Socio-Technical Modeling, Control, and Optimization for Urban Mobility

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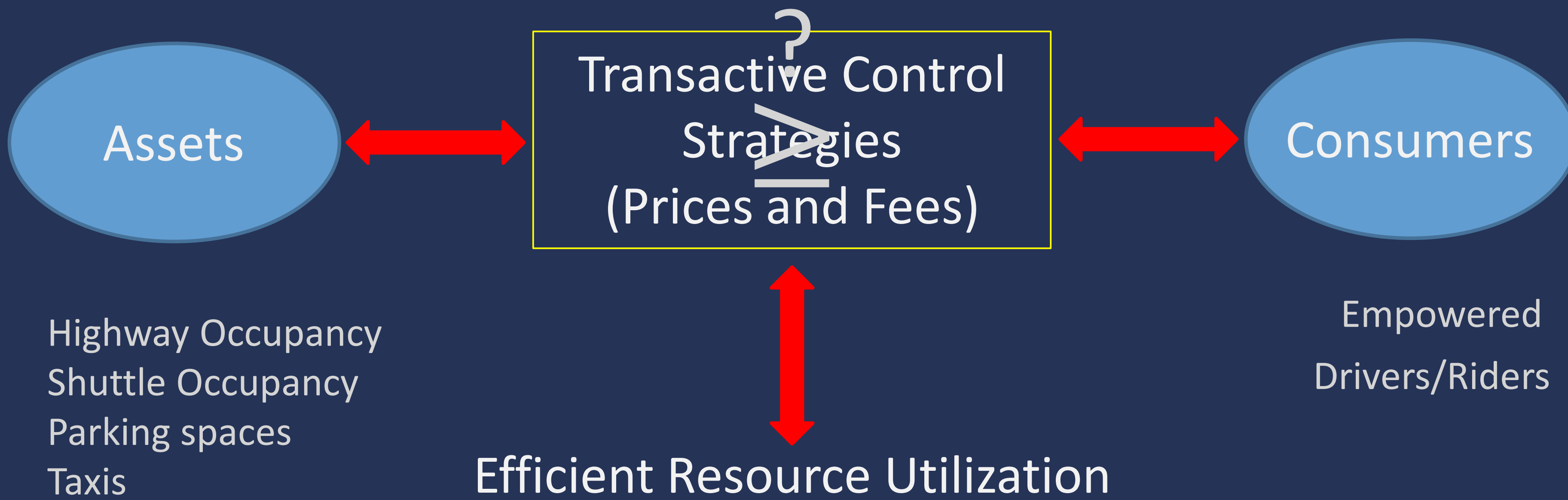
Sponsor: Ford-MIT Alliance

Empowered Consumers + Urban Mobility

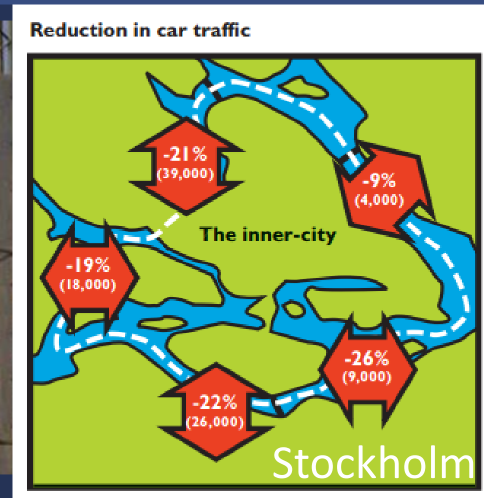


Example 1: Dynamic Toll-pricing for congestion reduction
Example 2: Shared Mobility on Demand using Dynamic Routing and Pricing

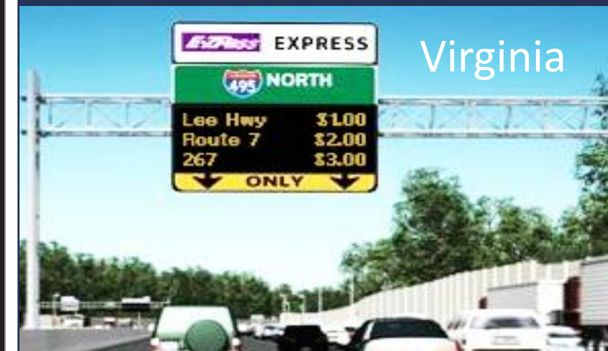
EXAMPLE 1: DYNAMIC TOLL PRICING

Motivation: Alleviate Traffic Congestion

33% reduction in inbound car traffic, 30% decrease in minutes of delay experienced



time spent in traffic dropped by 33% (morning peak) and 50% (evening peak)



average speeds of 60 mph maintained

8.8 to 13.3% reduction in travel times

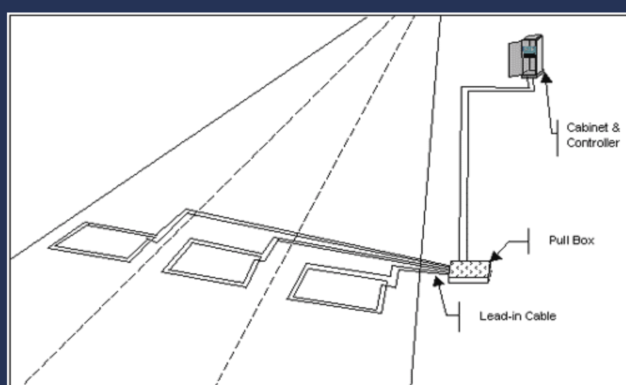
drivers save up to 20 minutes avoiding delay in the worst congestion

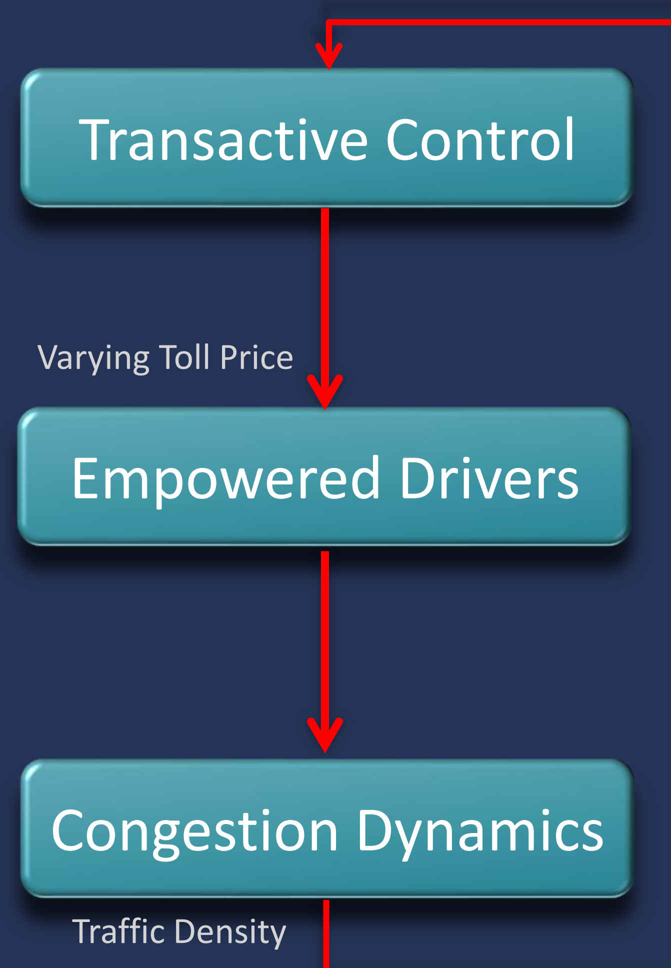
average speeds of 50 mph maintained 95% of the time, with 85% driver satisfaction

Varying toll prices aids Urban Mobility!

