Generation and Transmission Expansion Planning for Renewable Energy Integration

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Abstract

In recent years the expansion planning problem has become increasingly complex. As expansion planning (sometimes called composite or integrated resource planning) is a non-linear and non-convex optimization problem, researchers have traditionally focused on approximate models of power flows to solve the problem. The problem has also been split into generation expansion planning (GEP) and transmission network expansion planning (TNEP) to improve computational tractability. Until recently these approximations have produced results that are straight-forward to combine and adapt to the more complex and complete problem. However, the power grid is evolving towards a state where the adaptations are no longer easy (e.g. large amounts of limited control, renewable generation, comparable generation and transmission construction costs) and necessitates new approaches. Recent work on deterministic Discrepancy Bounded Local Search (DBLS) has shown it to be quite effective in addressing the TNEP. In this paper, we propose a generalization of DBLS to handle simultaneous generation and transmission planning.

Keywords - Generation Expansion Planning, Transmission Network Expansion Planning, Renewable Energy

1 Introduction

One of the major challenges facing the world in the 21st century is the problem of how to provide clean and sustainable energy to meet increasing demand for electric power. Many countries are actively seeking ways to address this challenge, including the United States, where the Department of Energy has stated a goal of having 20% of the U.S.'s energy come from wind by 2030 [23]. One of the difficulties of integrating large amounts of wind energy into electric power systems is that often the areas with the best potential to produce wind energy are located in areas that are deficient in existing transmission infrastructure. This has raised new challenges for expansion planners.

Typically, planners and investors are able to decouple decisions on where to build new generation (generation expansion planning (GEP)) from decisions on where to build new transmission (transmission network expansion planning (TNEP)). This is because the relative costs of GEP and TNEP have been uncomparable (the cost to build new generation often vastly exceeds the cost of transmission) and conventional generation can, in principle, be built almost anywhere (if zoning restrictions, water requirements, etc., are ignored). Generation and transmission expansion decisions are also often controlled by disjoint sets of stakeholders, which makes implementing a combined approach difficult. However, in planning for wind generation, the complete decoupling of the two problems is not necessarily the best approach. The potential to generate energy is highly dependent on where the generators are built and the distances to connect wind power to existing systems bring the relative costs of transmission and generation closer in scale.

Planners often rely on approximate models of power flow (typically linearized DC) when planning for expansion. Such approximations are attractive due to their small computational requirements and the fact that, in practice, the approximations are sufficient for the needs of planners (demand for AC power is small, systems are well-behaved, large amounts of dispatchable generation, etc.). However, given the scale of system planning for integrating wind energy (e.g. the western United States) and wind energy's intermittency, such models do not fully capture all the detrimental power flow behaviors that arise in such situations (voltage drops, etc.). To address these questions, this paper presents a novel approach, referred to as Discrepancy-Bounded Local Search (DBLS), for embedding ideas from simulation optimization [8] in a local search procedure. This procedure generalizes constructive heuristics [3, 19], for various types of expansion planning, utilizes constraint-based local search [12, 20], and is related to global search techniques such as limited discrepancy search. [9, 10, 24] The key idea of the approach is the encapsulation of the power flow model within a simulation black box. The DBLS is allowed to query the black box for power flow information about proposed expansion plans. Unlike traditional simulation optimization that uses the "black box" only for evaluation (objective function) or feasibility checking, our approach uses information (i.e. flows) from the simulation to help drive the choices of the DBLS algorithm. In short, the key contributions of this paper include:

- An expansion planning approach that abstracts the details of how power flows are modeled.

- An expansion planning approach that uses non-linear models of power flow.
- An algorithm that generalizes existing heuristics for expansion planning.
- An algorithm that scales to large-scale, realistic problems.
- An algorithm for combining generation and transmission expansion (composite or integrated resource planning).
- A coupling of simulation and optimization that allows the simulation results to influence the optimization procedures.
- A demonstration of the merits of a combined approach to motivate generation and transmission expansion planners to coordinate efforts and provide government entities with information to appropriately target subsidies for renewable generation.

