Scalable Electric Vehicle Smart Charging Using Collaborative Autonomy

Steve Chapin, PhD, PI
Lawrence Livermore National Lab

Vehicle Technologies Office
Annual Merit Review Presentation

Project ID elt200

June 3, 2020
Arlington, VA

LLNL-PRES-XXXXXX
This work was performed under the auspices of the U.S. Department of Energy by Lawrence Livermore National Laboratory under contract DE-AC52-07NA27344. Lawrence Livermore National Security, LLC

Overview

Timeline

- Project Start: Oct ‘18
- Project End: Sep ‘21
- Percent complete: 60%

Budget

- Total Project
  - DOE $2.4M
- FY 2019: $766K
- FY 2020: $805K ($265k received)
- FY 2021: $832K

Barriers Addressed

- Grid Interaction: Smart Charging/Smart Grid Interface
  - Demand response (DR)/ ancillary services at the local/multi-vehicle and regional/aggregate fleet levels

Partners

- Lead: LLNL
- Industry: ChargePoint

Relevance

Impact

- We will reduce demand variability and improve grid reliability by implementing collaborative-autonomy-based demand response techniques, enabling smart chargers to respond to voltage and frequency events in the power grid in a timely fashion. Our approach takes advantage of the distributed nature of the system and increases overall resiliency and security while meeting the demands of both the grid and charging customers.

Objectives

- Develop a collaborative algorithm that will enable local groups of charging station controllers to coordinate demand response and ancillary services such as frequency and voltage regulation
- Meet technological, policy, and contractual constraints imposed at the level of the smart charging stations
- Accommodate practical considerations (dynamic Electric Vehicle (EV) load, multiple charging networks) to provide platform for innovation
- Real-world demonstration using commercially available chargers and EV.

Managing demand response for EV charging through collaborative autonomy takes advantage of the distributed nature of the charging system and allows for a scalable approach while improving grid reliability and resilience.

Milestones

Milestones	Year 1				Year 2				Year 3			
	1	2	3	4	1	2	3	4	1	2	3	4
Objective 1: Develop Resilience-Driven Demand Response Algorithm												
1.1: Investigate software and hardware techniques and requirements	■											
1.2: Create a simulator to test algorithm		■	■	■								
1.3: Design Algorithmic Framework		■	■									
1.4: Test performance of algorithm				■								
Objective 2: Extend Framework to Incorporate Cost Minimization for Individuals												
2.1: Improve performance of ADMM* framework					■	■						
2.2: Extend the framework to manage multiple self-interested parties						■	■					
2.3: Test real-time and cost minimization performance in simulation								■				
Objective 3: Technology Demonstration Transition to Industry												
3.1: Refine software and algorithmic framework									■	■		
3.2: Technology demonstration with Skyfall hardware-in-the-loop simulation										■	■	■
3.3: Collaborate with ChargePoint to Explore Technology Transition											■	■

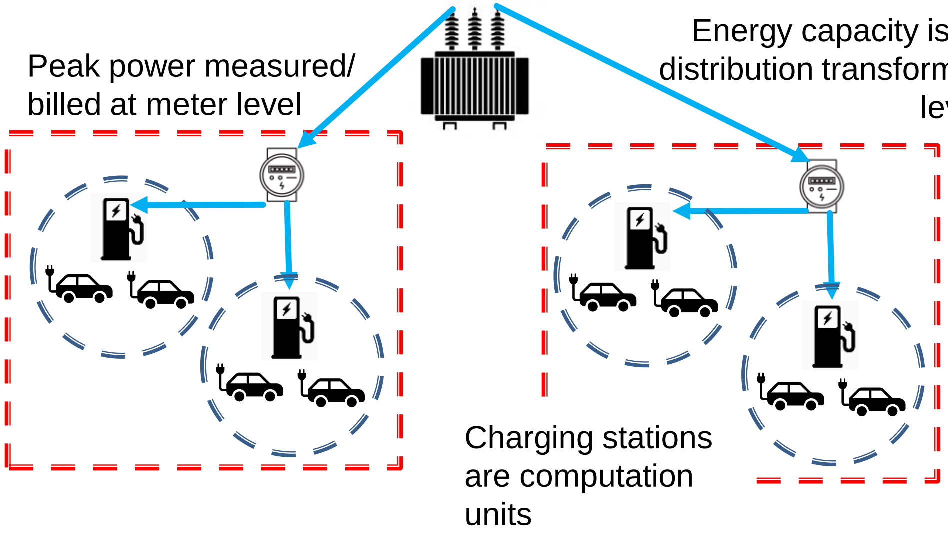
*ADMM = Alternating Direction Method of Multipliers

Any proposed future work is subject to change based on funding levels.

Approach

Collaborative Autonomy

- Use powerful distributed optimization methods, such as ADMM, to implement demand response and ancillary services
- Use computational power of charging stations to compute charging schedules without centralized control



Simulation, Testing, and Demonstration

- Hardware-in-the-loop simulation (real devices running actual code) for testing at Skyfall, LLNL's cyber-physical testbed (Raspberry Pis acting as proxies for Electric Vehicle Supply Equipment (EVSE))
- Simulation at scale (up to 10,000+ charging stations for demand response, down to short time intervals for ancillary services) using coupled simulations through HELICS
- Demonstration on deployed charging equipment

Our approach combines optimization modeling, distributed computing platform development, and hardware-in-the-loop/ coupled simulations using the HELICS co-simulation platform and HPC to develop, validate, and demonstrate decentralized algorithms for EV charge management.

Technical Accomplishments and Progress

FY 2019 (past)

- Defined requirements
- Centralized implementations of two models with rudimentary demand response (proof of concept)
- Initial work on Skynet (decentralized platform)

FY 2020 (current)

- Extended “Price Taker” model to operate at multiple levels
  - Across vehicles at a charging station
  - Behind meter
  - Between meters in a single distribution feeder & between distribution feeders
- Fully decentralized implementation (no central coordination of any kind)
- Support for Ancillary Services and multiple competing parties
- Robustness/reliability: Recovery from node loss during computation
- Skynet extended with consensus algorithms, distributed operations (e.g., all-reduce), and ported to Raspberry Pi.

