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An Optimization Framework for Decision Making in Large, Collaborative Energy Supply Systems

As demand for electricity in the U.S. 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. This work explores how an accurate and state-of-the-art computational model of a large, regional 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 a case study involving a regional portion of a large grid will be explored, along with a discussion of future research directions.
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Introduction

The electric power infrastructure of the U.S. 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 [3,4], particularly when accommodating distancing and partitioning [5]. Each region is unique not only in regard to its existing grid assets and demand but also in regard 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 an existing electric power infrastructure. We present a preliminary case study of this

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algorithm using the subset of a large power grid (the Oregon/Washington, or "OR/WA" region of the Western Interconnect in the U.S.) 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 subnetworks. This requires that the 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 tradeoffs 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 the use of optimization to determine the best course of action for a given user scenario input to the simulation.

Other related previous literature involves the exploration of power systems optimization from different fronts. The power systems sustainability assessment framework developed by Andrade et al. uses a two-tiered approach; the current work uses a structurally similar inner- and outer-loop optimization method [8]. Multiple multi-objective optimization frameworks have also been explored as applied to power systems: the economic and energy consumption objectives of a hospital microgrid optimization [9], an overarching thermodynamic optimization approach that includes objectives of economics and emissions [10], and the five-objective approach by Widiyanto et al. that models energy economy, energy security, environmental protection, socio-economic development, and technological aspects to determine optimal power generation systems configurations in developing countries [11]. The work presented in this paper is also multi-objective; utilizing an optimal power flow (OPF) analysis to optimize existing grid structures, while an outer-loop approach allows for the consideration of various objectives, including optimal system performance.

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 [12,13]. MATPOWER is a package designed for solving power flow and OPF 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 OPF [14]. Additional information such as generation costs will provide the user with the lowest cost per kilowatt-hour delivered.

The dc power flow (DCFP) 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 ac power flow: 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 [15]. 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 are explored. The two-stage optimization allows us to consider the effect of overall system-level objectives on the OPF. Potential system-level tradeoffs include the performance metrics such as cost and system resiliency; these are derived from the power system configuration present in the case study (the OR/WA grid).

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 (Fig. 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.

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. However, multiple objectives can also be captured in the model. Using multi-objective optimization, design tradeoffs can be explored between cost and other system parameters. The formulation for the multi-objective approach is given in the following equations:

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

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

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

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

$$h_2 : D_{\text{Satisfied}} - D_{\text{predicted}} \leq 0 \tag{5}$$

$$h_3 : L_j \leq L_{j_{\text{Nominal}}} \quad j \in \mathbb{Z} | j \leq 10 \tag{6}$$

$$g_1 : L_k = \frac{\sum_{k=1}^{N_{B\times s}} (L_k)}{N_{\text{Bus}}} \quad k \in \mathbb{Z} | k \leq N_{\text{Bus}} \tag{7}$$

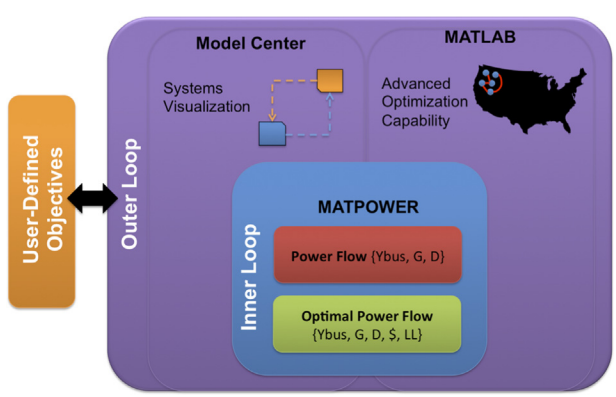

Fig. 1 Two-stage optimization framework

The decision variable A_N is an adjacency matrix representing the topology of power generation sources in the 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 [16]. It also allows the user to import data and coding from other software packages such as MATPOWER [12]. 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 [12–14]. For this model, the case study (herein referred to as the "case study" or OR/WA) input data is filtered from the larger Western Electricity Coordinating Council (WECC) database; similar distillation of regional grids from larger grids will be explored in the future work. 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 [14].

