LA-UR-10-06901

Approved for public release;
distribution is unlimited.

Title: Strategic Planning for Power System Restoration

Author(s): Russell Bent
Pascal Van Hentenryck
Carleton Coffrin

Intended for: 2011 International Conference on Vulnerability and Risk Analysis

Strategic Planning for Power System Restoration

Carleton Coffrin
Brown University
Providence, RI
02912, USA

Pascal Van Hentenryck
Brown University
Providence, RI
02912, USA

Russell Bent
Los Alamos National Laboratory
Los Alamos, NM
87545, USA

Abstract

This paper considers the power system restoration planning problem (PSRPP) for disaster recovery, a fundamental problem faced by all populated areas. PSRPPs are complex stochastic optimization problems that combine resource allocation, warehouse location, and vehicle routing considerations. Furthermore, electrical power systems are complex systems whose behavior can only be determined by physics simulations. Moreover, these problems must be solved under tight runtime constraints to be practical in real-world disaster situations. This work is threefold; It formalizes the specification of PSRPPs, introduces a simple optimization-simulation hybridization necessary for solving PSRPPs, and presents a complete restoration algorithm that utilizes the strengths of mixed integer programming, constraint programming, and large neighborhood search.

1 Background & Motivation

Every year seasonal hurricanes threaten coastal areas. The severity of hurricane damage varies from year to year, but significant power outages are always caused by seasonal hurricanes. Power outages have significant impacts on both quality of life (e.g. crippled medical services) and economic welfare. Therefore, considerable human and monetary resources are always spent to prepare for and recover from power threatening disasters. At this time, policy makers work together with power system engineers to make the critical decisions relating to how money and resources are allocated for preparation and recovery of the power system. Unfortunately, due to the complex nature of electrical power networks, these preparation and recovery plans are limited by the expertise and intuition of the power engineer. Furthermore, the National Hurricane Center (NHC) of the National Weather Service in the United States (among others) is highly skilled at generating ensembles of possible hurricane tracks but current preparation methods often ignore this information.

This paper aims to solve this disaster recovery problem more rigorously by combining optimization techniques and disaster-specific information given by NHC predictions. The problem is not only hard from a combinatorial optimization standpoint, but it requires modeling of a complex physical system (i.e. the electrical power network) which is a challenging sub-problem. The electrical power industry has developed several tools for modeling the power system's behavior (e.g. T2000, PSLF, Powerworld, PSS), each with its own strengths and weaknesses. Furthermore, the electrical power industry recognizes there is not a single model for understanding the behavior of an electrical power network. For that reason, this work seeks to build solution procedures that are independent of any specific electrical power simulation tool.

The paper considers the following abstract disaster recovery problem: How to store supplies throughout a populated area to minimize the amount of time each customer is without electricity after a disaster has occurred. It makes the following technical contributions:

1. It formalizes the Power System Restoration Planning Problem (PSRPP).
2. It proposes a Constraint Programming and Simulation Hybrid System for optimization of complex network-flow systems

3. It proposes a multi-stage hybrid-optimization decomposition for PSRPPs, combining Constraint Programming, Large Neighborhood Search, and Power Simulation.

4. It validates the approach on power restoration for hurricane recovery in the United States.

Section 2 of this paper reviews similar work on power system recovery and vehicle routing problems. Section 3 presents a mathematical formulation of the power system recovery problem and sets up the notations for the rest of paper. Section 4 discusses the methodology for a hybrid simulation-optimization framework. Section 5 presents the a high level model of the problem. Section 6 reports experimental results of the algorithm on some benchmark instances to validate the approach and Section 7 concludes the paper.

2 Previous Work

Power engineers have been studying power system restoration (PSR) since at least the 1980s (see [1] for a comprehensive collection of work) and the work is still ongoing. The goal of PSR research is to find fast and reliable ways to restore a power system to its normal operational state after a black-out event. This kind of logistics optimization problem is traditionally solved with techniques from the Industrial Engineering and Operations Research sciences. However, PSR has a number of unique features that prevent the application of traditional optimization methods, including:

1. **Steady-State Behavior:** The flow of electricity over a power system is governed by the laws of physics (e.g., Kirchoff's current law and Ohm's law). Hence, evaluating the behavior of the network requires solving a system of non-linear equations. This can be time-consuming and there is no guarantee that a feasible solution can be found.

