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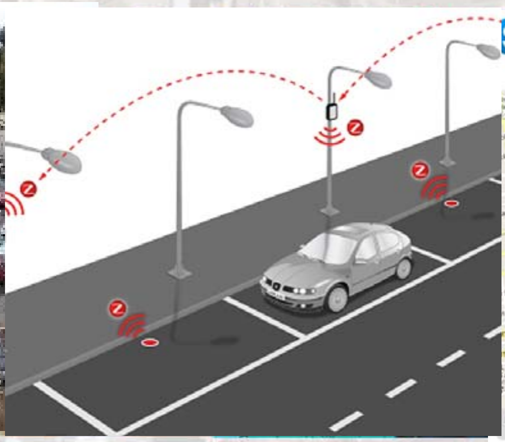
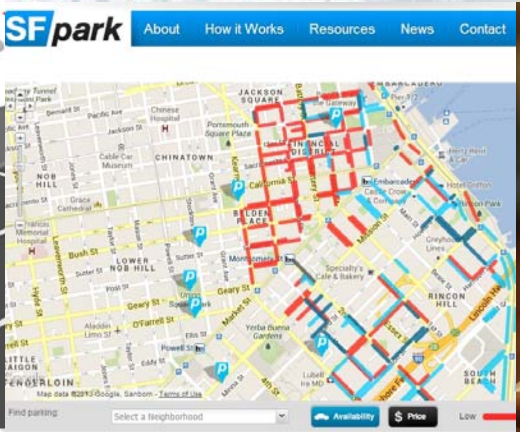
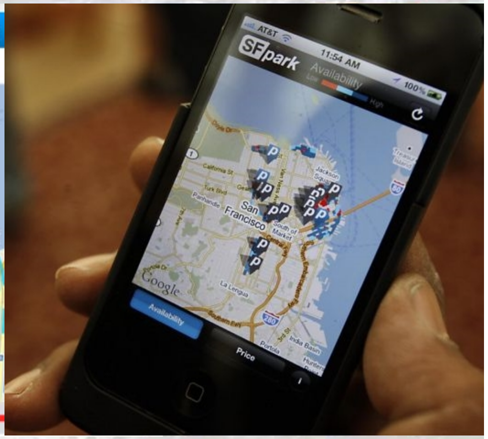
Urban Parking Space Management via Dynamic Performance-Based Pricing

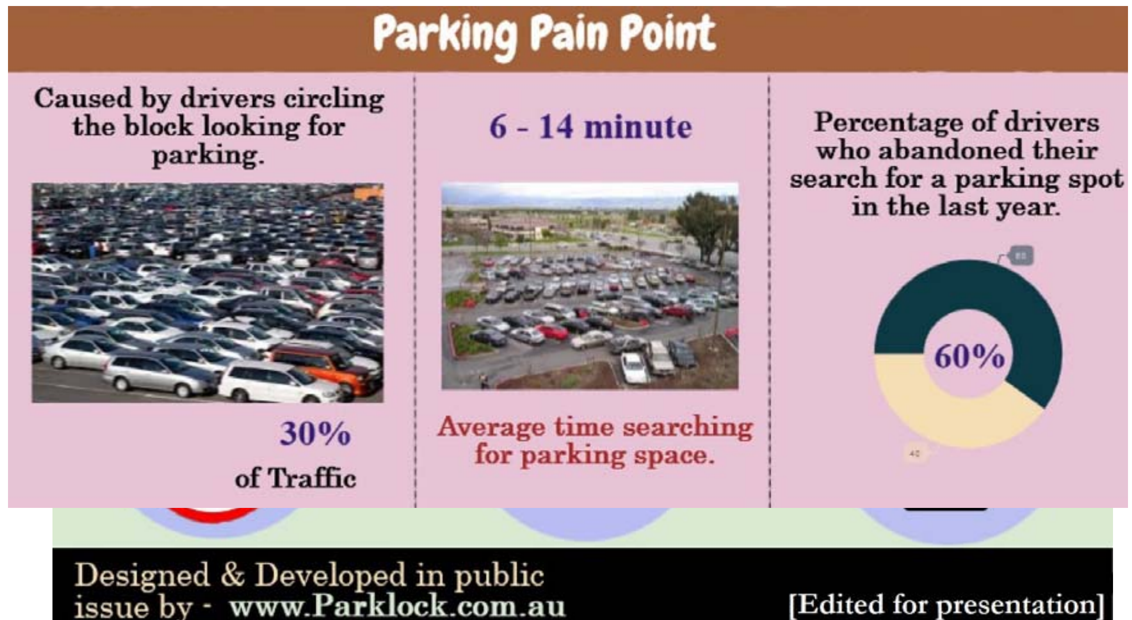
Daniel Mackowski, Yun Bai, Yanfeng Ouyang
Department of Civil and Environmental Engineering



The Parking "Pain"

- A large share (~30%) of city traffic is from cars looking for parking (Shoup, 2006)
  - High congestion
  - Excessive emissions
  - Wasted productivity
- 60% of drivers abandon looking for parking at least once/yr (IBM, 2011)
  - Lost economic opportunity



The time and frustration of finding parking decreases users' quality of life

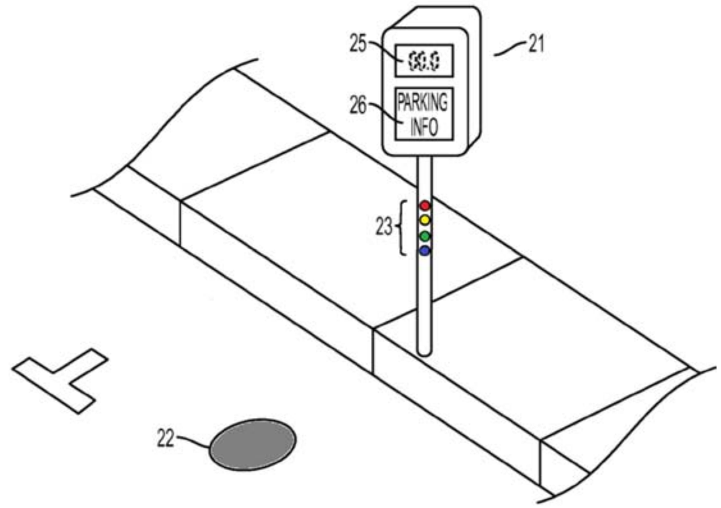
The U.S. Parking Industry

- $25+ billion annual gross revenue
  - 100+ million parking spaces
  - ~5 million parking meters
- Limited parking supply
  - $16,167 to build one new space
- Consumer parking decision based on:
  - Cost (34%), security (29%), and location (25%)
- How can we better manage existing parking infrastructure taking consideration of user behavior?