In this research, the dc power flow approximation is used since this research is 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 [15]. 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 the following equations:

$$\text{Find} \quad \mathrm{P}_g, \theta \tag{8}$$

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

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

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

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

$$\theta_i^{\text{ref,min}} \leq \theta_i \leq \theta_i^{\text{ref,max}} \quad i \in I_{\text{ref}} \tag{13}$$

$$p_g^{i,\min} \leq p_g^i \leq p_g^{i,\max} \quad i \in \mathbb{Z} | i \leq N_g \tag{14}$$

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 $N_B \times N_g$ generator connection matrix), and P_g (the active power generated). The inequality constraints h_f and h_t consist of two 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.

Case Study Data Processing. The presented case study region contains 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 34801.5 MW. Power is transmitted between three intertie zones via a network of 4631 transmission lines (branches) and 1721 load points [17].

An initial challenge involved determining best practices for distilling regional case-study data from the larger grid in a format that is compatible with the multi-objective optimization framework that is the major contribution of this work. For this particular case, the larger grid (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 regional case study system from the complete WECC dataset (WECC area is shown in Fig. 2). The data were divided into two subsystems, and the external subsystem outside of the case study 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. This regional isolating procedure is applicable to further research from any larger grid; the best practices for doing so (as related to creating data that is applicable within the presented optimization framework) enable application to any grid.

The equivalent model is created using the "Equivalencing" toolbox in PowerWorld [19]. Before building the equivalent, there

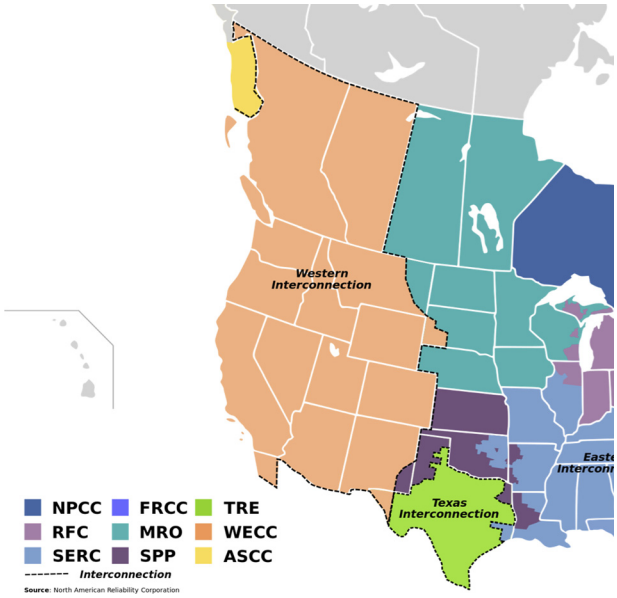

Fig. 2 Western interconnection, including OR/WA subset [18]

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. To retain and use that information, the "Convert Equivalent Shunts to PQ Loads" checkbox is selected. 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 parameter sets, an appropriate equivalent model can be generated.

To convert the case study data 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 case study 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 Fig. 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 $(p_0, f_0), (p_1, f_1), \ldots, (p_n, f_n)$ 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 $f(p) = c_n p^n + \cdots + c_1 p + c_0$

Fig. 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. To expose variation, 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 $\text{Sub}_{\text{OR/WA}}$ data set, consists of 374 buses (of which 200 have loads, either positive or negative), 619 branches, and 27 generators, spread over the case study area. In total, the $\text{Sub}_{\text{OR/WA}}$ data set contains 1 coal generator, 14 hydropower generators, 11 natural gas generators, and 1 "other" generator [20]. The second data set is the larger case-study grid (of which the $\text{Sub}_{\text{OR/WA}}$ 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, three are coal, 301 are hydropower generators, 69 are natural gas generators, one is nuclear, two are wind, 17 are wood or wood waste, and 11 are other or unknown [20]. While two specific data sets are employed for testing, the optimization framework developed and tested in this work is applicable on any dataset, given necessary user formatting the grid data.

