowered the deviation of speed, and allowed vehicles to reroute themselves.

Fig. 18 shows this AV policy's CO_2 emissions for the high volume day projected to 2045 compared to the baseline high volume day. Fig. 19 then breaks down this emissions distribution further by curbside. While each curb reaches high capacity in the first year of saturation, we can see increase in emissions at Curbside D, in particular. As previously mentioned, this is because terminal D has the least curb space. Terminal A registers the next highest measures since it gets higher volume compared to the other terminals. As shown, emissions increases significantly with the new travel mode distribution change, and an extra 83 million kgs of CO_2 would be consumed up through 2027, when the baseline reaches capacity starting in 2028. An extra 10 million kgs of CO_2 alone are generated in the first year when the policy reaches saturation. This can be seen in Fig. 20 which illustrates in detail the emission of the high demand day in 2018, when the high AV penetration policy has already reached saturation. We can see the autonomous vehicle high penetration scenario increases the emissions and reaches maximum capacity after one year. Even though the emissions are high due to saturation,

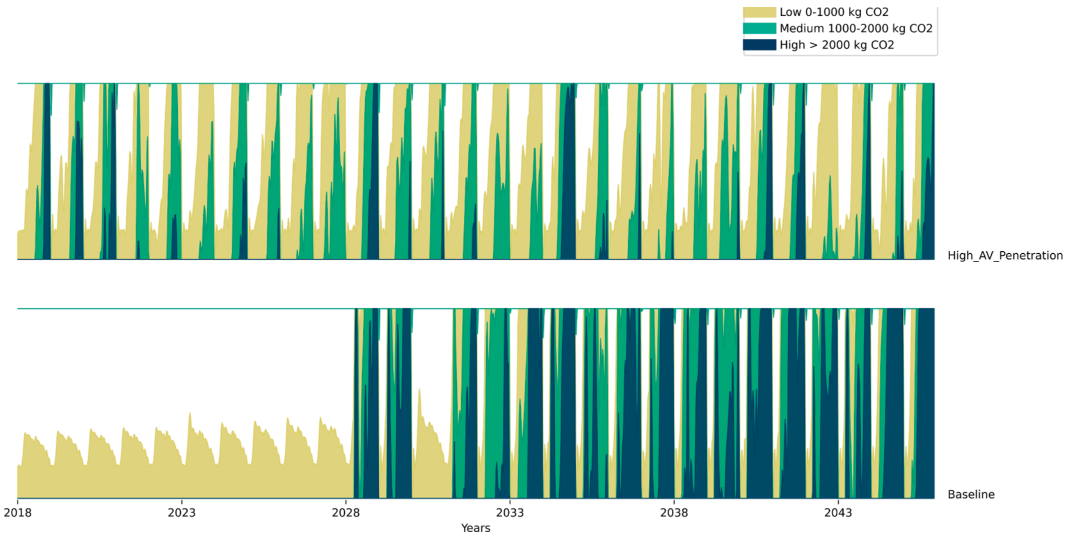


Fig. 18. Time of day emissions for the autonomous vehicle high penetration scenario: high volume day, projected to 2045.

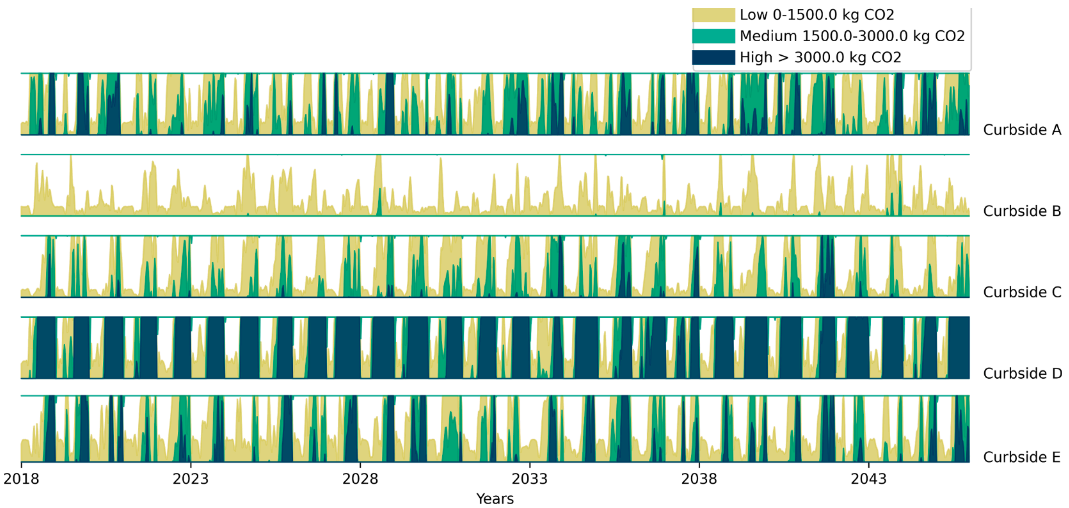


Fig. 19. Time of day emissions for the autonomous vehicle high penetration scenario: curbside distribution, high demand day, projected to 2045.

