Examples of Machine Learning Applications and Experiments at MISO

Yonghong Chen
Midcontinent ISO

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MISO work on the application of machine learning (ML)

- Neural network has been used for load forecast for ~20 years
- Forecast vendors apply advanced data science methods for load, wind and solar forecast

- Resource portfolio change and increasing uncertainty prompt grid operators to adapt to more probabilistic driven operations
  - Opportunity for more applications of data science

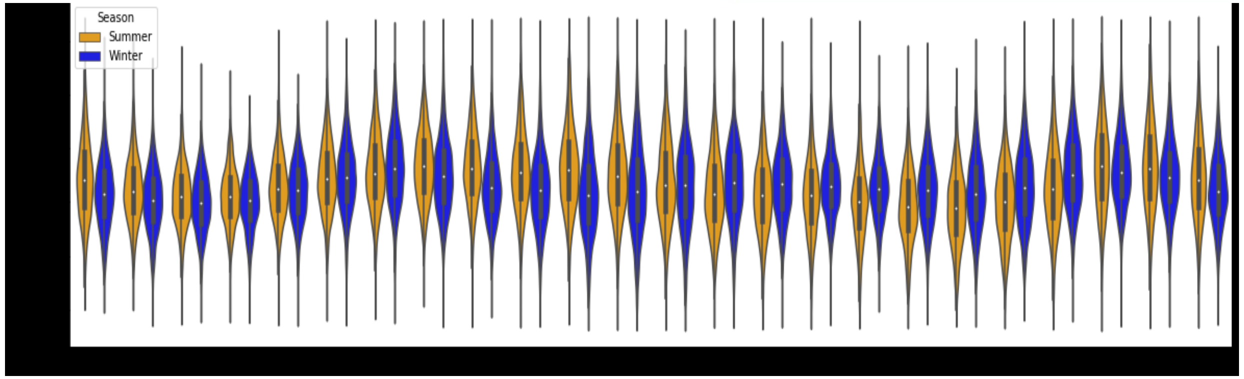
- Examples of recent ML related work
  - Define dynamic reserve requirement
  - Intra-day storage optimization with probabilistic price forecast
  - Synergistic Integration of ML and mathematical optimization for unit commitment (collaboration with University of Connecticut)

Define dynamic reserve requirement

30-min short term reserve (STR) to cover (t+30min, t+3h) uncertainty

- STR was implemented in Dec. 2021 to manage system wide and sub-regional uncertainties
- Uncertainty distributions present seasonal and hourly differences
  - Net input uncertainty
  - generation outage / derate uncertainty
  - Real time commitment

2.5-3h net input uncertainty



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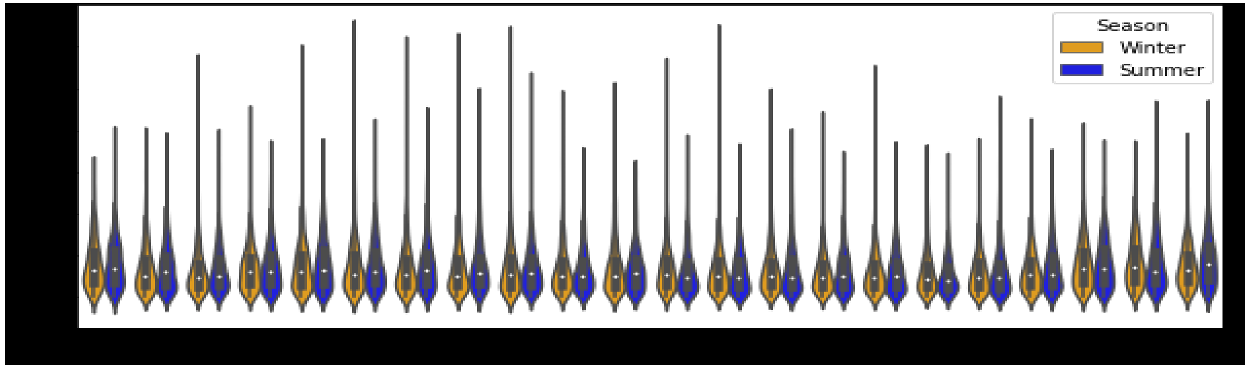
2.5-3h net Gen Outage / Derate uncertainty