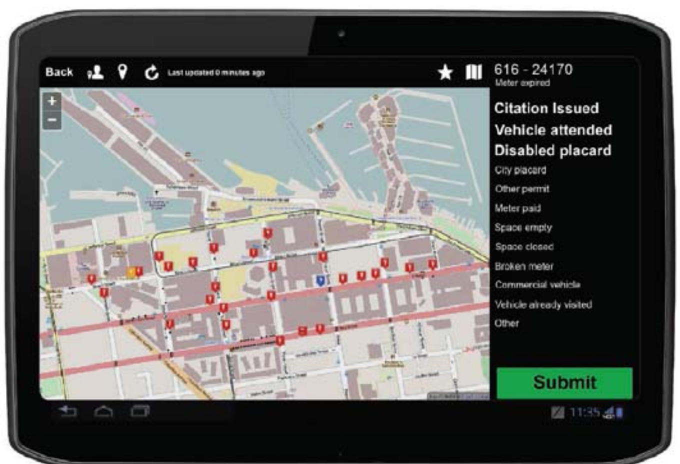
Source: International Parking Institute (2014).
https://www.parking.org/media/overview-of-the-us-parking-industry.aspx

Solution - “Smart Parking”

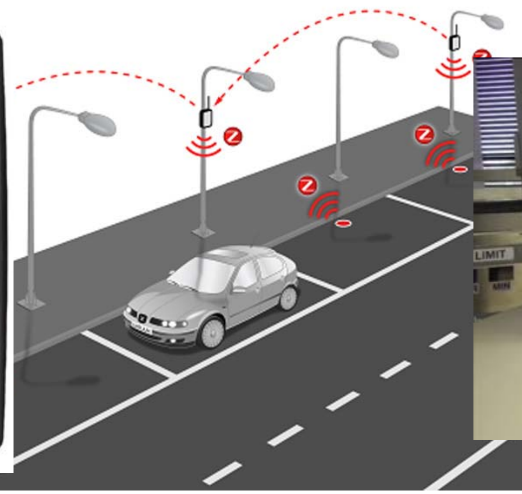
- Parking management systems that utilize information technology
  - Sensing & communication
- These systems are able to:
  - Provide users with real-time price and availability information
  - Guide users to best available parking spots
  - Update prices on each block remotely
  - Display parking reservation

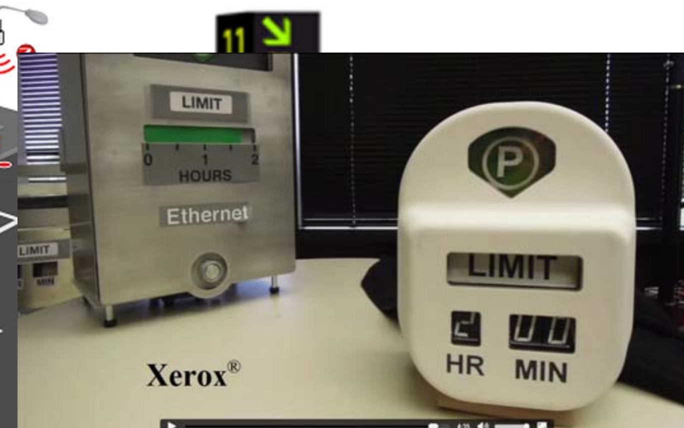


Xerox (2014). U.S. Patent No. 8,671,002



SF*park* (2014)