Literature Review Up until the early 1990's the literature contained considerable research dedicated to the study of integrated resource or composite expansion planning. Reference [15] provides a survey of the state-of-the-art at that time. Since deregulation, when transmission and generation ownership was split in the U.S. and other countries, a comparatively smaller amount of the literature has been devoted to this problem. As a result, some of the open problems stated in [15] (e.g., determining which power flow models should be used in planning) remained relatively unexplored. Recently, however, attention has returned to this problem as it has become clear that uncoordinated expansion planning between generation and transmission can lead to undesirable behavior such as loop back flows [22] and negative generation prices [1]. Thus, papers like [18] have begun to look at how to address this problem through mechanisms like better market design. We consider another aspect of the problem, how to solve the composite problem as a whole so that this solution can be used to help guide market design and government incentives.

The algorithm described in this paper is a generalization of an algorithm for transmission expansion planning presented in [2] that shares a number of similarities with [11]. Both present a tree-based local search procedure which contain a truncation or discrepancy criteria.

In this paper, we assume pessimistically that generation is fixed in order to model the worst case for expansion planning (100% renewable generation with fixed output and no load control). This is not unlike the assumptions of [7, 19], which assumed generation was fixed due to market decisions. Also related is the work of [6, 14] which is the basis for many of the results contained in [23]. These papers provide the fundamental motivations for the work of this paper. They studied how to best integrate large amounts of wind power into power grids spread over large geographic areas using transportation models of power transmission.

The remainder of this paper is organized as follows. Section 2 formally defines the expansion planning problem. Section 3 describes the algorithm used to generate expansion plans and heuristics used to guide the algorithm to reduce physical violations and cost. Section 4 discusses the experimental results and Section 5 concludes this paper.

2 Problem Definition

Buses The expansion planning problem is described in terms of a set of buses, $\mathcal{B}$, that represent geographically located nodes in a power network e.g. generators, loads, and substations. Each bus, i, is defined by parameters g_i, l_i, ι_i^-, ι_i^+, which represent generation, load (demand for power), minimum voltage (per unit) and maximum voltage (per unit). $P(g_i)$ and $Q(g_i)$ are used to denote the real and reactive power of a generator at i. Similarly, $P(l_i)$ and $Q(l_i)$ are used to denote real and reactive components of load. For simplicity, $P_i = P(g_i) - P(l_i)$ and $Q_i = Q(g_i) - Q(l_i)$ is used to denote the real and reactive power injected at bus i. The decision variable c_i is used to define the number of generators at i each with generation $P(g_i)$ and $Q(g_i)$. c_i has discrete domain $\{c_i^-, c_i^- + 1, \ldots, c_i^+ - 1, c_i^+\}$. c_i^- is defined as the number of generators i starts with, ensuring that existing generators are included.

Transmission Corridors The expansion planning problem is also described by a set of edges, $\mathcal{E}$, called transmission corridors, connecting pairs of nodes. A transmission corridor i, j between buses i and j has a decision variable $c_{i,j}$ that defines the number of circuits (power lines) in the corridor. The variable has discrete domain $\{c_{i,j}^-, c_{i,j}^- + 1, \ldots, c_{i,j}^+ - 1, c_{i,j}^+\}$ where $c_{i,j}^-$ is defined as the number of circuits the corridor starts with. $c_{i,j}^+ = c_{i,j}^-$ when no circuits may be added to a corridor. A circuit is also defined by parameter $\psi_{i,j}$ which denotes the capacity of a single circuit in the corridor. Similarly, $r_{i,j}$, $x_{i,j}$, $b_{i,j}$ denote the resistance, reactance, and line charging of a single circuit in the corridor.

Expansion Planning Solution A transmission network solution, σ, is defined as a set of variable assignments $\bigcup_{i \in \mathcal{B}} c_i \leftarrow d_i \cup \bigcup_{i,j \in \mathcal{E}} c_{i,j} \leftarrow d_{i,j}$, where d_i is drawn from the domain of c_i and $d_{i,j}$ is drawn from the domain of $c_{i,j}$. By convention, unassigned variables are assumed to be c_i^- and $c_{i,j}^-$, respectively. $\sigma(c_i)$ and $\sigma(c_{i,j})$ are used to denote the variable assignments for σ.

