Toward deployment of MIT SRR controller in Pecan Street, Austin, TX: Progress and next steps

© Marija Ilic, Rupamathi Jaddivada, Michelle Lauer

ilic@mit.edu

NODES PROGRAM REVIEW MEETING,

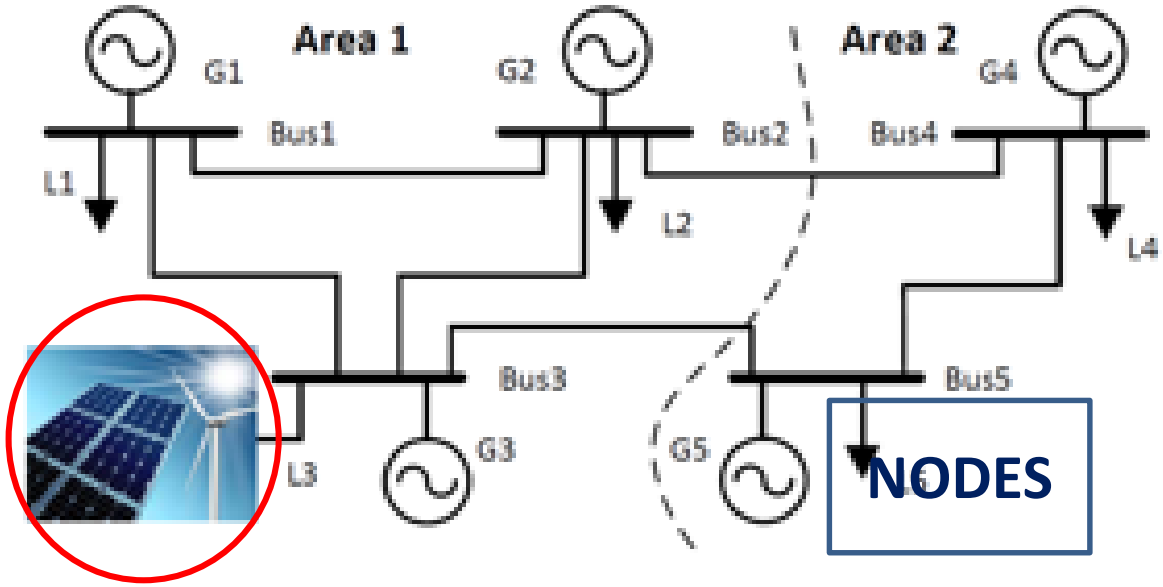
Pasadena, CA

February 13, 2019

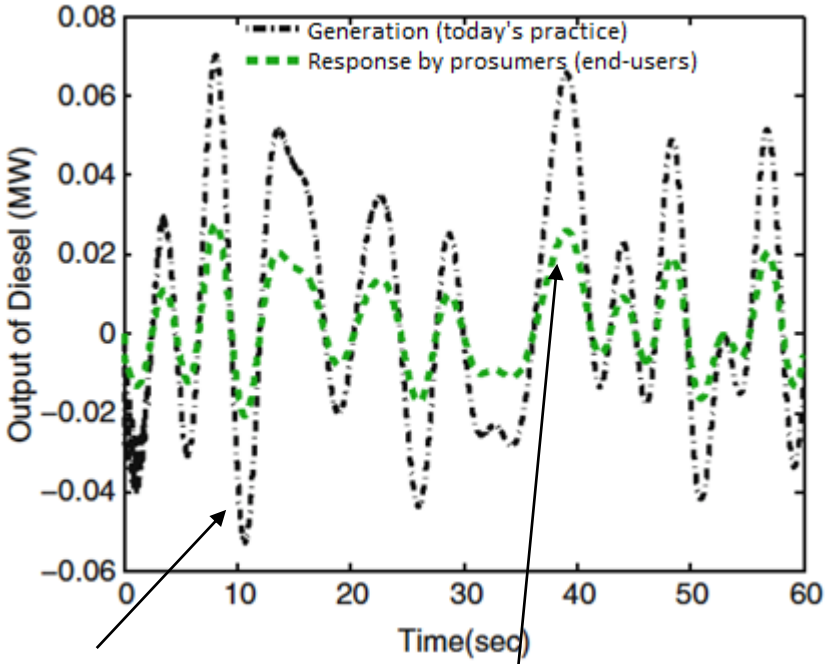
Outline

- Motivation
- Project Innovations
  - Technology-agnostic Synthetic Regulation Reserve (SRR) device controllers
  - Integrated NODES-level control
  - Patented Synthetic Regulation Reserve Provisioning System (SRPS)
  - Scalable distributed simulation platform
- Small-Medium Scale (SMS) simulation validation on Pecan Street
- Implementation plan for retrofitting of existing control in Pecan Street
- AI-enabled device consumption predictions to assist predictive control implementation for synthetic regulation reserves (SRR) provision
- DyMonDS-enabled secure block chain design

Potential benefits of NODES



Excessive renewable penetration



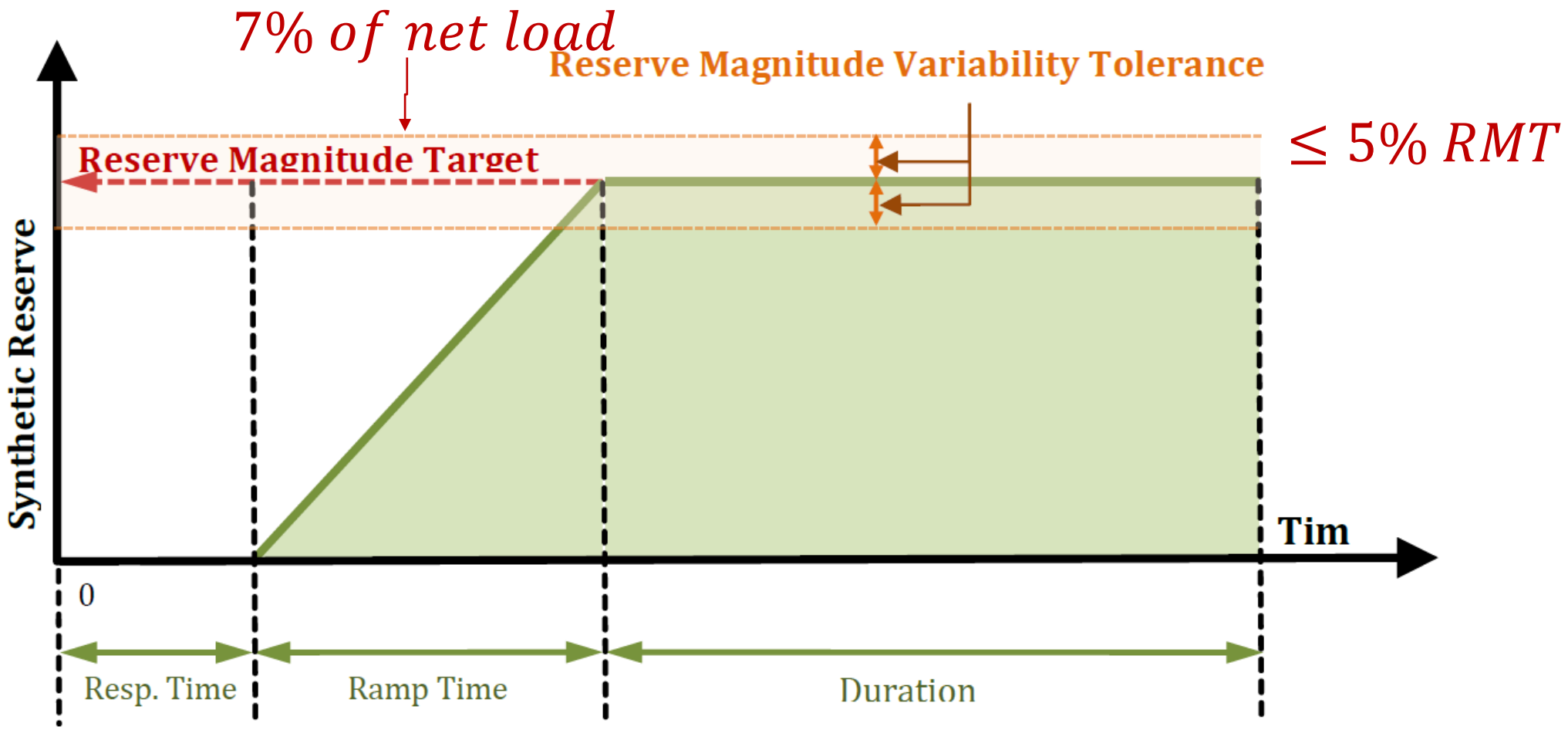
Excessive wear and tear

Much less fast generation required [1]

Value of fast flexible end-user response with excessive renewable penetration

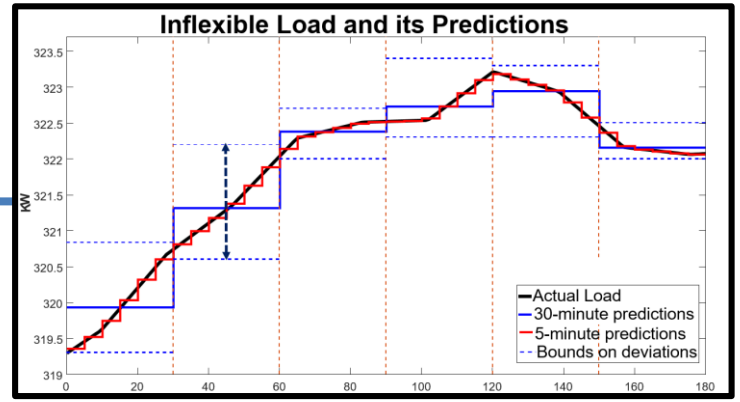
[1] Ilic, M., Xie, L. and Liu, Q. eds., 2013. *Engineering IT-enabled sustainable electricity services: The tale of two low-cost green azores islands* (Vol. 30). Springer Science & Business Media.

