Scheduling EVs with uncertain departure times

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Collaborators

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Introduction

- EVs are an energy intensive load to the grid!
- But users may have flexibility in their charging times.

Main question:

How do we schedule EV charging with deadlines?

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How do we schedule EV charging with deadlines?

Which also begs the question...

What happens if we don't know the deadlines exactly?

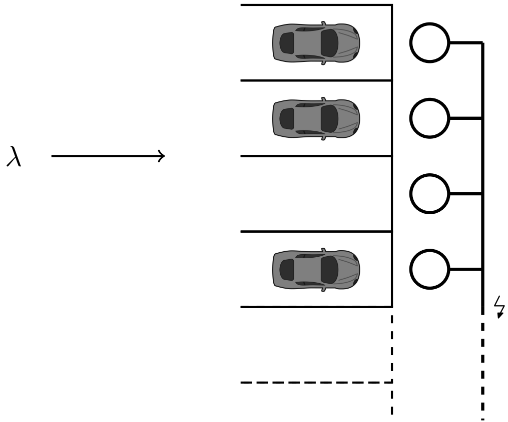
Main contribution:

Mean field analysis of EV scheduling with *uncertain* deadlines.

Highlights:

- We analyze the behavior of typical policies through fluid limits (mean field).
- Discuss the impact of *uncertainty* in the deadline.
- Analyze how to curb incentives to under-report deadlines.

Large parking lot with individual charging stations



Traffic parameters:

- λ = arrival rate of EVs.

Queueing model

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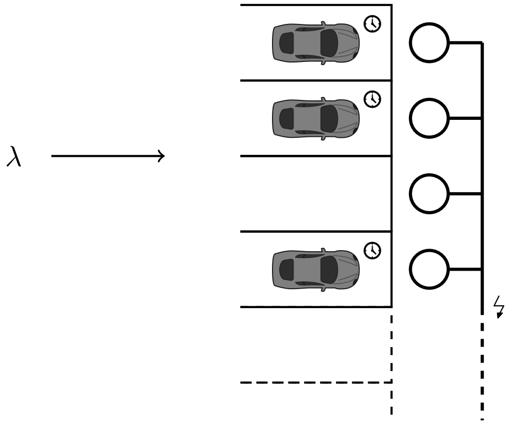

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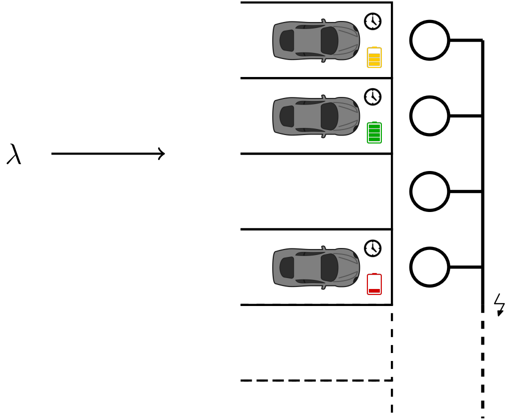

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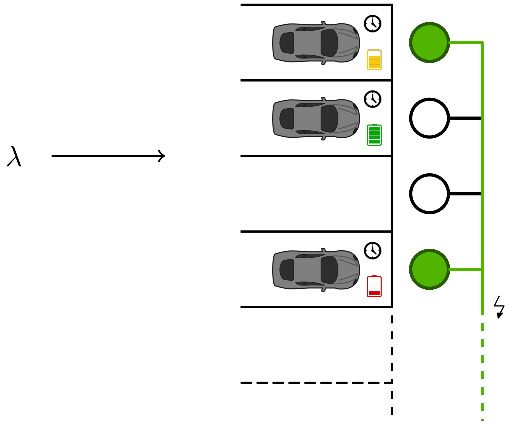

