Grid Optimization Competition on Synthetic and Industrial Power Systems

Farnaz Safdarian[1], Jonathan Snodgrass[1], Ju Hee Yeo[1], Adam Birchfield[1], Carleton Coffrin[2], Chris Demarco[3], Stephen Elbert[4], Brent Eldridge[4], Tarek Elgindy[5], Scott L Greene[3], Nongchao Guo[5], Jesse Holzer[4], Bernard Lesieutre[3], Hans Mittelmann[6], Richard P O'Neill[7], Thomas J. Overbye[1], Bryan Palmintier[5], Pascal Van Hentenryck[8], Arun Veeramany[4], Terrence W.K. Mak[8], Jessica Wert[1]
[1]*Electrical Engineering Department, Texas A&M University, College Station, TX USA*
[2]*Los Alamos National Laboratory, Los Alamos, NM USA*
[3]*Electrical Engineering Department, University of Wisconsin-Madison, Madison, WI USA*
[4]*Pacific Northwest National Laboratory, Richland, WA USA*
[5]*National Renewable Energy Laboratory, Golden, CO USA*
[6]*School of Mathematical and Statistical Sciences, Arizona State University, Tempe, AZ USA*
[7]*Advanced Research Projects Agency – Energy, Washington DC, VA USA*
[8]*School of Industrial Engineering, Georgia Institute of Technology, Atlanta, GA USA*

***Abstract*— This paper summarizes a grid optimization (GO) competition effort in the United States to find the best solution strategies for up to interconnect-scale power system networks with around 32,000 buses. The optimization problem is a mixed-integer, non-convex non-linear problem, (MINLP) and includes discrete variables such as unit commitment and line switching, control settings (transformer taps and phase shifters with impedance correction tables), and bus shunts. The case study includes six actual industry grids as well as 16 realistic synthetic grids created by three different dataset teams. The winners are selected and ranked based on scoring criteria, which consider the solution quality (such as objective functions) within time limits. Nine winner teams are selected from 26 competitor teams. The results achieved by different teams are described and the performance of different algorithms on synthetic grids and actual industry grids are compared and analyzed.**

***Index Terms*— Mixed-integer non-linear programming, optimal power flow, optimization, power systems, synthetic network models.**

I. Introduction

Since the most common optimization problems that need to be solved frequently for power system operation are to minimize the operation cost or maximize the overall efficiency of the electric grids, finding the optimal solution to these problems will save huge amounts of money. The realistic AC Power Flow (ACPF) optimization problems are non-convex and non-linear problems, and when integer variables are also included it is very challenging to find the optimal global solution, and heuristic methods play an important role in improving the algorithms. Advanced Research Projects Agency-Energy (ARPA-E) created the first Grid Optimization (GO) competition in 2018 [1]. The main goal of this project was to find the best solution in a limited time, ensuring that as the demand for energy grows and the power grid changes with the addition of distributed energy resources, these changes are met by modern grid solutions, thus revolutionizing optimization problems for power system operations.

These optimization algorithms need to be tested and validated on realistic power system models to be implementable on actual grids. Due to security concerns, the grid data is labeled Critical Energy Infrastructure Information (CEII) and are not accessible to the public. Therefore, even for research purposes, the actual power systems cannot be publicly released, making the validation and comparison of the operation and planning algorithms difficult. While historical IEEE test cases exist, they are mostly smaller, less complicated, and do not contain pertinent information such as transmission line lengths, geographic coordinates of buses, and MVA limits. Synthetic network models were created for the GO competition as described in Section IV. Since the synthetic grid models are publicly available, the performance of any proposed grid optimization or control algorithm can be readily examined and verified.

This paper summarizes the GO competition challenge 2 effort in the United States to find an efficient solution strategy in industry-level power systems with up to 32,000 buses. The required optimization problem is a non-convex, NP-Hard [2, 3] mixed-integer non-linear problem (MINLP) since includes discrete variables and voltage/reactive power control settings. The results achieved by different teams are described and the performance of different algorithms on synthetic grids and actual industry grids are compared and analyzed.