Empowered Consumers and Urban Mobility

(MnPass, Minneapolis, MN)

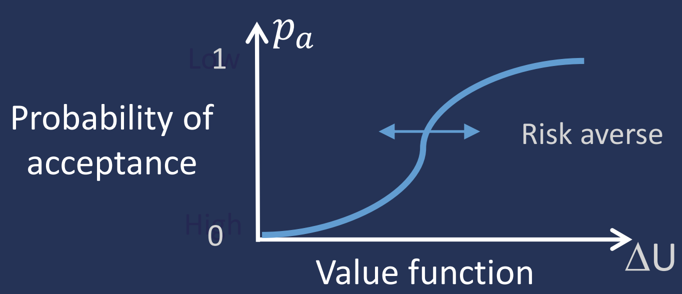




A Socio-Technical Model

Driver evaluation $\Delta U(\mu, \lambda, \theta)$ → **Driver Preference + Decision Making** → Probability of acceptance p_a → **Traffic Model** → Infrastructure response

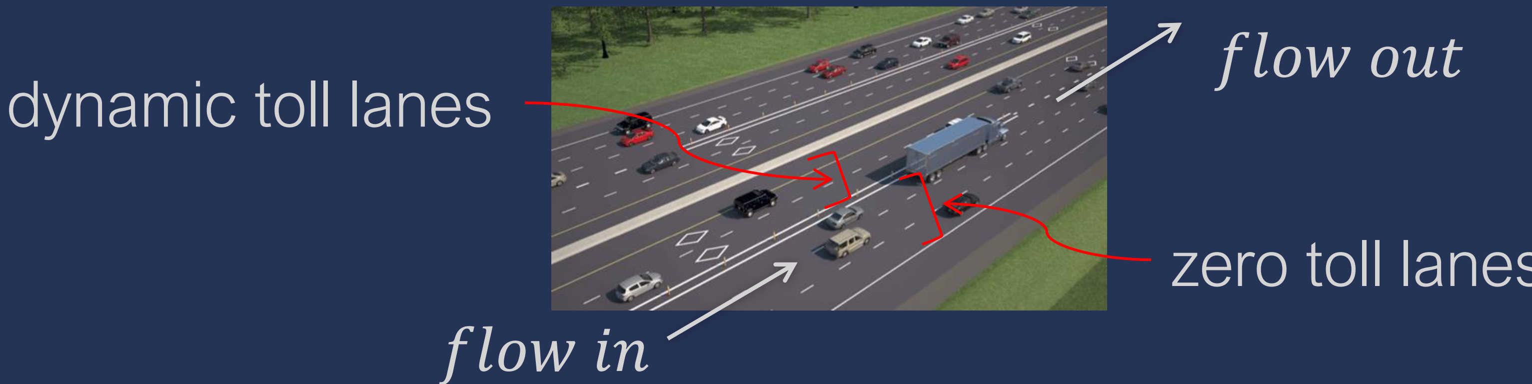
$$\Delta U = \alpha * (time\ savings) + \beta * Price + \gamma$$

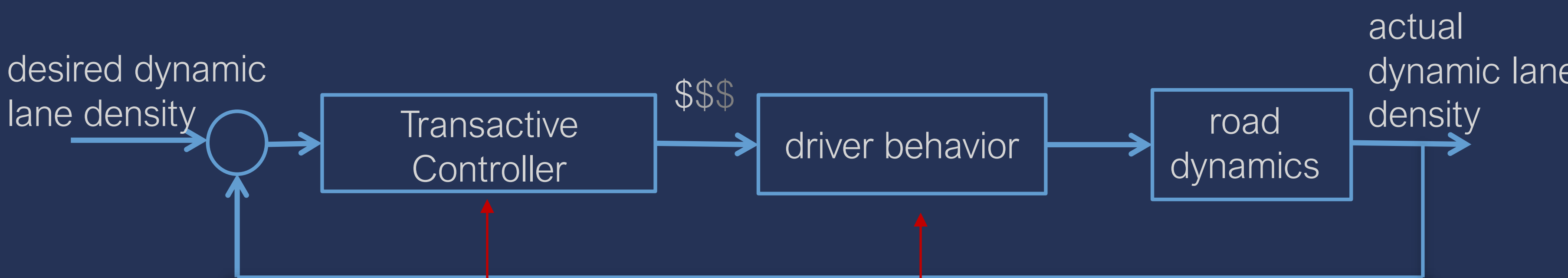


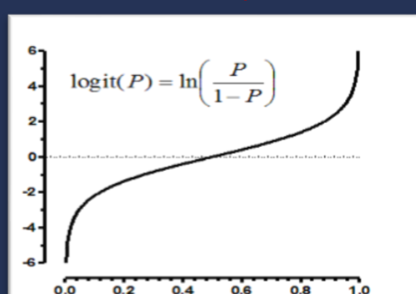
$$p_a = \frac{1}{1 + e^{-\rho \Delta U}}$$

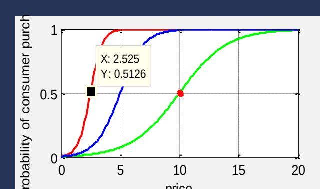
- Traffic model: Accumulator based
- Utility function: Cost and time savings
- Probability of Acceptance – population model