2. **Dynamic Behavior:** During the process of modifying the power system's state (e.g., energizing components and changing component parameters), the system is briefly subject to transient states. These short but extreme states may cause unexpected failures [2].

3. **Side Constraints:** Power systems are comprised of many different components, such as generators, transformers, and capacitors. These components have some flexibility in their operational parameters but they may be constrained arbitrarily. For example, generators often have a set of discrete generation levels, and transformers have a continuous but narrow range of tab ratios.

The PSR research recognizes global optimization is an unrealistic goal in such complex non-linear systems and adopts two main solutions strategies. The first strategy is to use domain expert knowledge (i.e. power engineer intuition) to guide an incomplete search of the solution space. These incomplete search methods include *Knowledge Based Systems* [16], *Expert Systems* [10, 3, 5], and *Local Search* [12, 13]. The second strategy is to approximate the power system with a linear model and solve the approximate problem optimally [17]. Some work has hybridized both strategies by designing Expert Systems that solves a series of approximate problems optimally [14, 9].

Interestingly, most of the work in planning PSR has focused on the details of scheduling power system restoration [2, 3]. More specifically, what is the best order of restoration and how should system components be reconfigured during restoration? In fact, these methods assume that all network components are operational and simply need to be reactivated. In this study we consider the restoration of damaged components which must be repaired before reactivation can occur. This introduces two additional decision problems: (1) Are replacement parts available for a given repair; (2) How can the restoration teams be routed effectively perform all of the repairs? To the best of our knowledge PSRPPs are the first PSR application that considers strategic storage decisions and vehicle routing decisions.

Given:

Power Network: $\mathcal{PN}$

Repositories: $R_{i \in 1..r}$
Capacity: RC_i

Vehicles: $V_{i \in 1..m}$
Capacity: VC
Start Depot: D_i^+
End Depot: D_i^-

Network Items: $N_{i \in 1..n}$
Item Type: NT_i
Maintenance Time: M_i

Items Types: $I_{i \in 1..t}$
Volume: IV_i

Scenario Data: $S_{i \in 1..s}$
Scenario Probability: P_i
Item Damage: $ND_i \subset \{1..n\}$
Travel Time Matrix: $T_{i,1..l,1..l}$

Output:
The items to store at each repository
Delivery schedules for each vehicle in each scenario

Let:
T_i = completion time of the last repair in scenario i
Unserved Power$_i(t)$ = the size of the blackout area in watts at time t in scenario i

Minimize:

$$\sum_i P_i * \int_0^{T_i} \text{UnservedPower}_i(t)\, dt$$

Subject To:
Vehicle and repository capacities
Vehicles start and end locations
Travel matrix times
Electrical power system behavior

Figure 1: Power System Restoration Problem Specification

3 The Power System Restoration Problem (PSRPP)

In formalizing PSRPPs, a populated area is represented as a graph $G = \langle L, T \rangle$ where $L_{1..l}$ represents those locations of interest to the restoration problem, i.e., the basic components of the electric power network (e.g., lines, buses, and generators), storage depots and repair vehicle locations. The vehicles can travel to any node of the graph but the edge distances, $T_{1..l,1..l}$, are not generally Euclidean and may be a metric space due to transportation infrastructure and road damage. The primary output of a PSRPP are: (1) which items should be stored at each warehouse; (2) for each scenario and each vehicle, a delivery schedule that minimizes the power restoration objective. Figure 1 summarizes the entire problem, which we now describe in detail.

Electrical Power Network An electrical power network model is necessary to understand the behavior of the power network. Especially how the behavior changes as the restoration procedure occurs. However, there are many competing models for representing electrical power networks. To remain flexible in that regard this specification considers an abstract power network model $\mathcal{PN}$. The only requirement on the abstract model is that it can implement the interface described in Section 4.

Electrical power networks are comprised of many different components, e.g. lines, generators, loads, capacitors, and transformers. In this work we classify each network item, i, in to a particular item type NT_i. We assume that items of type t are homogeneous in terms of their size IV_t. The power network model $\mathcal{PN}$ captures how different components effect the total power flow in the network.