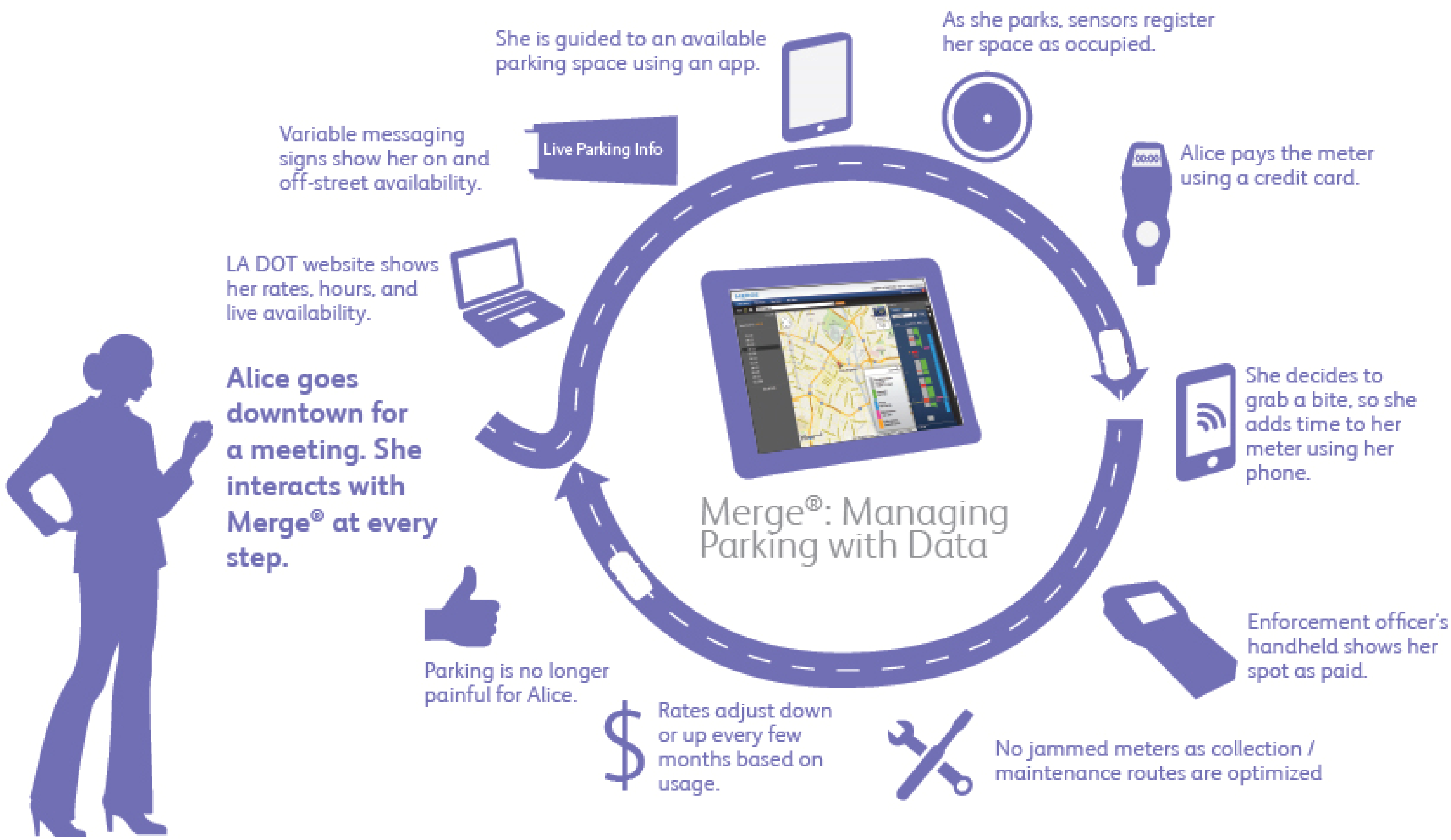




Display panels

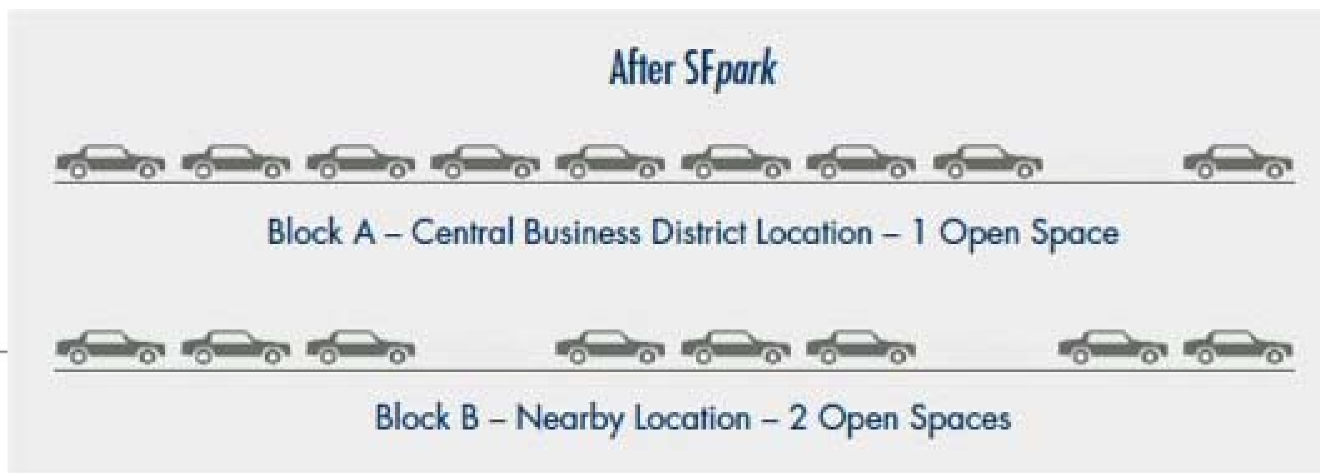
Urbiotica (2014)

Xerox's Merge™ in LA Express Park



Existing Systems

- LA Express Park Los Angeles's parking management system
  - $18.5 million to fund pilot in downtown (4.5 mi^2)
  - Mainly for parking information & guidance
- SFpark San Francisco's parking agency
  - **Goal**: One open spot per block (~85% occupancy)
  - **Method**: Demand responsive performance based pricing
    - Price varies by location (block by block), time-of-day, and day-of-week
    - SF*park* updates price tables every 6 weeks, not in real-time
    - Does not support parking reservation