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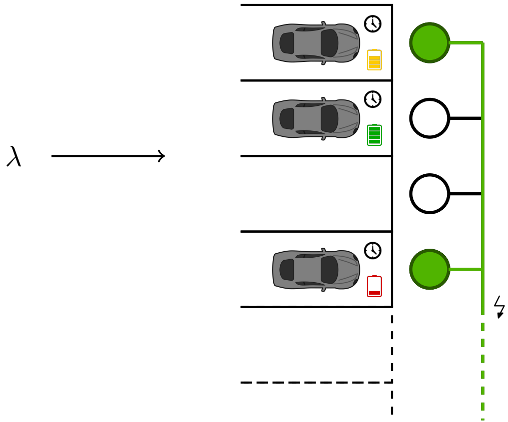

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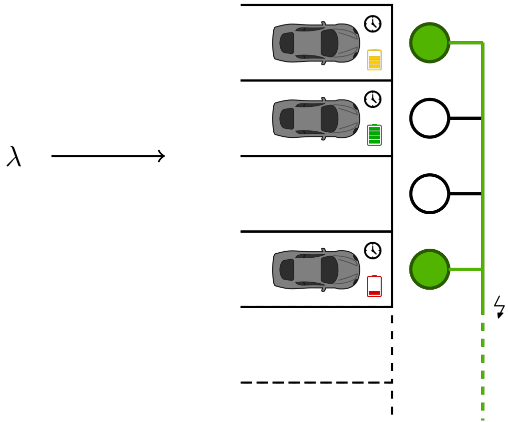

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We focus on the overload scenario $\rho > C$.

Least-Laxity-First Policy

Let us define, for a vehicle k at time t:

$$\sigma_k(t) := \text{remaining service time},$$
$$\tau_k(t) := \text{remaining sojourn time}.$$

Then the EV laxity is:

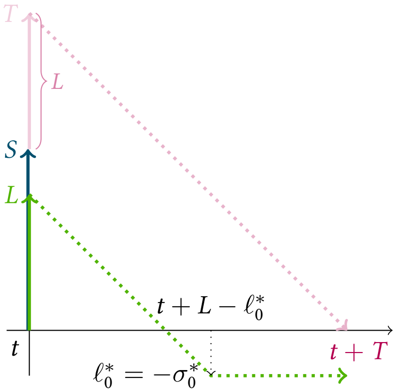
$$\ell_k := \tau_k - \sigma_k$$

- Idea: Amount of time left to begin service and meet the deadline.
- If ℓ_k becomes negative, the EV will depart with some reneging. Equal to $-\ell_k$ upon departure.

LLF policy: serve the C vehicles with lower laxities.

Least-laxity-first (LLF) in overload [Zeballos, F., Paganini TSG 2019]

Mean field behavior: $\lambda, C \to \infty$ with constant C/ρ



- Vehicle arrives at time t.
- Gets service at time $t + L - \ell_0^*$.
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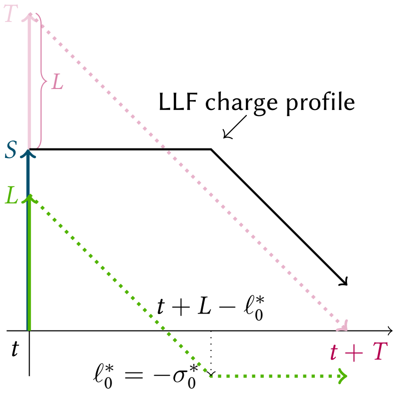

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Attained service:

$$S_a = (S - \sigma_0^*)^+.$$

Everybody reneges with σ_0^* or less.

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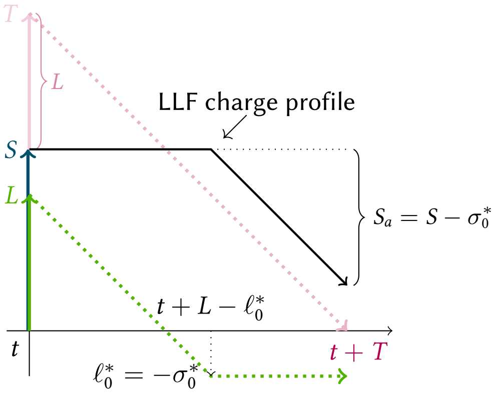

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Threshold condition:

$$\lambda E[(S - \sigma_0^*)^+] = C$$

Dealing with uncertain deadlines

- In practice the service time S is known upon arrival (smart chargers).
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Question:

How does the LLF scheduler behave when using these uncertain deadlines?

