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Title: Electric Power Transmission Network Design for Wind Generation in the Western United States: Algorithms, Methodology, and Analysis

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Electric Power Transmission Network Design for Wind Generation in the Western United States: Algorithms, Methodology, and Analysis

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***Abstract*—The current electric power grid is a result of incremental growth over the past 100 years under assumptions that a grid provides reliable and controllable generation of energy cheaply and with limited environmental impact. Moving into the twenty-first century, many of these assumptions will no longer hold; the existing grid is ill-equipped to handle the new requirements that it is being subjected to. This paper presents a novel hybridization algorithm to upgrade the existing electric power network to feasibly achieve future renewable energy generation goals. The algorithm was integrated with state-of-the-art electric power analysis approaches to produce feasible transmission networks to accommodate 20% wind power by 2030 goals.**

***Index Terms*—generation expansion planning, transmission expansion planning, simulation optimization, wind generation**

I. Introduction

Recent years have seen interest in the "smart grid" [1] (also known as green grid [2] or self-healing grid [3]) grow. This is evidenced by statements in references such as [4] that indicate the smart grid has the opportunity to reduce current electric power consumption by up to 4.3% and the large number of recent large-scale projects including (but not exclusively) Thyme [5], IntelliGrid [6], and the Smart Grid Maturity Model [7]. A common thread in many of these projects is a focus on the hardware, standardization, and social issues related to implementing the smart grid. Comparatively less work has studied the information science aspects of the smart grid, i.e. *developing the information technology of an adaptive system that robustly and efficiently routes power from generators to consumers*. Under this problem statement one of the important challenges that arises is planning and designing the physical structure of the grid to achieve an adaptive system. This challenge is readily apparent under the assumption that renewable generation, such as wind and solar, will play an increasing role in the generation of power. Under this scenario, the need for new grid design arises for two reasons. First, the areas with highest renewable energy production potential are often in transmission-deficient areas of the existing grid. Second, the intermittent nature of renewable generation places a higher premium on building redundancy into the grid for increased reliability. Simply stated, we are concerned with *how to optimally place and build renewable generation and upgrade the existing transmission system through balancing of economic costs, reliability, and robustness.* The purpose of this paper is two-fold: first to survey existing solutions to this problem and second, to present our results of a promising new direction for solving this problem. The key contributions of this paper are as follows:

1) A feasible transmission network for the western U.S. based on renewable generation profiles of [8].
2) A novel algorithm for tightly hybridizing optimization and simulation to upgrade transmission systems.
3) An empirical evaluation of the feasibility of the solutions to the generation expansion planning problem provided by the linear approximation algorithms of [9],[10].

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II. Problem Description and Analysis of WinDS

For our purposes, an electric power grid is modeled as a graph, $\mathcal{G}$, that consists of nodes, $\mathcal{N}$, and edges, $\mathcal{E}$. $\mathcal{N}$ represents physical locations in the power grid including generators, $\mathcal{N}_{\mathcal{GEN}}$, (producers of electric power), substations, $\mathcal{N}_{\mathcal{SUB}}$ (subsidiary stations where voltage conversions and switching occur), and loads, $\mathcal{N}_{\mathcal{LOAD}}$ (consumers of electric power). $\mathcal{E}$ represents physical connections between the nodes including power lines and transformers. The goal of an electric power network is to deliver electric power from $\mathcal{N}_{\mathcal{GEN}}$ to $\mathcal{N}_{\mathcal{LOAD}}$ at minimal cost (where cost is a function of power generation and power loss due to resistance on the power lines), subject to the physical limitations of the power grid. As will be discussed later, these constraints are a source of many of the difficulties inherent in transmission planning. There