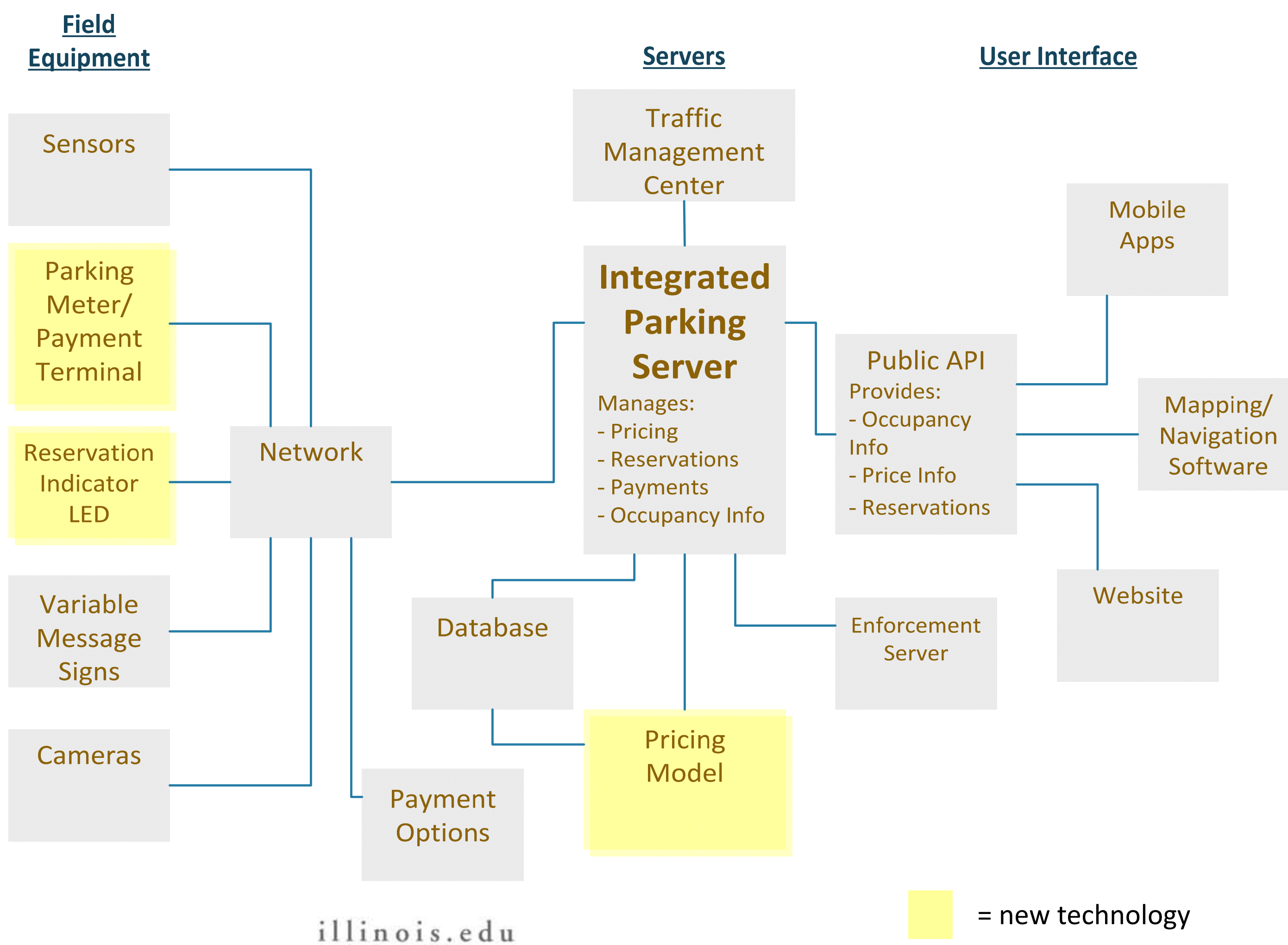
Remaining Challenges

- No model exists that can:
  - Account for drivers' independent/competing decision making process
  - Consider congestion reduction as an important objective
  - Be solved for large networks with varying demand data in near real-time
- No systems have implemented on-street parking reservations
  - Xerox recently patented the idea and is developing prototypes
- No balance between reducing congestion and improving economic surplus (including revenue)

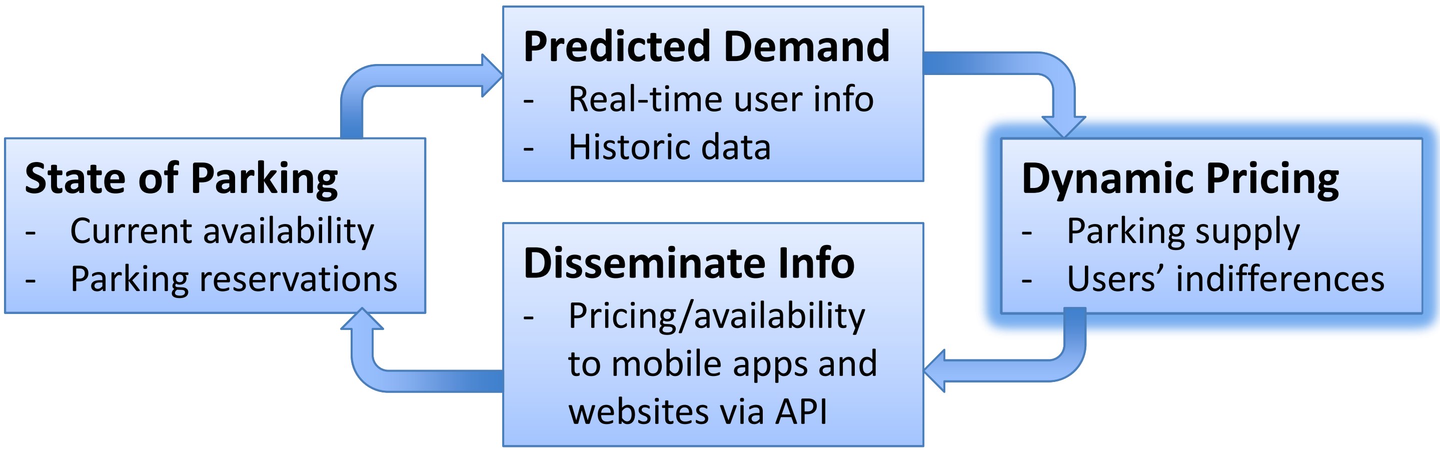
Proposed Parking Pricing and Management System

Components:

- an operating strategy to improve parking space utilization
- a dynamic pricing model based on real-time demand
- stand-alone software, information technology applications, and supporting hardware



Pricing Model Integration



Objective: occupancy target (e.g. 85%) *and* social surplus *or* revenue

Considering: drivers' independent/competing decision making

policy constraints (min/max price, price variation, …)

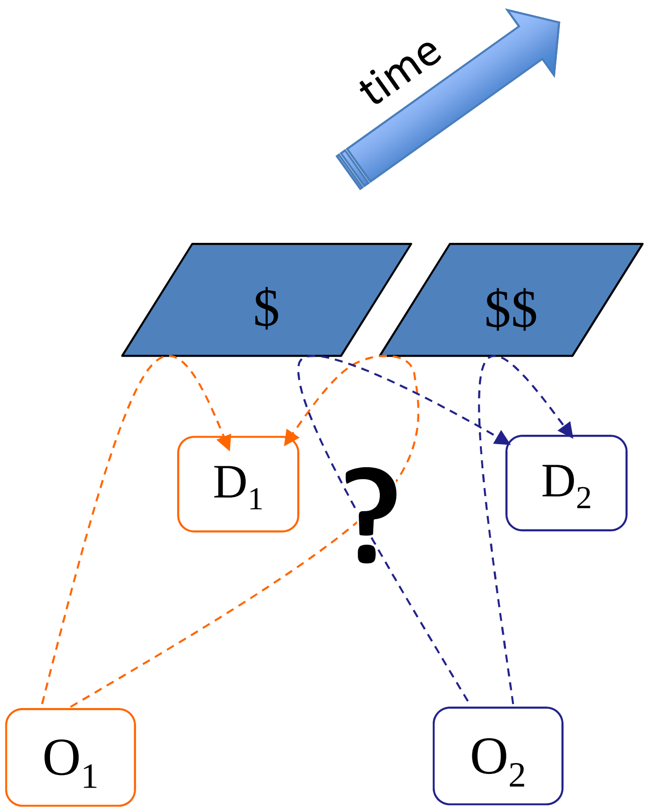
Assumptions: demand data known or predicted accurately

based on current travel and parking behavior

drivers are informed and analytic

Dynamic Pricing Model

- Bi-level Stackelberg-Nash game model formulated as a mathematical program with equilibrium constraints (MPEC)
- Upper level decision: price for each area
  - Set by the parking agency or operator
  - Constrained by established parking policies (e.g. maximum prices, price fluctuation limits)
- Lower level decision: each user's parking location choice
  - Based on travel utilities and availability
  - Follows Nash equilibrium, market clearing principles, and physical constraints (e.g. lot capacity, network flow balance)