Objective The objective function aims at minimizing the total watt hours of blackout that occur after the disaster. This is simply the amount of electrical demands that are unserved until some time T. More formally,

$$\textbf{Minimize} \sum_i P_i * \int_0^{T_i} \text{UnservedPower}_i(t)\, dt$$

It is not obvious if it is possible to use available optimization and simulation tools to reason over the continuous time domain. However, the restoration process can be seen as a series of discrete events. Those are the times that each job is completed and the state of the power network components (i.e. is it damage or not). The set of discrete events that effect the PSRPP objective can be calculated from the vehicle delivery schedules. Three pieces of aggregate information must be calculated: (1) the time that each job is completed $T_{i,j}$ (2) the time of the succeeding job $Next_{i,j}$ (3) a function that can calculate the amount of unserved power at some time Unserved Power$_i(t)$. Given these discrete events the integral above can be calculated with the following summation:

$$\textbf{Minimize} \sum_i P_i * \sum_j \text{UnservedPower}_i(T_{i,j})(Next_{i,j} - T_{i,j})$$

In Section 4 we discus the details of how the Unserved Power$_i(t)$ function can be implemented in practice.

Side Constraints The first set of side constraints concerns the storage locations which represent the electric company warehouses in the populated area. Each repository $R_{i \in 1..n}$ has a maximum capacity RC_i to store the repair items. The volume of the items stored at warehouse i cannot exceed RC_i.

The second set of side constraints concerns the routing. We are given a fleet of m vehicles $V_{i \in 1..m}$ which are homogeneous in terms of their capacity VC. At any time in the routing process the volume of items carried by vehicle i cannot exceed VC. Each vehicle has a unique starting depot D_i^+ and ending depot D_i^-, and after delivering an item j it must wait for the maintenance time M_j before continuing onto it's next delivery task.

Stochasticity PRSPs are specified by a set of s different disaster scenarios $S_{i \in 1..s}$, each with an associated probability P_i. After a disaster, some parts of the power network are damaged and each scenario has a set ND_i of network items that are inoperable due to the disaster damage. Finally, site-to-site travel times $T_{i,1..l,1..l}$ (where $l = |L|$) are given for each scenario and capture transportation infrastructure damage.

Unique Features Different aspects of this problem were studied before in the context of vehicle routing and power system restoration, and both have proven to be difficult problems in their own right. The vehicle routing community has produced many insightful algorithms for solving pickup and delivery routing problems (PDP). Unfortunately these techniques have focused on simple objectives (e.g. minimum travel distance) and are not easily adaptable to the kind of complex objective present in PSRPPs. The power system restoration community has produced many helpful strategies for calculating good restoration schedules. However, they usually ignore the intricacies of transportation and installation in these schedules. The optimization community has studied many problems involving uncertainty, however is uncommon to see second stage problems that involve difficult optimization problems (e.g. vehicle routing, power restoration scheduling). By combining all three aspects of these problems PSRPPs produce restoration preparations that are robust over several disaster contingencies and can be executed with all the details of transportation and installation taken into consideration.

4 A Framework for Optimization with Simulation

As we have discussed before, there are many different models for electrical power networks. This work seeks to develop optimization tools that are independent of any specific model. For this reason we adopt a very simple and abstract power simulation interface in the hope that it can be implemented by any power network model. In the context of restoration there is only one principle attribute for each item on the power network, that is, which items are fully operational and which items are inoperable due to physical damage. We call this information the damage state of the network. All of our algorithms ask one simple question, "Given a particular damage state, how much real power reaches the network load points?". More formally, given a power network model $\mathcal{PN}$, and a damage state $\mathcal{DS}_i$, we define the function:

$$\text{DemandsMet}(\mathcal{PN}, \mathcal{DS}_i)$$

That returns a real number representing the amount of power severed at each load node in the power network. This interface is very simple and the amount of reasoning we can do with it is limited, but this is the price of generality. If we adopt a more specific power network model we may be able to perform stronger reasoning, but one of the goals of this work is to understand how successful a very generic interface can be. The experimental results demonstrate that this simple interface is sufficient for designing effective local search algorithms. This simple interface also assumes that all the network loads have equal priority. Our future work will consider how to extend this interface to support priorities for emergency services and contractual obligations.