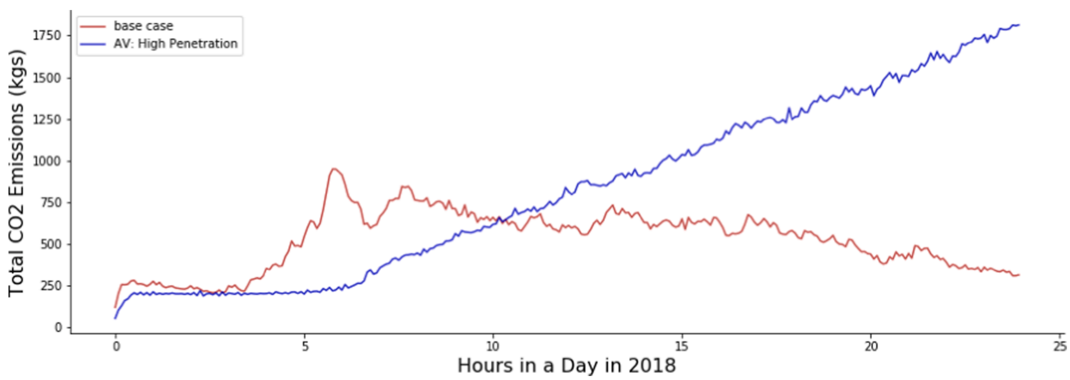


Fig. 20. Time of day fuel consumption for the autonomous vehicle high penetration scenario:2018 high volume day.

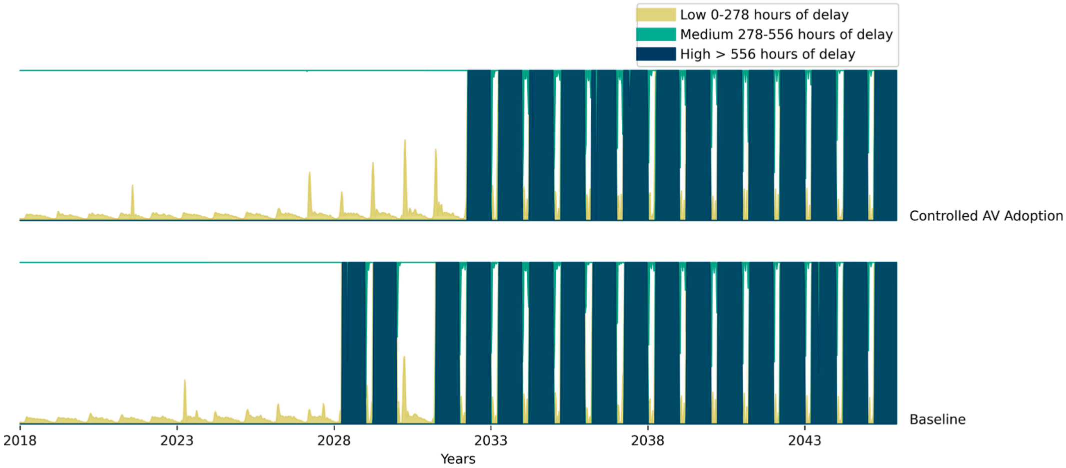


Fig. 21. Time of day wait time for the autonomous vehicle alternative scenario: high volume day, projected to 2045.

