Solving Bilevel Power System Problems Using Deep Convolutional Neural Networks

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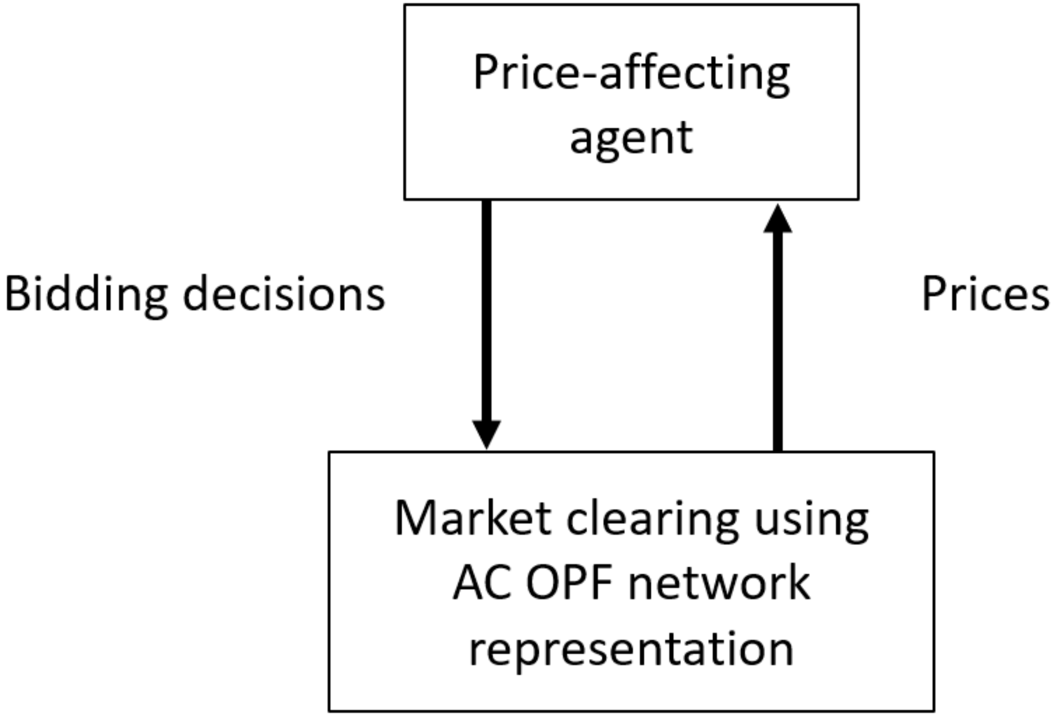
Bilevel optimization

$$\min_{x} F(x, y)$$

subject to

$$G_i(x) \leq 0 \qquad \forall i$$

$$y \in \{\arg\min_{y} f(x, y) : g_i(x, y) \leq 0 \ \forall i$$



Upper level:

- energy storage: bids energy quantity

Lower level:

- AC OPF: determines prices

Issues:

- AC OPF is nonconvex
- Continuous interaction

Solution approaches

- Convex Polar Second-Order Taylor Approximation AC OPF — single-level
- Bilevel AC OPF by Smoothing the Complementary Conditions — reduction