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 used to simulate the electrical grid, MATPOWER 5.0 (Tables 1 and 2). This software and all other software used to run the outer-loop optimization, were all written in MATLAB. Results for each experiment are given in Tables 3–4 and are discussed further in the following sections (Experiment 1–4).

Experiment 1. In this experiment, a baseline result is established for the $\text{Sub}_{\text{OR/WA}}$ and OR/WA data set. This is the result of an 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

Table 1 OPF results developed using MATLAB QUADPROG for experiments 1, 3, and 4 in the $Sub_{OR/WA}$ domain. All results are expressed in dollars/hour.

Experiment	Mean	Std. dev.	Min.	Max.
1	37,818	0.000051	37,818	37,818
3	37,818	0.000053	37,818	37,818
4	19,017	3356	8867	24,707

Table 2 OPF results developed using MATLAB MIPS 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	76,945	0	76,945	76,945
3	76,880	0	76,880	76,880
4	63,614	131	63,391	63,929

Table 3 *N-X* results for experiment 2 in the $Sub_{OR/WA}$ domain. All results are expressed in dollars/hour.

N-X	Mean	Std. dev.	Min.	Max.
N-2	37,818	0.000053	37,818	37,818
N-3	37,885	470	37,818	41,106
N-4	37,938	580	37,818	41,601
N-5	38,049	649	37,818	41,102

Table 4 *N-X* 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	76,997	198	76,882	78,010
N-3	77,151	660	76,880	81,172
N-4	77,563	1445	76,880	82,277
N-5	78,427	3990	76,906	98,488

toolbox (QUADPROG) was used for the $Sub_{OR/WA}$ 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. Fifty tests of each data set were conducted, and the mean, standard deviation, minimum, and maximum cost results 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 37,818 \$/hr for the $Sub_{OR/WA}$ data. For the OR/WA data, satisfying all loads requires 76,945 \$/hr.

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 $Sub_{OR/WA}$ domain, there is no difference in performance compared to the baseline results, indicating that the $Sub_{OR/WA}$ 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.

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 $Sub_{OR/WA}$ data, Zone 452 (a zone that includes a large metropolitan 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 $Sub_{OR/WA}$ 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 ten most heavily loaded buses with positive loads (see Figs. 4 and 6 for the load distributions for the $Sub_{OR/WA}$ data and the OR/WA data, respectively). These ten buses are responsible for 52% of the total load consumed by the system in the $Sub_{OR/WA}$ data, or 19.3% of the total load in the OR/WA data. The optimization is defined such that each of the ten 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

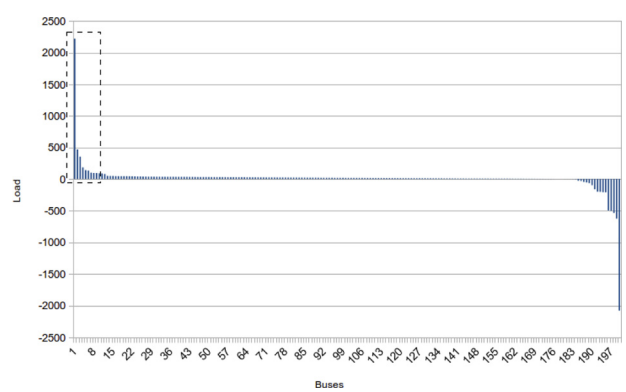

Fig. 4 The nominal load distribution at each of the 200 buses with loads in the $Sub_{OR/WA}$ data set. Some loads are negative, indicating an input of power at that bus. The leftmost ten loads (boxed) were chosen as control variables and are shown in more detail in Fig. 5.

