Smart EV Charging

GRID | Eric Sortomme

ALSTOM

Outline

- Introduction
- Electric Vehicle Charging Issues
- Intelligent Charge Control Technologies
- Smart Charging on Distribution Systems
- Vehicle-to-Grid Optimization

GRID | ALSTOM

Introduction

Why Electric Vehicles (EVs)?
  - Energy
  - Reduce
  - Lots of f

“We can brea d become the first countr ehicles on the road by 20
  - Presider

EVs in the U
  - 1500 Tesla Roadsters
  - 11000 Nissan LEAFs
  - 9000 Chevy Volts (PHEV)

GRID | ALSTOM

Introduction

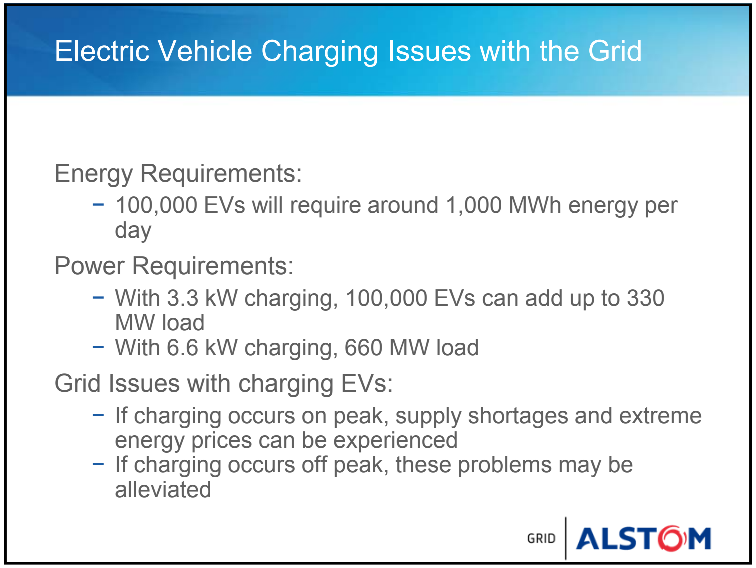
Additional EVs for sale in the US in 2012
  - Mitsubishi MiEV
  - Ford Focus EV
  - Tesla Model S
  - Toyota Rav4 EV
  - Honda Fit EV

Potential for tens of thousands of EVs sold in 2012
  - Hundreds of thousands of EVs at least by 2015

This will require hundreds of additional MWh per day

This can add hundreds of MW of load

GRID | ALSTOM



Electric Vehicle Charging Issues with the Grid

Energy Requirements:

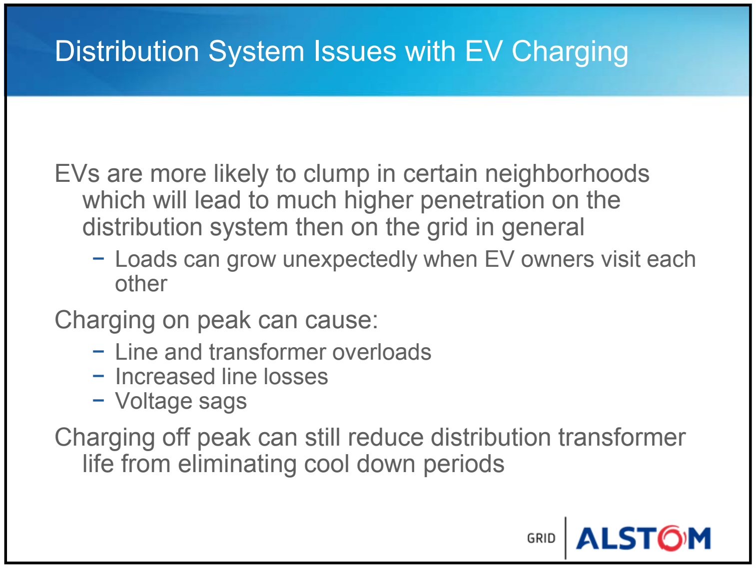
- 100,000 EVs will require around 1,000 MWh energy per day

Power Requirements:

- With 3.3 kW charging, 100,000 EVs can add up to 330 MW load
- With 6.6 kW charging, 660 MW load

Grid Issues with charging EVs:

- If charging occurs on peak, supply shortages and extreme energy prices can be experienced
- If charging occurs off peak, these problems may be alleviated



