

A K-Nearest Neighbor Heuristic for Real-Time DC Optimal Transmission Switching

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Abstract—While transmission switching is known to reduce generation costs, the difficulty of solving even dc optimal transmission switching (DCOTS) has prevented optimal transmission switching from becoming commonplace in real-time power systems operation. In this paper, we present a k nearest neighbor (KNN) heuristic for DCOTS which relies on the insight that, for routine operations on a fixed network, the DCOTS solutions for similar load profiles and generation cost profiles will likely open similar sets of lines. Our heuristic assumes that we have DCOTS solutions for many historical instances. Given a new instance, we find a set of “close” instances from the past and return the best of their solutions for the new instance. We present a case study on the IEEE 118 bus system, the 1354 bus PEGASE system, and the 2869 bus PEGASE system. We compare the proposed heuristic to DCOTS heuristics from the literature, to Gurobi’s heuristics, and to the result from a simple greedy local search algorithm. In most cases, we find better quality solutions in less computational time.

I. NOMENCLATURE

Sets

\mathcal{L}	Transmission lines
\mathcal{G}	Generators
\mathcal{B}	Buses
\mathcal{G}_b	Set of generators at bus b
$\mathcal{L}_b^{\text{from}}$	Set of transmission lines leaving bus b
$\mathcal{L}_b^{\text{to}}$	Set of transmission lines entering bus b

Parameters

B_l^{from}	Origin bus of transmission line l
B_l^{to}	Destination bus of transmission line l
S_l	Susceptance of transmission line l
\bar{F}_l	Thermal limit for transmission line l
\bar{P}_g	Upper limit of generator g dispatch level
\underline{P}_g	Lower limit of generator g dispatch level
D_b	Demand at bus b
C_g	Per-unit generation cost of generator g
M	Infeasibility cost
K	Maximum number of lines that can be opened

Variables

f_l	Power flow through transmission line l
p_g	Generator dispatch level for generator g
u_b	Load shed at bus b
v_b	Over-generation at bus b
θ_b	Phase angle for bus b
y_l	Indicator of whether or not line l is closed

II. INTRODUCTION

Transmission switching is an inexpensive way to reduce generation costs in a congested system. Ideally, we want to always dispatch the cheapest generators first, but line limits can make this dispatch impossible. This results in a so-called

out-of-merit-order dispatch. Due to Braess’ Paradox, by not allowing flow through certain lines, we can reduce network congestion and approach the desired merit-order dispatch [1]. The authors of [2] show that an optimal network topology for one load profile is not necessarily optimal for another, presenting a need for real-time switching as load fluctuates.

Transmission switching in real-time poses a challenge since the dispatch problem is solved every 5 minutes for many independent system operators (ISOs). This means that the dispatch problem itself should be solved in less than 5 minutes to allow time in the remainder of the 5-minute interval for feasibility checks and other post-processing. DCOTS is NP-hard, and also cannot be approximated within a constant factor [3], [4].

Several different formulations for DCOTS have been proposed, but they either scale poorly or require a limited set of candidate lines for switching, making them heuristics as well. In [4], the authors propose a cycle-based formulation for DCOTS and use it to derive valid inequalities used in a cutting plane solution approach. In [5], the authors propose a smaller formulation for security-constrained DCOTS based on the Power Transfer Distribution Factor (PTDF) power flow equations. This formulation is computationally efficient when the number of contingencies is small and the set of candidate lines for switching is limited. With a good method for choosing a the set of candidate lines, this formulation could be used as a DCOTS heuristic. Rather than a heuristic, [6] proposes an approximate model for DCOTS which is guaranteed to yield feasible solutions with the same generation costs but lower numbers of switched lines. However, using this approximation for large networks still entails solving a large mixed integer program (MIP), which does not yet scale well.

The difficulty of the MIP formulation of the problem has so far prohibited exactly optimizing the topology on large networks within the time limit imposed by real-time. However, numerous heuristics have been proposed. The authors of [7] use four different metrics based on sensitivity analysis of dc optimal power flow (DCOPF) in order to estimate the cost benefit of switching each line of the network. They then use these estimates to prioritize the lines, and iterate through this priority list, switching off lines which do in fact result in cost savings. Similarly, [8] uses one of the same sensitivity criteria to choose a subset of high priority lines. They then run a greedy algorithm over just this set of lines, switching off the line resulting in the most cost savings until there are no more cost-saving lines or until they reach a maximum cardinality of switched lines. The sensitivity-based heuristics are effective, but, as the number of lines in the network increases, they may not scale well since they rely on iterating through lists of lines in order to make the switching decisions.

Others have proposed using sensitivity information or historical data to limit the set of switchable lines so as to reduce the number of binaries in the DCOTS problem. The authors of [9] use sensitivity information to limit this set. In an effort to understand the economic impacts of switching via a case study on a congested network, [10] suggests a couple of heuristics for DCOTS. One involves a variation of the greedy algorithm used in [8], but uses a partitioning technique to explore multiple disjoint sets of feasible solutions in parallel. Another uses data from past instances to select a limited set of switchable lines which are all lines which were cost-beneficial to switch off in the past. They then solve the DCOTS problem allowing only these lines to be opened.

The idea of using data from past solves has recently begun to take hold in the form of learning-based heuristics. Since the dispatch problem is solved so frequently, and under normal conditions, demands and generation costs do not vary beyond around 10% and 5% respectively [11], a likely avenue for scalable DCOTS heuristics is to harness off-line computational power to develop a heuristic based on the solutions to historical instances of the problem.