$$\begin{array}{lllr} \text{minimize} & \sum_{i \in \mathcal{N}_{\mathcal{GEN}}} p_i c_i + \sum_{i \in \mathcal{N}_{\mathcal{GEN}}, j \in \mathcal{N}} y_{i,j} l_{i,j} & & \\ \text{subject to} & \sum_{i \in \mathcal{N}_{\mathcal{GEN}}} & p_i \geq P & (1) \\ & \forall_{i \in \mathcal{N}_{\mathcal{GEN}}} & p_i \leq P_i^+ & (2) \\ & \forall_{i \in \mathcal{N}_{\mathcal{GEN}}} & p_i \geq P_i^- & (3) \\ & \forall_{i \in \mathcal{N}, j \in \mathcal{N}} & f_{i,j} \leq y_{i,j} & (4) \\ & \forall_{i \in \mathcal{N}_{\mathcal{GEN}}} \sum_{j \in \mathcal{N}} & f_{i,j} = -p_i & (5) \\ & \forall_{i \in \mathcal{N}_{\mathcal{LOAD}}} \sum_{j \in \mathcal{N}} & f_{i,j} = d_i & (6) \\ & \forall_{i \in \mathcal{N} \setminus (\mathcal{N}_{\mathcal{LOAD}} \cup \mathcal{N}_{\mathcal{GEN}})} & \sum_{j \in \mathcal{N}} f_{i,j} = 0 & (7) \\ & \forall_{i \in \mathcal{N}, j \in \mathcal{N}} & f_{i,j} = -f_{j,i} & (8) \end{array}$$

Fig. 1. WinDS Optimization Model

is considerably more detail about the structure of the power grid that is beyond the scope of this paper.

The problem of Generation Expansion Planning (GEP) is that of where to construct new $\mathcal{N}_{\mathcal{GEN}}$ and the problem of Transmission Network Expansion Planning (TNEP) is that of how to build and upgrade $\mathcal{E}$ to accommodate changes to $\mathcal{N}_{\mathcal{GEN}}$ and $\mathcal{N}_{\mathcal{LOAD}}$. Both of these problems have received considerable attention over the last thirty years, however it has only been recently tied to the challenges of incorporating large amounts of renewable generation. The most advanced comprehensive work in this area is the WinDS project [8],[11] at the National Renewable Energy Laboratory (NREL) in Colorado. WinDS models the problem as a linear program (for computational tractability) and assumes direct connectivity from renewable sites to the existing network results in a physically consistent system. Figure 1 presents the intuition behind the model of [9],[10] in an abstract and simplified form (the full model has a considerably more complicated economic model and incorporates wind speed scenarios to model wind generation uncertainty).

In Figure 1, $\mathcal{N}_{\mathcal{GEN}}$ represents the set of possible generation sites in $\mathcal{G}$, $\mathcal{N}$ represents the set of nodes in $\mathcal{G}$, p_i is a decision variable on the amount of generation to place at site i, $y_{i,j}$ is the amount of capacity to add between sites i and j, c_i is the cost of building generation at site i, $l_{i,j}$ is the cost of adding capacity between site i and site j, d_i is the demand at a load, and $f_{i,j}$ is a decision variable for the amount of current to place on edge $\{i, j\}$. The first constraint ensures that the total amount of generation produced is greater than some threshold P. The second constraint enforces a maximum generation at each generation site based on NREL's renewable potential maps [12]. The third constraint enforces a minimal amount of generation at each site in order to model existing generation. The fourth constraint enforces capacities for flow on each edge in $\mathcal{E}$. The fifth constraint ensures that flow from generator nodes is equal to the actual production at those nodes. The sixth constraint ensures each load is receiving sufficient power. The seventh constraint ensures that the accumulated current at all other nodes is 0. The final constraint controls the bi-directionality of each edge. This formulation approximates a real (DC) power flow model and Kirchoff's first law on power flows (current conservation).