II. GO Competition Challenges

GO competition challenge 1 focused on optimizing the economic operation of the electric grid while considering various component outages, i.e., contingencies. One important goal of the competition was to compare various power system operation algorithms and benchmark their performance on a variety of realistic test cases. Three teams including Texas A&M University (TAMU), The University of Wisconsin-Madison

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(UW-Madison), and Pacific Northwest National Laboratory (PNNL) were assigned to create realistic but not real grid data. Competitors were tasked with solving a security-constrained optimal power flow (SCOPF) on networks ranging from 500 to 30,000 buses. Challenge 1 had time limits: "real-time" (10 minutes) and "offline" (45 minutes), with scoring methods considering the lowest cost and performance profiles [4]. The results of the GO competition challenge 1 are posted on [5].

As the innovations and developments resulting from challenge 1 were successful, ARPA-E created GO competition challenge 2 with the goal of finding the best optimization strategy for power systems operation over a variety of load and weather scenarios and with other improvements to have a more realistic model by adding topology optimization, component participation, demand response, and reactive power control and challenged competitors to find new ways to make the grid optimization faster and more secure. The objective of competition 2 instead of minimizing the operation cost, was to maximize the market surplus. The proposed algorithms were tested on another set of improved test cases. Three teams focused on transmission system models including TAMU [6], the UW-Madison [7], and Georgia Tech [8], while the National Renewable Energy Lab (NREL) focused on distribution system models [9]. While the strategies employed by these teams varied, all teams were able to create geographically based, large-scale, realistic synthetic power systems. The case study included six actual industry grids as well as 16 realistic synthetic grids created by three different dataset teams. Also, data from multiple scenarios were created considering variations in the load or weather, and the algorithms were studied under those scenarios. The winners are selected and ranked based on scoring criteria, which consider the solution quality (such as objective functions) with time limits.

III. Problem Formulation, Complexity and Benchmarking

The optimization problem is an AC SCOPF to maximize the market surplus subject to network and generator constraints and steady-state physics including line and generator limits, N-1 security constraints, co-optimization of generation and load dispatch with a price responsive demand model, component participation such as unit commitment with including ramping requirements, topology optimization such as line switching to add or remove branches from service, control settings such as on-load tap changer and phase-shifting transformers with impedance correction tables, and switchable shunts. The complete problem formulation for optimal power flow is available in [10].

The grid sizes are up to 32,000 nodes with around 40,000 edges and include up to 5000 contingencies. The mathematical program to solve this problem requires around 900,000,000 continuous decision variables, 250,000,000 discrete decision variables. The competitors were asked to solve this problem in less than five minutes in one set of divisions for a "real-time" solution and "offline" (60 minutes) in another set of divisions. Two other sets of divisions include the same time criteria but allow competitors to employ switching the status of transmission lines and transformers as permitted by the input datasets.

A benchmarking algorithm is created with the goal of providing an early test driving of the platform and datasets, developing and testing various solution approaches, and instance analysis, searching for unexpected issues in datasets, and estimating problem difficulty and optimality gaps. Heuristic algorithms are proposed for this problem and initially the impacts of the contingency are ignored, and discrete variables are relaxed to a continuous range based on rounding heuristics to improve the problem complexity. Then the relaxed non-convex NLP problem is solved.

The tested approaches include interior point algorithms (e.g. Interior Point Optimizer (IPOPT) [11] and KNITRO [12]), and second-order gradient descent like approaches. These approaches only provide local optimality but based on the experiments seem to be very near global optimality. Sequential Linear/Quadratic Programming such as Gurobi, and CPLEX are tested. The problem is linearized around an operating point in an iterative algorithm.

Most important discrete variables such as unit commitment are solved first. Topology control discrete variables such as line switching and optimization of shunts that are less important and impacted by unit commitment are solved later. Next, the variable bounds are improved based on the solution and the costs associated with discrete variable controls are increased.

