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U.S. DEPARTMENT OF ENERGY

Stochastic Sizing and Operation of Grid-Level Energy Storage Systems

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Background

- The increasing renewables generation
  - Intermittent and undispatchable
  - Exacerbates the frequency responses by replacing synchronous generators, reducing the system inertia, and increasing the fluctuation of power generation
- Energy storage system (ESS) is a promising solution to address such issues but still expensive

Objective

- To develop a framework for sizing, siting, and operation of energy storage systems (ESSs) to ensure efficiency, security, and reliability of the power grids
  - Considering correlated uncertainties and stability constraints in the planning and operational horizons

Technical Approach

- Formulated as a mixed-integer programming (MIP)-based Unit Commitment (UC) problem accounting for the long-term uncertainties of demand and renewable generation subject to constraints
  - Unit-Level: Generation capacity, start-up, ramp up/down, minimum uptime, ...
  - ESS: SOC tracking, charge/discharge
  - System-level: Demand variation, generator outages, frequency nadir (FN), rate of change of frequency (RoCoF), quasi-steady-state (QSS), and soft constraints (transmission capacity, reserve)
- Develop a scalable approach to solving the stochastic UC problem for ESS sizing, siting, and operation

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Technical Approach (cont'd) *

- Random field theory (RFT)-based modeling of long-term renewable uncertainties
- Consideration of (N-1) generator contingencies
- A new set of frequency dynamics constraints
- Surrogate Absolute-Value Lagrangian Relaxation (SAVLR) for stochastic MIP problems
- A rolling horizon-based SAVLR (SAVLRseq) to address the complexity and requirement of computational resource
- A machine learning (ML)-assisted stochastics optimization scheme

***: Summarized from the following publications**

[1] T. Zhao, N. Raghunathan, A. Yogarathnam, M Yue, and P. B. Luh, "A Scalable Planning Framework of Energy Storage Systems under Frequency Dynamics Constraints," the International Journal of Electrical Power and Energy Systems, Vol. 145, February 2023.

[2] B. Huang, T. Zhao, M. Yue, and J. Wang, "Two-Stage Adaptive Storage Expansion Strategy for Microgrids Using Deep Reinforcement Learning," accepted by *IEEE Transactions on Smart Grid*, to appear.

[3] N. Raghunathan, Z. Wang, P. B. Luh, M. A. Bragin, B. Yan, T. Zhao, M. Yue, "PCA-based Reduced-order Decomposition and Coordination Approach for Markov-based Stochastic UC with Distributed Wind and Storage," manuscript being prepared.

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ESS Planning Problem Formulation

- Mathematical formulation of ESS sizing and siting
  - Objective function: Capital costs + Operation costs

$$\min \sum_{i\in\Omega_E} c_i^E BE_i + cc \sum_{\omega} p_{\omega} \sum_t \Big(\sum_{i\in\Omega_G} \big(c_i^g g_{it}^{\omega} + c_i^{SU} SU_{it}^{\omega} + c_i^{NL} u_{it}^{\omega} \big) + \sum_{i\in\Omega_B} c_i^{ls} d_{it}^{s\omega} + \sum_{i\in\Omega_W} c_i^{rs} r_{it}^{s\omega} + \sum_{ij\in\Omega_l} c^s \big(\overline{s}_{ij} + \underline{s}_{ij} \big) \Big)$$

  - Subject to:
    - ➢ System coupling constraints: system demand, soft transmission capacity, FN, RoCoF, and QSS, ESS related
    - ➢ Unit-level constraints: ramping, min up/down, generation capacity, and start-up, ESS related

ESS Planning Problem Formulation (cont'd)

- Transmission capacity soft constraints:

$$\sum \alpha_{ij} \left\{ \sum_{y \in i} g_{yt}^{\omega} - b_{it}^{c,\omega} + b_{it}^{d,\omega} + r_{it}^{o\omega} - r_{it}^{s\omega} + d_{it}^{s\omega} - d_{it}^{\omega} \right\} = f_{ijt}^{\omega}, \quad \forall ij$$

DC power flow

$$\underline{f}_{ij} \leq f_{ijt}^{\omega} + \overline{s}_{ij}, \qquad \forall ij$$

$$f_{ijt}^{\omega} - \underline{s}_{ij} \leq \bar{f}_{ij}, \quad \forall ij$$

Transmission capacity

- Generator-related constraints:

$$u_{it}^{\omega} \underline{g}_i \leq g_{it}^{\omega} \leq u_{it}^{\omega} \bar{g}_i, \qquad \forall i \in \Omega_G$$