- Bilevel AC OPF using Deep Convolutional Neural Networks — data analytics

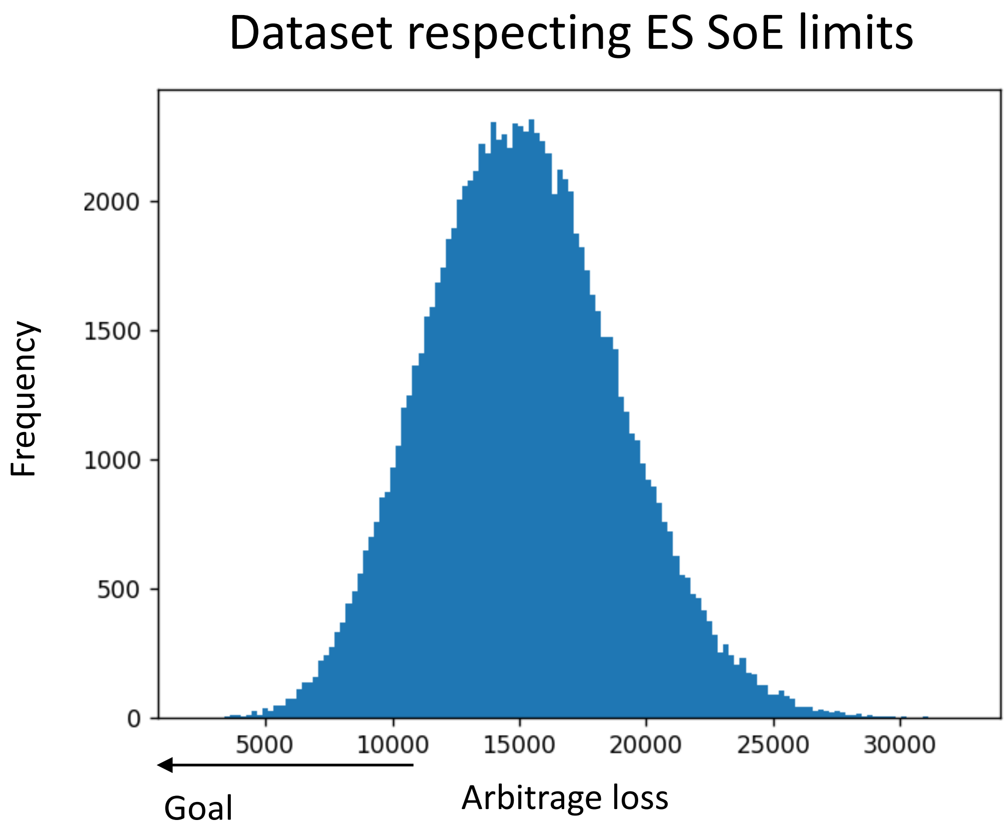
Bypassing the lower level

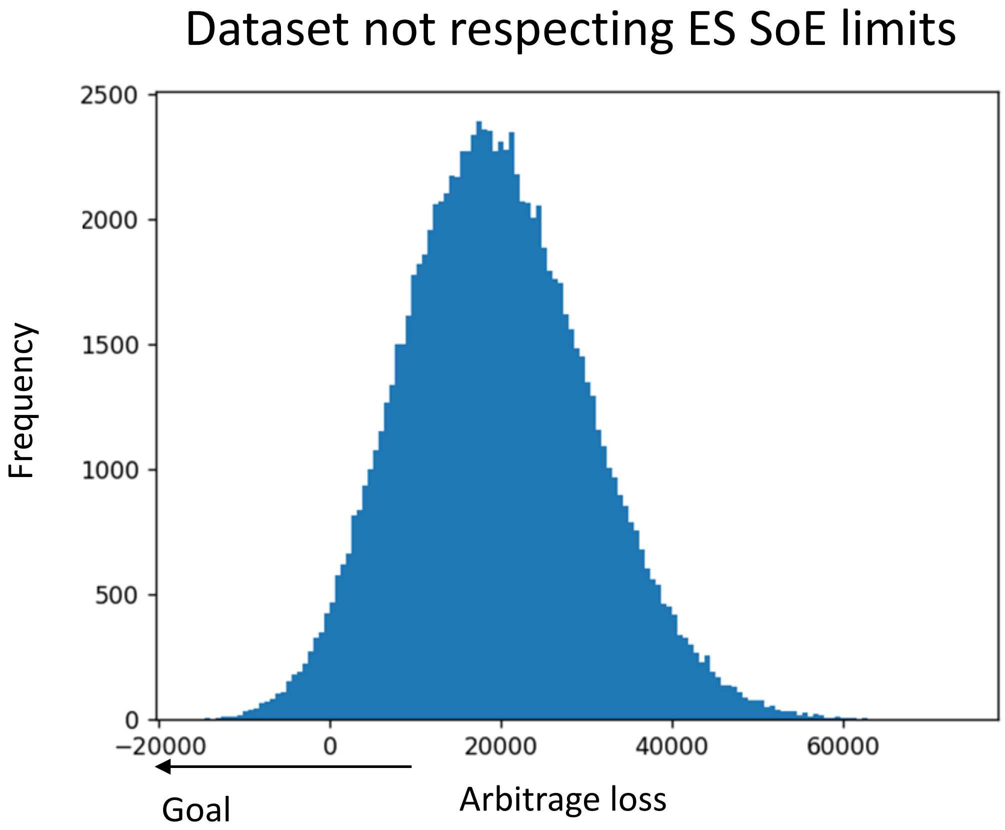
- We approximate objective function (total arbitration profit) with neural network:
    - LL is replaced by its response, i.e. as a function of input variables
- NN represents cumulative profit to reduce the error

$$
\begin{aligned}
&\min_{x} \bar{F}(x) \\
&\text{subject to} \\
&G_i(x) \leq 0 \qquad \forall i
\end{aligned}
$$

