

	Parameter	Type	Description	Values	Notes
Execution	Start hour	Editable	Defines the begin hour of the simulation.	0 (midnight) for normal scenario, 9 for others.	
	End hour	Editable	Defines the end hour of the simulation.	27 for normal scenario, 14 for others.	
	Driver support	Editable	Defines the number of cars at the beginning of the simulation.	Actually: Adding x drivers and y pickup cars for each TAZ, based on the beginning hour and real pickups/traffic data.	
	Time to stabilise	Editable	Timestamp needed to stabilise the digital mirror behaviour.	Actually inferred visually from the graphs of the indicators. Current security threshold is 2 hours (7200 timestamps).	
	Final timestamps to cut	Editable	Timestamps to cut at the end of the simulation. This has to be done because otherwise we consider indicators referred to rides not yet completed (i.e. with NaN values).	Actually inferred directly from the indicators. Current security threshold is 30 minutes (1800 timestamps).	
Environment	City map	Real data [16]	Map and points of interest of a city.	San Francisco.	Includes points of interest, speed limits, traffic lights, etc...
	TAZ involved	Real data [21]	Traffic Analysis Zones of the city involved in the event.	San Francisco.	
	Traffic generation policy	Real data [17]	Hourly mean of number of cars per TAZ.	Hourly mean of 5 consecutive workdays in SF.	Max. 180 hourly cars per TAZ. Gridlock above this threshold.

	Traffic speed policy	Real data [16]	Road speed limits.	San Francisco.	
Passenger	Generation policy	Editable	This parameter sets the probability of generating passengers.	100% (100% of the passengers scheduled are generated).	This parameter is useful to build scenarios regarding absence of passengers.
	Personality policy	Real data [2][3]	Generated passengers can have 3 different personalities, depending on the acceptance rate based on economic conditions (specifically the surge multiplier value): hurry , normal , greedy .	The probability of the personalities is actually the following: Hurry : 37% (age 16-24) Greedy : 18% (age 45-64) Normal : 45% (age 25-44).	Following [2], we see that older passengers are less likely to pay the surge price. By using data about passengers' age provided in [3], we discretised the age distribution in the 3 personalities.
	Acceptance distribution policy	Editable	The personality of the passenger defines the probability that he will accept the ride, given the current economic conditions (surge multiplier value).	The probability of the acceptance distributions (based on the surge multiplier value) is actually the following: Hurry : (-inf,1.5]: 100% (1.5,1.8]: 90% (1.8,2.1]: 80% (2.1,2.3]: 70% (2.3,+inf): 60% Greedy : (-inf,1.3]: 100% (1.3,1.5]: 80% (1.5,1.7]: 70% (1.7,1.9]: 50% (1.9,2.1]: 40% (2.1,+inf): 30% Normal : (-inf,1.4]: 100% (1.4,1.6]: 90% (1.6,1.8]: 80% (1.8,2]: 70% (2,2.2]: 60% (2.2,+inf): 50%.	

	Route length distribution	Real data [1]	For each TAZ, the other TAZ regions are grouped in 4 sets (short, normal, long, extreme), which represent the distance of the given TAZ with respect to the others.	The probability of a the ride lengths requested by passengers is actually the following: 36% short 22% normal 18% long 24% extreme.	The distances are labeled based on the distance quantiles between centroids (in meters). Specifically: [0,3305]: short (3305,5307]: normal (5307,7446]: long (7446,+inf): extreme.
Driver	Generation policy	Editable	This parameter sets the probability of generating drivers.	100% (100% of the drivers scheduled are generated).	This parameter is useful to build failure scenarios regarding absence of drivers.
	Personality policy	Real data [4][5][6]	Generated drivers can have 3 different personalities, depending on the acceptance rate based on economic conditions (specifically the surge multiplier value): hurry , normal , greedy .	The probability of the personalities is actually the following: Hurry : 21% Greedy : 24% Normal : 55%.	Considering the papers [4][5], which claim that the more experience the driver has, the more greedy he will be, and the thresholds referred to the number of trips in [5], we computed the proportion using the data provided by [6].

Acceptance distribution policy	Editable	The personality of the driver defines the probability that he will accept the ride, given the current economic conditions (surge multiplier value).	The probability of the acceptance distributions (based on the surge multiplier value) is actually the following: Hurry: (-inf,1]: 80% (1,1.2]: 90% (1.2,1.4]: 95% (1.4,+inf): 100% Greedy: (-inf,1]: 5% (1,1.2]: 30% (1.2,1.4]: 40% (1.4,1.6]: 50% (1.6,1.8]: 70% (1.8,2]: 80% (2,+inf): 100% Normal: (-inf,1]: 70% (1,1.2]: 80% (1.2,1.4]: 90% (1.4,1.6]: 95% (1.6,+inf): 100%.	
Move TAZ policy	Editable	Probability for a driver to change TAZ every 15 minutes, based on economic conditions (surge multiplier value).	It depends on the difference of the surge multiplier between different TAZs: (-inf,0]: 0% (0,0.3]: 5% (0.3,0.5]: 10% (0.5,0.8]: 20% (0.8,1.2]: 30% (1.2,1.5]: 50% (1.5,2]: 70% (2,+inf): 80%.	