Pricing Model Notation

Sets

- O, D, J : sets of origins (current location), destinations, and parking areas
- T : set of discrete time intervals
- N : set of durations

Parameters

- τ : number of time intervals in horizon
- c_j : capacity of parking area j
- κ_j : target occupancy level of parking area j (e.g. 85%)
- β : penalty for not meeting target occupancy level
- ζ: dummy parking lot to accept overflow demand
- $H(\cdot)$: demand function of parking users (assume linear = a-bu)
- v_{oj}, w_{jd} : driving distance (origin o to area j), walking distance (area j to destination d)
- θ, θ': slopes of indifference curves between price/walking distance, and price/driving distance
- $\varepsilon_l, \varepsilon_r, \gamma_j, \eta_j$: price policy parameters (change in price upper/lower bounds, min/max price)

Decision Variables

- p_j^t : parking price at parking area j at time t
- ρ_j^t : shadow price at parking area j at time t
- f_j^t : number of users parked at parking area j at time t
- g_j^t : number of users leaving parking area j at time t
- $q_j^{t,n}$: number of new users entering parking area j at time t for duration n
- $u_{od}^{t,n}$: disutility of users with trip od at time t for duration n
- $h_{j,od}^{t,n}$: demand for parking area j by users with trip od at time t for duration n

Pricing Model Formulation

Solved for the current time period (e.g. every 15 minutes) while considering future time periods and predicted demand

For each t_s from $0 \to T$, solve: **Occupancy** **Economic Surplus** **Revenue**

Agency (Leader) $$\min_{\mathbf{f,p,q,h,u,g}} \beta \sum_{t=t_s}^{t_s+\tau} \sum_{j \in J} \left| \kappa_j c_j - f_j^t \right| + \alpha_s \sum_{t=t_s}^{t_s+\tau} \sum_{j \in J} \left(\sum_{n \in \{1,2,\ldots N\}} n \cdot p_j^t \cdot q_j^{t,n} + \sum_{n \in \{1,2,\ldots N\}} \sum_{o \in O} \sum_{d \in D} \frac{1}{2} h_{j,od}^{t,n} (u_{\max} + u) \right) + \alpha_r \sum_{t=t_s}^{t_s+\tau} \sum_{j \in J} \sum_{n \in \{1,2,\ldots N\}} n \cdot p_j^t \cdot q_j^{t,n}$$

- objective

s.t. $f_j^t = f_j^{t-1} - g_j^t + \sum_{n \in N} q_j^{t,n}, \ \forall j \in J, t \in \{t_s, \ldots t_s + \tau\}$ - # of users

$q_j^{t,n} = \sum_{o \in O} \sum_{d \in D} h_{j,od}^{t,n}, \ \forall j \in J, n \in N, t \in \{t_s, \ldots t_s + \tau\}$ - network balance

$g_j^t = \sum_{m=\max(1,t-|N|)}^{t-1} q_j^{m,t-m}, \ \forall j \in J, t \in \{t_s, \ldots t_s + \tau\}$ - # of users leaving

$-\varepsilon_l \le p_j^t - p_j^{t-1} \le \varepsilon_r, \ \forall j \in J, t \in \{t_s, \ldots t_s + \tau\}$ - price variation

$\gamma_j \le p_j^t \le \eta_j, \ \forall j \in J, t \in \{t_s, \ldots t_s + \tau\}$ - min/max price

Users (Follower) $0 \le h_{j,od}^{t,n} \perp \left(np_j^t + \theta w_{jd} + \theta' v_{oj} + \rho_j^t \right) - u_{od}^{t,n} \ge 0,$

$\forall j \in J, o \in O, d \in D, n \in \{1,2,\ldots N\}, t \in \{t_s, \ldots t_s + \tau\}$ - equilibrium

$0 \le h_{\zeta,od}^{t,n} \perp \lambda_{\zeta,od}^{t,n} - u_{od}^{t,n} \ge 0, \ \forall o \in O, d \in D, n \in \{1,2,\ldots N\}, t \in \{t_s, \ldots t_s + \tau\}$ - overflow

$$\lambda_{\zeta,od}^{t,n} = \min\left\{ H^{-1}(0), \ \max_{j \in J} \left\{ n\left[p_j^{t-1} + (t+1-t_s)\varepsilon_r \right] + \theta w_{jd} + \theta' v_{oj} \right\} \right\}, \ \forall t \in \{t_s, \ldots t_s + \tau\}$$

$0 \le u_{od}^{t,n} \perp \sum_{j \in J \cup \{\zeta\}} \left(h_{j,od}^{t,n} \right) - H(u_{od}^{t,n}) \ge 0,$

$\forall o \in O, d \in D, n \in \{1,2,\ldots N\}, t \in \{t_s, \ldots t_s + \tau\}$ - market clearing

$0 \le c_j - f_j^t \perp \rho_j^t \ge 0, \ \forall j \in J, t \in \{t_s, \ldots t_s + \tau\}$ - capacity

Solution Method

To derive the Karush-Kuhn-Tucker (KKT) condition in equilibrium:

- Formulate the decision problem of each individual user
  - Parking decision based on disutility minimization
- Concave driver problem – Lagrangian dual
- Combine KKT conditions for all users and add market clearing conditions

For additional non-convex bilinear revenue terms:

- Consider τ=1 (myopic)
- Reformulate into an equivalent series of linear and quadratic terms and solve MIQP
- Similar to the derivation in Hobbs et al. (2000)

Illustration

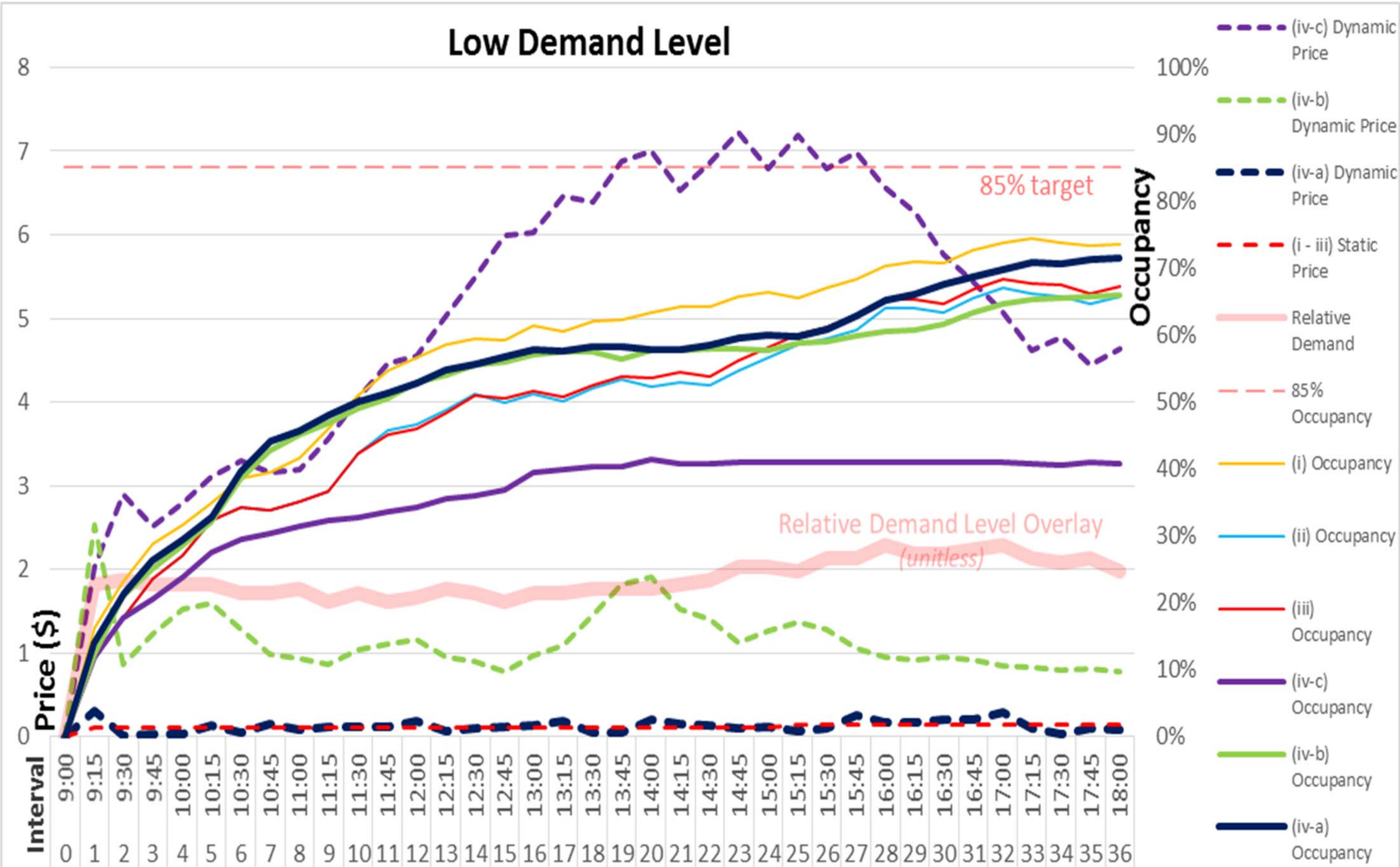
Simulated the model for a neighborhood in the SF*park* program

- 20 parking areas (including one 205 space garage)
- 36 time intervals (every 15 minutes from 9am-6pm)
- 2 origins (cars), 3 destinations (stars), and 5 unique parking durations

Scenarios:

- Three sets of demand: **low, medium, and high**
- Three objectives: occupancy target, economic surplus, revenue
- Four scenarios
  - **i. Traditional**
  - **ii. Static Information**
  - **iii. Dynamic Information**
  - **iv. Dynamic Pricing**

Price and Occupancy (avg over space)