Distribution System Issues with EV Charging

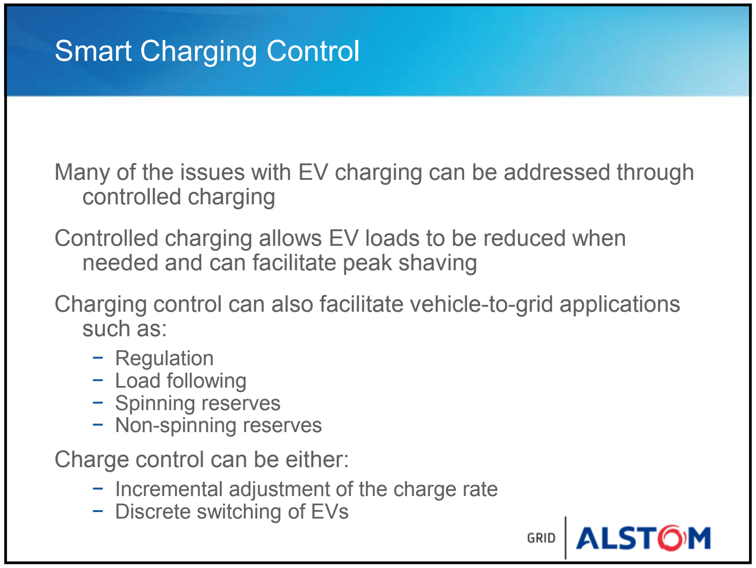
EVs are more likely to clump in certain neighborhoods which will lead to much higher penetration on the distribution system then on the grid in general

- Loads can grow unexpectedly when EV owners visit each other

Charging on peak can cause:

- Line and transformer overloads
- Increased line losses
- Voltage sags

Charging off peak can still reduce distribution transformer life from eliminating cool down periods



Smart Charging Control

Many of the issues with EV charging can be addressed through controlled charging

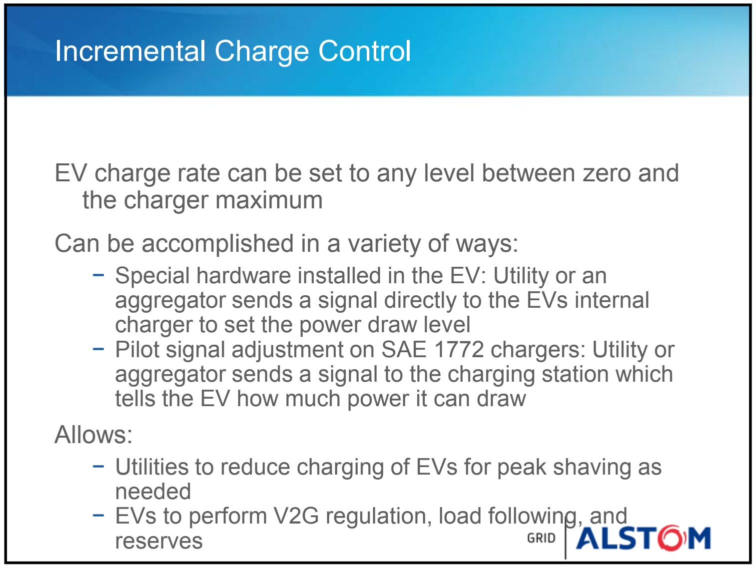
Controlled charging allows EV loads to be reduced when needed and can facilitate peak shaving

Charging control can also facilitate vehicle-to-grid applications such as:

- Regulation
- Load following
- Spinning reserves
- Non-spinning reserves

Charge control can be either:

- Incremental adjustment of the charge rate
- Discrete switching of EVs



Incremental Charge Control

EV charge rate can be set to any level between zero and the charger maximum

Can be accomplished in a variety of ways:

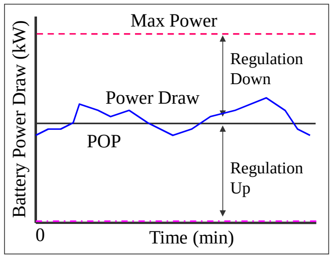
- Special hardware installed in the EV: Utility or an aggregator sends a signal directly to the EVs internal charger to set the power draw level
- Pilot signal adjustment on SAE 1772 chargers: Utility or aggregator sends a signal to the charging station which tells the EV how much power it can draw

Allows:

- Utilities to reduce charging of EVs for peak shaving as needed
- EVs to perform V2G regulation, load following, and reserves

V2G Through Incremental Charge Rate Adjustment

- Involves adjusting the charge rate around a fixed scheduled rate called the Preferred Operating Point (POP)
- Can perform regulation up and reserves by decreasing from the POP
- Can perform regulation down and reserves by increasing above the POP