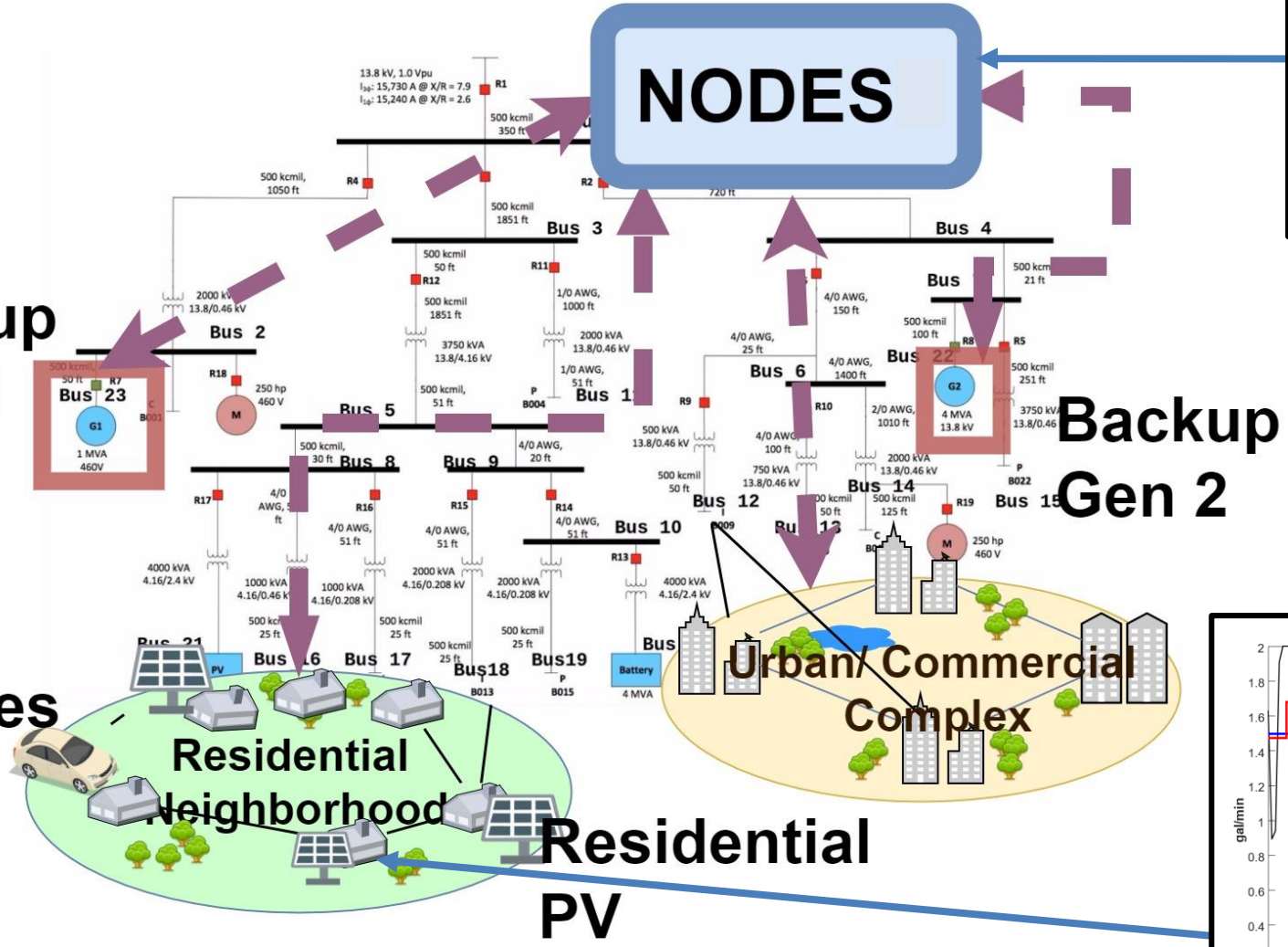
Performance metrics set for NODES category – II of synthetic regulation reserves in Pecan street

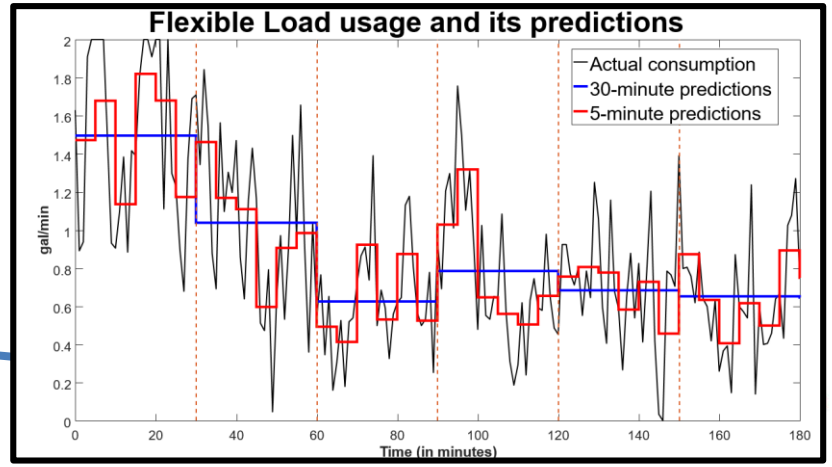


5 seconds 5 minutes 30 minutes (95% availability)

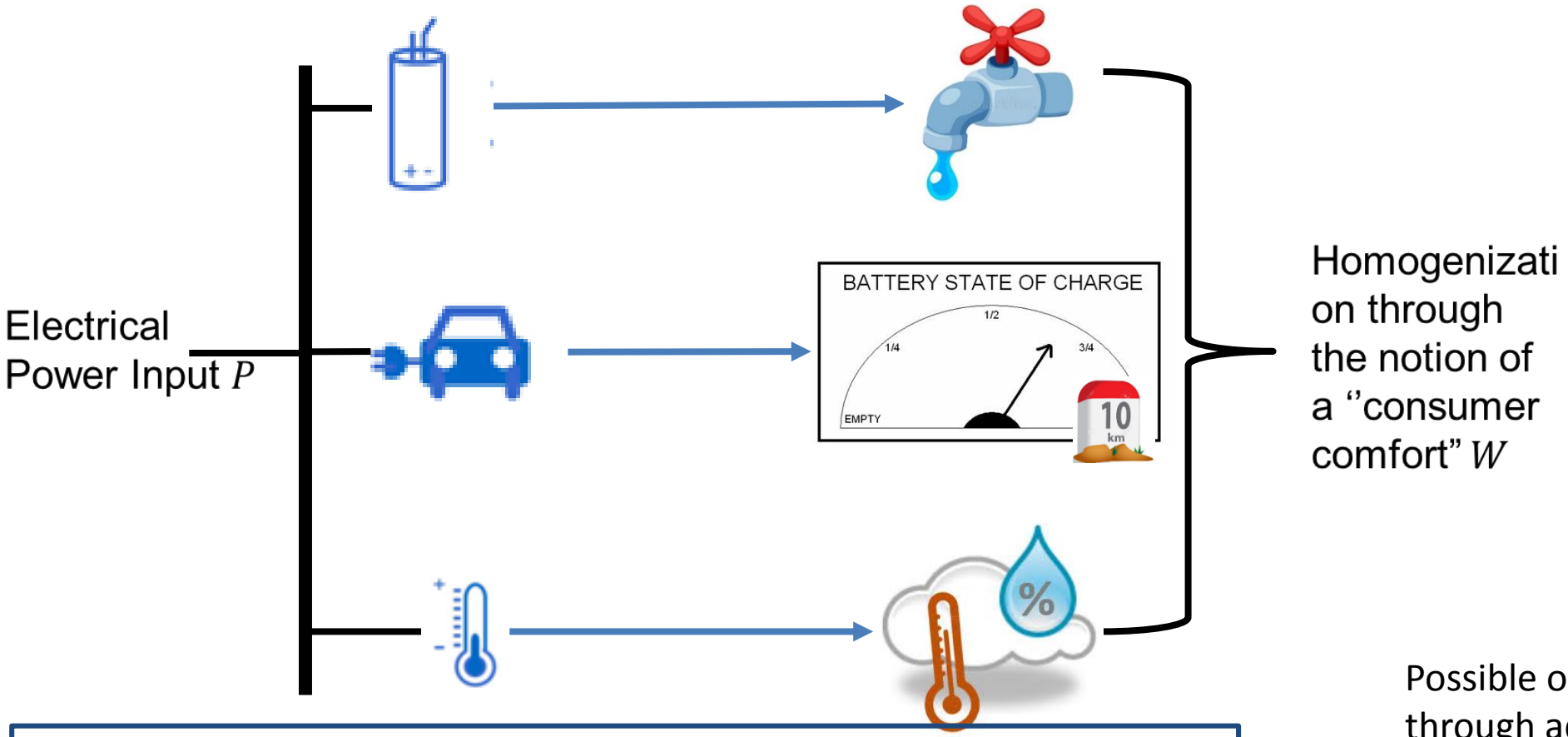
Typical neighborhood and its aggregation by NODES







Generalized droops for device-level energy flows [2]



$$P[k+1] - P[k] = \sigma(W[k+1] - W[k])$$

Possible only through advanced internal controllers

[2] Popli, N. , Jaddivada, R., O'Sullivan, F., and Ilić, M.D., 2018. Harnessing Flexibilities of Heterogeneous Generation and Controllable Demand Technologies in System Operation, (Submitted to IEEE Transaction on Power Systems)