LLF with uncertain deadlines

Two deadlines:

- Real (hidden) sojourn time T_k. Users depart on expiration.
- Declared sojourn time T'_k (assumed random, possibly correlated with T_k).

Therefore, the user has an observed laxity:

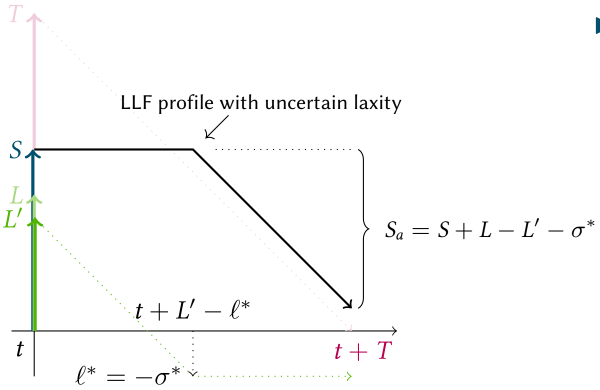
$$\ell'_k = \sigma_k - \tau'_k$$

with τ'_k the remaining declared sojourn time.

Assumption: the scheduler only uses the declared information, and serves in increasing order of their *observed laxity* ℓ'.

Uncertain LLF

Mean field behavior: $\lambda, C \to \infty$ with constant C/ρ



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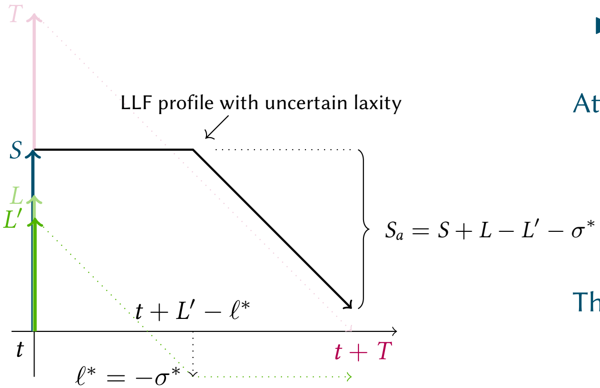

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Attained service:

$$S_a = (S + L - L' - \sigma^*)^+$$

Threshold condition:

$$\lambda E[(S + L - L' - \sigma^*)^+] = C$$

Remark: The threshold only depends on S

A parametric example

Exponential service time, uniform uncertainty

Assume:

- $S \sim \exp(\mu)$.
- $U = T' - T = \text{Uniform}[-\theta, \theta]$.

Focus now on individual uncertainties:

$$E[S_a \mid U] = E[(S + L - L' - \sigma^*)^+\} \mid U],$$

Proposition

In an LLF system in overload, with $S \sim \exp(\mu)$ service times and independent uncertainty $U = T' - T$ in declared deadlines, the attained service for a given uncertainty is:

$$E[S_a \mid U] = \frac{e^{-\mu(U+\sigma^*)}}{\mu}. \tag{1}$$

Performance comparison

To compare the performance, let us compute:

$$RG(U) = \frac{E[S_a - S_a^0 \mid U]}{E[S]} = \frac{E[S_a \mid U] - E[S_a^0]}{E[S]}.$$

the relative average gain against the full information case, for a given uncertainty level.

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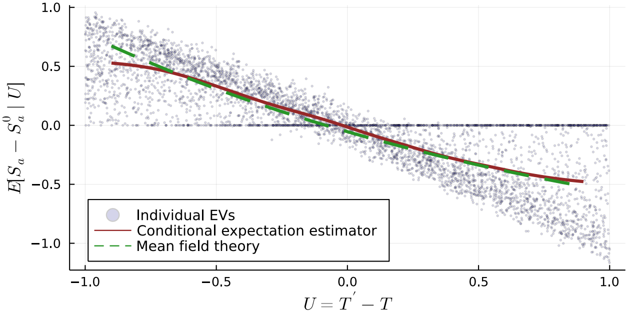
For the parametric model this yields:

$$RG_{LLF}(U) = \frac{C}{\rho}\left(\frac{\mu\theta}{\sinh(\mu\theta)}e^{-\mu U} - 1\right).$$

