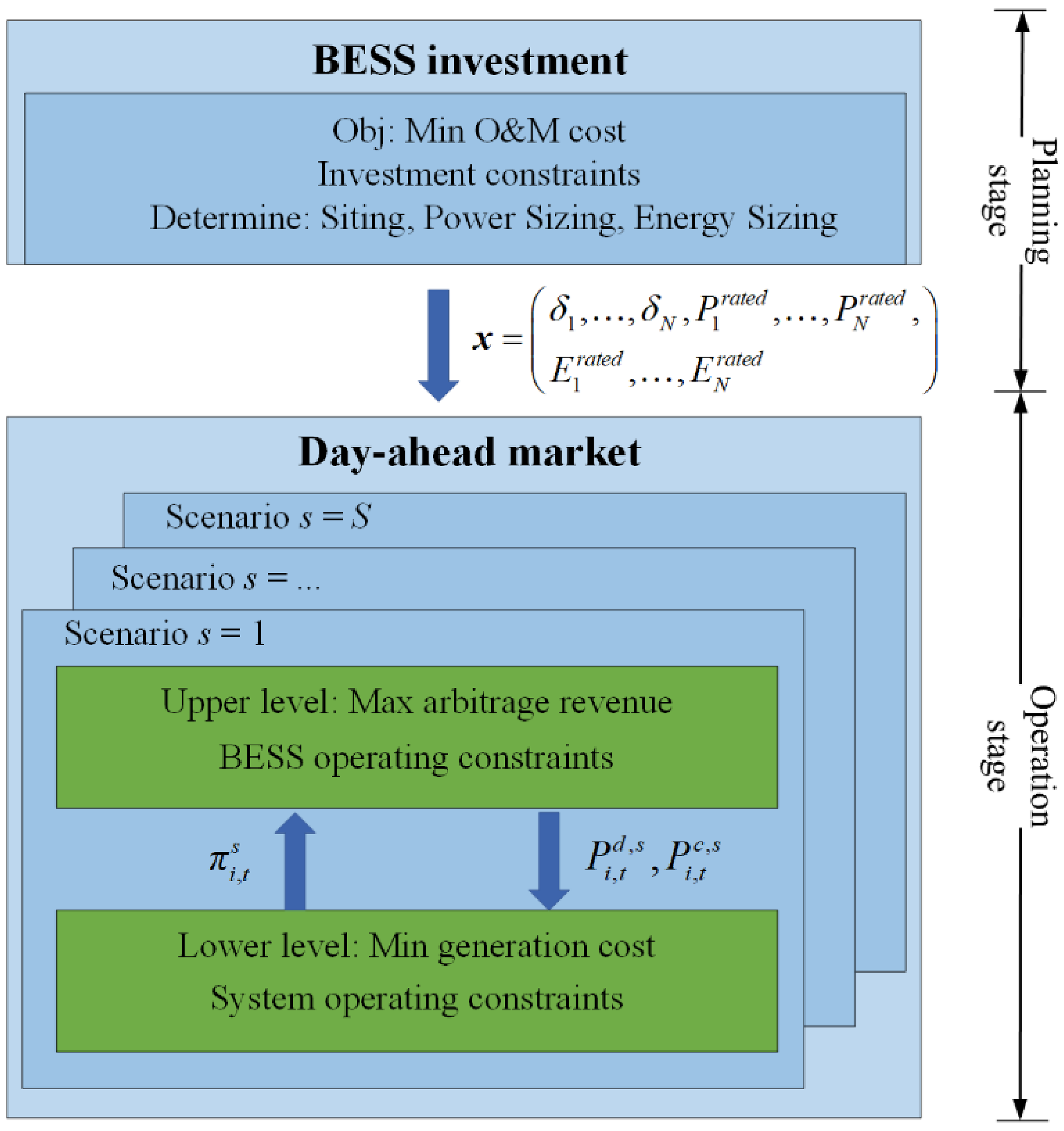
Profit-Oriented BESS Siting and Sizing in Deregulated Distribution Systems

Xiaofei Wang, Fangxing Li, Qiwei Zhang, Qingxin Shi, Jinning Wang
The University of Tennessee, Knoxville

Contributions

- The DLMP is applied as the price signal to incentivize the BESS planning in a deregulated distribution system.
- A TS-SBP arbitrage model is established.
- A *k*-means-based scenario extraction algorithm is proposed to extract the most representative patterns of LMP and system load profiles.
- BESS candidate bus reduction and inactive voltage constraint reduction are proposed to reduce the computational complexity of this large-scale optimization problem.