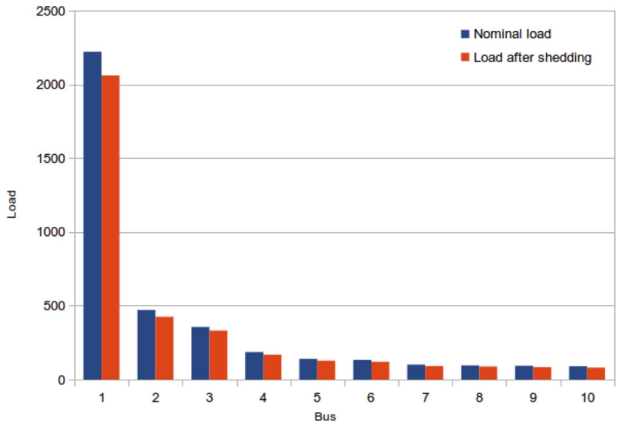

Fig. 5 The best solution found for the $Sub_{OR/WA}$ data, compared to the nominal load. On average, 9.7% of the load was shed at each bus.

optimization is constrained to shed up to 10% of the load at each of these buses.

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. Thirty 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 Fig. 5 for the results found for the $Sub_{OR/WA}$ data) indicates that by shedding an average of 8.86% of the load at each of the ten 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 $Sub_{OR/WA}$ data set required 2 hrs on a single eight-core machine, and over 18 hrs for the OR/WA data. This could be sped up significantly by using additional machines, as genetic algorithms are easily parallelized. It should also be noted that load shedding of this amount (nearly 9%) may not be advisable under certain conditions, and the feasibility of these scenarios must be analyzed on a case-by-case basis prior to real-world application. However, given the heuristic optimization method employed—which does not guarantee global optimality and generates a family of potential solutions of varying optimality—it may be that a potential solution that is less mathematically optimal may be more convenient for real-world application.

It is significant that the most dramatic improvement after optimization is found for the $Sub_{OR/WA}$ data set. For the OR/WA data set, the best solution found (see Fig. 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 $Sub_{OR/WA}$ data, or potentially the underlying OR/WA data itself. Further experimentation will be required to better understand these effects.

Best Practices. During the experimentation with the $Sub_{OR/WA}$ and OR/WA data, it was found that these data sets were sensitive to the choice of algorithm used to perform the OPF analysis. Two different algorithms were tested: an algorithm that comes with the MATLAB optimization toolbox (QUADPROG), which was used for the $Sub_{OR/WA}$ data; and the MATLAB Interior Point Solver (MIPS, an algorithm affiliated with MATPOWER) was used for the OR/WA data. The 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 encountered in the conversion process was that certain generators present in the

