

Design of cyberphysical autonomous mobility platforms

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Workshop III: Large Scale Autonomy: Connectivity and Mobility Networks



NYU

**TANDON SCHOOL
OF ENGINEERING**



The transportation field has changed significantly

1950s-60s



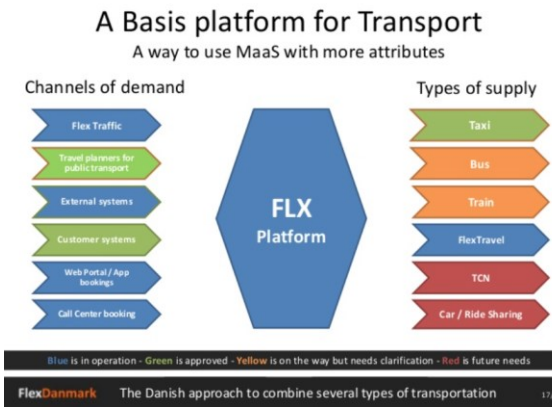
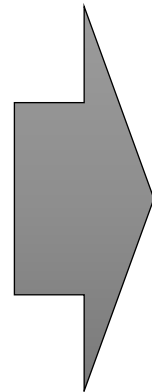
https://livinghistoryfarm.org/farminginthe50s/life_14.html



A section of the Transbay Tube being lowered into San Francisco Bay.

<https://www.bart.gov/about/history/history2>

Last 5 years



BP invests in city mobility start-up MaaS Global

SOURCE: PRESS RELEASE, 7 NOVEMBER 2019

8 November 2019 Editor News, Technology 0



Whim app allows customers to access and connect on a single platform all available transport options in a city - from taxis, buses, bikes and rental cars, to ride-hailing services, shared e-scooters and e-bikes (illustration: MaaS Global)



Uber + masabi + RTD

Cal-ITP Program

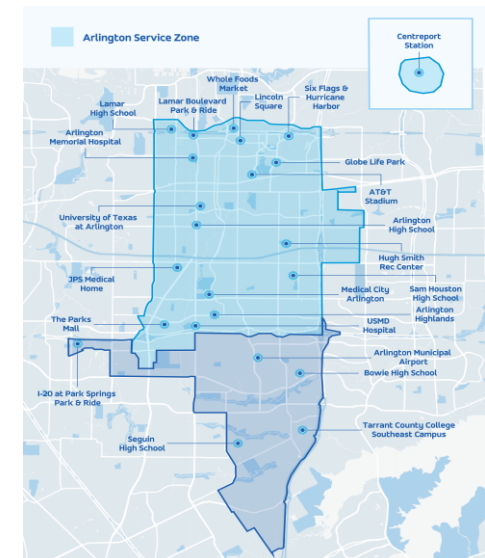
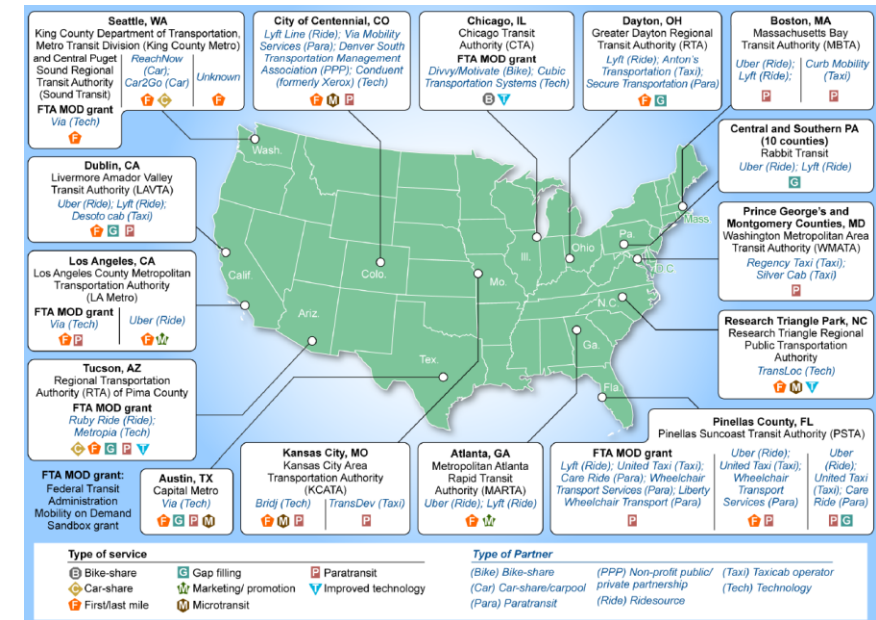


Cal-ITP1 Research and fact-finding on Integrated Transportation Systems.

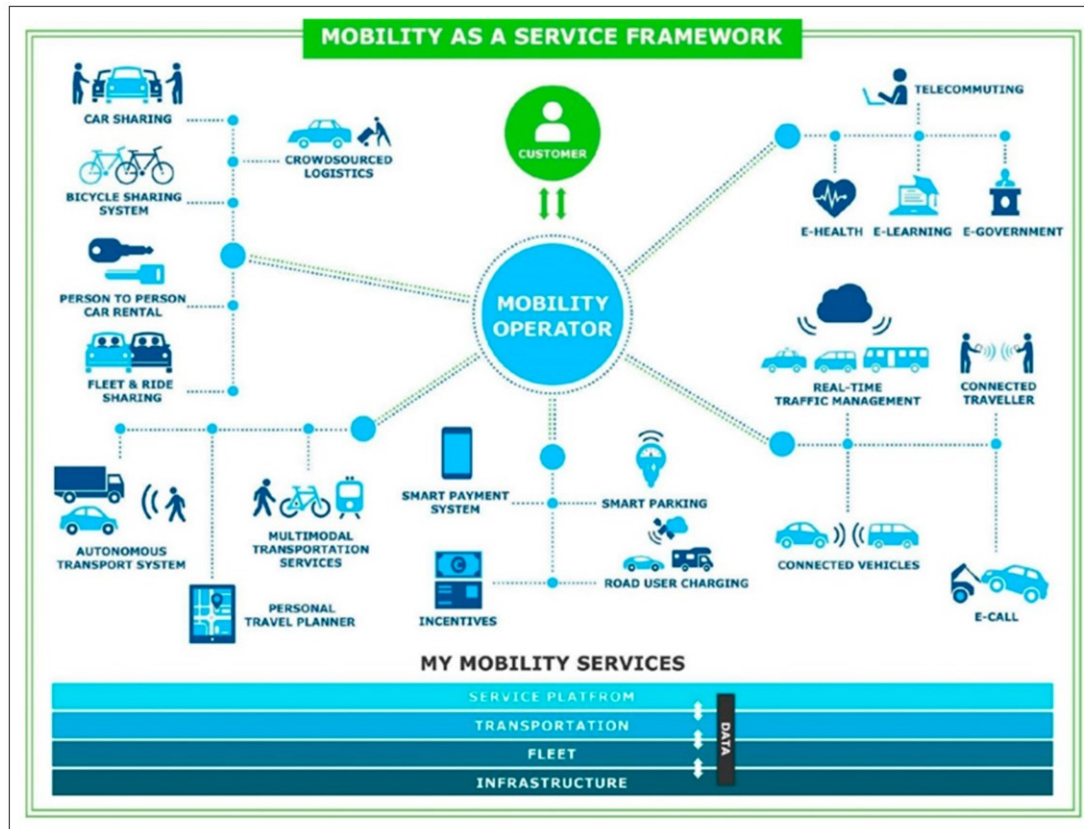
Cal-ITP2 California Integrated Travel Project Symposium in Davis, CA.

Cal-ITP3 Statewide Payment Systems and Mobility Service Data solutions, with a focus on Public Transit and Passenger Rail.

Cal-ITP Future Mobility Service Data for other mobility services, Wayfinding tools and guidelines, User Data & Accounts, Customer Service & Feedback systems.