Technical Accomplishments and Progress II

FY 2019 (past)

- Defined requirements
- Centralized implementations of two models with rudimentary demand response (proof of concept)
- Initial work on Skynet (decentralized platform)

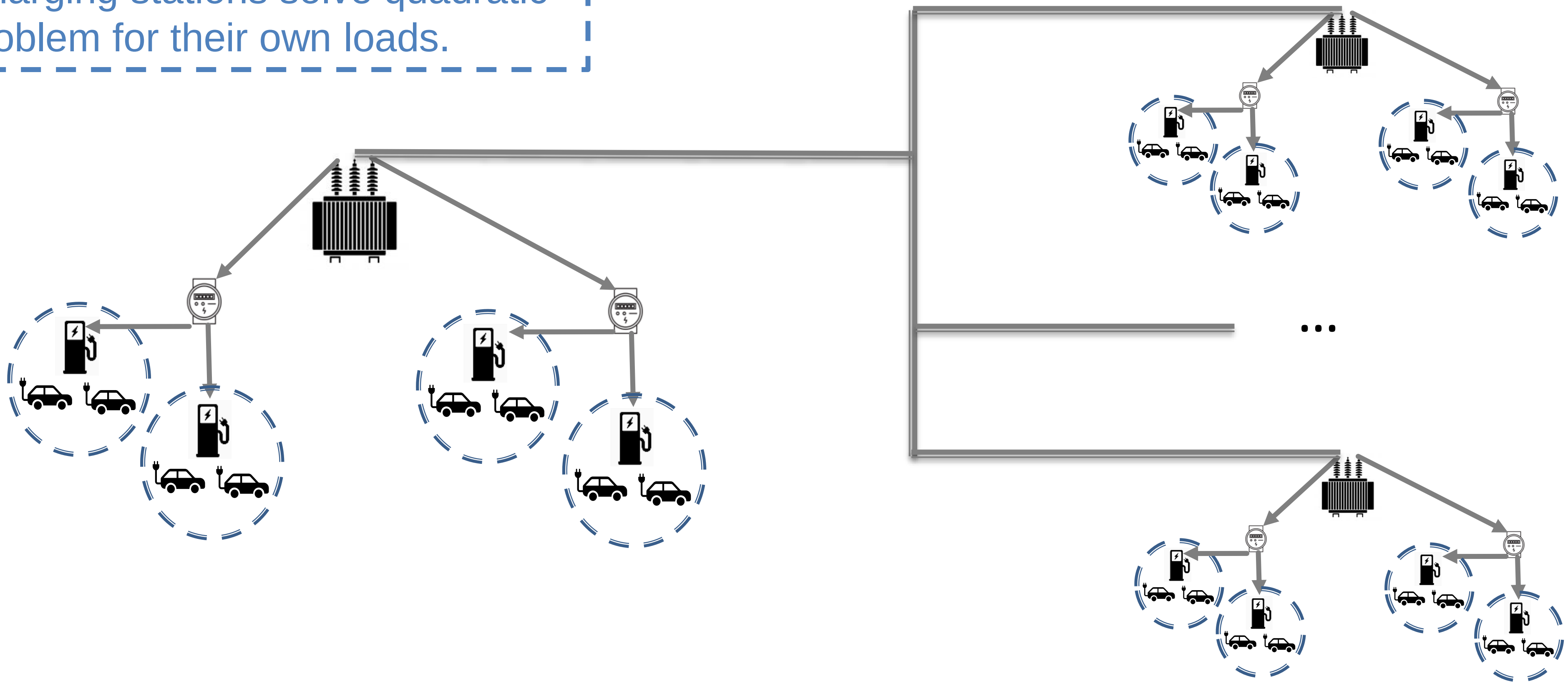
FY 2020 (current)

- Extended “Price Taker” model to operate at multiple levels
  – Across vehicles at a charging station
  – Behind meter
  – Between meters in a single distribution feeder & between distribution feeders
- Fully decentralized implementation (no central coordination of any kind)
- Support for Ancillary Services and multiple competing parties
- Robustness/reliability: Recovery from node loss during computation
- Skynet extended with consensus algorithms, distributed operations (e.g., all-reduce), and ported to Raspberry Pi.

The next several slides will dig deeper into these extensions to the model and implementation.

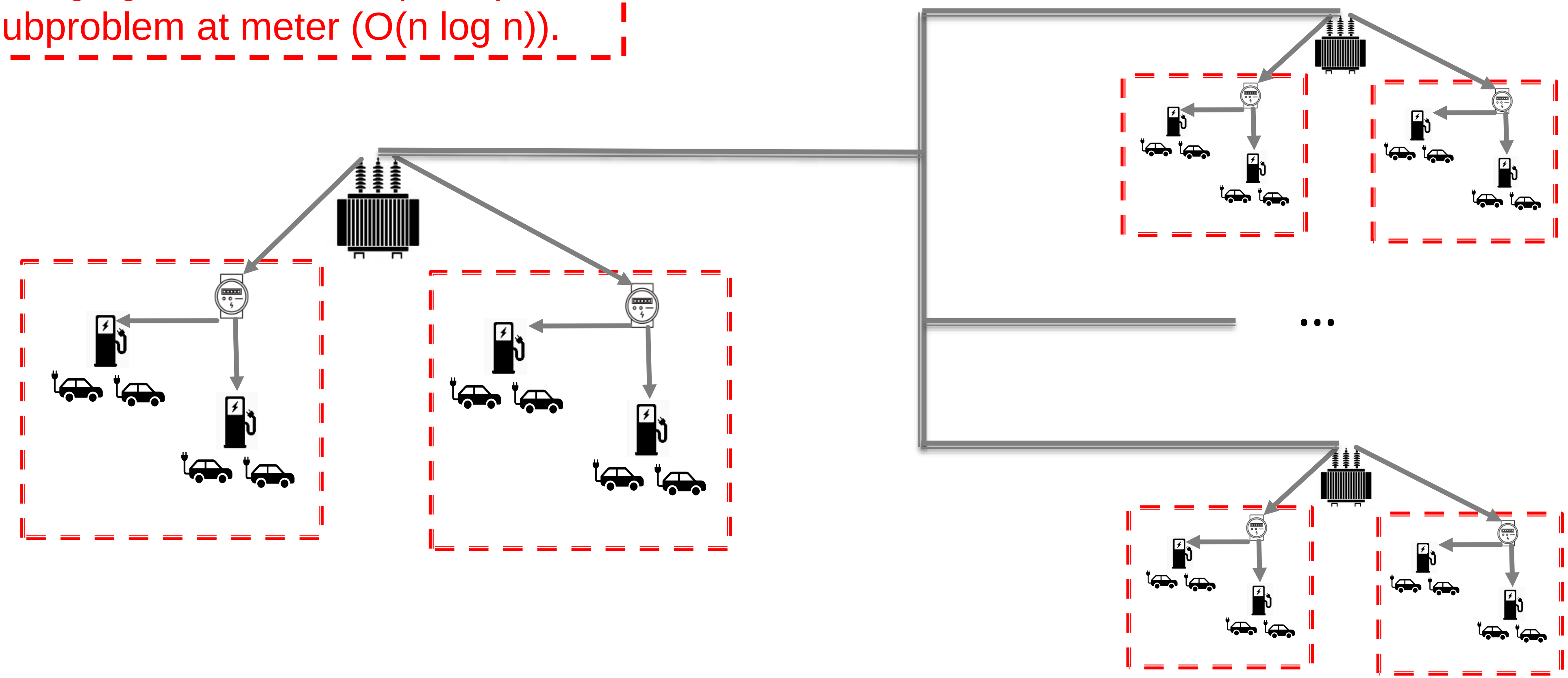
Implementation of Extended Model: Multi-level Problem Structure

