Energy Management Systems for Microgrids

Claudio Cañizares
Department of Electrical & Computer Engineering
Power & Energy Systems (www.power.uwaterloo.ca)
WISE (www.wise.uwaterloo.ca)

With content and slides from Dr. Daniel Olivares, former MASc student Jose Daniel Lara, Dr. Mehrdad Pirnia and PhD student Bharat Solanki.

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Outline

- Kasabonika Lake First Nation (KLFN) community microgrid data collection
- Energy Management Systems (EMS) overview
- EMS models:
  - Deterministic
  - Uncertainty management:
    - Stochastic programming
    - Robust optimization
    - Affine arithmetic
- Conclusions

Acknowledgements

NSERC SMART MICROGRID NETWORK nsmg-net

HATCH

NSERC CRSNG

Natural Resources Canada / Ressources naturelles Canada

Canada

hydro one

KASABONIKA LAKE FIRST NATION

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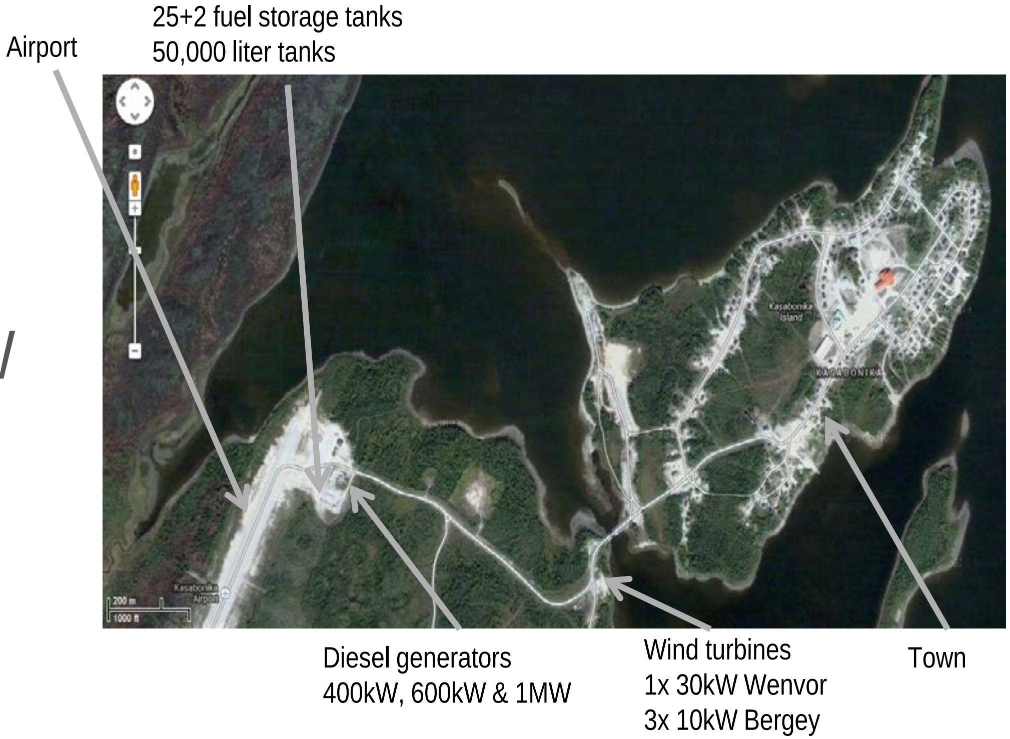
KLFN Microgrid Data Collection

Kasabonika
Lake

KLFN Microgrid Data Collection

- Community:
  - Approximately 900 people.
  - 500 km north of Thunder Bay.
  - Winter-road access.
- Electricity generation:
  - 0.4 MW, 0.6MW, and 1 MW diesel generator in operation.
  - 1.6 MW diesel generator planned.
  - 3x 10 kW Bergey WTs.
  - 1x 30 kW Wenvor WT.
  - 10 kW solar PV array.



KLFN Microgrid Data Collection

Local grid dataloggers:

1. Diesel generator plant.
2. 3x Bergey WTs.
3. Store.
4. Water treatment plant.

Dent meters:

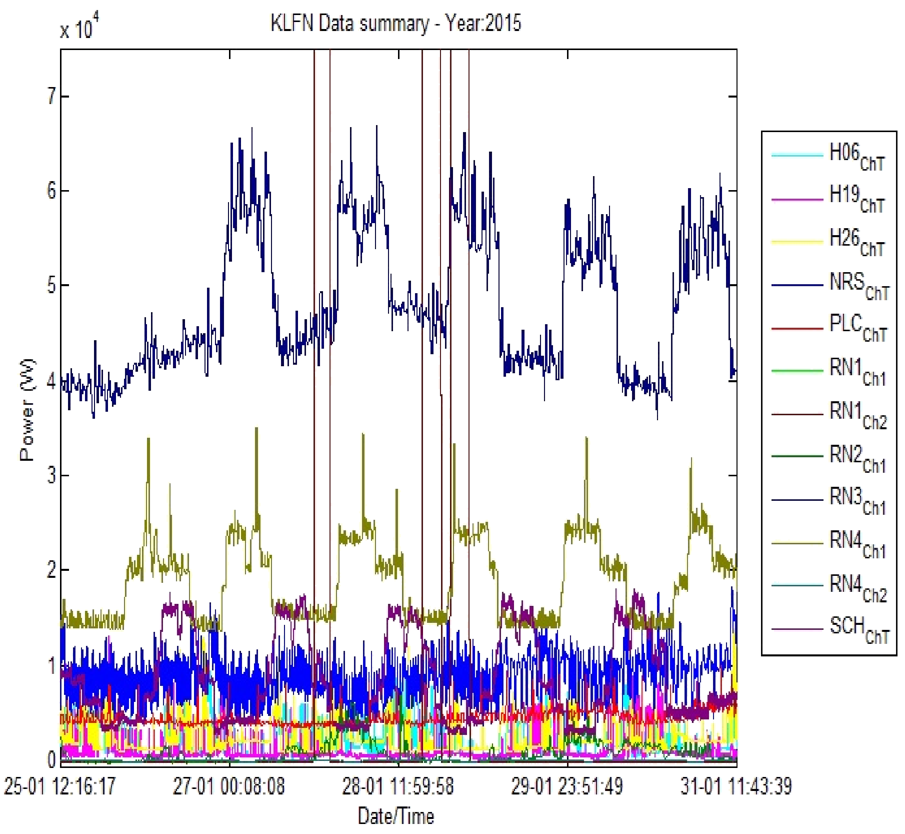
5. Sewage plant.
6. School.
7. Police station.
8. Nursing station.
9. Wenvor WT.

Laptop dataloggers:

10. 13 Houses across the community.

KLFN Microgrid Data Collection

- Data summary:
  - Dataloggers collected information for approximately one year.
  - Some information missing but a representative sample for all locations has been collected.



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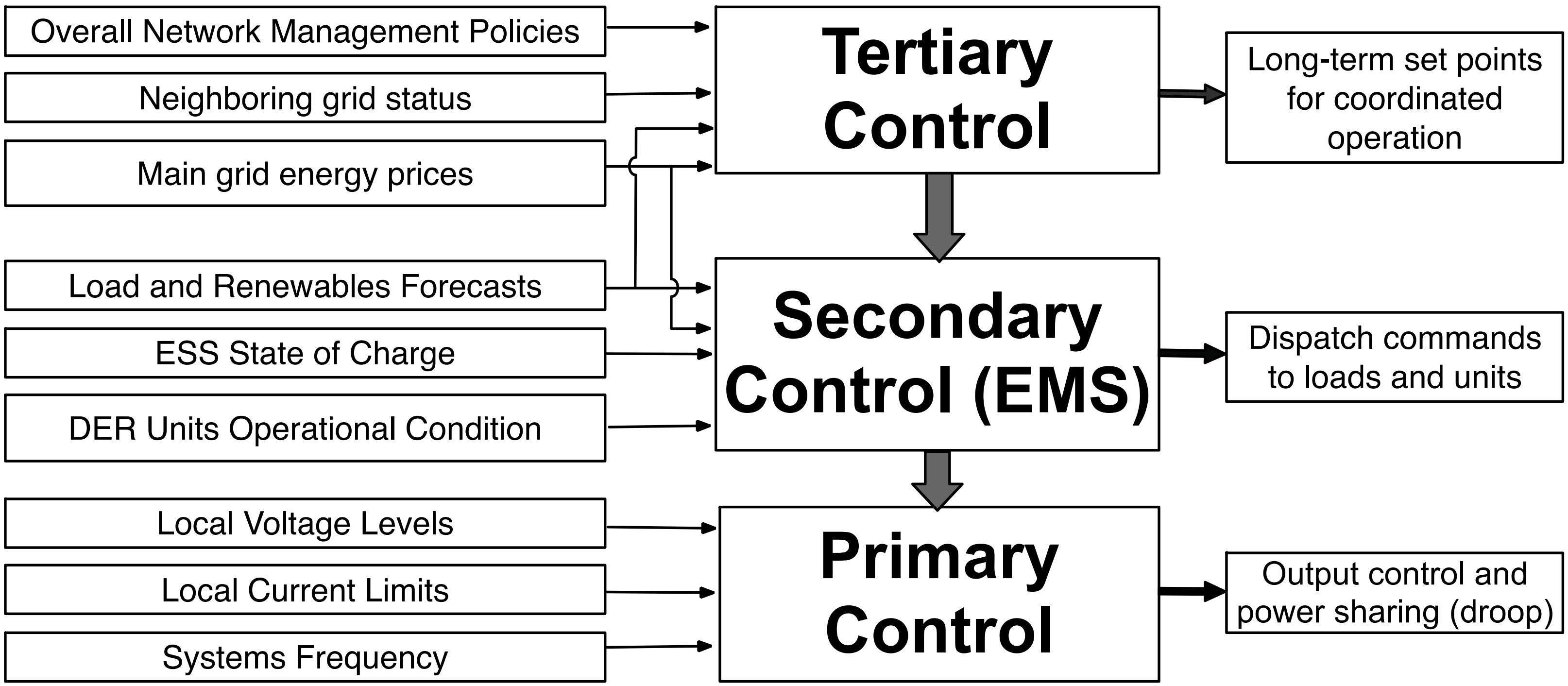
KLFN Microgrid Data Collection