There has been recent interest in applying machine learning methods to power systems problems. In [11], the authors present three learning-based methods which use historical data to solve the security constrained unit commitment problem. The authors of [12] apply k nearest neighbors, an artificial neural network, and decision tree regression to learn sets of high-priority lines to consider for switching. They then use a greedy algorithm based on [8] which uses this line prioritization to generate a topology. In addition, they use machine learning methods to train an algorithm selection oracle which, given an instance, chooses which among these algorithms to run.

We propose a k nearest neighbors approach different than that of [12]. We apply the method for learning initial feasible solutions from [11] to DCOTS: Rather than training an oracle to map parameter vectors to sets of high priority lines as in [12], we instead use k nearest neighbors to learn topologies directly from the instance data. More specifically, we assume that we have a large collection of solved instances of DCOTS. Given a new instance, our heuristic selects the nearest k instances in parameter space out of this solved collection. We then test the quality of each of the topologies of the k near instances and return the lowest-cost topology as our switching solution. We show through our case studies on the IEEE 118 bus network and the PEGASE 1354 and 2869 bus networks that, even for larger networks, the number of solved training instances needed is moderate. A collection of 300 training instances yields solutions which are usually within 2% of the best known solution and, in most cases, are within 1% of the best known solution. Interestingly, we find that the KNN heuristic tends to outperform heuristics from the literature particularly when the system is more congested. Another advantage of the method is that it scales well for larger networks. We never iterate through lists of lines. Instead, the effect of the size of the network is on training time, which is done offline, and on the computation time for the linear program (LP) solves which check the cost of the near topologies. However, this effect is minimal since there are only k such solves.

In the remainder of the paper, we give the DCOTS model in Section III, an overview of our heuristic approach in Section IV, details on the networks used in our case study in Section V, computational results benchmarking our heuristic against others from the literature in Section VI, and we conclude in Section VII.

III. DCOTS MODEL

We use the following single-period formulation for DCOTS:

$$\min \sum_{g \in \mathcal{G}} C_g p_g + M \sum_{b \in \mathcal{B}} (u_b + v_b) \quad (1)$$

$$\text{s.t. } f_l \leq S_l(\theta_{B_l^{\text{from}}} - \theta_{B_l^{\text{to}}}) + 2\pi S_l(1 - y_l) \quad \forall l \in \mathcal{L} \quad (2)$$

$$f_l \geq S_l(\theta_{B_l^{\text{from}}} - \theta_{B_l^{\text{to}}}) - 2\pi S_l(1 - y_l) \quad \forall l \in \mathcal{L} \quad (3)$$

$$\sum_{g \in \mathcal{G}_b} p_g + \sum_{l \in \mathcal{L}_b^{\text{to}}} f_l - \sum_{l \in \mathcal{L}_b^{\text{from}}} f_l = D_b - u_b + v_b \quad \forall b \in \mathcal{B} \quad (4)$$

$$-\bar{F}_l y_l \leq f_l \leq \bar{F}_l y_l \quad \forall l \in \mathcal{L} \quad (5)$$

$$\theta_{B_l^{\text{from}}} - \theta_{B_l^{\text{to}}} \geq -\frac{\pi}{6} - 2\pi(1 - y_l) \quad \forall l \in \mathcal{L} \quad (6)$$

$$\theta_{B_l^{\text{from}}} - \theta_{B_l^{\text{to}}} \leq \frac{\pi}{6} + 2\pi(1 - y_l) \quad \forall l \in \mathcal{L} \quad (7)$$

$$\sum_{l \in \mathcal{L}} (1 - y_l) \leq K \quad (8)$$

$$\underline{P}_g \leq p_g \leq \bar{P}_g \quad \forall g \in \mathcal{G} \quad (9)$$

$$-\pi \leq \theta_b \leq \pi \quad \forall b \in \mathcal{B} \quad (10)$$

$$u_b, v_b \geq 0 \quad \forall b \in \mathcal{B} \quad (11)$$

$$y_l \in \{0, 1\} \quad \forall l \in \mathcal{L} \quad (12)$$

This is the model used in [2] with the addition of load shed and over-generation so that the model is feasible for all possible topologies y . Generation costs are minimized in the first term of (1), and the second term penalizes infeasibility in the balance constraint. We set M to be 10^6 , several orders of magnitude higher than the maximum generation cost. Equations (2) and (3) are the McCormick relaxation of Ohm's law. The nodal balance constraint with slacks included on the right-hand side is given in (4). Equation (5) sets the line flow to 0 when the line is opened and enforces transmission limits when the line is closed. In (6) and (7), we bound the phase angle differences when the line is closed. This is to help the accuracy of the dc approximation. We enforce a maximum cardinality of lines which can be opened in constraint (8). In practice, we expect the value of K to be 5 or 10. This is because switching large numbers of lines at once, even in large networks, makes finding an AC feasible dispatch difficult [13]. In addition, most of the cost savings from switching can be attained by switching a small number of lines [4]. Equations (9)-(12) enforce variable bounds. Note that when the transmission switching binaries y_l are fixed, this formulation is the B- θ formulation for DCOPT, a linear program.

IV. HEURISTIC APPROACHES

A. KNN Heuristic

Our proposed heuristic relies on the assumption that the DCOTS problem has likely been solved on the same network

many times. We assume the variable data are the load profiles and the generation costs. All other parameters are known, and are constant on a given network. We can therefore characterize an instance of DCOTS as the vector of generation costs appended to the vector of demands. If q is such a vector, we will denote an instance of DCOTS as $I(q)$. Suppose we have a collection of solved DCOTS instances \mathcal{Q} , each with an ϵ -optimal transmission switching solution. Given a new instance $I(q)$, we propose a heuristic based on k nearest neighbors to find a transmission switching solution: Among the set of solved instances, we find the nearest k instances as measured by their parameter vectors' distance from q using a p -norm for some p . We then test the transmission switching solutions from each of these k closest instances. We return the transmission switching solution which has the best objective value. The algorithm is presented formally in Algorithm 1.

