Proceedings of the ASME 2015 Power and Energy Conversion Conference
PowerEnergy2015
June 28-July 2, 2015, San Diego, California

PowerEnergy2015-49509

DECISION MAKING FOR THE COLLABORATIVE ENERGY SUPPLY SYSTEM OF OREGON AND WASHINGTON

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ABSTRACT

As demand for electricity in the United States continues to increase, it is necessary to explore the means through which the modern power supply system can accommodate both increasing affluence (which is accompanied by increased per-capita consumption) and the continually growing global population. Though there has been a great deal of research into the theoretical optimization of large-scale power systems, research into the use of an existing power system as a foundation for this growth has yet to be fully explored. Current successful and robust power generation systems that have significant renewable energy penetration - despite not having been optimized a priori - can be used to inform the advancement of modern power systems to accommodate the increasing demand for electricity. Leveraging ongoing research projects at Oregon State University and the National Energy Technology Laboratory, this work explores how an accurate and state-of-the-art computational model of the Oregon/Washington (OR/WA) energy system can be employed as part of an overarching power systems optimization scheme that looks to inform the decision making process for next generation power supply systems. Research scenarios that explore an introductory multi-objective power flow analysis for the OR/WA grid will be shown, along with a discussion of future research directions.

MOTIVATION

The electric power infrastructure of the United States and many parts of the world is at the early stages of an unparalleled transformation to modern intelligent power systems [1,2]. At the heart of the modern power system are advanced sensors, communications, and controls that manage the increasingly complex array of power generation, energy storage, and load assets. Power industry researchers and stakeholders are just beginning to observe major shifts toward more renewable energy, distributed generation, energy storage, demand response programs, electric vehicles, synchrophasors on the transmission system, and flexible fossil energy power plants. One of the greatest challenges of moving toward a modern power system is to optimize the integration and operation of existing grid assets with these new technologies [3–5]. Each region is unique in regards to its existing grid assets and demand, but also in regards to its vision of a modern power system that will serve its future needs. This vision is guided by many factors including state and local policy, access to different types of generation, estimates of future power demand, and economic outlook. The modern power system must consider and balance the cost, reliability, and environmental impact.

Planners of future modern power systems need powerful tools to help them manifest their vision. Working toward the goal of an optimized design and roadmap to create modern power systems, this paper describes recent work that creates the foundation for a large-scale power systems optimization algorithm that can be applied to any region and make use of existing electric power infrastructure. We present a preliminary instance of this algorithm using the Oregon/Washington (OR/WA) power grid to model power flow and reliability.

INTRODUCTION

Goals for the Project

A primary objective of power grid optimization is maintaining system operability while considering various generation sources, transmission infrastructure, and demand populations. Understanding subsystem relationships creates a challenge for researchers to create computer simulation models that effectively capture significant interactions between these sub-networks. This requires that our model be able to accurately capture the underlying physics of the power grid, the costs related to different grid configurations, and the generation-demand relationship.

Previous Literature

One potential approach to this problem is given by Mavris and Griendling, who created a Relational-Oriented Systems Engineering and Technology Tradeoff Analysis (ROSETTA) tool that explores the trade-offs between Quality Function Deployment, modeling and simulation, and theoretical mathematics to manage power demand response [6,7]. This approach blends qualitative information from subject matter experts with simulation models in an agent-based simulation. This approach is therefore dependent on the input of subject matter experts and the construction of the agent-based simulation. In contrast, the approach presented in this work utilizes a model-based approach to the problem, to enable use of optimization to determine the best course of action for a given user scenario input to the simulation.

To accurately simulate conditions in a given power system, physics-based computation techniques must be utilized. MATPOWER is an analysis toolbox designed to operate within the MATLAB computing environment, which is widely used in the power systems engineering community [8,9]. MATPOWER is a package designed for solving power flow and optimal power flow problems. The power flow problem is a numerical analysis of a power system in steady-state conditions using voltage magnitudes and phase angles at each bus. The input data consist of Ybus data, generator limits, and transmission line data. The outputs of these calculations are the active and reactive power injections at each bus. Optimizing generation while enforcing transmission line limits requires the use of linear programming with the power flow data. This is known as the optimal power flow [10]. Additional information such as generation costs will provide the user with the lowest cost per kilowatt-hour delivered.

The dc power flow approximation is a linear and simplified version of an ac power flow. A dc power flow looks purely at active power flows, neglecting transmission losses, voltage support, and reactive power management. Looking only at active power will enable us to capture the grid physics, estimate costs, and capture the generation-demand relationship at a fraction of the computation time of a full ACPF; therefore, a DCPF is preferred for the decision-making context of this model. The dc-OPF solver in MATPOWER takes in linear constraints and quadratic cost functions. In this case, the voltage magnitude and reactive power are eliminated from the problem completely, and active power flow is modeled as a linear function of the voltage angles [11]. MATPOWER will then output total generator costs and active power limits.