Recall the power restoration objective from Figure 1, this objective can be calculated using the DemandsMet function is the following way: Given some time t let damage state $\mathcal{DS}_t$ bet the set of non-operation items at time t. Also let MaxPower be the maximum amount of power served when the power system is fully repaired. Then the power restoration objective can be modeled as follows,

$$\textbf{Minimize} \sum_i P_i * \int_0^{T_i} \text{MaxPower} - \text{DemandsMet}(\mathcal{PN}, \mathcal{DS}_t)\, dt$$

The constraint programming (CP) paradigm (from the artificial intelligence community) has proven to be effective for solving a variety of combinatorial optimization problems. Specifically constraint programming is often the state-of-the-art solution technique for complex scheduling and vehicle routing problems. Because we are developing an algorithm for a combined scheduling and vehicle routing problem with many side constraints a constraint programming framework is a natural choice. However, due to the complexity of the problem we use large neighborhood search (LNS) to find high-quality solutions with in the runtime requirements. In the rest of this paper we give the high level intuition for how the DemandsMet function can be used in algorithms for modeling the behavior of an electrical power network.

5 The Basic Approach

This section presents the basic approach for solving the PSRPP. Previous work on location routing (e.g. [7, 4, 15]) has shown that reasoning over a storage problem and a routing problem simultaneously is extremely hard computationally. Furthermore we suffer from additional computation challenges due to the overhead of electric power simulation. To address these difficulties, we propose two primary stages in our algorithm that decomposes the storage, customer allocation, and routing decisions. The two primary stages, and the key decisions of each stage are as follows:

1. **Storage & Customer Allocation**: Which repositories store the repair items and how are the items allocated to each damaged item in each scenario?
2. **Restoration Routing**: For each scenario, what is the best routing plan to minimize the power restoration objective?

The decisions of each stage are independent and can use the optimization technique most appropriate to their nature. The first stage is formulated as a Mixed Integer Program (MIP). This is very natural as MIPs are excellent for two-stage stochastic programming. The second stage is solved using CP but LNS is used for larger instances where a pure CP approach is impractical. This is also a natural choice as CP and LNS are successful at combinatorial optimization of Vehicle Routing Problems (VRP) with unique side constraints. Previous work has shown that problem decomposition can bring significant runtime benefits with minimal degradation in solution quality [6].

Benchmark	r	m	s	n	Max($\|ND_i\|$)	LNS Timeout (seconds)
BM1	8	13	3	326	22	1200
BM3	8	13	18	266	61	1200
BM4	8	13	18	326	121	1200

Table 1: PSRPP Benchmark Statistics

Stochastic Storage The stochastic storage problem consists in choosing where to store repair items and how those items are allocated to the scenario damage. In practice, the repository storage constraints may prevent full restoration of the electrical grid after a disaster. Therefore, a smart selection of restoration items is necessary to ensure the maximum amount of power is served in each disaster scenario. For this reason we choose to model this as a multi-objective optimization problem consisting of two parts. The first part of the objective consists of minimizing the total unserved demands after all the restoration is complete. The second part consists of minimizing the distance of each repair item to its damage location. The relative importance of the objectives are controlled with parameters W_p and W_t respectively. More precisely, given a decision variable D_{sij}, that indicates that an item from repository i is used to repair network item j in scenario s, then the stochastic storage objective consists in minimizing,

$$W_p * \sum_s P_s * (\text{MaxPower} - \text{DemandsMet}(\mathcal{PN}, \{j : \bigvee_i D_{sij} = 0\})) + W_t * \sum_s P_s * \sum_{i,j} T_{sij} * D_{sij}$$

subject to the repository storage capacity constraints, RC_i.

Restoration Routing Once the storage and repair allocation are computed, the uncertainty is revealed and the second stage reduces to a deterministic multi-depot, multiple-vehicle capacitated routing problem whose objective consists in minimizing the power restoration objective (defined in Section 3). This problem is similar to classic Pickup and Delivery VRPs however evaluation of the power restoration objective requires the use of an electrical power model. More precisely, given a decision variable T_i that represents the repair time of item i and $Next_i$ the time of the job succeeding i, then the restoration routing objective consists in minimizing,

$$\sum_i (\text{MaxPower} - \text{DemandsMet}(\mathcal{PN}, \{j : T_j \leq T_i\})) * (Next_i - T_i)$$

subject to the travel time matrix and vehicle capacity constraints. The addition of power simulation to the objective function adds considerable computational complexity compared the classic routing objectives (e.g. minimum travel distance).

