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A Decision Support Framework for Grid-Aware Electric Bus Charge Scheduling

Geoffrey Pettet*, Malini Ghosal†, Shant Mahserejian†, Sarah Davis†, Siddharth Sridhar†, Abhishek Dubey*, Michael Kintner-Meyer†

*Vanderbilt University, Nashville TN, USA | †Pacific Northwest National Laboratory, Richland WA, USA
{geoffrey.a.pettet, abhishek.Dubey}@vanderbilt.edu,
{malini.ghosal, shant.mahserejian, sarah.davis, siddharth.sridhar, Michael.Kintner-Meyer}@pnnl.gov

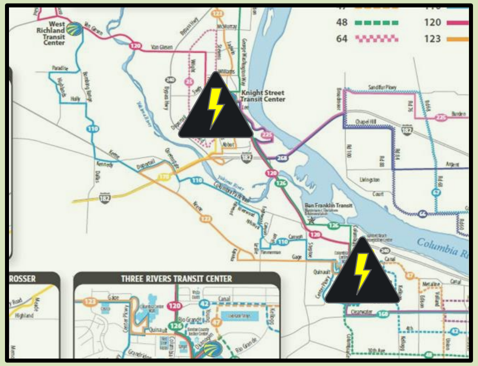
In collaboration with Philip Pugliese, Chattanooga Area Regional Transportation Authority

Electric Bus Charge Scheduling

<u>Motivation</u>: **minimize energy cost** of electric transit services while ensuring the extra power demand does **not overload the power grid**

<u>Problem</u>: schedule bus charging at chargers located along route

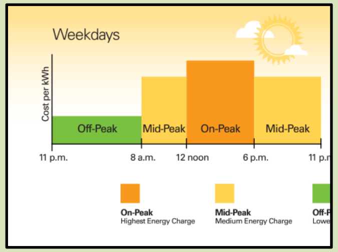
Electric Buses



Geo-located chargers

<u>Constraints</u>:

<u>EVs increase grid demand</u>: avoid grid overloading and failures



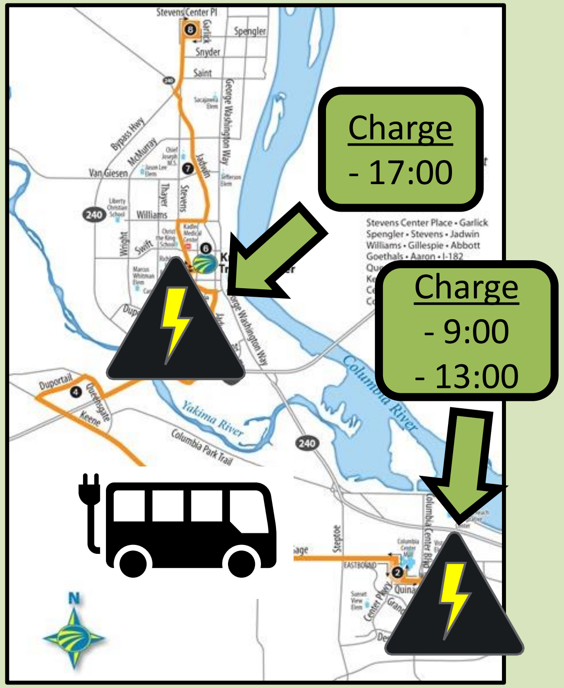
<u>Energy prices fluctuate</u>: avoid over-spending on energy

Must maintain level of service => avoid delays or running out of charge

Decision Support Framework

Simulation

Replicates the transit system to estimate the impact of potential charging schedules



Traffic Simulator

Models ***travel times*** and ***battery discharge*** under varying traffic conditions

Traffic network →

OpenStreetMaps
- Roadway Network
- Transit Schedules

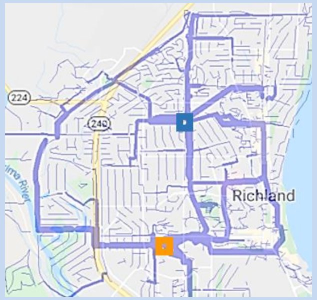
Simulation of Urban MObility
- Micro traffic simulator
- Built in EV bus models

Grid Impact Model

Captures the impact charging actions have on the power grid

GridLAB-D

Impact metric derived from…
- Line losses
- Power phase balancing
- Etc.



