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Applications of Operations Research in Domestic Electric Utilities

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APPLICATIONS OF OPERATIONS RESEARCH IN DOMESTIC ELECTRIC UTILITIES

A Thesis submitted in partial fulfillment of the requirements for the degree of Master of Science in Mathematical Sciences at Virginia Commonwealth University.

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Abstract

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UTILITIES

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Since its inception in the 1950s, operations research has been used in a number of industries, including the energy industry. Documentation of its use in exploration, production, gasoline blending, oil spill management, coal mining, coal handling, and coal mixing is extensive. However, considerably less documented research exists for one significant customer of many of these products: the electric utility. This work reviews refereed literature from United States operations research journals that document the use of operations research in United States electric utility operations. Applications that centered

specifically on the areas of thermal energy generation, transmission, distribution, capacity planning, electric power service options, and other general operations-related activities were included. Applications solely related to plant siting, general energy policy, or work that focused on electricity as a commodity and primarily investigated the use of financial instruments, were not included.

CHAPTER 1 Introduction- The Electric Utility

Electric utilities play a vital role in supporting the needs and many wants of most citizens in the United States. For most individuals, electricity is used throughout the day to power tasks great and small; however many may not have an understanding of the measures electric utilities take to ensure that the electricity they have come to rely on is provided in a safe, reliable, and efficient manner. The primary functions of an electric utility are the generation, transmission, and distribution of electricity. Electricity is generated at a power plant then sent to load centers by means of high voltage transmission lines. When the electricity nears its customers, the voltage is stepped down at distribution stations and sent through distribution lines. The customers along distribution networks have the voltage of their electricity stepped down once more before it is supplied to their homes or businesses. Utility customers can be divided into the categories of industrial, commercial and residential. Stable operations of the utility are characterized by customer load and system losses equaling the power being generated. However, customer loads can frequently fluctuate on an hourly basis. Load is mainly determined by weather, such as temperature, humidity and cloud cover, but is also a function of day of the week, time of day, and whether a given day is a holiday or not.

Many customers are oblivious to the impact that their behavior has on their electricity costs. When the aggregate demand across an electric utility's service territory is low, the price of electricity is relatively low. However, when the demand is high, the price of electricity becomes more expensive. Baseload power plants have relatively low operations costs and typically run as many hours per year as they can in order to meet the low, baseload customer demand. As demand increases, additional power plants with higher operational costs are ramped up to meet the demand, or electricity is purchased from other electric utilities and this is what causes the price of the electricity to rise. In addition to managing day to day demand, it is an even greater task for the electric utility to attempt to anticipate the electricity needs of customers in the future, especially when creating additional electricity generating capacity requires planning at least ten years in advance. For example, who could have imagined twenty years ago that products such as flat screen televisions and cell phones would proliferate, and that consumers would begin to inhabit increasingly larger homes? The substantial capital investments required to build the electric generating facilities financially quantify the gravity of their decisions. On top of all this, regulations regarding the environment are also subject to change, which means that some of the economic justification to build one type of generating facility, such as a coal-fired power plant, could no longer be valid by the time that the construction is complete. As such, operations research has been utilized to help electric utilities to make informed, logical decisions in the dynamic and stochastic environment they must function in.

Electric utilities in the United States have undergone a number of changes in the recent past. The nature of electricity generation, which is characterized by capital-intensive investments and the need for a large customer base over which to economically defray costs, allowed electric utilities to exist as relative monopolies for a long period of time.

Electricity was regionally generated, transmitted, and distributed by a heavily regulated and vertically integrated company (Baldick et al. 2006). In this regulated environment, each state had a State Corporation Commission (SCC) to regulate the activities of the utility companies in its jurisdiction. Utilities were required to demonstrate to the respective SCCs that their expenditures were prudent, and by doing so they would be able to include these costs in the customer rate base and collect a determined rate of return on them. Profits were governed by this rate of return, which was determined by the regulatory commission. However, over the past three decades, many states began to proceed with deregulation bills which removed electric utilities from their protected monopoly existence, and caused their financial prudence and efficiency to be regulated by competition with other power generators and utilities to serve their customers.

The central goal of deregulation was to reduce the rising cost of electricity and eliminate price discrepancies between different geographic regions by fostering competition (Takriti et al. 2000). In a regulated environment, savings that resulted from improved operations or reliability were not solely for the benefit of the electric utility, but were shared with their customers as well in the form of a decreased rate base. However, in a deregulated environment, the electric utilities had more motivation to find opportunities to save money for two key reasons. First, their shareholders could potentially realize significant financial rewards. Second, the deregulated market contains power producers who sell electricity into power pools where power suppliers purchase the electricity and sell it to their customers. Through improved operations, a large corporation with power generators, power traders, and an electric utility could potentially improve profitability across all parts of the business. In the United States, the Public Utilities Regulatory Policy Act of 1978 initiated deregulation by encouraging the development of nonutility generation, and by requiring utilities to buy power from these independent generators; a series of other related legislation would follow. In years to come, deregulation caused the system load on a utility to become increasingly unpredictable, and electricity prices to become more volatile (Takriti et al. 2000). Although deregulation encouraged utilities to build new infrastructure within the service territories of other utilities, the huge capital investment costs were prohibitive. This element of deregulation never fully developed. After previously moving towards deregulation, now many state legislatures have passed bills to return to the regulated environment.

While the use of operations research (OR) techniques in electric utilities was documented in Unites States OR journals sparingly during the regulated era, the introduction of deregulation led to an increase in published works in the field. This was likely due to the increased financial opportunities. Also, while in the beginning certain OR techniques were repeatedly used, such as Benders decomposition, Lagrangian relaxation and branch and bound, the introduction of deregulation seemingly provided the incentive for operations research practitioners to experiment with new approaches, such as variants of Newton's method and shortest path algorithms to solve some of their existing problems. Interested researchers have conducted theoretical work that could be applied to electric utility operations; however at the time of publication the work had not been directly applied. Based on the publications discussed in this document, although operations research methods have been used to address issues encountered by electric utilities, there is still room for operations research techniques to continue to contribute to the field. The intention of this work is to highlight the work that has already been done, show the advancements that were made when researchers extended work done by their peers instead of trying to develop an entirely new approach, and indicate where enhancements could be made in the future.

CHAPTER 2 Unit Commitment Problem

The unit commitment problem (UCP) involves optimally scheduling electric power generator operations to supply variable demand over a time horizon, such as one day or one week. Because the demand is variable, the time horizon is normally divided into one hour intervals. The operational capacity, operating constraints, and operating costs can vary widely for different generators for reasons such as the age, the fuel used, and the manufacturer. The general formulation of the UCP includes minimization of electricity production costs. These costs are heavily dependent on fuel and start up costs, which are a function of the temperature of the boiler. It is assumed that the boiler cools at an exponential rate and the colder the boiler, the more it costs to restart. In general, the UCP is modeled with a large-scale, nonlinear mixed integer program (Valenzuela & Mazumdar, 2003).

The unit commitment problem is often solved using mixed integer programming because the commitment variables that indicate whether the unit is on or off are binary. Heat characteristics of the generators represented in the UCP are nonlinear, causing the problem to be nonlinear. The UCP is also nonconvex, so it can have multiple local optimal solutions. The combination of these three traits would make it difficult, if not impossible, to prove optimality of a solution mathematically (Erwin et al., 1991). As a result of this previous approaches have employed algorithms to generate near optimal solutions that are within an acceptable tolerance.

Muckstadt and Koenig (1977) presented a mixed integer programming model for the power system scheduling problem that included a Lagrangian relaxation and branch and bound procedure for solving the problem. Their approach could be used to address which generating units should be used in a given time period (unit commitment problem), and how to allocate the system demand across the committed generating units. The problem was modeled as a multiperiod problem to allow for one hour increments in a 24 hour period of time. Units were limited to run within their maximum and minimum operation constraints when committed. A convex, piecewise linear total production cost curve was assigned for each unit to represent the total fuel and maintenance costs associated with each generator. The costs of starting up and shutting down generating units and transmission line losses were also included. Generator start up costs vary depending on how long the unit was shut down, and this is evidenced in the cost of the required fuel. Other contributors to cost that apply to both shutting down and starting up are labor and maintenance costs. Total energy produced must equal the total demand and system energy lost in transmission. In electric power operations, these transmission line losses are typically included as a penalty factor that adjusts the production cost curve for each generating unit, which was the approach taken by Muckstadt and Koenig (1977). The mixed integer programming model included demand constraints and reserve constraints, which ensure that total planned capacity was at least a minimum quantity in a given period. The time-dependent nature of start up costs was ignored to simplify the approach.

Lagrangian relaxation was used to decompose the problem into single generator subproblems. This decomposition was a unique contribution of Muckstadt and Koenig (1977) because previous work, which was largely found in electric power journals, did not fully exploit the problem's decomposable structure. A few previous works decomposed the problem into individual time periods; however the advantage of decomposition by generator was that constraints and costs that are driven by the state of the generator from one period to another would be accounted for (Muckstadt and Koenig, 1977). Lagrange multipliers allowed the demand and reserve inequality constraints to be incorporated in the objective function, creating a relaxed problem that was easier to solve. The solution of the relaxed problem provided a lower bound on the optimal solution of the original problem. A branch and bound method was used to solve the Lagrangian relaxation. Each node of the branch and bound tree represented the combination of generators that should be on and off. Each generator subproblem was solved using a shortest path algorithm, the Lagrangian multipliers were updated, and the resulting bounds would direct the search through the tree. Searching for the set of multipliers that maximize the lower bound was essentially a process to solve the Lagrangian dual of the original problem. Muckstadt and Koenig (1977) noted that Lagrangian bounds tighten quickly and reduce the size of the tree to be enumerated. However, when a solution space has many feasible solutions that are near the optimal solution, the general efficiency of branch and bound algorithms quickly degrades, and this trait was inherently present in their model. An actual application of their research was not included in the article; however a computational evaluation of the resulting model showed that their technique was effective for solving problems within acceptable error tolerances. The error tolerance was user defined as x%, such that while searching for a solution, a node on the branch and bound tree would not be considered as a potential solution unless the difference between the solution of the last iteration and the lower bound of the node was less than x% of that lower bound. Muckstadt and Koenig (1977) used an error tolerance of 1%, and incorporating the error tolerance reduced the need to investigate all the branches, which reduced the run time. The algorithm was not an optimal procedure, but rather an approximation method. Muckstadt and Koenig (1977) was seemingly one of the earliest contributions to the unit commitment problem contained in a refereed domestic operations research journal. Muckstadt and Koenig (1977) presented this unit commitment problem to other OR professionals, sparked their interest, and as such was frequently referenced in later works.