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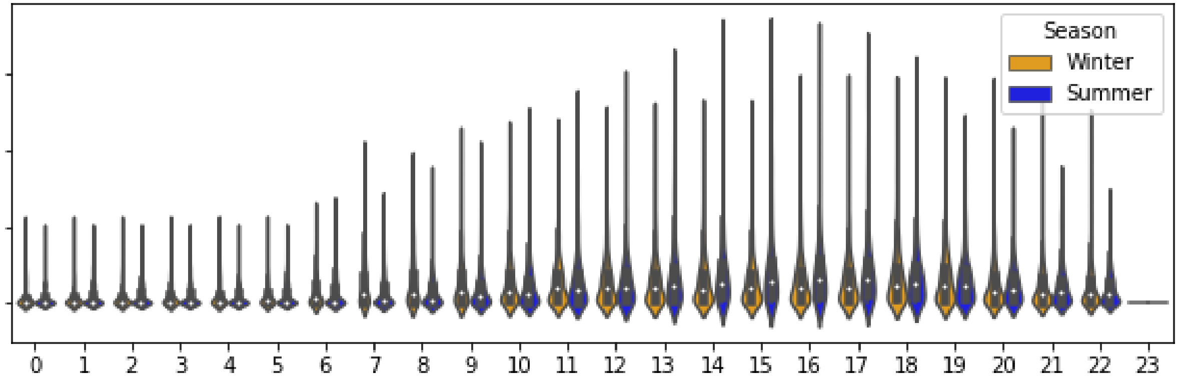
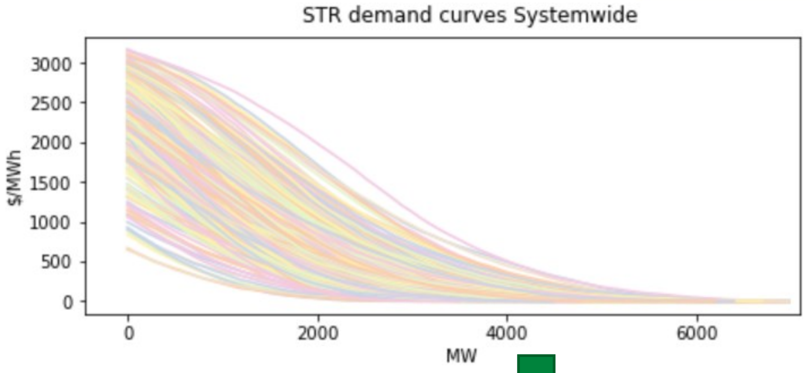
Real time commitment distribution with 0.5-2.5h lead time