Diesel generator plant RN1 Channel 1 - Lower load Timeframe: Jun/14 - Oct/14		Percetile													
		50th	1st		5th		25th		75th		95th		99th		
Description	Units	Value	Value	% w.r.t. 50th per.	Value	% w.r.t. 50th per.	Value	% w.r.t. 50th per.	Value	% w.r.t. 50th per.	Value	% w.r.t. 50th per.	Value	% w.r.t. 50th per.
Active Power_A+B+C	kW	458.41	206.32	-55.0%	231.29	-49.5%	327.44	-28.6%	527.86	15.1%	622.19	35.7%	678.74	48.1%
Reactive Power_A+B+C	kVAR	78.69	36.34	-53.8%	43.59	-44.6%	56.42	-28.3%	91.87	16.8%	105.38	33.9%	115.17	46.4%
Voltage_A_RMS	V	605.09	598.09	-1.2%	599.96	-0.8%	602.76	-0.4%	607.48	0.4%	611.87	1.1%	620.35	2.5%
Voltage_B_RMS	V	600.01	593.97	-1.0%	596.18	-0.6%	598.44	-0.3%	601.88	0.3%	605.84	1.0%	614.22	2.4%
Voltage_C_RMS	V	593.58	587.05	-1.1%	588.31	-0.9%	591.48	-0.4%	596.43	0.5%	599.41	1.0%	603.06	1.6%
Frequency_A	Hz	60.06	59.94	-0.2%	59.97	-0.1%	60.01	-0.1%	60.09	0.1%	60.12	0.1%	60.15	0.1%
Total power factor	-	0.99	0.97	-1.1%	0.98	-0.7%	0.98	-0.3%	0.99	0.2%	0.99	0.5%	0.99	0.6%
Current A RMS	A	172.50	71.86	-58.3%	84.64	-50.9%	128.19	-25.7%	213.44	23.7%	290.10	68.2%	333.92	93.6%
Current B RMS	A	333.07	147.19	-55.8%	172.97	-48.1%	235.89	-29.2%	387.92	16.5%	453.70	36.2%	501.62	50.6%
Current C RMS	A	247.14	109.47	-55.7%	127.18	-48.5%	181.32	-26.6%	298.45	20.8%	369.60	49.6%	409.64	65.8%
Voltage Imbalance (neg seq)	V	1.58	0.75	-52.8%	0.88	-44.1%	1.20	-24.2%	2.03	28.7%	2.65	67.7%	3.15	99.5%
Voltage Imbalance (zero seq)	V	0.00	0.00	-76.3%	0.00	-59.4%	0.00	-31.2%	0.00	15.7%	0.00	44.5%	0.00	51.9%
Current Imbalance (neg seq)	A	18.70	3.56	-81.0%	5.98	-68.0%	12.35	-34.0%	22.39	19.7%	26.97	44.2%	30.26	61.8%
Current Imbalance (zero seq)	A	20.74	5.88	-71.6%	7.79	-62.4%	13.86	-33.2%	24.54	18.3%	29.36	41.6%	32.96	58.9%
Voltage_A_FFT_THD	-	1.74	1.14	-34.5%	1.31	-24.4%	1.50	-13.7%	2.07	19.1%	3.02	73.8%	3.28	88.6%
Voltage_B_FFT_THD	-	1.75	1.11	-36.5%	1.28	-27.2%	1.47	-16.0%	2.05	17.2%	2.73	55.9%	2.94	67.5%
Voltage_C_FFT_THD	-	1.40	0.94	-32.5%	1.09	-22.0%	1.27	-9.0%	1.60	14.5%	2.50	78.4%	2.77	98.1%
Current_A_FFT_THD	-	7.49	4.46	-40.5%	5.11	-31.7%	6.31	-15.7%	9.19	22.7%	11.55	54.3%	12.96	73.1%
Current_B_FFT_THD	-	5.63	3.06	-45.7%	3.66	-35.0%	4.65	-17.4%	6.97	23.7%	9.07	61.1%	10.33	83.5%
Current_C_FFT_THD	-	5.25	3.10	-40.9%	3.54	-32.6%	4.44	-15.3%	6.12	16.5%	7.37	40.5%	8.38	59.8%

Energy Management Systems (EMS) Overview

- IEEE PES TF in Microgrid Control, "Trends in Microgrid Control," *IEEE Transactions on Smart Grid*, vol. 6, no. 4, July 2014, pp. 1905-1919:



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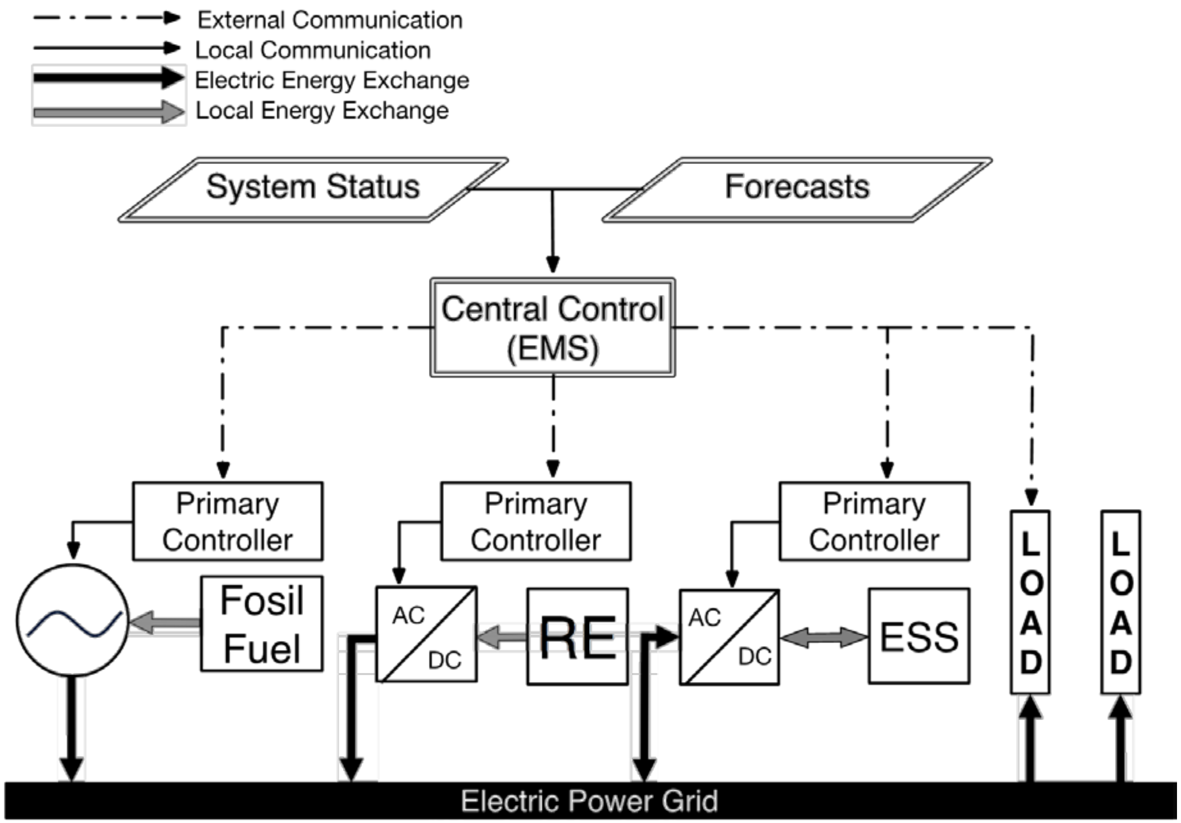
EMS Overview