Bertsekas et al. (1983) cited the work of Muckstadt and Koenig (1977), and sought to add to the field by presenting a methodology that could solve more realistic unit commitment problems. The publication was not documented in an operations research journal; however it was briefly included in this work because a number of later operations research publications referenced it. Bertsekas et al. (1983) demonstrated that the subgradient method used in Muckstadt and Koenig (1977) to solve the dual problem did not provide sufficient information to consistently find a good feasible solution to the primal problem. As a result of this, the largest problem solved in Muckstadt and Koenig (1977) had only fifteen generating units over 12 time periods. Bertsekas et al. (1983) modified the Muckstadt and Koenig (1977) model by eliminating the branch and bound approach, instead solving an approximated version of the dual problem with Newton’s method. The Bertsekas et al. (1983) algorithm actually performed better with larger problems than previous algorithms did for two key reasons. First, it demonstrated a relative decrease in the duality gap (the difference between the primal and dual optimal solutions) as the number of generating units increased. Second, the computational requirements of their algorithm would only grow linearly as the number of generating units increased. As a result of this, Bertsekas et al. (1983) solved problems with over 200 thermal generating units and 24 time periods.

Bard (1988) investigated a unit commitment problem in which hundreds of thermal electric generators need to be scheduled on an hourly basis for up to one week in advance. He noted the limitations and strengths of previous OR work of Muckstadt and Koenig (1977), Bertsekas et al. (1983), and Ammons and McGinnis (1983). The Bard (1988) objective was to minimize unit start up costs and production costs, and the relaxed problem incorporated demand and reserve constraints in the objective function. The typical constraints to this problem were noted, and fell within the categories of coupling units to meet the load in a given period, and the necessity for generating units to provide a reserve margin to meet potential fluctuations in load or cover unexpected equipment failure. Included in the Bard (1988) algorithm, but not in the constraints, were operating and technical constraints, such as generating unit minimum up and down time. These constraints were omitted from the dual because he suspected that more system constraints would increase the difficulty in solving the dual and result in a larger duality gap.

Bard (1988) created a mixed integer nonlinear program, used Lagrangian relaxation to separate the problem by generator like Muckstadt and Koenig (1977), and solved the subproblems with a nested dynamic program. While features such as start up restrictions and shut down costs were not included in his work for the sake of presentation, he asserted that they could be included, and dualizing the resulting formulation would allow one to reestablish separability in the problem. The algorithm in Bard (1988) was the first of its kind to explicitly include ramping constraints, and used a different approach to find feasible solutions to the primal problem. He showed that ramping significantly increased computational requirements because the solution times were one order of magnitude higher when including them, as opposed to excluding them. However, the algorithm functioned in polynomial time instead of exponential. The algorithm was able to do so by using a variant of Newton's method instead of branch and bound. While the approach was not applied to a real world problem, he computationally evaluated the algorithm, which produced a duality gap of less than 1% in each example.

A real world application of the unit commitment problem was addressed at the Southern Company by Erwin et al. (1991). The company owned five electric utilities, 239 units, and had a generation mix that consisted of 76% coal, 17% nuclear, 6% hydro, and 1% gas and oil. The company also had a transmission network with over fifty tie lines to neighboring utilities. The problem before Southern Company was to determine the most cost effective way to utilize their generation facilities to meet anticipated loads, knowing that one third of their entire system budget could be attributed to fuel costs. In the past, unit commitment was determined by experienced operators using a priority list of rules, primarily tied to the average production costs of the units, and expert judgment. However, in a competitive market Erwin et al. (1991) believed that significant savings could be realized if they used mathematical programming techniques to reduce their overall production costs. Some issues considered by Erwin et al. (1991) were the weekend shutdown problem for generators; whether generating units with a failed component should be serviced immediately or during periods of low demand (only when responsible personnel are confident that safety would not be compromised); and whether paying the costs of overtime personnel would be justified by the reduction in down time. Additionally, off system sales to other utilities had become a valuable part of Southern Company's business and were of high interest to corporate leaders.

Their problem was complex because of the variety of generation options, power transactions, and the many operational constraints mentioned below.

- The load constraint ensured that the sum of electric generation and purchases equaled the system loads plus sales each hour.
- The spinning reserve constraint mandated that the utility carry enough spin reserves to cover contingencies, such as unexpected outages or sudden load swings. Spinning reserves are online reserves that can respond in ten minutes or less to supply sudden load demand.
- The maximum spinning reserve contribution constraint was used to comply with national guidelines, which state that only a small portion of the capacity for an individual unit that can respond in ten minutes can be part of the spinning reserves for the system.
- Ramping rate constraints dictated that unit load changes in consecutive hours do not exceed the ability of the unit to respond.

- Minimum and maximum load constraints ensured that generators operated within their defined minimum and maximum capacities.
- The minimum up and down time constraints prevented units from running less than the required minimum duration, or being shut down for less than the required minimum duration.
- Simultaneous start ups were limited by start up crew constraints, because a minimum number of trained personnel needed to be present to conduct generator start ups.
- Fuel burn minimum and maximum constraints were set for weekly, daily and hourly periods. This accounted for minimum “take-or-pay” fuel contracts or maximum burn stipulations.
- Area reserve constraints assigned a portion of spinning reserves to cover a specific area for security reasons.
- Power flows from one area to another could not exceed capability of the transmission network

Given the large amount of information that needed to be included, Erwin et al. (1991) sought to utilize a model that produced a practical optimal strategy, which meant that solutions were robust enough that they could not be manually beaten by system operators. Therefore, due to the nonconvex characteristic of the problem, in their findings optimum represents this practical optimal strategy, and not the formal mathematical optimum.

Erwin et al. (1991) chose to utilize a software package capable of forecasting system loads to schedule their thermal and hydro power plant fleet optimally. Central to the software was the Wescouger optimization program created by ABB Power Systems. This program employed dynamic programming (DP) and branch and bound techniques to generate optimal or near-optimal solutions that minimized total system production costs (Erwin et al., 1991). They selected DP because it accurately modeled their operational constraints and the nonlinear cost characteristics, and it possessed the ability to optimize discrete variables. However, the disadvantage to using it was the resulting large set of feasible solutions. To manage this, the intelligent branch and bound feature was created to guide the DP search with artificial intelligence rules and heuristics.

Once implemented, the system was validated in a number of ways. Testing and a smooth transition were accomplished by having experienced operators compare their unit commitment recommendations to those of the program. This allowed the operators to calculate the costs of each strategy, and ultimately grow comfortable with the recommendations generated by the program. The load forecasting component of the system used weather parameters to forecast future hourly loads. An energy costing component projected future energy prices of sale contracts. The program ultimately allowed Southern Company to quantify the difference between their forecasts and the actual operation of the system, and document system savings. The software became a key scheduling tool at Southern Company and over the seven year period after adopting the software the company was able to save over $140 million in fuel costs.

In Johnson et al. (1998) operations research and systems engineering staff developed the Hydro-Thermal Optimization (HTO) system to tackle the unit commitment problem at Pacific Gas & Electric (PG&E). PG&E had a variety of power plants, including hydro and thermal (fossil fuel, geothermal, and nuclear plants), and wanted to operate them more efficiently in preparation for deregulation which would allow for competition amongst electricity generators. Previously, PG&E's unit commitment was handled by merit-order scheduling. In this context, merit-order scheduling is the process of scheduling generators to run based on the increasing order of their per megawatt hour cost of operation. The generators with the lower operating costs would be used at full capacity before those with higher operating costs would be scheduled for service. The goal of the HTO system was to optimize the company's daily and weekly production schedule by minimizing their costs while reliably meeting the customer demand. These schedules would be used to determine when specific units would run and the profitability of buying or selling electricity to others on their regional grid.

General characteristics of fossil fuel power plants are important to consider in the problem formulation. The fuel costs of fossil fuels plants are significant. Start up is expensive, bringing them online and offline frequently is taxing on the system, and they are unable to ramp up or ramp down quickly. Daily or weekly forecasting for these types of plants called for a mixed-integer nonlinear formulation of the UCP, with decision variables for operating levels of each unit and for on-off states (Johnson et al., 1998). The paper presented an objective function that minimized system production costs of PG&E's entire hydrothermal system. These costs included maintenance costs, fossil fuel costs, and energy transaction costs. For fossil fuel power plants, this was subject to minimum and maximum production levels, maximum ramping capabilities, and minimum up and down time. It was noted that if one were solving an all-thermal system case, it could be solved using dynamic programs of varying dimensions (Johnson et al., 1998). System wide constraints included rules for operating individual power plants and individual purchase transactions. Once programmed, their problem included over 100,000 variables and 600,000 constraints. Like Bertsekas et al. (1983), Johnson et al. (1998) chose to use Lagrangian relaxation as the primary approach to obtain a solution in their HTO System. In the output, the supplies and demands did not necessarily balance for each time step because the problem is nonlinear and nonconvex. However, by using Lagrangian relaxation, Johnson et al. (1998) found the theoretical lower bound on the minimum value of the objective function, which enabled them to estimate the solution's proximity to the optimal solution. Empirical data from their algorithm showed that HTO solutions were no worse than one percent above the lower bound of the optimal objective function. After the implementation of the project, PG&E attributed the model for reducing their annual fuel spending by 1%, which was approximately $12 million.