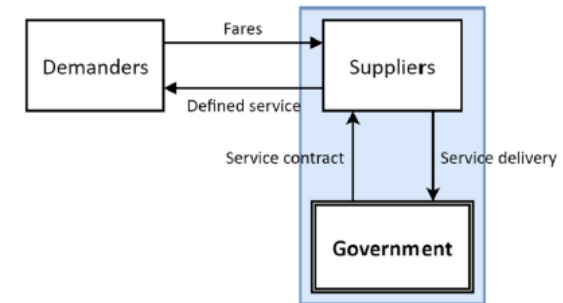


Trend 1: Mobility-as-a-Service (MaaS)

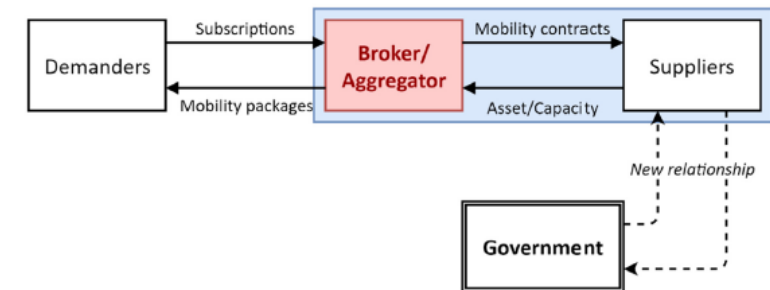


“MaaS combines **transport services** from **public** and **private** transport providers through a **unified gateway** that creates and manages the trip, which users can pay for with a **single account**.” – Hensher (2017)

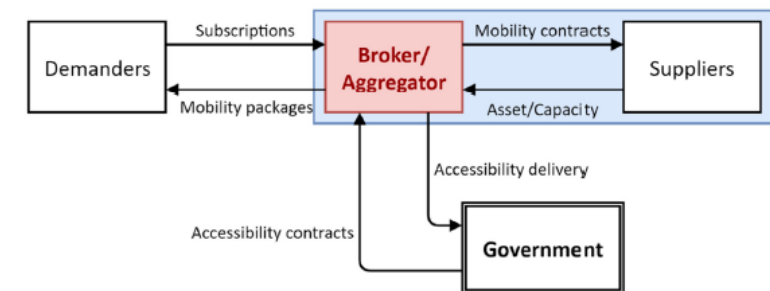
A: Conventional public transport under status quo



B: Mobility as a service under economic deregulation



C: Mobility as a service under government contracting



Wong, Y. Z., Hensher, D. A., & Mulley, C. (2020). Mobility as a service (MaaS): Charting a future context. *Transportation Research Part A: Policy and Practice*, 131, 5-19.

Trend 2: SAV fleets

Testing of First Autonomous Shuttle on Public Roads in California Begins

March 7, 2018



CA DMV grants permission for shared autonomous vehicle testing at Bishop Ranch

<https://news.theregistrarsf.com/testing-first-autonomous-shuttle-public-roads-california-begins/>



omous vehicles operate as temporary bus service

WEpod autonomous vehicles operate as temporary bus service

NEWS - 09 NOVEMBER 2016

From Tuesday 8 November two self-driving WEpods named WURby and WEily, are operating as a weekly bus service on the campus of Wageningen University and Research. On Tuesdays from 11:00 to 13:00 passengers are welcome to board the bus on its fixed route with 10 stops. TU Delft is one of the partners in this project, contributing to the software and sensors that enable the vehicle to travel autonomously.

<https://www.tudelft.nl/en/2016/tu-delft/wepod-autonomous-vehicles-operate-as-temporary-bus-service/>

3,920 views | Jan 31, 2018, 05:19pm

Ugly But Useful: Stockholm Introduces Driverless Buses



Heather Farmbrough Contributor



The first 100 of Baidu's "Level 4" self driving buses have rolled off the production lines, said Robin Li, chief executive of China's largest search engine operator on Wednesday.



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The self-driving buses, which can seat up to 14 people, were co-developed by Baidu, which is transforming itself into an artificial intelligence (AI) company, and bus maker King Long United Automotive Industry Co. Level 4 operations means that the vehicles can take over all driving in certain conditions.

With no steering wheel and high automation, the buses will be put into use in cities including Beijing, Xiongan, Shenzhen and Tokyo, Li said at the Baidu AI Developer forum being held in Beijing. "They will help with shuttle services around nuclear power stations and senior communities in Japan," for example, said Li. Baidu will partner with SB Drive, a subsidiary of SoftBank Group, to export the self-driving buses to Japan.

<https://www.scmp.com/tech/article/2153694/baidu-says-first-100-self-driving-buses-have-rolled-production-lines>

<https://www.forbes.com/sites/heatherfarmbrough/2018/01/31/ugly-but-useful-stockholm-introduces-driverless-busses/#44bad00360f4> ³

Research questions

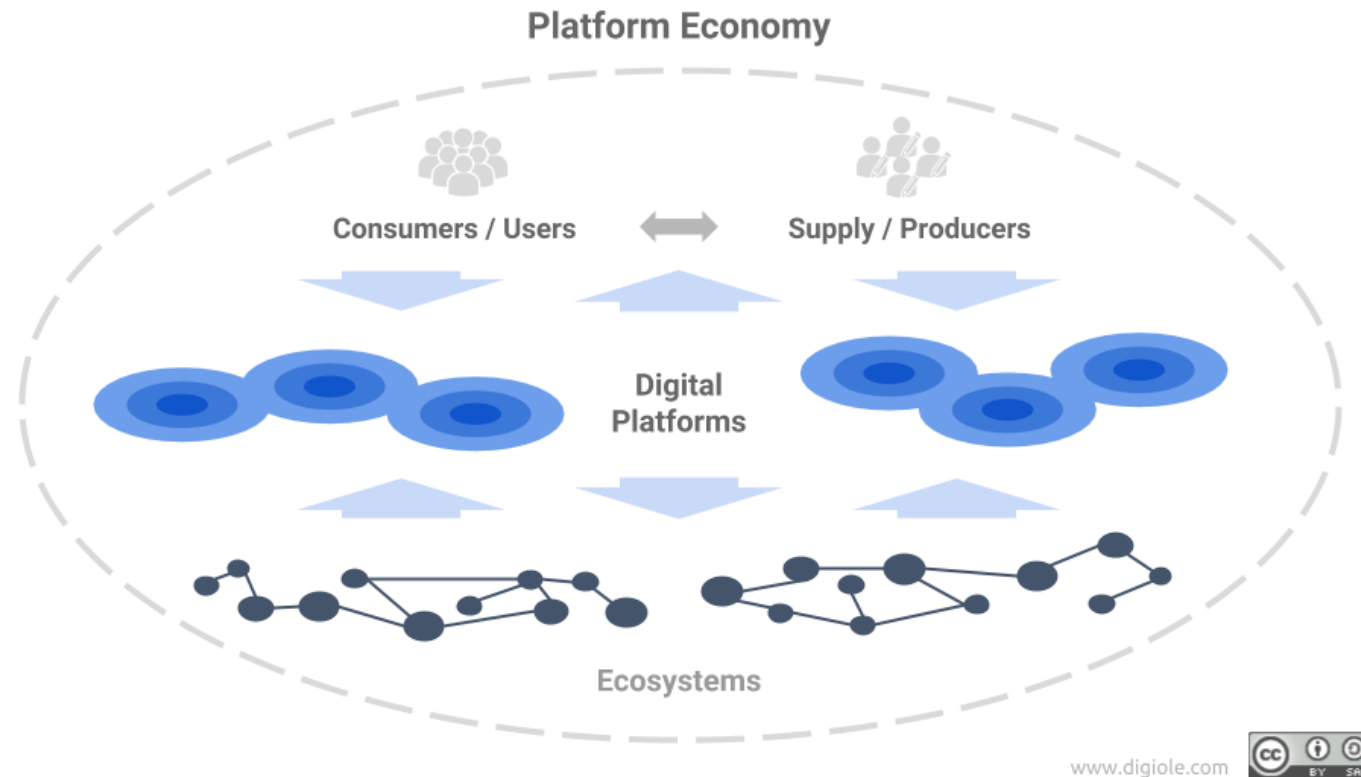
- How to evaluate the stability of an ecosystem of mobility providers?
 - If a new service enters the market? If a service improves its technology?
- How can public agencies facilitate these ecosystems?
 - Comparing between different interventions: infrastructure investments, subsidies, taxes, regulating toward social optimum
- How might automation affect these systems?