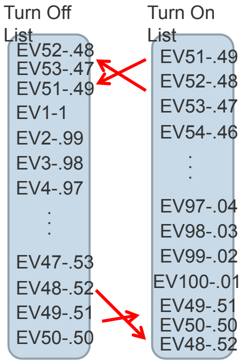


V2G Using Discrete Switching of EVs

- Involves switching EVs on and off to make the aggregate EV charge rate match the regulation signal but with discrete switching of EVs rather than incremental adjustment
- For each scheduling period, each EV is assigned a target percentage of the total aggregator energy dispatched during that period
  - This is based on the EVs schedule using V2G optimization algorithms
  - Gives each EV a priority level
- The EVs are then divided into two lists based on priority:
  - **Turn Off List:** This list is for the EVs with the highest priority. They start the period turned on to meet the POP. When regulation up is needed the EV with at the bottom of the list is turned off and added to the bottom of the Turn On List
  - **Turn On List:** This list is for EVs with lower priorities. They are initially off. When regulation down is needed, the EV at the top of the list is turned on and added to the top of the Turn Off List
- After a specified number of periods, the priorities are recalculated and the lists reformed

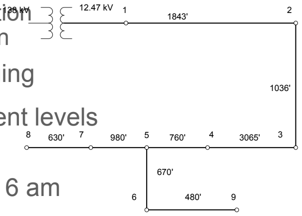
Visualization with A Group of 100 EVs

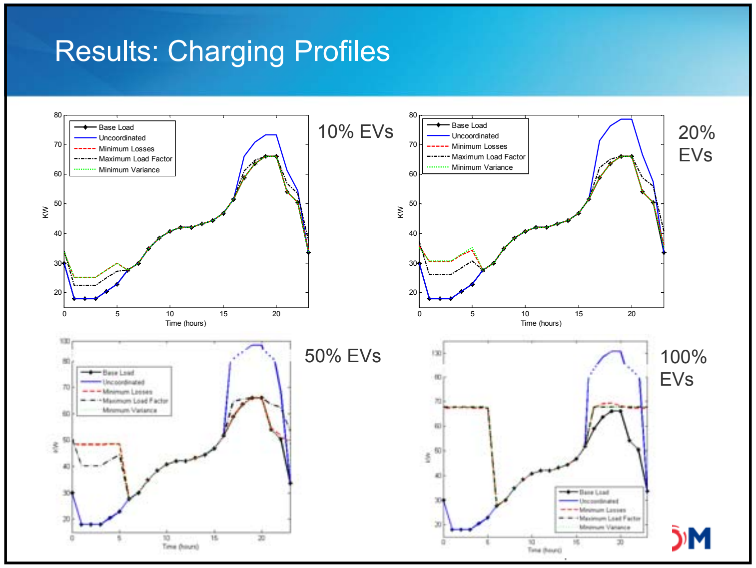
- Lists are populated based on priority
- A regulation up dispatch signal is received that requires two EVs to turn off
- A regulation up dispatch signal is received that requires 1 EV to turn off
- A regulation down dispatch signal is received that requires 1 EV to turn on
- A regulation down dispatch signal is received that requires two EVs to turn on



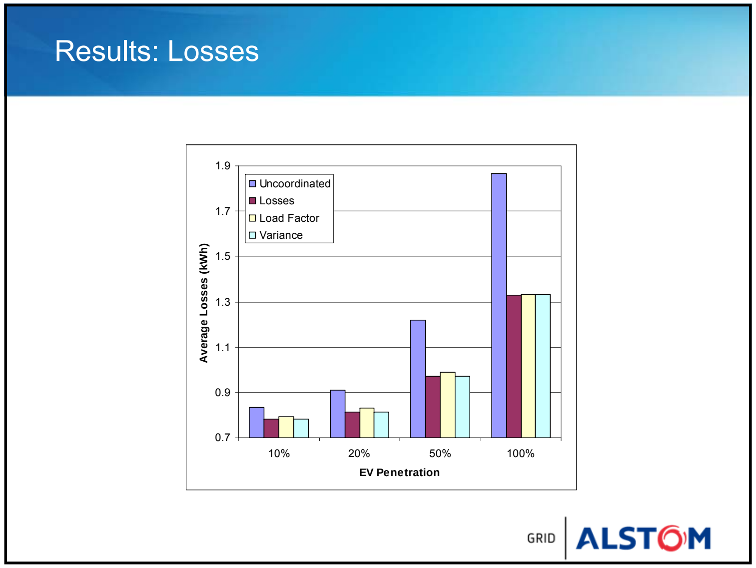
Case Study: Smart Charging to Flatten Distribution Load Profile and Minimize Losses Using Incremental Charge Adjustment