Region	Demand MW	Non-Wind MW	Wind MW
70	670	0	1645
71	770	0	684
72	40	0	0
73	830	6276	0
74	705	0	6831
Total	3015	6276	9160

TABLE I
WINDS 2030 FORECASTED VALUES FOR DEMAND/SUPPLY IN WYOMING (BY WIND REGION)

Limitations of WinDS In short, the WinDS optimization model features detailed representations of major generation and consumption elements. As seen from the optimization model in Figure 1, WinDS lacks corresponding detailed representations of transmission elements. The transmission elements are notionally represented and as a result, WinDS only proposes new dedicated (long distance) transmission lines. However, dedicated transmission lines are often uneconomical (especially over long distances) as they fail to utilize existing reserve capacity in system and often create situations where portions of the grid are severely underutilized. Despite expansion of the network to 2030 conditions, most operable elements will be linked to large amounts of "legacy" transmission capacity and constrained by the historic placement of centralized generating plants. Indeed, even if construction of long distance transmission lines occurs, the lines may not be used in the expected fashion due to legacy conditions. Finally, as the WinDS optimization model does not include elements of reactive (AC) power, WinDS may suggest transmission expansions that are physically infeasible.

We now describe examples where the lack of detailed transmission representations results in faulty solutions or unexpected behavior. In WinDS, the 14-state western electric operating region (WECC) was subdivided into 95 regions corresponding to areas of high wind potential. Wind regions serve as the basic unit of spatial resolution for all WinDS simulations. Wyoming was subdivided into five wind regions (70-74). For reference, forecasted demand and supply values utilized by WinDS for Wyoming are listed in Table I. Table I indicates one wind region in Wyoming will install non-wind generating capacity by 2030, while three regions will install wind generating capacity to utilize large available wind resources. Because electric supply will significantly exceed Wyoming's demand by a large ratio, a net export

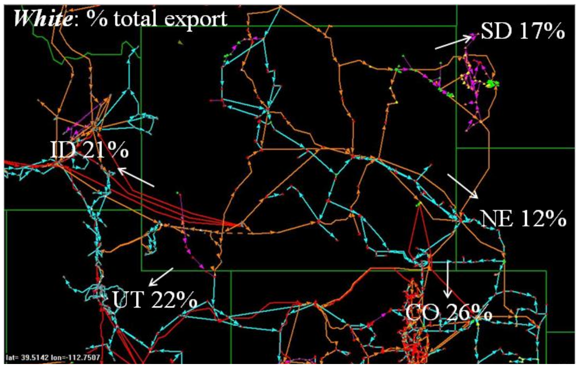

Fig. 2. Power flow 2030 simulated transmission elements in Wyoming and Surrounding Areas.

flow pattern is produced. The model resolves this export condition by building new long-distance lines to connect directly southeastern Wyoming to Denver and Salt Lake City to satisfy their demand. We used reference [13] to estimate network performance including line flows, voltage adequacy and control stability for both DC and AC power flows. Our result provides important insights into problems incompletely addressed by WinDS.

In Figure 2, "% Total Export" indicates directional flows leaving Wyoming towards adjacent load centers. The meshed nature of existing network topology suggests wind energy from Wyoming will be transmitted via many intervening circuits to different load centers. This solution provides greater circuit redundancy and increased levels of operational reliability than dedicated circuits can provide. In addition, this solution conforms to design methods used commonly and accepted by utility planners. More comprehensive design methods that optimize power flows (and reduce lost energy) over long distances are needed to support dedicated transmission lines. This solution suggests that the expected behavior of power flows in the WinDS model (only Denver and Salt Lake City receiving power) will not occur and this could lead to undesirable behavior.

Indeed, our initial attempts at directly modeling these transmission systems exhibited such undesirable behaviors. First, a visualization of power flows near Denver in Figure 3 indicate several off-normal conditions, notably "loop back" where power sent to Denver is returned to Wyoming. Loop back is often observed in heavily loaded meshed networks near load centers; it prevents efficient delivery of incoming power and arises from uneven distribution of higher and lower capacity flow paths that have not been optimized. In this case, 1,635 MW of power flows toward Denver over two circuits from Wyoming, while 305 MW flows back. A second undesirable behavior we discovered is shown in Figure 4 where new dedictated transmission is not sufficient for