Dataset

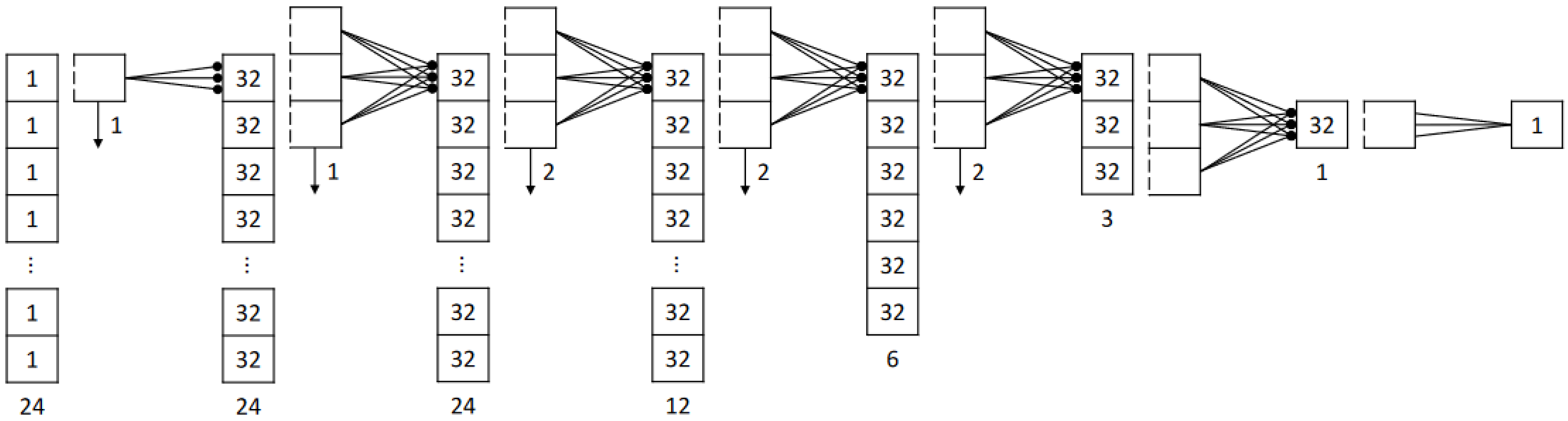
- Better NN trained with dataset not respecting ES SoE limits due to more favorable histogram





Convolutional neural network

- Physics informed structure: select time period has lesser impact on distant time periods



Integrating NN in optimization

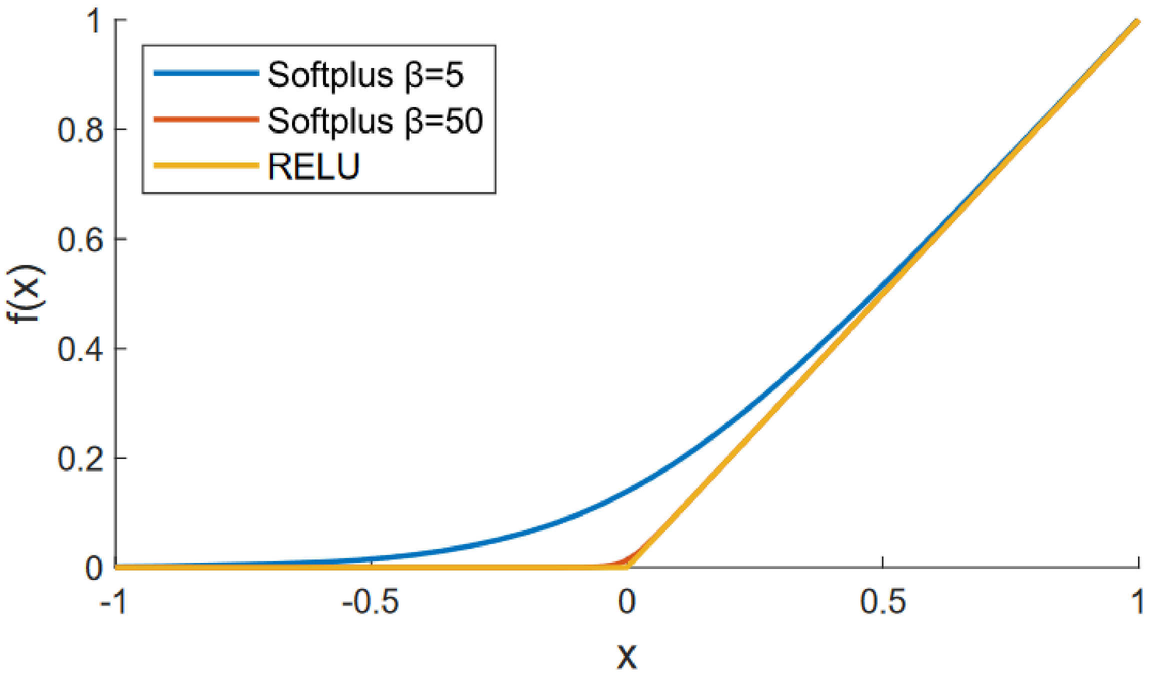
Activation function:

- Smooth function allows for computing large NN using nonlinear solvers

NN evaluation:

- Nested substitutions to reduce the number of variables and constraints

We used softplus with β=50



Algorithm

```
repeat
    Generate a new random dataset (10^5 entries)
    Evaluate LL response for the dataset
    Train 60 NNs to approximate LL response
    Optimize the ULs with inserted NNs into objective
    function
    Determine actual profits by optimizing LL with fixed
    ES (dis)charging schedule
    Select the best actual solution out of:
      • the best direct result;
      • the result obtained averaging decisions from all
        optimized NNs;
    For the next iteration, reduce and concentrate the
    dataset spatial size in the neighborhood of the best
    solution found from this iteration
until The best solution is worse than in the preceding
iteration
```

Results – accuracy (part 1)

Iter	Total time [s]	Mean p_t^{ES} actual profit	Best NN actual profit	Best NN computed profit	Single-level reduction actual profit [1]	DC OPF actual profit
1	8386	2016.0583	**2016.2954**	2011.5968	2016.8762	1986.4979
2	7158	**2016.8395**	2016.7695	2018.1744		
3	6965	**2016.8414**	2016.8271	2017.5707		
4	6910	**2016.8416**	2016.8339	2016.9533		
5	6903	**2016.8505**	2016.8015	2017.2495		
6	6882	2016.8452	2016.8096	2017.1350		

- 3_lmbd (bus 3)

Iter	Total time [s]	Mean p_t^{ES} actual profit	Best NN actual profit	Best NN computed profit	Single-level reduction actual profit [1]	DC OPF actual profit
1	8305	1564.0254	**1564.1351**	1564.3315	1565.2053	1431.5387
2	8724	1564.5929	**1564.6218**	1572.8308		
3	8886	**1564.9676**	1564.8713	1568.1618		
4	9088	1564.9433	1564.9370	1570.1936		

- 57_ieee (bus 1)

[1] K. Šepetanc, H. Pandžić and T. Capuder, ``Solving Bilevel AC OPF Problems by Smoothing the Complementary Conditions -- Part II: Solution Techniques and Case Study,'' Arxiv, June 2022.

Results – accuracy (part 2)

Iter	Total time [s]	Mean p_t^{ES} actual profit	Best NN actual profit	Best NN computed profit	Single-level reduction actual profit [1]	DC OPF actual profit
1	10234	5503.2526	**5512.4143**	5525.5078	No solution	4927.1127
2	10186	5503.2608	**5512.6547**	5520.6102		
3	10159	5503.8406	**5512.7558**	5519.5750		
4	10192	5503.7870	5512.1032	5513.6247		

- 73_ieee (bus 101)

Iter	Total time [s]	Mean p_t^{ES} actual profit	Best NN actual profit	Best NN computed profit	Single-level reduction actual profit [1]	DC OPF actual profit
1	33482	1396.5797	**1397.0175**	1377.6627	No solution	1199.9745
2	36481	1396.7220	1397.0172	1399.9574		

- 300_ieee (bus 1)

[1] K. Šepetanc, H. Pandžić and T. Capuder, ``Solving Bilevel AC OPF Problems by Smoothing the Complementary Conditions -- Part II: Solution Techniques and Case Study,'' Arxiv, June 2022.

Computation time

- Only dataset creation time scales up with network size
  - can be parallelized
- Computed on single node: 2x 20 core Intel Xeon CPU

	Dataset creation [s]	NN training [s]	Solving meta-models (mean $\pm$ std) [s]	Component total time [s]
3_lmbd	471	5118	$60\times(7.7 \pm 10.0)$	6051
57_ieee	1774	5129	$60\times(11.7 \pm 10.6)$	7605
73_ieee_rts	3644	5125	$60\times(4.0 \pm 2.6)$	9009
300_ieee	28256	5245	$60\times(2.0 \pm 1.9)$	33621

Conclusion

- Developed numerical scheme for solving bilevel problems with nonconvex and nonlinear lower levels
- Great accuracy is achieved using CNN
- Good computability of NN is achieved due to smooth activation function and nested substitutions
- Dataset creation can be parallelized

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