1. Charging stations solve quadratic problem for their own loads.



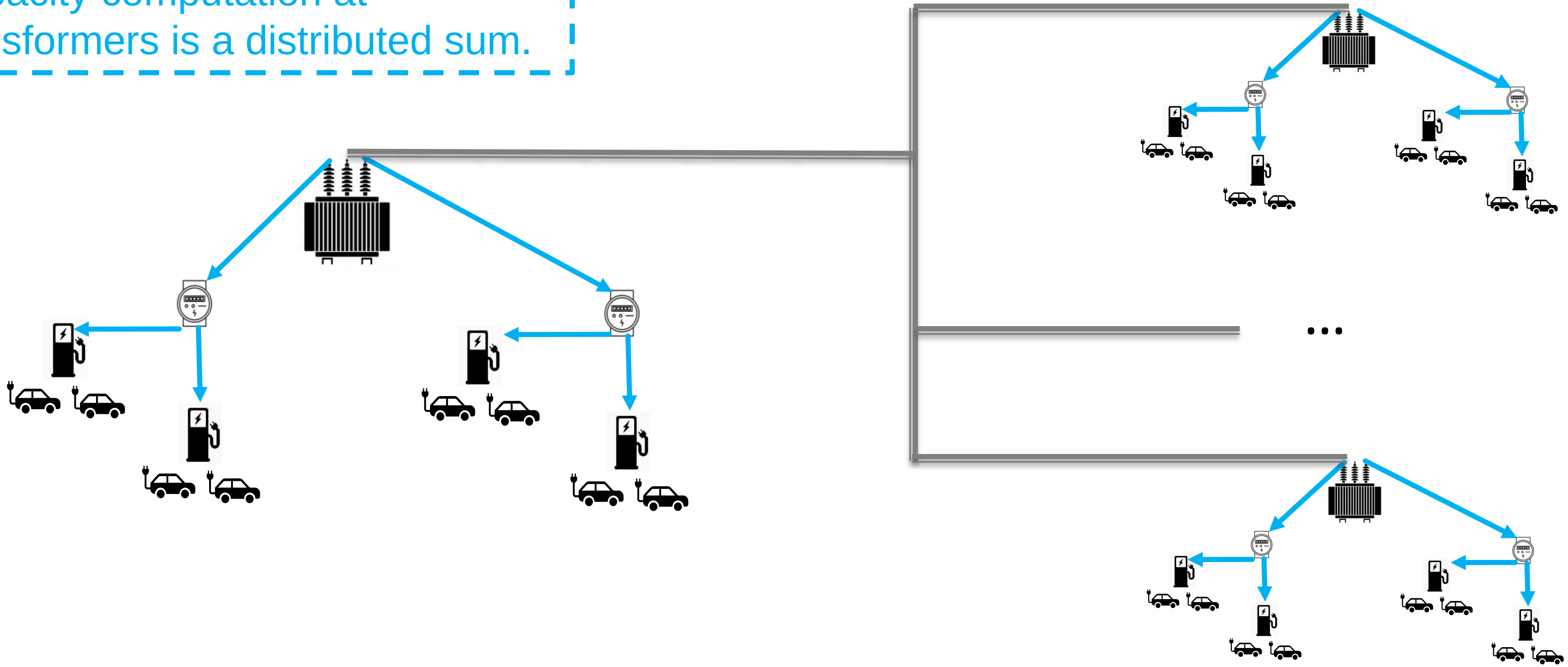
Implementation of Extended Model: Multi-level Problem Structure II

2. Charging stations solve peak power subproblem at meter (O(n log n)).



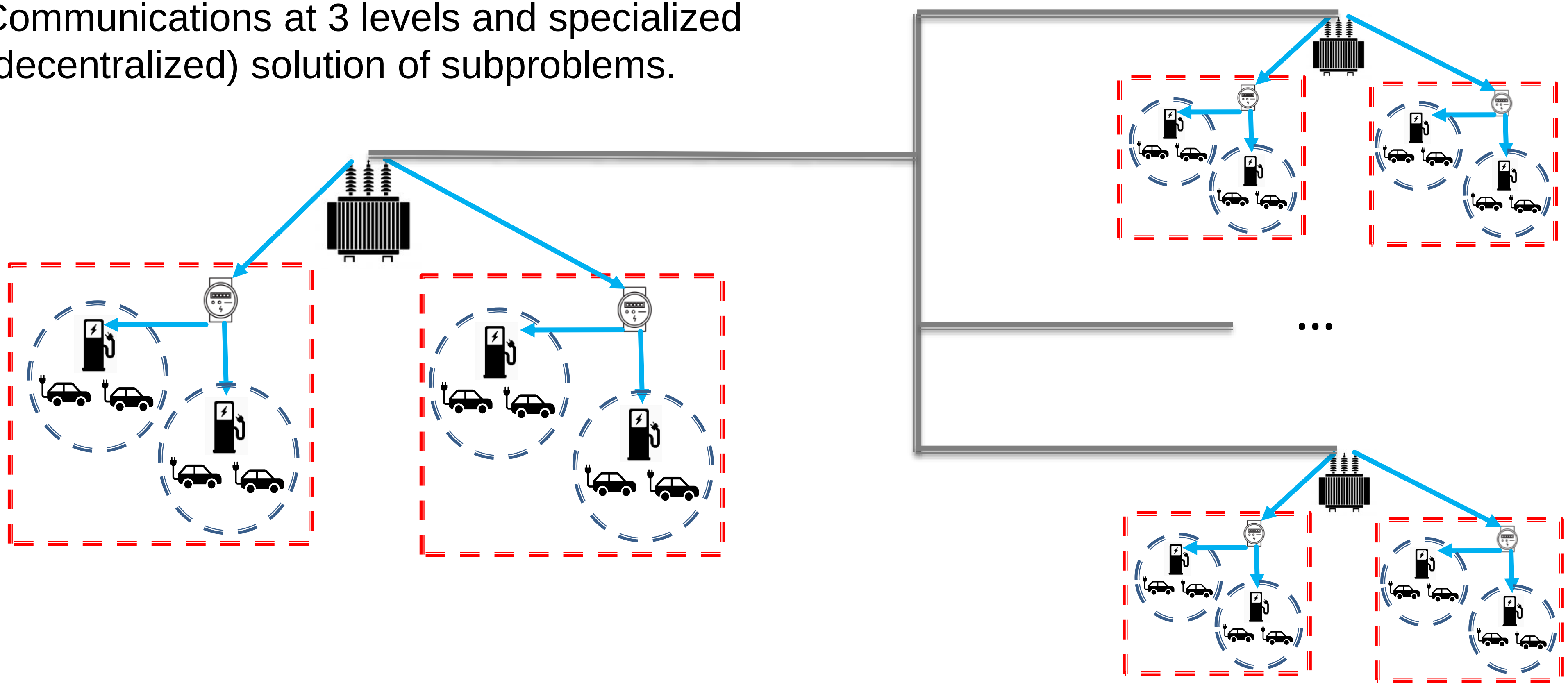
Implementation of Extended Model: Multi-level Problem Structure III