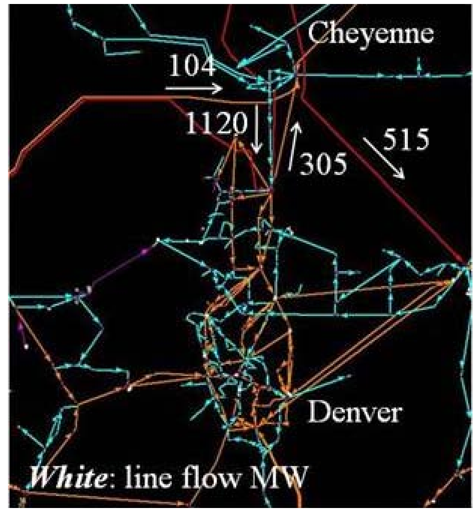

Fig. 3. Power flow 2030 simulated flow detail near Denver.

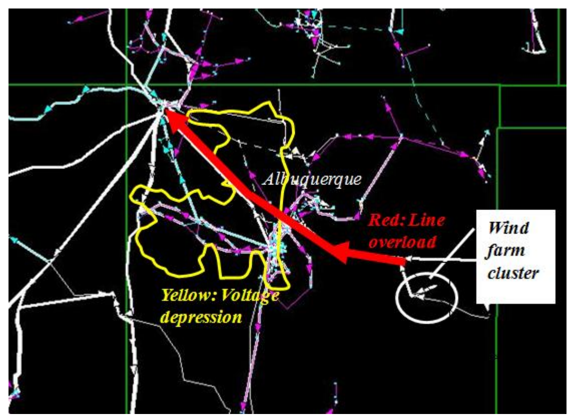

Fig. 4. Unstable Grid Example in New Mexico

handling the new wind generated energy in eastern New Mexico that was suggested by WinDS. In this scenario, the transmission solution results in a high number of physical violations (voltage collapse and line overloads).

Other Models It is important to note that WinDS is not the only model for optimally placing renewable (or other generation). Other work here typically focuses on the pure GEP problem with linear (or no) approximations of the transmission requirements or a pure TNEP with fixed generation assumptions for computa Excellent surveys in [14], [15], [16], [17] provide overviews of this work. In general, [14] confirms that most approaches do not fully account for the transmission requirements of building new generation due to the non-linearities in the power flow equations.

More recently, reference [18] considers transmission planning for DC power flows (similar to that of WinDS) for the GEP in the context of a game theory framework

OPTIMIZENETWORKDESIGN($\mathcal{N}, \mathcal{E}$)
1 $violations \leftarrow S(\mathcal{N}_{\mathcal{GEN}}, \mathcal{N}, \mathcal{E})$;
2 **while** $|violations| > 0$
3 **do** $l \leftarrow$ CHOOSEEDGE($violations$);
4 $\quad \mathcal{E} \leftarrow (\mathcal{E} \cup$ CALCULATENEWLINEPROPERTIES$(l)) \setminus l$;
5 $\quad violations \leftarrow S(\mathcal{N}_{\mathcal{GEN}}, \mathcal{N}, \mathcal{E})$;
6 **return** y;

CHOOSEEDGE($violations$)
1 **return** $\text{argmax}(\{i, j\} \in violations) f_{i,j} - y_{i,j}$;

CALCULATENEWLINEPROPERTIES(l)
1 **if** UPGRADEEXISTS(l)
2 $\quad$ **then return** UPGRADE(l);
3 $\quad$ **else return** $l \cup l$;

Fig. 5. Abstract Network Design Optimization Algorithm

for determining the best generation expansion. Reference [19],[20] considers the tradeoffs between different objective functions (cost, emissions, etc.) in a linear model of the GEP problem and suggests that transmission topology planning in conjunction with the GEP is a topic of future work. Relevant work on the TNEP is described in [21], [22], [23] which focuses on transmission planning problems for Brazil. Their approach is similar to our approach (that will be discussed in the next section) in that they explore modifications to the transmission network topology using search techniques such as simulated annealing. They differ from our approach in that they use a DC power flow model to evaluate candidate solutions and do not explore GEP aspects. [24] considers a TNEP for an objective focused on minimizing coronoa power loss. They capture some aspects of AC power flow in the sense they are calculating power losses based on voltage, but the flows are still modeled as DC. Their approach is to iterate on an infeasible solution by adding lines until the DC flows become feasible. [25] looks at heuristic approaches for solving the TNEP. The main result is that it is important to add multiple lines at the same time to improve the performance of heuristics.