METHODOLOGY

In this work, a preliminary exploration of a two-stage optimization framework designed to better understand varying objectives of large-scale power systems is explored. The two-stage optimization allows us to consider the effect of overall system-level objectives on the optimal power flow. Potential system-level trade-offs include performance metrics such as cost and system resiliency based on the present-day OR/WA power system configuration.

The framework proposed here consists of an inner loop (i.e., power flow) and outer loop (i.e., system-level) optimization process to consider system performance (Figure 1). The outer loop optimization was conducted in both ModelCenter and MATLAB, and the inner loop optimization was performed in MATPOWER. The ultimate vision for this algorithm is that a user be able to (1) constrain multiple parameters for, (2) order specific behaviors from, and/or (3) add/subtract to entities contained in the database to be examined, and see possible power-flow optima which address all these constraints together.

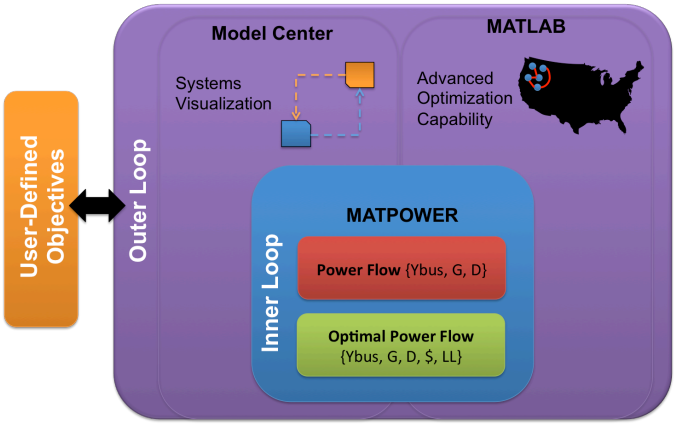

Figure 1: Two-Stage Optimization Framework

Outer-Loop Optimization Model

The outer-loop optimization contains overarching performance objectives directly relating to both system requirements (e.g., predicted demand) and designer preferences (e.g., increased system reliability). Currently, the outer loop optimization model's focus is to optimize system performance based on the existing available power generation sources in Oregon and Washington. However, multiple objectives can also be captured in the model. Using multi-objective optimization, design trade offs can be explored between cost and other system parameters. The formulation for the multi-objective approach is given in Equations 1-7, with relevant variable names given in Table 1.

$$\text{Find} \quad A_N \tag{1}$$

$$\text{minimize:} \quad f_1(A_N) = COE \tag{2}$$

$$f_2(A_N) = A(N-x) \tag{3}$$

$$\text{subject to:} \quad h_1 : G_i - G_{\max} \le 0 \qquad i \in \mathbb{Z} \mid i \le N_{Generators} \tag{4}$$

$$h_2 : D_{\text{Satisfied}} - D_{\text{Predicted}} \le 0 \tag{5}$$

$$h_3 : L_j \le L_{j_{\text{Nominal}}} \qquad j \in \mathbb{Z} \mid j \le 10 \tag{6}$$

$$g_1 : L_k = \frac{\sum_{k=1}^{N_{Bus}} (L_k)}{N_{Bus}} \qquad k \in \mathbb{Z} \mid k \le N_{Bus} \tag{7}$$

Table 1: Variable Identification for Equations 1-7

A_N	Adjacency Matrix
COE	Cost of Energy
$N-x$	The number of branches minus *x*; a user-defined quantity for stability testing
G_i	Power generated at generator *i*
$G_{\max}$	Maximum power generation at each generator
$D_{\text{Satisfied}}$	Satisfied Demand
$D_{\text{Predicted}}$	Predicted Demand
L_j	Actual Load at bus *j*
$L_{j_{\text{Nominal}}}$	Nominal Load at bus *j*
N_{Bus}	Number of buses

The decision variable A_N is an adjacency matrix representing the topology of power generation sources in the OR/WA system. The optimization system operates on this adjacency matrix when determining the value of the objectives functions, given as f_1 and f_2. The first objective function, f_1, is the minimization of the cost of energy, and is calculated in both dollars per hour (what a balancing authority would expect to pay to produce power at the various generators that are being dispatched) and dollars per hour per MW (dividing the $/hour quantity by the total load in MW satisfied for all customers). The second objective function, f_2, is relevant for one of the four particular studies carried out to test the system, and explores minimizing the impact (and to measure the resiliency) of the theoretical removal of a particular number of branches (x) from the system.

The system is subject to various inequality (h) and equality (g) constraints, depending on the particular test scenario. The first inequality constraint, h_1, states that no generator is capable of developing more power than its nameplate capacity dictates. The second inequality constraint, h_2, ensures that the demand that is satisfied matches the actual demand present in the system. The third inequality constraint, h_3, is relevant to the load shedding study, and states that the top ten buses with positive loads will reduce their output to less than their nominal value. The equality constraint, g_1, is applicable to the load averaging study, and states that the load at each bus is set to the average load over all buses.