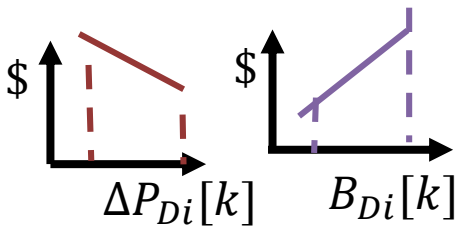
DER as a distributed decision maker

DER i ∈ *Node I*

$$\min \sum^{6} \lambda_e^I[k] P_{Di}[k] - \lambda_r^I[k] B_{Di}[k]$$

$$\dot{W}_i^{min}[k]T_t \le \Delta W_i[k] \pm \frac{B_{Di}}{\sigma_i} \le \dot{W}_i^{max}[k]T_t$$

Technology-agnostic device-level controllers



Energy and Reserve Capacity bids

Energy and reserve prices within Node I

$\lambda_e^I[k]$, $\lambda_r^I[k]$

Generalized flexibility constraints

arket Interface of SRR Device control

Limits on comfort requirement/ physical controller limits

ΔW_i^{min}, ΔW_i^{max}

$\dot{W}_i^{min}$, $\dot{W}_i^{max}$

Exogenous Consumption

Consumption dispatch signal

$\Delta P_{Di}[k]$

SRR signal

$\Delta P_{Di}[n]$

DER Controller Implementation

Retrofitted Local Control

Control Input u_i

Input u_i

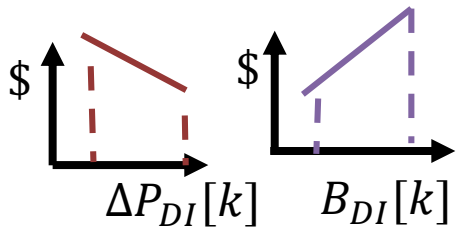
Output of interest y_i

Simulated DER

Ctrl Interface of SRR Device control

EESG @MIT

MIT NODES aggregation algorithm



System energy and reserve prices

$\lambda_e^S[k]$, $\lambda_r^S[k]$

NODE I

$$\min_{\Delta P_{DI}[k], B_{DI}[k]} \sum_k \lambda_e^S[k] P_{DI}[k] - \lambda_r^S[k] B_{DI}[k]$$

$$\sum_{i \in I} \Delta P_{Di}^{min}[k] \leq \Delta P_{DI}[k] - \Delta \hat{P}_I^u[k] \leq \sum_{i \in I} \Delta P_{Di}^{max}[k]$$

$$\sum_{i \in I} B_{Di}^{min}[k] \leq B_{DI}[k] - \hat{B}_I^u[k] \leq \sum_{i \in I} B_{Di}^{max}[k]$$

Aggregate Energy and Reserve bids

Inflexible demand and bounds on its deviation predictions within Node I

$\Delta \hat{P}_I^u[k]$, $\hat{B}_I^u[k]$

DER minimum and maximum limits of each $i \in I$

$\Delta P_{Di}^{min}[k]$, $\Delta P_{Di}^{max}[k]$, $B_{Di}^{min}[k]$, $B_{Di}^{max}[k]$,

EESG @MIT

NODES-level decision making for clearing energy and reserve capacity bids of DERs

Node I

$$\min_{\Delta P_{Di}[k], B_{Di}[k]} \sum_{k=1}^{6} \left[\sum_{i \in S_N} C_i^e(P_{Di}[k]) + C_i^r(B_{Di}[k]) \right]$$

$$\Delta P_{DI}[k] - \sum_{i \in I} \Delta P_{Di}[k] - \Delta \hat{P}_I^u[k] = 0 \qquad (\lambda_e^I[k])$$

$$B_{DI}[k] - \sum_{I \in I} B_{Di}[k] - \hat{B}_I^u[k] \geq R^{margin} \qquad (\lambda_r^I[k])$$

$$\Delta P_{Di}^{max}[k] \leq \Delta P_{Di}[k] \leq \Delta P_{Di}^{max}[k]$$

$$B_{Di}^{max}[k] \leq B_{Di}[k] \leq B_{Di}^{max}[k] \qquad \forall i \in I$$

Node level dispatched quantity

$\boldsymbol{\Delta P_I[k], B_I[k]}$

$\boldsymbol{\Delta \hat{P}_I^u[k]}$

$\boldsymbol{\hat{B}_I^u[k]}$

DER bids with minimum and maximum limits for each $\boldsymbol{i \in I}$

$\boldsymbol{C_I^e, C_I^r,}$

$\boldsymbol{\Delta P_{DI}^{min}[k], \Delta P_{DI}^{max}[k],}$

$\boldsymbol{B_{DI}^{min}[k], B_{DI}^{max}[k],}$

Cleared Energy and Reserve capacity prices within Node $\boldsymbol{I}$

$\boldsymbol{\lambda_e^I[k], \lambda_r^I[k]}$`

DER Energy and Reserve capacity Dispatch

$\boldsymbol{\Delta P_{Di}[k], B_{Di}[k]}$

EESG @MIT

MIT SRPS algorithm embedded in NODES

Node level synthetic regulation reserve dispatch/ AGC Signal $\boldsymbol{\Delta P_I[n]}$

Integrated approach to computing device/house specific SRR signals

$$\Delta P_{DI}[n] - \sum_{i \in I} \Delta P_{Di}[n] - \Delta \hat{P}_I^u[n] = 0$$

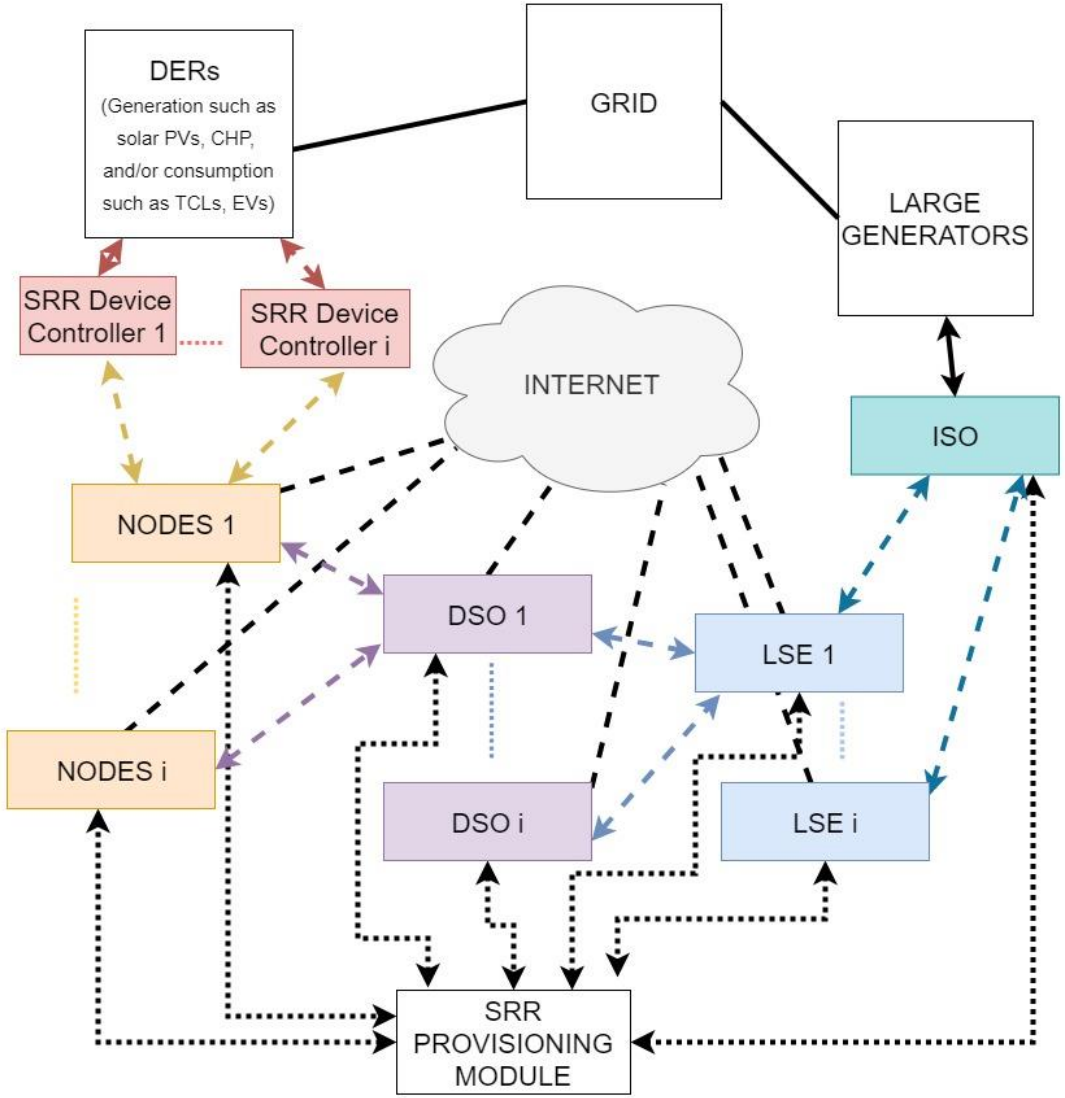
$$\Delta P_{Di}[n] \leq B_{Di}[k]$$

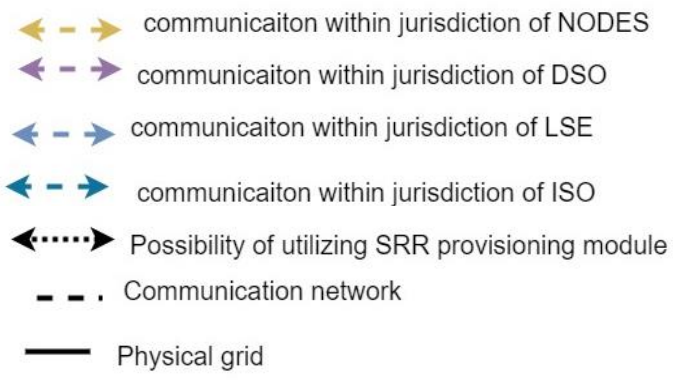
Fast time scale Inflexible demand predictions