Outline

1. Platform economics for MaaS markets
2. Market evaluation of cyberphysical platforms
 - a) Model
 - b) A scalable algorithm
 - c) Numerical examples
 - d) Evidence of methodology with Luxembourg microtransit service
3. Impacts of automation

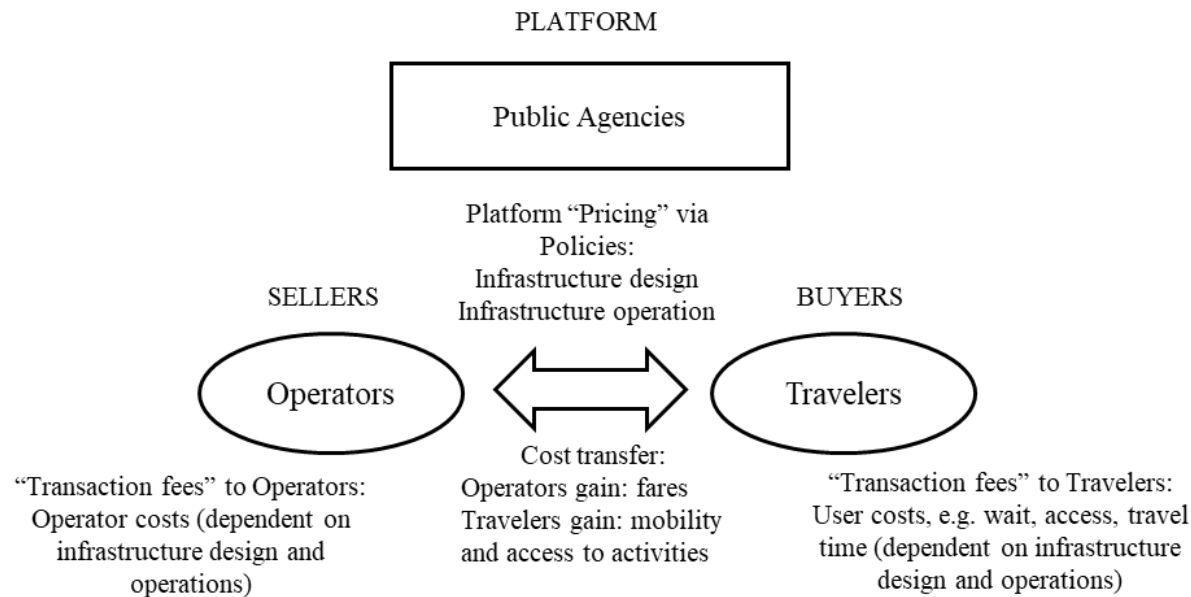
Platform economics for MaaS markets

Multisided platforms



“Multi-sided markets are markets in which one or several platforms enable interactions between en-users and try to get the two (or more) sides ‘on board’ by appropriately charging each side.” – Rochet and Tirole, 2006

Cities are multisided cyberphysical platforms (Chow, 2018)



- The two sets of end users are the **Travelers** (buyers) and the mobility **Operators** (sellers)
- Platforms may interface **physically** (built environment) or **digitally** (travel apps, e-commerce)
- Cities’ “platform pricing” take several forms:
 - **Built environment** affects travel costs
 - **Taxes/subsidies** further augment costs to operators/travelers
 - **Regulations** define the pricing structures

There is a need to model such systems as platforms

Sample use cases for a planning model for a public-operated MaaS platform.

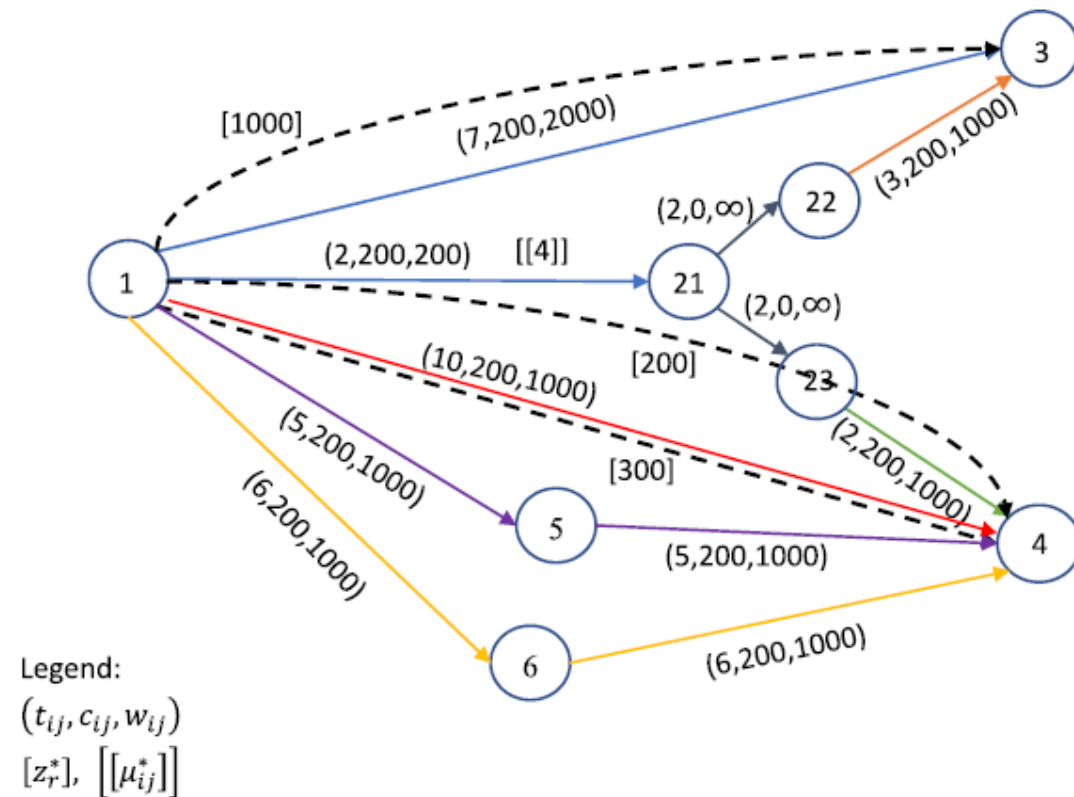
Use case	Model parameters	Required model output
<i>Technology</i> : evaluate/regulate market due to new algorithm or operating policy from an operator <i>Subsidy</i> : platform may subsidize one or more of the operators	Changes to travel disutilities of travelers (which may be in-vehicle, access, or wait time), link operating costs, or link capacities of operators Change in threshold for an operator to leave a market (they might be able to operate at a loss up to a threshold); cost allocation for that operator may align with welfare maximizing instead of profit maximizing	Impact on operator-routes that stay in market, passenger link flows, and how their stable price range changes Links that can be operated in this setting, revenues and flows under the changed setting
<i>Tax</i> : platform may impose a surcharge on a subset of operators <i>Merger</i> : two or more operators in a platform may merge or ally	Changes to operating cost for the operators The stability conditions would treat those operators as a single operator	Changes in operating links, flows, and shifts in stable pricing range as a result of surcharge Changes in revenue and ridership due to the merger
<i>Investment</i> : evaluate/regulate market due to increased investment by an operator on their fleet size, new service coverage area, etc. <i>Disruption</i> : links may be closed or degraded	New candidate links/nodes in network, changes to link capacities Closure of links/nodes in network, changes to link capacities	Whether those links stay in the market, subsequent flows, prices for new services as well as impacts on other operators Whether those links stay in the market, subsequent flows, prices for new services as well as impacts on other operators

Market evaluation of cyberphysical platforms

Pantelidis, T. P., Chow, J. Y. J., & Rasulkhani, S. (2020). A many-to-many assignment game and stable outcome algorithm to evaluate collaborative mobility-as-a-service platforms. *Transportation Research Part B: Methodological*, 140, 79-100.

Ma, T. Y., Chow, J. Y. J., Klein, S., & Ma, Z. (2020). A user-operator assignment game with heterogeneous user groups for empirical evaluation of a microtransit service in Luxembourg. *Transportmetrica A: Transport Science*, 1-28.

How to evaluate platforms that operate with multiple operators?