Case study's feeder network

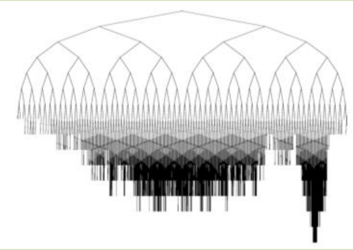
State updates, Estimated rewards →

← Charging actions to evaluate

Decision Agent

Evaluates potential charging schedules by estimating their long-term effects

Monte Carlo Tree Search
- Represents control process as game tree
- Asymmetrically grows tree, balancing exploration and exploitation
- Estimates values of actions using surrogate models
- Online algorithm; no training needed (unlike reinforcement learning). Adaptable to dynamic environments



Notable application: world-champion defeating Go program[1]

Reward Function

$$r_c = -e + \beta g - \varphi n_f$$

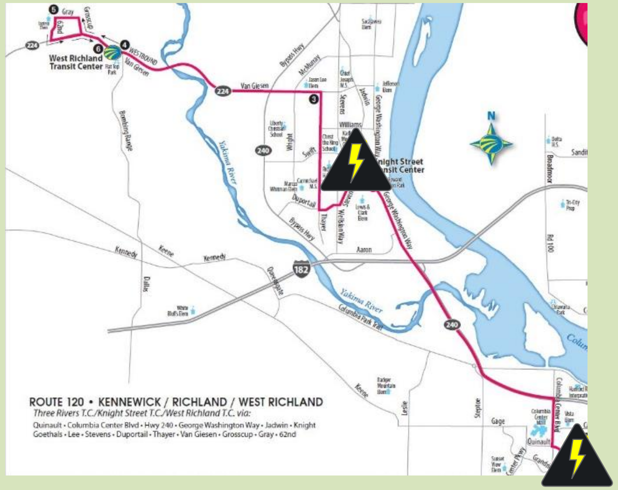
- energy costs (e)
- power grid impact (g)
- Number of failed buses (n_f)
- Tradeoff parameter (β)

[1] Silver, David, et al. "Mastering the game of Go with deep neural networks and tree search." *nature* 529.7587 (2016): 484-489.