Simulation Expansion planning algorithms use a simulator, $\mathcal{S}$, for determining the behavior of power for σ. $\mathcal{S}(\sigma)$ returns true when it is able to compute the behaviors. This is important as some implementations of $\mathcal{S}$ use convergence approaches (e.g. Newton's method) that do not have guarantees on whether or not they are able to obtain a solution. $\mathcal{S}_{Pg_i}(\sigma)$ and $\mathcal{S}_{Qg_i}(\sigma)$ denote the real and reactive power generated at bus i as provided by $\mathcal{S}$ ($\mathcal{S}$ may adjust generation if a load imbalance occurs or through dispatching). $\mathcal{S}_{f_{i,j}}(\sigma)$ denotes the flow in corridor i, j and $\mathcal{S}_{v_i}(\sigma)$ the voltage at bus i. For simplicity, this notation is shortened to $f_{i,j}$ and v_i when $\mathcal{S}(\sigma)$ is understood from context.

An expansion planning solution, σ, is feasible when the following constraints are satisfied, i.e.

$$\begin{cases} c_{i,j}^- \leq c_{i,j} \leq c_{i,j}^+ & (i, j \in \mathcal{E}) \quad (1) \\ c_i^- \leq c_i \leq c_i^+ & (i \in \mathcal{B}) \quad (2) \\ \mathcal{S}(\sigma) = \text{true} & \quad (3) \end{cases}$$

Physical constraints are relaxed and incorporated into the objective function in order to keep the search space connected (similar to Lagrangian Relaxation). The over capacity generation of σ is calculated as the sum of generation that exceeds the generation values of the buses, i.e. $\varrho(\sigma) = \sum_{i,j \in \mathcal{B}} (\max(0, \mathcal{S}_{P(g_i)}(\sigma)) - P(g_i)) + \max(0, \mathcal{S}_{Q(g_i)}(\sigma)) - Q(g_i))$ The overload of σ is calculated as the sum of flow that exceeds the capacity of the circuits, i.e. $\eta(\sigma) = \sum_{i,j \in \mathcal{E}} \max(0, f_{i,j} - \psi_{i,j} c_{i,j})$. The voltage violation of σ is calculated as the sum of voltages that fall below ι_i^- or above ι_i^+, i.e. $\nu(\sigma) = \sum_{i \in \mathcal{B}} \max(0, \iota_i^- - v_i, v_i - \iota_i^+)$. Finally, the cost of σ is defined by $\kappa(\sigma) = \sum_{i,j \in \mathcal{E}} c_{i,j} \kappa_{i,j} + \sum_{i \in \mathcal{B}} c_i \kappa_i$, where κ_i is the cost of putting a generator at bus i and $\kappa_{i,j}$ is the cost of putting a circuit in corridor i, j. The objective function, $f(\sigma)$, is then a lexicographic multi-objective function of the form $\min f(\sigma) = \langle \varrho(\sigma), \eta(\sigma), \nu(\sigma), \kappa(\sigma) \rangle$

3 DBLS Algorithm

In reference [2] a branch and bound algorithm is presented for the TNEP. This algorithm builds on simulation optimization ideas by encapsulating the behavior of the network into a "black box" that may be queried by the algorithm for information about how a solution behaves (i.e. $\mathcal{S}(\sigma)$) and embedding it in a discrepancy bounded local search (DBLS) that limits the full exploration of a branch and bound search tree. The intuition behind DBLS is to generalize heuristics that make good decisions on how to construct expansion plans, but make a few bad decisions from time-to-time. DBLS embeds the heuristic in a search tree as the branching heuristic and explores those solutions that are within δ violations (discrepancies) of the heuristic, where δ is a user-specified parameter. DBLS provides a natural way to incorporate constructive heuristics from the planning literature, e.g. [3, 19], into a more general framework and is related to the approach of [11]. The formal model of DBLS for expansion planning is presented in Figure 1.