- Looks at charge control with the objectives of:
  - Feeder loss minimization
  - Feeder load variance minimization
  - Feeder load factor maximization
- Compares with uncontrolled charging
- Uses a nine bus feeder with different levels of PHEV penetration
- PHEVs charge between 6 pm and 6 am
- Each PHEV charges 10 kWh at 1.8 kW

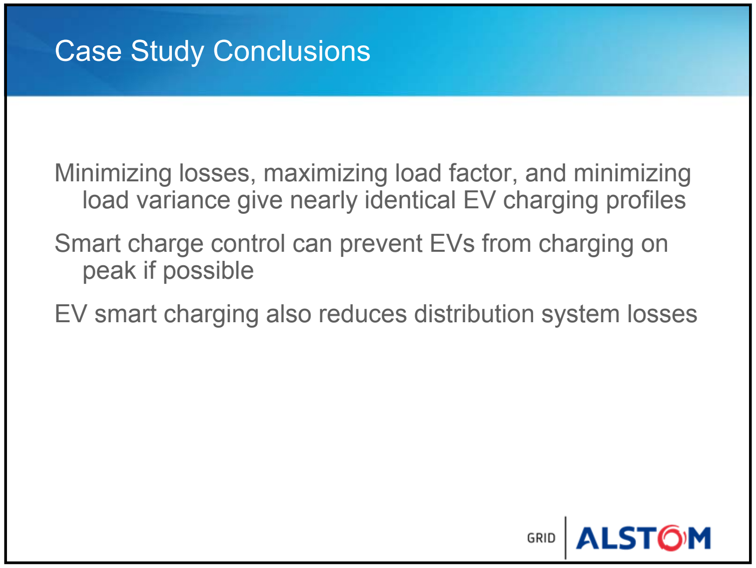




Results: Charging Profiles



Results: Losses

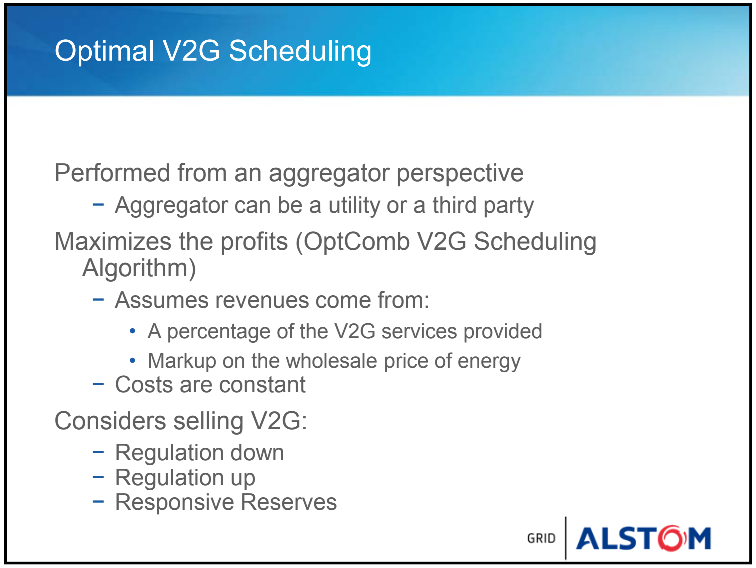


Case Study Conclusions

Minimizing losses, maximizing load factor, and minimizing load variance give nearly identical EV charging profiles

Smart charge control can prevent EVs from charging on peak if possible

EV smart charging also reduces distribution system losses



Optimal V2G Scheduling

Performed from an aggregator perspective
- Aggregator can be a utility or a third party

Maximizes the profits (OptComb V2G Scheduling Algorithm)
- Assumes revenues come from:
  - A percentage of the V2G services provided
  - Markup on the wholesale price of energy
- Costs are constant

Considers selling V2G:
- Regulation down
- Regulation up
- Responsive Reserves

V2G Optimization Constraints

- Charger limits
  - Set either by the maximum charge rate of the internal charger or the maximum rate of the charging station
- Battery capacity limits
  - Cannot charge beyond a 90% SOC limit for battery life
  - Often set by OEMs
- EV availability constraints
  - Forecasted transport profiles with associated probabilities
  - Uses the expected values of available EVs
  - EVs can leave unexpectedly and must be compensated
- Ancillary service constraints
  - Regulation up and responsive reserve capacity cannot be greater than the POP
  - POP and all capacities must be greater than zero
- System Constraints
  - System load constraint: Maximum POP inversely proportional to the system forecasted load (OptLoad Algorithm)
  - Real time price constraint: Maximum POP inversely proportional to the system forecasted price (OptPrice Algorithm)