6 Benchmarks & Results

Benchmarks The benchmarks were produced by Los Alamos National Laboratory and are based on the infrastructure of the United States. The disaster scenarios were generated by state-of-the-art hurricane simulation tools similar to those used by the National Hurricane Center. Their sizes are presented in Table 1(The table also depicts the algorithm parameters). The size of the largest ND_i set is included because it is a good metric for difficulty of a benchmark. It is also important to emphasize that, these benchmarks are significantly large in size compared similar work in this field.

The Algorithm Implementation and the Baseline Algorithm The final algorithm was implemented in the Comet system [8] and the experiments were run on Intel Core 2 Duo CPU 2.53GHz machines running OS X 10.5. The power simulator IEISS (a proprietary power simulation tool of LANL) was used to evaluate the behavior of the power system. To validate our results, we compare our PSRPP algorithm to a variant of the same algorithm that models what is done in practice. The baseline algorithm is designed to model the decision making process of an

Benchmark	BM1	BM3	BM4
Baseline	192866	606090	668064
PSRPP	141919	328673	355695
Improvement	26.4%	45.8%	46.8%

Table 2: PSRPP Benchmark Results (Power Restoration Objective)

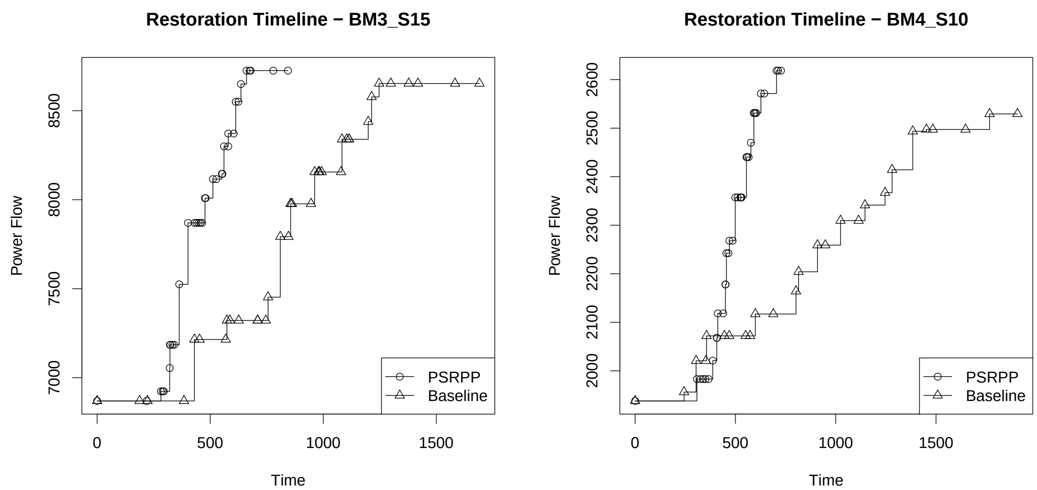

Figure 2: PSRPP Routing Results Comparison

electric power utility before and during the recovery process. There is little documentation on the process utilities use for stockpiling supplies for disaster recovery. Therefore, we design a simple greedy heuristic to model the storage decision process. Having no information about which disasters will occur, the utility may assume each item in the network has an equal probability of being destroyed in a disaster. In that case we should stockpile restoration items relative to their occurrence in the network (subject to the storage capacity constraint). Furthermore, it is not clear where to store the restoration items, so we choose to place them in equal quantity in each warehouse. After a disaster has occurred the utility's process goes roughly like this: (1) the power system engineers use their intuition for the network to prioritize the restoration actions based upon contractual obligations and restoration of emergency services; (2) restoration teams are dispatched to make the necessary repairs; (3) crews prefer to fix all broken items near the area they are dispatched to. We model this process in the routing stages of the PSRPP algorithm in the following way: (1) the restoration order is fixed by a greedy heuristic that has full understanding of the electrical network's behavior. It repeatedly chooses to repair the item that will bring the largest increase in network flow. This roughly captures the knowledge that a power systems engineer uses to organize a restoration effort; (2) the routing problem is similar to the one discussed in Section 5 but the routing objective is different because each vehicle crew works independently to do their repairs as fast as possible. The objective seeks to minimize the total travel distance of each vehicle and not power restoration objective. This variant of the PSRPP algorithm roughly approximates current power system restoration procedures and is thus a good baseline for comparison.