$\boldsymbol{\Delta \hat{P}_I^u[n]}$

$\mathbf{\Delta P_{Di}[n]}$ **DER Reserve Dispatch**

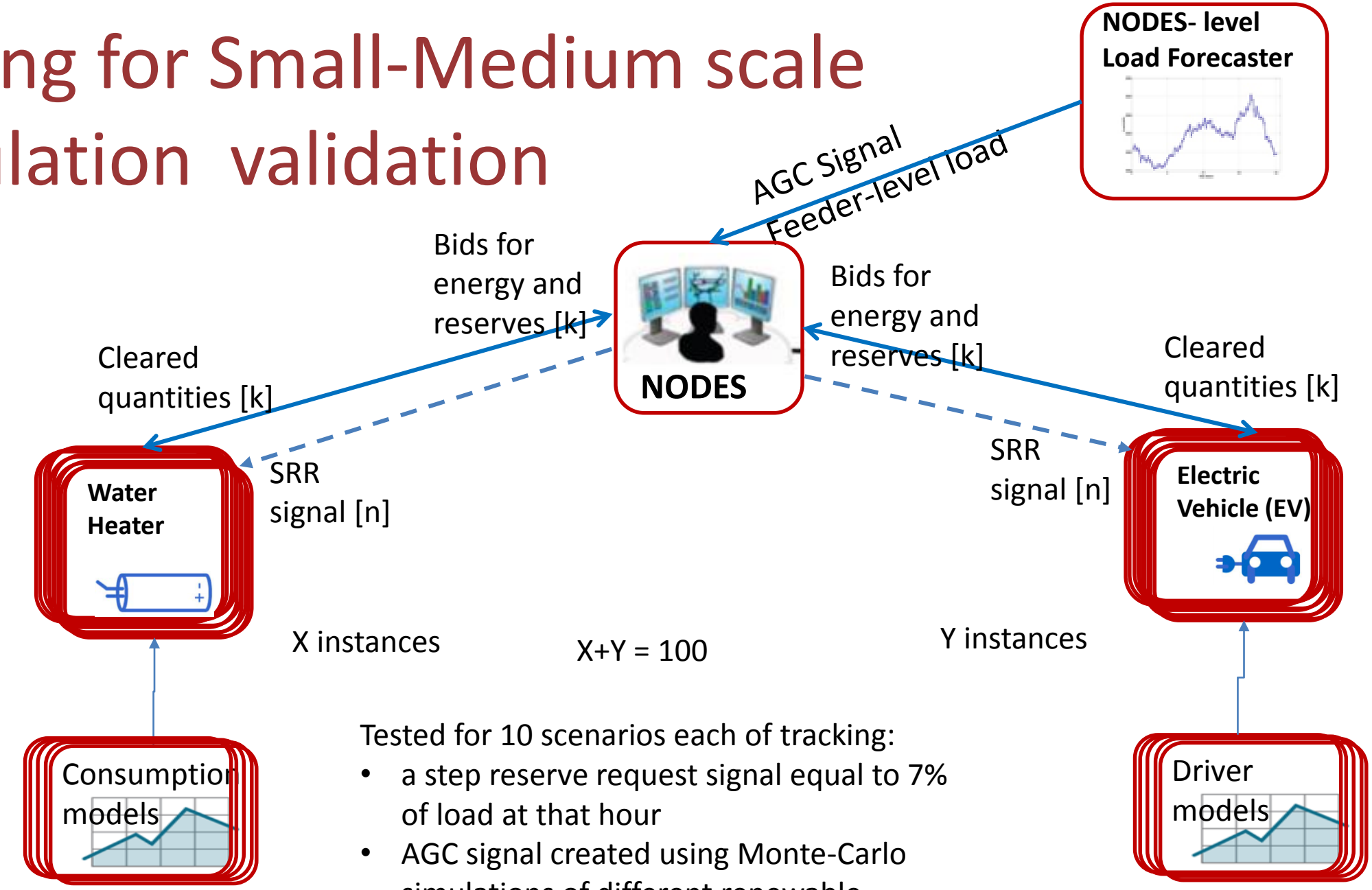
MIT SRPS platform [3]





[3] Ilic, M. and Jaddivada, R., Methods and systems for secure scheduling and dispatching synthetic regulation reserve from distributed energy resources, Utility patent Application No. 16/206,009, Filed on November 30, 2018

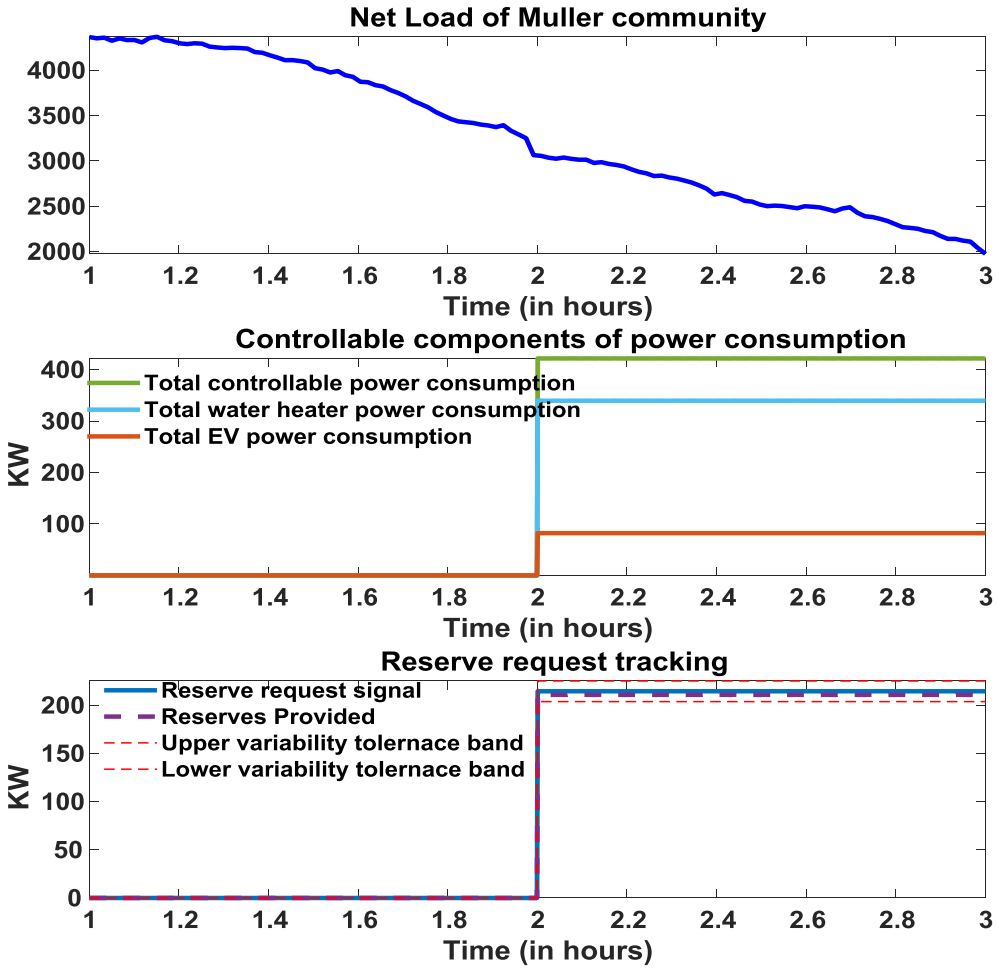
Setting for Small-Medium scale simulation validation

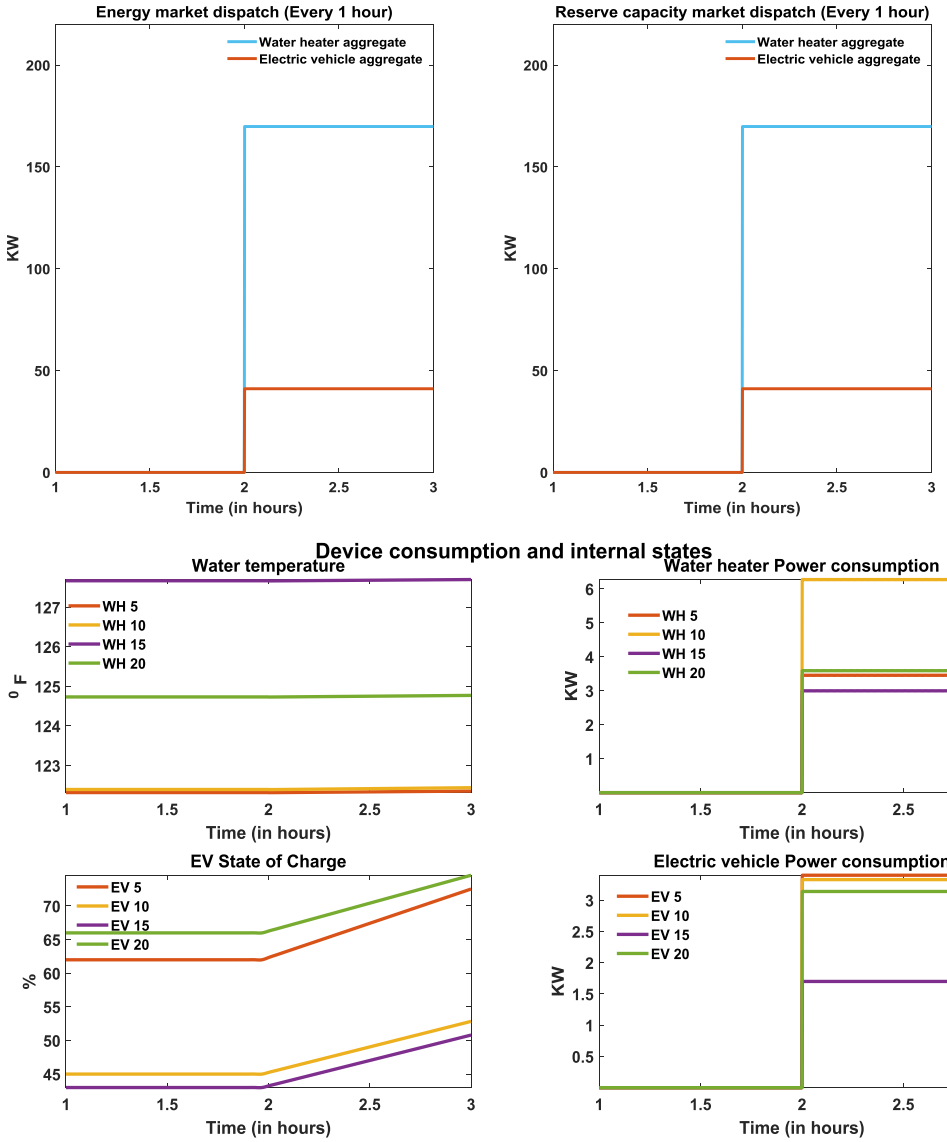


Tested for 10 scenarios each of tracking:

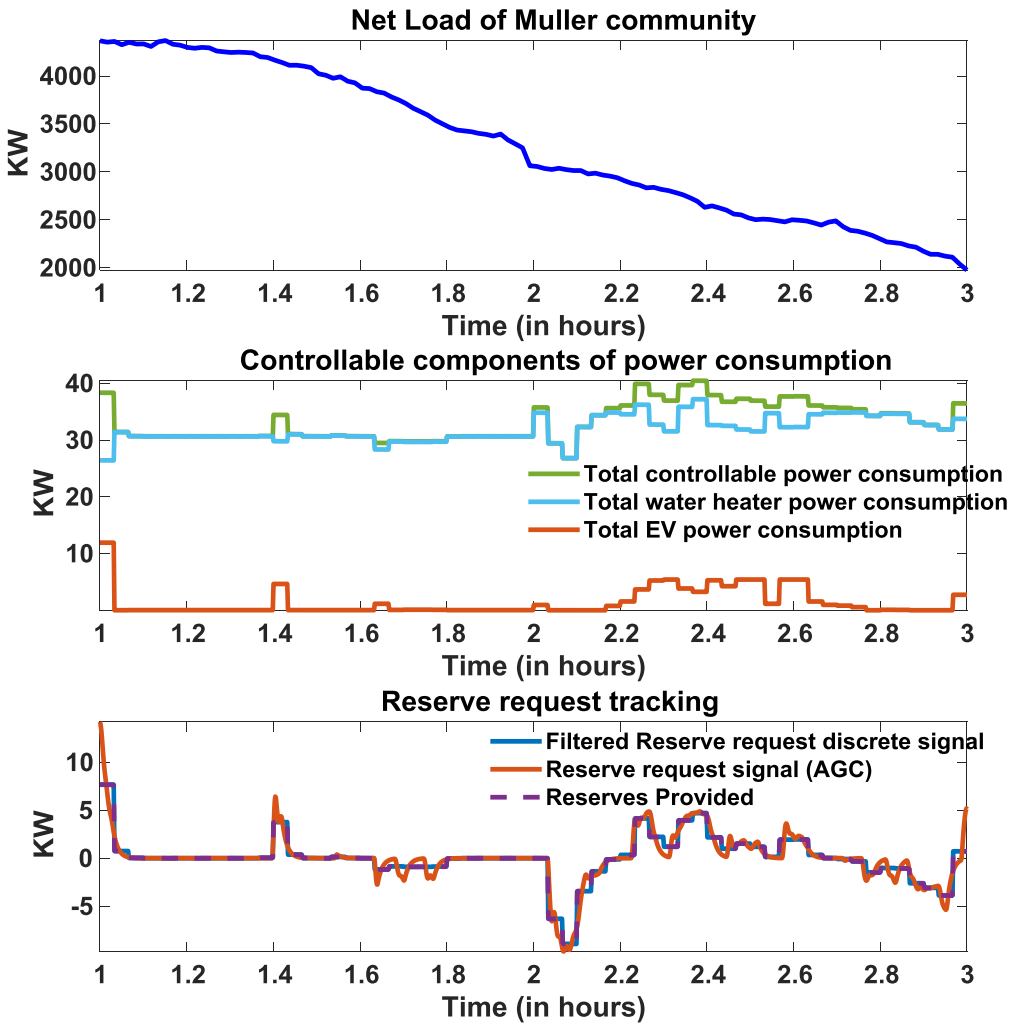
- a step reserve request signal equal to 7% of load at that hour
- AGC signal created using Monte-Carlo simulations of different renewable penetration levels

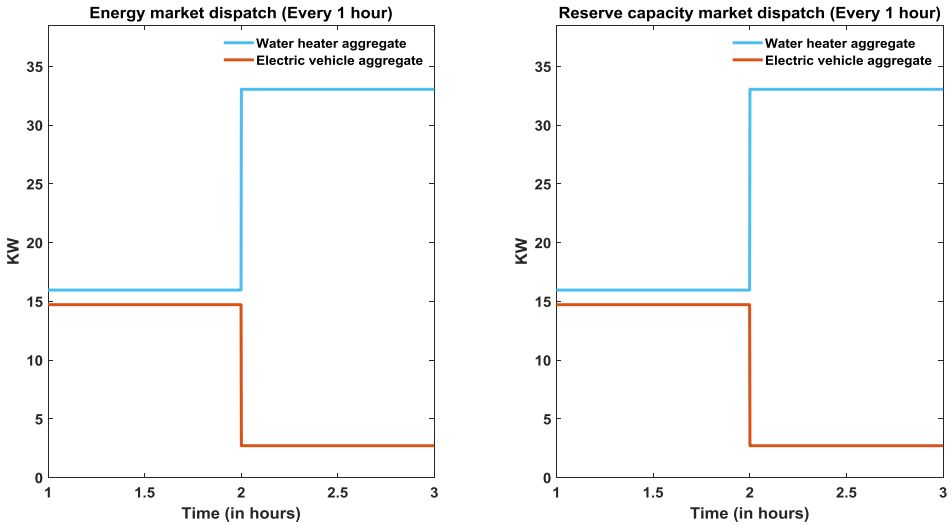
Sample Test 1: 75 water heaters and 25 EVs to track a ‘regulation-up’ signal of 214.5 KW:

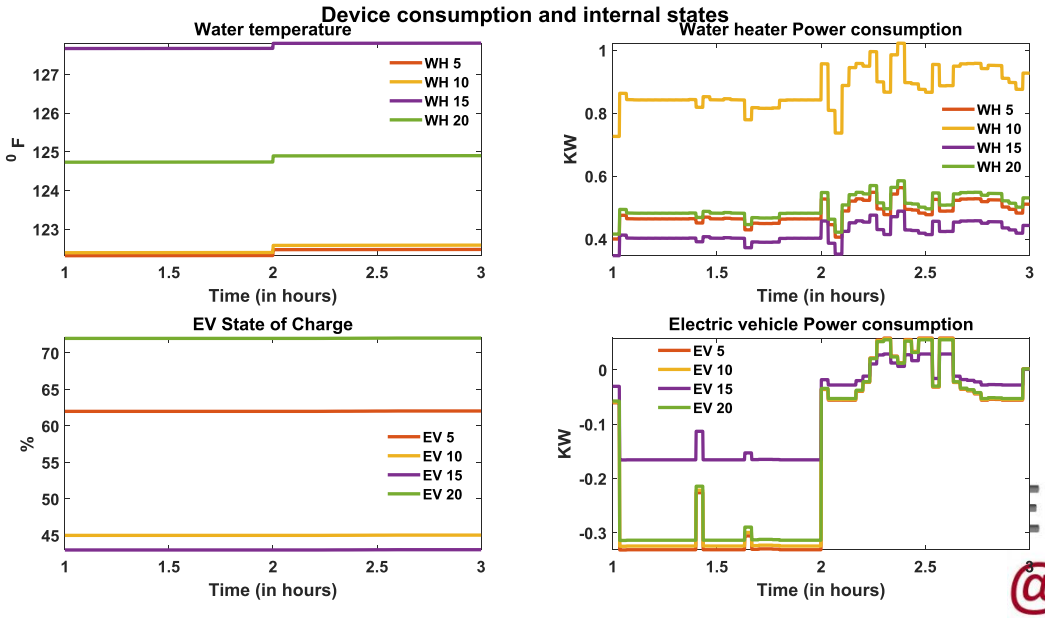




Sample Test 2: 50 water heaters and 50 EVs to track AGC signal at 2AM







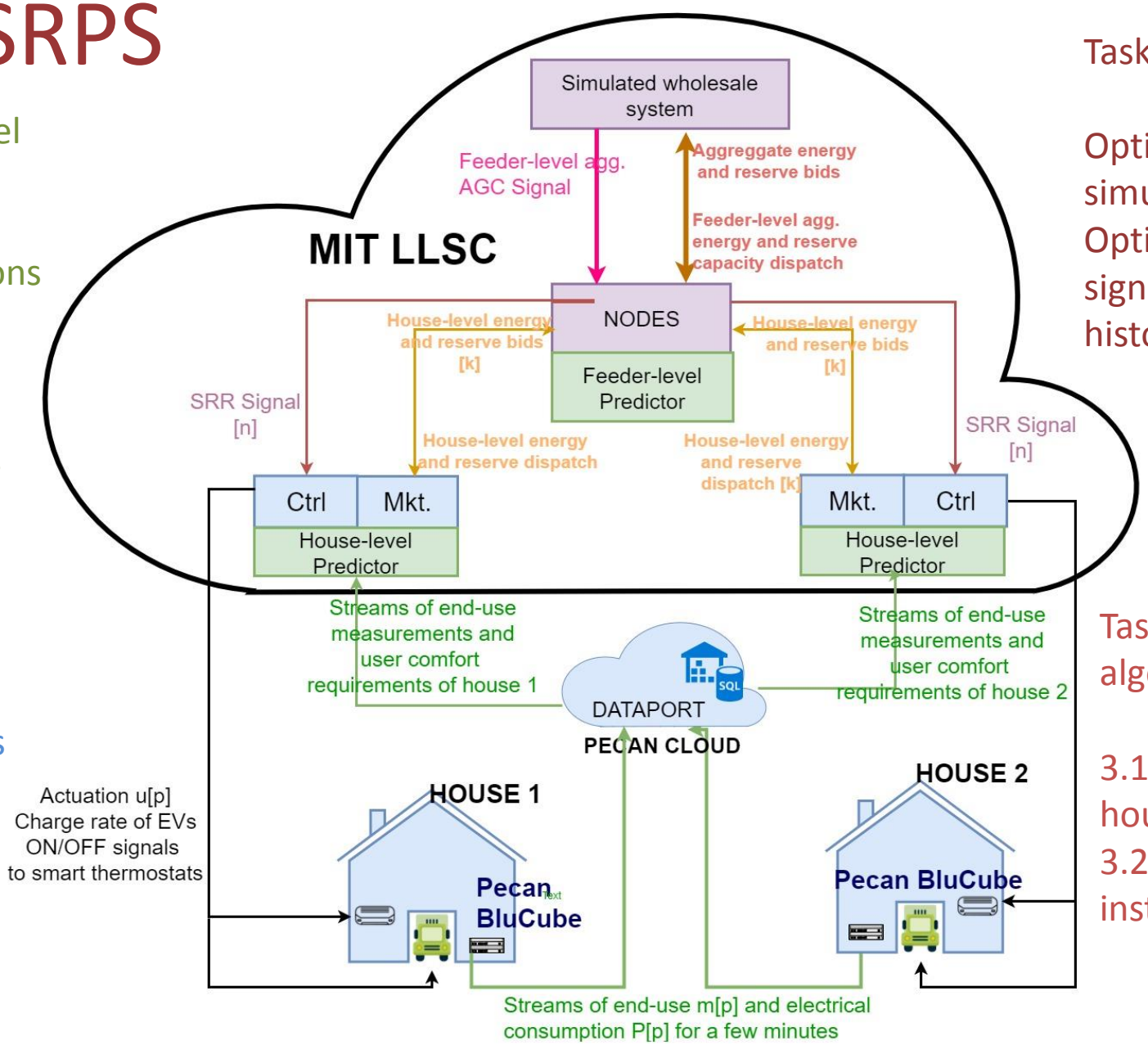
Implementation plan for deploying DyMonDS-enabled SRPS

Task group 1: SRR house-level predictor

1.1. Device-specific predictions (for aiding ctrl interface)
1.2. House-level predictions (for aiding market interface)
1.3. Feeder-level predictions

Task group 2: SRR device-specific control algorithm

2.1. Embedding developed SRR device control algorithms
2.2. Converting analog control to digital ON.OFF signals to be sent through Pecan APIs



Task group 4: Whole sale level

Option 1: ERCOT Market simulation
Option 2. Feeder-level AGC signal creation through historical data of ERCOT

Task group 3: NODES algorithms deployment at

3.1. Each of the 50 simulated house instances
3.2. Simulated NODES instance

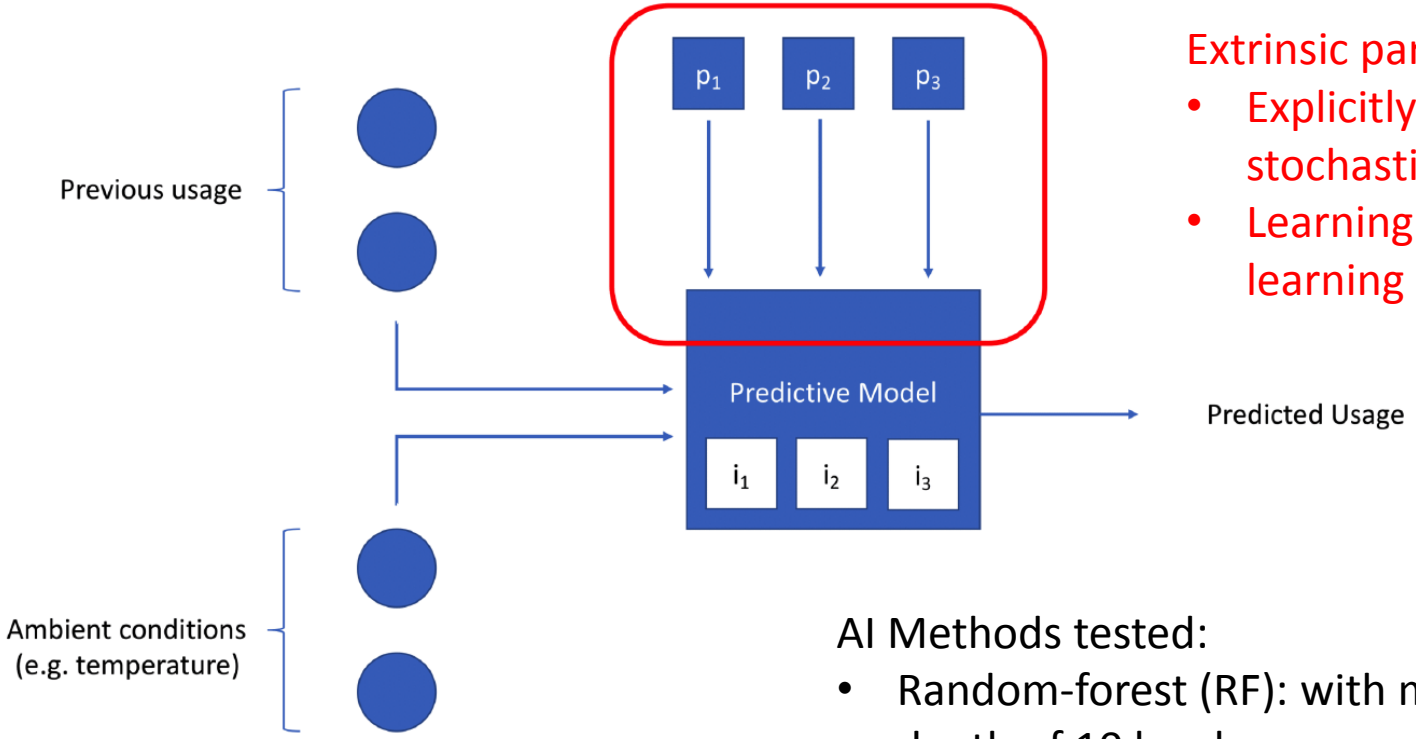
Progress with the implementation & Next steps

- Task-group 1: Prediction modules
  - Showed the power of AI-enabled tools for house-level predictions
  - Compared the statistical and AI-enabled methods
  - Existing consumption models are being retrofitted with these new modules
- Task-group 2: Device-level control modules
  - Have already constructed the control modules for use in SMS simulation validation
  - Conversion of the analog signals to digital ON/OFF signals to communicate to Pecan is work in progress

Progress with the implementation & Next steps

- Task-group 3: NODES-level control modules
  - Completed construction of algorithms for aggregation and dispatch
  - Feeder-level prediction models to be integrated with the NODES-level control algorithms
  - Exploring the possibility of implementing secure blockchain
- Task-group 4: End-end market simulation
  - Exploring the possibility of utilizing AI-enabled tools for predicting the feeder-level signals

Recent progress: Stochastic and AI-enabled tools for house-level predictions [4]



Extrinsic parameters

- Explicitly supplied in stochastic models
- Learning in machine-learning methods

AI Methods tested:

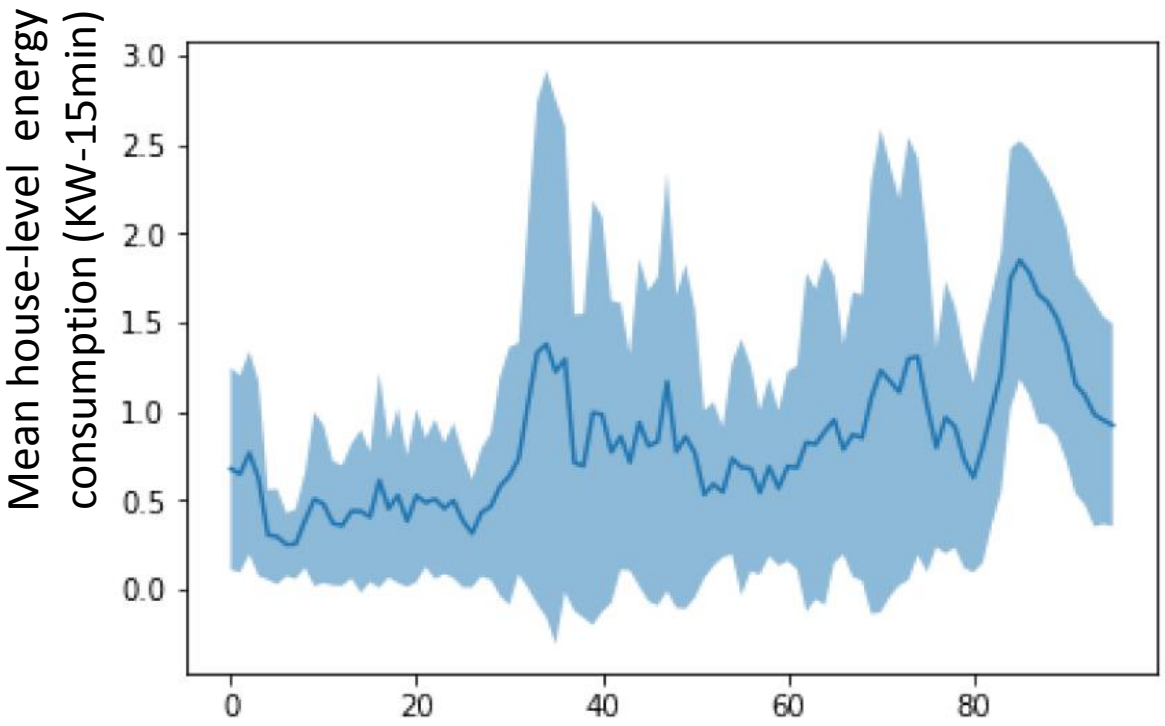
- Random-forest (RF): with maximum depth of 10 levels
- Multi-layer perceptron (MLP)
- Support Vector Regression (SVR)

Considered error Metrics:

- Mean Absolute Error (MAE) = $\frac{1}{n}\sum_{j=1}^{n}|y_j - \hat{y}_j|$
- Mean Square Error (MSE) = $\frac{1}{n}\sum_{j=1}^{n}\left|y_j - \hat{y}_j\right|^2$

[4] Lauer, M., 2019. MIT Masters Thesis. Real-Time Computationally-Efficient Household Energy Consumption Prediction: Approaches and Applications.