- Assignment of travelers to a MaaS network is not just determining flows that make sense to them, but also making sense to operators (which links to operate, what price* to charge)
- Blue owns (1,3) and (1,21) – serving (1,3) would compete with Orange for OD (1,3), but Orange can also cooperate with Blue through path (1,21,22,3), and (1,21) can also benefit Green
- The system also exhibits flow capacities that affect the route choices of travelers
- Each link is owned by at most one operator

*price assumed to be a fixed charge to users to access that operator any number of times per trip

Assumptions

Travel utility is transferable between travelers and operators:

- Transit operators' performance includes traveler disutilities like wait time
- Shared rides (detours) for discounts
- Increased access time to “virtual stops” for discounts
- Transfers/layovers for discounts

Operators charge single access, constant fares per traveler-path

If utility is transferable, we can model the MaaS platform market as an **assignment game**

- In a one-to-one assignment game (Shapley and Shubik, 1971):
 - Set of buyers P and set of sellers Q are matched together which generates utility U_{ij} for each pairing of buyer $i \in P$ to seller $j \in Q$ at a cost of c_j
 - The optimum matching x_{ij} between the two sets is found using a **matching subproblem** to maximize payoffs $a_{ij} = \max(0, U_{ij} - c_j)$
 - Given that optimal matching, a **stable outcome subproblem** determines the cost allocations p set between seller and buyer that satisfy the incentives of buyers ($u_i = U_{ij} - p$) and sellers ($v_j = p - c_j$)
 - There can be multiple stable cost allocations: a stable mechanism that maximizes u_i is “buyer-optimal”, one that maximizes v_j is “seller-optimal”
 - An optimal matching that has an empty stable outcome space is not sustainable

One-to-one assignment game

Matching subproblem

$$\begin{aligned} & \max \sum_{i \in P} \sum_{j \in Q} a_{ij} x_{ij} \\ & \text{s.t.} \\ & \sum_{i \in P} x_{ij} \leq 1, \quad \forall j \in Q \\ & \sum_{j \in Q} x_{ij} \leq 1, \quad \forall i \in P \\ & x_{ij} \in \{0,1\}, \quad \forall j \in Q, i \in P \end{aligned}$$

Constraints of stable outcome subproblem
(objective depends on cost allocation
mechanism)

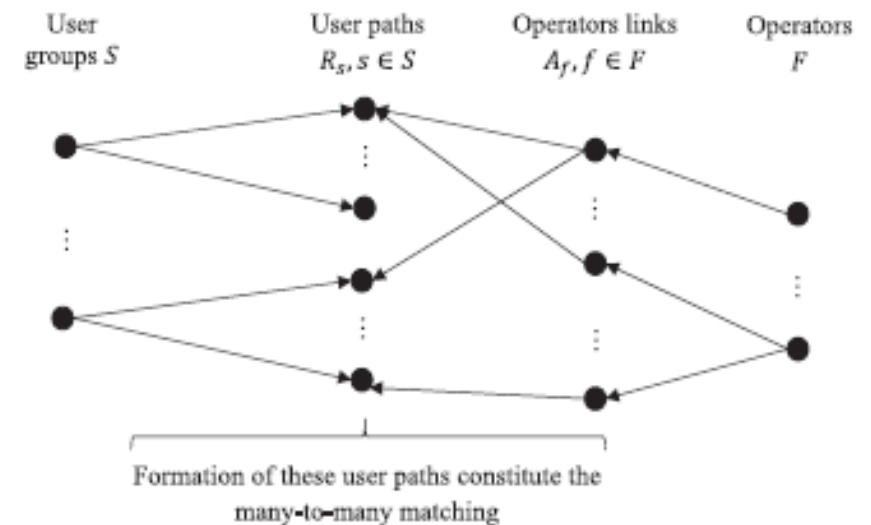
$$u_i + v_j \geq a_{ij}, \quad \forall i \in P, j \in Q$$

$$\sum_{i \in P} u_i + \sum_{j \in Q} v_j = \sum_{i \in P} \sum_{j \in Q} a_{ij} x_{ij}$$

$$u_i, v_j \geq 0$$

Challenges to overcome for MaaS platforms

- Many-to-many assignment game: multiple operators serve multimodal trip, multiple travelers share a ride
- Link capacities lead to network effects that need to be captured by stable outcome subproblem
- Matching subproblem is a multicommodity capacitated network design problem



Some notation

Parameters

- t_{ij} : disutility experienced on link (i, j) on a directed graph $G(N, A)$
- c_{ij} : operating cost of link (i, j)
- d_s : demand of user group $s \in S$
- w_{ij} : flow capacity of link (i, j)

Decision variables

- x_{ij}^s : flow of user group $s \in S$ on link (i, j)
- y_{ij} : binary variable for whether a link is operated
- p_{rf} : price charged by operator $f \in F$ to travelers $s \in S$ on path $r \in R_s^*$
- z_r : the flow on path $r \in R_f$ served by operator $f \in F$

Assignment game model for MaaS market

Matching subproblem (link variables)

$$\begin{aligned} \min Z = & \sum_{(i,j) \in A} \sum_{s \in S} t_{ij} x_{ij}^s + \sum_{(i,j) \in A} c_{ij} y_{ij} \\ \text{s.t.} & \\ & \sum_{j \in N_i(+)} x_{ij}^s - \sum_{j \in N_i(-)} x_{ji}^s = \begin{cases} d_s, & i = O(s) \\ -d_s, & i = D(s), \forall i \in N, s \in S \\ 0 & \end{cases} \\ & \sum_{s \in S} x_{ij}^s \leq w_{ij} y_{ij}, \quad \forall (i,j) \in A \\ & x_{ij}^s \geq 0, \quad \forall (i,j) \in A, s \in S \\ & y_{ij} \in \{0,1\}, \quad \forall (i,j) \in A \end{aligned}$$

Stable outcome subproblem (path variables)

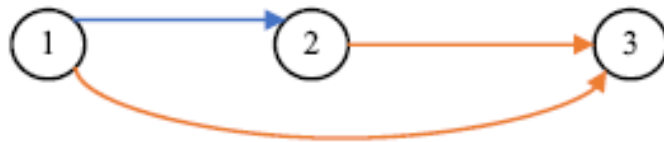
$$\begin{aligned} u_s + \sum_{f \in F_r} p_{rf} &= U_s - \sum_{(i,j) \in A_r} t_{ij}, \quad \forall r \in R_s^*, s \in S \\ u_s &\geq 0, \quad \forall s \in S \\ p_{rf} &\geq 0, \quad \forall r \in R, f \in F \\ \sum_{r \in R_f} p_{rf} z_r^* &\geq \sum_{(i,j) \in A_f} c_{ij} y_{ij}^*, \quad \forall f \in F \end{aligned}$$

Does this mean we need to enumerate alternate paths?

Although paths are non-unique,

- Link flows and total path costs are unique →
 - Revenues gained by operators and total consumer surplus are unique
 - A unique stable outcome space for a given matching, but cannot guarantee the opposite
- Model can be used for *ex post* evaluation to quantify changes in a market

Model can be used to analyze stylized examples



(a)

In case (a), Orange would collaborate with Blue only if its price p_o can be charged higher than:

$$p_o \geq \frac{c_{12} + c_{23}}{d} - t_{13} - c_{13} + t_{12} + t_{23}, \text{ if } t_{12}d + t_{23}d + c_{12} + c_{23} \leq t_{13}d + c_{13}$$



(b)

In case (b), Orange would enter the market as shown only if its price doesn't exceed the following:

$$p_{2o} \leq \begin{cases} t_{23}^b - t_{23}^o + c_{23}^b, & \text{if } x_{23}^b = 0 \\ 0, & \text{if } x_{23}^b > 0 \end{cases}$$

(a) choosing between cooperation and competition; (b) small operator against a larger operator.

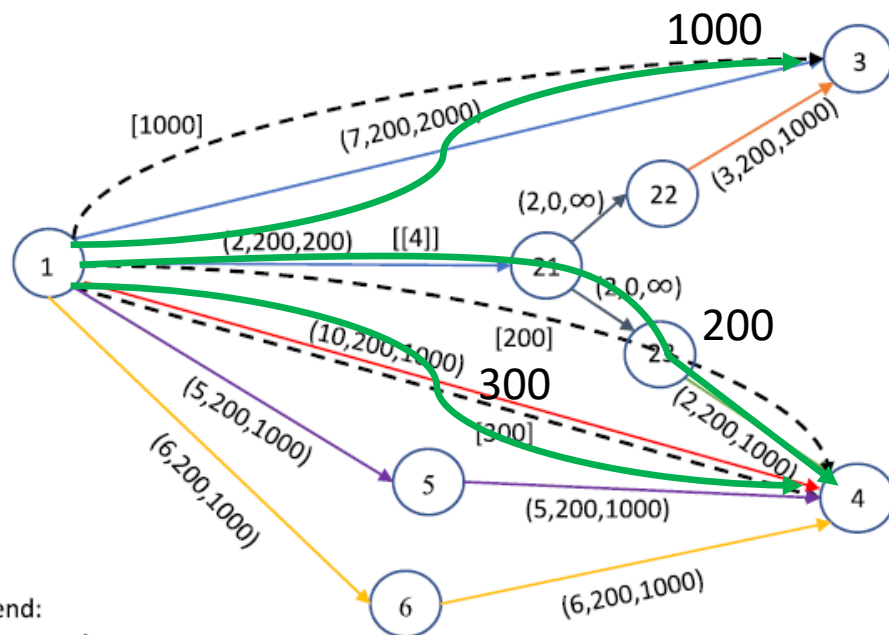
Algorithm to generate constraints without explicit path enumeration

Algorithm 1 Constraint generation for Eq. (6) without explicit path enumeration.