3. Capacity computation at transformers is a distributed sum.



Implementation of Extended Model: Multi-level Problem Structure IV

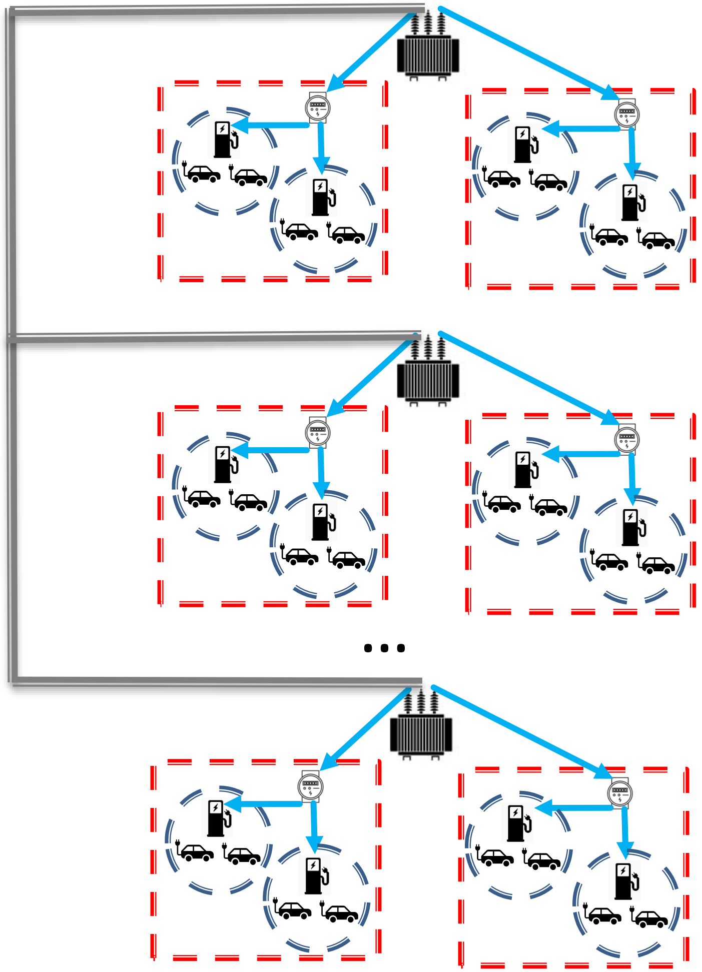
Communications at 3 levels and specialized (decentralized) solution of subproblems.



Multi-level Problem Structure, Refactored

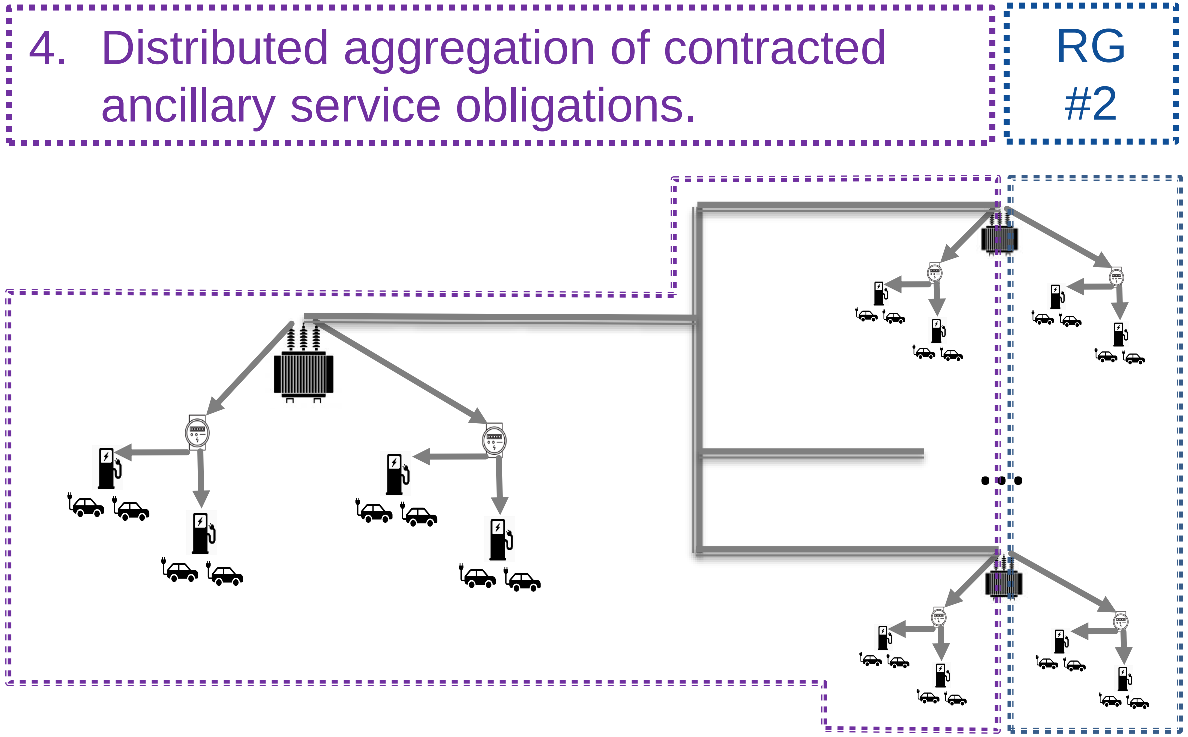
Legend:		
	■ (blue)	Per-station load
	■ (red)	Peak power (meter level)
	■ (cyan)	Capacity (feeder)