Generation lower and upper limits considering on/off status

$$\sum_{y=t-\tau_i^+}^{t} SU_{iy}^{\omega} \leq u_{it}^{\omega}, \quad \forall i \in \Omega_G$$

$$\sum_{y=t-\tau_i^-}^{t} SD_{iy}^{\omega} \leq u_{it}^{\omega}, \quad \forall i \in \Omega_G$$

Minimum up and down time of conventional generators

$$u_{it}^{\omega} - u_{i(t-1)}^{\omega} = SU_{it}^{\omega} - SD_{it}^{\omega}, \quad \forall i \in \Omega_G$$

Startup or shutdown logic

$$g_{it}^{\omega} - g_{i,t-1}^{\omega} \leq RU_i, \quad t = 2,3,\cdots,n_t, \forall i \in \Omega_G$$

$$g_{i,t-1}^{\omega} - g_{it}^{\omega} \leq RD_i, \quad t = 2,3,\cdots,n_t, \forall i \in \Omega_G$$

Ramp rate up and down limits

ESS Planning Problem Formulation (cont'd)

- ESS-related constraints

ESS power limits
$$0 \le b_{it}^{c,\omega} \le \alpha_{it} BP_i^{ch}, \quad \forall i \in \Omega_E$$
$$0 \le b_{it}^{d,\omega} \le \beta_{it} BP_i^{dch}, \quad \forall i \in \Omega_E$$

$$\alpha_{it} + \beta_{it} \le 1, \quad \forall i \in \Omega_E$$

Charging and discharging do not occur simultaneously

Change of ESS state of charge (SoC)
$$SOC_{i,t}^{\omega} = SOC_{i,t-1}^{\omega} + \eta_i^{ch} b_{it}^{c,\omega} \Delta t - b_{it}^{d,\omega} \Delta t / \eta_i^{dch}, \forall i \in \Omega_E$$

SoC limits
$$0.3 * BE_i \le SOC_{it}^{\omega} \le BE_i, \quad \forall i \in \Omega_E$$
$$SOC_{i,n_t}^{\omega} = SOC_{i,0}^{\omega} = 0.5 BE_i, \quad \forall i \in \Omega_E$$

- Reserve constraints: Generation (generators + renewables + ESS) – load ≥ reserve

$$\sum_{i \in \Omega_G} (u_{it}^{\omega} \bar{g}_i) + \sum_{i \in \Omega_E} \left(b_{it}^{c,\omega} + BP_i^{dch} - b_{it}^{d,\omega}\right) + \sum_{i \in \Omega_W} (r_{it}^{o\omega} - r_{it}^{s\omega}) + \sum_{i \in \Omega_B} (d_{it}^{s\omega} - d_{it}^{\omega}) \ge R_t^{\omega}$$

$$\sum_{i \in \Omega_G} (u_{it}^{\omega} \bar{g}_i) + \sum_{i \in \Omega_E} \left(b_{it}^{c,\omega} + SOC_{i,t}^{\omega} / \Delta t - b_{it}^{d,\omega}\right) + \sum_{i \in \Omega_W} (r_{it}^{o\omega} - r_{it}^{s\omega}) + \sum_{i \in \Omega_B} (d_{it}^{s\omega} - d_{it}^{\omega}) \ge R_t^{\omega}$$

ESS Planning Problem Formulation (cont'd)

- Quasi-Steady-State Frequency:

$$\frac{\Delta g_{t,\mathrm{u}}^{\omega\kappa}}{\Delta f_{qss}^{\omega\kappa}} = \sum_{i\in\{\Omega_G,\Omega_W\}\backslash\Omega_\kappa} \frac{u_{it}^{\omega}\bar{g}_i}{DR_i f^0},$$

$$\Delta f_{qss}^{\omega\kappa} \leq \Delta f_{qss}^{max}$$

- Rate of Change of Frequency (RoCoF):

$$H_t^{\omega\kappa} 2RoCoF^{\max} \geq \Delta g_{t,\mathrm{u}}^{\omega\kappa},$$

$$H_t^{\omega\kappa} 2RoCoF^{\max} \geq \Delta g_{t,\mathrm{o}}^{\omega\kappa},$$

with $$H_t^{\omega\kappa} = \left(\sum_{i\in\Omega_G\backslash\Omega_\kappa} u_{it}^{\omega}\bar{g}_i H_i + \sum_{i\in\Omega_W\backslash\Omega_\kappa} (r_{it}^{o\omega} - r_{it}^{s\omega}) H_i \right) / f_0$$ System inertia (MWs/Hz)

ESS Planning Problem Formulation (cont'd)

- Frequency nadir limit:

$$\sum_{i\in\{\Omega_G,\Omega_W\}\backslash\Omega_\kappa} g_{it}^{R\omega\kappa} \geq \Delta g_{t,\mathrm{u}}^{\omega\kappa},$$