Algorithm 1: KNN for Transmission Switching

Input: Set of solved instances
 $\mathcal{Q} = \{I(q^1), I(q^2), \dots, I(q^n)\}$ with ϵ -optimal transmission switching solutions
 $\{y^1, y^2, \dots, y^n\}$, $p \geq 1$, $k \in \mathbb{Z}^+$, and an unsolved instance $I(q^{n+1})$

Output: Heuristic solution y^{n+1} for instance $I(q^{n+1})$

```

1  $T \leftarrow \emptyset$ 
2 let  $\hat{q}^{n+1} = \frac{1}{\|q^{n+1}\|_2} q^{n+1}$ 
3 for  $I(q^i) \in \mathcal{Q}$  do
4   let  $\hat{q}^i = \frac{1}{\|q^i\|_2} q^i$ 
5   let  $d_i = \|\hat{q}^{n+1} - \hat{q}^i\|_p$ 
6   if  $|T| < k$  then
7      $T \leftarrow T \cup \{I(q^i)\}$ 
8   end
9   else
10    for  $I(q^j) \in T$  do
11      if  $d_i < d_j$  then
12         $T \leftarrow (T \setminus \{I(q^j)\}) \cup \{I(q^i)\}$ 
13      end
14    end
15  end
16 end
17  $LB \leftarrow \infty$ 
18 for  $I(q^j) \in T$  do
19   Fix the transmission switching solution  $y^j$  in  $I(q^{n+1})$  and solve.
20   Let the optimal value be  $v_j$ 
21   if  $v_j < LB$  then
22      $LB \leftarrow v_j$ 
23      $y^{n+1} \leftarrow y^j$ 
24   end
25 end

```

Note that the solution will respect the cardinality constraint since all the solutions to the training instances do. However, the solution is not guaranteed to be feasible, which is why we have included slacks on the nodal balance constraint in the DCOTS formulation. Since we are already using the dc approximation for power flow, the solution would already have to be corrected for feasibility in practice, so we allow these

small violations. In addition, we found that, in practice, when we chose $k = 10$, we never encountered an infeasible solution.

The scalability of this algorithm relies mainly on the value of k , and the number of training instances in \mathcal{Q} . Thus, though the size of the network can dramatically increase the training time, the only effect it has on the algorithm is its influence on the computational time for the k DCOPF solves in the loop beginning at line 18 of Algorithm 1. The time taken in the loop beginning at line 3 depends on $|\mathcal{Q}|$. In our experiments, we found that $|\mathcal{Q}| = 300$ was sufficient. We tested Algorithm 1 with both Euclidean and ℓ_∞ -norms.

B. Greedy Local Search

We compare the above heuristic to the four heuristics from [7], to a greedy local search algorithm, presented as the line enumeration algorithm in [12], and to Gurobi's primal heuristics. For completeness, we describe the greedy algorithm here. We first calculate the cost, fixing all lines closed. Then, for each line, we fix only that line open and calculate the cost. If none of the lines improve the cost when opened, we are done. Else, we fix open the line that improves the cost the most. We repeat this process on the remaining set of lines that could be opened, terminating either when we see no improvement from any of the lines or when we have opened as many lines as the cardinality constraint will allow. The algorithm is given formally in Algorithm 2. Note that this

Algorithm 2: Greedy Local Search

Input: DCOTS instance $I(q)$

Output: Heuristic solution y for instance $I(q)$

```

1  $S \leftarrow \mathcal{L}$ 
2  $\kappa \leftarrow 0$ 
3 while  $\kappa < K$  do
4    $LB \leftarrow \infty$ 
5   for  $l \in S$  do
6     In  $I(q)$ , fix  $y_l = 0$  and  $y_k = 1$  for all  $k \in S \setminus \{l\}$ 
7     Solve  $I(q)$  and let  $v$  be the optimal value
8     if  $v < LB$  then
9        $LB \leftarrow v$ 
10       $m \leftarrow l$ 
11    end
12  end
13  Fix  $y_m = 0$ 
14   $S \leftarrow S \setminus \{m\}$ 
15 end

```

algorithm scales very poorly since it requires solving nearly $K \cdot |\mathcal{L}|$ linear programs. Also note that, in a very congested system, where the solution with all lines closed is not feasible, this algorithm also does not guarantee a feasible solution, and the heuristics from [7] do not either.

C. Sensitivity-Based Heuristics

We also compare to the four sensitivity-criteria-based heuristics from [7]. For brevity, we do not describe the algorithms in detail here, but note that each of these heuristics uses sensitivity information from the DCOPF problem in order

TABLE I
TEST INSTANCE SIZES

Test Case	Number of Buses	Number of Generators	Number of Lines
Blumsack118	118	19	186
PEGASE1354	1,354	260	1,991
PEGASE2869	2,869	510	4,582

TABLE II
AVERAGE RELATIVE GAP OF THE SOLUTION WITH NO LINES SWITCHED OPEN COMPARED TO THE BEST KNOWN SOLUTION.

