

Robust Electric Vehicle Balancing for Autonomous Mobility-on-Demand Systems

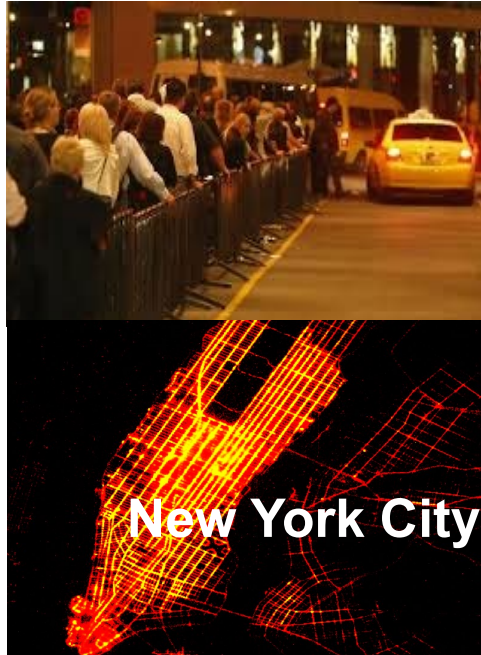
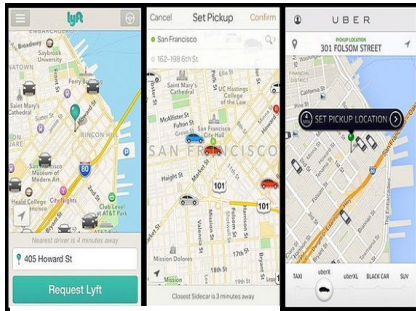
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Challenges: Unbalanced, Inefficient Mobility Services