Stochastic models for house-level predictions of Pecan 15-minute load (June 2016) [4]

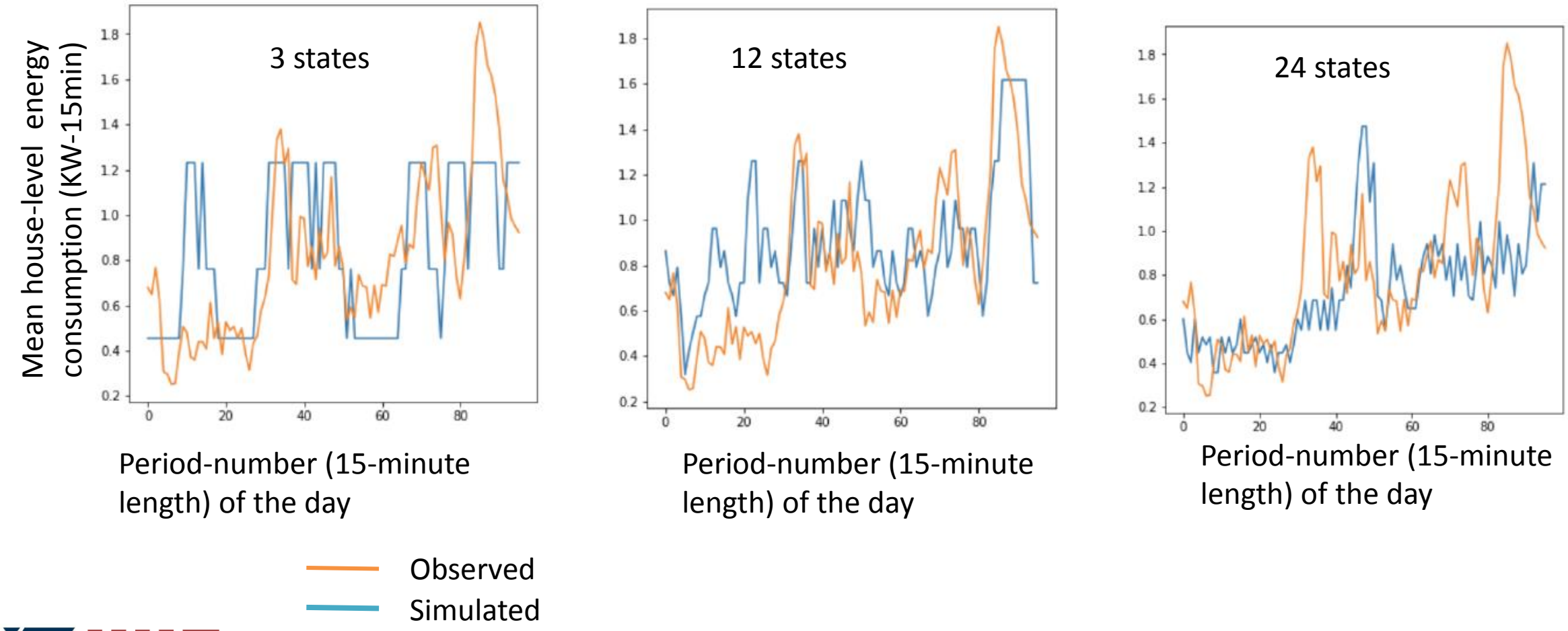


$$\begin{bmatrix} 10 & 6 & 1 & 0 & 0 & 0 \\ 6 & 6 & 4 & 0 & 0 & 0 \\ 0 & 3 & 7 & 3 & 3 & 0 \\ 0 & 1 & 3 & 7 & 5 & 0 \\ 0 & 0 & 0 & 6 & 5 & 4 \\ 0 & 0 & 1 & 0 & 3 & 12 \end{bmatrix}$$

Transition matrix assuming 6 states of the mean energy consumption

Diagonal dominance indicating the likelihood of the consumption to stay in the same state for consecutive time periods

Performance of the stochastic models with different number of assumed states [4]



Comparison of the baseline persistent models against machine learning methods [4]

Features considered:

feature	RF importance (H1)	RF importance (H2)
temperature	0.0148	0.0106
dew_point	0.00850	0.00683
humidity	0.00963	0.00573
apparent_temperature	0.0181	0.00916
pressure	0.00960	0.00602
wind_speed	0.00869	0.00621
cloud_cover	0.00469	0.00298
precip_probability	0.00171	0.00225
sin_hour	0.00559	0.0101
cos_hour	0.0224	0.0172
sin_minute	0.00139	0.000784
cos_minute	0.00160	0.000961
sin_dayofyear	0.00723	0.00882
cos_dayofyear	0.00856	0.00777
dayofweek_0	0.000335	0.000528
dayofweek_1	0.000756	0.000237
dayofweek_2	0.000495	0.000502
dayofweek_3	0.000478	0.000291
dayofweek_4	0.00114	0.000273
dayofweek_5	0.000411	0.000339
dayofweek_6	0.000506	0.000593
1_intervals_before	**0.713**	**0.740**
2_intervals_before	0.0318	0.0224
3_intervals_before	0.0234	0.0151
4_intervals_before	0.0255	0.0599
5_intervals_before	0.0204	0.0188
6_intervals_before	0.0151	0.0124
7_intervals_before	0.0256	0.0106
1_days_before	0.00172	0.00323
2_days_before	0.00236	0.00356
3_days_before	0.00285	0.00362
4_days_before	0.00219	0.00288
5_days_before	0.00346	0.00358
6_days_before	0.00305	0.00270
7_days_before	0.00267	0.00307

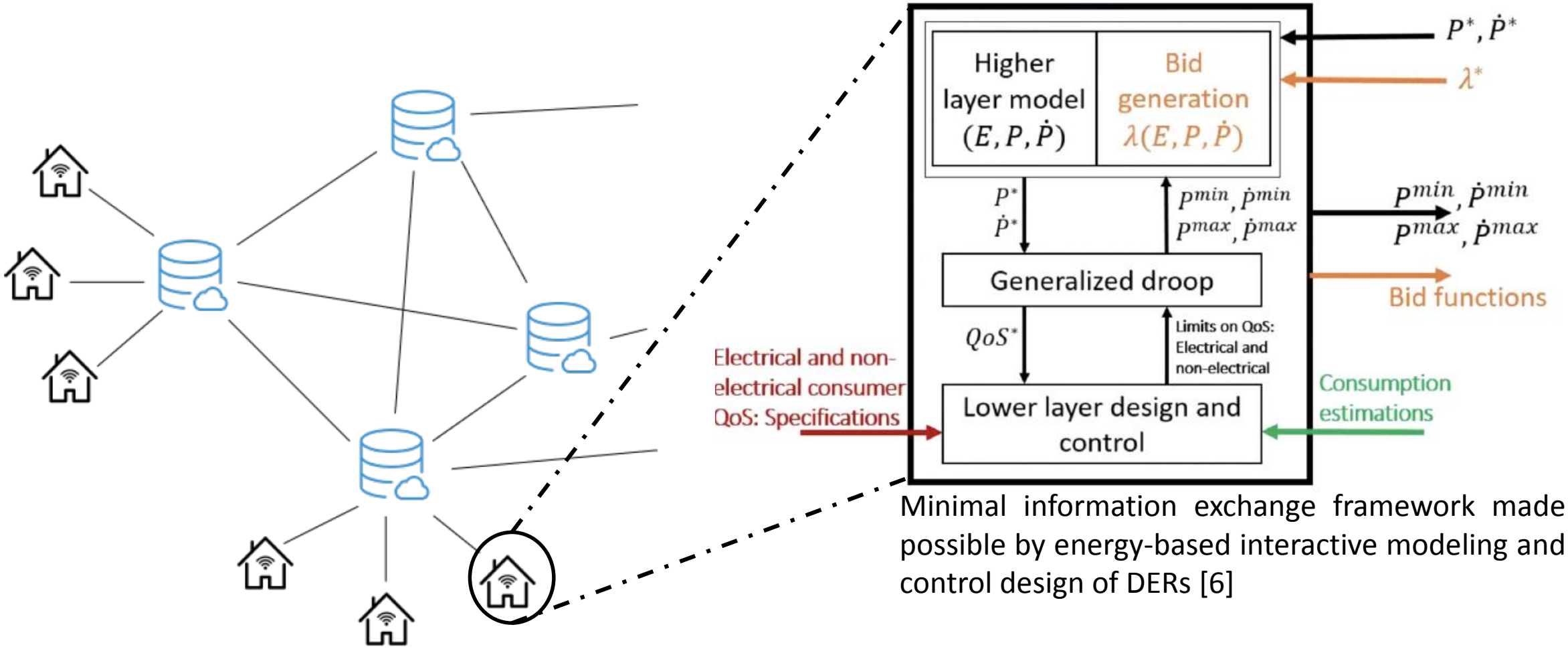
	MAE	MSE	Size(bytes)
PSS	0.370	0.475	8
Stat	0.410 (+1.11%)	0.449 (-5.47%)	1.11e5
RF	0.344 (-7.03%)	0.315 (-33.7%)	8.36e5
MLP	0.350 (-5.41%)	0.333 (-29.9%)	7.89e4
SVR	0.354 (-4.32%)	0.350 (-26.3%)	8.40e5