1. Each charging station solves a quadratic problem with linear constraints for its own load.
2. Do distributed sums
   a) Capacity usage of stations under each feeder
   b) Estimated peak power for all stations under each meter
3. Compute agreement subproblems
   a) Solve capacity subproblem for each distribution feeder (O(n))
   b) Solve peak-power subproblem for each meter (O(n log n))
4. Update dual multipliers. If convergence not yet reached, loop back to step 1.



Support for Ancillary Service: Spinning Reserve

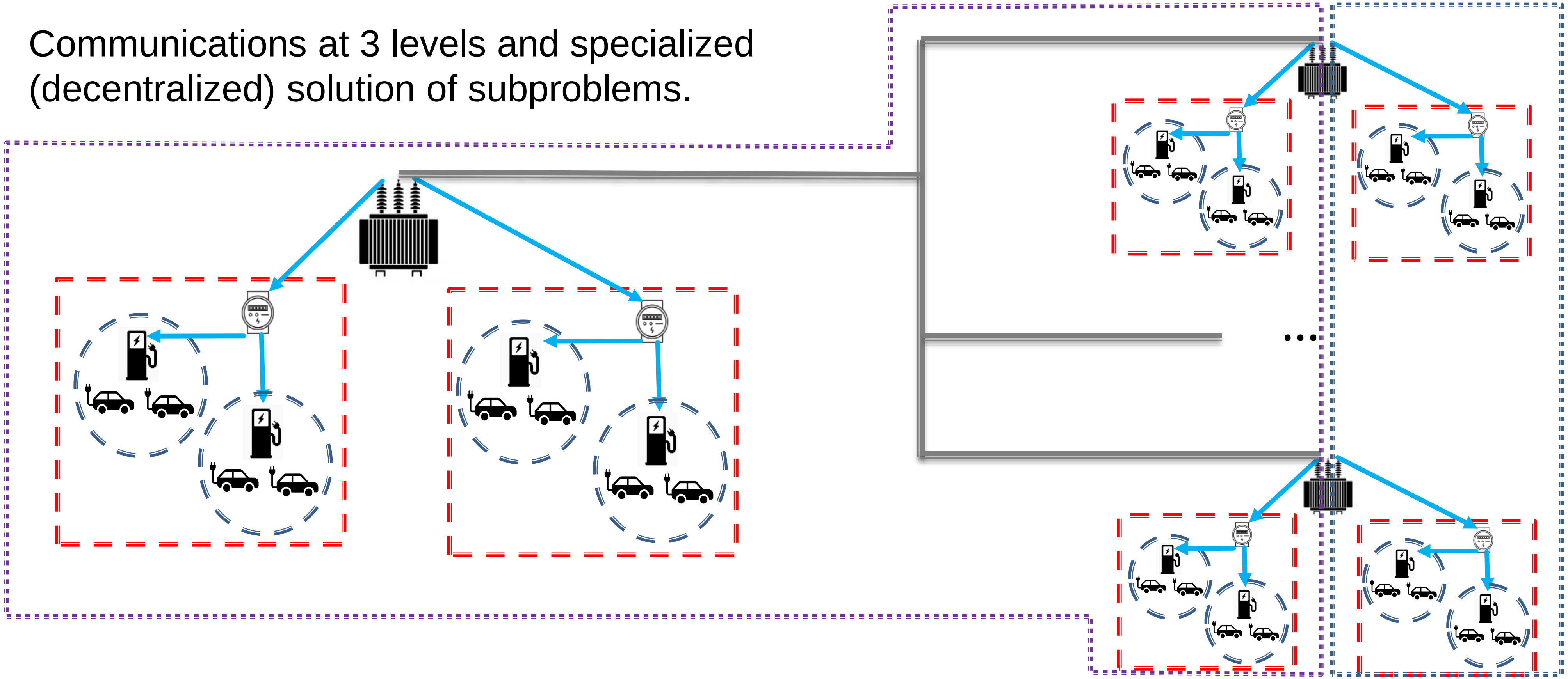
- Add *reserve groups* of coordinated EVSE
- Willing to provide spinning reserve, increasing or decreasing demand (the latter simulating generation for V1G systems)
- Must compute schedule that allows sufficient provisioning to, e.g., still reach desired SoC “later” if we slow charging “now”
- Only EVSE within each group participate in that group’s computation



Simulation results show that this will scale to maximum level allowed under CAISO tariff rules.

Modified Algorithm Including Spinning Reserve II

Communications at 3 levels and specialized (decentralized) solution of subproblems.



Ancillary services model supports multiple competing parties.

Modified Algorithm Including Spinning Reserve

1. Each charging station solves a quadratic problem with linear constraints for its own load.
2. Do distributed sums
   a) Capacity usage of stations under each feeder
   b) Estimated peak power for all stations under each meter
   c) Provision spinning reserve over all EVSE in the reserve group
3. Compute agreement subproblems
   a) Solve capacity subproblem for each distribution feeder (O(n))
   b) Solve peak-power subproblem for each meter (O(n log n))
   c) Solve reserve commitment for each reserve group (O(n))
4. Update dual multipliers. If convergence not yet reached, loop back to step 1.

Legend
- Per-station load
- Peak power (meter level)
- Capacity (feeder)
- Spinning Reserve (group)

Each group computes spinning reserve provisioning using only its own EVSE.