Takriti and Birge (2000) investigated the broad problem of determining which facilities in a set should be scheduled, and at what levels during a planning horizon. They evaluated production problems that involve facility setups which require integer variables, random demand, and continuous production decisions, and applied their findings to the electric utility problem. The model of Muckstadt and Koenig (1977) was deterministic and could fail to find a suitable solution using branch and bound on a real world size problem. The model in Bertsekas et al. (1983) was also deterministic, however their model structure and duality gap upper bound were extended by Takriti and Birge (2000) to the stochastic problem. Takriti and Birge (2000) created a stochastic mixed integer program with a varying right hand side. They applied their formulas to an electricity generation problem, and extended the general mixed integer model approach by adding a constraint to link machines or facilities together within each period. Uncertainty was considered by identifying a set of possible scenarios that were assigned a probability of occurrence. Although the work of Takriti and Birge (2000) was not applied, numerical analysis of a hypothetical problem demonstrated that operating cost savings could be realized with their approach.

Takriti et al. (2000) explored the stochastic unit commitment problem in the context of a deregulated market. They noted that the deregulated market contains power producers who sell electricity into power pools where power suppliers purchase the electricity and sell it to their customers. It was also noted that a deregulated market led to an increase in the unpredictability of system loads, and volatile electricity prices. As such, Takriti et al. (2000) added to the existing UCP body of work by incorporating power trading and fluctuation in fuel and electricity prices in their model by using a set of scenarios to model the uncertainty. Takriti et al. (2000) knew that representing the unit commitment problem as a multistage program would prohibit the incorporation of uncertainty, due to the model size. Therefore, they provided a Lagrangian relaxation and Benders decomposition approach for solving the stochastic UCP, and suggested quadratic approximation and the line search method as basic techniques for updating the dual multipliers. The problem was decomposed into two stages; the UCP and a fuel allocation linear program, which allowed the algorithm to efficiently find an optimal solution to the problem. Although Takriti et al. (2000) was not directly applied to an actual problem, significant value was found in including uncertainty in the problem formulation, and numerical results demonstrated a duality gap of 0.1% after a series of updates. Their algorithm was capable of generating solutions very near optimal. At the time, the strengths of their model made it practical for use by an electric utility.

Valenzuela and Mazumdar (2003) conducted additional research on the unit commitment problem, also in the context of a deregulated electricity market. The publication made an important point regarding the unit commitment problem in a regulated environment versus in an unregulated environment. In a regulated environment, the UCP is formulated as a minimization of production costs while satisfying certain constraints because the cost of electricity is fixed at a tariff rate. However, in an unregulated environment, the cost of electricity is not fixed, and varies, as an hourly market price. They noted that the set of scenarios used in Takriti et al. (2000) was problematic because of the difficulty in generating representative scenarios, and assigning realistic probabilities to them. Instead, Valenzuela and Mazumdar (2003) forecasted market prices based on representations of electricity production and consumption. Their approach differed from previous publications because of their constraint selection, the model for the spot market, and the solution technique. Fuel constraints were omitted, unlike in the work of Takriti et al. (2000), and the spot market was represented as two generating units. However, the submodels in Valenzuela and Mazumdar (2003) were similar to those of Bard (1988) except that the Lagrange multiplier values were replaced by electricity spot market prices, and the expected value was maximized. They developed three formulations of the problem, which used dynamic programming, statistical analysis and asymptotic probability computations. The price of electricity was represented with a probability distribution that was based upon demand, generating unit reliabilities and temperature changes. Valenzuela and Mazumdar (2003) evaluated normal, Edgeworth, and Monte Carlo approximations, and found that each of them accurately solved their formulation of the unit commitment problem in under fifteen minutes on a personal computer, which was considered a reasonable amount of time. They intended to continue their research to determine whether the three solution approaches are in fact equally effective.

CHAPTER 3 Production Costing & Expansion Planning

3.1 Production Costing

Estimation of annual production costs is an especially important component of long range capacity planning at electric utilities. Long range capacity planning considers the tradeoffs between the production costs and the fixed costs associated with current or proposed generation units. Each of these cost components are typically forecast over multiyear periods, such as ten years, and require projections of future values such as fuel costs, fuel availability, interest and inflation rates. To reduce the effort in modeling the production costing, the prices of inputs to the production and the demand estimates are generally computed by other means prior to inclusion in the model. The demand is traditionally represented by an annual load duration curve, or LDC. The capacity expansion problem is also typically modeled in a nonspatial manner, which means that plant location and the associated transmission and distribution investments that would be required are not considered (Noonan and Giglio, 1977). Long range planning and production costing are closely related and often researchers focusing on one will give some level of acknowledgement to the other.

Noonan and Giglio (1977) developed an optimization program that determined what types and sizes of generating units should be constructed so that total discounted cost was minimized while meeting forecasted demand at a specified level of reliability. They referred to the problem as the Generation Planning Problem, and it is of particular interest because of the uncertainty and volatility facing electric utilities in fuel supplies, fuel prices, electricity demand and environmental regulations. Determining the mix of thermal, hydroelectric and pumped hydro generation plants involves consideration of the balance between investment and operating costs. Plant sizing involved consideration of economies of scale versus the opportunity cost of temporarily having excess production capacity. For each year of a planning horizon, the optimization program in Noonan and Giglio (1977) would determine the types and sizes of generating plants that should be constructed to satisfy demand. Individual generator derating, which incorporates forced outages and scheduled maintenance, was also an important factor of system reliability and included in the Noonan and Giglio (1977) model. Their model extended work previously done by economists by using a mathematical program that accurately reflected investment and operating costs with decision variables that system planners normally work with. The model also included reliability constraints that reflect the restrictions on the power system, thereby significantly complicating the problem approach. For each year in the planning horizon, the probability of demand not being met could not exceed a specified level of risk. The problem was defined as a chance constrained mixed integer program, and time was discretized into one-week periods. The prices of inputs for the production and demand were estimated outside of the program prior to inclusion. The solution algorithm used Benders Decomposition, mixed integer linear program code, and successive linearization. The complicating constraints involved only the investment decisions. Therefore, the production costs were represented in the objective as a function of the investment decision variables. Using Benders decomposition, the algorithm would iteratively solve a production cost subproblem under a given investment plan, which in turn would supply inputs for the relaxed master problem. The relaxed master problem was a mixed integer linear program where the reliability constraints were replaced with linearized constraints, which could be solved with a standard programming code. As this process was repeated, the cost lower bound would converge to the minimum cost of the original program, and thus yield an investment plan within a specified error tolerance of the true optimum.

To provide the end user of the program with more computational efficiency, Noonan and Giglio (1977) maintained small-scale linearized master programs by only allowing one set of linearized reliability constraints to relax the master program at each Benders iteration. However, doing so made the resulting approach a heuristic where convergence could not be assured. The authors did ensure that their model incorporated the full set of investment and operating decision variables that system planners must normally consider.

The program developed in Noonan and Giglio (1977) was provided to power plants in the six New England states to use for regional level planning. The New England Generation Planning Task Force (NEGPTF) had previously employed a trial and error search using a simulation program to develop generation expansion plans, and was content with past results. Noonan and Giglio (1977) performed a test study on a generation expansion problem that had already been addressed by the NEGPTF six years prior. NEGPTF found the program results to be believable when compared to the simulation results, and also found the Noonan and Giglio (1977) program to be practical in terms of its computational requirements. Interestingly, the key motivation for the NEGPTF to implement the program was not for the sake of optimization, but rather to reduce their manual effort and allow them to compute new formulations of the problem more quickly. Consequently, a user-oriented version of the program was created and at the time of publication it had been formally used by the NEGPTF for two years.

Until the work of Ammons and McGinnis (1983), previous production costing methods relied on methods based upon expensive simulation or linear programming that made assumptions that degraded the quality of the solution. The Ammons and McGinnis (1983) noticed that the previous work of Noonan and Giglio (1977) and a couple of dissertations all contained one of two undesirable traits. The first was simplifying the production costing by aggregating all the generation units or assuming a constant marginal production cost. This caused a potential loss of accuracy. The second trait was using a detailed simulation to solve the problem, which was undesirable because of the substantial computational power required.

Ammons and McGinnis (1983) proposed a method that incorporated quadratic production costs for each individual generation unit and optimization submodels to produce a system electricity production cost versus electricity output curve. Continuous units that operate between a minimum and maximum capacity and discrete units which operate at a set capacity or are shut down were included in the model. After formulation, they found that the problem could be solved using a partitioning procedure. In application, their dynamic programming algorithm simplified into a shortest path problem. An empirical study using data from a large utility company verified the effectiveness of the model. The company had 86 continuous units and 37 discrete units. Ammons and McGinnis (1983) found that their optimization model required less than one percent of the computing resources required by a detailed simulation of the same problem. Yet, the resulting production cost estimates were within one percent of the estimates from the large simulation model.