Employing the objectives and constraints described above, the outer-loop of the two-stage optimization method was coded in both ModelCenter and in MATLAB. ModelCenter,is a graphical environment for automation, integration, and design optimization that enables users to create models by integrating individual design analysis and subsystem design modules [12]. It also allows the user to import data and coding from other software packages such as MATPOWER [8]. This use of this software assisted in concept validation during the preliminary research phase, allowing us to explore the feasible trade space and work toward identifying internal subsystem trends and relationships.

Inner-Loop Optimization Model

The inner-loop optimization system calculates instantaneous power flow based on physical relationships present in the system, such as generation, demand, and existing topology. The power flow is a numerical analysis performed in MATPOWER, consisting of a power system in steady-state conditions using voltage magnitudes and phase angles at each bus [8–10]. For this model, the OR/WA input data is filtered from the Western Electricity Coordinating Council (WECC) database. The output is the active power injections required at each bus to keep the system within operating specifications. If any power flow violations are detected, the power-flow solution will be calculated again. Linear programming is used to optimize generation ramping while enforcing transmission line limits required to avoid an overload. The simulation fidelity can be increased by adding additional details such as generation costs (at each source), and will provide the user with the lowest cost per kilowatt-hour delivered option. This is known as the optimal power flow, or OPF [10].

In this research we use the dc power flow approximation since we are explicitly addressing energy consumption and it is a widely accepted assumption for power system problems in very large networks. In a dcOPF solver, the power flow equations are linearized and neglect reactive power and off-nominal voltage magnitudes, thus modeling active power flow as a linear function of the voltage angles [11]. This simulation contains its own set of subsystem objectives, constraints, and decision variables. The objective of the dcOPF is to minimize the cost of the active power injections (i.e., generator ramping) required to maintain system stability based on a single loading scenario. The inner-loop optimization is defined by Equations 8-14, with relevant variables defined in Table 2.

$$\text{Find} \quad P_g, \theta \tag{8}$$

$$\text{minimize} \quad f_1 = \sum_{i=1}^{n_g} f_p^i(p)_g^i \tag{9}$$

$$\text{subject to} \quad g_P(\Theta, P_g) = B_{bus} + P_{bus,\,shift} + P_d + G_{sh} - C_g P_g = 0 \tag{10}$$

$$h_f(\Theta) = -B_f\Theta - P_{f,\,shift} - F_{\max} \le 0 \tag{11}$$

$$h_t(\Theta) = -B_f\Theta - P_{f,\,shift} - F_{\max} \le 0 \tag{12}$$

$$\theta_i^{ref,\,\min} \le \theta_i \le \theta_i^{ref,\,\max} \qquad i \in I_{ref} \tag{13}$$

$$p_g^{i,\,\min} \le p_g^i \le p_g^{i,\,\max} \qquad i \in \mathbb{Z} \mid i \le N_g \tag{14}$$

Table 2: Variable Identification for Equations 8-14

$f_p^i(p)_g^i$	Polynomial cost function of active power injection at each generator
B_{Bus}	Susceptance
$P_{\text{bus, shift}}$	Transformer Phase Shift Angle
P_d	Active Power Demand
G_{sh}	Shunt Conductance
C_g	Sparse $N_B x N_g$ Generator Connection Matrix
P_g	Active Power Generated
$F_{\max}$	Maximum Flow
θ^{ref}	Reference Bus Angle
p_g	Active Power Injections

For the inner-loop optimization, the objective function f_1 is a summation of individual polynomial cost functions (which are dependent on active power injection and voltage angle) at each generator. The objective function is subject to an inequality constraint g_P that specifies the power balance as a function of B_{Bus} (the bus susceptance), $P_{\text{bus, shift}}$ (the transformer phase shift angle, in degrees), P_d (the active power demand), G_{sh} (the shunt conductance), C_g (the sparse $N_B x N_g$ generator connection matrix), and P_g (the active power generated). The inequality constraints h_f and h_t consist of 2 sets of n_i branch flow limits as nonlinear functions of the bus voltage angles and magnitudes, one for the *from* end and one for the *to* end of each branch. Finally, variable limits include equality constraints on any reference bus angle and upper and lower limits on all bus voltage magnitudes and active power generator injections.

In summary, the two-stage optimization model first solves the power flow problem for the existing OR/WA power grid using a dcOPF simulation in MATPOWER. The power flow solution produces decision variables for the number and location of agents to the outer-loop optimization. This allows a designer to explore multiple design scenarios and test cases, based on their requirements and preferences.

Data Processing

The Oregon and Washington (OR/WA) areas of the Western Electricity Coordinating Council (WECC) region contain a variety of power generation plants (e.g. coal, hydro, geothermal, natural gas, wind, etc.) which house a total of 404 generators. Together, these generators have a maximum generating capacity of 34,801.5 MW. Power is transmitted between 3 intertie zones via a network of 4,631 transmission lines (branches) and 1,721 load points [13].