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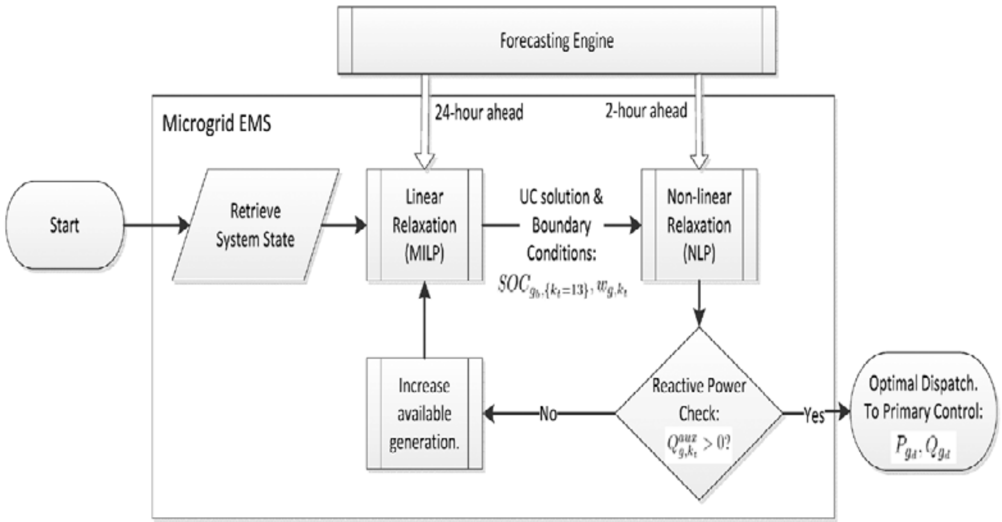
EMS Overview

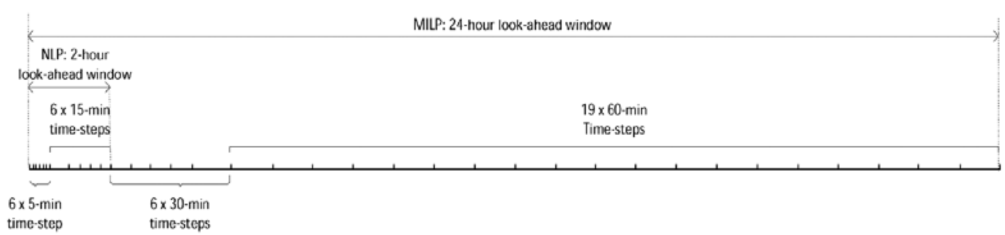
- EMS objectives:
  - Find the optimal or near optimal unit commitment of units.
  - Find the optimal or near optimal dispatch of units.
  - Find the optimal or near optimal voltage settings.
- Challenges for EMS in microgrids:
  - Intermittent and hard to predict generation.
  - System states are coupled in time due to Unit Commitment (UC) decisions and Energy Storage Systems (ESS).
  - Multiple objectives (e.g. total cost, GHG emissions)
  - Multiple owners and sometimes conflicting objectives.

EMS Deterministic Model

- D. Olivares, C. A. Cañizares, and M. Kazerani, “A Centralized Energy Management System for Isolated Microgrids,” IEEE Transactions on Smart Grid, vol. 6, no. 4, July 2014, pp. 1864-1875:
  - Objective:
    - Minimize fuel, start-up and shut-down costs, plus load shedding high costs if an option (simple DSM program).
  - Constraints:
    - Network equations using *abc* impedance matrix models for lines/cables plus KVL and KCL equations, with network current and voltage limits.
    - ZI load models per-phase.
    - Synchronous and induction generator models based on *dq0* steady state representation.
    - DER with VSC interface modeled as current injection model with limits and losses.
    - Energy storage models based on using a simplified book-keeping model for the State-Of-Charge (SOC), plus hydrogen-tank constraints for hydrogen storage.
    - Minimum up- and down-times, ram-up and -down limits, and a reserve constraint.
  - A Model Predictive Control (MPC) approach is used.

EMS Deterministic Model I





- Decoupled approach:
  - UC and Economic Load Dispatch (ELD) performed with different update rates.
  - Two different resolutions and horizons of forecast.
  - Multi-stage ELD to optimize ESS operation.
  - Delivers UC decisions and operating points to DERs (power output of DG, output/input of ESS, shiftable/shedable loads commands, etc.).
  - Detailed 3-phase model to represent unbalanced conditions typical of microgrids (distribution networks).

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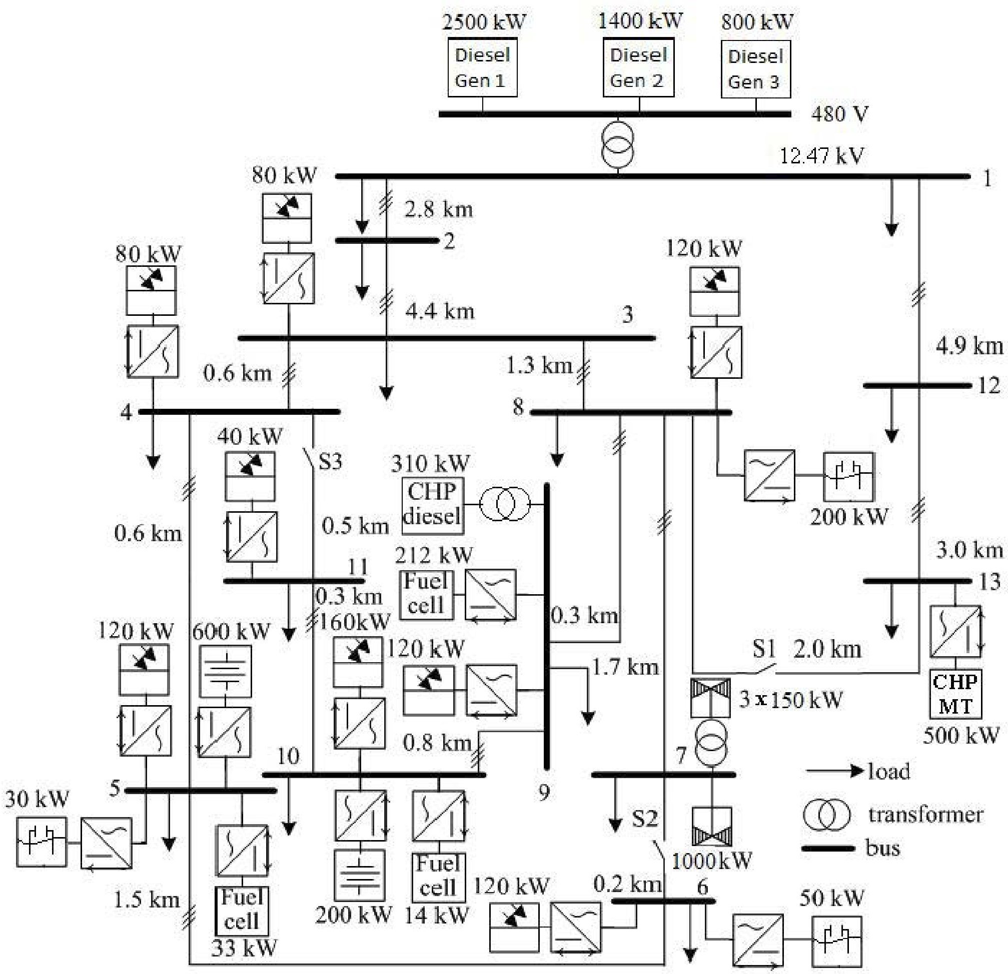
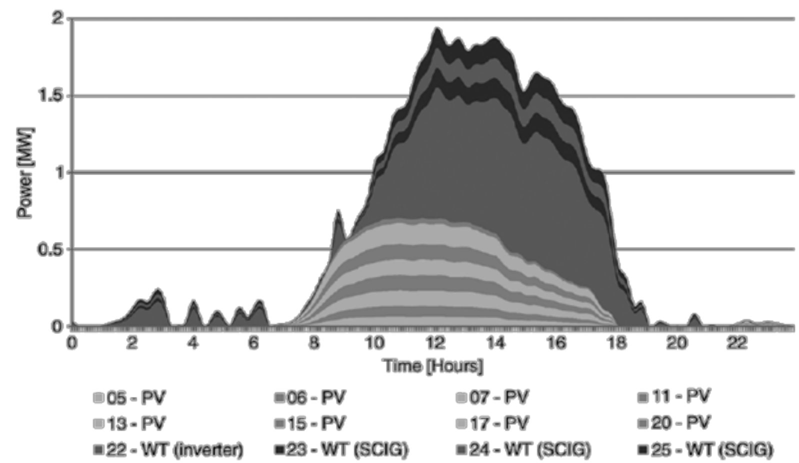
EMS Deterministic Model I Example