Total reserve ≥ system power imbalance

$$0 \leq g_{it}^{R\omega\kappa} \leq \frac{u_{it}^{\omega} v_i}{\sum_{i\in\{\Omega_G,\Omega_W\}\backslash\Omega_\kappa} u_{it}^{\omega} v_i} \Delta g_{t,\mathrm{u}}^{\omega\kappa}, \forall\kappa, \forall i \in \{\Omega_G,\ \Omega_W\}\backslash\Omega_\kappa,$$

$$2H_t^{\omega\kappa}(f_0 - f_{MIN} - f_{db}) \sum_{i\in\{\Omega_G,\Omega_W\}\backslash\Omega_\kappa} u_{it}^{\omega} v_i \geq \left(g_{t,\mathrm{u}}^{\omega\kappa}\right)^2$$

System inertia × (freq0-freqmin) × system ramp rate ≥ system power imbalance^2

$$0 \leq g_{it}^{\omega} + g_{it}^{R\omega\kappa} \leq u_{it}^{\omega} \bar{g}_i, \quad \forall i \in \Omega_G\backslash\Omega_\kappa$$

Total generation and reserve ≤ total capacity

- Other frequency-related constraints

$$bc1_t^{\omega\kappa} \leq \sum_{i\in\Omega_E}\left(b_{it}^{c,\omega} + BP_i^{dch} - b_{it}^{d,\omega}\right)$$

$$bc2_t^{\omega\kappa} \leq \sum_{i\in\Omega_E}\left(BP_i^{ch} - b_{it}^{c,\omega} + b_{it}^{d,\omega}\right)$$

Increased/decreased power from ESS after contingencies

$$b_{it}^{d,\omega}(\Delta t_{IR} + \Delta t_{PFR}) \leq SOC_{it}^{\omega}$$

Used ESS energy ≤ remaining capacity

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Uncertainty Modeling for Planning Scenario Development

- A sequential Monte Carlo simulation method is used to generate (N-1) scenarios based on generator failure rates and repair rates
- An RFT framework suitable for simulating RF representation of climate variables
  - Non-Gaussian, intermittent, dependent, periodic, and of a desired marginal probability distribution and a spatio-temporal correlation structure.

Target is to generate correlated RVs (X1, X2)

- with predefined target marginal distributions

$F_{X_1}(x_1) := \mathrm{P}(X_1 \leq x_1) \quad F_{X_2}(x_2) := \mathrm{P}(X_2 \leq x_2)$

- Target correlation -- Pearson's correlation coefficient

$$\rho_{X_1X_2} := \mathrm{Corr}[X_1,\ X_2]$$

$X_1 = F_{X_1}^{-1}(\Phi(Z_1)), X_2 = F_{X_2}^{-1}(\Phi(Z_2))$

$\longleftarrow$

$\Phi(\cdot)$ standard Gaussian cumulative distribution function (CDF)

Auxiliary correlated RVs (Z1, Z2)

- both have the standard **Gaussian marginal distribution**
- the joint distribution is the bivariate Gaussian with **zero mean, unit variance**
- correlation coefficient:

$$\widetilde{\rho}_{Z_1Z_2} := \mathrm{Corr}[Z_1, Z_2]$$

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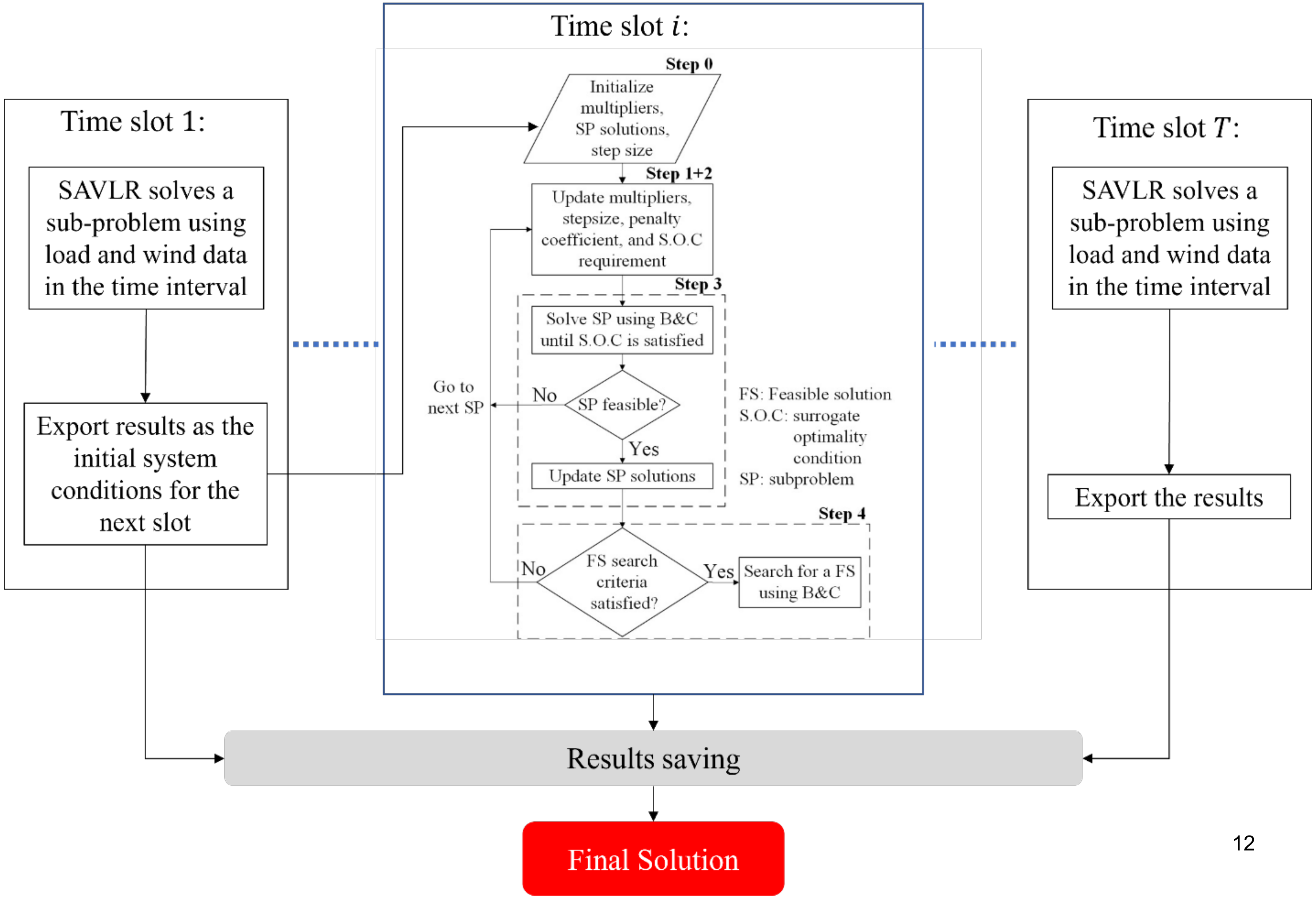
$F_{X_1}^{-1}(\cdot)$ and $F_{X_2}^{-1}(\cdot)$ denote the inverse cumulative distribution functions (ICDF)

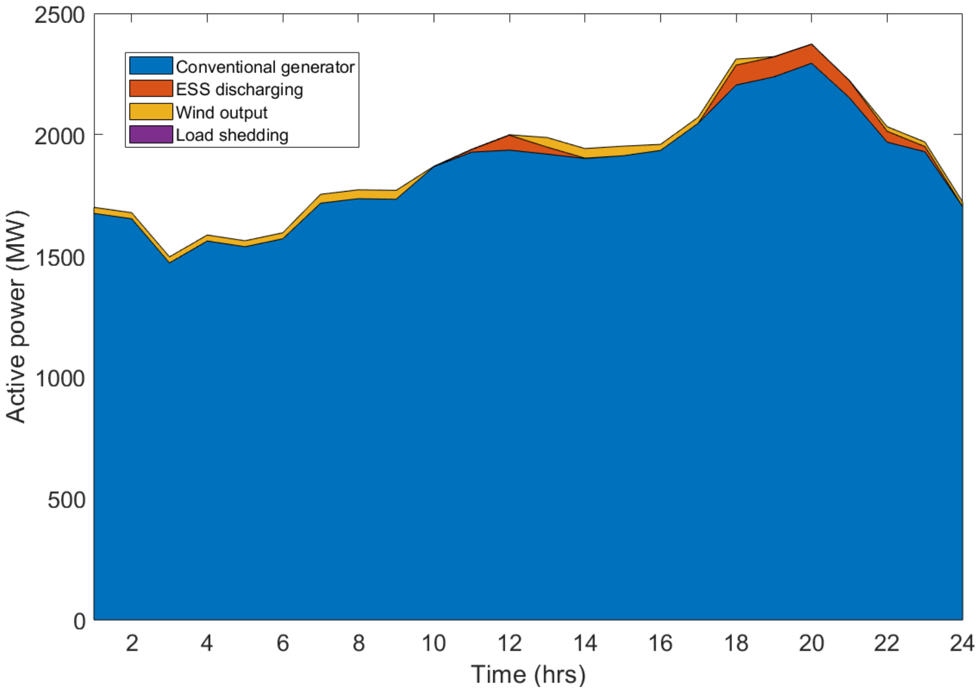
Surrogate Absolute Value Lagrangian Relaxation (SAVLR) and SeqSAVLR

- SAVLR is a vast improvement over traditional Lagrangian Relaxation (LR)
  - Exploit separability to reduce complexity
  - Faster and guaranteed convergence
- Constraints tightening
- SeqSAVLR
  - Divide a long-time horizon into multiple shorter time slots and solve the sub-problems sequentially on a rolling basis.