Test Case	Cardinality 5	Cardinality 10	No Cardinality Constraint
Blumsack118	29.44%	31.88%	32.55%
PEGASE1354	1.11%	1.06%	1.05%
PEGASE2869	0.54%	0.35%	0.35%

to calculate criteria to indicate lines which are likely to be cost-beneficial to open. Each heuristic uses a different such criterion to order the lines for consideration in a greedy algorithm. That is, we follow the procedure from Algorithm 2, but the set S is ordered based on the criterion. The four criteria are the Line Profits criterion, the Price Difference criterion, the Total Cost criterion, and the PTDF-Weighted Cost criterion.

D. Gurobi Heuristics

Last, we compare to Gurobi's performance when we run it with the Heuristics parameter set to 1, meaning that it spends all its time on primal heuristics. We also warm start these runs with the solution where all lines are closed, which is an obvious feasible solution in all but very congested cases.

V. TEST CASES

We test the heuristic on the 118 bus test system as modified in [14], and on the 1354 and 2869 bus PEGASE systems [15]. The PEGASE systems were downloaded from v19.05 of the IEEE PES Power Grid Library [16]. Details of these instances are shown in Table I. For each of these systems, we generate 300 instances following the methodology from [11]. For completeness, we describe the process here: Suppose that d^0 is the original vector of demands and c^0 is the original vector of generation costs. For $i \in \{1, 2, \dots, 300\}$, for each bus $b \in \mathcal{B}$, draw β_b^i from a uniform distribution on the interval $[0.9, 1.1]$. Then let $d_b^i = \beta_b^i d_b^0$. This process results in 300 demand profiles d^1, d^2, \dots, d^{300} . We generate the generation costs in exactly the same way except that we only allow 5% variation around the nominal generation cost, so we draw from a uniform distribution on $[0.95, 1.05]$.

We solve all 300 of the instances to 1%-optimality or to a time limit of 0.5 hour, whichever comes first. We randomly select 30 instances of these 300 as test instances and leave the other 270 for training. In Table II, we show the average relative gap of the solution where no lines are opened for the 30 test instances on each of our test systems. In Figure 1 we show the percentage of lines which have flow equal to the transmission limit, which is another indication of the congestion of the system. The 118 bus test case, though smallest, is the most congested, and hence benefits the most from switching. In particular, it continues to save on costs when it can open more than 10 lines, whereas both the PEGASE test cases usually

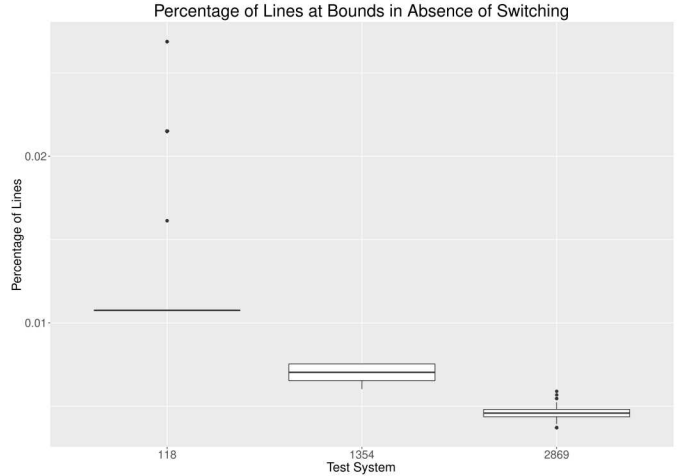


Fig. 1. Percentage of lines in each test system which have flow equal to the transmission limits when switching is not allowed

switch between 5 and 10 lines regardless of the cardinality constraint, and, in addition, they have a much smaller cost savings when switching is an option. However, note that, even in the 118 bus case, most of the cost savings can be attained by switching only 5 lines.

VI. COMPUTATIONAL RESULTS

We report results with $k = 10$ and using both the ℓ_2 -norm and the ℓ_∞ -norm to measure the distance from the training instances. We give our heuristic and the Gurobi heuristics a time limit of 5 minutes. We give the four heuristics from [7] a time limit of 10 minutes to forgive inefficiencies in our implementation. For all the heuristics, we test for cardinality limits of 5 and 10, and also with no cardinality constraint. For the 118 bus test case, we also compare to the greedy local search algorithm, but we find it to be the worst-performing heuristic in this case and intractable for larger test instances.

Our model and all our heuristics are implemented in Pyomo [17], [18], relying on Gurobi as the solver [19]. We solve on a server with 96 Intel Xeon 2.30GHz processors and 529GB RAM.

Our results for the 30 test instances are shown in the boxplots in Figures 2, 3, and 4. In all plots, the middle line is the median value of the statistic shown, the bottom and top of the box are the 1st and 3rd quartiles respectively, and the “whiskers” extend to the largest (in absolute value) value from the box which is no further than 1.5 times the interquartile range. Outliers beyond that range are shown as individual points.

The plots in the left-hand column of each figure show the distributions of solution quality for each of the heuristics, where we measure solution quality as the relative gap of the objective from the best-known solution for the test instance. That is, the gap is given by $\frac{z - \hat{z}}{\hat{z}}$, where z is the cost of the heuristic solution and \hat{z} is the cost of the best known solution for the instance. Note that, since we only solved the training instances to 1%-optimality and we stopped at a time limit, it is possible to find a new best-known solution via any of the tested heuristics. Thus, our best-known solution is not necessarily the solution we calculated during training: It is the best known solution across training and all of the presented heuristics.