Framework of the TS-SBP model



Problem Formulation

First Stage: Optimal Siting & Sizing

$$\max \quad -\sum_{i\in\Omega_{BS}}\left(c^{Mf}P_i^{rated}+c^{Mv}E_i^{rated}\right)+E\left[f\left(\boldsymbol{x},s\right)\right] \quad (1)$$

$$s.t. \quad \sum_{i\in\Omega_{BS}}\delta_i \le N_{BS}^{\max} \quad (2)$$

$$\sum_{i\in\Omega_{BS}} k^p P_i^{rated}+k^e E_i^{rated}\le C^{Bgt} \quad (3)$$

$$P^{\min}\delta_i \le P_i^{rated}\le P^{\max}\delta_i \quad (4)$$

$$E^{\min}\delta_i \le E_i^{rated}\le E^{\max}\delta_i \quad (5)$$

$$E_i^{rated}=4\cdot P_i^{rated} \quad (6)$$

$$E\left[f\left(\boldsymbol{x},s\right)\right]=365\cdot\sum_{s\in S}p\left(s\right)f\left(\boldsymbol{x},s\right) \quad (7)$$

Second Stage: BESS Operation in a Deregulated Distribution Market

- Upper level

$$f\left(\boldsymbol{x},s\right)=\max\sum_{t\in\Omega_T}\sum_{i\in\Omega_{BS}}\pi_{i,t}^{s}\cdot P_{i,t}^{BESS,s}$$
$$=\max\sum_{t\in\Omega_T}\sum_{i\in\Omega_{BS}}\pi_{i,t}^{s}\cdot\left(\sqrt{\eta_i}P_{i,t}^{d,s}-P_{i,t}^{c,s}\big/\sqrt{\eta_i}\right) \quad (8)$$

$$s.t. \quad E_{i,t+1}^{s}=E_{i,t}^{s}+P_{i,t}^{c,s}-P_{i,t}^{d,s} \quad (9)$$

$$E_{i,t=0}^{s}=E_{i,t=T}^{s} \quad (10)$$

$$SOC_i^{\min}\cdot E_i^{rated}\le E_{i,t+1}^{s}\le SOC_i^{\max}\cdot E_i^{rated} \quad (11)$$

$$0\le P_{i,t}^{c,s}\le P_i^{rated},\ 0\le P_{i,t}^{d,s}\le P_i^{rated} \quad (12)$$

- Lower level

$$\min h\left(\boldsymbol{z},\boldsymbol{y},s\right)=$$
$$\sum_{t\in\Omega_T}\left(\sigma_{sub,t}^{p,s}P_{sub,t}^{G,s}+\sigma_{sub,t}^{q,s}\widehat{Q}_{sub,t}^{G,s}+\sum_{i\in\Omega_G}\left(\sigma_{i,t}^{p,s}P_{i,t}^{G,s}+\sigma_{i,t}^{q,s}\widehat{Q}_{i,t}^{G,s}\right)\right) \quad (13)$$

$s.t.$

$$P_{sub,t}^{G,s}+\sum_{i\in\Omega_G}P_{i,t}^{G,s}+\sum_{i\in\Omega_{BS}}P_{i,t}^{BESS,s}=\sum_{i\in\Omega_N}P_{i,t}^{D,s}+P_t^{L,s}:\lambda_t^{p,s} \quad (14)$$

$$Q_{sub,t}^{G,s}+\sum_{i\in\Omega_G}Q_{i,t}^{G,s}=\sum_{i\in\Omega_N}Q_{i,t}^{D,s}+Q_t^{L,s}:\lambda_t^{q,s} \quad (15)$$