Toll-pricing controller: Nonlinear PI





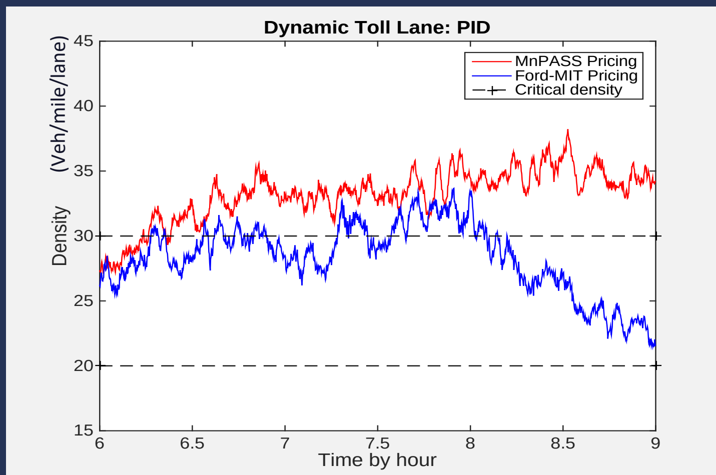


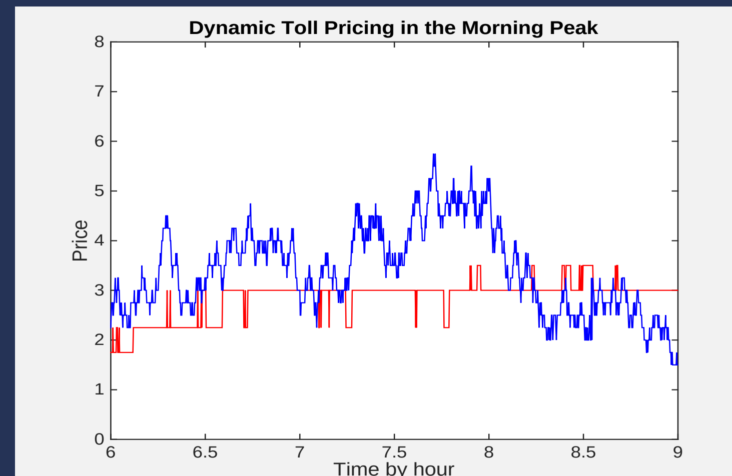


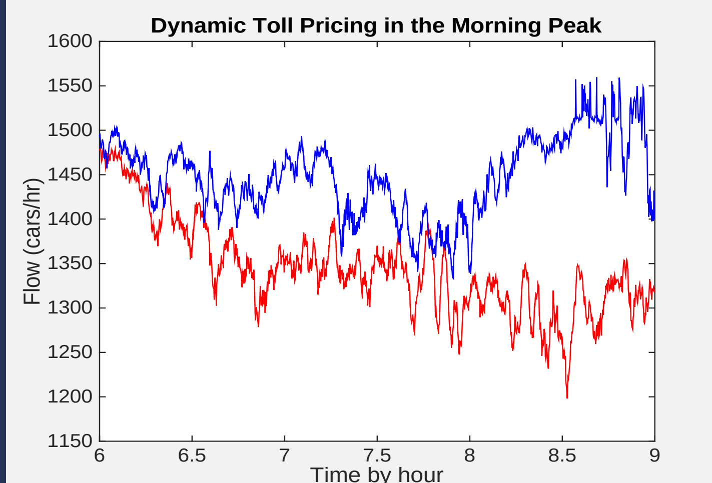
- Logistic Function
- Identify parameters
- Use inverse nonlinearity in the price-controller

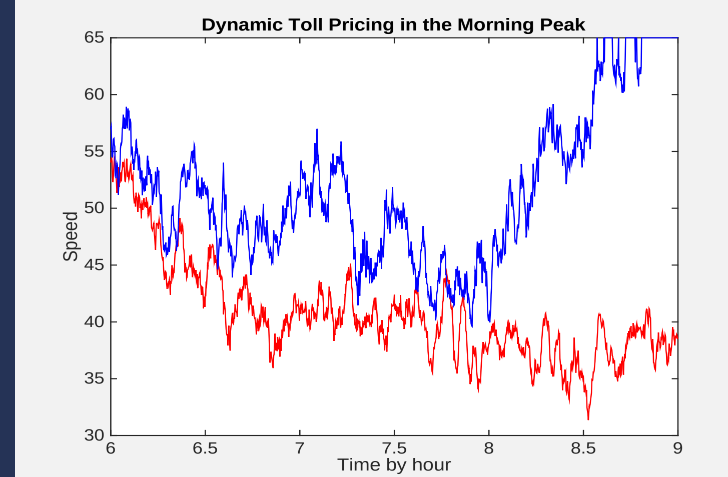
Response to High Input Flow

High input flow is introduced in the middle of the operating period to test the systems' ability to prevent congestion. Our model-based control (blue) is successful in keeping the HOT density low compared to MnPASS (red).