Case Study

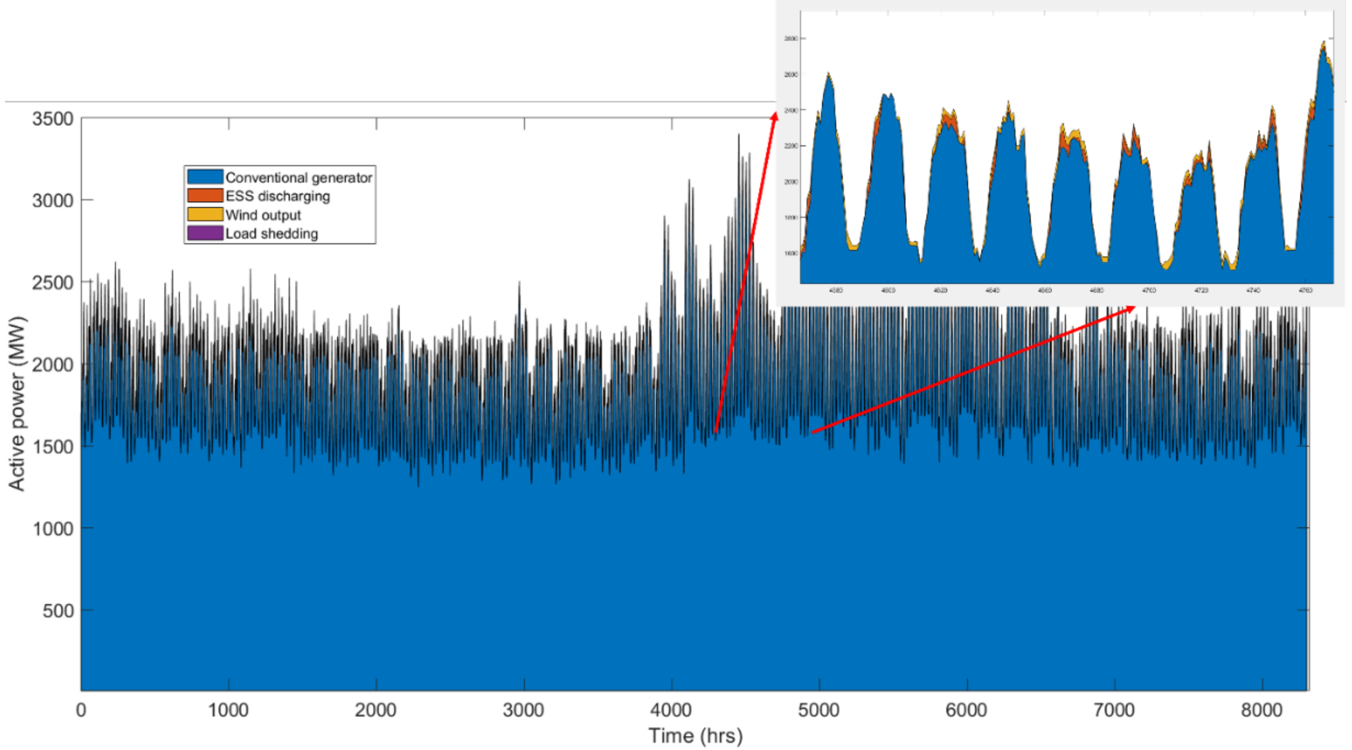
SAVLR to solve a 24-hour planning of 118-bus system



Comparison of different solutions for the one-year planning problem in 118-bus system

Method	Lower bound	Feasible cost	Lower bound finding time	Solution time
Branch-and-cut	2.286×10^8	\	15m40s	\
SAVLR	\	2.3579×10^8	\	50m30s
seqSAVLR	\	2.3617×10^8	\	37m28s

SeqSAVLR to solve a one-year planning of 118-bus system



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Case Study (cont'd)

Comparison of different solutions for the one-year planning in 2,383-bus Polish System

Method	Lower bound	Feasible cost	Lower bound finding time	Solution time
Branch-and-cut	\	\	\	\
SAVLR	\	\	\	\
seqSAVLR	\	1.7896×10^{10}	\	50h43m02s

- Computation remains a challenge when considering all constraints, especially dynamics constraints