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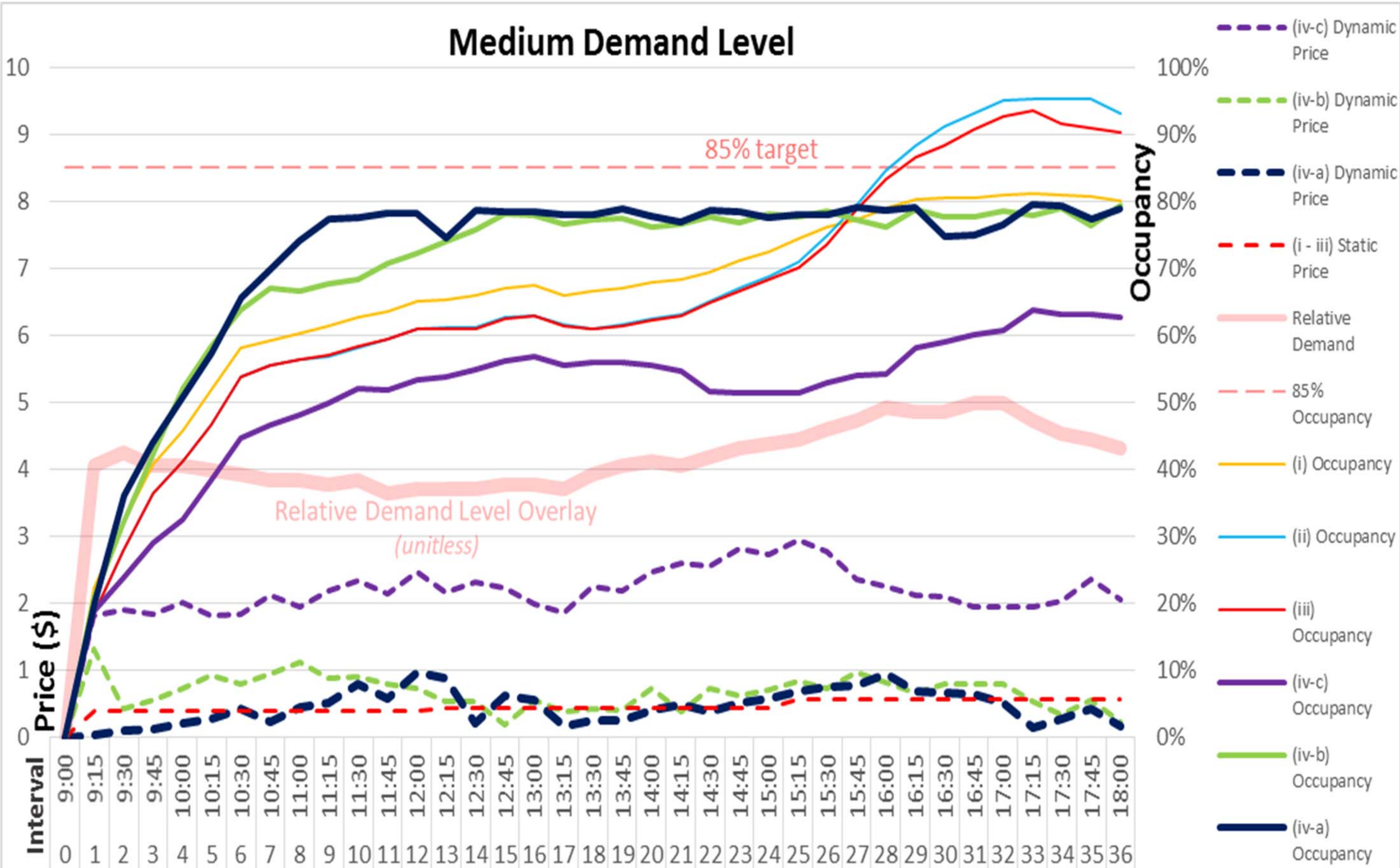

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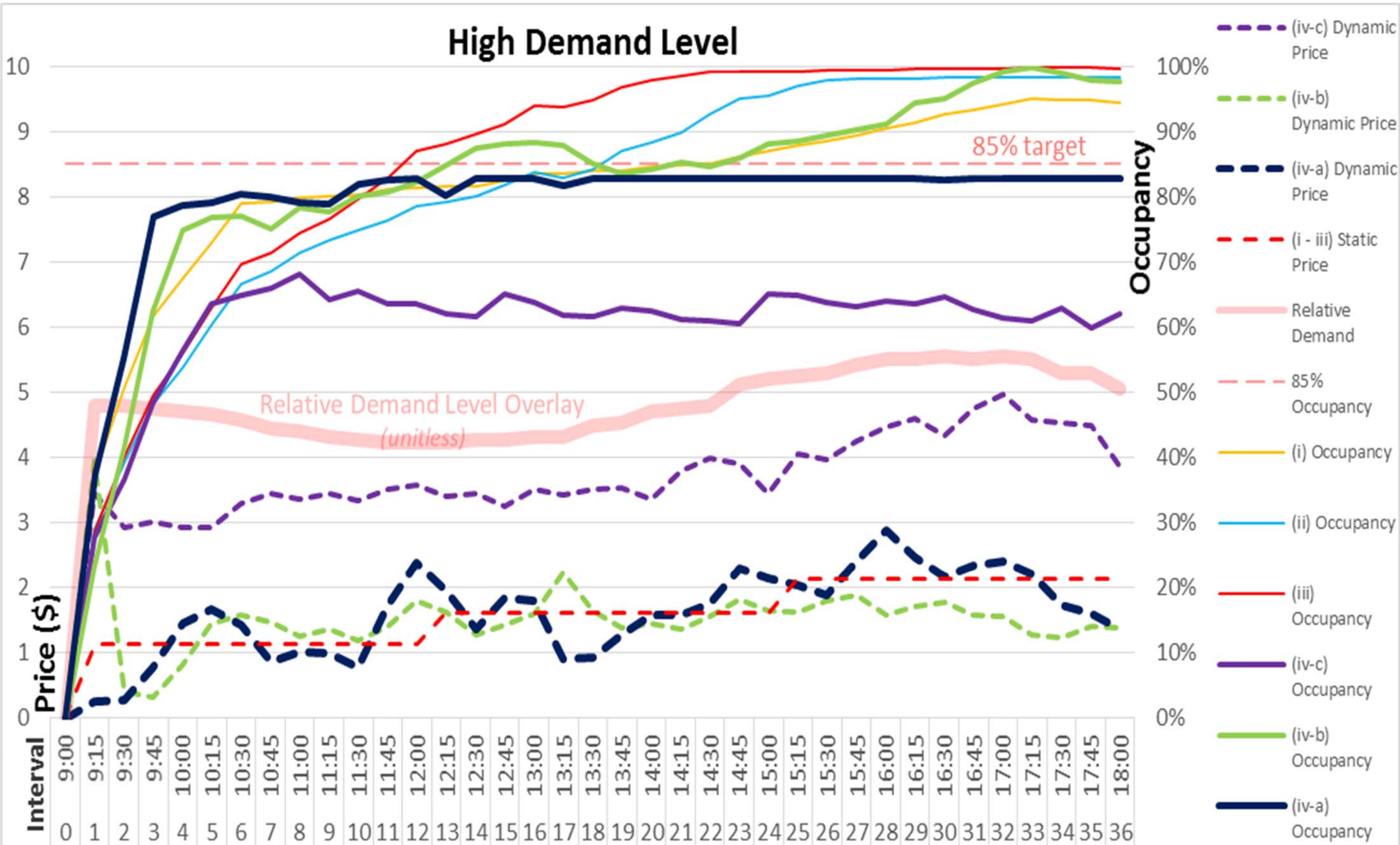