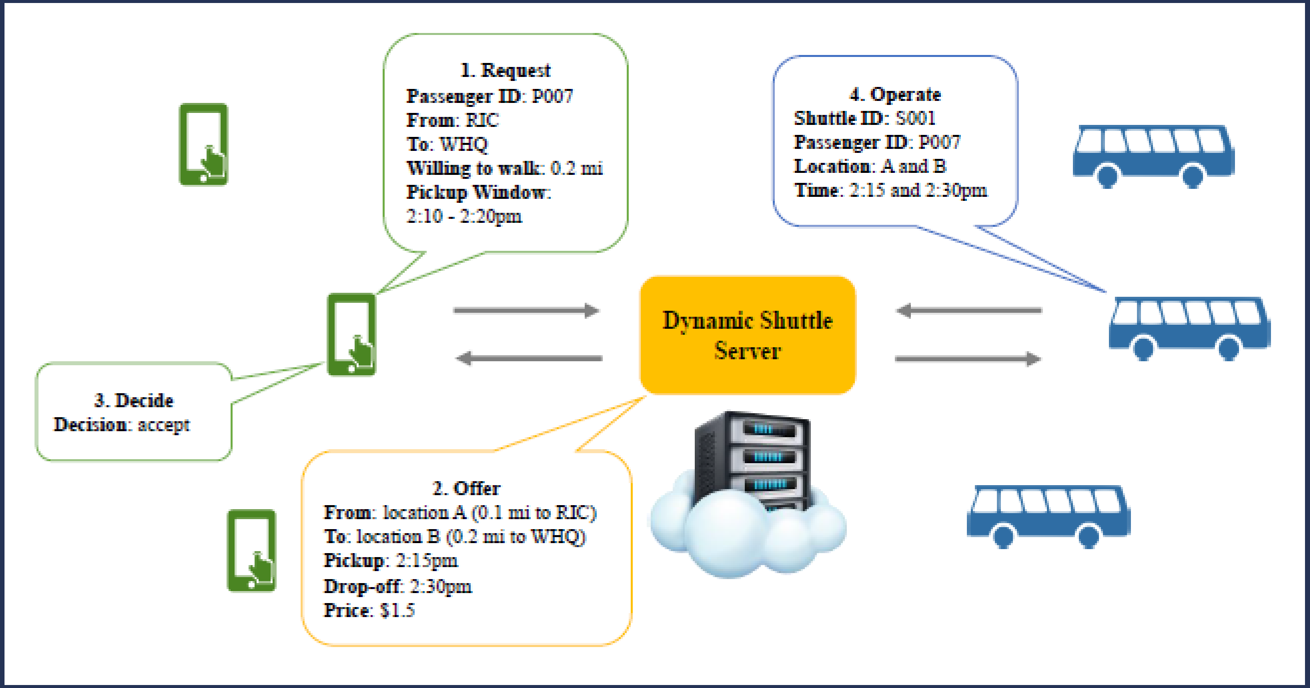






EXAMPLE 2: SHARED MOBILITY ON DEMAND

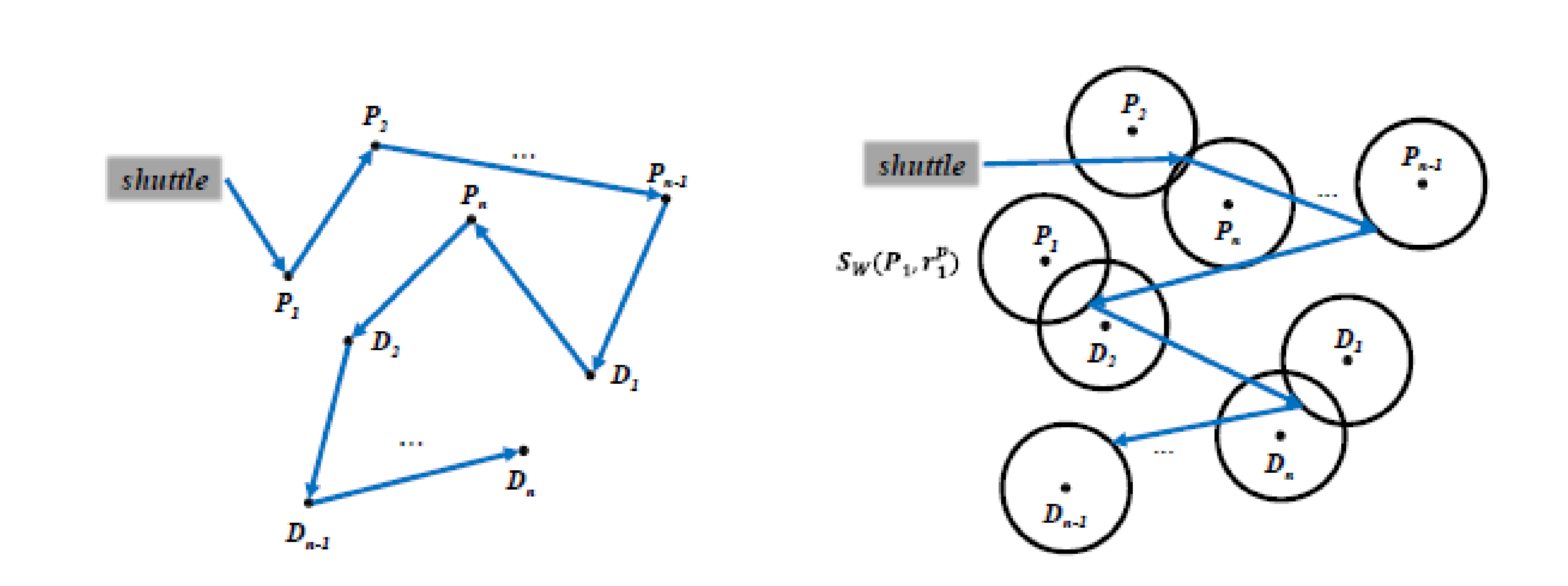
A Shared Mobility on Demand (SMoDS) Solution



1. *Request:* passengers request shuttle rides with specified pickup/drop-off locations, maximum distances willing to walk.
2. *Offer:* the shuttle server distributes offers to passengers with ride details including pickup locations, walking distances, pickup times, drop-off locations, drop-off times, and prices.
3. *Decide:* passengers decide whether to accept or decline the offers.
4. *Operate*: the shuttle server sends out ride details to passengers.

Leads to a Constrained Optimization Problem

Dynamic Routing



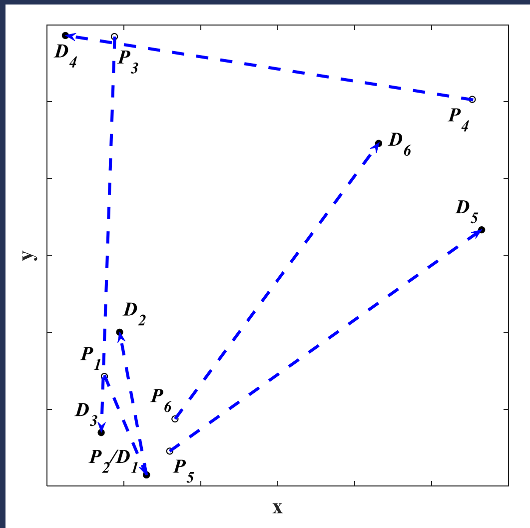
(a) Complete door-to-door mode

(b) Semi door-to-door mode

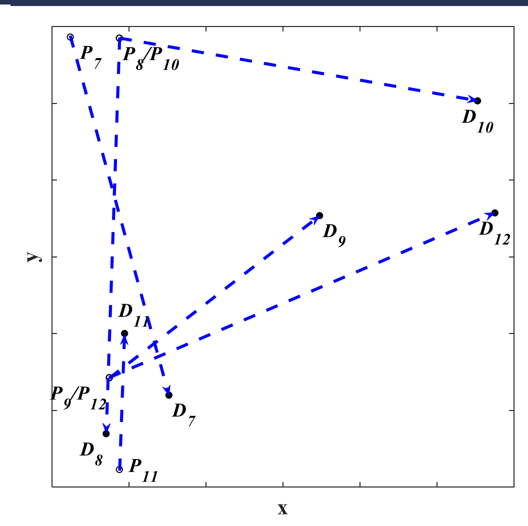
Determine optimal sequence S of routing points R

$$\boxed{\min_{(\boldsymbol{S},\boldsymbol{R})\in \boldsymbol{S_f}\times \boldsymbol{R_f}} \boldsymbol{C}(\boldsymbol{S},\boldsymbol{R})}$$

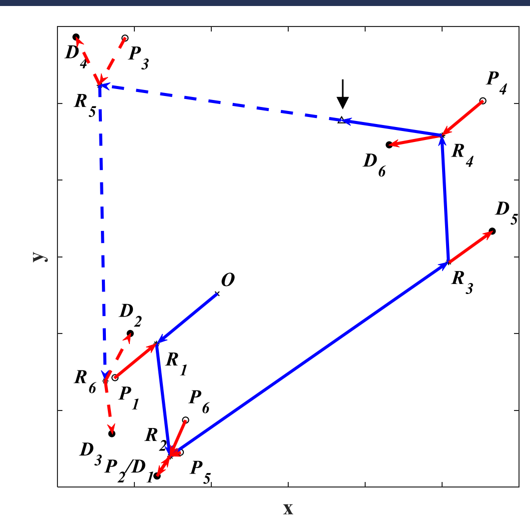
Numerical Results (Dynamic Routing; all passengers accept the ride-offer)



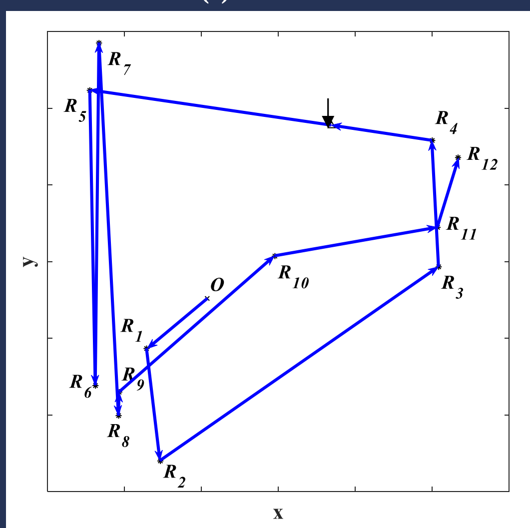
(a) 1st batch



(b) 2nd batch



(c) Original route of the 1nd batch



(d) Static routing

Clustering pattern

1st batch:

$C_1 = \{E_1^p\}$

$C_2 = \{E_2^p, E_5^p, E_6^p, E_1^d\}$

$C_3 = \{E_5^d\}$

$C_4 = \{E_4^p, E_6^d\}$

$C_5 = \{E_3^p, E_4^d\}$

$C_6 = \{E_2^d, E_3^d\}$

2nd batch

$C_1{}' = \{E_7^p, E_8^p, E_{10}^p\}$

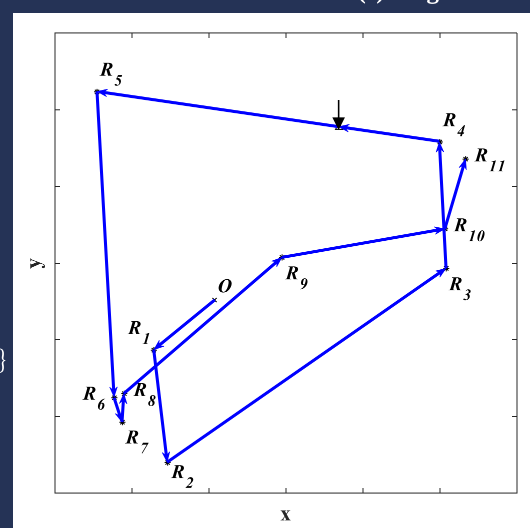
$C_2{}' = \{E_9^p, E_{11}^p, E_{12}^p, E_7^d, E_8^d\}$

$C_3{}' = \{E_{11}^d\}$

$C_4{}' = \{E_9^d\}$

$C_5{}' = \{E_{12}^d\}$

$C_6{}' = \{E_{10}^d\}$



(e) Dynamic routing

Clustering pattern

Before update

$C_1 = \{E_1^p\}$

$C_2 = \{E_2^p, E_5^p, E_6^p, E_1^d\}$

$C_3 = \{E_5^d\}$

$C_4 = \{E_6^p, E_6^d\}$

$C_5 = \{E_3^p, E_4^d\}$

$C_6 = \{E_2^d, E_3^d\}$

After update

$C_0{}' = \{E_2^p, E_4^p\}$

$C_1{}' = \{E_3^p, E_7^p, E_8^p, E_{10}^p, E_4^d\}$

$C_2{}' = \{E_9^p, E_{12}^p, E_2^d, E_3^d, E_8^d\}$

$C_3{}' = \{E_{11}^p, E_7^d\}$

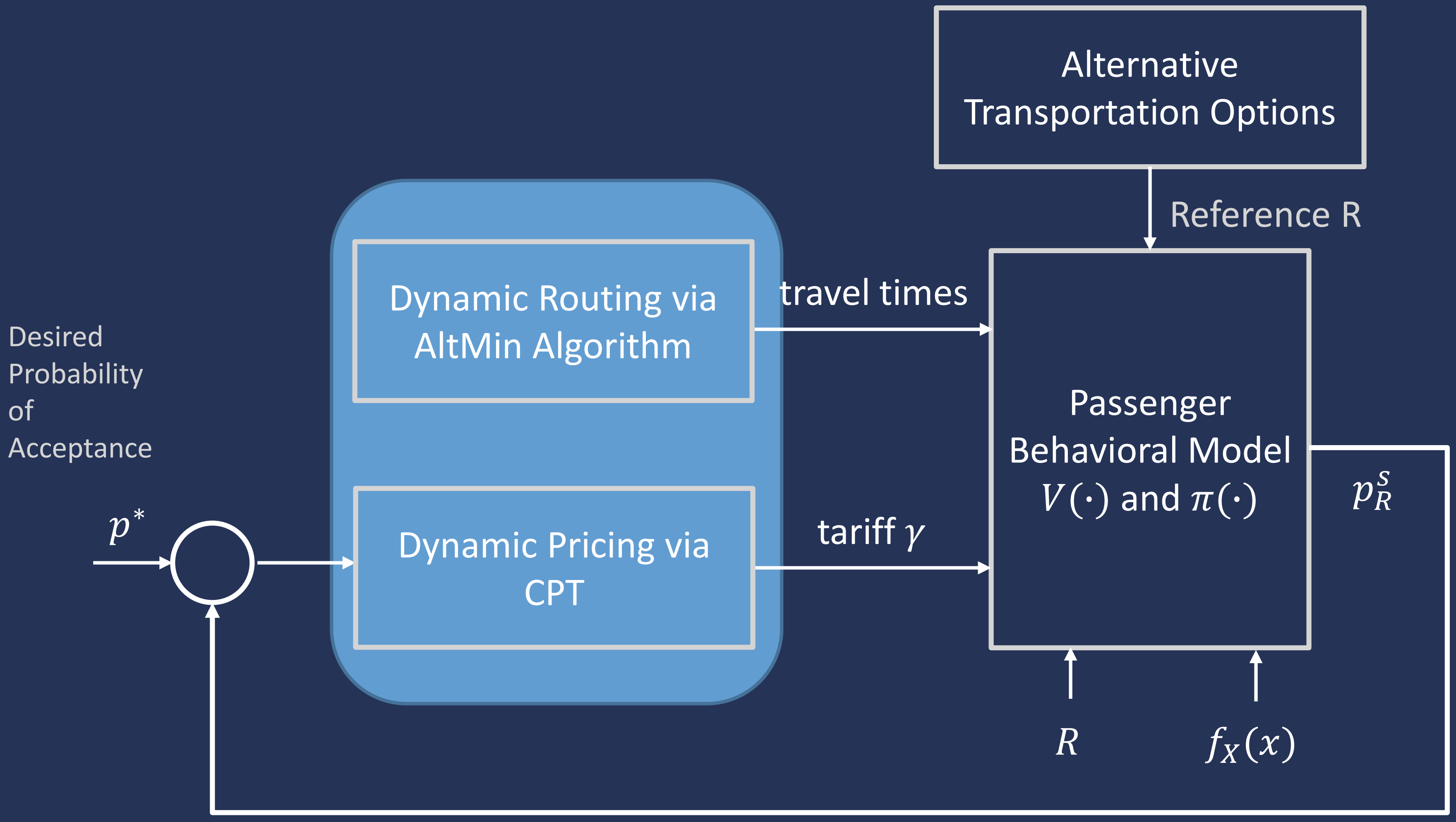
$C_4{}' = \{E_{12}^d\}$

$C_5{}' = \{E_{11}^d\}$

$C_6{}' = \{E_{10}^d\}$

$C_7{}' = \{E_9^d\}$

A Schematic of the SMoDS Solution



p_R^S: subjective probability of acceptance framed by R

Conventional Utility Theory

- Several alternatives with utilities $U_{a_1}, \dots, U_{a_n}$
- Corresponding probabilities $p_1, \dots, p_n$