Obligatory Equations

$$\underset{POP_i(t),MxAP_i(t),MnAP_i(t),RsRP_i(t)}{\text{maximize}} \quad In - C$$

subject to:

$$\sum_{t=1}^{T_{trip,i}} \left(E(FP_i(t))Comp_i(t)\right)Ef_i + SOC_{I,i} \le M_{Ci}$$

$$\sum_{t} \left(E(FP_i(t))Comp_i(t)\right)Ef_i + SOC_{I,i} - Trip_i \le M_{Ci}$$

$$(MxAP_i(1) + POP_i(1))Comp_i(1)Ef_i + SOC_{I,i} \le M_{Ci}$$

$$MnAP_i(t) \le POP_i(t)$$

$$RsRP_i(t) \le POP_i(t) - MnAP_i(t)$$

$$\left(MxAP_i(t) + POP_i(t)\right)Comp_i(t) \le MP_i(t)$$

$$MxAP_i(t) \ge 0$$

$$MnAP_i(t) \ge 0$$

$$RsRP_i(t) \ge 0$$

$$POP_i(t) \ge 0$$

Where:

In is the income of the aggregator

C is aggregator costs

Mk is aggregator markup over wholesale energy price

α is the percentage of regulation revenue taken by the aggregator

$SOC_{I,i}$ is the initial state of charge of the i^{th} EV

$P_{RU}(t)$ is the forecasted price of regulation up for time *t*

$P_{RD}(t)$ is the forecasted price of regulation down for time *t*

Comp

Support Equations

$$In = \alpha \sum_{t} \left(\left(P_{RU}(t)R_U(t) + P_{RD}(t)R_D(t) + P_{RR}(t)R_R(t)\right) \cdot EVPer(t)\right)$$
$$+Mk \sum_{i} \sum_{t} \left(E(FP_i(t)) \cdot EVPer(t)\right)$$

$$R_U(t) = \sum_{i=1}^{cars} MnAP_i(t)$$

$$R_D(t) = \sum_{i=1}^{cars} MxAP_i(t)$$

$$R_R(t) = \sum_{i=1}^{cars} RsRP_i(t)$$

$$Comp_i(t) = 1 + \frac{Dep_i(t)}{1 - Dep_i(t)}$$

$$Ex_D = \frac{\int_{RS_{\min}}^{0} RS \cdot \Pr(RS) \cdot dRS}{\int_{RS_{\min}}^{0} RS \cdot dRS}$$

$$Ex_U = \frac{\int_{0}^{RS_{\max}} RS \cdot \Pr(RS) \cdot dRS}{\int_{0}^{RS_{\max}} RS \cdot dRS}$$

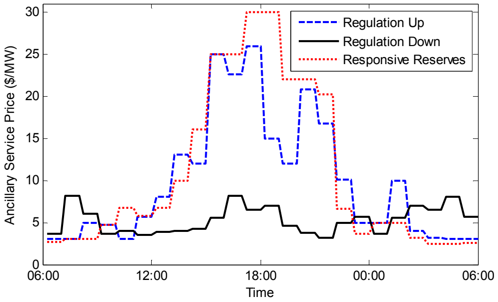
$$Ex_R = \frac{\int_{0}^{RRS_{\max}} RRS \cdot \Pr(RRS) \cdot dRRS}{\int_{0}^{RRS_{\max}} RRS \cdot dRRS}$$

$$E(FP_i(t)) = MxAP_i(t)Ex_D + POP_i(t) - MnAP_i(t)Ex_U - RsRP_i(t)Ex_R$$

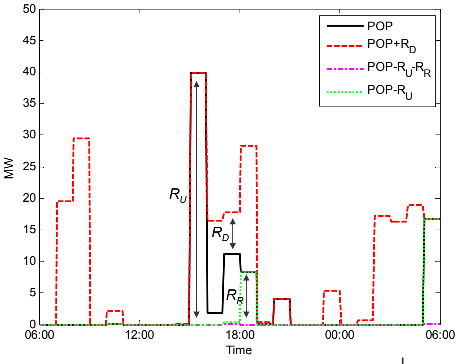
Case Study: V2G Optimization in Houston, TX