The quadratic convex relaxation for ACOPF with realistic side constraints are introduced in [13]. Parallel derivative computations are used, and the Julia and JuMP languages are used for programming. The open source benchmarking algorithm is available at [14].

IV. Datasets and Case Studies

The case studies used in challenge 2 include 16 synthetic grids with 84 scenarios created by three data teams that are available in [15], and six industry (actual) datasets composed of 36 scenarios that cannot be made publicly available. The scenarios are created based on changes in the load and the availability of renewable energy resources.

All power flow network configuration data files are provided in a specific format as an input for competitors. The input data is validated based on actual grids. The difficulty of each grid is assessed and the existence of a feasible solution for each grid is verified. A summary of the synthetic and industry cases used in the competition is given in subsections A and B, respectively.

A. Synthetic Grids

Texas A&M University (TAMU) synthetic grids:

The TAMU synthetic grid models are created using publicly available data provided by the U.S. Census Bureau and generator information provided by Energy Information Administration (EIA). These grids are created over certain geographic footprints with providing latitudes and longitudes but since the structure of these grids is not the same as industry grids, they do not include CEII. The fundamental steps for the creation of synthetic power system models including geographic load, generator substations, and assignment of transmission lines are presented in [16]. The overall approach for building these networks, which is explained in [6] and [16] includes substation planning, transmission planning, and reactive power planning.

Key challenges in the creation of these grids include geographic constraints such as lakes, mountains, and urban areas, as well as network topology parameters, power flow feasibility for the base and N-1 contingency conditions, computational challenges arising from the n^2 possible combinations of branches (where n is the number of buses), multiple competing metrics, and consideration of contingency conditions that further increases computational time. The North American Eastern Interconnect (EI) and Western Electricity Coordinating Council (WECC) cases are used as a benchmark to validate the synthetic grids. References [17, 18] present some metrics for validating synthetic grids for achieving realistic data sets. Graph theory is used for topological metrics such that nodes are buses; and edges are transmission lines. Table I shows a summary of important characteristics of Texas A&M University (TAMU) synthetic grids.

TABLE I
IMPORTANT CHARACTERISTICS OF TAMU GRIDS

Grid / Number	GOTX600	GOTX2000	GOTX12K	GOTX31K
Buses	617	2020	12209	31777
Substations	737	1250	7500	15500
Areas	1	1	7	24
Transmission Lines	723	2318	13216	34713
Transformers	130	538	2,184	6858
Loads	405	1392	6986	16578
Generators	94	194	2009	4663
Shunts	50	98	724	1996
Phase Shifters	2	2	5	4
Total Load GW	8	17	51	372

University of Wisconsin (UW-Madison) synthetic grids:

The UW-Madison grids are created using the methods described in [7]. First, synthetic substations with associated geographic coordinates and load were created as described in [19]. The peak load value was determined for each of the 50 states in the US, utilizing historical data from utility companies, independent service operators (ISOs) or regional transmission organizations (RTOs). Next, databases of land use category and intensity were utilized to disaggregate a percentage of the peak load in each state across each of the census tracts in that state. Next, week-long to year-long load profiles for various load types were obtained from New York State Electric and Gas Corporation (NYSEG), and NREL. These load profiles were combined with the disaggregated peak load data across each census tract to create a year's worth of synthetic load data with hourly resolution. Then, synthetic substations with associated geographic coordinates and synthetic load data were combined with publicly available generator information from the EIA 860 report [20] as the required input data for creating synthetic power system grid models.