Additional evaluation showed that their model would have modest computational requirements over a wide range of problem size parameters. By using fewer computing resources, their model could allow utilities to consider more planning scenarios, or make evaluations on a more frequent basis, which could enhance the quality of their business decisions. Given the size and generation mix of the utility used in the empirical evaluation, the model seems to be suitable for production costing applications at other utilities of considerable size. Ammons and McGinnis (1983) also noted that their model could be incorporated into mixed integer programming approaches, such as the one in Noonan and Giglio (1977), without significant effort. The condition is that the solution procedure be based on Benders decomposition. The work of Ammons and McGinnis (1983) was not applied to an actual real world problem; however its computational efficiency demonstrated that it could be a practical tool for electric utilities. Their algorithm was suitable for inclusion in generation capacity expansion models where the production costing is a distinct function.

Ryan and Mazumdar (1992) presented a Markovian model of the generating system with a deterministic, time-varying demand function to create a stochastic integral of production cost over a time interval. They recognized that the cost of producing electricity was important to utilities and regulators, although for different reasons. Utilities use estimates of this cost for capacity expansion planning, fuel management, and operational planning, while regulatory bodies use them to set the rates customers will be charged. Therefore, any approach that they developed could potentially be used by electric utilities and their regulatory agencies. They noted that in many situations, using expected production costs would not be sufficient for incorporation in expansion plans. For example, if an electric utility has several large nuclear power plants, and a couple of peaking power plants, a forced outage of a nuclear plant would result in significant costs to run the peaking plants in its stead. In this case, more useful information could be obtained if a variance term is included with the expected value of production costs. To help address this, Bloom et al. (1984) incorporated production cost modules to evaluate capacity alternatives in their capacity expansion planning.

Probabilistic models of the power generating system and the forecast load were used to calculate expected production costs for many utilities. Ryan and Mazumdar (1992) were especially interested in calculating the variance in the expected production cost. The variance is important because it represents the uncertainty associated the generation system whose production costs are being evaluated (Shih et al., 1999). Ryan and Mazumdar (1992) contributed to prior work by quantifying the variance over an arbitrary time interval, instead of in one unit time interval as had been done in the past. The probabilistic simulation model consisted of a variable number of generating units that are started up based on a merit order, which is typically driven by the individual cost of operation. Each unit in the loading order had capacity, a forced outage rate, and a variable operating cost. Finally, the load of the system in a given hour was represented by a load duration curve. The operating state of each unit was modeled as a continuous Markov chain, and its load was modeled as a deterministic time-varying function. They developed an approximation to reduce the computation time for the variance by simplifying the integrals involved in the calculations. Although Ryan and Mazumdar (1992) was not applied to a real world problem, it demonstrated that the time sequence of the load levels would not significantly affect the variance, which means that the practice of calculating variance may become routine with electric utilities, and even regulators who calculate estimates of productions costs.

Shih et al. (1999) investigated generation system production costing by modeling the cost as a random variable that depends on generating unit availability and load size. Specifically, they sought to approximate the mean and variance for production costs. Shih et al. (1999) noted that Ryan and Mazumdar (1992) revealed that to compute the exact production cost variance, additional research would need to explore each generating unit's operating state during different time intervals. Ryan and Mazumdar (1992) demonstrated this principle on a three unit generating system, which showed that enumerating all the system states for a larger, more realistic problem would be prohibitive.

Shih et al. (1999) employed a model similar to Ryan and Mazumdar (1992), however they represented the load as discrete-time Markov chains (DTMC), instead of as a deterministic time-varying function. The available generating capacity of each unit was also represented as a DTMC. They chose DTMC as their stochastic model because discrete hourly time series load data could be easily used to estimate parameters, and the DTMC formulation would enable them to use the Kemeny-Snell formula to compute asymptotic variance. They performed computations using recursive formulas to evaluate daily, weekly, monthly, and quarterly changes. Shih et al. (1999) compared their results to those of a Monte Carlo simulation. The findings showed that the estimate of the mean was accurate for any time period, and the standard deviation estimate was accurate for time periods of at least 672 hours.

Hobbs and Ji (1999) developed a new bounding method to solve the distribution problem for a multiarea electric power system. Such a system would be divided into areas that have their own sets of generators with varying loads and potential for failure. The electric power system in the United States now has extensive transmission tie line interconnections, which have become of increasing interest due to power trading in a deregulated environment. These transmission tie lines produce multiarea systems. Most production costing methods by the late 1990s ignored transmission constraints; however Hobbs and Ji (1999) believed that electric utilities needed a better understanding of how transmission constraints impact production costs. They noted that previous work fell into two categories. The first category involved using contingency evaluations for production costing, either by exploring several scenarios for outages and demand, or by using a true probabilistic approach such as Monte Carlo sampling of outage and demand states. The second category avoided the computational effort of the first category and was based on the load duration curve (LDC). LDC based methods were discussed in Bloom (1983).

The Hobbs and Ji (1999) production costing problem calculated the expected operation cost by including the cost of power generation and the cost of consumer losses due to supply shortfalls averaged over random generator outage states. Hobbs and Ji (1999) chose not to solve the problem directly, but instead established lower and upper bounds on the expected operation cost by using two simpler problems. The lower bound was calculated using a deterministic linear program. The transmission flows were modeled with a linearized version of Kirchhoff's laws and expected values replaced generator capacities. The upper bound was a stochastic optimization problem that used generalized Benders decomposition (GBD) to choose flows between areas that minimize cost, and a GBD to solve the single area production costing problem for each area under the chosen flows (Hobbs and Ji, 1999). The bounds were tightened iteratively by partitioning the outage and load state space. These bounds were considered practical because they are typically easier to determine than the solution to the traditional stochastic problem. Hobbs and Ji (1999) was not applied to an actual problem at a utility, but included sample computations to represent a large power system. Future extensions could include the resistance losses, which have been previously represented as quadratic functions and excluded.

3.2 Expansion Planning

Crawford et al. (1978) used multiobjective decision analysis to help the Consumers Power Company plan a new 765 kV transmission line. While the company had already determined the type of transmission that was necessary for their expansion, they chose to employ decision analysis to help them select the tower size, the conductor type, and the number of subconductors per bundle for the soon to be constructed lines. The 765 kV transmission line was relatively new to the United States, so design practices had not yet been defined. Prior to using decision analysis, the project team considered a number of technical factors, which narrowed down the list of potential options to alternatives that would meet their initial requirements. Four attributes were defined as 1) the initial cost outlay in the first year, 2) the cost of losses and tax annuity through the twentieth year of operation, discounted to the first year, 3) the cost of losses and tax annuity from year twenty one through year fifty of operation, plus the cost of reconductoring (if necessary), and 4) the number of audible noise complaints received in the first three years. Discretized probability distributions were defined for each of the attributes and a utility function was elicited by using standard lottery techniques. Expected utility calculations were made, and after performing sensitivity analysis two options were recommended to the decision makers at Consumer Power Company. The recommendations were accepted, however further investigation was required on the part of the decision makers to determine if any omitted factors might aid in differentiating between the two options.

Keeney and Sicherman (1983) used decision analysis to produce illustrative, but not definitive results in helping a utility decide between adding a coal or nuclear power plant to meet baseload demand. The EPRI supported the development of their general technical choice model, which was used to help Utah Power and Light (UPL). UPL had already identified the two types of plants, and two potential sites for the plants. Keeney and Sicherman (1983) followed four steps to help them through the rest of the process. First was structuring the problem, second was assessing the possible impacts of the technical options, third was determining the value structure, and fourth was evaluating and comparing the options. The problem was structured with an objective hierarchy with six primary objectives, some of which were broken into components. The primary objectives were economics, feasibility, health and safety, public attitude, socioeconomic impact, and environmental impact. Fourteen attributes were defined to measure the degree to which the lowest level objectives would be satisfied. The value structure was quantified with a utility function, and a computer model was used to evaluate the options. The coal plant was deemed the best option because of its high feasibility, even though the nuclear power plant had lower costs. Additional sensitivity analysis could be used to explore the impact of matters such as future government action, high inflation, and changes in fuel costs.

Bloom (1983) presented an unapplied model of the electric generating capacity expansion problem of determining a minimum cost capacity expansion plan to meet forecasted demand reliably. Bloom (1983) noted the early work of Noonan and Giglio (1977); however the emphasis of his approach was on considering reliability standards based on probabilistic measures. The approach could be divided into two parts: finding the optimal investments for new generating capacity, and determining the operating cost and reliability for the system. Benders decomposition was used in his model, so first a set of subproblems would determine the minimum cost of operation and the reliability, and produce multipliers to be incorporated in the master problem. Next the master problem would generate trial solutions for the optimal capacity expansion plan. Each subproblem produced a set of dual multipliers that were returned to the master problem, which in turn was updated and resolved to determine a new trial capacity plan. This process simplified a complex nonlinear program. Essentially it became an iterative process of solving linear programs and a set of nonlinear optimizations which did not require an explicit programming algorithm; which meant that a variety of programming models could be used to obtain the final solution (Bloom, 1983).

Bloom et al. (1984) built on the theoretical work on long range generation planning contained in Bloom (1983). The original model was modified and extended to be included as part of the Electric Generation Expansion Analysis System (EGEAS) that was being developed for the Electric Power Research Institute. EGEAS was a modular program comprised of a linear program, a dynamic program, and the generalized Benders decomposition model, in addition to auxiliary components such as an integrated database, data entry software and report-writing software. The production costing calculations were performed using the Gram Charlier series, a statistical tool. One reason for using the Gram Charlier series was its ability to perform convolutions in closed form. Unfortunately, this introduced a key problem as well: errors due to truncation as it dropped the higher order terms. Ultimately the computational results of the original model in Bloom (1983) were compared to those for the EGEAS dynamic programming model. Both were applied to data derived from PG&E, which included a total of 128 existing and planned generating units. Each method presented pros and cons which would have to be used to determine which model to use, based on the preference of the user. Bloom et al. (1984) noted that the model in Bloom (1983) was limited to use in problems with thermal generators only. Since many utilities have more than thermal units in their generation mix, the EGEAS could prove more beneficial in practical applications. Utilities with hydroelectric plants or pumped storage power plants in addition to their thermal plants, for example, could derive more benefit from the method of Bloom et al. (1994) than Bloom (1983).