- Compared the optimal V2G scheduling algorithms over a from July 20, 2010 to October 21, 2010
  - Aggregator receives 20% of ancillary services revenues and 0.01$/kWh over the price of energy
- Considers 24 hour scheduling of EV charging based on most probable driving profiles
- Uses ERCOT market and system data
- Driving distances taken from National Highway Travel Survey
  - Hypothetical Group of 10000 EVs
    - 500 Tesla Roadsters
    - 2000 Th!nk Citys
    - 2500 Mitsubishi i-MiEVs
    - 2000 BMW Mini-Es
    - 3000 Nissan Leafs

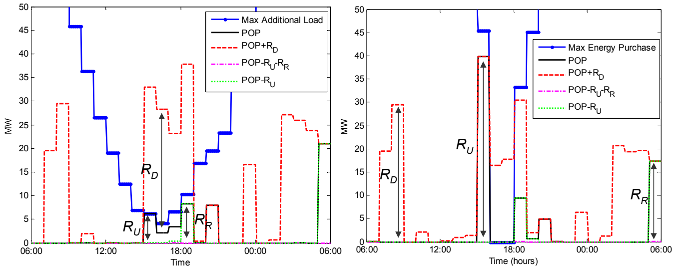
Examining August 2, 2010



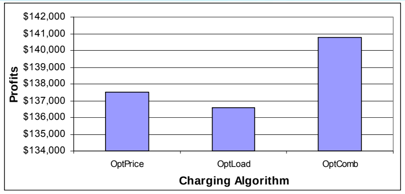
Profile Results OptComb

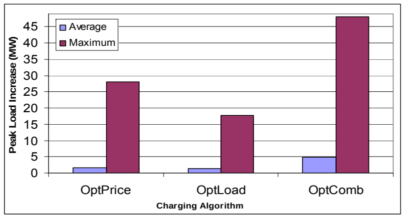


Profile Results OptLoad and OptPrice

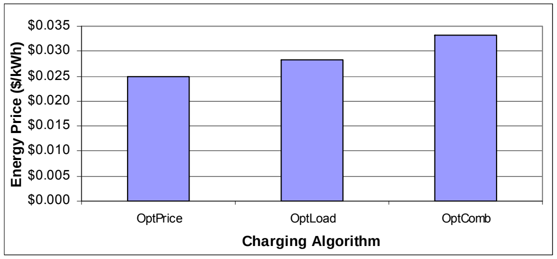


Quarterly Results





Customer Costs



Communication Signals

Dispatch Algorithm	Avg. Signals Per Car Per Hour
Incremental Dispatch	188
Single Dispatch List Recalculation	52
Fifth Dispatch List Recalculation	12

Case Study Conclusions

V2G can provide significant regulation and reserves capacities

V2G generates valuable revenues for both customers and the aggregators

Customers can also receive significant benefits which gives an incentive to participate in V2G programs

Discrete dispatch reduces the communication burden by over 90%

V2G On Constrained Distribution Systems

The optimization algorithms to not consider distribution system impacts

These can be included through a feeder specific load factor constraint

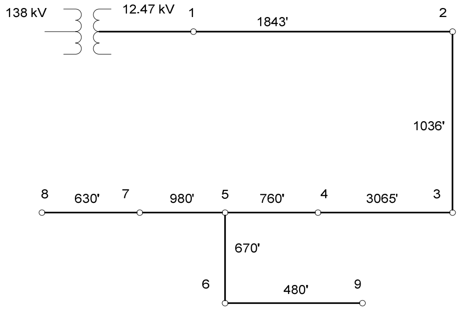
This load factor constraint can then be developed to integrate into the optimal V2G formulation

- Keeps load factor above a certain desirable level while performing V2G
- Gives the OptFeeder Scheduling Algorithm

Case Study: V2G on Constrained Distribution Feeders

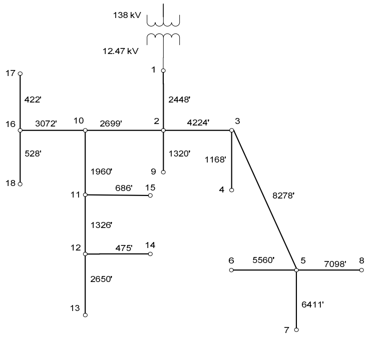
- Same EV group on the ERCOT system
  - 130 day period
- EVs distributed on 50 test feeders with a penetration level of 50%
  - Three types of feeders
- Compares the four algorithms for
  - Feeder voltages, losses, and overloads

Feeder Type 1



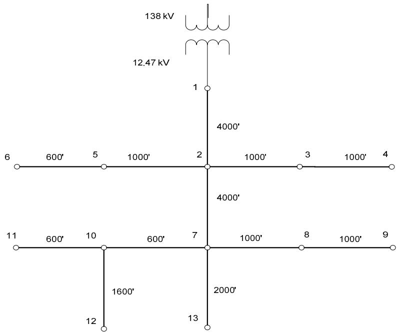
There are 10 systems of this type. Load buses are 2-9.