TABLE II
IMPORTANT CHARACTERISTICS OF UW-MADISON GRIDS

Grid / Number	FLA	ISO-NEW	NENY	GASCAL	SOUTH
Buses	4224	6049	6889	8316	16789
Substations	1797	3145	3019	4725	7911
Areas	2	6	10	7	7
Transmission Lines	2605	4920	4248	7723	14724
Transformers	2325	3086	3619	4249	8654
Loads	1673	3368	4625	4457	6986
Generators	399	406	609	813	2009
Shunts	436	236	212	1179	724
LTC	1846	2735	760	440	997
Phase Shifters	3	3	5	3	2
Total Load GW	50	25	48	88	103

For transmission planning, rather than discard a large number of the potential transmission lines that could be constructed in the synthetic network, the University of Wisconsin network creation algorithm retains most of the $n^2/2$ potential paths, and utilizes optimization techniques to ensure only a small subset of these potential paths are included in the final network. A three-level algorithm was designed to create the synthetic grids. For a given generation and load scenario, the inner loop computed the flows on each of the potential and existing transmission lines utilizing a modified network flow algorithm. These resulting flows were passed to the middle loop which modified the network topology by adding the potential path with the highest flow and changing the line limits for existing lines. After the termination of the middle loop, the outer loop updated the load and generation scenario and computed a new net injection scenario that was passed to the inner loop. This process was repeated until all load and generation scenarios were considered or a target bus to branch to bus ratio is met. After the initial topology was established using the three-level algorithm, initial network parameters were assigned based on the line MVA limits in the middle loop. DC power flow calculations were run sequentially, with a subset of the overloaded or substantially underutilized transmission lines being upgraded or downgraded after each DC power flow calculation. This resulted in the subnetworks at each voltage level becoming disconnected, so the three-level network creation algorithm was again run on the subnetworks at each voltage level to ensure each subnetwork was mostly connected. For each subnetwork, transmission lines were added to the network until the target bus to branch ratio was met. Finally, this DC "planning case" was modified to become ACOPF feasible using a modified version of the algorithm described in [21]. A summary of Wisconsin grids is shown in Table II.

Georgia Tech (GA) synthetic grids:

The GA network data is a snapshot of the French transmission grid provided by the French Transmission System Operator (TSO) Réseau de Transport d'Électricité (RTE) for the N70_S2000 case. Other synthetic grids were originally created by the UW-Madison team for the GO Competition Challenge 1 and explained in more detail in chapters 3, 4, and 7 of [7], but modified and the required data for the GO Competition Challenge 2 was provided by Georgia Tech team.

The N70_S2000 grid contains information about each bus, transmission line, transformer, generator, and load. However, all component names are obfuscated, which prevents direct identification of the real network information. Geo-coordinates for each bus are then reconstructed by combining the grids' information with publicly-available data, namely, the location and voltage level of all substations in France [22]. The reconstruction of geo-coordinates is formulated as an optimization problem, where the objective seeks to minimize the reconstruction error on the length of transmission lines, constraints enforce that each substation is assigned to a compatible location, and other constraints that ensure no two substations are assigned to the same location [23]. Table III shows a summary of important characteristics of GA grids.

TABLE III
IMPORTANT CHARACTERISTICS OF GA GRIDS

Grid Number	**N70_S2000**	**N81_WILIAMN**	**N82_NEISOV9**	**N82_NEISOV6**	**N12_WILIAMN**	**N14_105TX2ND4U**	**N20_UW_LA2MN**
Buses	2312	3288	3970	4601	8718	10480	19402
Areas	18	1	1	1	1	1	1
Transmission Lines	2188	3577	4563	5204	9991	9991	23145
Transformers	857	1455	2138	2180	4897	4897	11754
Loads	1529	4198	2744	3369	12744	7846	5819
Generators	479	707	391	408	368	1209	968
Shunts	322	23	13	17	107	1730	2451
LTC	773	0	0	0	5	5	12
Phase Shifters	0	0	0	0	26	26	36

Total Load (GW)	25	52	25	29	48	48	155

A. *Industry Grids*

Industry grids are actual grids, which are used for the GO competition 2 but are CEII and cannot be published. The main challenge with these grids was selecting, organizing, and adjusting the real data according to the competition format. Table IV shows a summary of important characteristics of industry grids.