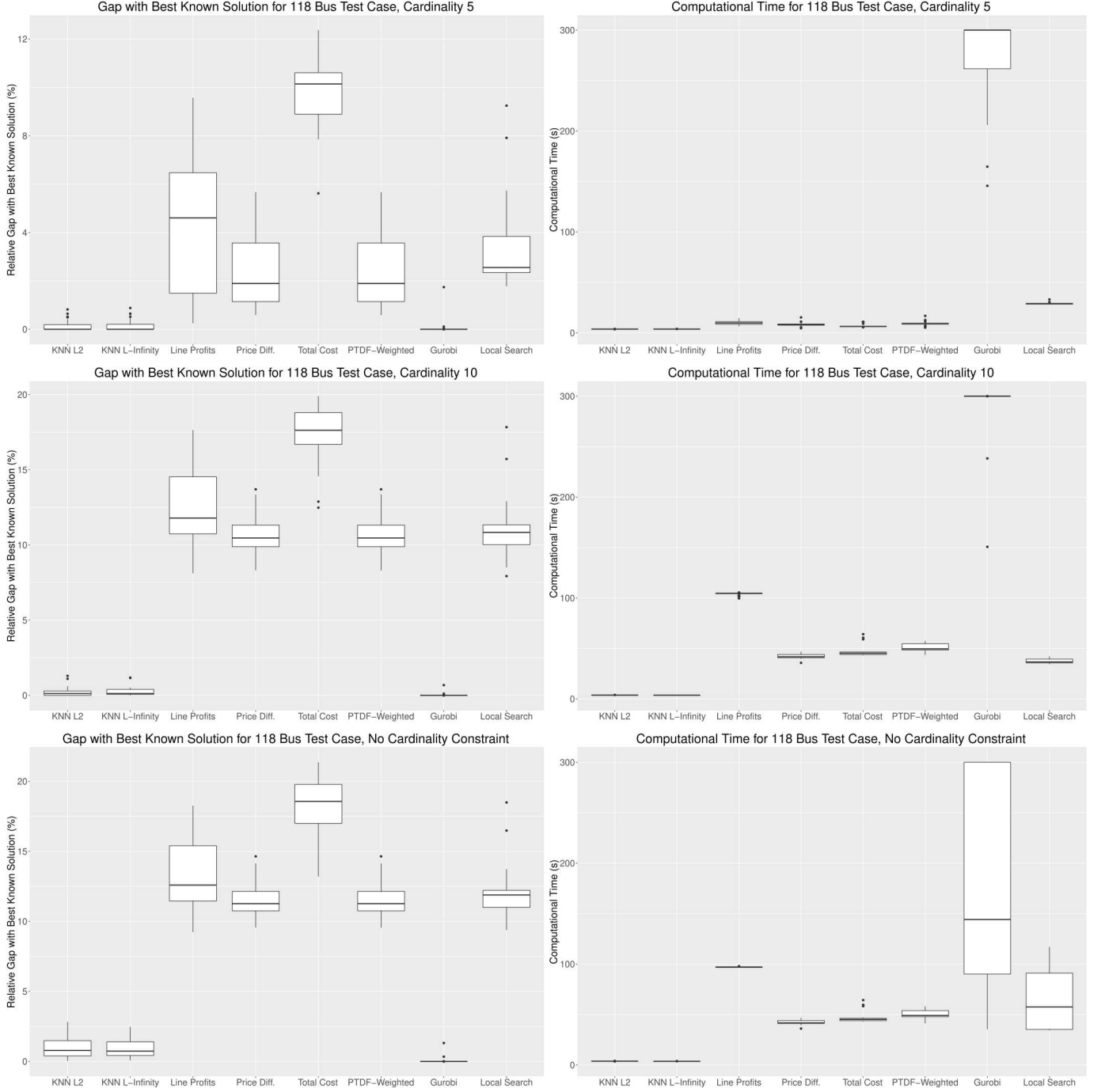


Fig. 2. Solution quality and computational time results for the 118 bus test case for the three different cardinality options.

The right-hand column of plots shows the distributions of computational times for each of the heuristics. Note that, for the Total Cost and PTDF-Weighted Cost heuristics, we do not include the time needed to calculate the Load Outage Distribution Factor (LODF) matrix since that only needs to be done once for a network and so can be treated as data.

A. Computational Time

In all of our test cases and for all the variations in the cardinality constraint, the KNN heuristic has one of the least computational times. Even on the 2869 bus case, it runs for a minute on average. This is because the time is completely

independent of the cardinality of the set of opened lines and is also relatively agnostic to the size of the network. Regardless of these, the time to calculate the solution from the KNN heuristic is the time to find the k closest instances from among the 270 training instances, and the time to solve the k DCOPF problems fixing the solutions from these k instances. Thus, the time only scales up slowly as the network sizes increase, increasing the DCOPF solve times slightly. In contrast, for the sensitivity-based heuristics and for the greedy local search algorithm, the time scales up with increased cardinality and with the number of lines in the system. The Gurobi heuristics also do not appear to scale well for increases in the cardinality