Results

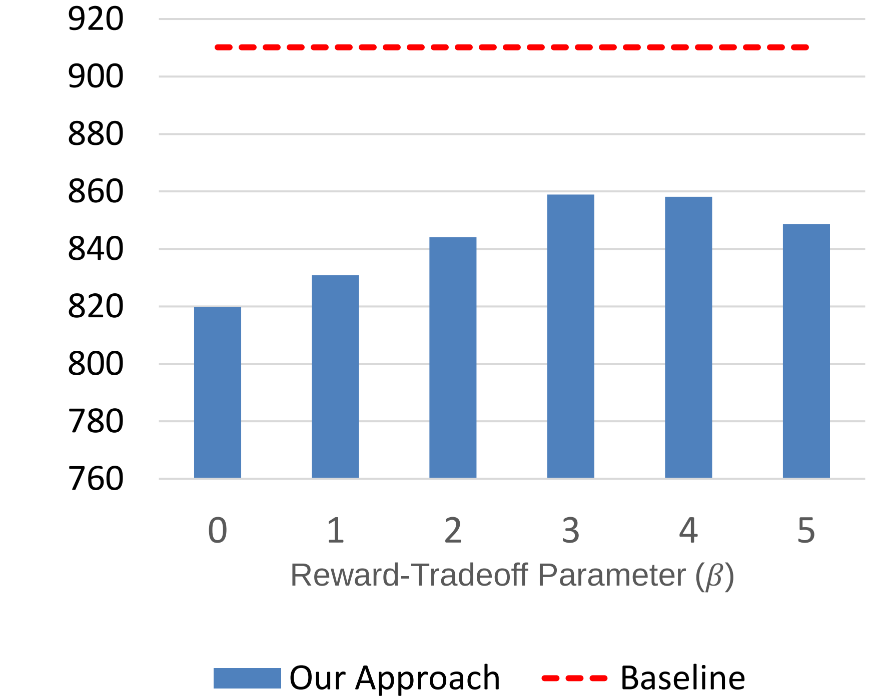
Experimental Setup

- 5 EV bus routes in Richland, WA
- 2 chargers placed at major bus stations
- Compared our framework to *greedy policy:* charge bus when it stops at a charger if SOC under prescribed threshold

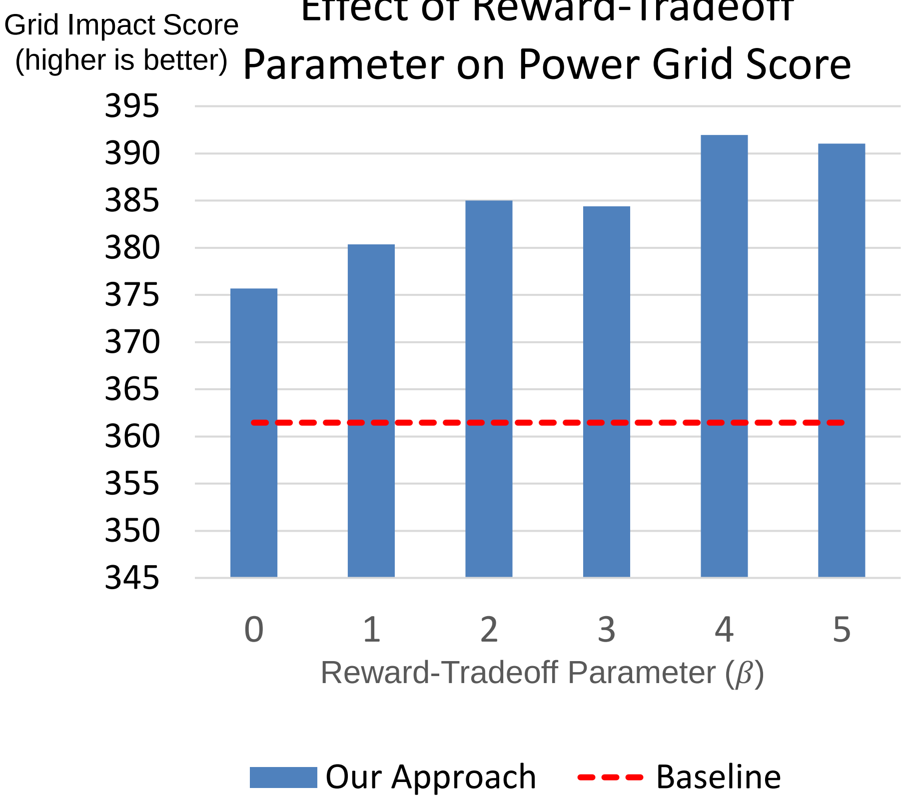


Example of a route with two chargers

Effect of Reward-Tradeoff Parameter on Energy Cost



Effect of Reward-Tradeoff Parameter on Power Grid Score



Tradeoff parameter (β) allows customization to a particular city's needs

Energy cost savings of up to 10% while decreasing power grid strain

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Conclusions/Recommendations

- EV buses introduce power grid demand => charge scheduling must be *grid-aware*
- A decision support framework underpinned by **traffic** and **power grid** simulations is an effective and adaptive management system
- This exploratory analysis shows that such a framework can improve both grid impacts and energy costs to run a bus system for a midsized city
- It motivates continued work, including
  - Examining how to optimally place chargers along routes
  - Testing framework generalizability to other sized cities
  - Integrating with route scheduling
  - Possible extensions: paratransit, rideshare, delivery fleets

Next Steps: collaboration with Chattanooga city to integrate with route scheduling and paratransit services

CARTA

*Images courtesy of the Chattanooga Area Regional Transportation Authority (CARTA)