Borison et al. (1984) created a state-of-the-world decomposition approach to address uncertainty and dynamics in the generation expansion planning problem. They included deciding on the types of power generation facilities to build or purchase, how many of them to add, and when to actually purchase or begin constructing them. Their approach simplified a difficult dynamic probabilistic problem into a simpler primal-dual method that was solved by using basic static deterministic techniques. A dynamic approach was not taken because it would greatly increase the number of decisions that must be evaluated under varying conditions. Instead, the problem was decomposed into a set of subproblems that were linked through Lagrange multipliers. The subproblems were solved individually in the primal iteration and the multipliers were updated in the dual iterations. Their approach relied on the premise that operating costs are determined using merit order, which is often the case in practical applications. The solution was the true minimum discounted expected cost for the generation expansion plan. This model was not applied to a real world application but could be enhanced in future formulations to reflect real world applications through modifications to include probabilistic treatment of forced outages and energy related constraints.

Keeney et al. (1986) used multiattribute decision analysis to evaluate how Baltimore Gas and Electric Company (BG&E) should address their need for an additional 600 MW of electricity generation capability. In general, BG&E needed to make a technology choice between building one of two conventional coal-fired power plants now, or delaying their decision to 1) build a conventional coal-fired power plant with scrubbers, 2) build a conventional coal-fired power plant without scrubbers, but designed for use with compliance coal and adaptable to scrubbers, 3) build an atmospheric fluidized bed coal-fired (FBC) power plant, 4) build a Texaco Integrated Coal Gasification Combined Cycle (IGCC) power plant or 5) build a KILnGAS IGCC power plant to meet any additional electricity demand by purchasing it from other power plants.

Regulations determine the levels of greenhouse gases and other pollutants that can be released from power plants. Power plants have alternatives for complying with these regulations, and often do so by using scrubbers or compliance coal. Scrubbers are used at power plants to capture some airborne pollutants so that they are not released into the atmosphere. Compliance coal is a type of coal that has a relatively smaller content of the elements that produce pollutants after combustion, and therefore reduce needs to manage such pollutants after combustion. FBC power plants emit less sulfur dioxide and nitrogen oxides than traditional coal plants. IGCC plants burn coal that has been turned into gas (synthetic gas, or syngas). Prior to combustion some impurities such as sulfur dioxide are greatly reduced by filtering the synthetic gas. Selecting one of options three through five would require a delay because the technology was not commercially available at the time. These technology choices, and the specific time instances when a choice would need to be made, were captured in a decision tree. Specific uncertainties were incorporated in the decision tree as well, and included government regulation, new technology availability, fuel availability over the lifetime of the facility, demand for electricity, whether the facility would be available on the scheduled completion date, and whether new technology would operate as designed.

The purpose of the analysis was to provide insight on the desirability of each option and why, to support technology choice discussions both inside and outside the company, to create a framework to address “what if” questions, to develop rationale for understanding the technology decisions, and to demonstrate the technology choice model to BG&E, thereby showing them how to use it in the future (Keeney et al., 1986). Analysts from the Generation Planning business unit and senior executives all participated in a five step approach. They characterized strategies, specified objectives, determined impacts of the strategies, assessed the desirability of various potential impacts, and integrated the information. Baltimore Gas and Electric’s objective hierarchy included economic impact, management impact, socioeconomic impact, public attitudes, feasibility, health and safety, and environmental impact. Fifteen attributes were defined for inclusion in the multiattribute utility function. They were customer cost, shareholder return, public attitudes, feasibility, decision difficulty, corporate image, environmental impact, mortality, morbidity, visual impact, water usage, transportation impact, community disruption, local employment, and local tax revenue. The resulting base case analysis recommended the conventional coal-fired power plant with scrubbers, designed for an in-service date in 1994 as the best strategy. The expected value of perfect information (EVPI) was also calculated for certain attributes of particular interest. By doing so, they found that input cost information is very important, especially facility construction costs, operating and maintenance costs, and fuel costs. After recommendations were made, the perception that leaders of Baltimore Gas and Electric had of decision analysis in general, was that it structured the questions they should be asking, provided a framework to review in the future, and documented the process they went through for use in appearances before regulatory commissions to defend their decisions (Keeney et al., 1986). Ultimately, the Technology Choice Framework was transferred to BG&E to update information in their current decision, and use for future decisions as well.

Mobasheri et al. (1989) responded to a shortcoming in long term resource planning at Southern California Edison Company. Nuclear accidents, record inflation increases, oil crises, increasing environmental concerns and changes in their interactions with regulatory bodies changed the landscape for resource planning. They had previously used forecasts, and a review of the effectiveness of the ten year forecasts was eye-opening. The forecasted rate of growth was double what they actually experienced, and they planned for almost four times more capacity than they actually built (Mobasheri et al., 1989). This motivated their decision to plan for uncertainty in the future by creating a series of potential scenarios and preparing response strategies for each. They did not rely on a single forecast based on multiple assumptions, but instead incorporated uncertainty into their analysis by exploring potential scenarios. The four components of a scenario are driving forces, prime movers, predetermined elements and uncertainties. The scenario planning process involved three primary steps: 1) develop a number of scenarios, 2) examine the implications of each scenario and 3) develop strategies to manage each of the alternative future states. Their strategy to handle each scenario included five key categories, which were oil and gas units, transmission network, Public Utility Regulatory Policies Act (PURPA) resources, energy management, and new generation resources. The approach of Mobasheri et al. (1989) was fundamentally different from previous forecasting techniques that attempted to reconstruct the past to create a tool for predicting the future. Instead, scenario planning incorporated probabilistic values for what could happen to create a set of potential future states so that contingency plans could be established. The scenario planning framework was established at the company and at the time of publication had been in use for two years. One key benefit of the approach was its positive reception by regulators.

Ford (1990) examined the ability of efficiency standards to reduce the uncertainty of an electric system by examining their projected effects on the Northwest Electric System. The author found that the effect of efficiency standards had hardly been studied and thus the primary focus of the work was to determine to what extent efficiency standards would reduce the growth in rate uncertainty and demand uncertainty over time. Efficiency standards require that conservation methods, such as weather-stripping, be used in the construction of new buildings. It is a fact that efficiency standards inherently reduce the demand for electricity because they reduce the unintentional loss of electricity around windows, doors, etc. However, the expectation of many planners was that the efficiency standards would yield the most savings in forecast scenarios with rapid growth in buildings. Uncertainty was measured by the projected width of tolerance intervals over a twenty year planning period (Ford, 1990).

Decision analysis techniques, such as those found in Keeney et al. (1986), and the Conservations Policy Analysis Model (CAPM) were employed by Ford (1990) to tackle the problem. CAPM, which was previously used by the Bonneville Power Administration, a part of the US Department of Energy, contained over 150 user-defined parameters and projected the electricity demand from industrial, agricultural, commercial and residential customers. Ford (1990) focused on long-term sources of uncertainty, such as the increase in coal prices, and regional economy growth; and modeled the uncertainty in the Northwest Electric System with a set of uncertain parameters, such as inflation rate, residential water heat savings, and program administration cost. Latin Hypercube Sampling was the design chosen to sample values of the independent variables. Forty equal probability intervals were created across the range of each parameter, where forty was the number of simulations to conduct. The conditional distribution indicated which value to choose from each parameter value interval, and the values were randomly assigned to the forty model simulations. After completing the simulations, the software HYPERSENS was used to conduct the sensitivity analysis. Ultimately, the model showed that including efficiency standards in planning resulted in an 8.5% reduction in the tolerance range for projections of regional electricity demand over a sixteen year planning horizon. In order to usefully quantify this reduction in variation of the demand projections, Ford (1990) considered the strategy of the utility to build for the medium demand forecast and acquire coal options for the difference between the medium and high forecasts. Therefore, the decline in costs to acquire and hold the coal options for the utility was valued at $250 million.

CHAPTER 4 Electric Power Service Offerings

Electric utilities typically have more complex relationships with their industrial and commercial customers than with their residential customers. This is primarily due to the large amount of electricity nonresidential customers consume, as well as the likelihood that they will have their own back up generators. Interruptible or curtailable service contracts are agreements between electric utilities and nonresidential customers, and an Electric Power Research Institute survey found that as of 1987, over 70% of large investor owned utilities utilized these contracts. The contracts allow industrial and commercial customers to receive a discount on their bill if they agree to have their service interrupted at critical times during the utility's operation. For example, a paper mill may have an interruptible contract with their electric utility, and also have an oil generator located onsite that they use during emergency power outages. On one of the hottest days of the year, the electric utility may have a substantial demand for electricity, when one of its baseload generators breaks down. Assuming that the utility does not have enough generating capacity to fully replace what was lost, it could decide on one, or a combination of several options. The utility could try to buy expensive electricity from another generating company if they have capacity available, to cut power to their firm customers (which is always the last resort), or to contact the paper mill and interrupt their service for a number of hours until necessary maintenance is complete. The paper company would agree, provide the electricity it needs from its own generating source, and receive the appropriate financial benefit, as outlined in their contract. Oftentimes these contracts have restrictions on how many times a customer can be interrupted in a given period of time.