Numerical Results

		Scenarios					
		Static Pricing			Dynamic Pricing (iv)		
Demand Level	Performance Metric	(i) Traditional	(ii) Static Information	(iii) Dynamic Information	(a) Occupancy	(b) Economic Surplus	(c) Revenue
Low	Total excess distance *(miles)*	122.64	48.52	37.33	0.00	0.65	0.00
	Occupancy distribution *% lot-hrs empty / above target*	39.9/48.1	26.1/32.9	26.7/31.9	26.9/0.0	8.1/0.6	15.7/0.0
	Lost customers	197	197	197	197	224	418
	Economic surplus *(utils)*	3,045	3,242	3,251	3,337	3,413	3,029
	Parking revenue	$251.97	$190.71	$189.49	$129.23	$190.80	$601.24
Medium	Total excess distance	522.27	257.99	166.13	0.00	5.54	0.92
	Occupancy distribution	20.6/64.0	7.2/51.7	8.2/50.0	6.3/0.0	7.1/1.7	21.4/0.3
	Lost customers	460	414	402	402	410	767
	Economic surplus	8,946	9,401	9,414	9,724	10,056	8,824
	Parking revenue	$1,050.38	$970.33	$970.33	$611.07	$661.49	$1,840.78
High	Total excess distance	1,622.23	1,213.13	721.22	4.91	346.48	3.69
	Occupancy distribution	5.4/79.0	0.7/80.7	0.7/81.5	1.8/0.6	2.1/39.2	12.8/0.4
	Lost customers	1,514	1,150	1,121	954	927	1,571
	Economic surplus	25,774	26,508	26,404	27,946	28,971	24,896
	Parking revenue	$4,033.71	$4,765.75	$4,847.42	$3,637.19	$3,249.96	$5,948.67

- Improved parking allocation, reduced excess vehicle travel, comparable/fewer lost users, (optionally) increased revenue
- Potential in effectively balancing multiple objectives (e.g. occupancy and revenue)

Conclusion

Current consensus:

- Demand responsive pricing can better allocate parking, as seen in SF*park*

Our work:

- Dynamic pricing models can improve efficiency and users' experiences, especially when paired with on-street reservations

Future work:

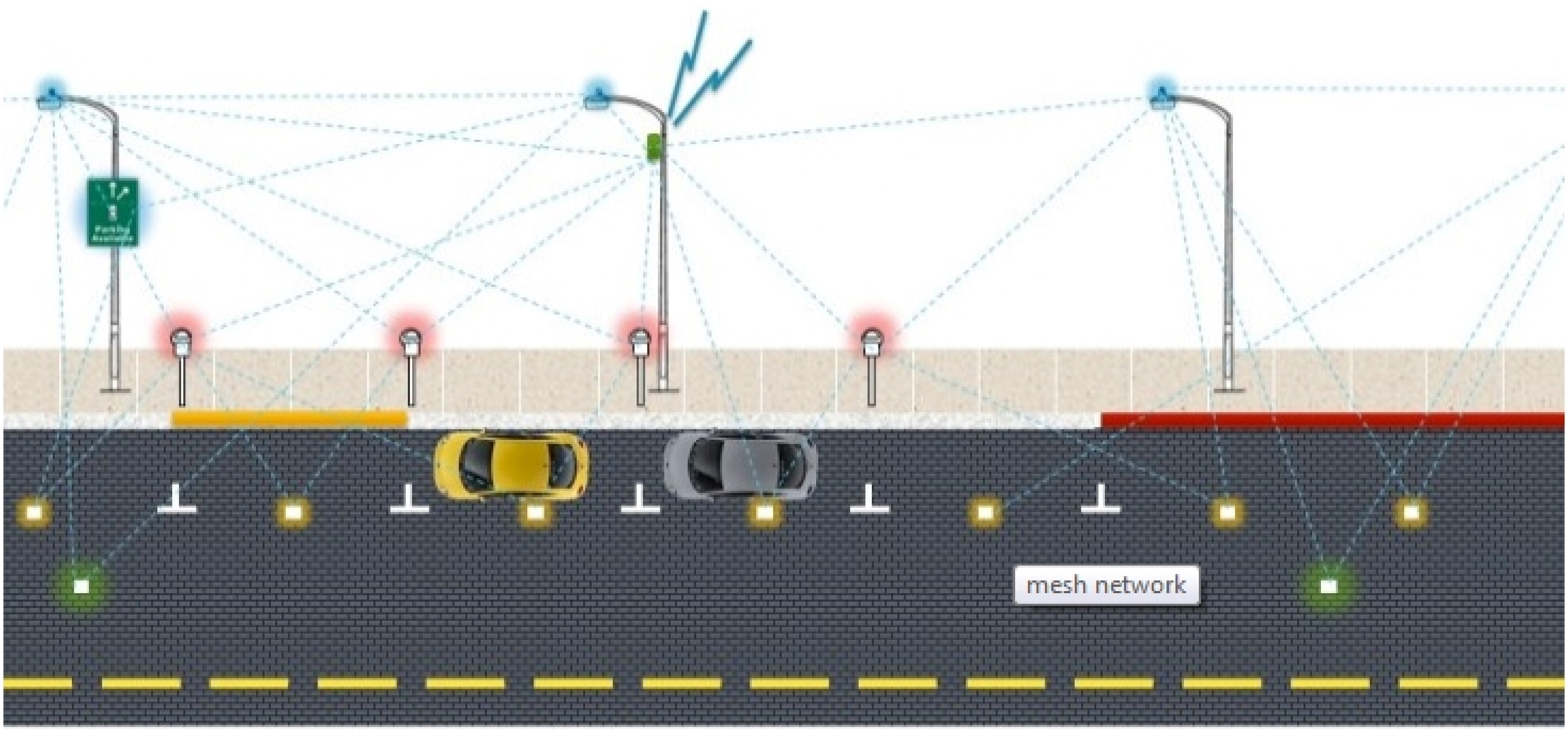
- Stochastic parking durations, heterogeneous user types (motorcycle, electric vehicle, tourist, …), non-linear demand curves
- Location of congestion and impact on non-parking traffic
- Real-world study, including implementation of on-street reservations

Future extensions:

- Consider impacts of changing travel behavior – commuter shuttles, ride sharing, …

Thank you!

yfouyang@illinois.edu



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