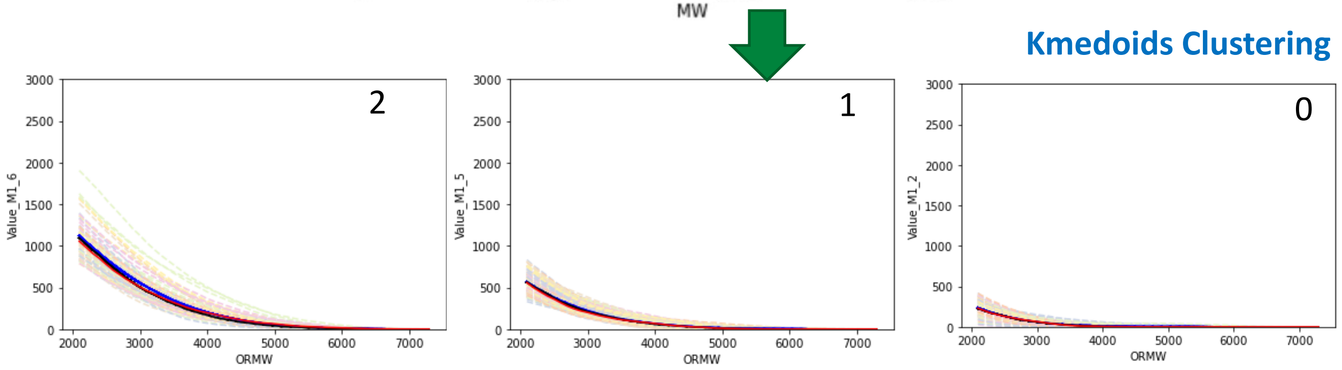


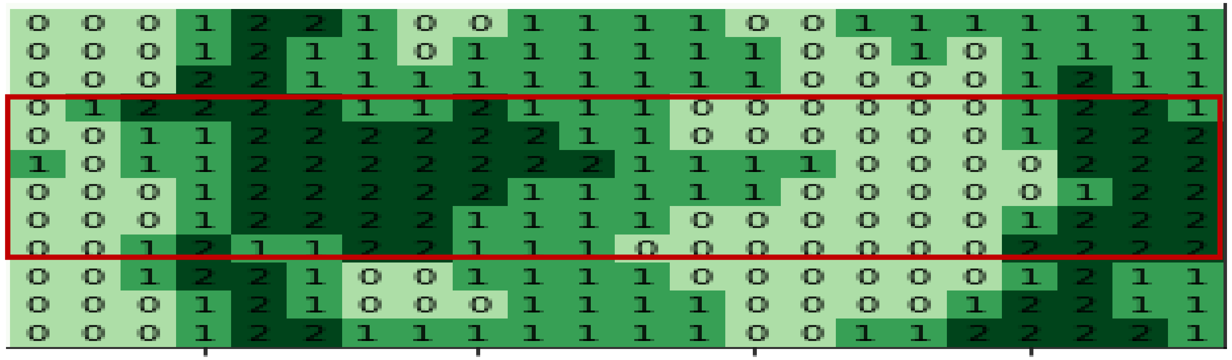
Deriving hourly STR requirement by season through clustering

- Monte Carlo simulation to derive STR demand curves by month and by hour
- Machine learning clustering to group **requirements** into
  - Two seasons
  - High, medium and low hours



Kmedoids Clustering





0	0	0	1	2	2	1	0	0	1	1	1	1	0	0	1	1	1	1	1	1	1
0	0	0	1	2	1	1	0	1	1	1	1	1	1	0	0	1	0	1	1	1	1
0	0	0	2	2	1	1	1	1	1	1	1	1	1	0	0	0	0	1	2	1	1
0	1	2	2	2	2	1	1	2	1	1	1	0	0	0	0	0	0	1	2	2	1
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0	0	0	1	2	2	1	1	1	1	1	1	1	0	0	1	1	2	2	2	2	1

Address sub-regional uncertainty with STR

- Using similar method to analyze sub-regional uncertainty
  - Currently post-reserve deployment transmission constraints ensure zonal reserve deliverability under the largest zonal generation outage events
  - **Define the maximum sub-regional/zonal uncertainty events for STR (seasonal and hourly settings)**

$Energyflow_{j,t}$

$\mathrm{STRResponse}_{z,e,t}$

$\sum_{z}\mathrm{STRResponse}_{z,e,t}$

$\mathrm{STRResponse}_{z,e,t}$ $\mathrm{ZonalSTR}_{z,t}$

$\mathrm{ZonalSTR}_{z,t}$

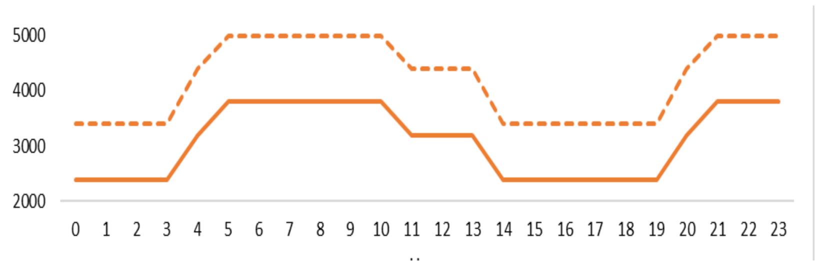
$\mathrm{STR}_{r,t}$ $\mathrm{ZonalSTR}_{z,t}$