Caves and Herriges (1992) asserted that when the number of electricity interruptions is contractually limited, then the matter of optimally dispatching those interruptions should be considered. They noted that the working paper for Oren and Smith (1992) proposed a dispatch algorithm meant to maximize the likelihood of interrupting loads on the day that the system load peaks. Caves and Herriges (1992) proposed an alternative algorithm for optimally dispatching interruptions using a stochastic dynamic programming approach, because it would explicitly recognize the repetitive nature of the dispatch problem. Like Oren and Smith (1992), Caves and Herriges (1992) assumed that the interruptible load would be interrupted in its entirety, or not at all. Thresholds for interruptions were a function of the remaining number of days in the period, the number of interruptions available, and the degree of uncertainty that existed for future price and cost variations (Caves and Herriges 1992). In addition to the dispatch algorithm, the authors also developed a process for optimally designing the parameters of an interruptible contract program. An illustrative example of the dispatch routine was provided by using data from Niagara Mohawk Power Corporation. The results indicated that achieving optimal dispatch priority could be quite valuable, and at the time of publication the Niagara Mohawk Power Corporation was using the routine in their own interruptible contracts program.

Oren and Smith (1992) investigated interruptible contracts in a study conducted at the New England Electric System (NEES) in partnership with the Electric Power Research

Institute (EPRI). They considered two problems, which were determining how existing contracts should be used, and determining the incremental value of additional interruptible contracts. Work previously published regarding interruptible contracts was found in economic journals, and focused on supply uncertainty. Oren and Smith (1992) focused on reduction in demand fluctuations. Also, prior work did not address the operational implications of implementing an interruptible program, while Oren and Smith (1992) focused on operational dispatching of the interruptions. First, they developed a methodology for dispatching the load reductions from a set of interruptible contracts, which addressed a practical problem at NEES. A decision support tool in the form of a spreadsheet was created for and used by the system dispatcher to identify the most economical approach for dispatching interruptions. Secondly, Oren and Smith (1992) created an approach for NEES to evaluate the benefits and costs of expanding their interruptible contract program. They found that for NEES, there was less benefit in executing additional interruptions on the existing interruptible contract customers than in obtaining new interruptible contract customers.

Smith (1993) investigated real time pricing (RTP), and developed a model for RTP that would balance electric supply and demand in a variety of operating scenarios, but also address the unit commitment decision of the utilities and the subscription decisions of the customers. RTP is an electric power service that allows for differentiated electric service to customers. Estimated supply and demand conditions will cause prices to vary over time, and prices are announced a day or several hours in advance to allow customers to react and choose whether or not to purchase power for a given time period. According to Smith

(1993), this can ultimately cause smoothing in demand, reduce the need for reserve capacity, and postpone the need for expensive capacity expansions. When Smith (1993) was published, twelve US utilities were conducting RTP programs, including Niagara Mohawk Power Corporation and PG&E. Smith (1993) provided a methodology to analyze and plan real time prices to reflect the utility and customer costs, with short term and long term options for each. He noted the unit commitment work of Muckstadt and Koenig (1977), and used it as a basis for a component in his model.

Smith (1993) used a piecewise-linear model and minimized the sum of utility supply costs and customer welfare costs. This was done because the optimal solution could become difficult to obtain using mixed integer programming because of the large number of scenarios, time periods, and customers to consider. Given the piecewise linear structure of the model, this was addressed by using a greedy algorithm to approximate the optimal prices. Smith (1993) found that the greedy algorithm was more efficient than Lagrangian relaxation methods used for nonlinear unit commitment problems. While the work of Smith (1993) was not applied, the algorithm was deemed appropriate for planning real-time prices over medium and long time horizons. Extensions of this research could include extensions that add to models of the impact on the electric customer, which the author believed would be valuable to understand. As demand increases in the future, the expansion of RTP has the potential to mitigate customer consumption and impact unit commitment decisions. RTP could also be used to manage the dispatch of interruptible contracts, where an interruption is dispatched if the RTP exceeds some threshold.

The work of Baldick et al. (2006) presented more academic research that the authors believed could be extended to the electric utility industry. They considered interruptible electricity contracts with electricity retailers that allow electric service to be interrupted in exchange for financial compensation or a reduction in the price of electricity actually delivered. Interruptions are allowed a certain number of times within a specified time period. Baldick et al. (2006) were interested in quantifying the value of such contracts to the electricity retailer, especially by allowing it to reduce exposure to electricity demand and supply fluctuations. They modeled the value of the interruptible contracts by using stochastic dynamic programming.

Baldick et al. (2006) allowed for multiple interruptions over multiple dates, they allowed for a variety of interruptible contracts, and most importantly, they included the impact of the interruption on the spot market. This was important because often times an electricity retailer benefits from interrupting a contract not because they avoid servicing the contract, but because reducing the total system load yields lower prices system wide. Similar to Caves and Herriges (1992), Baldick et al. (2006) modeled electricity supply and demand as stochastic processes, but extended their work by quantifying the benefit of interruption using a model of supply and demand of electricity. The parameters for supply and demand were estimated statistically for the purpose of structurally modeling the spot electricity price. They believed that the structural approach was better than a reduced-form approach because it captured the interaction between the decision of an electricity retailer and spot electricity prices. Reduced form models used in electricity derivatives publications assume that price is not influenced by market participants, however interrupting a large electric retailer will lower the demand and the expected price. Their structural model of the electricity market, where prices are determined by supply and demand, could account for the interaction between interruption and electricity price. They modeled pay-in-advance contracts and pay-as-you-go contracts, allowing for partial load interruption of both types given a one day notice, and determined which were most valuable to the electricity retailer under a set of circumstances. Finally, Baldick et al. (2006) asserted that their structural model could be useful in the optimal asset allocation problem for an electricity retailer, and the optimal design of new contract types, both of which they intended to further explore.

CHAPTER 5 Other Operational Areas

5.1 Outages

Most of the electricity generated in the United States is produced by fossil fuel power plants or nuclear power plants. In order to operate safely, efficiently, and in compliance with regulatory agencies, the power generating equipment at these plants have outages. They can have outages for planned or unplanned maintenance, or for the replacement of spent fuel with fresh fuel, which is known as refueling. In rare cases the plants may be shut down if major equipment failure causes an emergency. Routine maintenance is performed throughout the power generation plants, and most notably on the generators. Often times to complete the maintenance, the generator must be completely shut down for an extended period of time. Utilities typically own more generation capacity than is necessary to meet the baseload demand of their customers, and manage this downtime by increasing the electricity production of another, more expensive generator, or by purchasing additional electricity from their regional power grid.

Master maintenance schedules for five to twenty years in advance are created by electric utilities to reflect planned outages for preventive maintenance on their generators, which is performed at least once a year. Individual changes would be made by outage planners to account for variance in weather conditions, customer demand, and unavailability of other generators due to delays or unplanned outages. Taha and Wolf (1996) addressed scheduling generator maintenance schedules in their work for Entergy Electric System. They created a decision tree based methodology to replace a process that could take several days with one that would take less than one hour. Taha and Wolf (1996) found that previous contributions in outage planning were based on master schedules or weekly schedules. Optimization techniques including integer programming, dynamic programming, heuristics, simulated annealing, decomposition and expert systems had been used to minimize the cost of power replacement subject to earliest and latest start date requirements for the generator units (Taha and Wolf, 1996). Utilization of the techniques would produce a set of recommended start dates for the outages. They also found that other researchers had found ways to adjust the weekly schedule; however the methods were theoretical in nature, and not suitable for practical application. It was difficult to estimate the required cost parameters, and none of the methods accounted for potential delays in returning generator units to operation, which is a well known real world problem. Therefore, Taha and Wolf (1996) created a tool based on three key factors for evaluating a weekly outage plan: change in customer demand, unexpected generator breakdowns, and possible delays in returning units from planned outages. Each week was represented by a decision tree. For a given tree, the first set of branches would account for high, medium, or low customer demand. From each of those three branches, a second stage of branches would reflect four levels of reduction in capacity as a result of mechanical failure. Finally, extending from each of those branches would be a third stage of branches that would show the possibility of a unit returning from planned maintenance late. Each branch would have a probability of occurrence, and a megawatt (MW) value. These values were obtained from historical data. They did not use the traditional average value analysis as it did not reflect short term variations in demand. Instead, a deficiency statistic, D, was used to represent the shortage conditions. Weeks with unacceptable risk were identified by D, and allowed the outage planner to construct new decision trees with more acceptable risk levels. The input of customer demand was forecast as the historical demand plus the estimated average annual growth. Unfortunately, the company did not have any historical data for the late return of units from maintenance outages, so the developers based the associated probability on the communicated experiences of the outage planners. At the time of publication, their software had been used by Entergy Electric System outage planners for over three years, and assisted them by isolating high risk weeks, quickly developing maintenance schedules and allowing for quick response to short-notice changes.

In Sweetser (1998) a project team was created to improve the availability of a coal-fired steam generator at an electric power plant owned by a regional electric and gas utility in Colorado. While the availability goal was 90 percent, the unit was actually running 82 percent of the time. The cost of such a shut down to the company was computed as the difference between the per megawatt hour cost of electricity purchased and/or produced by another generator, and the per megawatt hour cost that would have been realized on the generator down for maintenance. This downtime cost can vary even within a day, due to the cyclical fluctuations of demand (Sweetser, 1998). Demand increases in the morning when people awake and begin to prepare for work. The demand is relatively high during the day, and begins to decrease later in the evening as people return home and get ready to retire for the night. Extreme heat and cold can cause these swings to be even more pronounced, and intuitively, higher demand begets higher electricity costs. In order to familiarize himself with the operations, the author, an operations research analyst, worked in each of the job positions that are primarily responsible for running the generator and monitored a scheduled outage. As a result of this, and analysis of historical data, the author implemented changes in the timing, planning, and coordination of the outage. The historical data supported a reduction in the time allocated for certain activities, and a cost-benefit analysis was performed to justify personnel overtime costs which would reduce the total time required for the generator to be down. Although Sweetser (1998) did not explicitly use operations research tools, or cite other publications to address the problems that were found, he did use the analytical thinking skills honed in his operations research training. In the end, the number of scheduled outages was not reduced in this article, however the duration of the outages was. The plant manager was able to verify that an average of 12 hours would be saved per outage, which would result in an annual savings of $545,000 to $2,000,000 depending on current market pricing.