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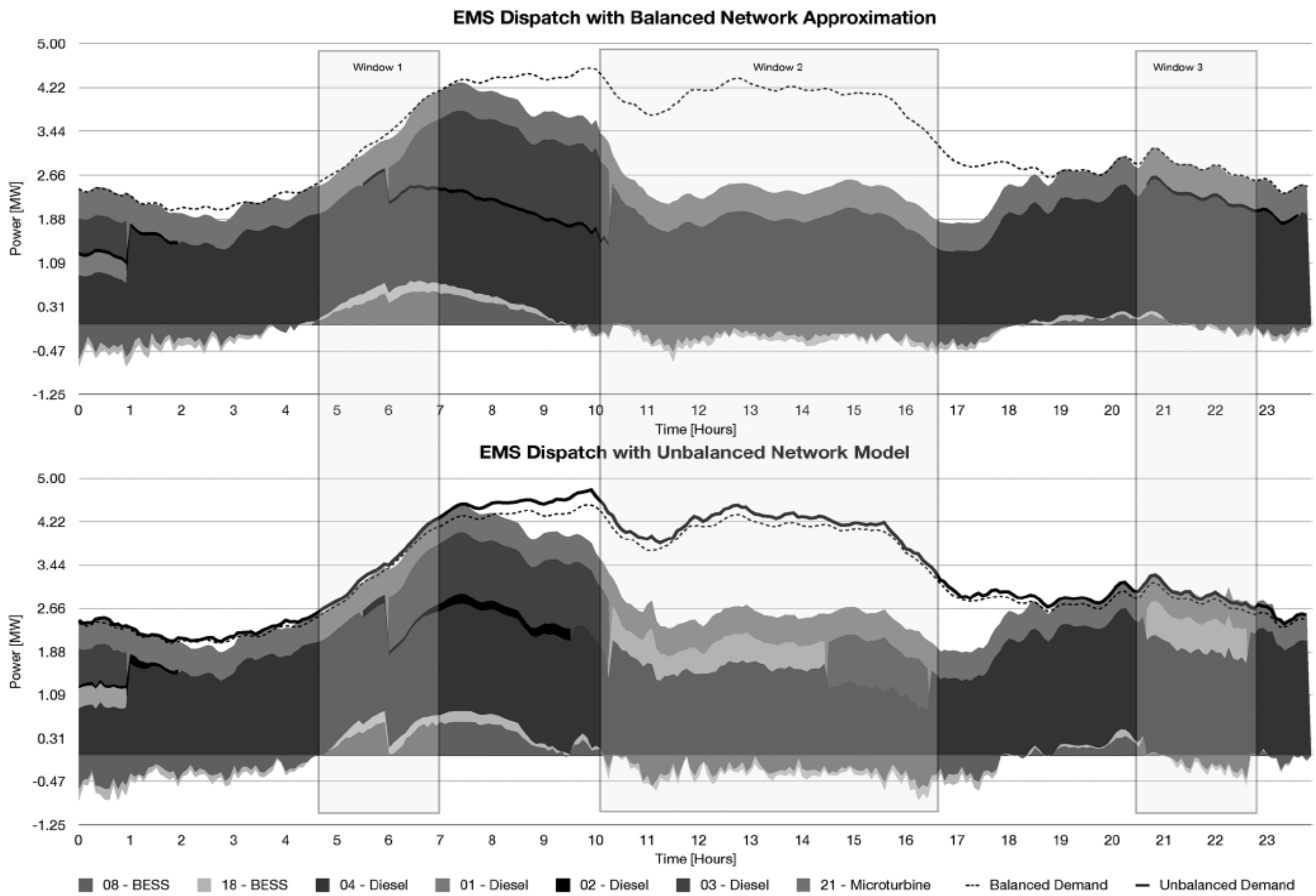
EMS Deterministic Model I Example



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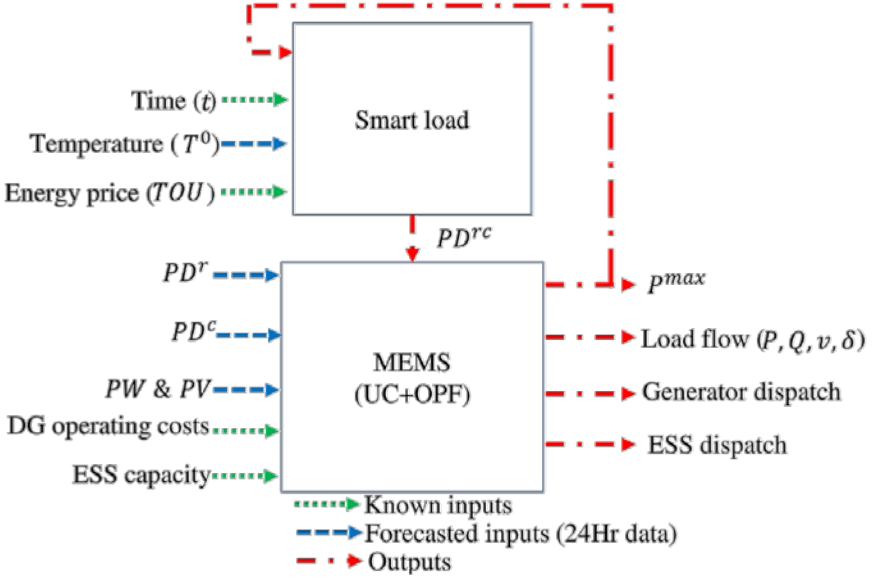
EMS Deterministic Model II

- Microgrid EMS (MEMS) considers:
  - Residential controllable loads.
  - Unit Commitment (UC) for Distributed Energy Resources (DERs) and power flow constraints simultaneously.
- A Neural Network (NN) based Residential Controllable Lod Porfile Estimator (RCLPE) is used to determine smart load models.
- MPC is used to account for uncertainties associated with renewables and electricity demand.

- B. V. Solanki, A. Raghurajan, K. Bhattacharya, and C. A. Cañizares, “Including Smart Loads for Optimal Demand Response in Integrated Energy Management Systems for Isolated Microgrids,” IEEE Transactions on Smart Grid, accepted November 2015, 10 pages:



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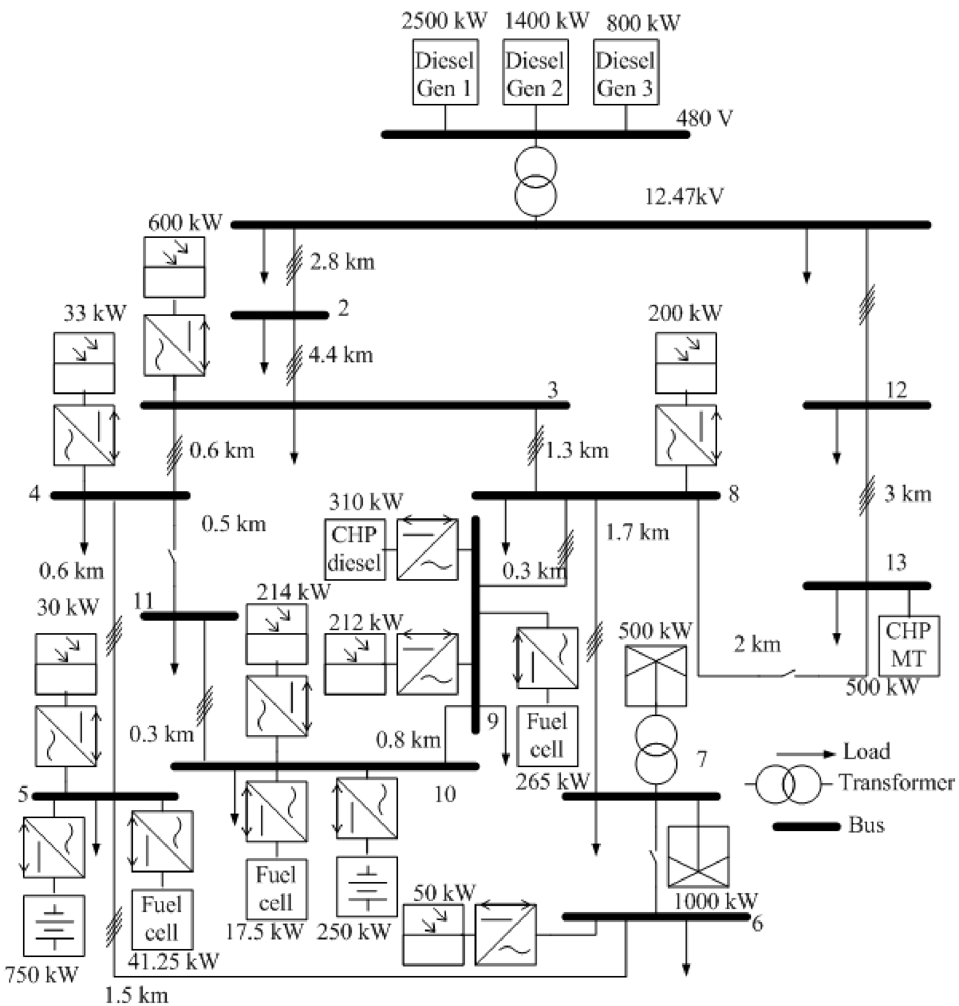
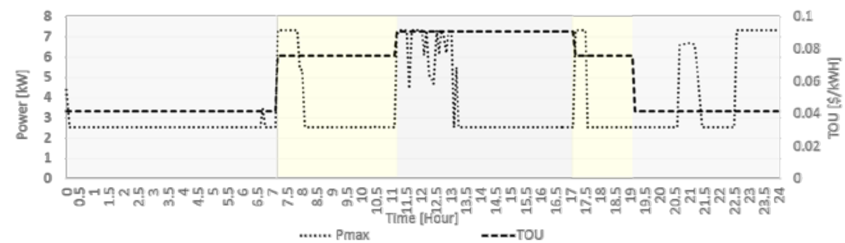
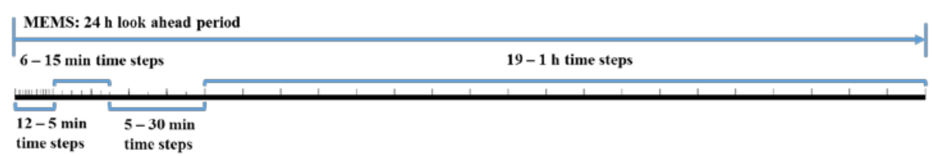
EMS Deterministic Model II Example