Risk based normal and emergency STR requirements (seasonal update)

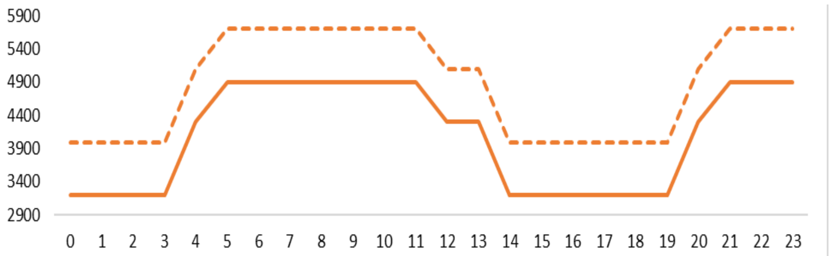
— Summer Normal (cover 97% risk)
- - Summer Emergency (cover 99% risk)

— Winter Normal (cover 97% risk)
- - Winter Emergency (cover 99% risk)

NC STR to cover uncertainty event much larger than G-1



Systemwide STR



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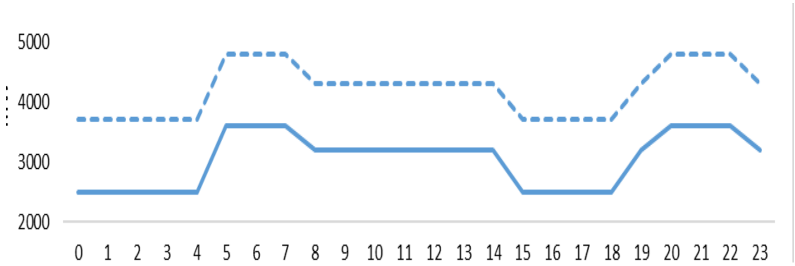
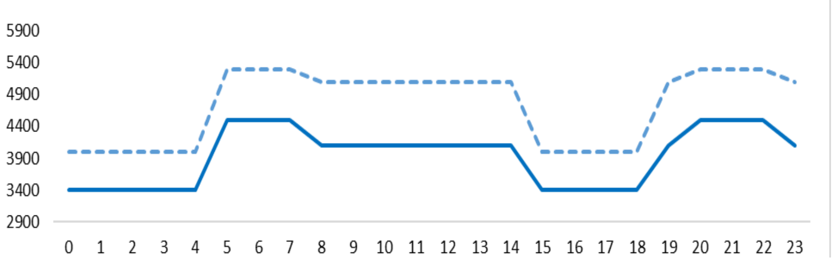