An initial challenge of this work was that the WECC data purchased as test input for this algorithm were, by default, formatted for the power system simulator PowerWorld, and therefore were incompatible with MATPOWER. We also had to separate the OR/WA system from the complete WECC dataset (WECC area is shown in Figure 2). The data was divided into two subsystems, and the external subsystem outside of the OR/WA boundary required a representative equivalent. Since boundary buses join each subsystem, external subsystems not required for the inner-loop model must be approximated. For the inner-loop model, supplemental data was extracted from the WECC data provided in PowerWorld.

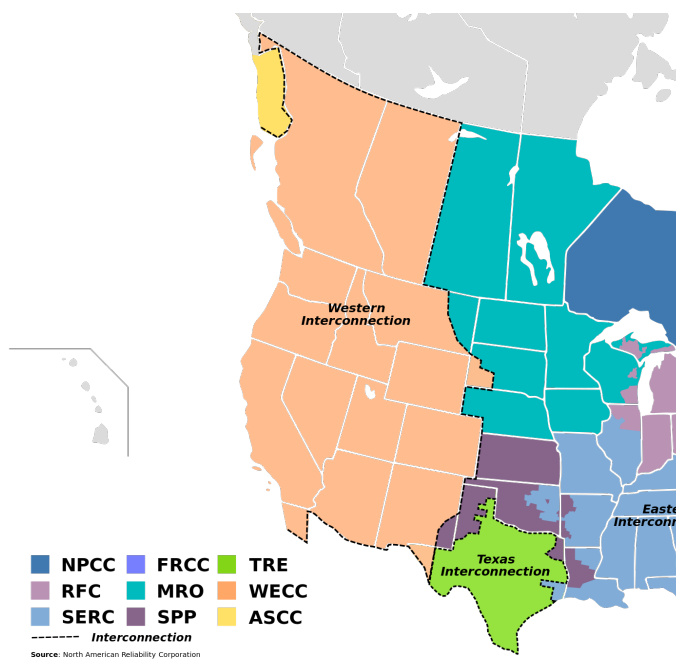

Figure 2: Western Interconnection, Including OR/WA Subset [14]

The equivalent model is created using the "Equivalencing" toolbox in PowerWorld [15]. For this system, the study area is "40(NORTHWEST)" which encompasses only Oregon and Washington (remaining parameters are considered external). Before building the equivalent, there are multiple options that need to be selected. First, since the external system is not to be considered, the "Delete All External Generators" checkbox must be selected checked. As the system goes through the equivalencing process it adds shunt elements to the boundary buses. As we would like to retain and use that information in our data, we checked the "Convert Equivalent Shunts to PQ Loads" checkbox. Equivalencing also creates empty zones, areas and substations from removing buses within them, so "Delete Empty Areas/Zones/Substations that occur from Equivalencing" is also selected. With these parameters set, an appropriate equivalent model can be generated.

To convert the OR/WA matrix to a MATPOWER-ready format, the PowerWorld data was first filtered to only include system assets (buses, branches, generators, and generator cost data) located within the OR/WA area. When viewed in PowerWorld, the original data set contains some data that are not required for the formulation while other data are not shown. Therefore, some data columns needed to be deleted or added to meet specifications. In order to meet MATPOWER formulation criteria, some of the data columns in PowerWorld required conversion from text to numerical values. Individual data columns were then arranged so that they conformed to the MATPOWER case struct. Once the selected data were filtered and arranged accordingly within PowerWorld, the data were exported into four discrete comma-separated value format (.csv) files for bus, branch, generator data and generator cost data. A MATLAB code was then created to combine all four data sets, make the necessary conversions, and generate a ".m" (MATLAB) file to integrate into the MATPOWER simulation. Example data types relevant to the dataset used are included in Figure 3.

Table B-1: Bus Data (`mpc.bus`)

name	column	description
BUS_I	1	bus number (positive integer)
BUS_TYPE	2	bus type (1 = PQ, 2 = PV, 3 = ref, 4 = isolated)
PD	3	real power demand (MW)
QD	4	reactive power demand (MVAr)
GS	5	shunt conductance (MW demanded at $V = 1.0$ p.u.)
BS	6	shunt susceptance (MVAr injected at $V = 1.0$ p.u.)
BUS_AREA	7	area number (positive integer)
VM	8	voltage magnitude (p.u.)
VA	9	voltage angle (degrees)
BASE_KV	10	base voltage (kV)
ZONE	11	loss zone (positive integer)
VMAX	12	maximum voltage magnitude (p.u.)
VMIN	13	minimum voltage magnitude (p.u.)