TABLE III
DETAILS OF INDUSTRY GRIDS

Grid Number	MS RBB	FRANCE-EHV-LYONBB	GO TxSPP	France_BB	AUS2	GOTx WECC
Buses	403	3411	3593	6705	16955	22720
AC Lines	438	3628	2160	7384	16071	17859
Transmission Lines	112	871	2004	1578	4675	10110
Loads	384	2959	1355	5696	9419	8369
Generators	139	969	602	2042	1868	4203
Shunts	9	56	370	77	1630	1635
Generator Contingencies	138	968	80	2024	0	100
Branch Contingencies	276	2220	421	4555	3803	900

V. DATA VALIDATION AND SOLUTION EVALUATION

Data checker and solution evaluator software were developed and were publicly available from the start of the competition at [24]. The data checker is used to verify that every instance of the competition problem is formatted correctly and satisfies the data properties asserted in the competition formulation. The solution evaluator is used to evaluate a solution provided by a solver for a problem instance. Solution evaluation verifies that the required solution files exist and ensures that it is formatted correctly, while evaluating the variable bounds and constraints, and computing the total objective value. The solution evaluator computes the maximization objective, which is the total market surplus MS, including benefits from energy consumption, minus costs and penalties.

Instances of the problem were constructed for multiple scenarios of multiple networks. Each power system network model consists of the buses, lines, transformers, generators, loads, and other power system components. Scenarios for each network were generated by varying conditions of weather, load, fuel markets, equipment maintenance, and limits on equipment flexibility imposed by hypothetical operating practices. For the final event, a total of 84 networks including synthetic and industry grids and 120 scenarios were studied.

A prior point solver, packaged with the data checker and solution evaluator, was developed to construct a baseline objective value for each scenario. The prior point solver creates a feasible solution by setting every variable equal to the value it held in the prior operating point provided in the data. Then these variable values are projected onto simple bounds and bounds that can be derived from constraints, to ensure the feasibility of the prior point solution.

The algorithms from all competitors were run and evaluated on all scenarios in all divisions on a common hardware platform consisting of a cluster of up to 6 nodes and 144 cores. For each network, a network score was computed as a combined score for all of scenarios of that network. A dataset score was computed as a combined score from all scenarios. The dataset scores for all competitors determined the rankings within each divisions.

VI. Numerical Results and Analysis

A popular approach to solving large-scale non-convex MINLP problems uses interior-point quasi-second-order-gradient-descent algorithms such as IPOPT [11] or KNITRO [12] which require the computation of the gradient and Hessian of each constraint at each iteration. In addition, sequential linear quadratic programming algorithms that linearize around an operating point are usually being implemented using Gurobi or CPLEX solvers. These solvers are often used as subroutines for building sequential algorithms. However, both methods only provide local optimality. Different strategies are proposed by different teams and the general strategies of the top six winners are explained below in more detail.

1) *Gravity X team: ranked first*

This team grouped the discrete variables into batches and then solved a sequence of non-convex continuous problems while rounding some of the discrete variables after each solution using an iterative Batch Rounding algorithm inspired by MINLP heuristics such as feasibility pump [25] and fix-and-relax method [26]. They found a subset of important variables and active constraints and ignored non-active constraints. They utilized IPOPT solver, which is an open-source solver. For initialization, all voltage magnitudes are set to one per unit and their angles to zero. The Gravity language, which is a fast-modeling language with symbolic differentiation and disjunctive constraint support, is used to model and solve the MINLP problem. Also, instead of solving ACOPF for all contingencies, they solved the base case and made some adjustments on the problematic buses of the solution for each contingency. This team ran more than 2650 experiments in the testing environment sandbox to improve their algorithm and tune parameters. For simplification, this team ignored line switching constraints.

2) *NU_Columbia_*Artelys team: ranked second

This team used a combination of the solver KNITRO for optimization and the IPOPT method as a filter function. They used a KNITRO merit function for step-size computation and provided a balance in optimality and feasibility. They used Python for simulation and AMPL as an intermediary between their Python code and KNITRO. This team only considered binary variables and modeled integers as the summation of binary variables. Also, instead of solving ACOPF for all contingencies, they solved the base case and made some adjustments on the problematic buses of the solution for each contingency. They used an initial solution as a candidate, ran KNITRO on the relaxation iteratively, fixed integer variables and then reran the whole problem. They observed which buses from the initial solution were infeasible beyond a certain threshold, then fixed integer variables elsewhere and ran the problem with the integer variables fixed.