DBLS takes as arguments a starting solution σ, (often the current state of the network, i.e. $\bigcup_{i \in \mathcal{B}} c_i \leftarrow c_i^- \cup \bigcup_{i,j \in \mathcal{E}} c_{i,j} \leftarrow c_{i,j}^-$), a set of variables, $\mathcal{X}$, drawn from $\bigcup_{i \in \mathcal{B}} c_i \cup \bigcup_{i,j \in \mathcal{E}} c_{i,j}$, a heuristic discrepancy parameter, δ, a worsening discrepancy parameter α, and a divergence discrepancy parameter β. The δ parameter is used to control the number of times the branching heuristic may be violated in the search and is decremented in line 16. As $f(\sigma)$ is non-monotonic, i.e. adding components can make $\eta(\sigma)$ and $\nu(\sigma)$ rise or fall (sometimes referred to as Braess's paradox), the parameter α is used to limit the number of times in a row that $f(\sigma)$ may worsen (lines 8-10). Finally, as it is possible for $\mathcal{S}(\sigma)$ to fail (diverge) for a given σ, a parameter β is introduced to limit the number of times in a row that $\mathcal{S}(\sigma)$ may fail (lines 11-13).

Line 4 chooses a variable to explore based upon the results provided by $\mathcal{S}$. It is here that the results of $\mathcal{S}$ drive the search. Line 5 provides the heuristic for ordering the domain of x. When $\varrho > 0$, $\eta(\sigma) > 0$ or $\nu(\sigma) > 0$ the domain is ordered by component additions, no change ($\sigma(x)$), and component removals, i.e.

$$\langle \sigma(x) + 1, \ldots, x^+, \sigma(x), \sigma(x) - 1, \ldots, x^- \rangle$$

otherwise it is ordered in reverse, i.e.

$$\langle \sigma(x) - 1, \ldots, x^-, \sigma(x), \sigma(x) + 1, \ldots, x^+ \rangle$$

Line 5 unassigns the current variable assignment of x and lines 6-16 iterate over the ordered domain of the variable. It is worth noting that line 7 implicitly updates attributes associated with the new σ and is where $\mathcal{S}$ is executed.

Restarts were also found to be productive when DBLS was first presented in [2]. The restart procedure is described in the function OPTIMIZEPLAN, where the algorithm is continuously restarted until the solution no longer improves.

```
OPTIMIZEPLAN(σ, X, δ, α, β)
repeat
        σ* ← σ;
        σ ← DBLS(σ, X, δ, α, β);
  until f(σ) ≥ f(σ*);
return σ*;
```

```
DBLS(σ, X, δ, α, β)
 1  if δ ≤ 0 or α ≤ 0 or β ≤ 0
 2    then return σ;
 3  x ← CHOOSEVARIABLE(X, σ);
 4  ⟨d_1, d_2, ..., d_k⟩ ← ORDERDOMAIN(x);
 5  σ ← σ \ [x ← σ(x)];
 6  for i ← 1 ... k
 7  do σ_i ← σ ∪ [x ← d_i];
 8     if f(σ_i) < f(σ)
 9       then α_i ← 0;
10       else α_i = α − 1;
11     if S(σ_i)
```

then $\beta_i \leftarrow 0$;
else $\beta_i = \beta - 1$;
if $f(\sigma_i) \leq f(\sigma^*)$ **and** $\mathcal{S}(\sigma_i)$
then $\sigma^* \leftarrow \sigma_i$;
$\text{DBLS}(\sigma_i, \mathcal{X} \setminus x, \delta - i, \alpha_i, \beta_i)$;
return σ^*;

Figure 1: Discrepancy Bounded Local Search

In this paper three implementations of CHOOSEVARIABLE are used. For ease of presentation, $\mathcal{E}(\mathcal{X})$ is used to denote those corridors that have circuit variables in $\mathcal{X}$, i.e. $\bigcup i, j \in \mathcal{E} \mid c_{i,j} \in \mathcal{X}$. $\mathcal{B}(\mathcal{X})$ is used to denote those buses that have capacitor variables in $\mathcal{X}$, i.e. $\bigcup i \in \mathcal{B} \mid c_i \in \mathcal{X}$.