Table B-3: Branch Data (`mpc.branch`)

name	column	description
F_BUS	1	"from" bus number
T_BUS	2	"to" bus number
BR_R	3	resistance (p.u.)
BR_X	4	reactance (p.u.)
BR_B	5	total line charging susceptance (p.u.)
RATE_A	6	MVA rating A (long term rating)
RATE_B	7	MVA rating B (short term rating)
RATE_C	8	MVA rating C (emergency rating)
TAP	9	transformer off nominal turns ratio, (taps at "from" bus, impedance at "to" bus, i.e. if $r = x = 0$, $tap = \frac{\lvert V_f \rvert}{\lvert V_t \rvert}$)
SHIFT	10	transformer phase shift angle (degrees), positive ⇒ delay
BR_STATUS	11	initial branch status, 1 = in-service, 0 = out-of-service

Table B-2: Generator Data (`mpc.gen`)

name	column	description
GEN_BUS	1	bus number
PG	2	real power output (MW)
QG	3	reactive power output (MVAr)
QMAX	4	maximum reactive power output (MVAr)
QMIN	5	minimum reactive power output (MVAr)
VG	6	voltage magnitude setpoint (p.u.)
MBASE	7	total MVA base of machine, defaults to `baseMVA`
GEN_STATUS	8	machine status, > 0 = machine in-service ≤ 0 = machine out-of-service
PMAX	9	maximum real power output (MW)
PMIN	10	minimum real power output (MW)

Table B-4: Generator Cost Data† (`mpc.gencost`)

name	column	description
MODEL	1	cost model, 1 = piecewise linear, 2 = polynomial
STARTUP	2	startup cost in US dollars*
SHUTDOWN	3	shutdown cost in US dollars*
NCOST	4	number of cost coefficients for polynomial cost function, or number of data points for piecewise linear
COST	5	parameters defining total cost function $f(p)$ begin in this column, units of f and p are \$/hr and MW (or MVAr), respectively (MODEL = 1) ⇒ $p_0, f_0, p_1, f_1, \ldots, p_n, f_n$ where $p_0 < p_1 < \cdots < p_n$ and the cost $f(p)$ is defined by the coordinates (p_0, f_0), (p_1, f_1), …, (p_n, f_n) of the end/break-points of the piecewise linear cost (MODEL = 2) ⇒ $c_n, \ldots, c_1, c_0$ $n+1$ coefficients of n-th order polynomial cost, starting with highest order, where cost is $f(p) = c_n p^n + \cdots + c_1 p + c_0$

Figure 3: Data Types

RESULTS

In this work, a series of experiments to test a combination of an outer loop optimization with an inner loop of MATPOWER optimization and evaluation were conducted. For each test study, two data sets were employed. Both of these data sets are taken from a snapshot of time during the summer when the power grid is under heavy load. The smaller of these two sets, herein referred to as the PGE (Portland General Electric) data set, consists of 374 buses (of which 200 have loads, either positive or negative), 619 branches, and 27 generators, spread over the Oregon area. In total, the PGE data set contains 1 coal generator, 14 hydropower generators, 11 natural gas generators, and 1 "other" generator [16].

The second data set is the larger Oregon-Washington grid (of which the PGE data set is a subset), which is referred to throughout the remainder of this work as the OR/WA data set. The OR/WA data set has 4013 buses (1761 with loads), 4665 branches, and 404 generators. Of the generators, 3 are coal, 301 are hydropower generators, 69 are natural gas generators, 1 is nuclear, 2 are wind, 17 are wood or wood waste, and 11 are "other" or unknown [16].

The data sets originated in the software PowerWorld, and were cleaned and converted using a MATLAB script to make the data compatible with the software we used to simulate the electrical grid, MATPOWER 5.0. This software, and all other software we used to run the outer loop optimization, were all written in MATLAB. Results for each experiment are given in Tables 3-6 and are discussed further in the following sections.

Experiment 1

In this experiment, a baseline result is established for the PGE and OR/WA data set. This is the result of an Optimal Power Flow (OPF) analysis, which minimizes the cost of using the available generators by attempting to use the least expensive generators possible to meet the given loads. Different optimization algorithms for each data set were employed: the MATLAB optimization toolbox (Quadprog) was used for the PGE data, and the MATLAB Interior Point Solver (MIPS) was used for the OR/WA data, due to convergence issues when using the MATLAB optimization toolbox. 50 tests of each data set were conducted, and the mean, standard deviation, minimum, and maximum cost result were determined. "Cost" in this case refers to the cost to the power company for running all the generators involved at the particular power output found by the OPF, and is expressed in dollars/hour. From the results in Tables 3 and 4, it can be seen that with no optimization or alteration of the data, satisfying all customer loads will cost 37818 $/hour for the PGE data. For the OR/WA data, satisfying all loads requires 76945 $/hour.

Table 3: Results for Experiments 1, 3, and 4 in the PGE domain. All results are expressed in dollars/hour.

Experiment	Mean	Std. Dev.	Min	Max
1	37818	0.000051	37818	37818
3	37818	0.000053	37818	37818
4	19017	3356	8867	24707

Table 4: Results for Experiments 1, 3, and 4 in the OR/WA domain. All results are expressed in dollars/hour.