1. **For** each user in the set S **do**
 2. **Set** $R_s^* = \{r \in R_s | \omega(r) \leq \omega(r') \ \forall r' \in R_s\}$
 3. **For** each optimal path $r \in R_s^*$ **do**
 4. **For** π in $\Pi(F_{R_s^*})$ **do**
 5. Generate $u_s + \sum_{f \in (F_r \cap F_{\bar{r}_\pi})} p_{rf} \geq U_s - \omega^s(\bar{r}_\pi)$, where $\bar{r}_\pi = \arg \min \{\omega^s(r) | r \in R_s \text{ s.t. } \pi \cap F_{R_s^*} = \emptyset\}$
-

$\Pi(F_{R_s^*})$ is a set of permutations of coalitions of operators drawn from the route being considered, i.e. if there are 3 operators on a route, it would iterative check the removal of ($\{1\}$, $\{2\}$, $\{3\}$, $\{1,2\}$, $\{1,3\}$, $\{2,3\}$, $\{1,2,3\}$)

Numerical test



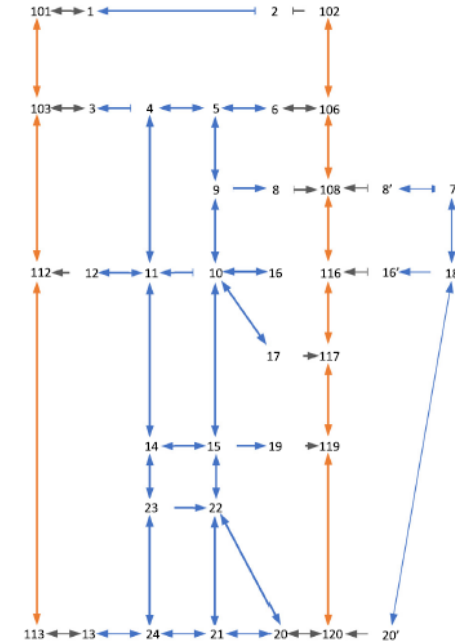
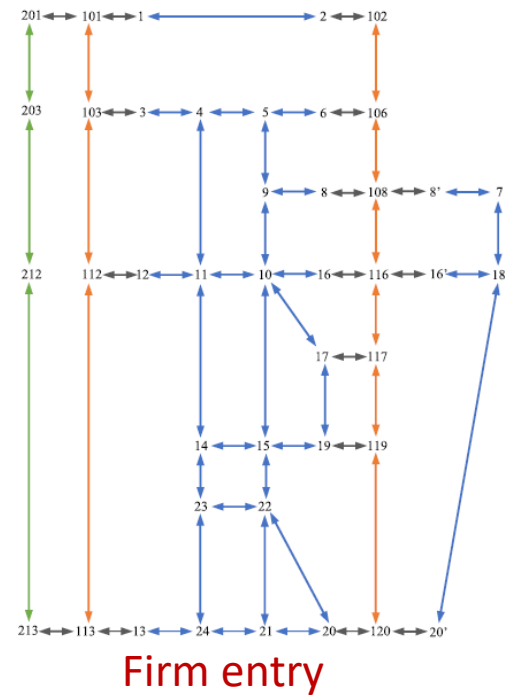
Legend:
 (t_{ij}, c_{ij}, w_{ij})
 $[z_r^*], [\mu_{ij}^*]$

Example network with 6 nodes, 6 operators, and 2 OD pairs assigned to 6 paths.

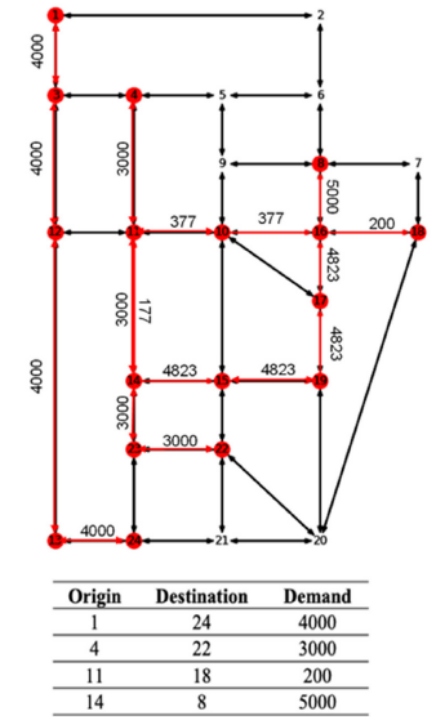
Solution to example M2M problem.

		Buyer-optimal	Seller-optimal
(Operator,user-route)	Flow $\sum_{r \in R_f} z_r$	Price p_{rf}	Price p_{rf}
(A, (1,3))	1000	\$0	\$13
(A, (1,21,23,4))	200	\$3.67	\$13
(C, (1,21,23,4))	200	\$1.0	\$1
(D, (1,4))	300	\$0.67	\$10
User group-route	$U_s - \sum_{(i,j) \in A_r} (t_{ij})$	$U_s - \sum_{(i,j) \in A_r} (t_{ij}) - \sum_{f \in F_r} p_{rf}$	$U_s - \sum_{(i,j) \in A_r} (t_{ij}) - \sum_{f \in F_r} p_{rf}$
((1,3),(1,3))	\$13	\$13	\$0
((1,4),(1,21,23,4))	\$14	\$9.33	\$0
((1,4),(1,4))	\$10	\$9.33	\$0
Operator		$\sum_{r \in R_f} p_{rf} z_r - \sum_{(i,j) \in L_f} c_{ij} y_{ij}$	$\sum_{r \in R_f} p_{rf} z_r - \sum_{(i,j) \in L_f} c_{ij} y_{ij}$
A		\$333.33	\$15,600
B		\$0	\$0
C		\$0	\$200
D		\$0	\$3000
E		\$0	\$0
F		\$0	\$0

Example: Sioux Falls



(a)



(b)

Table 4
Comparison of aggregate measures of different scenarios with $U_5 = 20$

Parameters: Scenarios:	Revenues (\$) [$f = 1, 2, 3$]	Avg. operator fare (\$) [$f = 1, 2, 3$]	Avg. operated link revenue (\$)	Operator ridership $\sum_{r \in R_f} z_r$ [$f = 1, 2, 3$]	Runtime: Model generation / Solution (msec) (original LP)
Network duopoly (Base scenario)	[24424,18000]	[2,2]	2497	[12200,9000]	6259.2 / 20.4
Government rail acquisition	[42417,7]	[3.47,0.0008]	2497	[12200,9000]	6259.2 / 20.4
Firm entry	[60422,10000,0.75]	[5,2,0.0002]	3912	[12200,5000,4000]	12095.6 / 35.6
Binding capacity increase ($w_{58} = 4900$)	[24500,18000]	[2,2]	2497	[12200,9000]	6259.2 / 20.4
Binding capacity increase ($w_{58} = 5000$)	[15600,27000]	[1,3,3]	2663	[12200,9000]	5300.8 / 15.5
Technological change	[27506,40500]	[2,25,4,5]	3400	[12200,9000]	6259.2 / 20.4

Link flow assignment results for Sioux Falls network.