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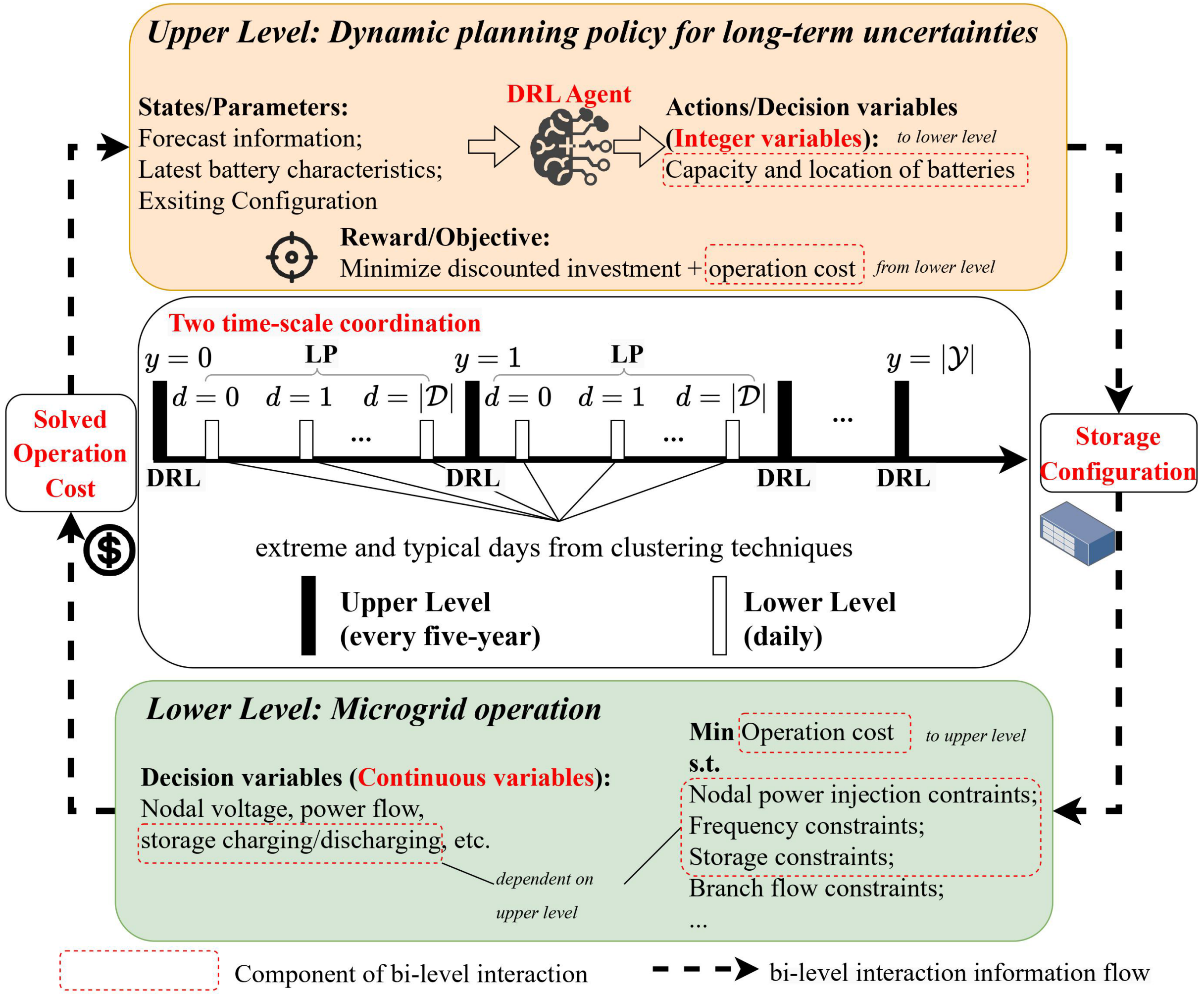
Two-stage Learning-assisted Stochastic Optimization

- We propose an approach by combining deep reinforcement learning (DRL) and MIP together with a novel sequential expansion model
  - Provides dynamic planning policies to adapt to volatile future battery prices and long-term renewables/load growth
    - At the upper level, a DRL agent is used to determine the installation locations and capacity sequentially.
    - At the lower level, a tractable linear programming (LP) problem is formulated and solved to fulfill the optimal operation

Two-stage Learning-assisted Stochastic Optimization (cont'd)

- DRL enabled by decoupling of discrete and continuous variables
- Decoupled timescales at upper and lower levels, e.g., every five years vs. 24 hours
- Adaptability to stochastic scenarios