DR control [%]	Objective function [$]	Energy served by ESS [kWh]	Energy curtailed [kWh]	Load factor	Peak demand [kW]
0	83,781	3,037	528	0.580	7,575
20	62,447	2,870	351	0.589	7,431
40	42,464	2,808	185	0.6	7,287
60	25,099	2,760	41	0.611	7,141
100	19,941	2,416	0	0.631	6,851



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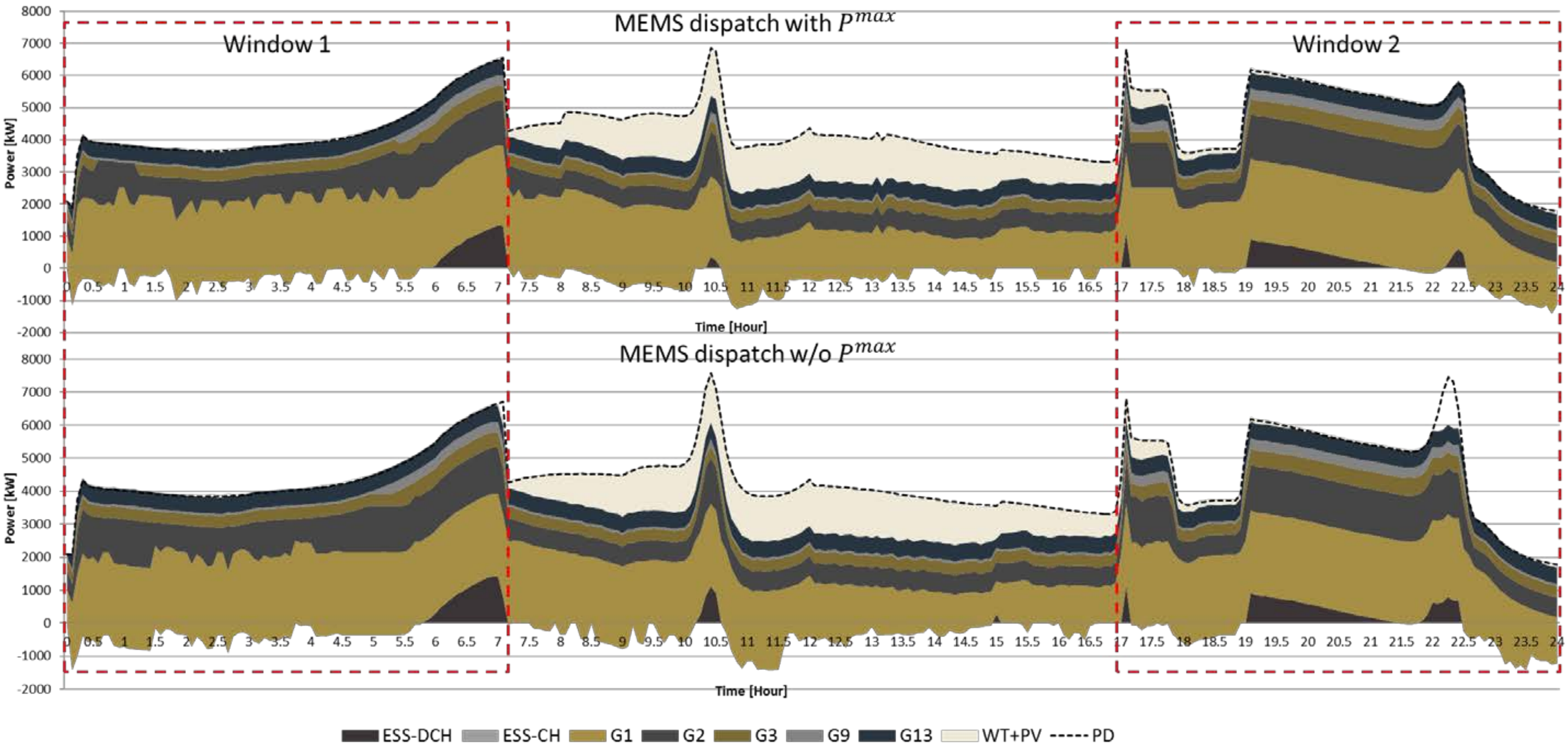
EMS Deterministic Model II Example



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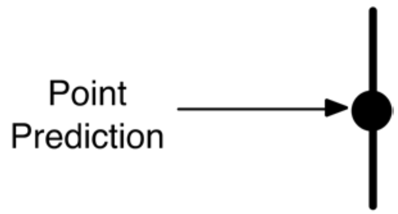
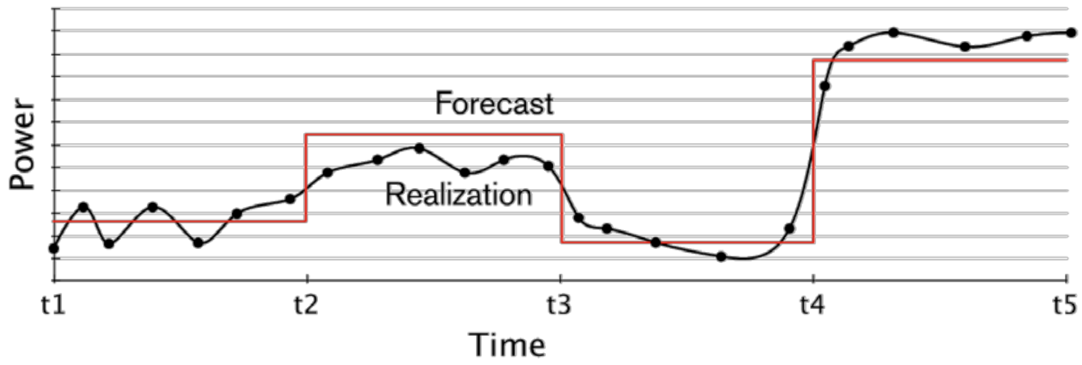
Uncertainty Modeling in UC

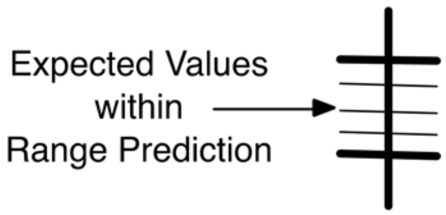
- Uncertainty in the UC can be addressed in three ways:
  - Wait-and-see (deterministic with MPC/RCH models):
    - Close tracking of the problem with small time steps, solving the dispatch problem using the most current information, and including an explicit reserve requirement.
    - Assumes that point forecasts are accurate and the system natural reserve can handle the mismatches, otherwise shed load.