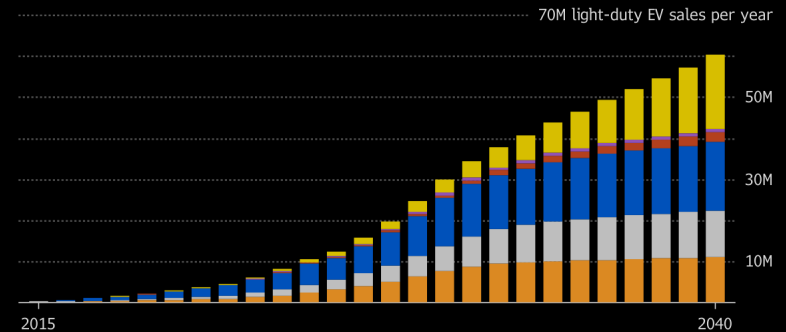
New York City

Taxis idle: 300 million miles/year
\$200 million waste

In the Fast Lane

China is set to lead in the global electric-vehicle revolution

Europe U.S. China Japan Korea Rest of World



Source: Bloomberg New Energy Finance

Bloomberg

MOBILITY ON DEMAND MARKET

Market Value
(2018)
>\$110 BN

CAGR (2019-26)
10%

Market Value
(2026)
>\$250 BN

NA market is
anticipated to witness
robust growth over
the forecast timeline

Europe market will
witness a rapid
growth by 2026

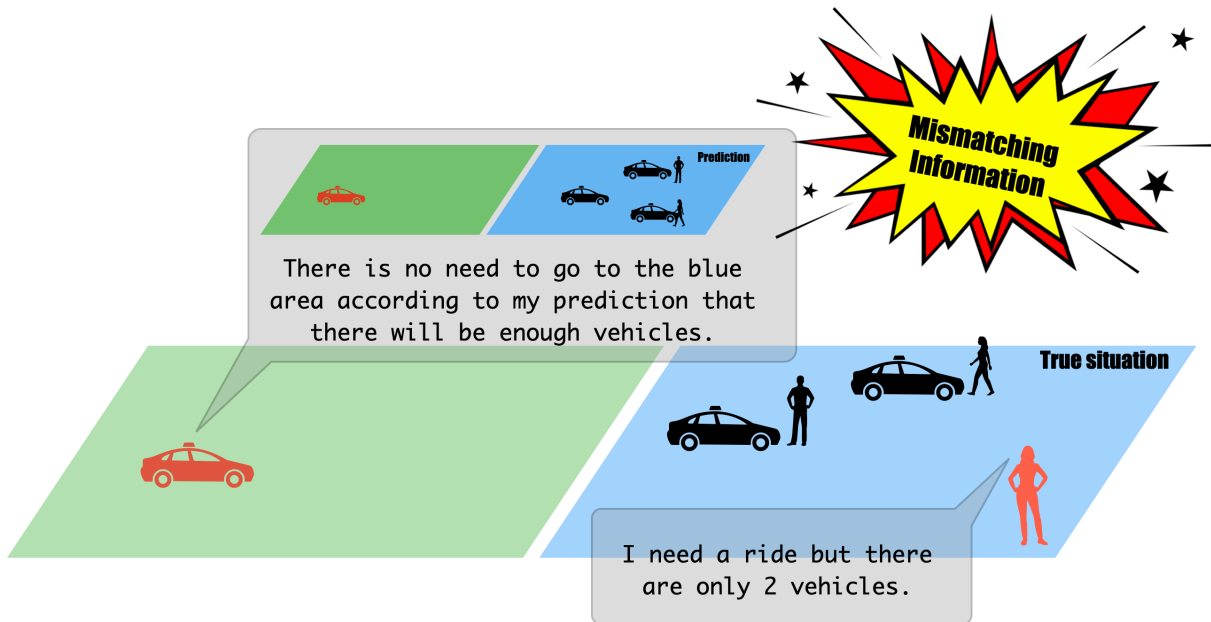
Peer-to-Peer (P2P) car sharing is
predicted to provide opportunities
for the growth of the mobility on
demand market



Example: Autonomous Mobility-on-Demand (AMoD) Systems

- Literature: assume known or accurate prediction of demand distribution
- EVs' unique dynamic charging process, hard to predict and schedule

Why Model Uncertainties Matter



Example: demand model uncertainty: vehicle balance or dispatch towards wrong demand information

Contributions and Novelties:

1.Data-Driven Distributionally Robust Optimization (DRO)

Data → predicted demand and supply with **Uncertainty Quantification**

→ **Robust Decision** to improved AMoD fairness and efficiency

2.Robust Multi-agent Reinforcement Learning Methods

DRO EV AMoD under Both Demand and Supply Uncertainties

Demand and charging spots prediction: $r \sim F_r^*$, $c \sim F_c^*$, $F_r^* \in \mathcal{F}_r$, $F_c^* \in \mathcal{F}_c$

EV balance for mobility and charging: $X^{1:\tau} = \{X^1, X^2, \dots, X^\tau\}$ $Y^{1:\tau} = \{Y^1, Y^2, \dots, Y^\tau\}$

EV supply for mobility demand: S_i^k , Low battery EV to charge: T_i^k

$$\begin{aligned}
 & \min_{X^{1:\tau}, Y^{1:\tau}, S^{1:\tau}, T^{1:\tau}} \max_{\{F_r \in \mathcal{F}_r, F_c \in \mathcal{F}_c\}} \mathbb{E} \left[\sum_{k=1}^{\tau} \left(\boxed{J_D(X^k, Y^k)} + \beta \sum_{i=1}^n \frac{c_i^k}{(T_i^k)^\alpha} \right) \right] \\
 & \text{s.t. } \boxed{l_i^k S_i^k \leq r_i^k \leq h_i^k S_i^k} \rightarrow \boxed{\text{Fair mobility service}} \\
 & \quad S_i^k = f_1(X^{1:k}, c^{1:k}), \quad T_i^k = f_2(Y^{1:k})
 \end{aligned}$$

Balance cost
Fair charging

1. Novelty: Decouple mutual dependency between the EV supply and mobility demand: charging fairness objective, mobility fairness constraint

→ decision variables on denominator, not linear or quadratic form opt

2. Theorem: DRO → Equivalent convex optimization, computationally tractable



Robust and Constrained MARL Method under Model Uncertainties

- Contributions:
- 1. Formulate a robust and constrained MARL problem under state transition kernel uncertainty for EV AMoD systems.
- 2. Minimize the balancing cost while balance the city's charging and service quality, under model uncertainty.
- 3. Algorithm ROCOMA to train robust policy and develop the first robust natural policy gradient (NPG) to improve the efficiency of policy training.