Experiment	Mean	Std. Dev.	Min	Max
1	76945	0	76945	76945
3	76880	0	76880	76880
4	63614	131	63391	63929

Experiment 2

In this experiment, the robustness of the various networks to disruption is tested. To do this, "N-X" tests are conducted, where X is 2, 3, 4, or 5. For example, an "N-2" test is performed by randomly removing two branches from the network, making sure that these two branches do not cause the network to break up into "islands". The new network is evaluated, and if MATPOWER converges to a solution, the cost is recorded. This method was repeated 50 times and statistics from each trial run were recorded.

As indicated by the results shown in Tables 5 and 6, the mean cost to satisfy all loads rises as X increases. Standard deviation also increases significantly. For the N-2 analysis in the PGE domain, there is no difference in performance compared to the baseline results, indicating that the PGE network is robust to two failures. As X increases, the potential severity also increases. However, it is possible for the removed branches to be in an area that is not critical, so the minimum cost does not change much if at all.

Table 5: Experimental results for Experiment 2 in the PGE domain. All results are expressed in dollars/hour.

N-X	Mean	Std. Dev.	Min	Max
N-2	37818	0.000053	37818	37818
N-3	37885	470	37818	41106
N-4	37938	580	37818	41601
N-5	38049	649	37818	41102

Table 6: Experimental results for Experiment 2 in the OR/WA domain. All results are expressed in dollars/hour.

N-X	Mean	Std. Dev.	Min	Max
N-2	76997	198	76882	78010
N-3	77151	660	76880	81172
N-4	77563	1445	76880	82277
N-5	78427	3990	76906	98488

Experiment 3

In the third experiment, a "smoothing" scenario is tested, that is, for a particular area of the network, loads for all buses in that area are set to the average of all loads in that area. As the data sets employed in this work are a "snapshot" of the loads at one particular time, this tests what might occur if the loads were averaged over a period of time, i.e. a day or season. For the PGE data, Zone 452 (the Portland area) was selected for the smoothing operation, a total of 147 buses. For the OR/WA data, smoothing was applied over most of the entire PGE area, a total of 311 buses. As indicated in Tables 3 and 4, there is either no or very little difference between the smoothed scenarios and the baseline performance, which implies that the current system could accommodate multiple load snapshots.

Experiment 4

For the final experiment, the capability of the system was tested by combining the outer optimization loop with a sophisticated search algorithm that performs in combination with a MATPOWER inner optimization loop. This test is to determine if costs can be reduced by shedding load at a small subset of buses. Load shedding is a drastic protection measure, or remedial action scheme, where in order to save the system from the effect of too much customer demand, some of the

customers are instead disconnected from the grid. While it may seem trivial that costs can be reduced by simply shedding as much load as possible, this is in fact not the case, and the choice of how much load to shed and where is quite complex. It should be noted that in this experiment, rolling blackout scenarios are not solved. Instead, loads are shed only as an exercise to test the combination of inner- and outer-loop optimization algorithms.

In this test scenario, loads are shed in the top 10 most heavily loaded buses with positive loads (see Figures 4 and 6 for the load distributions for the PGE data and the OR/WA data, respectively). These 10 buses are responsible for 52% of the total load consumed by the system in the PGE data, or 19.3% of the total load in the OR/WA data. The optimization is defined such that each of the 10 loads is a separate continuous control variable. Preliminary parametric tests indicate that the overall network is quite sensitive to load shedding at these buses, so the loads at these buses are good control variables for the cost. The outer loop optimization is constrained to shed up to 10% of the load at each of these buses.

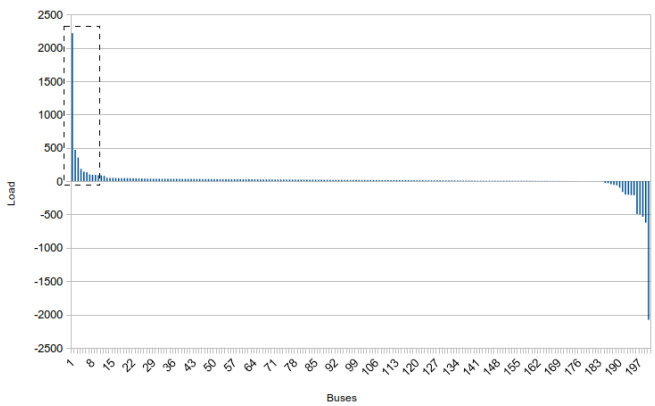

Figure 4: The nominal load distribution at each of the 200 buses with loads in the PGE data set. Some loads are negative, indicating an input of power at that bus. The leftmost 10 loads (boxed) were chosen as control variables and are shown in more detail in Figure 5.

As previously mentioned, the network is highly sensitive to changes in load, and so the optimization surface is quite complex, with many local minima. This search space is not amenable to search using standard gradient descent methods; therefore a parallel genetic algorithm was developed to search for a solution. 30 trial runs were performed for each data set, and statistics were recorded over the group of runs, which can be found in the last row of Tables 3 and 4.