5.2 Fuel Inventory

Another issue of concern for many power stations is determining how much of the necessary fossil fuel to keep in inventory. Fuel inventory management involves balancing the cost of acquiring and holding fuels with the risk of depleting the inventory. The cost of experiencing a fuel shortage can be realized in the marginal cost of switching a plant over from combusting its primary fuel to a secondary, more expensive fuel, such as oil. The cost could also take the form of buying the electricity from another utility, instead of producing it. Morris et al. (1987) stated that drastic changes in electricity demand and unprecedented rates of increase in fuel prices caused the rules of thumb previously used by experienced power plant staff to order fuel to become insufficient. Therefore, the EPRI along with 15 electric utilities developed the Utility Fuel Inventory Model (UFIM), which contained a simulation submodel and two analytical submodels. It could be used for the operation of any type of power plant or for any type of fuel. The work of Morris et al. (1987) focused on:

- showing the value of integrating the simulation and analytical submodels to solve the decision problem,
- helping the user understand the inventory problem,
- showing how the use of other models can enhance the judgment of the decision maker, and
- providing an application example that demonstrates the financial savings that can be achieved with the aid of the UFIM.

Morris et al. (1987) asserted that while inventory theory models did exist to address some of the individual problems in the UFIM, there was no inventory theory model that captured the entire problem covered by the UFIM. The problems faced by electric utilities are unique, and include issues such as inventory deliveries being interrupted due to transportation delays, and inventory depletion varying due to generator availability and system load. Even factors such as shortage costs and supply costs can vary on a month to month basis. In their approach, the model sought to identify a strategic policy for the most cost effective inventory levels during periods without supply disruptions. Because it was deemed a steady state problem, a recurrent Markov decision process which minimized discounted cost over an infinite time period was modeled (Morris et al., 1987). This was the Policy Development Submodel. Contrarily, demand and supply disruptions, due to events such as coal worker strikes or natural disasters, could not be modeled with infinite time horizon equilibrium. Therefore, disruptions were represented with a finite-duration dynamic programming model. This was the Disruption Management Submodel. Lastly, the Simulation Submodel was incorporated because of its wide range of statistical outputs and customizability to specific plants. Also noted was its ability to foster credibility with the end users of the model, the fuel inventory managers, by creating an understanding of how the inventory system works. The auxiliary models were included to breakdown the basic issues in the fuel management problem. A realistic case of all three models could be run on an IBM mainframe in one to two minutes. More details regarding the logic within the model were included in (Morris et al., 1987). The UFIM was applied at Consumers Power Company and resulted in a policy change at four of their five coal-fired power plants. When the work of Morris et al. (1987) was documented, over 50 different utilities were using the UFIM; furthermore, an EPRI survey of 11 utilities found that $12.5 million was saved in 1986 alone.

Discussion of the Utility Fuel Inventory Model continued in Chao et al. (1989). At the time of publication, UFIM had been implemented at over 70 utilities with savings valued at over $125 million. Chao et al. (1989) also discussed applications of UFIM at other utilities. Tampa Electric used UFIM to reduce their coal inventory, although it needed to be supplied across a 1700 mile system. San Diego Gas and Electric used UFIM to study rare events where back up fuel was needed at their back up power plant, and estimated the results saved them between $1 million and $3 million per year. Texas Utilities used the model to determine their required inventory levels. Tennessee Valley Authority, which serves customers across seven states, used UFIM to understand how market conditions affect low-cost inventory policies. Kansas City Power and Light used the model to define policies for monitoring and managing disruptions to their coal supply. They estimated an expected value of savings at $3 million per year. Southern California Edison used UFIM to set inventory policies. Finally, Southern Company, which at the time was the largest utility purchaser of coal in the country, changed to plant-specific inventory policies and as a result expected to save approximately $20 million per year.

5.3 Environmental Matters

Managing requirements mandated by organizations such as the Environmental Protection Agency (EPA) is another matter for electric utilities. Madden et al. (1983) were responsible for evaluating and selecting a particulate emissions control device for a coal-fired plant owned by Ohio Edison. The EPA was overseeing their compliance with the Clean Air Act, which limited the amount of sulfur dioxide and small particles of ash (particulates) that could be emitted from a power plant. Madden et al. (1983) recounted how Ohio Edison’s project team employed decision analysis to select the type of scrubber to use on several units at the plant. Several other units had already been brought into compliance through other methods. Their decision needed to be made in the presence of numerous uncertainties. The sulfur content of the coal to be burned was unknown. The method that the EPA would use to measure compliance was unknown. The ruling of the EPA on what constituted the region from which the power plant could acquire their coal was unknown, and this impacted the sulfur content of the coal to be burned. However, with preliminary research the choice was narrowed to a selection between precipitators or fabric filters. Precipitators work by inducing a strong electric field to remove charged particles from the flue gas. Fabric filters, or baghouses, contain thousands of fiberglass bags to collect fly ash from the flue gas.

The decision analysis began with the estimation of probability distributions of installation cost for each scrubber. Probability distributions were also created to represent other variables that impact the operating cost of the equipment. Next a decision tree was created. The decision between scrubbers preceded a number of uncertain events on the tree. They were the direct and indirect capital costs, the operating and maintenance costs, power plant availability, replacement power costs, catastrophic failure costs, the sulfur content in coal, equipment nonavailability costs, the cost of noncompliance, equipment corrosion costs, and bag failure costs. Power plant availability described the percentage of time that the plant would not be shut down for forced outages or scheduled maintenance and not available to generate electricity. Replacement power cost referred to the cost to buy or produce additional power to restore the electricity output reduction caused by electricity consumed in the operation of the scrubber. Catastrophic failure cost would be incurred if the scrubber experienced a major failure. The equipment nonavailability cost would arise if the scrubber failed during the operation of the generator, and thereby cause emissions to exceed the limits. The noncompliance cost only affected the electrostatic precipitator, and would be imposed only if the EPA specified limits on fine particles. The precipitator was found to have a lower limit on the size of particles it can capture, and therefore regulations might necessitate an upgrade or replacement of the system. The equipment erosion cost was considered a possibility due to the precipitator coming in contact with sulfuric acid in the flue gas, and corrosion would require repairs. The bag failure cost applied only to the fabric filter replacement, and would result from inventory holding costs for spare bags, and the labor to replace them.

The resulting probability distributions were assigned to the decision tree. The levelized revenue requirements for each of the two scrubbers were presented as cumulative probability distributions, and expected values were calculated for each probability distribution. Madden et al. (1983) found that the precipitator had lower expected levelized revenue requirements than the fabric filter. The risk of potentially high costs was also lower for the precipitator than the fabric filter. Although the capital cost of the filter was lower, they determined that was much less significant than the two pros of the precipitator mentioned above. The results were presented, the leadership of the Ohio Edison Company agreed with the decision analysis results and purchased and installed the precipitators. As environmental regulations continue to tighten, the work of Madden et al. (1983) could be quite useful in applications at other utilities in the future. While they may currently be in compliance, a regulation change can compel them to investigate how to meet new restrictions.

The work of Balson et al. (1992) used decision analysis and risk analysis to manage environmental risk at a utility. Electric utilities operate in an environment where health, environmental, and economic risks associated with their operations must be managed. In particular, economic risks, such as fines and clean up costs, are often driven by matters that result from the by-products of fossil fuel combustion or nuclear power plant operations. Important to note is that although electric utilities may operate fully within regulations set by regulatory bodies, if someone in the public were to be negatively impacted by their operations, utilities can still be held legally accountable by the individual. In Balson et al. (1992), three examples were presented where they served as consultants to solve specific environmental concerns and comply with regulatory mandates. In the first case they needed to develop a strategy for the least expensive management of boiler cleaning waste. The alternatives were judged by the cleaning agent, whether to pre-rinse the boiler, the treatment and disposal method, and the cleaning frequency. Their final recommendations were projected to save the company over $100,000 for one boiler during a twenty year period. In the second case, the consultants needed to determine the associated risks of certain power plant emissions for a hypothetical person. They used a deterministic sensitivity analysis to determine a person's sensitivity to the maximum and expected levels of emissions such as formaldehyde and benzene. Balson et al. (1992) found that under the most exposure, there was an incremental increase of less than one in one million for developing cancer within the hypothetical person's lifetime. They also found that under expected levels of emissions exposure, power plant emission contribute less than 0.14% to the hypothetical person's total risk from all sources of toxins in the area. Finally, in the third case a utility wanted to be successful in their hydroelectric plant re-licensing efforts in the face of "equal consideration" legislation. The legislation stated that power and nonpower values of water resources needed to be treated equally. Balson et al. (1992) combined resource economics, cost-benefit analysis and decision analysis in a strategy that could be used by the utility to improve the net benefit of their plant when presented at the re-licensing hearing.