The first implementation is described in Figure 2. It chooses the generator variable that can be increased the cheapest and is invoked when $\varrho(\sigma) > 0$.

CHOOSEVARIABLE-GENERATOROVERCAPACITY$(\mathcal{X}, \sigma)$
$i \leftarrow \arg\min_{i \in \mathcal{B}(\mathcal{X}) \ \mid \ \sigma(c_i) < c_i^+} \kappa_i$;
return c_i;

Figure 2: Generation Over Capacity Branching Heuristic

The second implementation is described in Figure 3 and is based upon the constructive heuristic presented in [3]. It first chooses the variable corresponding to the corridor that is most overloaded (lines 1-3), if one exists. Otherwise the heuristic chooses the corridor within $n = 1$ hops of an overload that decreases an overload the most (lines 7-16). It then iteratively tries $n = 2, 3, 4, \ldots$ up to a user specified maximum until it finds a decreasing circuit addition (lines 6-17). If there are no corridors that satisfy this criteria, the heuristic selects the bus with the lowest voltage and chooses the variable for adding generators (lines 18-19). This heuristic is used when $\varrho(\sigma) = 0$ and $\eta(\sigma) > 0$ or $\nu(\sigma) > 0$.

CHOOSEVARIABLE-LINEOVERLOAD$(\mathcal{X}, \sigma)$
1 $i, j \leftarrow \arg\max_{i,j \in \mathcal{E}(\mathcal{X})} |f_{i,j}| - \psi_{i,j}\sigma(c_{i,j})$;
2 **if** $|f_{i,j}| - \psi_{i,j}\sigma(c_{i,j}) > 0$
3 **then return** $c_{i,j}$;
4 $\hat{\mathcal{E}} \leftarrow \mathcal{E}$;
5 **while** $|\hat{\mathcal{E}}| > 0$
6 **do for** $k \leftarrow 1 \ldots n$
7 **do** $i, j \leftarrow \arg\max_{i,j \in \hat{\mathcal{E}}} |f_{i,j}| - \psi_{i,j}\sigma(c_{i,j})$;
8 $\hat{\mathcal{B}} \leftarrow \text{NEIGHBORS}(i, n) \cup \text{NEIGHBORS}(j, n)$;
9 $\hat{\mathcal{E}}_{i,j} \leftarrow (\hat{\mathcal{B}} \times \hat{\mathcal{B}}) \cap \mathcal{E}(\mathcal{X})$;
10 **for** $\hat{i,j} \in \hat{\mathcal{E}}_{i,j}$
11 **do** $\hat{\sigma} \leftarrow \sigma \setminus [c_{\hat{i,j}} \leftarrow \sigma(c_{\hat{i,j}})]$;
12 $\hat{\sigma} \leftarrow \hat{\sigma} \cup [c_{\hat{i,j}} \leftarrow \min(c^+_{\hat{i,j}}, \sigma(c_{\hat{i,j}}) + 1)]$;
13 $\perp_{\hat{i,j}} \leftarrow \mathcal{S}_{f_{i,j}}(\hat{\sigma})$;
14 $\hat{i,j} \leftarrow \arg\max_{\hat{i,j} \in \hat{\mathcal{E}}_{i,j}} \perp_{\hat{i,j}}$;
15 **if** $\perp_{\hat{i,j}} \leq \mathcal{S}_{f_{i,j}}(\sigma)$
16 **then return** $c_{\hat{i,j}}$;
17 $\hat{\mathcal{E}} \leftarrow \hat{\mathcal{E}} \setminus i, j$;
18 $i \leftarrow \arg\min_{i \in \mathcal{B}(\mathcal{X})} v_i$;
19 **return** c_i;

Figure 3: Line Overload Branching Heuristic

The third heuristic is based upon the standard cost reduction stages of constructive heuristics [3, 19] and chooses those variables whose removal of components will decrease the cost the most (lines 1-2 of Figure 4). It is used when $\varrho(\sigma) = \eta(\sigma) = \nu(\sigma) = 0$.