Simulation example



Traffic parameters:

- $\lambda = 30.$
- $E[S] = 2hs.$
- $E[T] = 6hs.$
- $\theta = 1$ ($\pm 1h$ uncertainty)
- $C = 40,$

Dealing with incentives

- The average service of a given EV is decreasing on the reported uncertainty U.
  - People that under-report their deadlines get priority sooner.
  - Since they are served until departure, this leads to a longer service time.

- An incentive appears to under-report sojourn times.

Question: how can we handle mis-behaving users?

Curtailed LLF policy

Simple solution: Apply a curtailed version of the LLF policy.

Curtailed LLF policy:

- Serve vehicles in increasing order of their remaining declared laxities ℓ'.
- Stop service when the declared deadline expires, even if the vehicle is still present.

Curtailed LLF policy

Mean field behavior: $\lambda, C \to \infty$ with constant C/ρ

For the curtailed policy, the attained service in the mean field limit is:

$$S_a = \left(S - (L - L')\mathbf{1}_{\{L<L'\}} - \sigma^*\right)^+ ,$$

And the threshold satisfies:

$$\lambda E[\left(S - (L - L')\mathbf{1}_{\{L<L'\}} - \sigma^*\right)^+] = C.$$

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Remark: The indicator term reduces the gain to 0 for $L' < L$.

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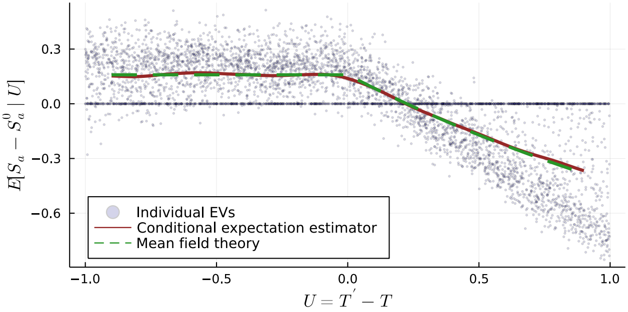

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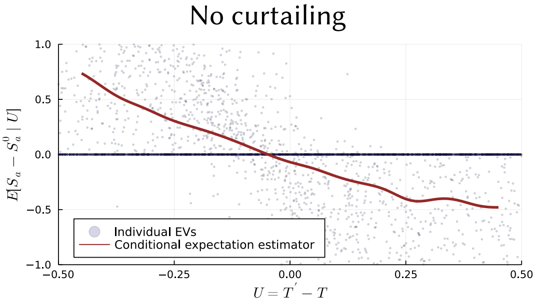
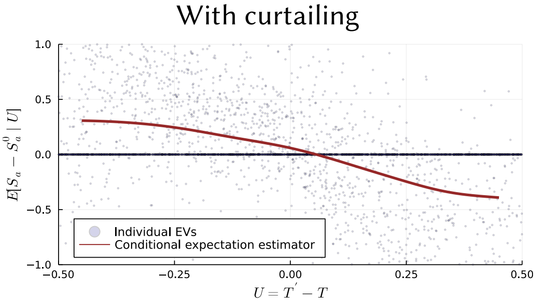
Real world scenario

- We simulate our algorithms using real world traces from a parking lot at a Silicon Valley firm (thanks to Steven Low).
- Multi-day period with time-varying demand and congestion.
- $C = 30$ charging stations, $\bar{T} = 2.25$ hs., $\bar{S} = 1.77$ hs.
- Uniform uncertainty with $\theta = 0.5$ hs.
- The parking works in overload 73% of the total simulation time.

Results





Remark: the curtailed policy works by curbing under-reporting deadlines in this scenario.

Conclusions

- We analyzed the behavior of the LLF policy working with uncertain deadlines.
- Through mean-field analysis, we derived explicit expressions for the system performance.
- We provided a suitable policy to curb the incentive to under-report deadlines.

Thank you!

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