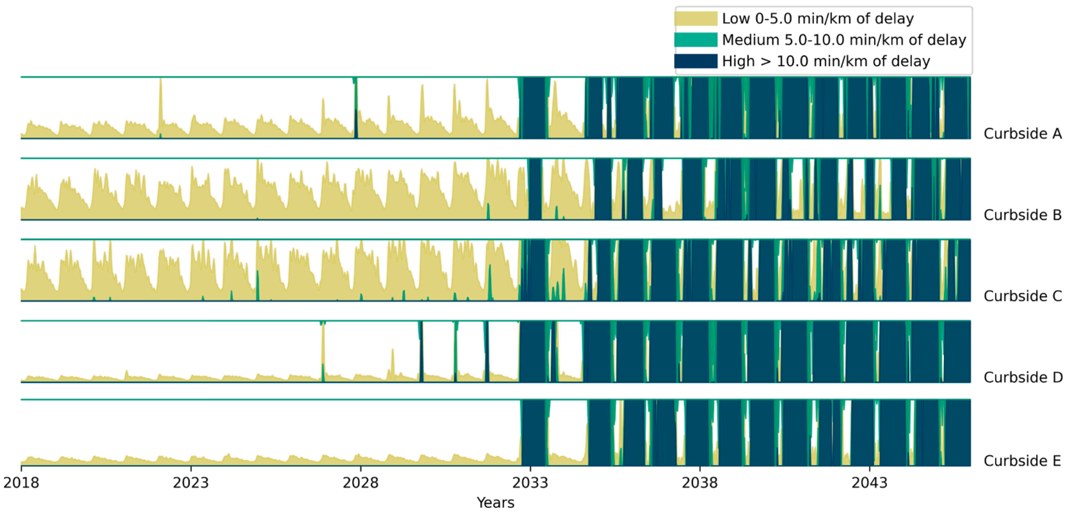


Fig. 22. Time of day wait time for the autonomous vehicle alternative scenario: curbside distribution, high demand day, projected to 2045.

their magnitude is not as high as for baseline saturated years. That is, as shown in Fig. 18, the baseline saturated years have more dark green color than the saturated high AV penetration scenarios. The high volume day is shown in particular to demonstrate some of the complexities with adapting to new technologies like autonomous vehicles and further show how planning for such scenarios is a necessity. For instance, one way to improve this policy would be to use centralized control to manage AV traffic or allow AVs to coordinate and communicate with infrastructure to avoid gridlock.

4.6.2. *Controlled AV adoption*

An alternative AV policy is a controlled AV adoption measure, where AVs are only used for the passenger vehicles, such as those used by private, TNC, and taxi modes, with no change in the usage of shared modes. To simulate this scenario, we use the distribution as shown in Table 2 and change the passenger vehicles' simulation parameters to describe AVs, as described in the AV high penetration scenario. The AVs were also simulated as EVs.

In contrast to the unrestrained high penetration AV scenario, this controlled 520 AV adoption policy reduces vehicle delay by 4% compared to the baseline case. It also postpones the network saturation to 2033 as shown in Fig. 21. Fig. 22 gives more detail regarding the distribution of congestion at the curbside. We can see that terminal D has higher wait time compared to other curbs, but each curb does reach high wait times in 2033. Similarly, in the unrestrained high penetration AV scenario, we saw Curbside D producing higher emissions as well. This policy reduces the wait time due to more efficient AV driving for the network while also resulting in decreased fuel use and emissions due to vehicle electrification.

Table 3
Summary comparison of policies against baseline scenario for a high demand day.

Policy Name	Year of Saturation	Average Daily Delay (%)	Average Daily CO_2 (%)	Average Annual Fuel Consumption (%)
Baseline	2028	N/A	N/A	N/A
TNC Electrification	2028	−3	−7	−7
TNC Pin Code Pickup	2029	−13	−1	−1
Increased Transit	**2042**	–23	−11	−11
Bus-Only Policy	2039	**−90.5**	−42	42
AV High Penetration	2018	N/A	N/A	N/A
Controlled AV Adoption	2033	−4	**−59**	**−62**

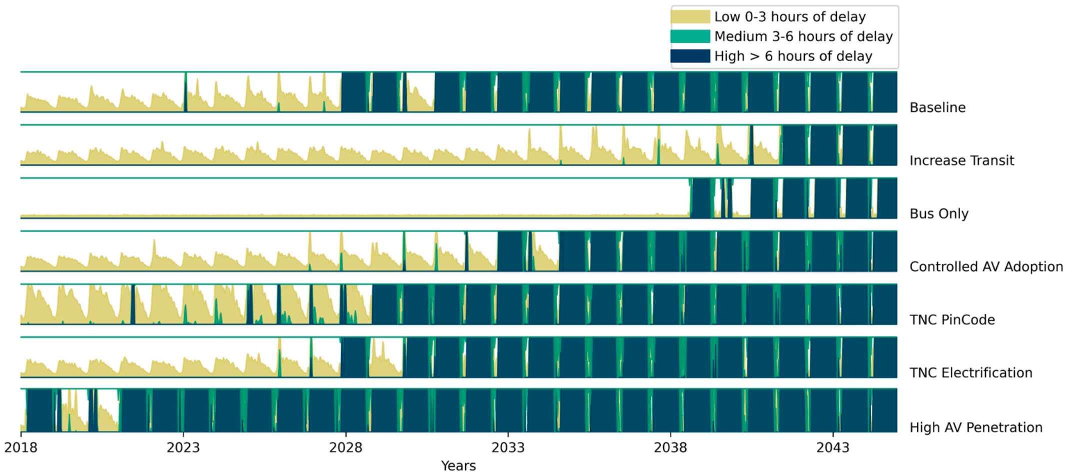


Fig. 23. Comparison of all policies: time of day delay for high demand day, projected to 2045.