$$V_{j,t}^{s}=V_{sub,t}^{s}+\sum_{i\in\Omega_N}Z_{j,i}^{p}\left(P_{i,t}^{G,s}+P_{i,t}^{BESS,s}-P_{i,t}^{D,s}\right)+\sum_{i\in\Omega_N}Z_{j,i}^{q}\left(Q_{i,t}^{G,s}-Q_{i,t}^{D,s}\right) \quad (16)$$

$$V^{\min}\le V_{j,t}^{s}\le V^{\max}:\omega_{j,t}^{v\min,s},\omega_{j,t}^{v\max,s},\forall j\in\Omega_N \quad (17)$$

$$P_i^{G,\min}\le P_{i,t}^{G,s}\le P_i^{G,\max}:\omega_{i,t}^{p\min,s},\omega_{i,t}^{p\max,s},\forall i\in\Omega_{MT} \quad (18)$$

$$0\le Q_{i,t}^{G,s}\le P_{i,t}^{G,s}\tan(\arccos\alpha_i):\omega_{i,t}^{q\min,s},\omega_{i,t}^{q\max,s},\forall i\in\Omega_{MT} \quad (19)$$

$$Q_i^{G,\min}\le Q_{i,t}^{G,s}\le Q_i^{G,\max}:\omega_{i,t}^{q\min,s},\omega_{i,t}^{q\max,s},\forall i\in\Omega_{SVC} \quad (20)$$

$$-Q_{i,t}^{G,s}\le\widehat{Q}_{i,t}^{G,s},\ Q_{i,t}^{G,s}\le\widehat{Q}_{i,t}^{G,s}:\kappa_{i,t}^{-,s},\kappa_{i,t}^{+,s},\forall i\in\Omega_G \quad (21)$$

$$\pi_{i,t}^{s}=\lambda_t^{p,s}+\lambda_t^{p,s}\cdot\frac{\partial P_t^{loss,s}}{\partial P_{i,t}^{D,s}}+\lambda_t^{q,s}\cdot\frac{\partial Q_t^{loss,s}}{\partial P_{i,t}^{D,s}}$$
$$+\sum_{j\in\Omega_N}\left(\omega_{j,t}^{v\min,s}-\omega_{j,t}^{v\max,s}\right)Z_{j,i}^{p} \quad (22)$$

Overall Solution

Algorithm 2: Overall Solution Procedure

1. Decomposition: Since there is a finite set of scenarios, (25) can be reformulated as:

$$\max \quad 365\cdot\sum_{s\in S}p\left(s\right)\left(-\boldsymbol{c}^T\boldsymbol{x}_s+\boldsymbol{\pi}_s{}^T\boldsymbol{y}_s\right)$$

Decompose it into S subproblems.

2. Initialization: For each $s\in S$, compute:

$$\left(\boldsymbol{x}_s,\boldsymbol{y}_s\right)\in\arg\max-\boldsymbol{c}^T\boldsymbol{x}_s+\boldsymbol{\pi}_s{}^T\boldsymbol{y}_s$$

3. Candidate buses reduction: Obtain the aggregated binary variable: $\hat{\boldsymbol{\delta}}=\sum_{s\in S}p_s(s)\boldsymbol{\delta}_s$, where $\hat{\boldsymbol{\delta}}=\left\{\hat{\delta}_1,\ldots,\hat{\delta}_{\Omega_N}\right\}$; remove $\hat{\delta}_i$ with low values; the rest are the most probable buses.

4. Voltage constraints reduction: Check $\boldsymbol{V}_s=\left\{V_1,\ldots,V_{\Omega_N}\right\}$, $s\in S$, identify buses at which voltage constraints are never violated; then, remove constraints at these buses.

5. Solving: With reduced candidate buses and voltage constraints, compute: $\left(\boldsymbol{x},\boldsymbol{y}_s\right)\in\arg\max-\boldsymbol{c}^T\boldsymbol{x}+365\cdot\sum_{s\in S}p\left(s\right)\boldsymbol{\pi}_s{}^T\boldsymbol{y}_s$.