Link	Flow	Link	Flow	Link	Flow
(20, 21)	6400	(23, 22)	8100	(19, 15)	15500
(14, 11)	15400	(9, 5)	11000	(20, 22)	10917
(22, 23)	8100	(15, 19)	15500	(103, 101)	6000
(2, 1)	3800	(10, 16)	16183	(11, 14)	15400
(13, 113)*	11000	(117, 17)*	16200	(17, 117)*	16200
(106, 102)	6600	(1, 101)*	6000	(19, 119)*	15100
(10, 15)	16617	(112, 113)	10900	(21, 20)	6300
(23, 24)	6200	(3, 4)	7200	(103, 3)*	5800
(4, 11)	6900	(7, 18)	15900	(6, 5)	8800
(102, 106)	6600	(22, 20)	10817	(102, 2)*	6600
(18, 20)	15583	(1, 2)	3800	(16, 18)	17983
(112, 12)*	10400	(108, 116)	6700	(24, 23)	6200
(18, 7)	15900	(112, 103)	6400	(14, 23)	6000
(17, 10)	7200	(18, 16)	17983	(23, 14)	6000
(16, 116)*	10100	(119, 117)	15600	(120, 20)*	2900
(8, 108)*	11500	(12, 11)	12200	(24, 13)	12100
(15, 22)	26917	(16, 10)	16183	(13, 24)	12100
(24, 21)	14300	(9, 10)	22000	(20, 120)*	2900
(108, 8)*	11500	(116, 117)	13200	(116, 16)*	10100
(106, 6)*	9600	(117, 119)	15600	(21, 24)	14400
(116, 108)	6700	(11, 12)	12200	(119, 120)	2900
(22, 21)	12600	(120, 119)	2900	(108, 106)	12000
(11, 4)	7000	(10, 17)	7200	(15, 10)	16817
(22, 15)	27017	(101, 103)	6000	(101, 1)*	6000
(5, 6)	8800	(21, 22)	12600	(103, 112)	6400
(113, 13)*	10900	(4, 3)	7200	(5, 4)	13100
(11, 10)	18300	(106, 108)	12000	(15, 14)	11100
(5, 9)	11000	(3, 103)*	5800	(7, 8)	10600
(8, 7)	10600	(119, 19)*	15100	(8, 9)	3000
(117, 116)	13200	(4, 5)	13100	(2, 102)*	6600
(10, 9)	22100	(9, 8)	3000	(12, 112)*	10300
(14, 15)	11100	(113, 112)	11000	(20, 18)	15483
(23, 22)	8100	(6, 106)*	9600	(10, 11)	18500

Links with * represent operator transfers

Algorithm can scale up

Pricing and ridership breakdown by operator.

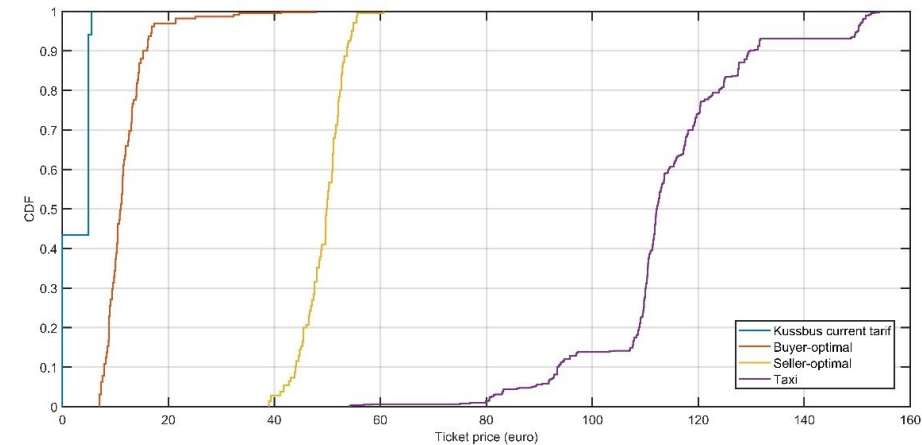
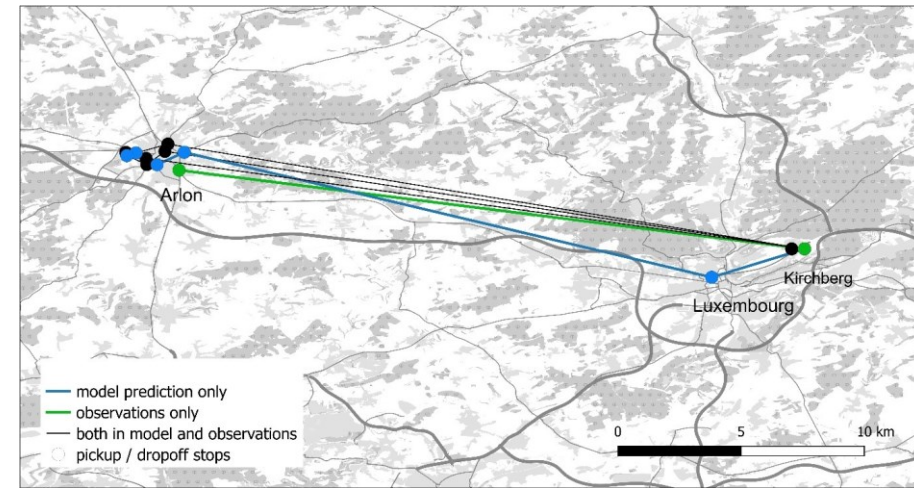
Operator	Revenue (\$)	Avg fare (\$)	Min fare (\$)	Max fare (\$)	Passengers	Operating costs (\$)
Bus Service (1)	6,509,832	23.68	1.00	38.00	274900	186
Rail (2)	217,466	1.00	1.00	1.00	217466	128

Insights

- Proposed algorithm can take 17 sec to solve Sioux Falls example that would require more than 2 hrs with explicit path enumeration
- The base scenario assumes seller-optimal for both. Government rail acquisition intervention changes the objective to buyer-optimal but the savings end up going to private operator, not the users, due to shared trips
- Addition of a new competitor can result in significant advantages to a third party; Operator 1 benefited greatly by being able to increase its price because a new Operator 3 entered to compete with Operator 2
- Capacity increases even for single links have nonlinear effects: exceeding a threshold improvement can lead to a significant shift in assignment and stable outcomes, which can also impact revenues of other operators

Significance/next steps

- The assignment game method has been applied to the Kussbus microtransit service in Luxembourg and correctly predicted its failure
- Currently advising NY State DOT on procuring the next statewide mobility services program
- Next research objectives:
 - Integrate congestible capacity route choice SUE into the assignment game
 - Consider assignment game from a multimodal activity-scheduling context



Stable outcome space for the Kussbus service, which ended up closing down later

Impacts of automation

AVs can add optimal learning into fleet operations

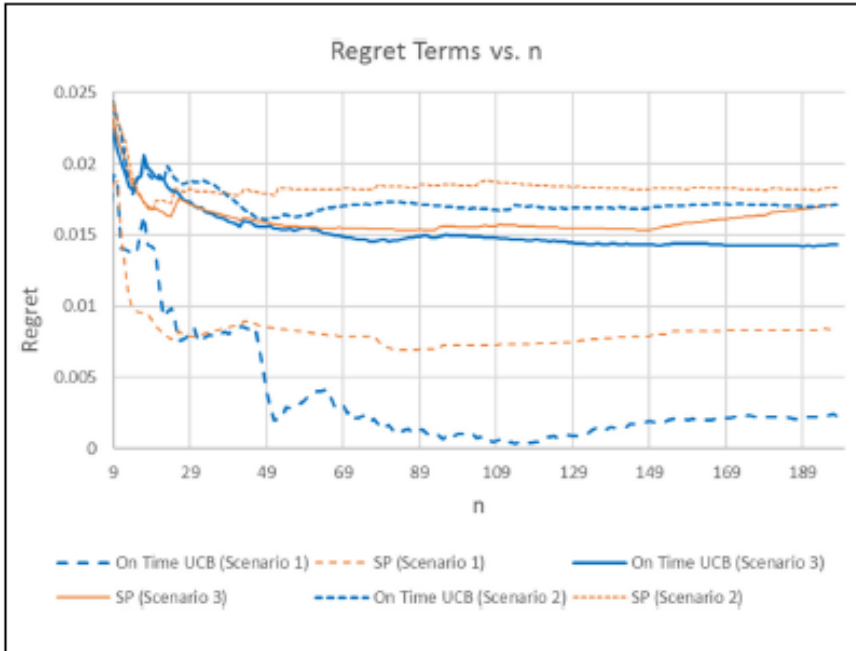


Figure 5. Regret measures of shortest path algorithm and on-time UCB algorithm.