From these results it can be seen that a significant improvement in cost is obtained by shedding a very small percentage of the load. The best solution (see Figure 5 for the results found for the PGE data) indicates that by shedding an average of 8.86% of the load at each of the 10 controlled buses - a total of 371 MW or 4.97% of the total load across all buses - costs can be reduced as much as 76.6%. Alternatively, the cost/MW of the nominal and best solutions can be examined: for the nominal solution, it requires $5.06/MW to generate the required power. The best solution requires $1.25/MW, an improvement by a factor of 4.

A caveat to these results is that, as can be seen by the high standard deviation of this result, it is necessary to apply significant computational power to generate many trial runs of a genetic algorithm to be confident of the final solution. In this experimental setup, computation for the PGE data set required 2 hours on a single 8-core machine, and over 18 hours for the OR/WA data. This could be sped up significantly by using additional machines, as genetic algorithms are easily parallelized.

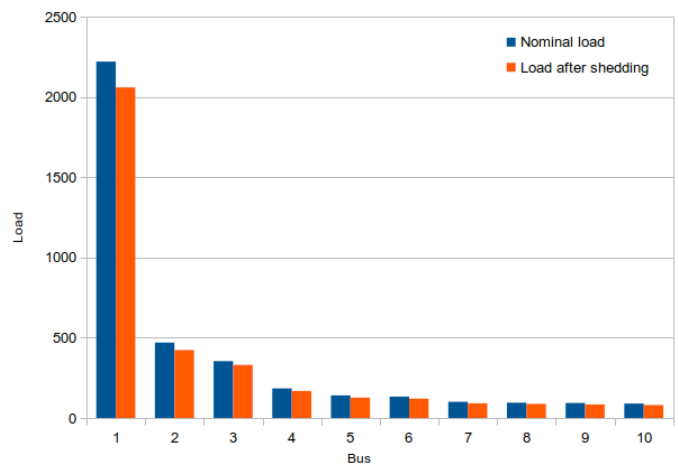

Figure 5: The best solution found for the PGE data, in red, compared to the nominal load, in blue. On average, 9.7% of the load was shed at each bus.

It is significant that the most dramatic improvement after optimization is found for the PGE data set. For the OR/WA data set, the best solution found (see Figure 7) cut costs by at most 17.6%, or from a cost/MW perspective, decreased costs from $2.56/MW to $2.15/MW. This may be due to the smaller percentage of total load the outer optimization loop controls, an inner loop optimization algorithm that is not as robust as that used for the PGE data, or potentially the underlying OR/WA data itself. Further experimentation will be required to better understand these effects.

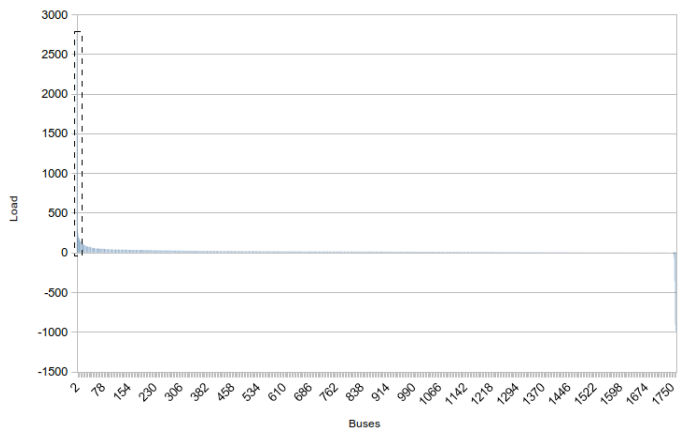

Figure 6: The nominal load distribution at each of the 1761 buses with loads in the OR/WA data set. As with the PGE data set, some loads are negative, and the leftmost 10 loads (boxed) were chosen as control variables and may be seen in more detail in Figure 7.

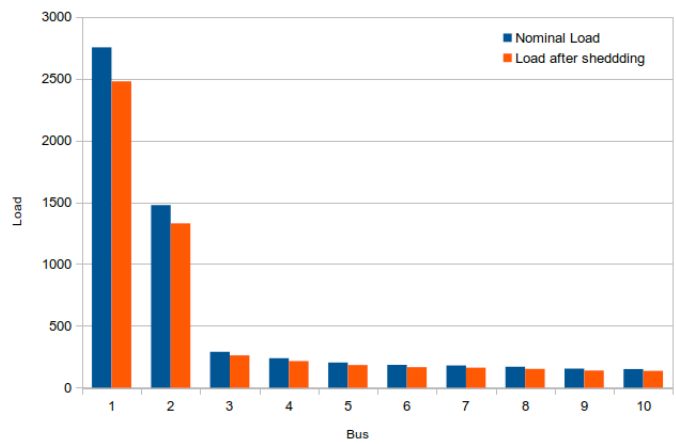

Figure 7: The best solution found for the OR/WA data set, in red, compared to the nominal load, in blue. On average, 10.3% of the load was shed at each bus