CHOOSEVARIABLE-COST$(\mathcal{X}, \sigma)$
1 $i, j \leftarrow \arg\max_{i,j \in \mathcal{E}(\mathcal{X}) \ \mid \ \sigma(c_{i,j}) > c^-_{i,j}} \kappa_{i,j}$;
2 $i \leftarrow \arg\max_{i \in \mathcal{B}(\mathcal{X}) \ \mid \ \sigma(c_i) > c_i^-} \kappa_i$;
3 **if** $\kappa_{i,j} \geq \kappa_i$
4 **then return** $c_{i,j}$;
5 **return** c_i;

Figure 4: Cost Reduction Branching Heuristic

4 Experimental Results

The generalized DBLS approach is tested on a variation of the RTS-96 IEEE problem and on a model of New Mexico's transmission network.

RTS-96 Benchmark In order to evaluate our approach we considered the expansion planning benchmarks from the TNEP literature [7] that are based on the RTS-79 and RTS-96 problems of [16, 17]. The problems allow up to 3 additional circuits in the 34 existing corridors and up to 3 circuits in each of 7 new corridors. The benchmarks pessimistically assume that generation cannot be dispatched. This is a worst case scenario, e.g. all generation is wind-based. The parameters for the circuit expansions are included in references [2, 7, 19]. The demand is from problem G0 in [7]. The initial generation values are taken from [17]. The possible generation expansions are listed in Table 1. The first column provides the bus where generation may be added. The second and third columns provide the real and reactive generation capacity additions. The fourth column provides the generation cost, which is designed to be similar scale to line capacity expansion costs. The final column provides the maximum number of times generation capacity can be added. The total maximum capacity is roughly the same as generation capacity in [7].

Bus	MW	MVar	Cost	Max
1	100	32	10000	4
2	100	16	20000	4
7	165	72	39600	4
13	200	160	75000	8
14	0	14	140	4
15	100	.08	9000	4
16	100	34	5000	4
18	200	140	100000	4
21	200	108	120000	4
22	150	-30	49500	4
23	265	120	159000	4

Table 1: Generator expansion options for RTS benchmarks.

The first results on this problem consider the case where $\mathcal{S}$ is implemented using the linear DC power flow model. DBLS is very quickly able to find an expansion plan that eliminates all generator overloads (after exploring 10 nodes in the search tree) and line overloads (after exploring 20 nodes in the search tree) regardless of the parameters of DBLS. This provides a strong indication that the branching heuristic used to guide the search towards feasible solutions is very good. However, the strength of the search strategy is seen when minimizing κ. Figure 5 shows the performance of the algorithm on κ for different settings of δ and $\alpha = \beta = 2$. The x-axis plots the execution time of the algorithm in terms of number of search tree nodes visited (expansion plans evaluated). The y-axis plots the best κ value seen in the search so far. There are two interesting observations. First, the search is able to find high quality solutions very quickly when $\delta = 1$ or 2. This provides some evidence that the branching heuristics used in the literature obtain reasonable solutions. Second, it is interesting to see that $\delta = 4, 5$ outperforms $\delta = 3$ for a period of time. This indicates that in the $\delta = 3$ search tree, there are some good solutions that are pruned early because of δ being too small (and $\delta = 4, 5$ discovers them). However, as the search progresses, $\delta = 4, 5$ spends more time in unproductive parts of the search tree and $\delta = 3$ eventually outperforms the higher discrepancy parameters. These results would suggest a strategy of incrementing δ in order to balance the ability to find high quality solutions quickly with the ability to perform a more complete search.