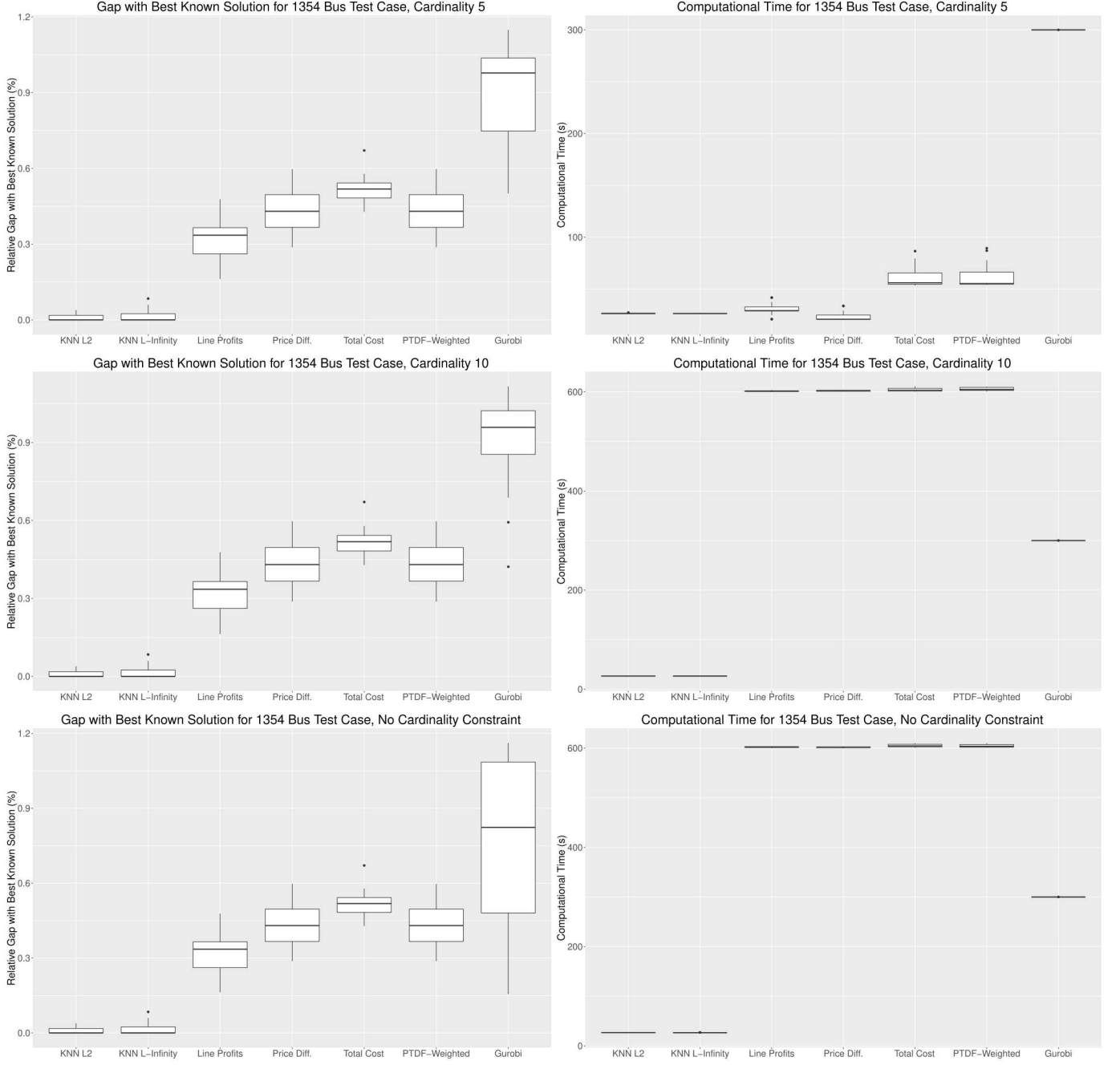


Fig. 3. Solution quality and computational time results for the 1354 bus test case for the three different cardinality options.

constraint right-hand side and for increased network size.

In the 118 bus case, the sensitivity-based heuristics have comparable computational times in the cardinality 5 variant. However, in all other cases, both the sensitivity-based heuristics and Gurobi run for at least a minute longer than the KNN heuristic, and Gurobi often reaches the 5 minute time limit. In the 1354 and 2869 bus cases, the computation times for the Line Profits and Price Difference heuristics are comparable in the cardinality 5 case, but both Gurobi and the sensitivity-based heuristics reach their time limits for less-restrictive cardinalities.

B. Solution Quality

In the 118 bus test case for all cardinalities, Gurobi's heuristics are competitive with the KNN heuristic in terms of solution quality. However, this is at the cost of computational time: The KNN heuristic runs on the order of seconds whereas Gurobi runs for at least a minute. For the 1354 bus case also, the KNN heuristic yields higher quality solutions, and it does so in less time in all but the cardinality 5 case.

In the 2869 bus case only, the Line Profits, Price Difference, and PTDF-Weighted Cost heuristics from [7] sometimes slightly outperform the KNN heuristic in terms of solution quality, despite the fact that they are terminated early by the time limit for the cardinality 10 case and the case without