III. ALGORITHM

We now describe our technique for overcoming the limitations of the WinDS model by directly incorporating the complex aspects associated with transmission modeling, i.e. the non-linear constraints associated with AC power. While there exist some optimization frameworks, such as constraint programming [26] and local search [27],[28] that can model non-linearities through appropriate expressions of constraints and objectives, such frameworks fail to utilize decades of simulation science that model the complex behavior of electric power systems [13], in particular those simulation systems that model utility behavior and may or may not have a pure mathematical formulation. This observation suggests a fundamental and interesting basic science problem: *hybridization approaches for combining the strengths of optimization and simulation effectively* or more precisely: *how can traditional optimization approaches exploit the information contained in simulations*? Hybridization of optimization approaches is an exciting idea from the operations research community as such approaches have been used to find solutions to previously unsolved problems [29],[30],[31]. Interestingly, general approaches for hybridizing simulation and optimization are relatively new within the literature (last 10-15 years); see [32],[33],[34],[35] for a few recent examples. Simulation has mainly been used as a method for optimization, as opposed to being used in conjunction with other optimization approaches. Existing hybridization approaches use simulation purely as a way to evaluate the feasibility or optimality of a solution [34],[36] or to evaluate policies [37]. Rarely are the results of the simulation used to help guide the search procedure within the optimization itself [36],[38]. The algorithm described here is a step in the direction of more tightly coupled optimization and simulation. It adopts a heuristic that uses simulation results to choose promising transmission expansions. This approach has guided the discovery of feasible infrastructure networks for adding 20% wind generation the U.S. electric power grid starting from the solutions posed by [8].

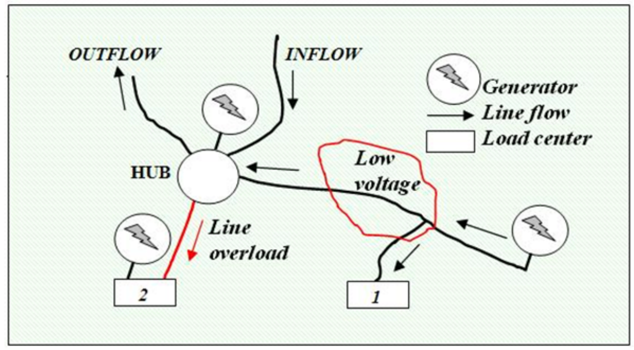

Fig. 6. Grid Reinforcement

The key idea behind the approach is to grant the algorithm access to a black box S that simulates an electric power network (in this specific case S is an AC power flow solver [13]). Abstractly, S is expressed as a constraint in the form $|S(\mathcal{N}_{\mathcal{GEN}}, \mathcal{N}, \mathcal{E})| \leq 0$ where $S(\mathcal{N}_{\mathcal{GEN}}, \mathcal{N}, \mathcal{E})$ is a function that returns a set of physical violations. For the problems of [8], $\mathcal{N}_{\mathcal{GEN}}$ is fixed. The overall structure of the algorithm appears in Figure 5.