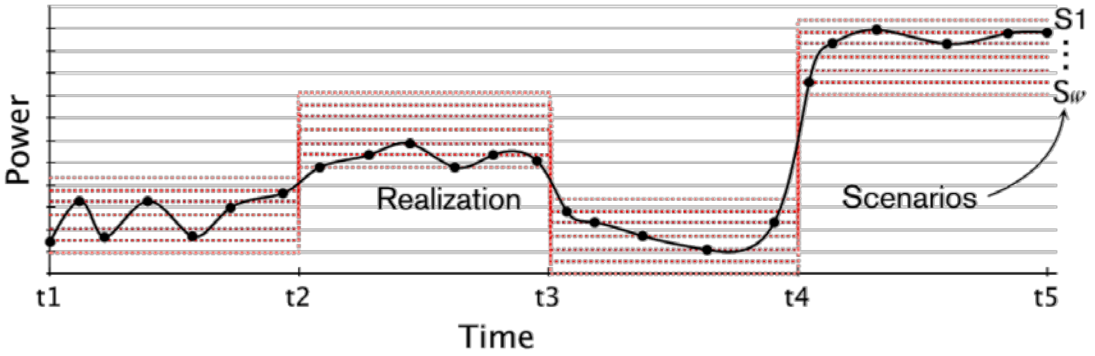




Uncertainty Modeling in UC

- Stochastic optimization:
  - Minimize the expected cost over a discrete representation of the uncertainty, leading to large-scale problems.
  - Accounts directly for the stochastic characteristic of wind power, improving the ability of the system to perform corrective actions without load shedding.
  - First stage variables provide probabilistic guarantee on the feasibility of all second stage expected outcomes.





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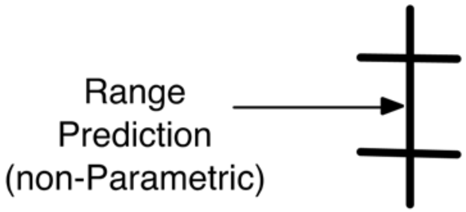
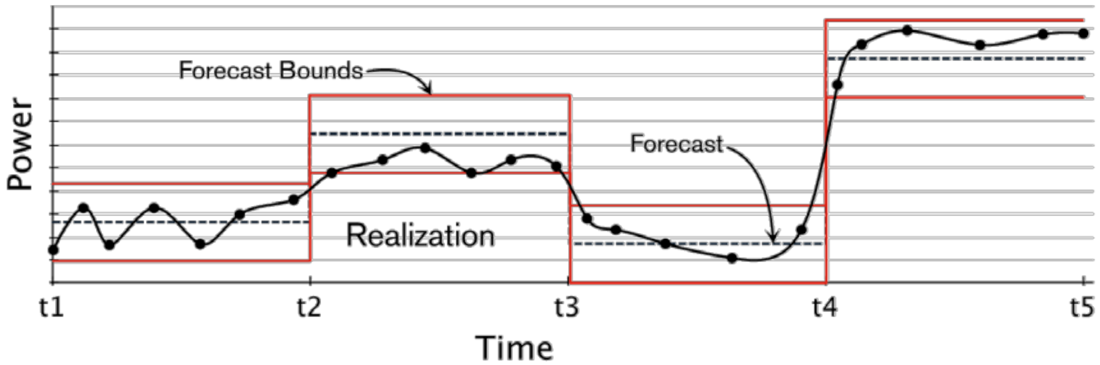
Uncertainty Modeling in UC

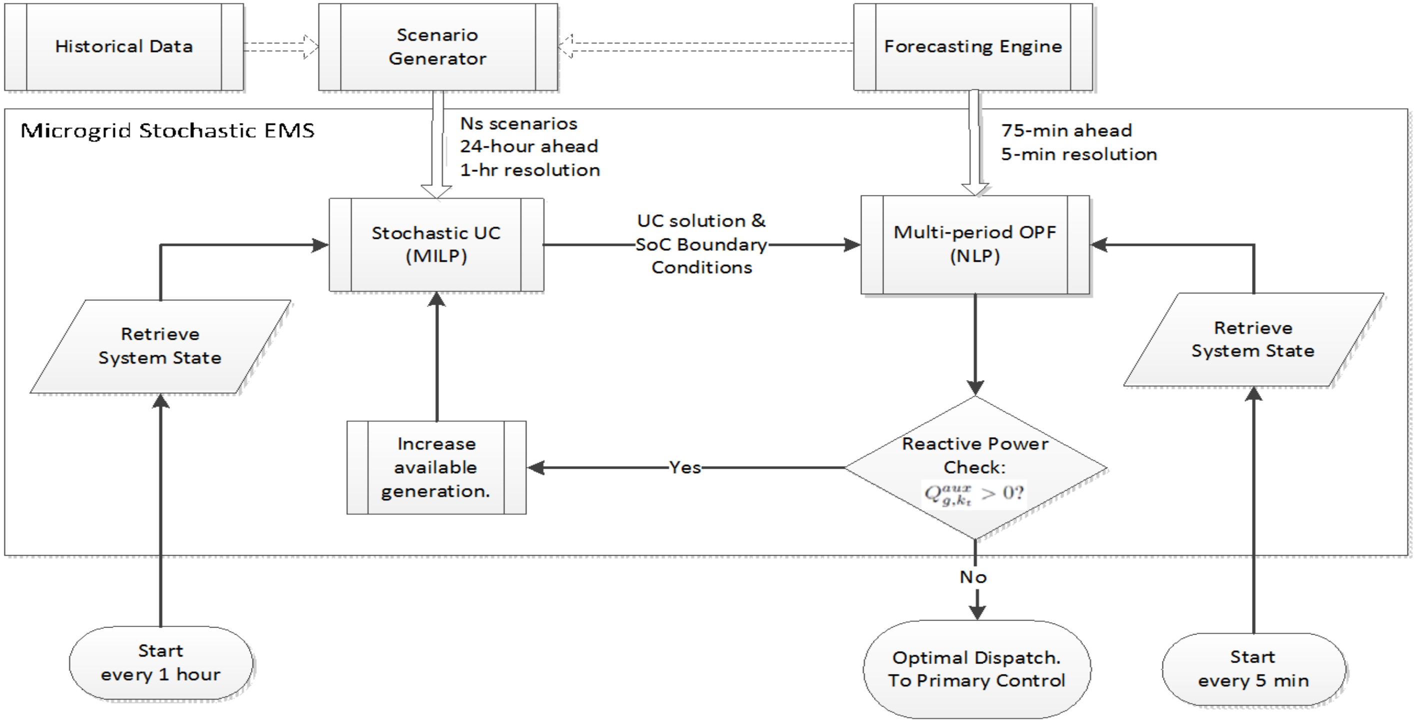
- Intervals (robust and AA-based optimization):
  - Does not require any probabilistic modeling.
  - Determines a solution that guaranties feasibility for any realization within the bounds of the uncertainty set.
  - Bounds can be given or calculated based on historical forecasts.
  - Uncertainty sets are able to relate the risk preference of the operator with the choice of the uncertainty set, incorporating probabilistic information if available.





SUC EMS

- D. Olivares, J. D. Lara, C. A. Cañizares, and M. Kazerani, “Stochastic-Predictive Energy Management System for Isolated Microgrids,” *IEEE Transactions on Smart Grid*, vol. 6, no. 6, November 2015, pp. 2681- 2693:



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SUC EMS Example

- For the previous microgrid test system, the following study cases allow to validate and compare the SUC approach against the MPC+RCH deterministic approach:
  - Available storage capacity (B250, B500).
  - Scenario generation approach (historic and statistic ensembles).
  - Length of the SUC look-ahead window (8-hour and 12 hour) .

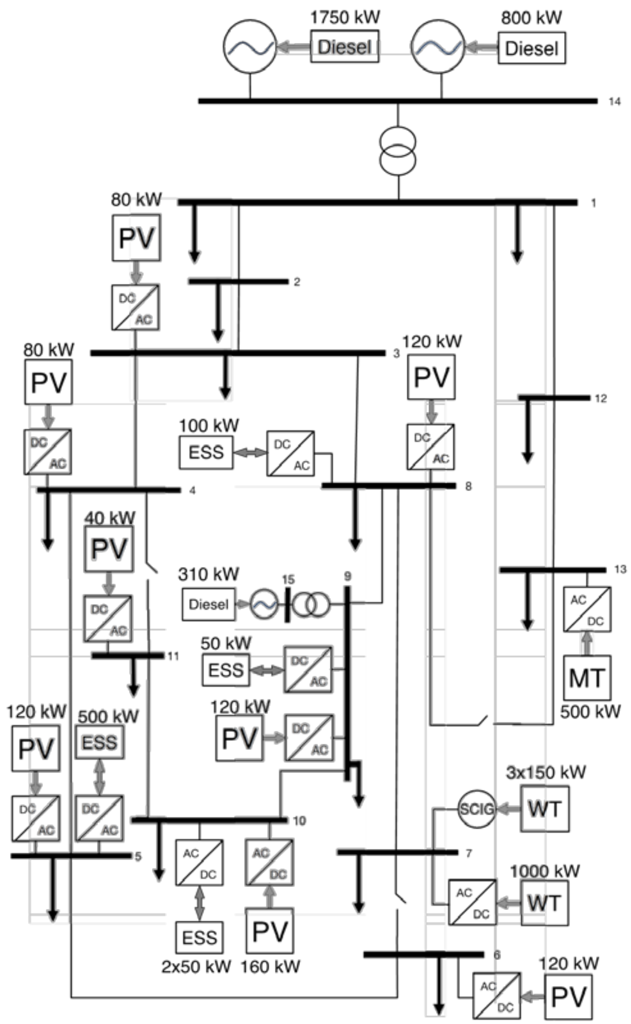
SUC EMS Example

- Cases with increased ESS capacity show a reduction of costs, due to a reduction in the use of diesel units.
- The Historical Data case shows the effect of a pessimistic representation of the uncertainty, yielding more conservative results with higher operation costs due to over commitment.
- Reduced look-ahead windows show poor performance in terms of operation costs, but without shedding load.
- The loss of load indices show that higher levels of ESS capacity yield lower values, thus improving the reliability of the system.