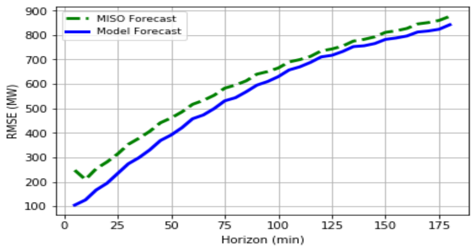
Systemwide STR

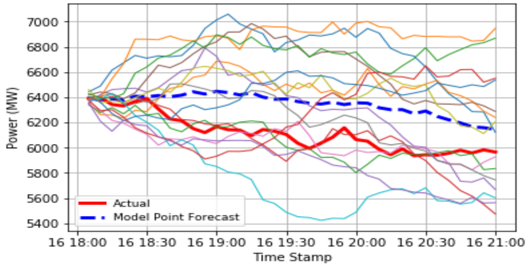


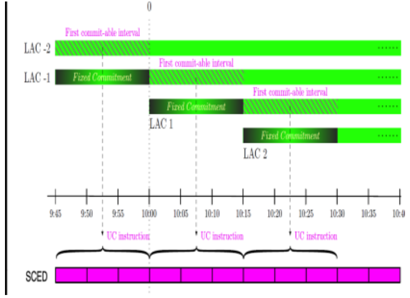
Addressing Uncertainties Through Improved Reserve Product Design, Yonghong Chen, IEEE Transactions on Power Systems, under review

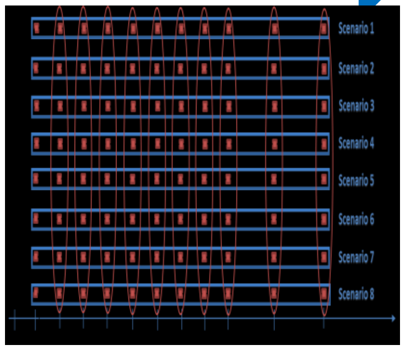
On-going research: scenario generation, simulation and optimization

Uncertainty Analysis, point forecast improvement and Scenario Generation | RT simulation | Stochastic LAC (SLAC)









Improve prediction

- **Wind, load, NSI**
  Improve point forecast by considering recent forecast error

Identify range of probability

- **Scenario generation**
  Generate scenarios with trajectories for individual wind, load and interchange for 5-min intervals in the next 3 hours

Recommend actions (over a rolling window)

- **Rolling horizon RT simulation**
- **Validate reserve designs** Better determine reserve requirements
- **Commitment** Identify optimal commitment across scenarios to manage uncertainty

Developed under ARPA-E SLAC. On-going research:

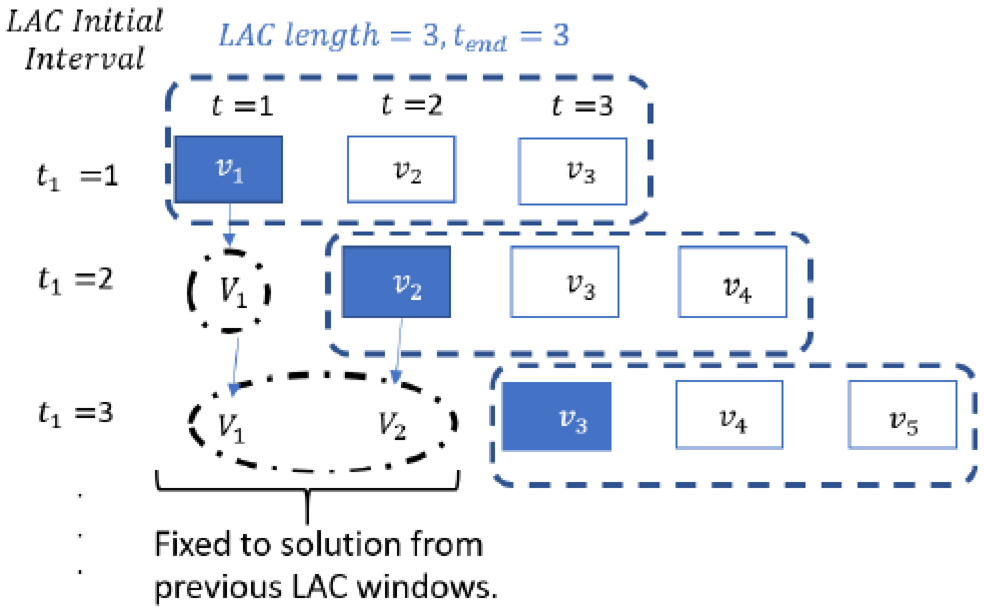
- ***EGRET Stochastic simulation to help validate design and operational processes for upcoming 6-8GW solar***
- ***Simplified version of scenario generation for operations***