Simulation Results

- All conducted on HPC system using MPI; no H-I-L or co-simulation yet
- All simulations run over 96 15-minute periods (1 day), with termination conditions of a 1W (1E-3 kW) tolerance or 1,000 iterations.
- Initial speed testing on Raspberry Pi shows approx. 5-6x slowdown

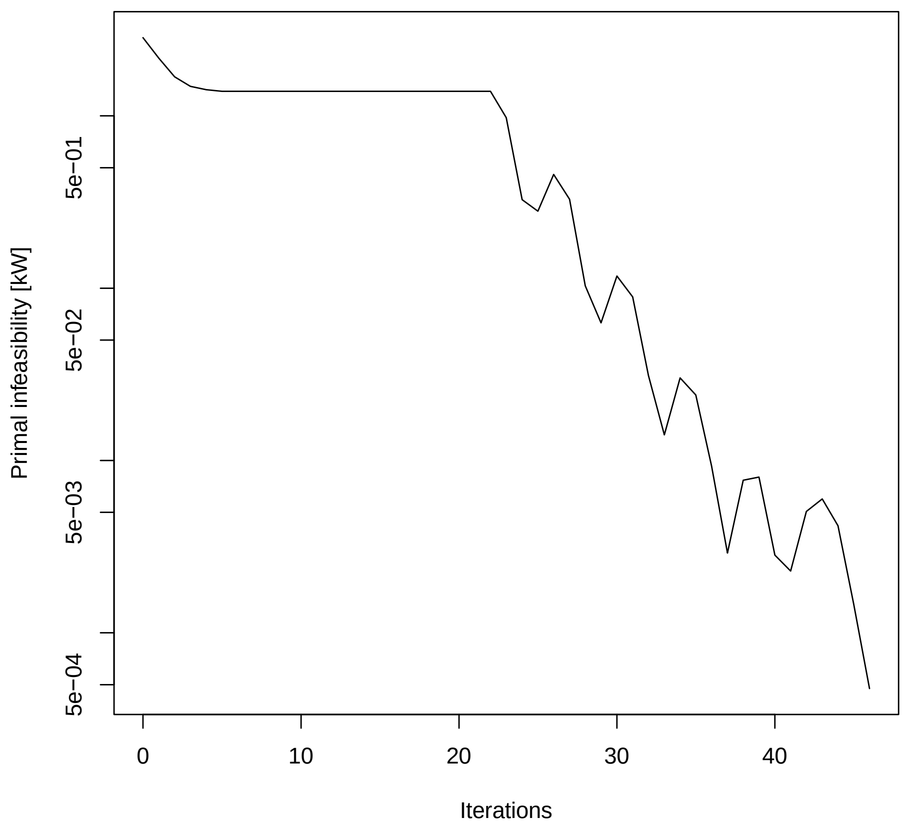
Feeders	Meters	Stations	EV	Iterations	Time (s)
1	2	4	47	46	1.75
1	5	25	306	185	10.66
2	6	36	438	293	15.60
4	20	100	1,232	1000*	59.9

*Terminated at iteration limit with a final error of 1.5W

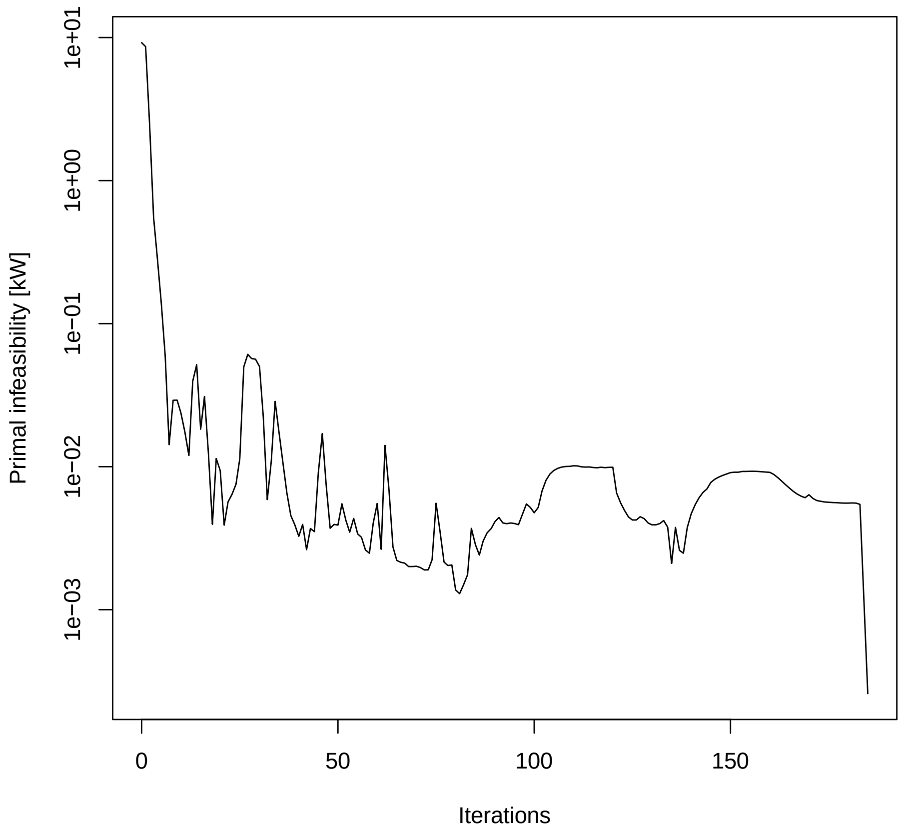
- Simulations included two spinning reserve groups, representing competing entities such as charge network operators.

Test results are well within our time window for demand response and spinning reserve.