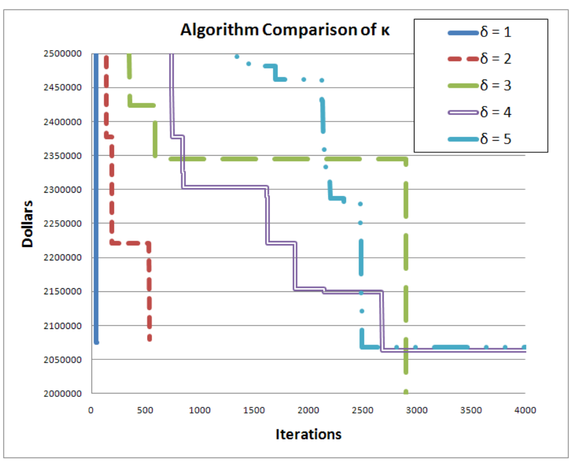


Figure 5: A comparison of DBLS for different choices of δ on the DC flow model.

The second set of experimental results consider the case where $\mathcal{S}$ is implemented with the full non-linear AC power flow equations as encapsulated by [5]. Given the difficulty in solving the initial problem with [5], the search starts with the expansion plan obtained using the DC power flow model (with the ability to undo any expansion proposed by the DC solution). The results here are striking. Unlike with the DC power flow example, the search has a difficult time addressing line capacity violations. This matches the observations of [2]. Figure 6 shows the performance of DBLS for different parameter settings of δ and $\alpha = \beta = 2$. Unlike the previous results, for small δ values the search does not find high quality solutions. This indicates that the branching heuristics developed for DC power flow models are not as strong of a guide for finding high quality solutions (though still a reasonable guide as there exists a solution with no overloads for $\delta = 5$ after searching more than 10,000 nodes in the search tree.)

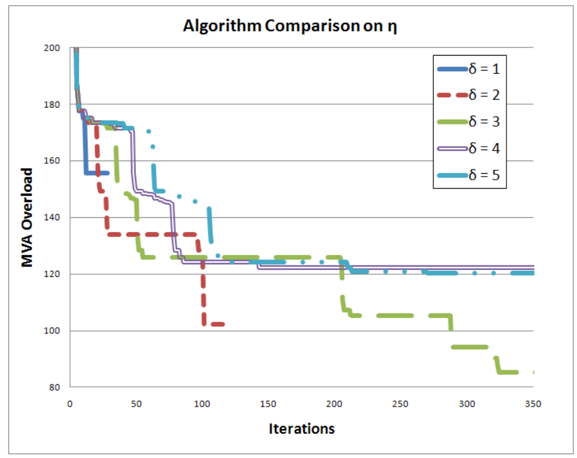


Figure 6: A comparison of DBLS for different choices of δ on the AC flow model.

Finally, it is interesting to compare the solutions obtained under the DC power flow model and the nonlinear AC power flow model. First, the best expansion plan for $\varrho = \eta = \nu = 0$ costs 2,077K. The solution for the AC power flow model costs 2,836K, a 36% increase in costs. Table 2 and 3 describe the solutions to the two problems. Notice that the DC solution needs considerable modification to produce a solution that does not violate any of the constraints under AC conditions. This supports the observations in [2] that it can be difficult to modify a plan based upon DC power flows to meet the requirements of AC power flows.

Bus	DC Gen Added	DC Cost	AC Gen Added	AC Cost
1	4	40K	4	40K
2	4	80K	4	80K
7	4	158K	4	158K
13	8	600K	8	600K
14	0	0K	0	0K
15	4	36K	4	36K
16	3	15K	3	15K
18	2	200K	3	300K
21	0	0K	0	0K
22	3	148K	3	148K
23	4	636K	3	477K
Total	36	1913K	36	1854K

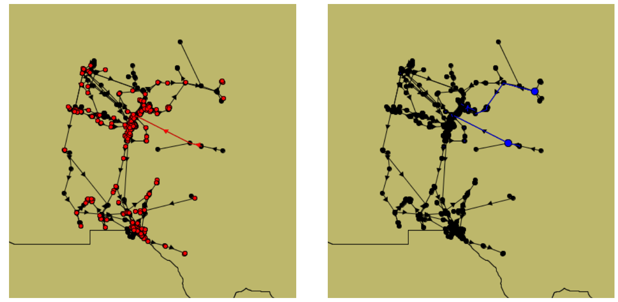
Table 2: Generator Expansions: DC vs. AC