Feeder Type 2

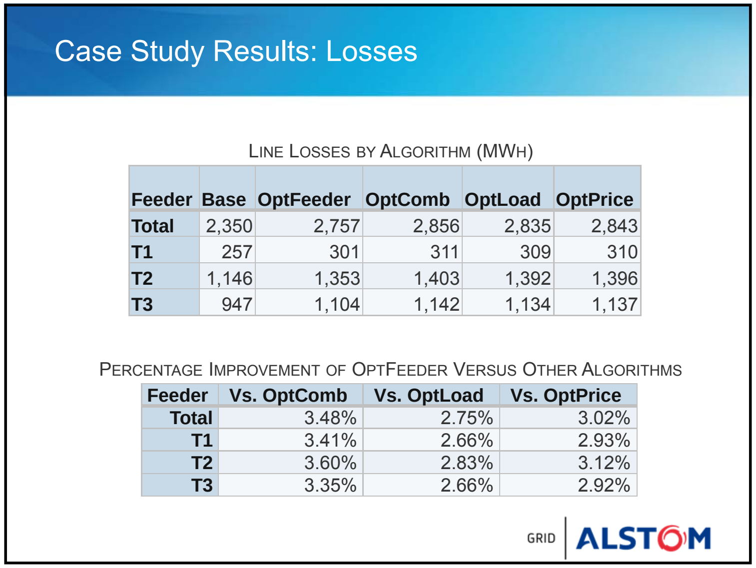


There are 20 systems of this type. Load buses are 2-18.

Feeder Type 3



There are 20 systems of this type. Load buses are 2-13.



Case Study Results: Losses

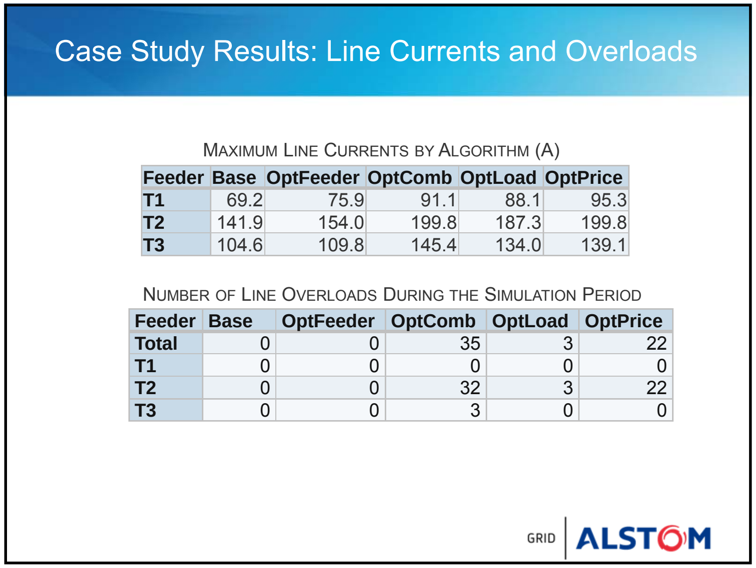
LINE LOSSES BY ALGORITHM (MWH)

Feeder	Base	OptFeeder	OptComb	OptLoad	OptPrice
Total	2,350	2,757	2,856	2,835	2,843
T1	257	301	311	309	310
T2	1,146	1,353	1,403	1,392	1,396
T3	947	1,104	1,142	1,134	1,137

PERCENTAGE IMPROVEMENT OF OPTFEEDER VERSUS OTHER ALGORITHMS

Feeder	Vs. OptComb	Vs. OptLoad	Vs. OptPrice
Total	3.48%	2.75%	3.02%
T1	3.41%	2.66%	2.93%
T2	3.60%	2.83%	3.12%
T3	3.35%	2.66%	2.92%