Tolerance (Termination Criterion) vs. Iteration



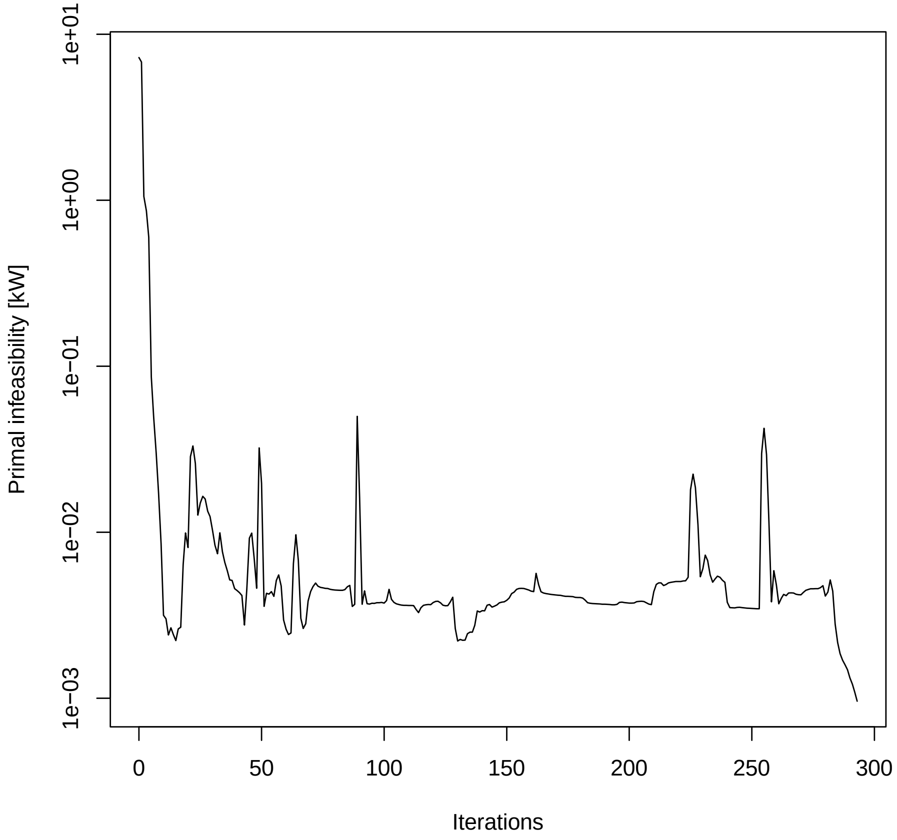
1 feeder, 2 meters, 4 stations, 47 EV



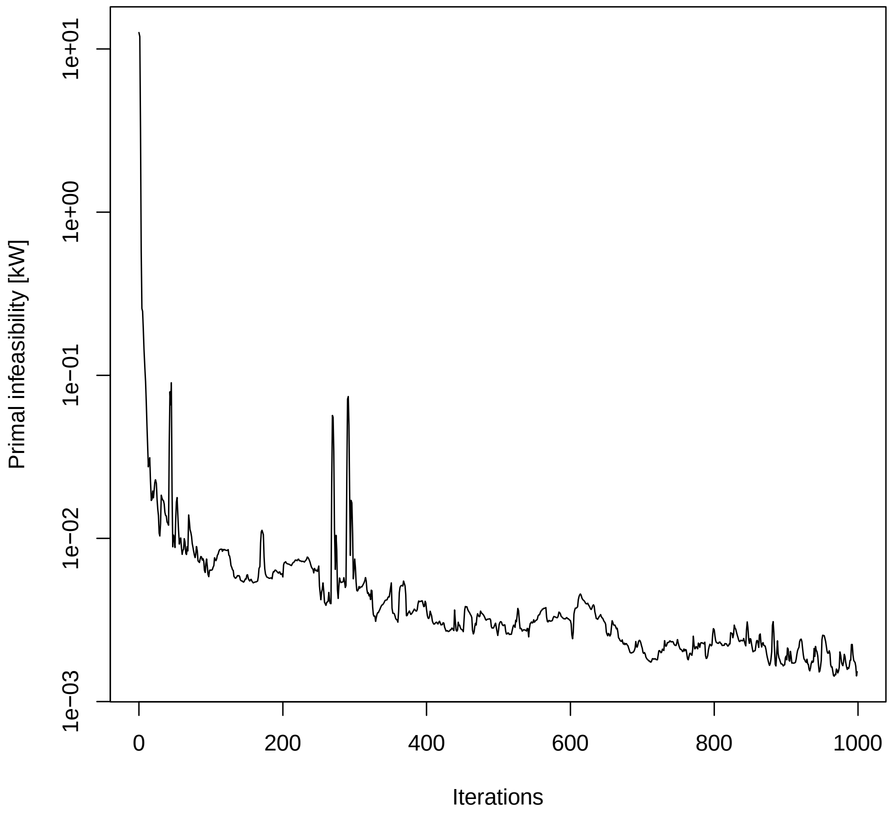
1 feeder, 5 meters, 25 stations, 306 EV

We are preparing a submission to IEEE Transactions on the Smart Grid

Tolerance (Termination Criterion) vs. Iteration II



2 feeders, 6 meters, 36 stations, 438 EV



4 feeders, 20 meters, 100 stations, 1,232 EV

We are preparing a submission to IEEE Transactions on the Smart Grid

Response to Previous Year Reviewers' Comments

- Scalability: Using HIL simulations to provide basis for larger software-only simulations; early results show scaling to limits allowed under CAISO tariff rules for spinning reserve. Will further investigate with more extensive HIL simulation.
- Practical Issues: We have extended the initial model to participate in demand response markets and for ancillary services. We will be working with data and grid topology maps from other projects within LLNL for co-simulation of grid and computation (ns3 + HELICS + GridLab-D).
- Partners: We have used RaspPi as intermediaries/stand-ins for EVSE, calibrated to the capabilities of a typical commercial EVSE. Following VTO suggestion to engage with hardware vendor (they have identified a candidate) using results of simulations to demonstrate initial feasibility. Have offer of testbed access with EVSE manufacturer.
- Alternatives to ADMM: We have not investigated alternatives to ADMM at this point, but the underlying Skynet platform will include additional optimization techniques in the future, which would allow us to do so.

Collaboration and Coordination with Other Institutions

- Charge interval data:
  - Subcontract in place with ChargePoint to purchase charge session data from Bay-Area counties. Purchase is on hold awaiting go-ahead from VTO.
  - Reached out to INL to obtain access to vehicle charging data from The EV Project; not available due to NDA with ChargePoint.

- Hardware prototyping and demonstration
  - Offer from EVSE manufacturer for testbed access (not a major charge network operator)
  - VTO will facilitate coordination with EVSE manufacturer for prototype

Remaining Challenges and Barriers

- Data sources: Our current simulations are based on synthetic demand, not historical charging session data. We are working with VTO to identify acceptable data sources.
- Access to EVSE partners: We are using the Raspberry Pis as proxies to allow us to run algorithms and interact with unmodified EVSE, and will show them to manufacturers as a proof-of-concept to encourage their participation.
- Co-simulation at scale: Integrating our computational framework with ns3 and GridLab-D through HELICS requires careful clock management. We are addressing this in concert with other LLNL projects integrating the same software for simulation, building on work from other DOE investments.
- COVID-19 shelter-in-place orders restrict access to physical hardware, but should be eased later in the year.

We have plans in place to overcome anticipated barriers working in concert with VTO and through technical advances in cooperation with other LLNL projects.

Proposed Future Research

Remainder of FY 2020

- Pairing RaspPi proxy with OpenEVSE for proof-of-concept
  – Open source, readily-available EVSE
- Incorporate fixed-schedule EV into model
  – Avoid repeatedly solving identical problem
- Incorporate client (EV) demand function (demand curve)
  – Increase system flexibility at lower cost
- More extensive simulations, including co-simulation with HELICS & ns3

FY 2021

- Pair RaspPi proxy with commercial EVSE
  – Based on demo of open source P.O.C.
- Expansion of ancillary service offerings.
- Co-simulation based on utility grid model at scale, including some hardware-in-the-loop w/P.O.C. (milestone)
- Technology transition to EVSE partner (milestone)

Any proposed future work is subject to change based on funding levels.