Circuit	DC Lines Added	DC Cost	AC Lines Added	AC Cost
1,2	0	0K	1	3K
1,5	0	0K	1	22K
2,4	0	0K	1	33K
2,6	0	0K	3	150K
3,24	0	0K	1	50K
5,10	0	0K	3	69K
6,7	0	0K	3	150K
6,10	1	16K	0	0k
7,8	2	32K	3	48K
8,10	0	0K	3	129K
10,12	1	50K	0	0K
10,11	0	0K	2	100K
11,13	1	66K	1	66K
14,16	0	0K	1	54K
15,24	0	0K	1	72K
16,17	0	0K	1	36K
Total	5	164K	25	982K

Table 3: Line Expansions: DC vs. AC. Circuits that have no additions in either solution are omitted.

New Mexico Our final set of experiments considers the power grid of the state of New Mexico in the United States. According to reference [21], New Mexico has extensive plans to incorporate wind and solar generation into its grid in order to satisfy demand for power within the state and to export power to other states. In this scenario, the circuit variables and costs are assumed to be the same as [21]. Renewable energy generation may be added to nine areas in the state (2 solar and 7 wind) with a range of capacity factors, also included in reference [21]. Using industry data, we assume that it costs 1.75 million to build 1 MW of name plate capacity for wind and 4 million for 1 MW of name plate capacity for solar. This cost is reduced considerably when subsidies (currently .018 cents per kilowatt hour in the United States and an additional .01 cents in New Mexico) and other factors are considered. For the purposes of this study, these reductions are not used as these are subject to change. In this scenario, we wish to build enough renewable generation such that 10% of the current demand can be satisfied by renewable energy. The existing grid for New Mexico is used with 10% of existing generation is removed, uniformly at random. This provides a setting to test DBLS on realistic models. Using these cost numbers, the combined cost to construct transmission and generation to meet this goal is roughly 7.3 billion dollars (this would be considerably less if subsidies are included in the construction cost estimates). It is interesting to note that under DC power flow models, the joint cost estimate is around 300 million dollars, a substantial decrease.

In this planning scenario, the bulk of the wind generation added is in the Guadalupe and Springer areas [21], that are close to existing capacity and have high capacity factors. When all generation is added, there is as much as 800 MVA of overloads in the system in 30 transmission corridors. The overloads are alleviated by adding 53 circuits in 41 corridors. The solution is shown in Figure 7.



(a) (b)

Figure 7: Expansion solution for New Mexico. The map on the left (a) shows the initial expansion plan. Red indicates physical violations or areas that shed load (the analogue of generation over capacity). The map on the right (b) shows the final plan. Blue lines represent added circuits and blue circles represent added generators.

5 Conclusion

The electric power system is currently undergoing a revolutionary transformation that requires new approaches for solving the expansion planning problem. The increased desire and need to incorporate sustainable power generation (wind and solar) that is less controllable has created a situation where it is important to account for joint planning and more complex power flow models. Prior work has shown that DBLS is a powerful approach for solving problems with non-linear representations for the TNEP. This paper has shown that generalizing DBLS to include generation expansion decisions is an effective approach to solve this problem. A core contribution of the algorithm is a general search procedure that *decouples* the model used for flows and achieves solutions to the expansion planning problem using non-linear models of power grids.

Given the success of the approach described in this paper, it will be interesting to explore how to generalize this approach to more types of expansion options such as voltage upgrades. Second, it will also be important to account for uncertainty in the planning process as described in [4], [13], in particular as it relates to the intermittent output of renewable energy. Finally, it will be important to the study the effects on expansion solution quality when dispatchable generation, storage, or load management is included in $\mathcal{S}$. This could dramatically change how power grid expansion is planned.

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