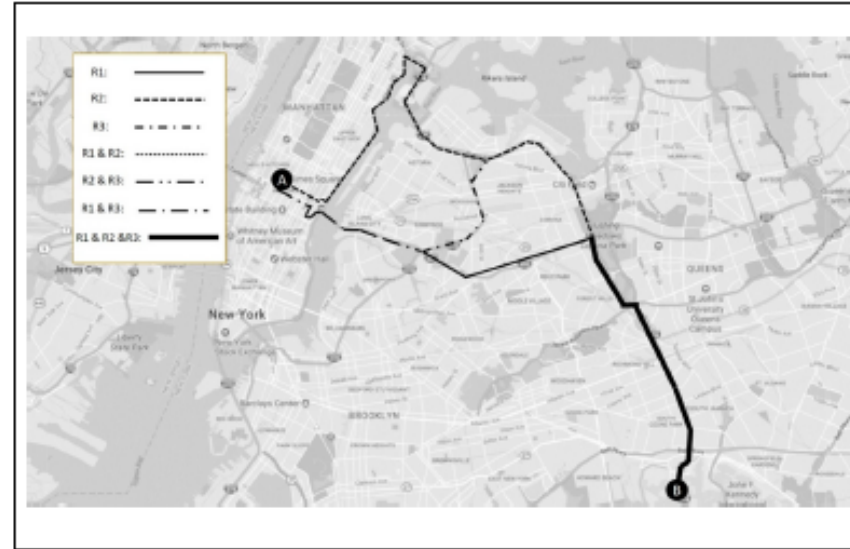


Figure 6. The top three paths considered in the sequential route selection experiment.

Table 3. Numerical Results after Running the Three Scenarios

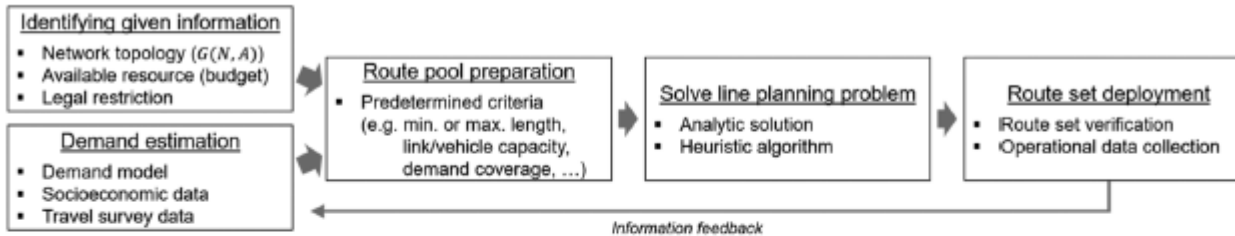
Scenario	SP on-time arrivals	On-time UCB on-time arrivals	SP mean rewards	On-time UCB mean rewards
1	47%	75%	0.0347	0.0394
2	87%	91%	0.0325	0.0351
3	70%	77%	0.0305	0.0320

Note: SP = shortest path; UCB = upper confidence bound.

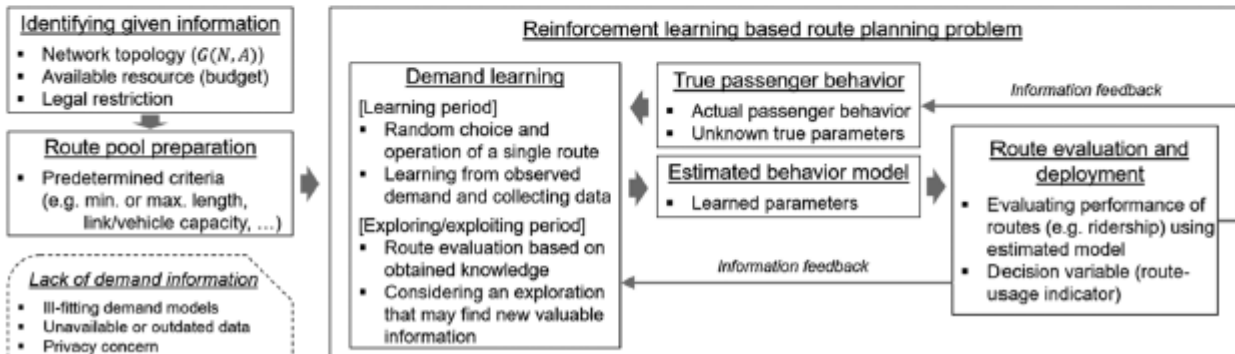
Zhou, J., Lai, X., & Chow, J. Y. J. (2019). Multi-armed bandit on-time arrival algorithms for sequential reliable route selection under uncertainty. *Transportation Research Record*, 2673(10), 673-682.

Optimal learning applied to SAV-based line planning as well

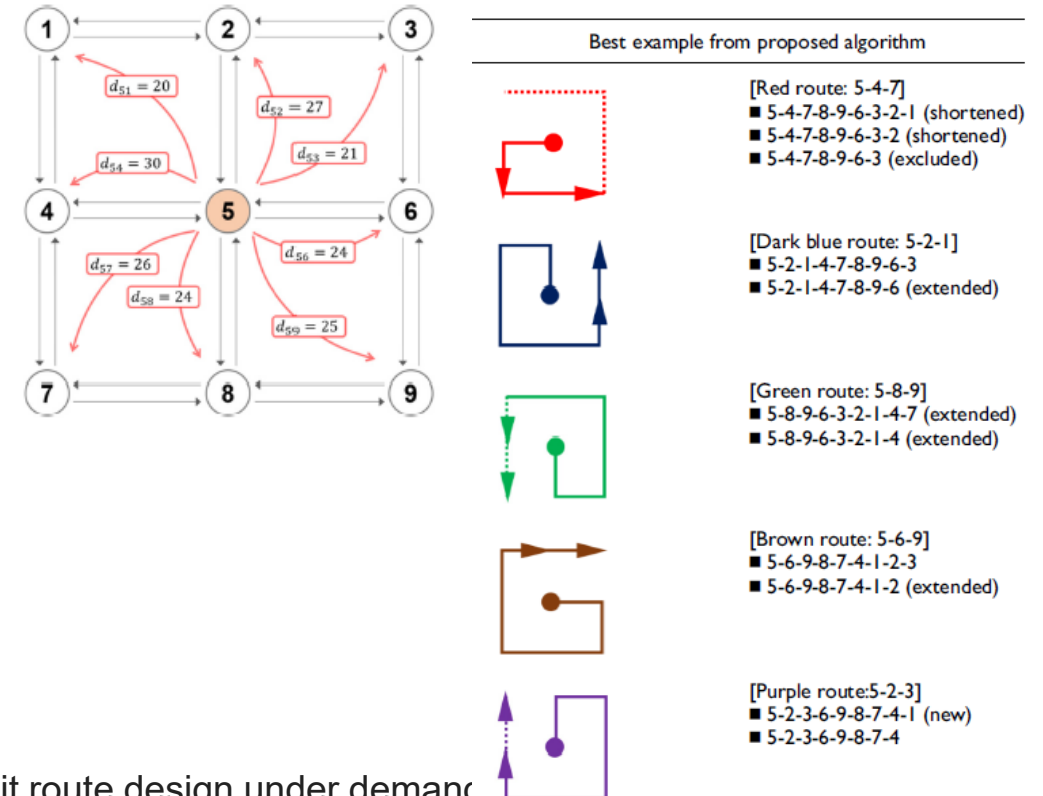
[Conventional route design problem]



[Proposed approach]