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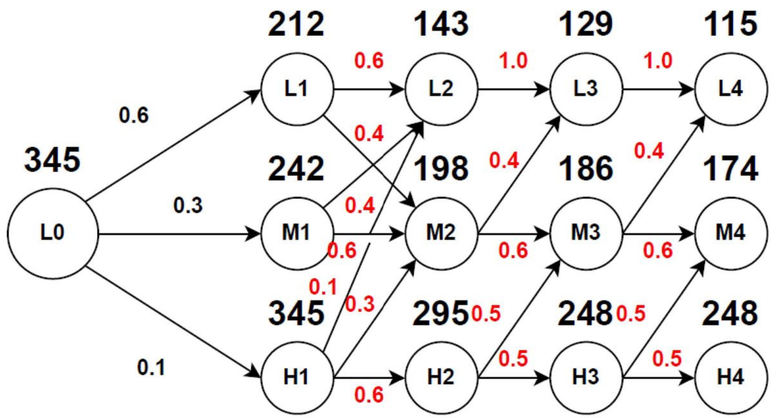
RL-based Solution to ESS Sizing and Siting

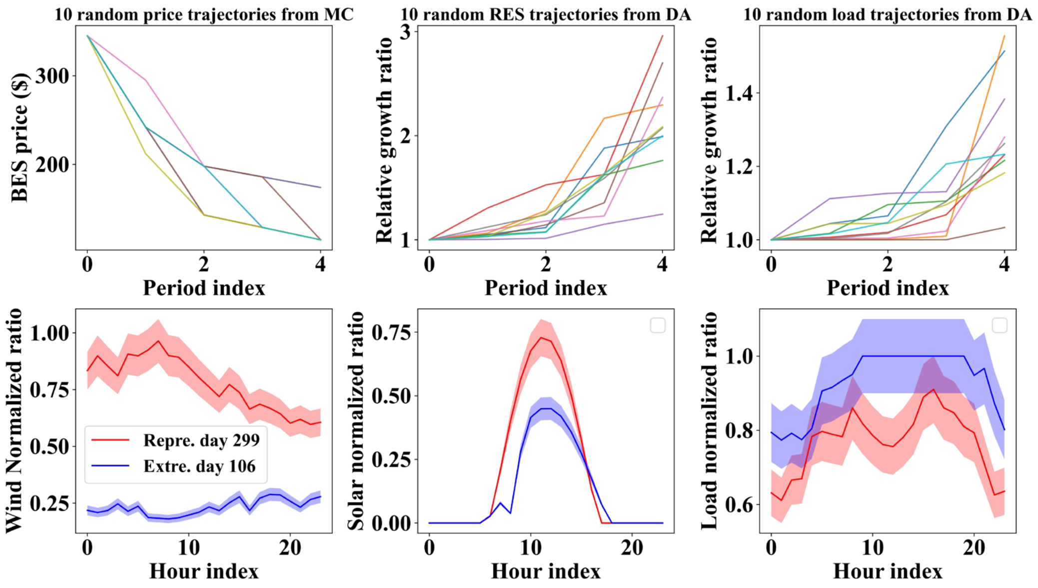
- The siting, sizing, and timing of ESS installation is multi-period decision-making and can be modeled as a Markov decision process (MDP) specified by a 5-tuple:
  - State space, action space, state transition, reward function, and reward discount
    - ESS price changes are modeled in a discrete-time Markov chain (DTMC)
  - Data argumentation technique is used to generate diversified load and RES profiles
  - Rainbow distributional DRL algorithm is adopted
  - After the offline training, ESS sites and capacities will be online inferred