4.7. *Summary results of all policies*

To summarize these results, a comparison of all the policies against the baseline scenario is presented in Table 3. The “Year of Saturation” column shows the year when each scenario reaches DFW’s network capacity for a high demand day. The average annual delay, CO_2, and fuel consumption change columns display the average annual percentage decrease or increase in vehicle delay, CO_2, and fuel consumption respectively, compared to the baseline measures for a high demand day. We calculated these average annual ratios using equation (2), where Y is the daily delay, CO_2, or fuel consumption for high demand day. We excluded years 2028 to 2045 from our calculations since the outputs from the baseline simulation becomes unstable from 2028 due to network saturation. The average annual ratios were not calculated for the *AV High Penetration policy* since it reaches saturation in 2018.

$$AverageAnnualChange = \frac{\sum_{n=2018}^{2027} Y_{Policy} - \sum_{n=2018}^{2027} Y_{Baseline}}{\sum_{n=2018}^{2027} Y_{Baseline}} \tag{2}$$

The year of saturation column in Table 3 shows that the *Increased Transit policy*, to increasing transit usage up to 15.5% in 2029, delays the airport saturation the most and correspondingly, the need for airport capacity expansion. This is because the increased use of the DFW transit train removes passengers from travel modes that require road and curbside capacity. By encouraging shared mobility, the *Bus-Only policy* registers the most reduction in delay. The automation and electrification of all passenger vehicle trips to/from the airport generated the largest decrease CO_2 emissions and fuel consumption. We also observe that the *AV High Penetration policy* performs the worst, reaching airport saturation in 2018, demonstrating the high cost of uncontrolled adoption of new technologies and the importance of planning for future mobility changes. Fig. 23 visually compares the effectiveness of different polices in terms of total network delay and confirms the observations stated above.

4.8. *Demonstration on an example COVID-19 scenario*

In this section, we demonstrate how our modeling framework can be used to model and evaluate the impact of the COVID-19 pandemic. We acknowledge that the assumptions we made about COVID-19 future impact and recovery process have high uncertainty since we do not yet understand the medium to long term impact of the pandemic. Instead, this scenario is provided as an example to demonstrate the usefulness of this modeling framework as it enables evaluation of many what-if future scenarios. For example, DFW could analyze many COVID-19 recovery scenarios, simulating air-travel rebounding at different point in the future and/or the air travel industry reorganizing (e.g. shifts in business vs. leisure travel demand), and adjusting their operations decisions as appropriate.

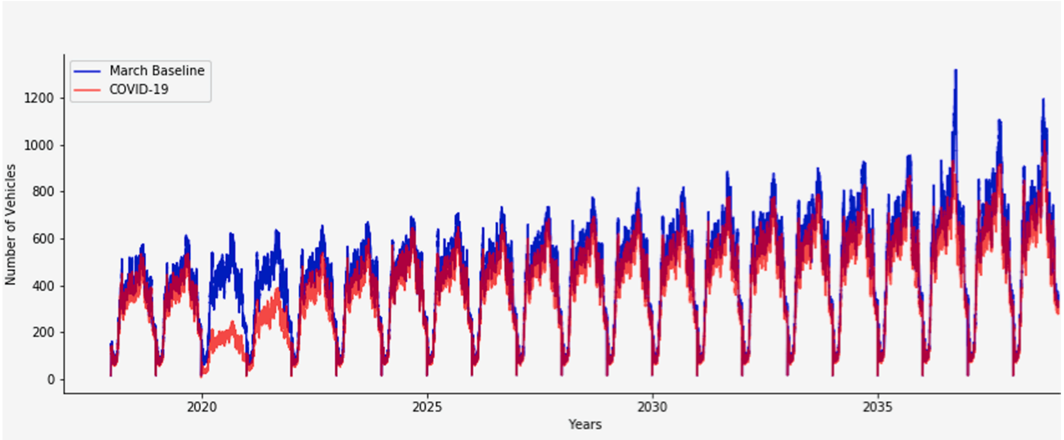


Fig. 24. Number of vehicles per time of day in DFW network for baseline vs. COVID-19 scenario.