RUC EMS

- Proposed in Jose Lara’s Sept. 2014 MASc thesis: “Robust Energy Management Systems for Isolated Microgrids Under Uncertainty”; paper in IEEE TSG is under review.
- The UC problem is modified to include storage, and consider the SOC of batteries at $t = t + 1$ as first stage variables, thus using the ESS as hedging.
- The objective is to obtain the least-cost uncertainty-aware solution for the first-stage (UC) variables, given a bounded uncertainty set.

RUC EMS Example



- The microgrid test is based again on the CIGRE MV benchmark system and features 3 diesel units with capacities of 1750 kW, 310 kW and 800 kW.
- The two larger diesel units replace the connection to the main grid.
- The system's total capacity is 6,400 kW.
- The RUC load is modeled as constant power and balanced.
- In the three-phase OPF the load is unbalanced with a combination of constant impedance and constant power.

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RUC EMS Example

Case	g	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
DET	G1	0	0	0	0	0	0	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0
	G2	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0
(6.3 -37%)	G1	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0
	G2	0	0	0	0	0	1	1	1	1	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1
(8 -21%)	G1	0	0	0	0	0	0	1	1	1	1	1	0	0	1	1	1	0	0	0	0	0	0	0	0
	G2	0	0	0	0	0	1	1	1	1	1	1	1	1	1	0	0	1	1	1	1	1	1	1	0
(8 -37%)	G1	0	0	0	0	0	0	1	1	1	1	1	0	0	1	1	1	0	0	0	0	0	0	0	0
	G2	0	0	0	0	0	1	1	1	1	0	0	0	0	0	0	0	1	1	1	1	1	1	1	0
(10 -21%)	G1	0	0	0	0	0	0	1	1	1	1	1	0	0	1	1	1	0	0	0	0	0	0	0	0
	G2	0	0	0	0	0	1	1	1	1	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1
(13 -10%)	G1	0	0	0	0	0	0	1	1	1	1	1	0	1	1	0	0	0	0	0	0	0	0	0	0
	G2	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0
(16 -21%)	G1	0	0	0	0	0	0	1	1	1	1	1	0	0	1	1	1	0	0	0	0	0	0	0	0
	G2	0	0	0	0	0	1	1	1	1	1	1	1	1	1	0	0	1	1	1	1	1	1	1	1
(16 -6.3%)	G1	0	0	0	0	0	0	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0
	G2	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0

- The commitment results for different uncertainty policies show the changes in the level of conservatism.
- The RUC formulation commits more capacity than the deterministic case between hours 12 to 24.
- The effect of the extra commitment are reflected in the reserve levels.

Affine Arithmetic

- Enhanced interval model for self validated numerical computing, in which system variables are modeled as affine forms of some "primitive" variables:
  - It keeps track of correlations between output and input quantities.
  - Resolves the Interval Arithmetic (IA) dependency problem and results in narrower intervals; for example, for interval $[\underline{x}\ , \bar{x}]$:
    - IA: $\hat{x} - \hat{x} = [\,\underline{x} - \bar{x}\,, \bar{x} - \underline{x}\,]$
    - AA: $\tilde{x} - \tilde{x} = 0$
  - Significantly more efficient than IA.
  - Affine representation of an uncertain variable:

$$\tilde{x} = x_0 + x_1\varepsilon_1 + x_2\varepsilon_2 + \cdots + x_n\varepsilon_n$$

AA-based OPF

- M. Pirnia, C. A. Cañizares, K. Bhattacharya, and A. Vaccaro, "An Affine Arithmetic Approach for Microgrid Dispatch with Variable Generation and Load," *Proc. Power Systems Computation Conference*, August 2014, 7 pages:

$$\min \quad F(\tilde{P}^G) = \sum_{i \in Th} \alpha_i {\tilde{P}_i^G}^2 + \beta_i \tilde{P}_i^G + c_i$$

$$\text{s.t.:} \quad \Delta\tilde{P}_i\left(\tilde{e}_i, \tilde{f}_i, \tilde{I}_{r_i}, \tilde{I}_{im_i}, \tilde{P}_i^G, \tilde{P}_i^D\right) = 0 \qquad \forall i \in N$$

$$\Delta\tilde{Q}_i\left(\tilde{e}_i, \tilde{f}_i, \tilde{I}_{r_i}, \tilde{I}_{im_i}, \tilde{Q}_i^G, \tilde{Q}_i^D\right) = 0 \qquad \forall i \in N$$

$$|\tilde{V}_i|^2 = \tilde{e}_i^2 + \tilde{f}_i^2 \qquad \forall i \in N$$

$$P_i^{min} \le \tilde{P}_i^G \le P_i^{max} \qquad \forall i \in NPG$$

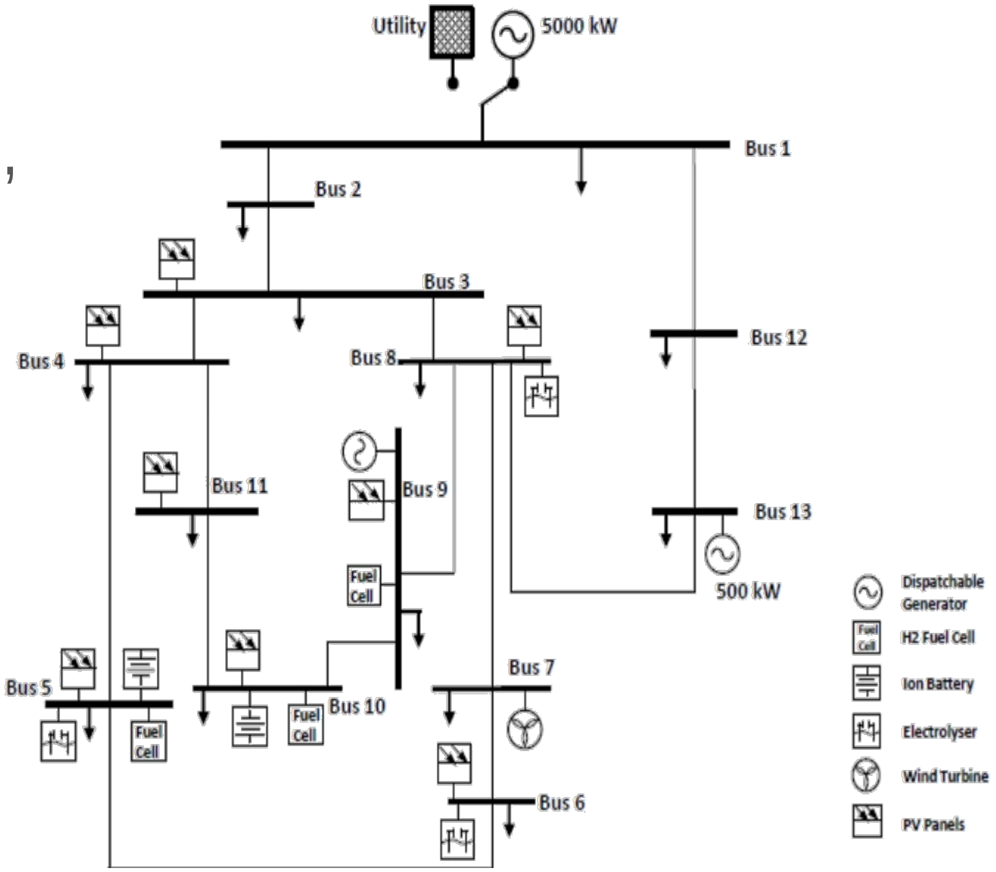
$$Q_i^{min} \le \tilde{Q}_i^G \le Q_i^{max} \qquad \forall i \in NPG$$

$$I_{ij}^{min} \le \tilde{I}_{ij} \le I_{ij}^{max} \qquad \forall ij \in L$$

$$V_i^{min} \le \left|\tilde{V}_i\right| \le V_i^{max} \qquad \forall i \in N$$

AA-based OPF Example

- AA-based OPF is implemented and solved in GAMS for a similar isolated test microgrid test as before, based on the CIGRE MV benchmark system.
- The intermittency of wind and solar generation is assumed to be managed with thermal generation via continuous regulation.
- Results are compared with MCS, assuming uniform distribution.