5.4 Miscellaneous

A number of activities also occur within a utility that are not unique to a utility company only, but nonetheless are a part of their operations. Bristol and Lipton (1973) worked on one such activity while trying to determine service center requirements for Niagara Mohawk Power Corporation (NIMO). At the time of the study, the company provided electricity to over one million customers in New York and natural gas to almost half a million customers. NIMO wanted to ensure they were meeting the needs of their customers, and were therefore evaluating the need for adding and/or renovating service centers which contained crews and supplies for maintenance and construction. Mixed integer programming (MIP) was used to locate the facilities, and the objective was to minimize yearly operational costs by locating service centers and assigning crews optimally. The yearly demand for service crews in each area, the crews available to each area, the cost of the service centers determined by their size, and the upper bounds on the size of existing or new service centers were constraints. Before creating the MIP, the company had planned to build a new service center, but the results indicated that renovation of one building would be more economical. This generated a net savings of $350,000 (Bristol and Lipton, 1973).

The work of Chelst et al. (1981) involved an investigation of a coal unloading system at a coal-fired power plant owned by Detroit Edison Company. The plant was experiencing problems meeting their coal needs with the existing system. While they hypothesized that the cause was breakdowns of the unloader system, a study was conducted to perform queuing analysis and determine the root of the problem. Data was collected on a number of operational matters, such as unloader outage frequency and duration, and the annual throughput of trainloads of coal. Other measures of interest were calculated, such as the mean time between breakdowns and average wait to begin unloading. They analyzed the system as it was with one unloader, and with a potential second unloader. Chelst et al. (1981) did not give a specific solution, but provided results of the study, including potential savings, costs, and queue parameters, to aid management in their decision of whether or not to add a coal unloader to the plant.

Wunderlich et al. (1992) employed optimization software containing a set of algorithms to route and schedule meter readers for Southern California Gas Company. The work was of interest to the company because of the money spent on meter reading each year, the long length of time previously required to develop new routes, and the four year backlog that currently existed on route restructuring (Wunderlich et al., 1992). A route was defined as one day of work, and initially a sample region was used for the formulation. The territory was represented as a network where arcs were the paths traveled by meter readers, and the nodes were intersections. Details such as walking routes, driving routes, walking and driving routes, and hills were incorporated as well. The problem was solved using the arc partitioning approach. The benefits of their work were annual saving of almost $900,000, and several intangible benefits as well. The duration of the routes they produced had less variability among them and thus was more equitable for workers. The system also allowed small or large updates to the routes to be performed relatively quickly. Finally, the software could be used by staff to forecast future budgets and resource requirements.

Strategic staffing was investigated in Khawaja (1999). He noted that switching from a protected regulated environment to a competitive, unregulated environment would lead many utilities to place additional emphasis on efficiency, and strategic staffing was one way to improve efficiency. Operating in an unregulated environment, a utility would need to increase the productivity and cost efficiency of their operations in order to meet construction and maintenance requirements and respond to competition (Khawaja 1999). The author sought to optimize transmission and distribution labor allocation with a three-part model approach. First was a forecasting model that estimated the number of transmission pole miles, which would be converted to labor demand forecasts. The number of miles of transmission line (transmission pole miles) is often used by utilities as part of their estimate for the number of employees required to maintain them. The second part was an analytical hierarchy process model. Last was a linear program that included inputs from the first two parts. The analytical hierarchy was used to determine how subjective criteria such as quality and service impact the decision between in-house labor and contractors. The analytical hierarchy had three main components; 1) describing the multicriteria problem as a hierarchy, 2) estimating the relative weights of importance for criteria at each level of the hierarchy, and 3) integrating the relative weights to develop an evaluation of the hierarchy with respect to the problem objectives. Expert Choice™ was the name of the analytical hierarchy software used. Khawaja (1999) recommended that labor be maintained at a stable level over the period studied, with in-house overtime being maximized when needed, and that contract labor only be used to meet short-term needs.

CHAPTER 6 Conclusion

Electricity is an integral part of life in the United States of America in the twenty first century, and as such the work of electric utilities is vitally important. Customers have an expectation that any amount of the electricity needed will be available to them at the flip of a switch and at a price they believe is affordable and fair. Behind the scenes, it is up to electric utilities to ensure that indeed electricity is supplied reliably, safely, and efficiently so that only necessary operational costs are incurred. Historically, on a regular day electricity demand is low during the night hours when most customers are resting, it increases in the morning and remains high during the day while people are active and working, and begins to decrease again in the evening as people settle in at home and prepare to retire for the night. Additional fluctuations are seen in electricity demand when the weather is hot, cold or humid, but even the day of the week and whether it is a holiday will impact electricity demand as well. The ways that electric utilities control their systems, prepare for and manage customer demand, and administer generating capacity growth in the future are the determining factors of whether the electric utilities operate in a cost-effective manner. Because electric utilities took proactive steps to increase efficiency and reduce costs during deregulation, with the gradual reintroduction of regulation, electric utilities will need to continue these efforts in order to demonstrate their prudence to customers and regulators alike. As the population and its technological devices such as cell phones, MP3 players, and flat screen televisions grow, the expectation is for electric utilities to keep up with the growth and be efficient.

This body of work summarized how operations research has been used to benefit electric utility companies in the past, in hopes of inciting developments in the future. Operations research principles were successfully used to improve efficiency, reduce operational costs, and increase profitability. OR journals reveal that a number of insightful stochastic and deterministic applications were developed in the areas of the unit commitment problem, production costing and generation capacity expansion. Additional smaller contributions were made in the areas of fuel inventory management, electric power service offerings and staffing matters. However, there is still more territory left to cover; a number of developments and enhancements could be made in the future. Fuel inventory management techniques have the potential to save significant amounts of money. Fuel accounts for a large part of an electric utility's budget. In fact, Erwin et al. (1991) stated that it was approximately one third of the budget of the Southern Company, a large regional utility. Only a few OR articles investigated this area, however any additional improvements in the area could generate valuable financial returns.

Demand is certainly growing, and new generation will be required in the future. The type of facility that will create an optimal generation mix is of increasing importance, as electric utilities now operate in a "green" environment, where people want to minimize negative impacts to the environment. New regulations, public opinion and the likelihood of successfully permitting a plant go hand in hand, and both must be considered in planning. This green consciousness also extends to emissions controls. Decisions will need to be made regarding how to bring older power plants into compliance, or how to achieve compliance in new power plants. New technologies for managing emissions, such as methods to alter the fuel before combustion, or carbon sequestration after combustion, are still being developed and provide more options from which to choose. Also, with oil and natural gas prices rising to record levels, and knowing that our domestic fossil fuel resources are being depleted, there is an active search for viable renewable fuels. What place should new, unproven technology have when planning to meet demand in the future?

Several areas for OR applications in the electric utility were mentioned here, however opportunities abound. OR, “the science of better,” has an extensive set of tools capable of addressing decision making and policy creation under uncertainty, which is the environment that electric utilities operate in. Even more, sensitivity analysis tools allow practitioners to evaluate their recommendations and determine how inevitable changes in inputs will impact proposed decisions. This work shows that while some researchers and practitioners collaborated or built on work previously done, others did not. Some who worked independently exhibited true creativity and made valuable additions to the field, however others just created a new method that excluded a different set of constraints than previous work, and still did not produce a tool useful for application. Practitioners and electric utilities must avail themselves to each other so that practical tools will be developed. Several companies, such as Niagara Mohawk Power Corporation and Consumers Power Company seem to have been proactive in this regard, for they were the recipients of several OR tools discussed in some of the reviewed publications. The EPRI can be leveraged by practitioners and utilities to achieve this goal because it exists to identify and fund useful projects for the electricity infrastructure in the United States. As time progresses and uncertainties such as the rate of individual customer demand growth, the viability of remaining fossil fuel reserves, and state regulatory commission rulings on whether utility regulation or deregulation is best for their constituents, operations research still has untapped potential to continue to help electric utilities to provide safe, reliable, cost-effective electricity service in the future.

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APPENDIX A: Useful Information

The information below is meant to describe some of the terms or solution approaches used and discussed in this paper. It is not meant to give a detailed account of all electric utility matters, but instead give the reader a foundation to understand the content herein.

Benders decomposition (generalized Benders decomposition; GBD) – used to solve optimization problems with complicating variables; variables that when temporarily fixed allow the optimization problem to be solved. Fixing the values of the complicating variables will reduce the remaining problem to a parameterized linear program, consisting of a master problem and set of subproblems, which update the master problem in an iterative process until the solution is found.

Derating- reducing the expected availability of a generator by accounting for forced outages and maintenance.

Duality gap- the difference between the primal and dual optimal solutions of a problem.

Electric Power Research Institute- an organization that identifies and manages research projects conducted for the benefit of electricity generation, transmission and distribution companies in the United States.

Lagrangian relaxation - a technique that enables one to relax a difficult optimization problem into an optimization problem that can be more easily solved. Difficult constraints are removed from the mathematical program and instead are represented in the objective function, where they will be penalties if they are not satisfied.

Merit order scheduling (aka economic dispatch) - process of scheduling generators to run based on the increasing order of their per megawatt hour cost of operation.

Nonutility generation- a power generation facility that is not directly owned by the utility.

Power plants- industrial facility that generates electricity.

Baseload power plants are essentially devoted to supplying continuous demand, which is the minimum level of demand required by a utility's customers. These plants are often more efficient, have a high fixed cost, and relatively low operating costs. Typically nuclear plants, coal-fired plants and biomass plants are in this category.

Peaking power plants often have low fixed costs and high marginal costs. They are normally run to meet increases, or peaks, in demand, such as the afternoons of summer days. Peaking plants are known to have lower efficiencies. Natural gas-fired plants are often used as peaking plants.

Ramping constraint- an operational constraint that limits the maximum change in hourly power production for a generator.

Tie lines- exist between neighboring utilities so that electricity produced by generators will have multiple paths to meet demand, which improves reliability.