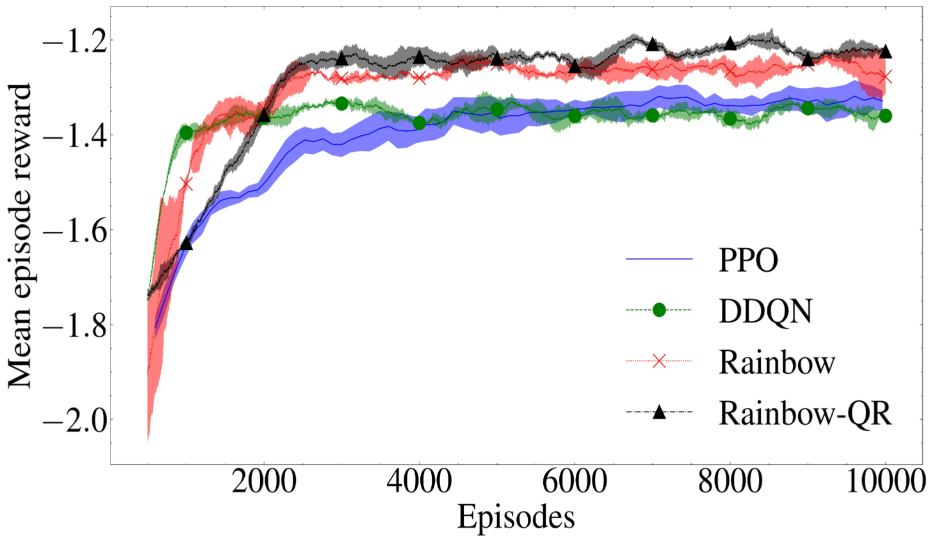
The DTMC for battery storage price

Case Study

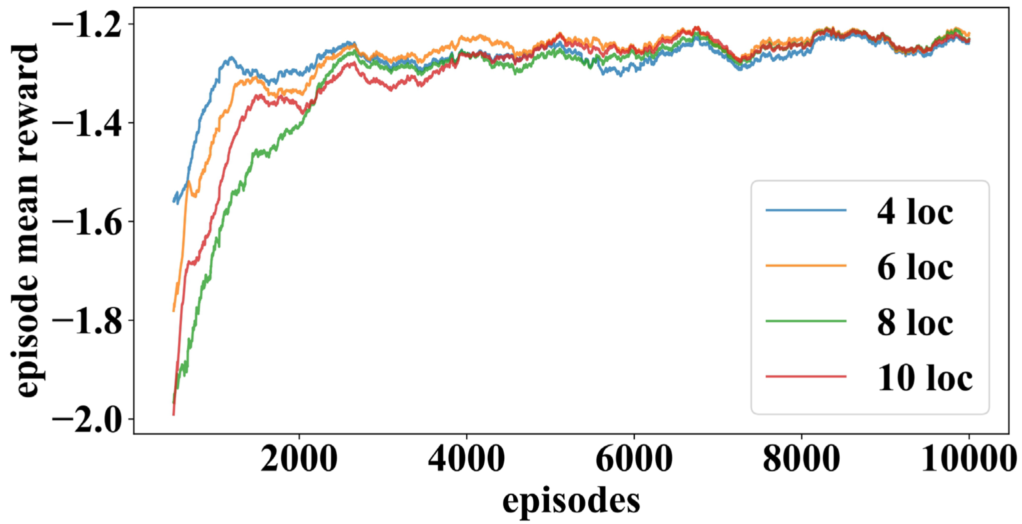
- A 33-bus radial microgrid with three dispatchable DGs, one PV cluster, and one wind cluster



Upper: period-level price, RES, and load trajectories; Lower: examples of hourly wind, solar, and load profiles with variation intervals



DRL learning performance



Training curves of different numbers of candidate nodes for ESS installation

Computational efficiency of DRL and MILP

Method	Number of candidate nodes			
	4	6	8	10
DRL	4.16 ± 0.11 ms	4.37 ± 0.10 ms	5.03 ± 0.28 ms	6.68 ± 0.18 ms
MILP solver	118.7±5.0 s	229.7±1.5 s	438.3±2.5 s	673.3±11.0 s

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Case Study (cont'd)

COMPARISON OF EXPANSION DECISIONS, COSTS, AND COMPUTATION TIME FOR DRL AND MILP

		Scenario I (low net load)			Scenario II (intermediate net load)			Scenario III (high net load)		
RES annual growth rate		5%			2%			1%		
Load annual growth rate		3%			2%			2.5%		
Method		DRL	MILP solver	BD*	DRL	MILP solver	BD*	DRL	MILP solver	BD*
Multi-period expansion decisions Format: capacity (kWh) @ node, - indicates no installation	0th year	-	-	-	-	-	-	-	-	-
	5th year	-	-	-	-	-	-	-	-	-
	10th year	1000@26	1000@26	1000@26	1000@26	1000@26	1000@30	1000@26	1000@30	1000@30
	15th year	-	-	-	-	-	-	500@26	500@26	500@30
	20th year	-	-	-	-	-	-	-	-	-
Total Cost (10^6\$)		1.69	1.69	1.69	1.49	1.49	1.49	1.81	1.81	1.81
Time required for generating decisions (s)†		0.004	167.032	total: 776.772 master: 14.776 sub: 761.996	0.004	226.467	total: 834.719 master:14.913 sub: 819.806	0.004	293.337	total: 1635.480 master: 48.831 sub: 1586.648

* BD: benders decomposition; †Average over three independent runs.

Conclusion and Future Works

- State-of-the-art uncertainty modeling
  - Spatiotemporal correlation of renewable generation
  - (N-1) generator outage scenarios
- Development of a scalable mathematical programming-based optimization framework
  - SAVLR and seqSAVLR for long-term planning
- Development of a bi-level DRL-assisted optimization framework
- Demonstration of ESS siting and sizing performances considering various constraints, especially frequency dynamics constraints
- Inclusion of dynamics constraints increases the complexity tremendously and ML-based constraints learning is being investigated

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