3) *GOT-BSI-OPF* team: ranked third

This team used a feasible region based homotopy-enhanced IPOPT method [27] to solve the ACOPF. Their hypothesis was that since the most challenging constraints for an ACOPF are inequality constraints, this team found the active inequality constraints to reduce the problem size. They first neglected thermal limits to reduce the nonlinear constraints to zero and then found the active inequality constraints to reduce the problem size. They applied a homotopy two-stage IPOPT with and without considering active thermal limits. They included any thermal limits that were violated or at their limit in the next step. If only constraints with thermal limit violations are solved, the number of thermal nonlinear constraints were reduced. They also did a sensitivity analysis for discrete variables and considered state estimation results from supervisory control and data acquisition (SCADA) online data. Based on their observation, the proposed two-stage method with and without thermal inequality constraints was more robust compared to the single stage IPOPT method. The convergence of the proposed Homotopy method for nonlinear problems is in [27]. This team has also studied the feasible region in [28]. Trust-tech methodology [29] is also used for unit commitment and other binary variables, based on branch-and-bound is used that can be added to heuristic algorithms such as Particle swarm optimization (PSO) and genetic algorithm (GA). The theory behind the proposed method is published in [30].

4) *Pearl Street* technologies: ranked fourth

This team proposed equivalent circuit programming for power flow model optimization. They developed software called SUGAR (Suite of Unified Grid Analyses with Renewables) [31], which is an equivalencing tool for power grid optimization and is mainly used for circuit optimization. They designed the adjoint circuit to achieve the desired properties of the optimal solution and then reverse engineered it to mathematical objectives and constraints on power system response. They implicitly modeled a relaxed discrete variable such as unit commitment, control models and line switching and achieved a fast solution.

5) *Electric Stampede team: ranked fifth*

This team used Python and coupled two optimization problems: one with mixed integer linear programming (CPLEX solver) and another one with continuous non-linear constraints (IPOPT). They first ignored unit commitment and ran an ACOPF. They then combined DCOPF with unit commitment and a linearized cost function. For simplification this team also removed line switching constraints.

6) *GMI-GO team: ranked sixth*

This team created two decoupled problems and handled integer decisions and nonlinear constraints separately. They used heuristics for unit commitment and line switching to ignore integer variables. IPOPT was used for solving an ACOPF, and similar to most other teams and benchmarking algorithms, contingencies were solved based on their ranks. The decoupled method solved the base case first and then IPOPT solver was used to modify the base case. They used various heuristics and unit commitment adjustments.

More information about the strategies used by the winners is available in [32].

Overall, it is observed that the Gravity X is the winner of the competition but for four industry cases, Gravity X did not perform as it did for synthetic grid, the main problem is because of active and reactive power imbalance on some buses. This can be an indication of problems in tuning control devices such as transformer controls, switchable shunts, or set points of generators.

VII. CONCLUSION

The GO competition is run as a significant effort to find the best solution within a time limit to non-convex MINLP power system operation and electricity market problems, particularly ACPF with contingencies, reactive power control and component participation constraints. The results and strategies of the top six strategies to solve these problems are analyzed and unusual behaviors and different performances are observed on top strategies on synthetic versus industry grids. For the synthetic network models, Gravity X is the overall winner with the highest objective value for all but two grids where it was second place. However, Gravity X did not perform well on four out of six industry grids because of a real or reactive power imbalance on some buses that lowered its score. In addition, most synthetic grids have the same top-ranked team for different scenarios while most industry gids have different top-ranked teams, with slight differences in the objective value. One reason is that the competitors did not have access to the full cases and had a limited amount of time to run simulations on the industry grids. However, the heuristic-based algorithms need many experimental runs to improve their solutions and tune parameters based on the resulting performance of the algorithms. Another reason is the existence of bad data and inaccurate models in industry cases.

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