The inputs to this algorithm are the $\mathcal{N}$ and $\mathcal{E}$ of an initial grid configuration. Line 1 calculates the set of violations for the initial choices of $\mathcal{N}_{\mathcal{GEN}}$ and $\mathcal{E}$. Line 3 chooses a violation to resolve. Line 3 is implemented by

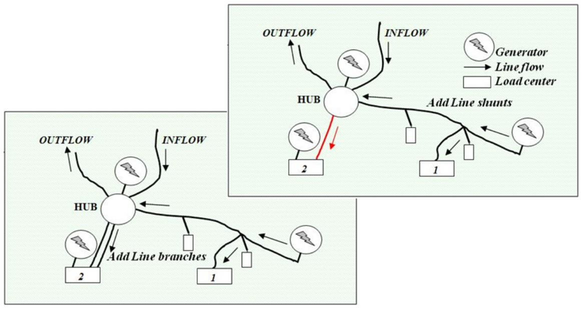

Fig. 7. Reinforcement options: a) Line shunts: capacitors, inductors. b) Line branches: multi-conductor lines or dual circuits

choosing the worst line overload (worst voltage condition if no overloads exist) from the set of violations (function CHOOSEEDGE). Line 4 calculates a new line property from a discrete set of possible line upgrades. Finally, line 5 simulates the new network. Lines 3-5 are repeated until all violations are eliminated and line 6 returns the $\mathcal{E}$ that achieves a feasible network.

Figures 6 and 7 provide some intuition as to the implementation of CALCULATENEWLINEPROPERTIES. In this example, CALCULATENEWLINEPROPERTIES must operate on violations described in Figure 6 (a voltage condition and an overload). CALCULATENEWLINEPROPERTIES alleviates the problems by upgrading one line with shunts and adding additional capacity through the construction of an extra transmission line as seen in Figure 7.

IV. Experimental Setting

We now describe the experimental setting and process for which the algorithm was utilized. The goal is to obtain a feasible electric power transmission network for WinDS model of 2030 demand and generation. The overall process is described in Figure 8. We started with the Federal Energy Regulatory Commission (FERC) 715 power flow model for the year 2016, the latest year for which utility projections are publicly filed. This represents a feasible starting point for the WinDS 2030 model and is known to have sufficient transmission capacity to route all the necessary power. The 2016 F715 model was adapted to 2030 WinDS projections by increasing all generating unit capacities and substation demands by a constant factor.

The resulting model represented the generation capacity and demand projected by WinDS at an aggregate level, thereby verifying some of the assumptions of the WinDS projections. Our closer inspection of the two models discovered that WinDS and F715 models had very large spatial pattern discrepancies for the projected growth that required reconciliation. Figure 9 illustrate these discrepancies. This required us to spatially reallocate both supply and demand to achieve the WinDS

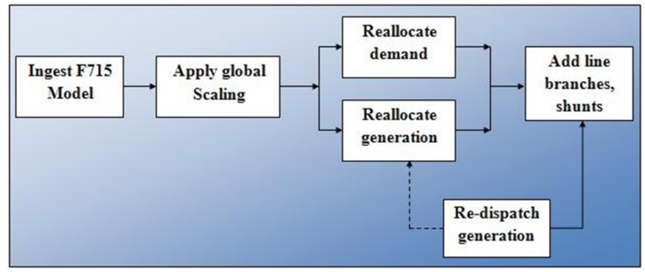

Fig. 8. Grid Modeling Process: Manual and automated steps required for assembly of a solvable grid model for the WinDS scenarios