GRID ALSTOM



Case Study Results: Line Currents and Overloads

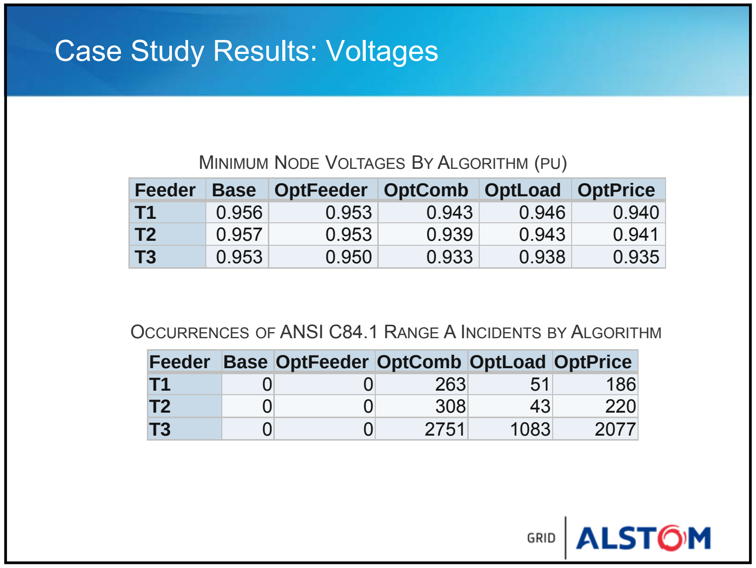
MAXIMUM LINE CURRENTS BY ALGORITHM (A)

Feeder	Base	OptFeeder	OptComb	OptLoad	OptPrice
T1	69.2	75.9	91.1	88.1	95.3
T2	141.9	154.0	199.8	187.3	199.8
T3	104.6	109.8	145.4	134.0	139.1

NUMBER OF LINE OVERLOADS DURING THE SIMULATION PERIOD

Feeder	Base	OptFeeder	OptComb	OptLoad	OptPrice
Total	0	0	35	3	22
T1	0	0	0	0	0
T2	0	0	32	3	22
T3	0	0	3	0	0

GRID ALSTOM



Case Study Results: Voltages

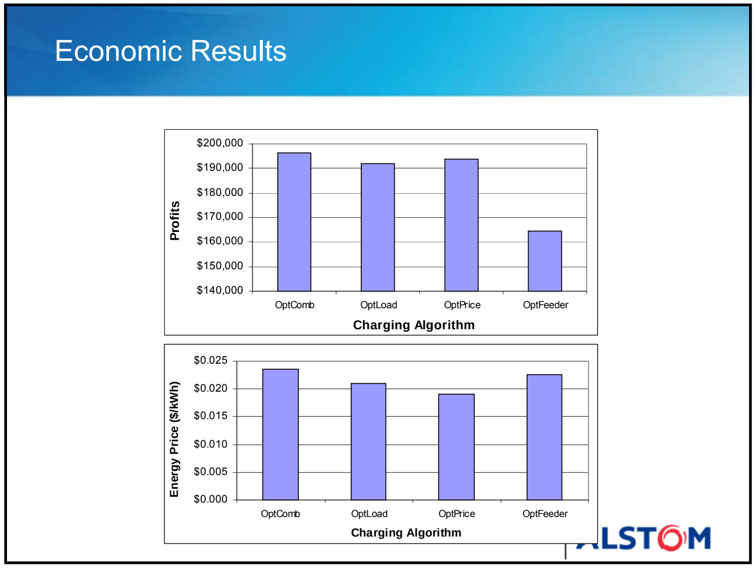
MINIMUM NODE VOLTAGES BY ALGORITHM (PU)

Feeder	Base	OptFeeder	OptComb	OptLoad	OptPrice
T1	0.956	0.953	0.943	0.946	0.940
T2	0.957	0.953	0.939	0.943	0.941
T3	0.953	0.950	0.933	0.938	0.935

OCCURRENCES OF ANSI C84.1 RANGE A INCIDENTS BY ALGORITHM

Feeder	Base	OptFeeder	OptComb	OptLoad	OptPrice
T1	0	0	263	51	186
T2	0	0	308	43	220
T3	0	0	2751	1083	2077

GRID ALSTOM



Economic Results

Case Study Conclusions

Feeder load factor constraint:
  - Eliminates overloads
  - Eliminates voltage sags
  - Reduces losses

The total revenues and profits are reduced

Final Conclusions

Controlled charging can be implemented in many different ways

Smart charging of EVs can shift peaks and extend equipment life

V2G can be implemented with minimal infrastructure while providing significant benefits to customers and utilities even when the distribution system is constrained

Thank you.

Questions?