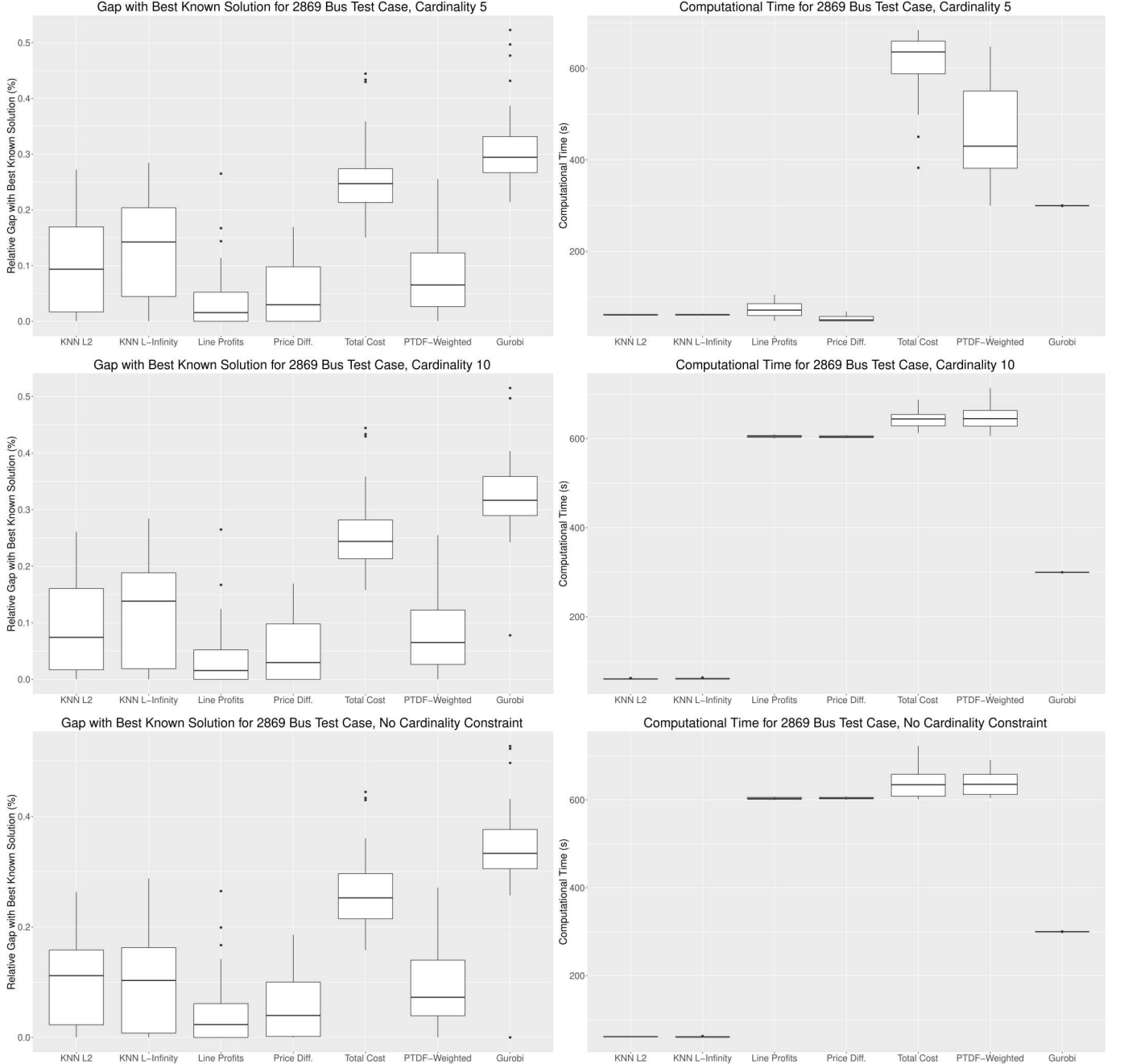


Fig. 4. Solution quality and computational time results for the 2869 bus test case for the three different cardinality options.

a cardinality constraint. However, these heuristics achieve on average a 0.06% improvement in solution quality as compared to the KNN heuristic. Because the 2869 case is not congested, the potential for cost savings from transmission switching is limited, so this difference in solution quality only translates to an average improvement of about \$1,100 in cost. In contrast, in the more-congested 1354 bus case, the KNN heuristic achieves on average a 0.31% improvement over the Line Profits heuristic, which translates to an average improvement of \$3,700.

In general, we see that the solution quality from the KNN heuristic is fairly constant across different sized networks and different cardinality constraints, usually achieving a relative gap between 0.1% and 1.0%. However, it seems that the

performance of the sensitivity-based heuristics is negatively impacted by highly congested cases, and so, in these cases especially, the KNN heuristic finds better solutions.

C. Parameter Tuning

The difference between the Euclidean and ℓ_∞ -norms is minimal in most of the experiments. Unsurprisingly, the two are essentially indistinguishable in terms of computational time. Overall, the ℓ_∞ -norm version of the heuristic has a more variable performance and usually is slightly worse on average. It also tends to have more extreme outliers, occasionally performing much worse than the Euclidean norm on a test instance. It therefore seems that the Euclidean norm

TABLE III
10-FOLD CROSS VALIDATION RESULTS: AVERAGE RELATIVE GAP OF THE KNN HEURISTIC SOLUTION COMPARED TO THE BEST KNOWN SOLUTION.

Test Case	Cardinality 5	Cardinality 10	No Cardinality Constraint
Blumsack118	0.10%	0.24%	0.66%
PEGASE1354	0.00%	0.00%	0.00%
PEGASE2869	0.01%	0.01%	0.01%

is preferable, as it has both a more consistent and slightly improved performance on the test instances.

As mentioned in Section IV-A, it is possible that the KNN heuristic returns a topology which requires load shed or over-generation. Since using the dc power flow approximation already means that post-processing is required to ensure true feasibility, we allow this to happen. However, we found that, in practice, our heuristic never returned a solution which had a positive value for load shed or over-generation. Assuming the infeasibility cost M is large enough, this could only happen if all k topologies we test are infeasible, so with k set to 10 we did not encounter this situation.

Though the results presented here all have 270 training instances and 10 as the value of k , we also experimented with the KNN heuristic's sensitivity to these parameters. Even for the large networks, 270 training instances appears sufficient: There was very little benefit in increasing to 500, though reducing to 100 did hurt the heuristic's performance. We also experimented with setting k to 3 and 5. Both of these perform well, though for smaller k we saw small amounts of load shed for the version of the 118 bus case without a cardinality constraint. Overall, since the computation time is manageable when k is 10 and the quality and feasibility are improved, the larger value seems preferable.