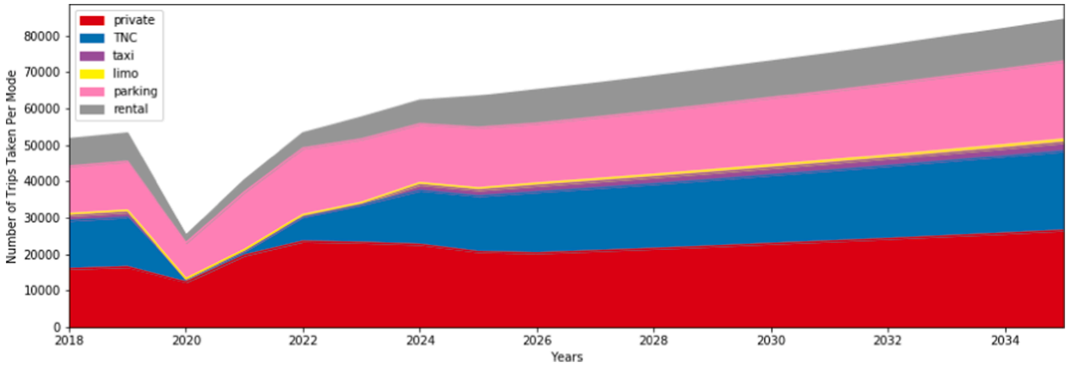


Fig. 25. Yearly change in travel mode due to COVID-19.

We present a COVID-19 scenario that models the drop in air-travel in year 2020, as observed by all major airports in the US after March 13, 2020, when COVID-19 was declared a global pandemic (Tsa checkpoint travel numbers for, 2020). We modeled a 45% decrease in traffic to/from the airport due to COVID-19 as estimated by the DFW team. We estimated that air-travel will start increasing slowly starting in 2021, and since COVID-19 vaccines are now available, air-travel may return to normal figures in 2022.

Fig. 24 shows the number of vehicles and fuel consumption simulation results for the COVID-19 scenario compared to the baseline case. Using the generator function, we also modeled passengers' shift from public/shared travel modes in favor of private modes to avoid contagion. As depicted in Fig. 25, we estimated that the majority of airports' passengers used private pickup/drop-off and parked their own cars (parking), while the use of TNCs, taxi, transit, limo, and rental cars significantly decreased. Fig. 25 also shows how the use of shared/public modes might start to increase slowly with time as the COVID-19 threat decreases.

5. Conclusion

In summary, this paper presented a modeling and simulation framework that represents travel modes, demand projections, and traffic management policies to enable airports to adapt and optimally operate in the face of current and emerging mobility changes. The framework has two main components: (1) a generator function for encoding travel modes, demand projections, and traffic control measures and (2) a simulation module that combines traffic demand files and network for simulation. The simulations allow objective evaluation of the effectiveness of curbside traffic management measures and the impacts of emerging technologies. We used this modeling framework to evaluate a number of traffic scenarios and control measures for the DFW airport: a baseline scenario, an increased transit policy, a TNC electrification policy, a TNC queueing policy, a bus-only policy, two AV adoption scenarios, and a COVID-19 scenario. The simulation results showed that increased transit use would provide the greatest opportunity to reduce congestion and emissions for the DFW surface transportation network, that shared mobility with the bus-only measure leads to highest savings in delays, that automating and electrifying all passenger vehicle trips would generate the highest reduction in fuel consumption and emissions, and that unrestrained AV adoption would have the most adverse impact on the airport. The model presented here was developed in close cooperation with DFW airport staff, but has been designed to allow for general application to other airports since a similar strategy may be suitable for transportation hubs, dense urban areas, and other critical components of the US transportation system.

Our ongoing and future research will investigate combining the presented modeling framework with a mode choice model to understand the behavior and incentives that enable the presented traffic management policies. This will include pricing schemes and measures that charge a fee for terminal curbside access that can encourage transit use and other shared-mobility modes. The mode choice model will also be combined with an optimization framework to enable us to analyze the best way to combine the various policies presented in this work to maximize reductions in emissions and congestion, while also postponing the need for capacity expansion. In addition, our future work will consider using the built-in SUMO calibrator on the tuned network to further reduce the calibration error and consider calibrating using link-level traffic volume data, which along with speed, provide a more complete estimate of traffic patterns compare to just using speeds.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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