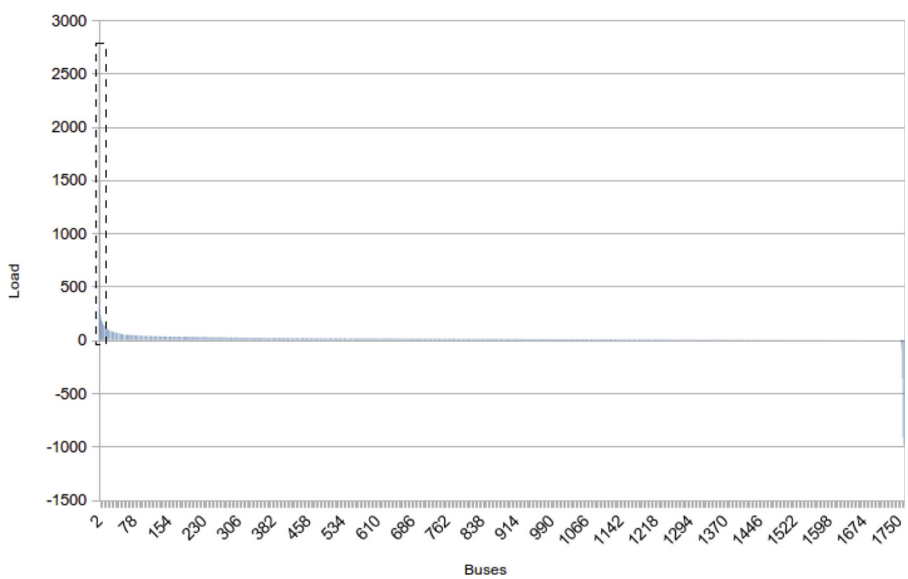

Fig. 6 The nominal load distribution at each of the 1761 buses with loads in the OR/WA data set. As with the $Sub_{OR/WA}$ data set, some loads are negative, and the leftmost ten loads (boxed) were chosen as control variables and may be seen in more detail in Fig. 7.

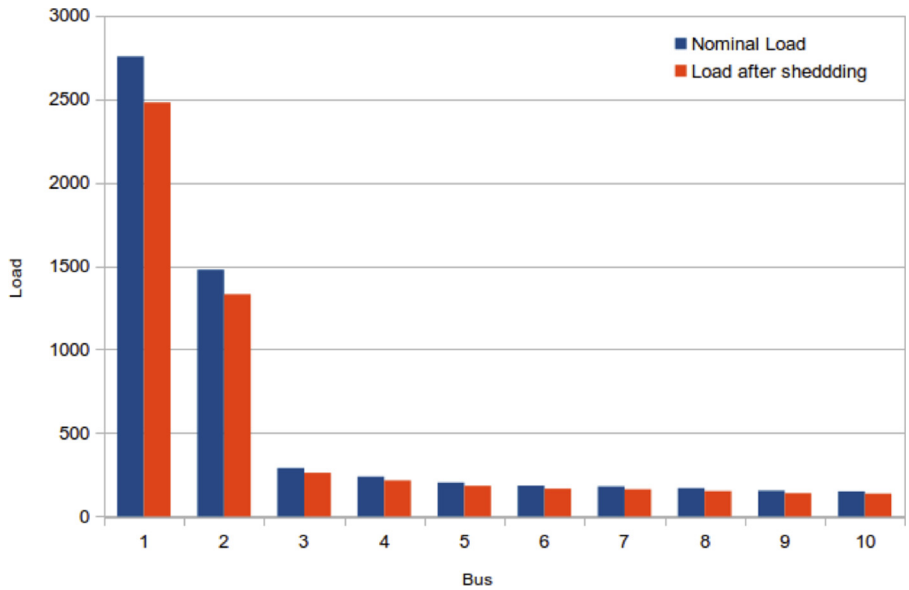

Fig. 7 The best solution found for the OR/WA data set, compared to the nominal load. On average, 10.3% of the load was shed at each bus.

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. 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 those were represented with zeroes 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 U.S. 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 OPF 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 $\text{Sub}_{\text{OR/WA}}$ 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.

Finally, it should be noted that using the $\text{Sub}_{\text{OR/WA}}$ and larger OR/WA datasets exposed some of the issues that currently restrict advancement in power systems optimization research. For example, 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 the current system.

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Nomenclature

A_N = adjacency matrix
B_{Bus} = susceptance
C_g = sparse generator connection matrix $N_B \times N_g$
COE = cost of energy
$D_{\text{Predicted}}$ = predicted demand
$D_{\text{Satisfied}}$ = satisfied demand
$f_p^i(p)_g^i$ = polynomial cost function of active power injection at each generator
$F_{\max}$ = maximum flow
G_i = power generated at generator i
$G_{\max}$ = maximum power generation at each generator
G_{sh} = shunt conductance
L_j = actual load at bus j
$L_{j_{\text{Nominal}}}$ = nominal load at bus j
$N - x$ = the number of branches minus x; a user-defined quantity for stability testing
N_{Bus} = number of buses
p_g = active power injections
P_d = active power demand
P_g = active power generated
$P_{\text{bus,shift}}$ = transformer phase shift angle
θ^{ref} = reference bus angle

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