D. 10-fold Cross Validation

We ran 10-fold cross validation on each of the test cases for each of the cardinalities with $k = 10$ and using the Euclidean norm. Results are shown in Table III. On average, across all of the test systems and cardinalities, the heuristic returns a result well within 1% of the best-known solution, with even better performance on the less-congested cases. In addition, the heuristic is consistent: The variance of the gaps in the cross validation did not exceed 0.005% for any of the test cases or cardinalities.

VII. CONCLUSION

We presented a KNN-based heuristic for DCOTS. We showed through a case study on three test instances that, especially for congested systems, this heuristic yields solutions competitive with heuristics from the literature, and in less computational time. In particular, the heuristic scales up well with the size of the network since it has only a weak dependence on the number of lines in the system.

Since transmission switching is a tool to reduce generation costs given real-time fluctuation in demand, it is a problem which should be solved quickly, but one for which data from past solves is plentiful. This makes it an ideal problem for machine learning techniques. In the future this same heuristic could be applied to AC optimal transmission switching. In addition, it could be used to find good warm starts for planning problems or day-ahead operational problems in power systems.

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REFERENCES

- [1] S. Blumsack, L. B. Lave, and M. Ilić, "A quantitative analysis of the relationship between congestion and reliability in electric power networks," *Energy Journal*, vol. 28, no. 4, pp. 73 – 100, 2007.
- [2] E. B. Fisher, R. P. O'Neill, and M. C. Ferris, "Optimal transmission switching," *IEEE Tran. Power Syst.*, vol. 23, no. 3, pp. 1346–1355, Aug 2008.
- [3] K. Lehmann, A. Grastien, and P. Van Hentenryck, "The complexity of DC-switching problems," Nov 2014. [Online]. Available: arXiv:1411.4369
- [4] B. Kocuk, H. Jeon, S. S. Dey, J. Linderoth, J. Luedtke, and X. A. Sun, "A cycle-based formulation and valid inequalities for dc power transmission problems with switching," *Operations Research*, vol. 64, no. 4, pp. 922–938, 2016.
- [5] P. A. Ruiz, E. Goldis, A. M. Rudkevich, M. C. Caramanis, C. R. Philbrick, and J. M. Foster, "Security-constrained transmission topology control milp formulation using sensitivity factors," *IEEE Tran. Power Syst.*, vol. 32, no. 2, pp. 1597–1605, March 2017.
- [6] M. Jabarnejad, "Approximate optimal transmission switching," *Electric Power Systems Research*, vol. 161, pp. 1 – 7, 2018.
- [7] P. A. Ruiz, J. M. Foster, A. Rudkevich, and M. C. Caramanis, "Tractable transmission topology control using sensitivity analysis," *IEEE Tran. Power Syst.*, vol. 27, no. 3, pp. 1550–1559, Aug 2012.
- [8] J. D. Fuller, R. Ramasra, and A. Cha, "Fast heuristics for transmission-line switching," *IEEE Tran. Power Syst.*, vol. 27, no. 3, pp. 1377–1386, Aug 2012.
- [9] C. Liu, J. Wang, and J. Ostrowski, "Heuristic prescreening switchable branches in optimal transmission switching," *IEEE Tran. Power Syst.*, vol. 27, no. 4, pp. 2289–2290, Nov 2012.
- [10] K. W. Hedman, R. P. O'Neill, E. B. Fisher, and S. S. Oren, "Smart flexible just-in-time transmission and flowgate bidding," *IEEE Tran. Power Syst.*, vol. 26, no. 1, pp. 93–102, Feb 2011.
- [11] A. S. Xavier, F. Qiu, and S. Ahmed, "Learning to solve large-scale security-constrained unit commitment problems," Feb 2019. [Online]. Available: arXiv:1902.01697
- [12] Z. Yang and S. Oren, "Line selection and algorithm selection for transmission switching by machine learning methods," in *2019 IEEE Milan PowerTech*, Jun 2019, pp. 1–6.
- [13] C. Coffrin, H. L. Hijazi, K. Lehmann, and P. Van Hentenryck, "Primal and dual bounds for optimal transmission switching," in *2014 Power Systems Computation Conference*, Aug 2014, pp. 1–8.
- [14] S. A. Blumsack, "Network topologies and transmission investment under electric-industry restructuring," Ph.D. dissertation, Carnegie Mellon University, Pittsburgh, PA, May 2006.
- [15] S. Fliscounakis, P. Panciatici, F. Capitanescu, and L. Wehenkel, "Contingency ranking with respect to overloads in very large power systems taking into account uncertainty, preventive, and corrective actions," *IEEE Tran. Power Syst.*, vol. 28, no. 4, pp. 4909–4917, Nov 2013.
- [16] S. Babaeinejadsarookolae et al., "The power grid library for benchmarking AC optimal power flow algorithms," 2019. [Online]. Available: arXiv:1908.02788v1
- [17] W. E. Hart, C. D. Laird, J.-P. Watson, D. L. Woodruff, G. A. Hackebeil, B. L. Nicholson, and J. D. Sirola, *Pyomo-optimization modeling in python*, 2nd ed. Springer Science & Business Media, 2017, vol. 67.
- [18] W. E. Hart, J.-P. Watson, and D. L. Woodruff, "Pyomo: modeling and solving mathematical programs in python," *Mathematical Programming Computation*, vol. 3, no. 3, pp. 219–260, 2011.
- [19] Gurobi Optimization, LLC, "Gurobi optimizer reference manual," 2018. [Online]. Available: <http://www.gurobi.com>