Best Practices

During our experimentation with the PGE and OR/WA data, we found that these data sets were sensitive to the choice of algorithm used to perform the OPF analysis. We tested two different algorithms: an algorithm that comes with the MATLAB optimization toolbox (Quadprog), which was used for the PGE data, and the MATLAB Interior Point Solver (MIPS, an algorithm affiliated with MATPOWER) was used for the OR/WA data. Our results with the Quadprog algorithm were significantly better than for MIPS, though it is unclear if this is due to the algorithm or the data set. The OR/WA data set would not converge using Quadprog, so this also makes it more difficult to compare results between data sets. These results suggest that choice of algorithm is very important, so in the future, it may be useful to test various other algorithms beyond the two selected in this work.

Direct conversion from PowerWorld data to MATPOWER was not readily feasible. One particular obstacle we encountered in the conversion process was that certain generators present in the PowerWorld data were listed as having a zero maximum generator capacity, therefore not representative of the real-world influence of the generator on the system. We found that this caused the cost/hour generated by MATPOWER to be unresolvable. To accommodate this, the zero-valued generators were not considered.

There are several ways to represent generator cost data. Usually they are a combination of constant terms (for example startup and shutdown costs) and a variable term that provides $/hr as a function of mw dispatched. In this study the original dataset did not provide startup and shutdown costs so we represented those with zeros in MATPOWER. The variable terms were given as a linear relationship and represented with two coefficients in MATPOWER.

CONCLUDING DISCUSSION

The purpose of this work is to serve as a preliminary exploration of how power systems can be optimized to be more robust against system perturbation, and to gain a foundational understanding of how the US power system should evolve to meet increasing demand. The two-stage optimization system, combining an overarching systems-level optimization with the highly vetted inner-loop optimal power flow analysis, capitalizes on recent advances in both traditional power systems research and optimization science.

The four introductory test cases explored in this work demonstrate the success of the developed system in multiple capacities. The optimization system was able to explore power grid robustness scenarios for both the OR/WA and smaller PGE data sets for different branch conditions, and was able to find system conditions that would prevent large-scale islanding for even the most severe branch removal scenarios. It has also been shown that this system - despite the current version employing a single heavy summer load snapshot - is capable of representing varied load conditions, something that will be explored in future work. Most significantly, it was made clear that deliberate and carefully applied load shedding can dramatically reduce the cost of energy, despite operating on a relatively small subsection of the total buses in each dataset. This result has substantial implications for maintaining a low cost of energy as the power system increases in size to accommodate growing power demand.

Lastly, it should be noted that using the PGE and larger OR/WA datasets exposed some of the issues that currently restrict advancement in power systems optimization research. Namely, the data that is needed for these types of analyses is proprietary and held behind multiple paywalls, requiring licensing and prohibiting public dissemination. Additionally, while the datasets are generally complete, currently there are omissions that significantly constrain future work in the area of renewable energy generation integration, as certain data are not included (i.e. some cost data, including startup and shutdown costs, and some generation data). It will be necessary to work

closely with power system authorities and utilities in order to have the appropriate data to be able to perform advanced optimizations with our current system.

FUTURE WORK

While the current work has been successful in exploring decision making for introductory analyses relating to retaining robustness and advancing large-scale power grids, there is significant motivation to continue to drive advances in this area. With respect to the current version of the two-stage optimization system presented here, it is a logical next step to explore different optimization algorithms and formulations, in order to ensure optimality. It will also be feasible to parallelize the current genetic algorithm such that it can run on a cluster, which will decrease overall computation time. It will also be possible to explore using open-source solvers, such that the systems are able to be publically disseminated without concern about user access to proprietary software.

Moreover, it is of interest to further explore the optimization methodology that is used on these types of problems (large-scale evolving systems optimization). As the US power grid continues to grow to accommodate increased demand, there will need to be deliberate decisions made with respect to the location and type of new generators that must come online, and improvements to these generators must be considered, including incentives, inflation rates, and cost of fuels. There is currently a lack of research related to optimization for evolving systems, and a dearth of resulting decision-making tools that are applicable to such problems. It is our intent to use the US power grid as a test case for novel optimization methods that incorporate variation in the solution space over time.

Long-term goals for this work include an online optimization system that will enable any user to be able to better understand the US power grid, and how it will need to change in the coming decades. Allowing for user-defined objectives, power authorities and utilities will be able to determine least-cost scenarios for increased generation, and researchers and students will be able to create and define large-scale grids that are optimized for cost, supply/demand match, and the reduction of environmental and biological impact.

ACKNOWLEDGMENTS

As part of the National Energy Technology Laboratory's Regional University Alliance (NETL-RUA), a collaborative initiative of the NETL, this technical effort was performed under the RES contract RES1100426/017. Additionally, the authors would like to acknowledge Mark Williams, Janet Nelson, and Fred Gromicko from URS, who have offered valuable feedback throughout the term of this project.

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