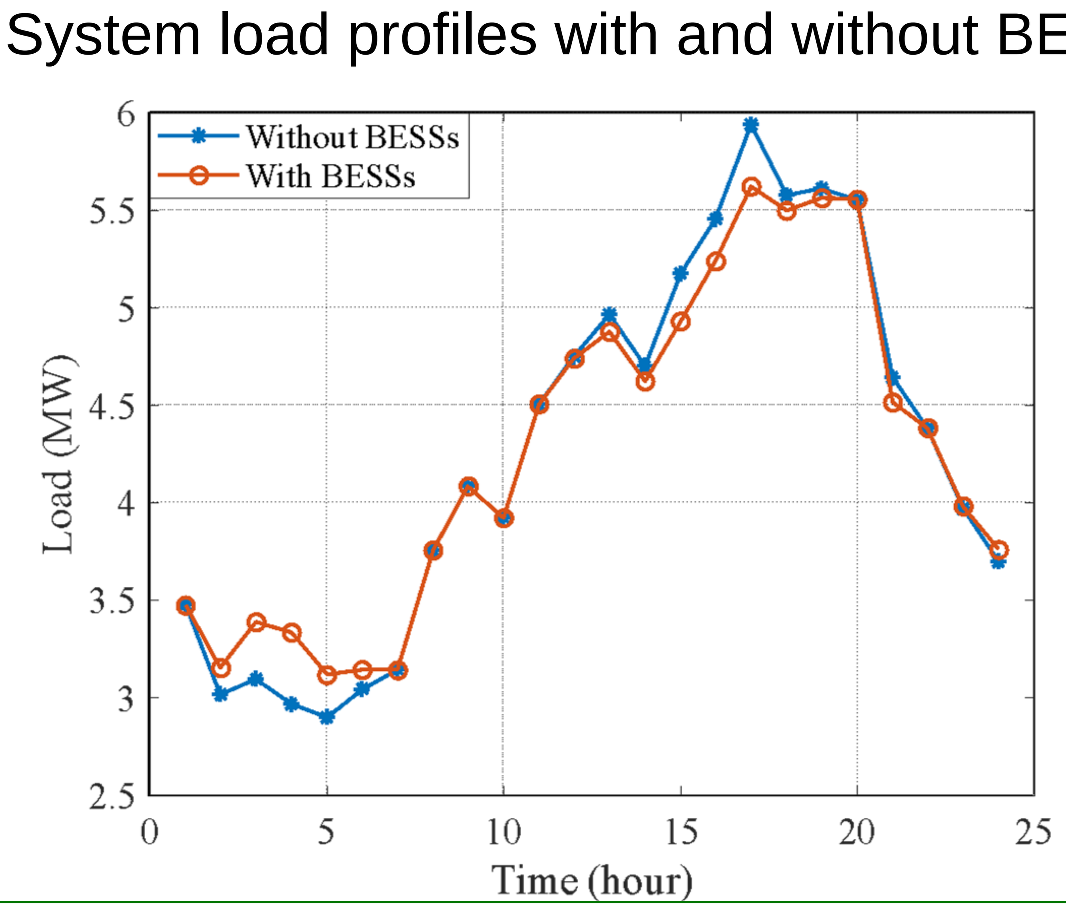
6. Voltage constraints update: Check whether the removed voltage constraints are violated or not. If yes, add the violated ones and go back to **Step 5**; otherwise, the algorithm terminates.

Simulation Results

Siting and sizing results

Cases	BESS bus (#)	Power/Energy (kW/ kWh)	Annual net profit ($)	Time (s)
Case 1	11, 15, 18, 31, 33	100/400, 149/597, 103/414, 107/426, 100/400	9302.22	7936
Case 2	11, 15, 18, 31, 33	100/400, 149/597, 103/414, 107/426, 100/400	9129.37	3442
Case 3	11, 15, 18, 31, 33	100/400, 149/597, 103/414, 107/426, 100/400	9129.38	1338
Case 4	11, 15, 18, 31, 33	100/400, 149/597, 103/414, 107/426, 100/400	9129.38	2390
Case 5	11, 15, 18, 31, 33	100/400, 149/597, 103/414, 107/426, 100/400	9129.38	1077

System load profiles with and without BESSs



Conclusions

- The DLMP can act as an effective price signal to incentivize BESS planning.
- The proposed two scale-reduction strategies are verified to improve computational efficiency and maintain accuracy.
- Optimal siting and sizing benefit both BESS investors and the DSO.