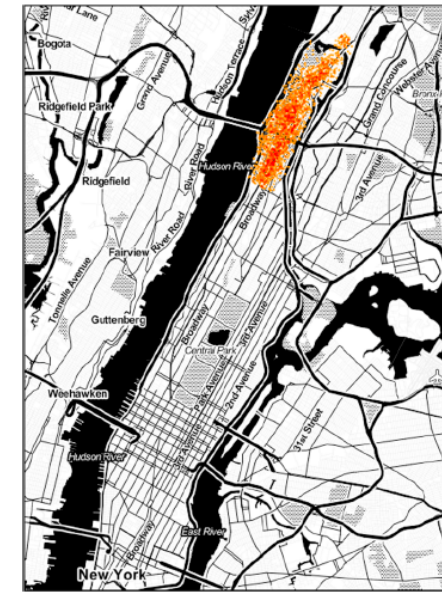
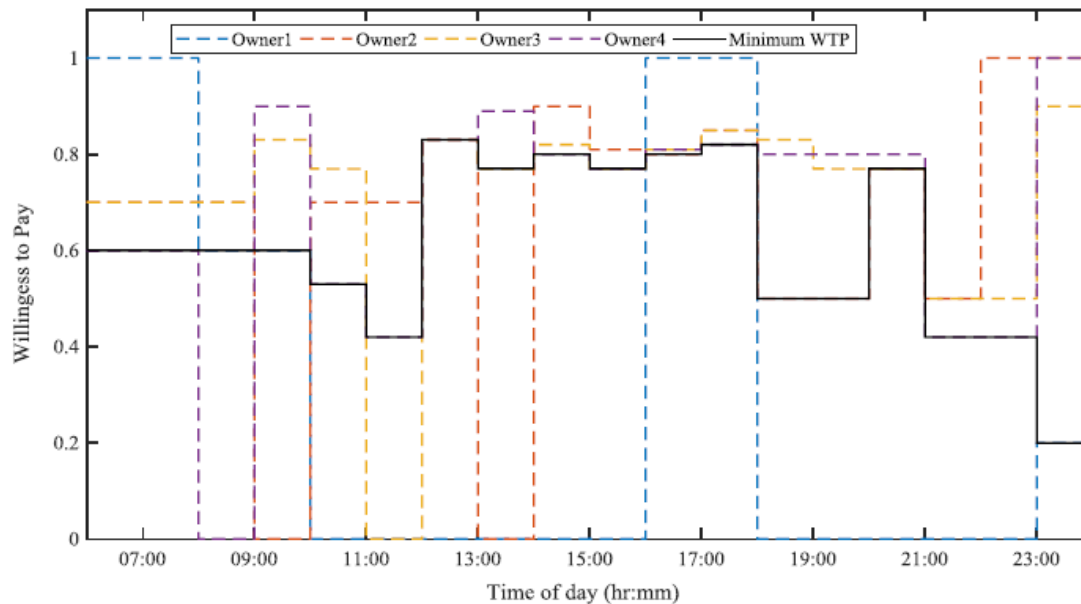
Line planning done sequentially with optimal learning can approach oracle line planning solution quality



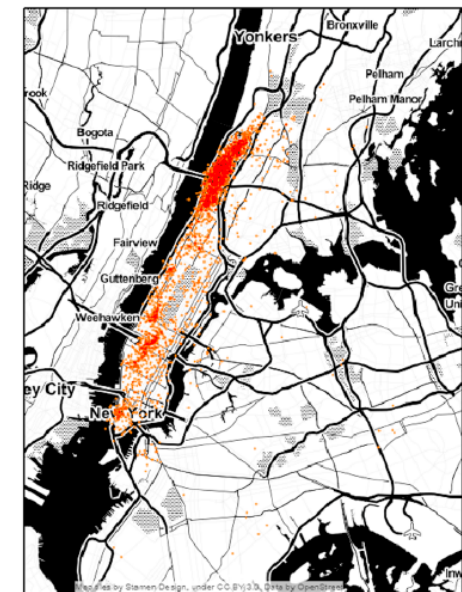
Yoon, G., & Chow, J. Y. J. (2020). Contextual bandit-based sequential transit route design under demand uncertainty. *Transportation Research Record*, 0361198120917388.

AVs' ownership can be shared between owners (like time-share plans)

- AVs can self-valet, so new fractional ownership business models can be added to the MaaS market
- Time of day prices can be derived from users' activity scheduling behavior



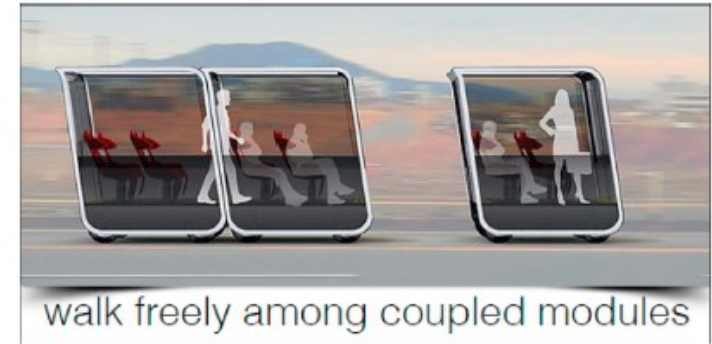
(a)



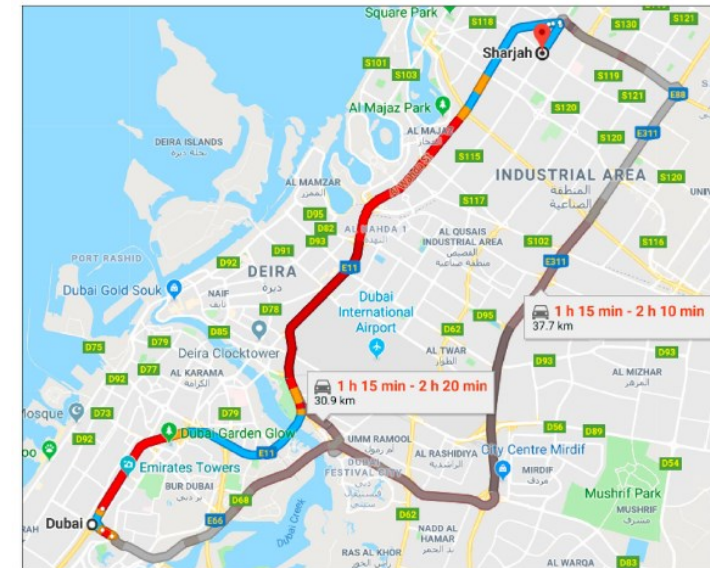
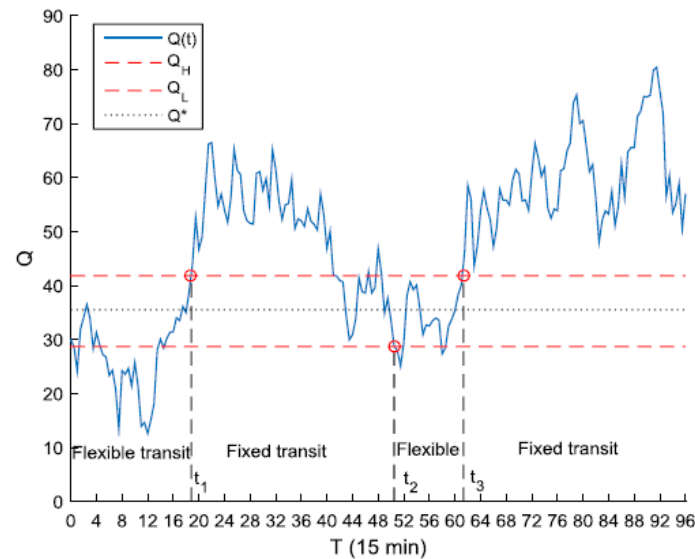
(b)

Allahviranloo, M., & Chow, J. Y. J. (2019). A fractionally owned autonomous vehicle fleet sizing problem with time slot demand substitution effects. *Transportation Research Part C: Emerging Technologies*, 98, 37-53.

Modular autonomous vehicles are feasible



- Dispatch can be more dynamic using stochastic optimization
- Shifts of transfers from stations to in-vehicle can reduce travel distance and wait time by 18-19% for Dubai-Sharjah corridor



Guo, Q. W., Chow, J. Y. J., & Schonfeld, P. (2018). Stochastic dynamic switching in fixed and flexible transit services as market entry-exit real options. *Transportation Research Part C: Emerging Technologies*, 94, 288-306.

Caros, N. S., & Chow, J. Y. J. (2020). Day-to-day market evaluation of modular autonomous vehicle fleet operations with en-route transfers. *Transportmetrica B: Transport Dynamics*, 1-25.

Conclusion

- MaaS markets need to be evaluated as cyberphysical platforms
- Design of such platforms can be evaluated using many-to-many assignment games
- Our approach can be applied to realistic networks to derive important insights
- It has been applied to Kussbus microtransit in Luxembourg and successfully predicted its instability
- Automation can further improve MaaS markets: optimal learning, new business models using self-valet, and modularity without drivers

Acknowledgments/Contact Info

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- Key researchers whose work I presented
 - Students: Saeid Rasulkhani, Ted Pantelidis, Jinkai Zhou, Gyugeun Yoon, Nick Caros, Ziyi Ma, Xuebo Lai
 - Collaborators: Tai-yu Ma, Sylvain Klein (LISER); Mahdieh Allahviranloo (CCNY); Qianwen Guo (FSU); Paul Schonfeld (UMD)
- Funding sources: NSF, USDOT (via C2SMART), FTA, NYSDOT