Summary

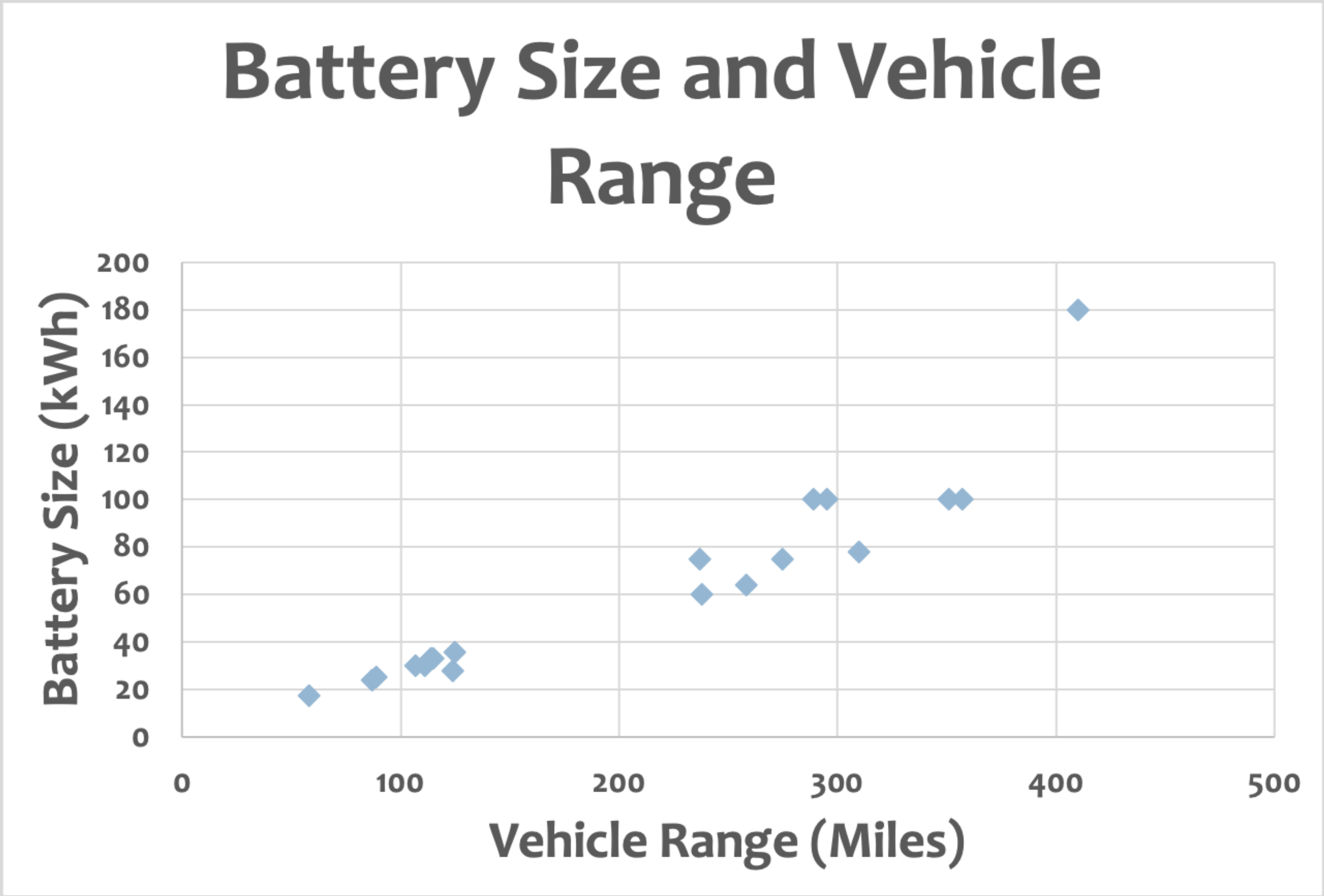
- Relevance
  - Anticipated growth in # of PEVs requires scalable charge management solutions for energy security
- Approach
  - Decentralized charge scheduling—no centralized control, increasing scale and robustness
  - Collaborative autonomy using charging stations as compute nodes
  - Testing, simulation, demonstration
- Technical Results
  - Demand response and ancillary services
  - Multiple competing parties (charging networks)
  - Implementation on Raspberry Pi for HIL simulation
  - Simulations using HPC scheduling for 1000s of vehicles
  - Paper to be submitted to IEEE Transactions on the Smart Grid
- Future Work
  - Co-simulation with HIL at scale
  - Integration of RaspPi proxy with EVSE (open source and closed)
  - Additional ancillary services
  - Enriched client (EV) behavior

Collaborative autonomy-based algorithms for managing demand response will enable scalable charging management while supporting ancillary services, ensuring grid reliability and improving resilience.

Any proposed future work is subject to change based on funding levels.

Technical Back-Up

Battery Size/Vehicle Range for EVs for Sale in USA



Interestingly, the plot is roughly the same with the X axis being the year a vehicle was introduced.

Optimal charging station subproblem

$$(\cdot, y_i^{k+1}) = \arg\min_{x_i, y_i} \; \langle c_i, x_i \rangle + \langle \gamma_i^k + \delta_i^k - \rho(u_i^k + v_i^k), y_i \rangle + \rho \|y_i\|_2^2$$
$$\text{s.t.} \quad (x_i, y_i) \in \Omega_i$$

- Optimize charge schedule for all vehicles at station *i* with current multipliers
- Quadratic problem subject to linear inequality constraints -> solve using Ipopt at every iteration

Meter peak load subproblem

$$
\begin{aligned}
(\cdot, \beta^{\dagger}) = \;& \arg\min_{z,\beta} \; z \\
& \text{s.t.} \quad z\,1_{T\times 1} \geq \nu - \frac{N}{\rho}\beta \\
& \qquad \langle \beta, 1_{T\times 1} \rangle = p, \;\; \beta \geq 0
\end{aligned}
$$

- Determines β, which is necessary to perform update to account for peak power
- Linear program, $\boldsymbol{O(n^{2+1/6})}$
- Developed and implemented greedy algorithm, $\boldsymbol{O(n \log(n))}$
  (n is number of periods)