Utility function of ride-sharing

$$u_i = \sum_{j=1}^{m} {U_{a_i}}^j {p_i}^j$$

$$U_{a_k} = f(\tau), \qquad \tau \in [t_p^1, t_p^2]$$

$$u_i = \int_{t_p^1}^{t_p^2} U_a(\tau) p_i(\tau) d\tau$$

u_1: Utility function of taking a private car;

u_n: Utility function of taking a bus

- Not adequate if uncertainty is large

Behavioral Dynamics of Human Beings: Prospect Theory

- In prospect theory*, the utility of the i^{th} option

$$u_i = \sum_{j=1}^{m} V({u_i}^j)\pi({p_i}^j)$$

- Human beings are irrational in two ways:
  1. How do we perceive utility $V({u_i}^j)$: loss aversion - losses hurt more than the benefit of gains

  2. How do we assess probability $\pi({p_i}^j)$: overreact to small probability events and underreact to large probability events

* Kahneman and Tversky, 1992

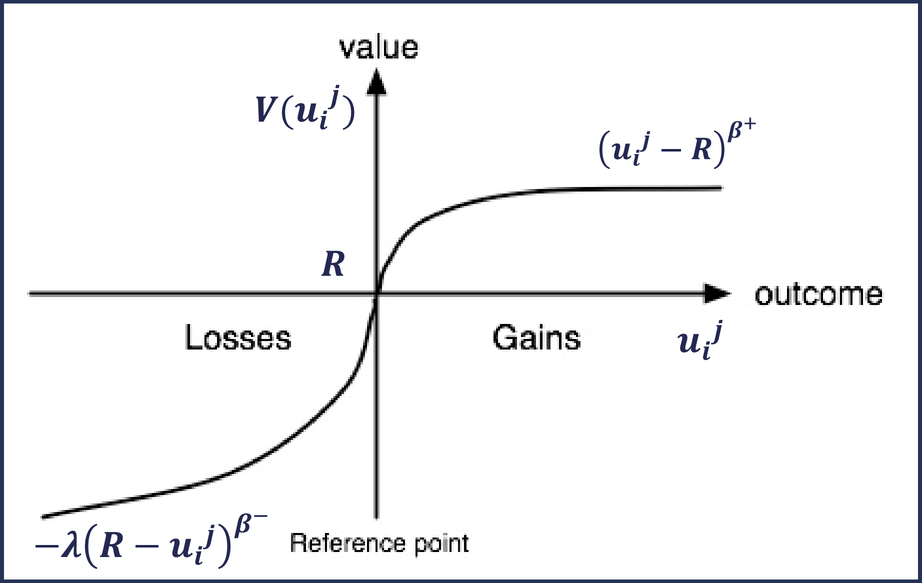
Irrationality – Loss Aversion

- Loss aversion: losses hurt more than gains feel good

$$V({u_i}^j) = \begin{cases} ({u_i}^j - R)^{\beta^+}, & \text{if } {u_i}^j > R \\ -\lambda(R - {u_i}^j)^{\beta^-}, & \text{if } {u_i}^j < R \end{cases}$$

- Framing effects: R is the reference point of the framing, where people feel neutral, differentiate gain from loss $(\lambda > 1)$

- Example: it is better to not have a \$5 loss than to gain \$5.

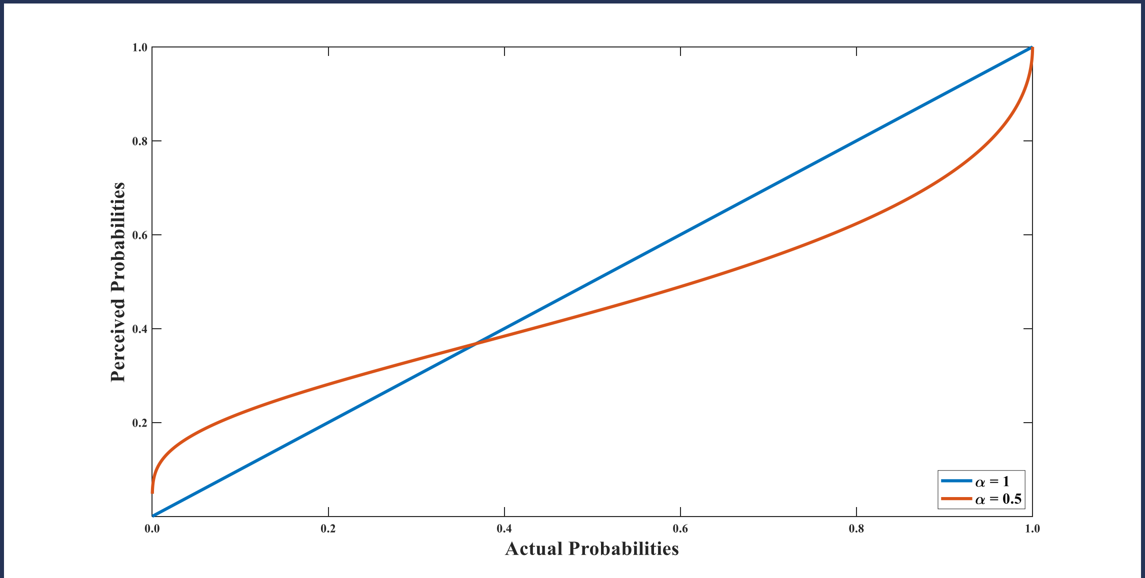


El Rahi et al., *Prospect Theory for Smart Grid,* 2017.

Irrationality – Overreact to Small Probability

- Overreact to small probability events and underreact to large probability events

$$\pi(p_i{}^j) = \exp(-(-ln p_i{}^j)^\alpha), \qquad \alpha < 1$$



El Rahi et al., *Prospect Theory for Smart Grid,* 2017.

- Example: people would not play a lottery with a 1% chance to win $100K and a 99% chance to lose $1K

Prospect Theory for Shared Mobility

- The utility function is a combination of time and price:

$$u = a + b_p T_{walk} + b_w T_{wait} + b_r T_{ride} + \gamma \rho$$

- $\tau \in [t_p^1, t_p^2], u : u(\tau)$

$$U_R^S = \int_{-\infty}^{R} V(u) \frac{d}{du}\{\pi[F_U(u)]\} du + \int_{R}^{\infty} V(u) \frac{d}{du}\{-\pi[1 - F_U(U)]\} du$$

- R: reference
- $F(\tau) = \int_{-\infty}^{\tau} df(\tau)$ - Cumulative Distribution Function (CDF)
  - Extract from demand pattern and historical data
  - $F(\tau)$ exists but unknown