B Knueven, M Faqiry, M Garcia, YC Chen, T Roger, W Trevor, Z Junshan, Stochastic Look-Ahead Commitment: A Case Study in MISO, 2021, http://www.optimization-online.org/DB_FILE/2021/10/8660.pdf

Real time storage optimization with probabilistic pricing scenarios

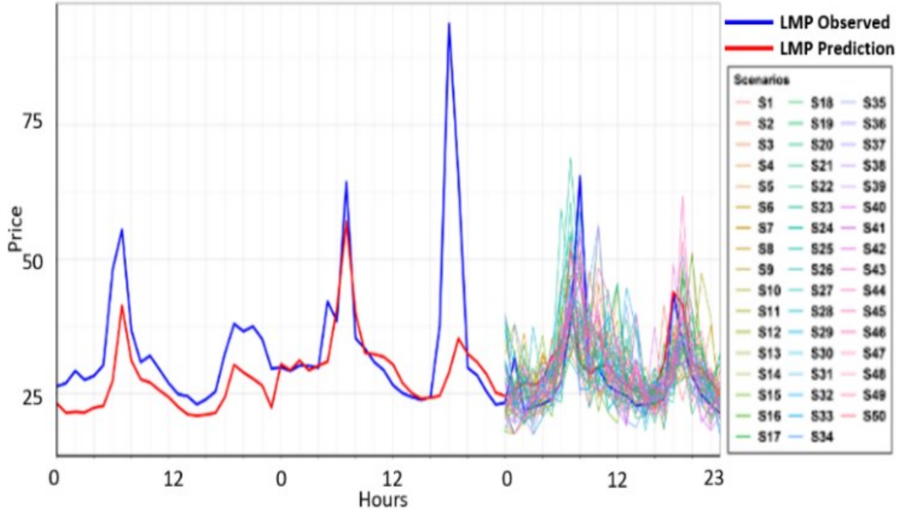
Research project on future real time storage optimization

- Real time rolling look ahead commitment only has 3-h forward information
- Storage with duration longer than 3-h may not be optimized effectively
  - Future prices may be much higher or lower than the immediate 3-h.



Probabilistic real time price forecast

- ARIMAX-based, single point RT-LMP forecast was developed
- A probabilistic RT-LMP forecast with a series of statistical scenarios are generated based on the interdependence structure of prediction errors
- LMP forecast scenarios are applied to risk neutral and risk averse versions of LAC commitment



Risk averse robust formulation: minimize current LAC production cost and profit loss outside of LAC

$$\min_{q,u,v} \sum_{g \in \mathcal{G}} \sum_{t=t_1}^{t_{end}} C(q_{g,t}, u_{g,t}) + \sum_{r \in \mathcal{R}} W_r,$$

$$W_r \geq - \sum_{t=t_{end}+1}^{T} \sum_{g \in \mathcal{G}_{psh,r}} LMP^{t_0}_{g,s,t}[(q^{gen}_{g,s,t} - q^{pump}_{g,s,t}) - (Q^{gen,DA}_{g,t} - Q^{pump,DA}_{g,t})], \quad \forall r \in \mathcal{R}, \forall s \in \mathcal{S}.$$

Risk neutral stochastic formulation: minimize current LAC production cost and expected storage loss outside of LAC

$$\min_{q,u} \sum_{g \in \mathcal{G}} \sum_{t=t_1}^{t_{end}} C(q_{g,t}, u_{g,t})$$

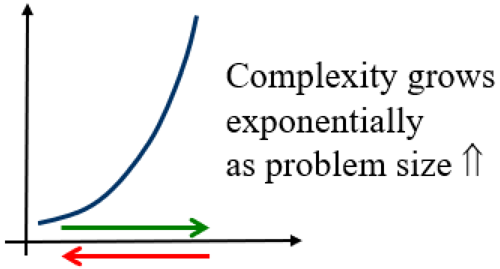
$$- \sum_{s \in \mathcal{S}} \sum_{t=t_{end}+1}^{T} \sum_{g \in \mathcal{G}_{psh}} P_s LMP^{t_0}_{g,s,t}(q^{gen}_{g,s,t} - q^{pump}_{g,s,t}).$$