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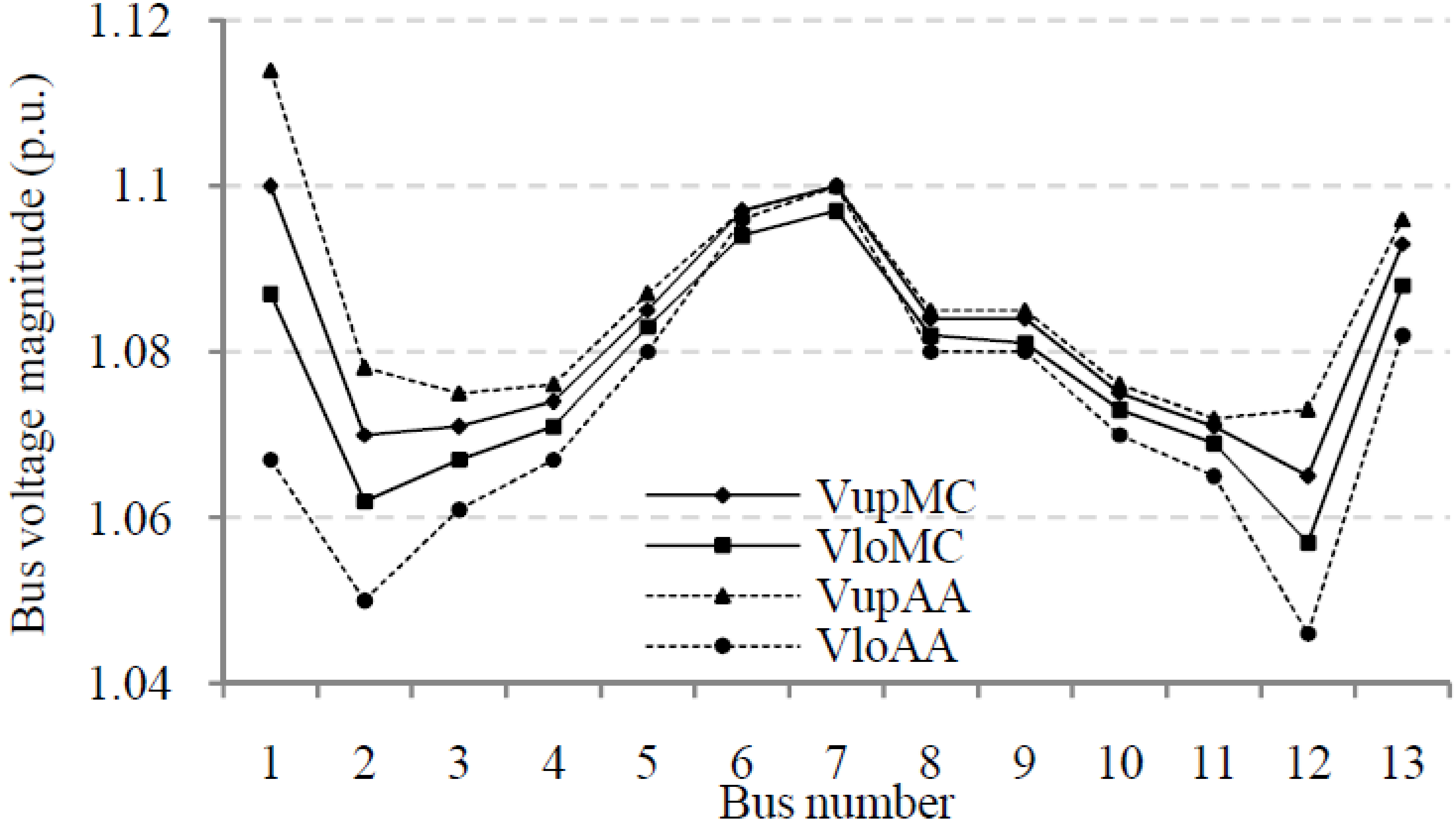
AA-based OPF Example



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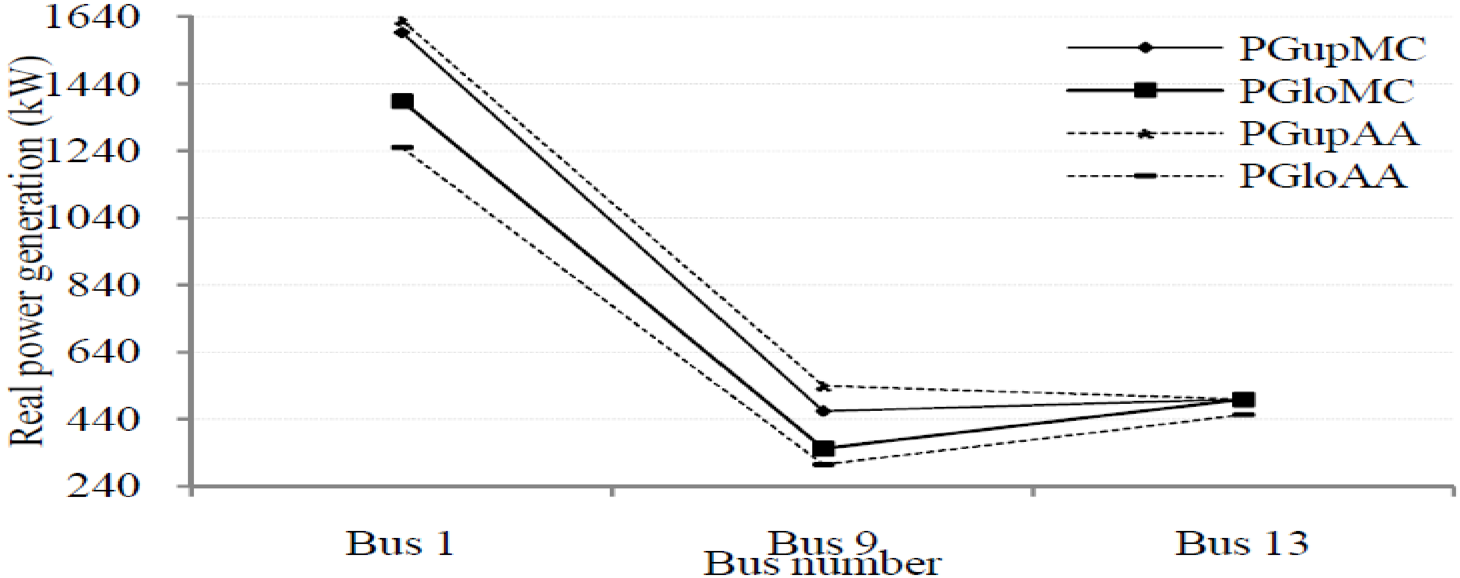
AA-based OPF Example



	MCS	AA	% difference
Total thermals upper bound (kW)	2557	2715	6%
Total thermals lower bound (kW)	2241	2007	-10%

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Conclusions

- Various EMS models for isolated microgrids have been developed, based on decoupling the problem in sequential MILP UC and NLP OPF problems, with different horizons and update rates.
- UC:
  - MPC:
    - Easiest to implement.
    - Adequate performance.
    - Results on lowest reserves but highest possible load shifting/shedding due to forecasts errors.
  - Stochastic programming:
    - More complex to implement but manageable.
    - Adequate performance if not “too many” scenarios.
    - Requires p.d.f. assumptions and proper selection of scenarios.
    - Results in more reserves and little load shifting/shedding.

Conclusions

- Robust optimization:
  - Even more complex to implement.
  - Adequate performance.
  - Does not require p.d.f. and user may define desired risk level through a budget of uncertainty Γ, which can be associated with intervals.
  - Reserves and load shifting/shedding depend on Γ value.
- AA (in the works):
  - Most complex implementation.
  - Performance and accuracy still to be determined.
  - Does not require p.d.f. and user may define desired risk levels through intervals.
  - Reserves and load shifting/shedding depend on chosen intervals.

Conclusions

- OPF:
  - RHC:
    - Relatively easy to implement.
    - Good performance.
    - Requires occasional UC revisions, which depend on system stress conditions.
  - AA:
    - There are 3 possible implementation approaches, with different levels of complexity and accuracy.
    - Performance depends on implementation.
    - Need for UC revisions should be less, depending on intervals chosen.

Conclusions

- The classical UC model has been implemented in Hatch's microgrid controller.
- The feasibility of embedding the OPF in a controller is still to be determined, but some preliminary studies have been carried out; however, studies to determine whether there is a need for modeling feeders are showing that OPF may not be necessary with an appropriate representation of unbalancing and voltage dependent loads in the UC.