Results Table 2 compares the quality of the power restoration objective of the PSRPP algorithm and the baseline algorithm. As you can see the PSRPP algorithm brings a 26% improvement over the baseline on smaller benchmarks and up to 45% on larger benchmarks. Each benchmark has several disaster scenarios, each with a unique vehicle routing problem. Figure 2 illustrates the benefits of the restoration routing aspects of this problem over the baseline on two scenarios the 15th scenario of benchmark 3 (left), and the 10th scenario of benchmark 4 (right). Results on other scenarios are similar but omitted for space reasons.

7 Conclusion

This paper presented a novel problem in the field of humanitarian logistics, the Power System Restoration Problem (PSRPP). The PSRPP models the strategic planning process for post disaster power system recovery. This paper proposed a multi-stage stochastic hybrid optimization algorithm that yields high quality solutions to real-world benchmarks provided by Los Alamos National Laboratory (LANL). The algorithm uses a variety of technologies, including MIP, constraint programming, and large neighborhood search, to exploit the structure of each optimization sub-problem. The experimental results on hurricane disaster benchmarks indicate that the algorithm is practical from a computational standpoint and produce significant improvements over existing relief delivery procedures.

References

[1] M. Adibi. *Power System Restoration(Methodologies & Implementation Strategies)*. 2000.

[2] M.M. Adibi and L.H. Fink. Power system restoration planning. *Power Systems, IEEE Transactions on*, 9(1):22 –28, feb. 1994.

[3] M.M. Adibi, L.R.J. Kafka, and D.P. Milanicz. Expert system requirements for power system restoration. *Power Systems, IEEE Transactions on*, 9(3):1592 –1600, aug. 1994.

[4] M. Albareda-Sambola, J. A. Diaz, and E. Fernandez. A compact model and tight bounds for a combined location-routing problem. *Computer & Operations Research, 32:407-428*, 2005.

[5] J.J. Ancona. A framework for power system restoration following a major power failure. *Power Systems, IEEE Transactions on*, 10(3):1480 –1485, aug. 1995.

[6] Elvin Coban and John N. Hooker. Single-facility scheduling over long time horizons by logic-based benders decomposition. In Andrea Lodi, Michela Milano, and Paolo Toth, editors, *CPAIOR*, volume 6140 of *Lecture Notes in Computer Science*, pages 87–91. Springer, 2010.

[7] L. I. Burke D. Tuzun. A two-phase tabu search approach to the location routing problem. *European Journal of Operational Research, 116:87-99*, 1999.

[8] Inc. Dynadec. Comet 2.1 user manual. http://dynadec.com/, 2009.

[9] J.A. Huang, L. Audette, and S. Harrison. A systematic method for power system restoration planning. *Power Systems, IEEE Transactions on*, 10(2):869 –875, may. 1995.

[10] J.A. Huang, F.D. Galiana, and G.T. Vuong. Power system restoration incorporating interactive graphics and optimization. pages 216 –222, may. 1991.

[11] James P. Ignizio. A review of goal programming: A tool for multiobjective analysis. *The Journal of the Operational Research Society*, 29(11):pp. 1109–1119, 1978.

[12] A.L. Morelato and A.J. Monticelli. Heuristic search approach to distribution system restoration. *Power Delivery, IEEE Transactions on*, 4(4):2235 –2241, oct. 1989.

[13] H. Mori and Y. Ogita. A parallel tabu search based approach to optimal network reconfigurations for service restoration in distribution systems. volume 2, pages 814 – 819 vol.2, 2002.

[14] T. Nagata, H. Sasaki, and R. Yokoyama. Power system restoration by joint usage of expert system and mathematical programming approach. *Power Systems, IEEE Transactions on*, 10(3):1473 –1479, aug. 1995.

[15] G. Nagy and S. Salhi. Nested heuristic methods for the location-routing problem. *Journal of Operational Research Society, 47:1166-1174*, 1996.

[16] T. Sakaguchi and K. Matsumoto. Development of a knowledge based system for power system restoration. *Power Apparatus and Systems, IEEE Transactions on*, PAS-102(2):320 –329, feb. 1983.

[17] M.H. Yolcu, Z. Zabar, L. Birenbaum, and S.A. Granek. Adaptation of the simplex algorithm to modeling of cold load pickup of a large secondary network distribution system. *Power Apparatus and Systems, IEEE Transactions on*, PAS-102(7):2064 –2068, jul. 1983.