Bing Huang, Arezou Ghesmati, Yonghong Chen, and Ross Baldick, A Pumped Storage Hydro Optimization in the Look-ahead Unit Commitment Using Price Forecasts, IEEE Transactions on Power Systems, under review

Synergistic Integration of Machine Learning and Mathematical Optimization for Unit Commitment

Surrogate Lagrangian Relaxation

- Decomposition and coordination - Lagrangian Relaxation (LR)
  - Reduce complexity exponentially through decomposition
  - Suffer from major difficulties of significant computational efforts and zigzagging of multipliers



- Surrogate Lagrangian Relaxation (SLR)
  - Overcame all major difficulties of traditional LR
    - No need to solve all subproblems. Just one, and not even optimally

    ⇒ "Good enough" solutions with ⇓ computation and zigzagging

    ⇒ Reduced number of iterations
  - Embedded with the ordinal optimization (OO) concepts
    - Obtaining good-enough solutions quickly by modifying solutions from previous iterations or by solving crude subproblems
- However, the above may not be sufficient when facing new challenges. Will ML be helpful?

- *M. A. Bragin, P. B. Luh, J. H. Yan, N. Yu and G. A. Stern, "Convergence of the Surrogate Lagrangian Relaxation Method," Journal of Optimization Theory and Applications, Vol. 164, Issue 1, 2015, pp. 173-201, DOI: 10.1007/s10957-014-0561-3*
- *J. Wu, P. B. Luh, Y. Chen, M. A. Bragin and B. Yan, "A Novel Optimization Approach for Sub-hourly Unit Commitment with Large Numbers of Units and Virtual Transactions," IEEE Transactions on Power Systems, early access, December 2021, DOI: 10.1109/TPWRS.2021.3137842*

ML-based decomposition & coordination

- UC formulation

$$\text{Min} \sum_{i=1}^{I}\sum_{t=1}^{T}\left[C_{i,t}^{NL}x_{i,t} + C_{i,t}^{Start}u_{i,t} + \sum_{b=1}^{B}C_{i,b,t}^{E}p_{i,b,t}\right], \qquad (1)$$

$s.t.$ system demand, transimission and unit-level constraints.

- SLR subproblems
  - Relax system-wide constraints, and decompose into J subproblen

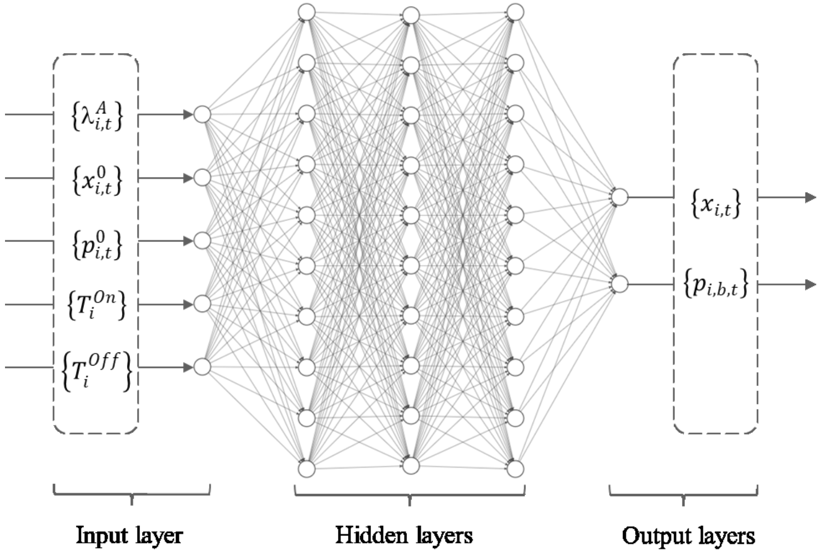
$$\text{Min } L_j(\lambda_j, \mu_j, x_j, u_j, p_j), \text{where}$$