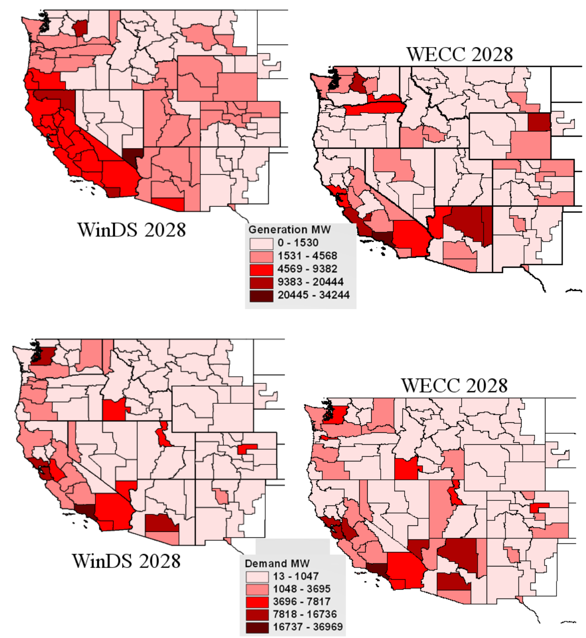

Fig. 9. WinDS vs WECC Generation and Demand

growth models. The initial F715 scaled model for 2030 was solvable by [13], albeit with 2,215 line overloads. The violations resulted from inadequate transmission capacity to meet the increased demand. We similarly attempted to solve the original WinDS demand and generation spatial allocations, however, this configuration resulted in numerical instabilities that [13] was unable to resolve. Thus, we chose to initially alleviate the constraint violations of the F715 scaled model and incrementally reallocate supply and demand to transition to the WinDS model to prevent the model from being numerically de-stabilized. Small spatial changes in demand and generation were introduced in two-year modeling steps (a total of six steps).

After reallocation the F715 model approximately conformed to WinDS projections in 2030 (some WinDS projections in California introduced such large numerical instabilities into the flow equations that we had to

Quantity	GW Total	GW Change	# Regions	Factor
Substation Demand	208.5	-33.7	29	0.87
		+33.7	66	1.28
Generating Unit Capacity	244.1	-153.4	28	.089
		0	14	1.00
		+153.4	53	1.22

TABLE II
WinDS 2030 forecasts (by wind region)

Component	# Added	Capacity	Units
Lines	1,489	84,075	MVA
Transformers	795	56,474	MVA
Shunts	1,081	47,597	MVAR

TABLE III
Final Algorithm Component Additions

approximate those values). Table II summarizes changes that were applied by this process. The algorithm of section 3 was invoked to upgrade the transmission capacity of the scaled F715 model and the subsequent reallocation steps. The function CALCULATENEWLINEPROPERTIES was implemented by allowing three types of upgrades on $\mathcal{E}$: adding transmission lines, adding transformers, and adding shunts. Transmission line capacity was increased by adding one or more parallel elements to existing overloaded lines. Transformer capacity was added by increasing ratings on existing overloaded transformers. Line shunts (multi-phase line to ground capacitors or inductors) were added to correct abnormal voltage profiles and to reduce reactive line flows as previously discussed in Figure 7. When possible, voltage control logic provided by [13] was used to correct voltage problems in order to minimize our proposed upgrades.

Focusing on the western U.S. model, Table II (also Figure 9) shows a profile of how demand and generation were reallocated across most of the 95 wind regions in this area. A total of 153.4 GW of generation was moved from 28 wind regions and added to 53 wind regions. No change in generation was made to 14 wind regions. The column titled "Factor" lists a constant that was applied to each wind region to accomplish reallocation.

V. Algorithm Analysis

We next discuss the performance of the algorithm described in section 3 as applied to the experimental setting of section 4. In order to move from the F715 2030 model to a feasible WinDS 2030 model, the algorithm required over 3,000 iterations (roughly 100 CPU minutes on a Dell Precision 670 with a 3.2 GHz processor and 2 GB of RAM running the Windows XP Operating System) per iteration of the spatial adjustment process (a total of 1800 iterations). It is important to note that these results do not include manual steps that were introduced when [13] could not resolve numerical instabilities in the models. This intervention constituted many man hours (decreasing the number of manual interventions is a

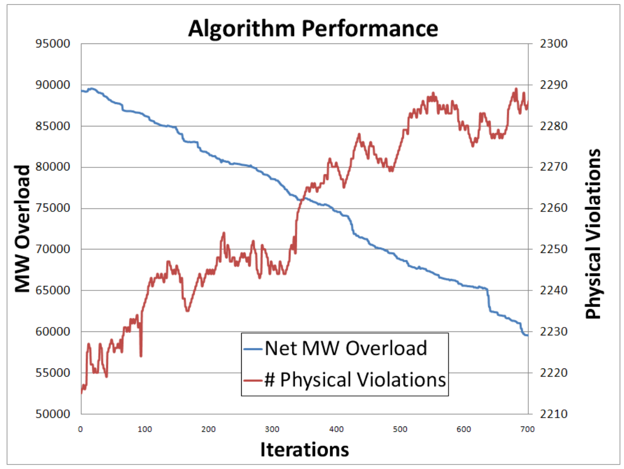

Fig. 10. Algorithm Performance

topic of future work). Table III highlights the number of components and capacities that were added to the power system model to sufficient upgrade transmission capacity. As point of reference, the model originally contained over 30,000 components (including 20,000 lines, 6500 transformers, and 1300 Shunts).