	Stop work distribution	Editable	Probability for a driver to stop working because of unprofitable surge multiplier, computed for each timestamp.	The probability of stop working is computed by multiplying the time without accepting rides with a factor which depends on the driver personality: Hurry: 0.000005 Normal: 0.00001 Greedy: 0.00005.	E.g., timestamps without working = 600 (10 minutes), greedy driver factor = 0.00005, $P(\text{stop}) = 600 \times 0.00005 = 0.03$ (i.e., 3%).
	Workshift policy	Real data + arbitrary trend [7][8][9]	Computes the probability for a driver to end the work every timestamp.	The distribution spans from 0.000001 (i.e., 0.0001%), when the driver starts working, to 3% after 4 hours (average time). Then, the % remains stable until 12 hours, when the driver is forced to stop (max. allowed by Uber).	The distribution has an exponential trend.
	Driver ratio	Real data [10] [11]	Defines the ratio between requests and drivers generated.	4	The pickup value (real data) refers to the hourly requests in specific TAZs. Thus, we hypothesise to generate $\text{pickup_value} / \text{driver_ratio}$ drivers. The real data refers to the fact that we know that in SF there are 50000 active drivers.
Ride-Sharing	Hourly mean requests	Real data [14] [15]	Hourly mean number of requests per TAZ.	Hourly mean of 5 consecutive workdays in SF.	
	Hourly std dev requests	Real data [14] [15]	Hourly std. dev. of requests per TAZ.	Hourly mean of 5 consecutive workdays in SF.	

	Base fare	Real data (Uber) [18]	Base fare applied to each request.	2.2	
	Minimum fare	Real data (Uber) [18]	Minimum amount of fare.	8	
	Service fee	Real data (Uber) [18]	Expenses concerning the service, to add to the computation of the price.	3.5	
	Cost per mile	Real data (Uber) [18]	Cost applied for each mile of ride covered.	0.91	
	Cost per minute	Real data (Uber) [18]	Cost applied for each minute of ride.	0.39	
	Time update surge multiplier	Real data [12]	Defines the periodic interval for updating the surge multiplier in each TAZ.	5 minutes (300 timestamps).	
	Lyft price model	ML model leveraging real data (Lyft) [19]	ML model (Random Forest) trained on Boston.		Takes in input length of the ride and surge multiplier value.
	Surge multiplier policy	Arbitrary algorithm inspired by real specifications [20] (independently computed for each provider)	Arbitrary algorithm to emulate the real surge multiplier (ML algorithm not available). It takes into account the ratio between active passengers and idle drivers, plus the number of unserved requests.	Min: 1 Max: 5	Could use ML to predict it in case we obtain the data (e.g. from API, which are currently not available).
	Max driver search area	Editable	Maximum radius within which to search for drivers.	3000 meters	This is done for optimization purposes.
	Max drivers available	Real data [12]	Max number of closest drivers available shown to the user in the app.	8	

	Uber/Lyft initial choice	Real data [13]	Simulates user choice between different providers based on current market share.	75% Uber, 25% Lyft.	More in detail: With 75% probability the user opens the Uber app to book a ride (25% Lyft). If the request is accepted the ride starts, otherwise the user turns to the other concurrent app to book a ride. If the request fails again, the user is not served.
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More information on the parameters modified in scenarios can be found in Table parameters.pdf.

[1] <https://data.cityofchicago.org/Transportation/Transportation-Network-Providers-Trips-2022/2tdj-ffvb/data>

[2] Kooti, Farshad & Grbovic, Mihajlo & Aiello, Luca & Djuric, Nemanja & Radosavljevic, Vladan & Lerman, Kristina. (2017). Analyzing Uber's Ride-sharing Economy. 574-582.

[3] [statista.com/statistics/822833/us-ride-sharing-uber-users-age/](https://www.statista.com/statistics/822833/us-ride-sharing-uber-users-age/)

[4] Peyman Ashkrof, Gonalo Homem de Almeida Correia, Oded Cats, Bart van Arem, Understanding ride-sourcing drivers' behaviour and preferences: Insights from focus groups analysis, Research in Transportation Business & Management, Volume 37, 2020, ISSN 2210-5395, <https://doi.org/10.1016/j.rtbm.2020.100516>.

[5] Cody Cook, Rebecca Diamond, Jonathan V Hall, John A List, Paul Oyer, The Gender Earnings Gap in the Gig Economy: Evidence from over a Million Rideshare Drivers, The Review of Economic Studies, Volume 88, Issue 5, October 2021, Pages 2210–2238, <https://doi.org/10.1093/restud/rdaa081>

[6] <https://data.cityofchicago.org/Transportation/Transportation-Network-Providers-Driver/Trips-2022/2tdj-ffvb/data>

[7] <https://www.businessinsider.com/how-much-uber-drivers-make-full-time-gas-driving-tips-2023-11?r=US&IR=T>

[8] <https://www.sciencedirect.com/science/article/pii/S221053952030078X>

[9] <https://www.uber.com/en-GB/newsroom/introducing-new-driver-hours-policy/>

[10] <https://www.sfgate.com/tech/article/Uber-Lyft-San-Francisco-pros-cons-ride-hailing-13841277.php>

[11] <https://www.theguardian.com/technology/2019/may/07/the-uber-drivers-forced-to-sleep-in-parking-lots-to-make-a-decent-living>

[12] Chen L., Mislove, A., & Wilson, C. (2015). Peeking Beneath the Hood of Uber. Proceedings of the 2015 ACM Conference on Internet Measurement Conference - IMC '15.

[13] <https://secondmeasure.com/datapoints/rideshare-industry-overview/>

[14] <https://www.sfcta.org/tools-data/maps>

[15] <https://movement.uber.com/?lang=en-US> (unfortunately no longer available)

[16] <https://sumo.dlr.de/docs/Networks/Import/OpenStreetMapDownload.html>

[17] https://data.sfgov.org/Transportation/SFMTA-Transit-Vehicle-Location-History-Current-Year/3344-v6h6/about_data

[18] <https://www.uber.com/global/en/price-estimate/>

[19] <https://www.kaggle.com/datasets/ravi72munde/uber-lyft-cab-prices>

[20] <https://www.vatech.com/manuals/379746#>

[21] <https://earthworks.stanford.edu/catalog/stanford-df986nv4623>