TABLE I
EXPERIMENTAL RESULTS FOR HOUSEHOLD-LEVEL PREDICTION

- 70 % of the data used to train the model and the rest is used as testing data.
- All the ML methods outperform baseline method
- ML methods need several orders of magnitude larger memory requirement compared to the baseline.
- Statistical models can not appropriately model the periodicity of data when it is noisy, but the ML methods implicitly do consider the periodicity involved

EESG @IIIT

Secure DyMonDS-enabled blockchain design [4,5]

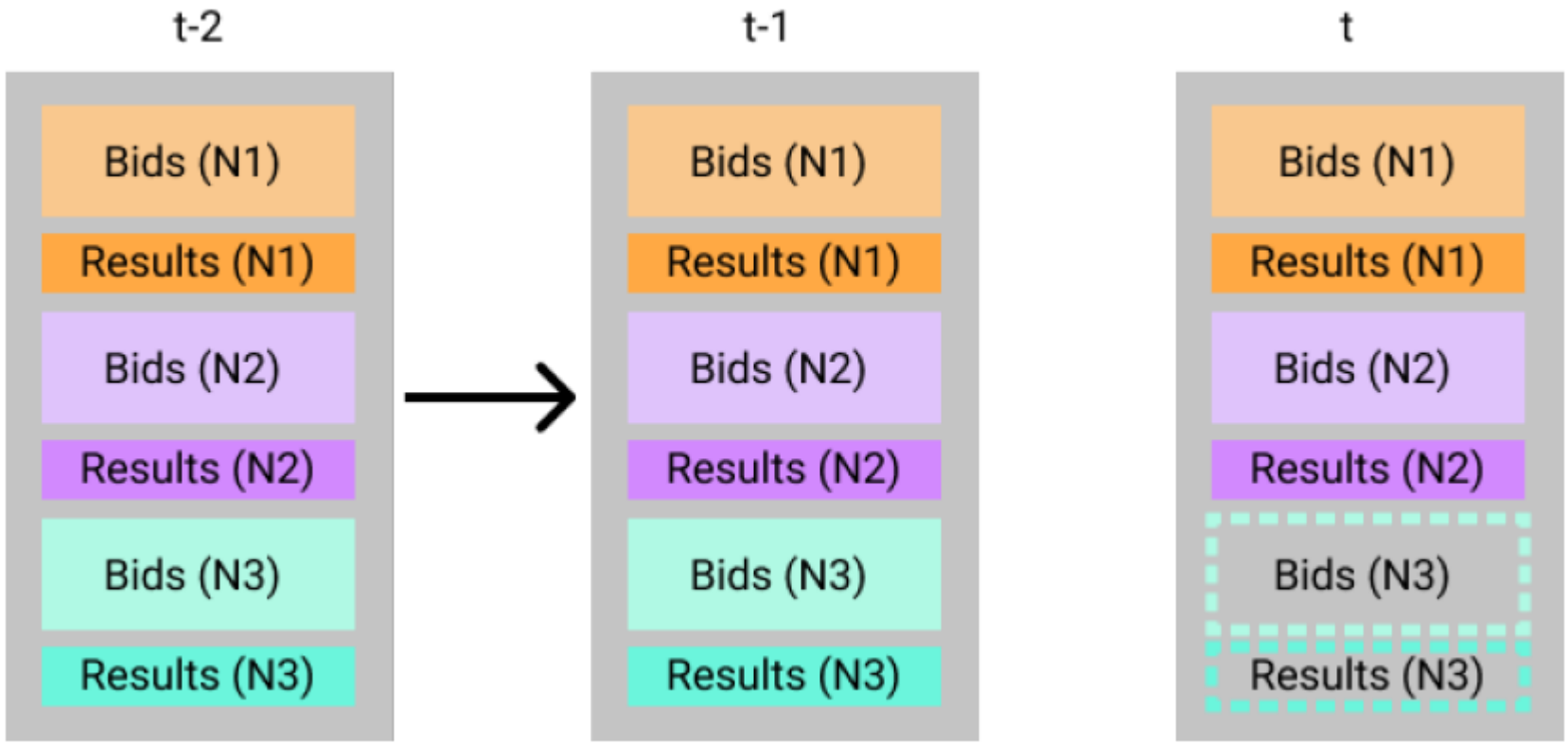


Minimal information exchange framework made possible by energy-based interactive modeling and control design of DERs [6]

[5] Lauer, M. , Ilic, M.D. and Jaddivada, R., 2019, May. Secure Blockchain-Enabled DyMonDS Design. In *Proceedings of the International conference on Omni-layer intelligent systems*. ACM (***accepted to appear***).

[6] Ilić, M.D. and Jaddivada, R., 2018. Multi-layered interactive energy space modeling for near-optimal electrification of terrestrial, shipboard and aircraft systems. *Annual Reviews in Control*.

Snapshot of blockchain ledger [4,5]



- Relies on the trust among the different NODES
- Blockchain is used as a shared database with protected read-write capabilities
- The data stored is at multiple NODES, thus is not at a risk of single point of failure
- Peer-to-peer learning-enabled validation is implemented to verify the logs before they get synchronized into the respective ledger copies
- Incorporating DyMonDS framework results in lesser memory requirement in the ledgers

Publications

Published Papers:

- Ilic, M.D. and Jaddivada, R., 2018, December. Fundamental Modeling and Conditions for Realizable and Efficient Energy Systems. In *2018 IEEE Conference on Decision and Control (CDC)* (pp. 5694-5701). IEEE.
- Ilic, M., Jaddivada, R., Miao, X. and Popli, N., 2019. Toward Multi-Layered MPC for Complex Electric Energy Systems. In *Handbook of Model Predictive Control* (pp. 625-663). Birkhäuser, Cham.
- Ilić, M.D., Jaddivada, R. and Miao, X., 2018, October. Rapid Automated Assessment of Microgrid Performance Software System (RAMPS). In *2018 IEEE PES Innovative Smart Grid Technologies Conference Europe (ISGT-Europe)* (pp. 1-6). IEEE.
- Ilić, M.D. and Jaddivada, R., 2018. Multi-layered interactive energy space modeling for near-optimal electrification of terrestrial, shipboard and aircraft systems. *Annual Reviews in Control*.
- Jaddivada, R. and Ilić, M., 2017, September. A distribution management system for implementing synthetic regulation reserve. In *Power Symposium (NAPS), 2017 North American*(pp. 1-6). IEEE.

Patents:

- Ilic, M. and Jaddivada, R., Methods and systems for secure scheduling and dispatching synthetic regulation reserve from distributed energy resources, Utility patent Application No. 16/206,009, Filed on November 30, 2018

Publications

Accepted and submitted papers:

- Lauer, M. , Ilic, M.D. and Jaddivada, R., 2019, May. Secure Blockchain-Enabled DyMonDS Design. In *Proceedings of the International conference on Omni-layer intelligent systems*. ACM (***To Appear***).
- Ilić, M.D., and Jaddivada, R., 2019. New Energy Space Modeling for Optimization and Control in Electric Energy Systems. ***(Under review for publication in MOPTA special issue of Springer journal).***
- N. Popli, R. Jaddivada, F.M. O'Sullivan, and M.D. Ili'c, 2019. Harnessing Flexibilities of Heterogeneous Generation and Controllable Demand Technologies Part–II: Multi-Rate Energy Scheduling and Reserve Commitment', ***(Submitted to IEEE Transactions on Power Systems)***
- N. Popli, R. Jaddivada, F.M. O'Sullivan, and M.D. Ili'c, 2019. Harnessing Flexibilities of Heterogeneous Generation and Controllable Demand Technologies Part–I: Physics-based Multi-Rate Flexibilities and Generalized Energy Droops'', ***(Submitted to IEEE Transactions on Power Systems)***
- S. Davaluri, M.D. Ili'c, R. Jaddivada "Toward P2P Protocols for enabling sustainable distribution and retail-level power sharing", EESG Working Paper No. R-WP-2-2019, (***Submitted to Mediterranean Conference on Embedded Computing)***.
- Lauer, M. , Ilic, M.D. and Jaddivada, R., 2019, May. "Household Energy Prediction: Methods and Uses". EESG Working Paper No. R-WP-3-2019, (***Submitted to Mediterranean Conference on Embedded Computing)***.

EESG @MIT

Publications

Working papers:

- M.D. Ili'c, M. Korpas, R. Jaddivada, "Interactive Protocols for Distributed Energy Resource Management Systems (DERMS)", EESG Working Paper No. R-WP-4-2019, ***(Under preparation for submission to IEEE Transactions on Power Systems)***
- M.D. Ili'c, R. Jaddivada, "Enabling Prosumer-Centric Transactive Energy Management (TEM)", EESG Working Paper No. R-WP-12-2018, July 2018 ***(Basis for USAEE 2018 Presentation at Washington, September 2018)***
- M.D. Ili'c, R. Jaddivada, "Toward Operationally-Feasible and Efficient Integration of Distributed Energy Resources (DERs)", EESG Working Paper No. R-WP-11-2018 , April 2018 ***(Basis for NIST TE challenge and NIST Final Report 2018)***

THANK YOU

Questions?

This material is based upon work supported by the Department of Energy and Department of the Navy under Air Force Contract No. FA8702-15-D-0001. Any opinions, findings, conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the Department of Energy and Department of the Navy.

EESG @MIT