Objective probability of acceptance

$$p^o = \frac{e^{U^o}}{e^{U^o} + e^{A^o}}$$

U^o and A^o: objective utility of the SMoDS and the alternative

Subjective probability of acceptance

$$p_R^S = \frac{e^{U_R^S}}{e^{U_R^S} + e^{A_R^S}}$$

U_R^S and A_R^S: subjective utility of the SMoDS and the alternative

Implication 1 – Fourfold Pattern of Risk Attitudes

Fourfold pattern of risk attitudes

a) Risk averse over high probability gains

b) Risk seeking over high probability losses

c) Risk seeking over low probability gains

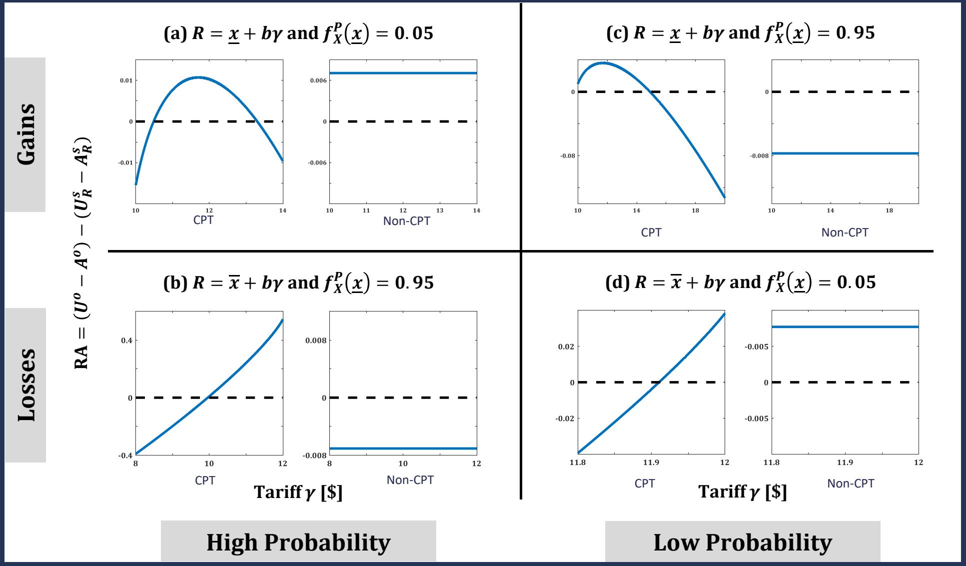
d) Risk averse over low probability losses

Conclusions:

Quantification of the qualitative statements

1. the presence of risk seeking passengers gives flexibility in increasing tariffs;
2. the presence of risk averse passengers requires additional constraints on tariffs.

Example: Two outcomes, probabilities of 0.95,0.05



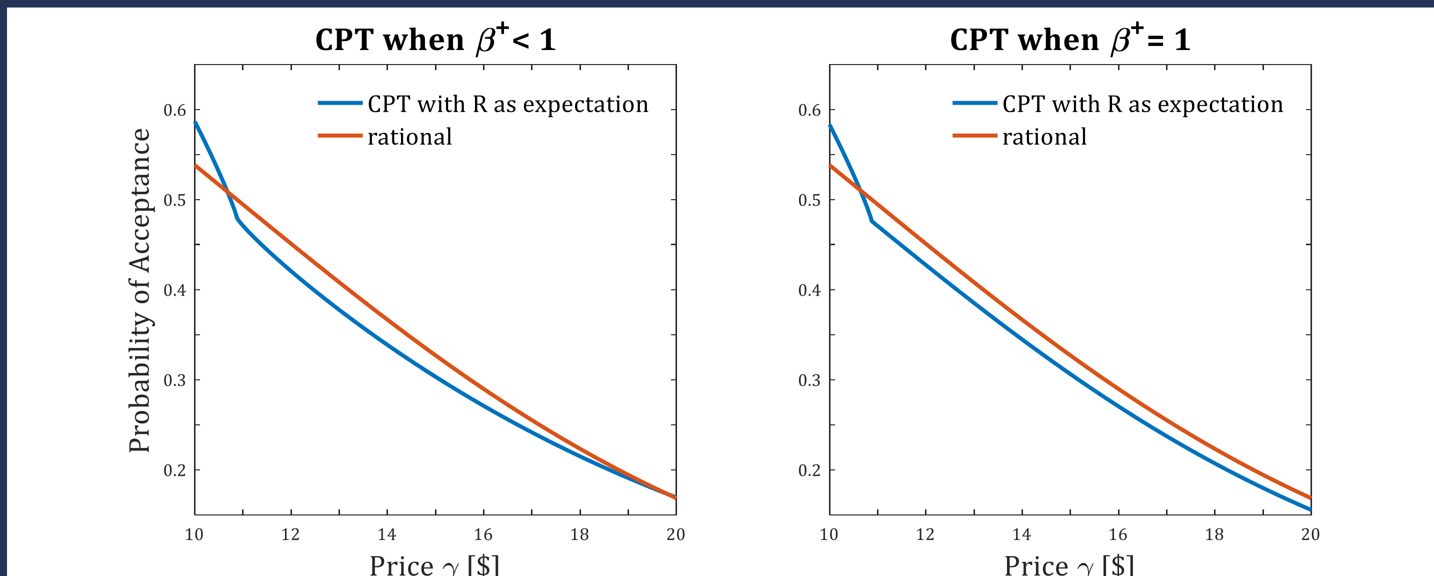
- Truncated Poisson distribution with two outcomes $\underline{x} + b\gamma$ and $\overline{x} + b\gamma$

- *Relative Attractiveness*

$$\mathrm{RA} = (U^o - A^o) - (U_R^S - A_R^S)$$

Implication 2 – Strong Risk Aversion over Mixed Prospects

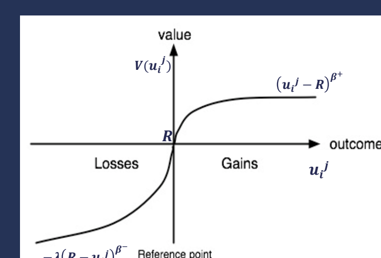
Mixed prospects: uncertain prospects whose portfolio of outcomes involves both losses and gains (ex. $R = \overline{U}$)



Conclusions:

1. **There exists λ and γ $s.t.$ $p^{s}_{\overline{U}} < p^{o}$**
2. The dynamic tariffs needs to be suitably designed so as to compensate for these perceived losses for this type of CPT passenger.