$$L_j(\lambda_j, \mu_j, x_j, u_j, p_j) \equiv \left\{\sum_{i\in I_j}\sum_{t=1}^{T}\left[C_{i,t}^{Start}u_{i,t} + C_{i,t}^{NL}x_{i,t} + \sum_{b=1}^{B}C_{i,b,t}^{E}p_{i,b,t}\right] + \sum_{t=1}^{T}\left(-\sum_{i\in I_j}\lambda_t p_{i,t} + \sum_{l=1}^{L}\left(\mu_{t,l}^{+} - \mu_{t,l}^{-}\right)\left(\sum_{n=1}^{N}\sum_{i\in(I_n\cap I_j)}\alpha_{n,l}p_{i,t}\right)\right)\right\}, \qquad (2)$$

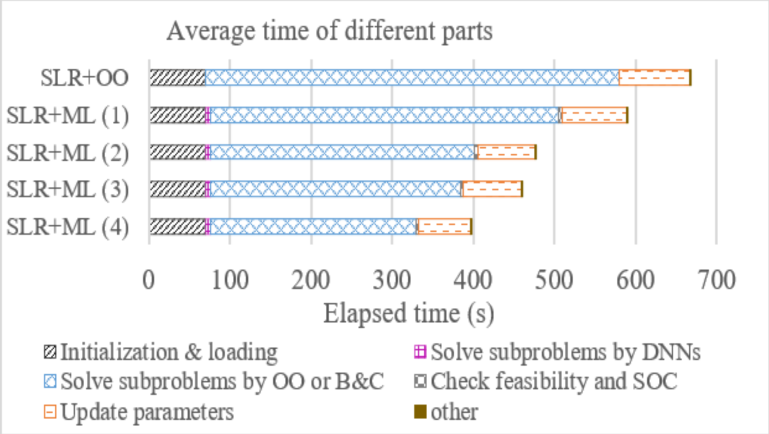
$s.t.$ unit-level constraints.

  - Input: multipliers and unit initial statuses $\left\{\lambda, \mu, x_{i,t}^{0}, p_{i,t}^{0}, T_i^{On}, T_i^{Off}\right\}$
    - Should be randomly generated for machine learning
  - Output: subproblem solutions $\left\{x_{i,t}, u_{i,t}, p_{i,t}, p_{i,b,t}\right\}$
- Good-enough subproblem solutions ~ Feasible and satisfy a simple convergence condition

$$L_j(\lambda^k, \mu^k, x_j^k, u_j^k, p_j^k) < L_j(\lambda^k, \mu^k, x_j^{k-1}, u_j^{k-1}, p_j^{k-1}) \qquad (3)$$



- Multilayer perceptron
- Offline and online learning
- Less sub problem solving time



- *J. Wu, P. B. Luh, Y. Chen, B. Yan and M. A. Bragin, "Synergistic Integration of Machine Learning and Mathematical Optimization for Unit Commitment," submitted to IEEE Transactions on Power Systems, 2022, and Preprint in TechRxiv: https://doi.org/10.36227/techrxiv.19653777.v1*

Other experiments and trials: mostly at early stage

- Outage Forecasting:
  - Forecasting of generation outages & derates to help improve situational awareness regarding the maintenance margin
- Net scheduled interchange (NSI) forecast
  - Intra-day time series
  - Difficult to capture behavior around emergency events
- Intelligent alarm
  - Improve the use of flooded alarm in MISO control room
  - Identify false alarm, nuisance alarm, and operating alarm
- Congestion forecast
  - Forecast real time congestion for day ahead market
- Generator startup and shut down profiles
  - Non-dispatchable and may contribute to large ramping needs in certain time window