Figure 10 provides a cross-section of the performance of the algorithm. This figure shows how net MW overload ($\sum_{\{i,j\}\in\mathcal{E}} max(0, f_{i,j} - y_{i,j})$) in the electric power network was reduced with the number of iterations (blue line) for the last iteration of spatial reallocation. Roughly speaking, the net MW overload is reduced linearly with the number of iterations. In this particular case, it was interesting to also plot the number of components ($|violations|$) that were in a violation state during the execution of the algorithm (red line). It is apparent, that in order to reduce the function $\sum_{\{i,j\}\in Edges} max(0, f_{i,j} - y_{i,j})$, the algorithm must *increase* $|violations|$, which seems counter-intuitive at first. Upon closer inspection of the networks that the algorithm produced, we observed that when large overloads were alleviated through an increase in transmission capacity, [13] recognized the increase in capacity and attempted to use it to more economically route power. This often resulted in the creation of many small overloads on nearby transmission lines. For example, the algorithm may add transmission capacity to alleviate an overload of one hundred MW on a power line. The result of adding this transmission capacity may remove the overload, but may also create five MW overloads on five nearby power lines due to the availability of increased capacity. As a result, the net overload was reduced by 75 MW, but the number of violations was increased by 4. This provides further evidence why the multiple line addition approach of [25] can be effective.

VI. Conclusion

This paper describes a critical problem that the electric power industry will face over the coming years. As environmental, economic, and political forces encourage the industry to adopt and construct more renewable generation, the challenge of how and where to build this generation will become more pressing. Early work by [9], [10] clearly outlines many of these issues. This paper has built upon this prior work by demonstrating a process and algorithm to upgrade the existing electric power network so that it can feasibly to achieve the renewable energy generation goals of [8]. The algorithm presents a novel hybridization approach for integrating traditional local search based optimization with electric power simulation models that is able to resolve a model with over 2,500 components in an infeasible state.

In the future, we plan to develop new neighborhood exploration procedures that exploit more of the information provided by the simulation (S) with a focus on determining heuristics to fully automate the construction of a feasible network and eliminating the manual (clean up) steps that are currently necessary. Once the complete feasibility algorithm is achieved we plan to embed the heuristics within a local search meta-heuristic to begin to efficiently search for the globally optimal feasible solution (similar to [23]). The next step will be to relax the new generation decisions of [8] in order to revisit those choices and find better solutions that appropriately balance the cost to upgrade the transmission system with choices of generation locations. Next, as we only examined adding transmission lines, transformers, and shunts to the network we also plan to exploring techniques for upgrading portions of the transmission system to higher voltages to alleviate the overloads and voltage conditions. Finally, we will want to incorporate more seasonal demand and generation profiles and contingency events within the optimization to more explicitly explore robustness considerations.

In addition, our approach generalizes naturally to a number of other grid planning problems. Decision variables can be added to modify the future network configuration by applying criteria of interest to utility planners. This could include capital costs of adding transmission capacity, environmental impacts of utilizing new versus existing transmission corridors, siting new generators in conjunction with storage locations and other important variables. The approach may also be used for dynamic topology problems. Our algorithm could optimally configure the power network in real-time due to changing conditions on the grid (changing generation pattern, changing demand, losing transmission equipment, etc.). This is especially important as more renewable generation and better storage devices are connected to the grid. The solution proposed here may be used by applying it to the *existing* conditions of the grid and only allowing the algorithms to modify attributes for components that exist.

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