- $R = \overline{U}$
- p^{s}_{R} and p^{o} versus γ

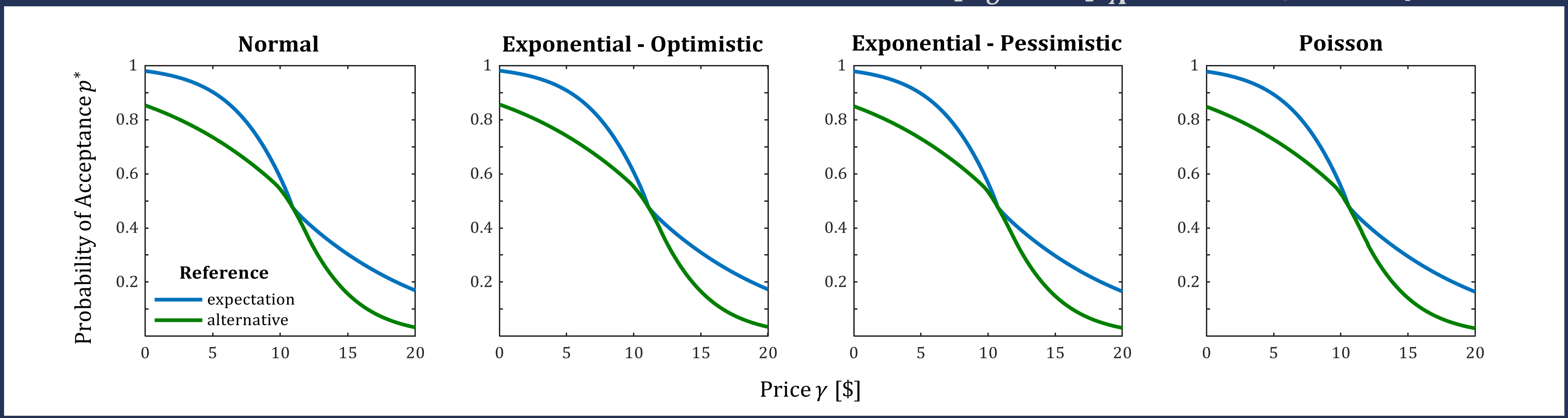


Implication 3 – Self Reference

Self reference: $R = \overline{U}$ for the uncertain prospect

(compare with $R = A^o$ for the certain prospect)

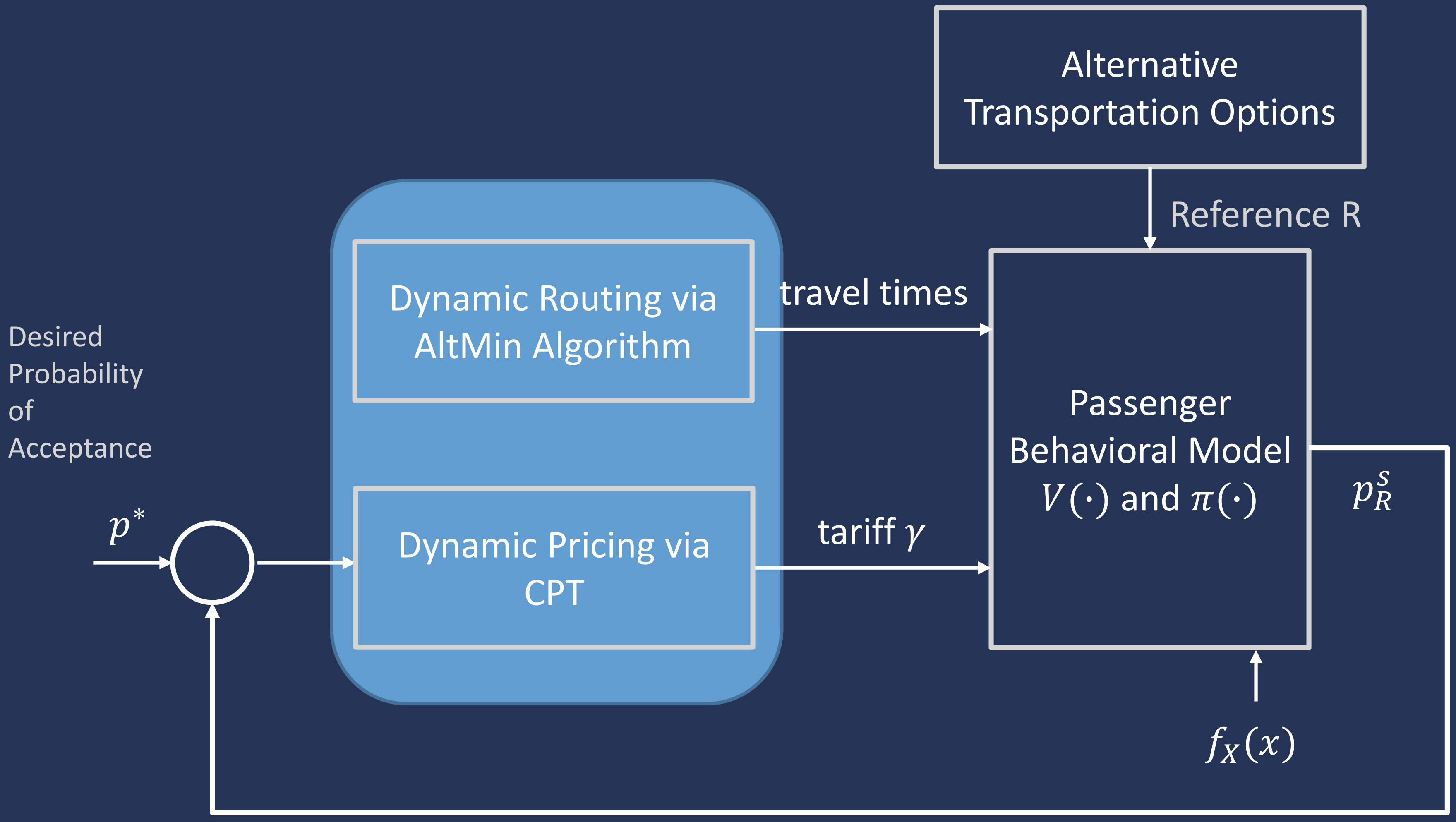
$p^s_{\overline{U}}$ and $p^s_{A^o}$ with respect to γ



Conclusions:

1. $\forall\gamma, p^s_{\mathbb{E}_{f_U}(U)} \geq p^s_{A^o}$, **i.e., the SMoDS is more attractive against the alternative if** $R = \overline{U}$ **rather than** $R = A^o$**.**
2. $R = \overline{U}$ **implies that the passengers are already subscribed the SMoDS, hence have higher willingness to pay**
3. **Invariant with** $f_X(x)$

Next step: Towards The Overall SMoDS Solution



p_R^S: subjective probability of acceptance framed by R

Summary

- Socio-technical modeling, optimization and control
  - Empowered consumers present new opportunities

- New methodologies
  - Transactive Control for Dynamic Toll Pricing*
  - Prospect Theory for Dynamic Pricing***
- Ongoing work
  - Fine-tune PT based ensemble models of riders
  - Validate SMoDS

* A.M. Annaswamy, Y. Guan, E.H. Tseng, Z. Hao, T. Phan, and D. Yanakiev, Transactive Control in Smart Cities. Proceedings of the IEEE, Special Issue on Smart Cities, 2017.

**Y. Guan, A.M. Annaswamy, and E. H. Tseng, A Novel Dynamic Routing Framework for Shared Mobility Services, ACM Transactions, Special Issue on Cyber-Physical Systems in Transportation, 2019.

***Y. Guan, A.M. Annaswamy, and E.H. Tseng, Cumulative Prospect Theory Based Dynamic Pricing for Shared Mobility on Demand Services, 2019.

Thank you!