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

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NODES PROGRAM REVIEW MEETING,
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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

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

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

7% of net load

Reserve Magnitude Variability Tolerance

≤ 5% RMT

5 seconds  5 minutes  30 minutes (95% availability)
Typical neighborhood and its aggregation by NODES
Generalized droops for device-level energy flows [2]

DER as a distributed decision maker

**DER i ∈ Node I**

\[
\min \sum \lambda^l[k] P_{Di}[k] - \lambda^r[k] B_{Di}[k]
\]

**Technology-agnostic device-level controllers**

\[
\Delta W_{i}^{\text{min}} [k] T_t \leq \dot{W}_{i}^{\text{min}} [k] T_t \leq \Delta W_{i}^{\text{max}} [k] T_t
\]

Limits on comfort requirement/physical controller limits

Energy and reserve prices within Node I

\[\lambda^l[k], \lambda^r[k]\]

Generalized flexibility constraints

Consumption dispatch signal

\[\Delta P_{Di}[k]\]

SRR signal

\[\Delta P_{Di}[n]\]

Exogenous Consumption

DER Controller Implementation

Simulated DER
MIT NODES aggregation algorithm

System energy and reserve prices
\[ \lambda^S_e[k], \lambda^S_r[k] \]

Inflexible demand and bounds on its deviation predictions within Node I
\[ \Delta P^u_I[k], \hat{B}^u_I[k] \]

Aggregate Energy and Reserve bids
\[ \Delta P_{DI}[k], B_{DI}[k] \]

\[
\begin{align*}
\min_{\Delta P_{DI}[k], B_{DI}[k]} & \quad \sum_k \lambda^S_e[k] P_{DI}[k] - \lambda^S_r[k] B_{DI}[k] \\
\sum_{i \in I} \Delta P_{Di}^{\text{min}}[k] & \leq \Delta P_{DI}[k] - \Delta \hat{P}_I^u[k] \leq \sum_{i \in I} \Delta P_{Di}^{\text{max}}[k] \\
\sum_{i \in I} B_{Di}^{\text{min}}[k] & \leq B_{DI}[k] - \hat{B}_I^u[k] \leq \sum_{i \in I} B_{Di}^{\text{max}}[k]
\end{align*}
\]

DER minimum and maximum limits of each \( i \in I \)
\[ \Delta P_{Di}^{\text{min}}[k], \Delta P_{Di}^{\text{max}}[k], B_{Di}^{\text{min}}[k], B_{Di}^{\text{max}}[k], \]
NODES-level decision making for clearing energy and reserve capacity bids of DERs

Node I

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

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

\[
\Delta P_{Di}[k] - \sum_{i \in I} \Delta P_{Di}[k] - \Delta P_{Di}^u[k] = 0
\]

\[
B_{Di}[k] - \sum_{i \in I} B_{Di}[k] - \hat{B}_{Di}^u[k] \geq R_{\text{margin}}
\]

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

\[
B_{Di}^{\min}[k] \leq B_{Di}[k] \leq B_{Di}^{\max}[k]
\]

\[
\forall i \in I
\]

Cleared Energy and Reserve capacity prices within Node I

\[
\lambda^I_e[k], \lambda^I_r[k]
\]

DER bids with minimum and maximum limits for each \( i \in I \)

\[
C_i^e, C_i^r,
\]

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

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

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

DER Energy and Reserve capacity Dispatch

Node level dispatched quantity \( \Delta P_{I}[k], B_{I}[k] \)
MIT SRPS algorithm embedded in NODES

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

Integrated approach to computing device/house specific SRR signals

$\Delta P_{Di}[n] - \sum_{i \in I} \Delta P_{Di}[n] - \Delta P^u_I[n] = 0$

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

Fast time scale Inflexible demand predictions $\Delta \hat{P}^u_I[n]$

DER Reserve
$\Delta P_{Di}[n]$ 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 3: NODES algorithms deployment at

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

Task group 4: Whole sale level

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

Considered error Metrics:
• Mean Absolute Error (MAE) = \( \frac{1}{n} \sum_{j=1}^{n} |y_j - \hat{y}_j| \)
• Mean Square Error (MSE) = \( \frac{1}{n} \sum_{j=1}^{n} (y_j - \hat{y}_j)^2 \)

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

Extrinsic parameters
• Explicitly supplied in stochastic models
• Learning in machine-learning methods

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

Mean house-level energy consumption (KW-15min)

Period-number (15-minute length) of the day

Transition matrix assuming 6 states of the mean energy consumption

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

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]

Mean house-level energy consumption (KW-15min)

Period-number (15-minute length) of the day

- 3 states
- Observed
- Simulated

- 12 states

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

Features considered:

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<td>0.354 (-4.32%)</td>
<td>0.350 (-26.3%)</td>
<td>8.40e5</td>
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</table>

**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.
Secure DyMonDS-enabled blockchain design [4,5]

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


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
Published Papers:


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
Accepted and submitted papers:


Working papers:


THANK YOU

Questions?

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