2017 Competition on Modern Heuristic Optimizers for Smart Grid Operation: Testsbeds and Results (Revised)

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Abstract

This paper summarizes the two testbeds, datasets, and results of the IEEE PES Working Group on Modern Heuristic Optimization (WGMHO) 2017 Competition on Smart Grid Operation Problems. The competition is organized with the aim of closing the gap between theory and real-world applications of evolutionary computation. Testbed 1 considers stochastic OPF (Optimal Power Flow) based Active-Reactive Power Dispatch (ARPD) under uncertainty and Testbed 2 large-scale optimal scheduling of distributed energy resources. Classical optimization methods are not able to deal with the proposed optimization problems within a reasonable time, often requiring more than one day to provide the optimal solution and a significant amount of memory to perform the computation. The proposed problems can be addressed using modern heuristic optimization approaches, enabling the achievement of good solutions in much lower execution times, adequate for the envisaged decision-making processes. Results from the competition show that metaheuristics can be successfully applied in search of efficient near-optimal solutions for the Stochastic Optimal Power Flow and large-scale energy resource management problems.

Keywords: Evolutionary Computation, Metaheuristics, Power systems, Optimization, Smart grids, Swarm Intelligence.

1. Introduction

The dawn of Smart Grids (SG) together with the high penetration of Distributed Generation (DG) poses a new level of complexity in power system operational planning [1]. Broadly speaking, the complexity resides in the consideration of stochastic variables in the mathematical formulation of optimization problems (associated with the increasing penetration of renewables) [2]. This paper introduces two testbeds, which constitute a valuable reference for testing and comparing heuristic optimization algorithms:

Testbed 1 concerns with the stochastic Optimal Power Flow (OPF) based active-reactive power dispatch. The implementation of the problem evaluation (i.e., calculation of objective function and constraints) is built upon the active-reactive OPF for the IEEE 57-bus system, including the stochastic behavior of wind, solar and small-hydro generation.

Testbed 2 considers an energy aggregator that can procure energy needs from several resources and the electricity market to make revenues from reselling energy to its customers. In addition, it uses its assets, e.g., storage units, to

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supply the load demand [3, 4]. However, to provide practical operational support for aggregators in SGs, a complex Energy Resource Management (ERM) problem must be solved. The ERM problem that an aggregator must solve considers a huge variety of Distributed Energy Resources, such as Electric Vehicles (EVs), Energy Storage Systems (ESS), and DG units including renewables [5]. Additionally, considering Demand Response (DR), Vehicle-to-Grid (V2G) capabilities, market bids and external suppliers, along with AC network power balance constraints, turns the ERM into a Mixed-Integer Non-Linear Programming (MINLP) problem [6, 7].

This paper shows how the 2017 Competition on Smart Grid Operation Problems was organized by the authors, whose main role was to develop the encrypted codes for calculation of objective function, evaluation of constraints, and automatic saving of results. To guide the reader throughout the essence of the implemented codes, the format and implementation aspects of the two testbeds, i.e., Testbed 1: Stochastic OPF based active-reactive power dispatch, and Testbed 2: Optimal scheduling of distributed energy resource, are overviewed. The paper also provides datasets as well as the characteristics and results achieved by the top three (winning algorithms). Nine algorithms participated in Testbed 1, whereas five algorithms participated in Testbed 2. These algorithms were developed by different researchers worldwide. They contributed by developing, tuning, and testing their algorithms. The participants were allowed to test their algorithms by considering a predefined computing budget, which was defined in terms of a limited number of function evaluations. Hence, it is worth pointing out that the performance of the participants' algorithms was compared by considering the obtained fitness value over a given number of attempts. This is more practical for real-world engineering problems. However, for other problem types, which are out of the scope of this paper, in which the convergence characteristic is of interest, the evaluation criteria could be extended to include a measure that accounts for both the fitness of the obtained best solution and the convergence characteristic.

Section 2 shows the competition structure and schedule. Section 3 and Section 4 present in detail the two proposed testbeds, respectively. The evaluation criteria are outlined in section 5. The best performing metaheuristic algorithms are presented and analyzed in section 6. Section 7 concludes the paper and provides final remarks.

2. Competition structure and schedule

The application of heuristic optimization algorithms to solve power system optimization problems is receiving significant attention due to their potential to deal with inherent mathematical complexities such as high-dimensionality, non-linearity, non-convexity, multimodality and discontinuity of the search space [8, 9]. Knowing this, the Working Group on Modern Heuristic Optimization (WGMHO) under the IEEE PES Power System Analysis, Computing, and Economics Committee organized a special panel in the 2014 IEEE PES General Meeting, which consisted of a competition focusing on the application of these tools for solving Optimal Power Flow (OPF) problems. That was the first step towards the development of power system optimization testbeds, which are aimed at ascertaining and performing comparative analysis on the general applicability and effectiveness of emerging tools in the field of heuristic optimization. The next step was the 2017 competition.

The 2017 Competition on Smart Grid Operation Problems[1], proposed by WGMHO, introduces two benchmark problems (also denoted as optimization testbeds):

[1] http://sites.ieee.org/psace-mho/2017-smart-grid-operation-problems-competition-panel/

- Testbed 1: Stochastic Optimal Power-Flow based active-reactive power dispatch.
- Testbed 2: Optimal scheduling of distributed energy resources.

The competition organizers provided explicit guidelines to challenge worldwide researchers to solve the benchmark problems, which are treated as black-box problems. The competitors are only allowed to improve the methodological framework of their algorithms. The platform used for this competition (including the datasets) was implemented in MATLAB ©. The schedule of the competition was as follows:

- 14 January 2017: Call for competition.
- 30 January 2017: Confirmation of participation.
- 30 March 2017: Submission of results and codes.
- 28 April 2017: Announcement of the best three ranked algorithms.
- 16-20 July 2017: Presentation of the winners at the IEEE PES General Meeting.

3. General description of Testbed 1

3.1. Target function

The target in the active-reactive power dispatch is to minimize the total fuel cost while fulfilling constraints (associated with nodal voltages, nodal balance of power, maximum active power output of slack generator, generator reactive power capability, and allowable branch power flows) for normal and selected N-1 conditions.

In the testbed 1 competition, the target is to minimize the total fuel cost of the traditional generators plus the uncertainty cost function (expected cost) for renewable generators. Each renewable generator is considered to be a dispatchable generator and depending on the available active power, it is considered an underestimated or overestimated condition [10, 11].

The available active power of a renewable generator is not known with certainty. Nevertheless, in some cases, it is possible to know the probability distribution of the primary energy source like the wind speed, solar irradiance or the river flow. In this way, considering the relation between the primary energy source and the available active power (Pai), it is possible to get the probability distribution of Pai.

In order to obtain the probability distribution of the available power from the known primary energy source probability distribution, it is proposed to develop Monte Carlo simulations. That is to say, through scenarios of wind speed, solar irradiance or river flow, given by random scenarios from the primary energy source probability distribution. Using the relation between the primary energy source and the injected power in the network, it is possible to get scenarios of the available active power, and through a histogram its probability distribution.

Using the Underestimated and Overestimated condition, it is proposed in this competition to calculate through Monte Carlo simulations an uncertainty cost function given by the different costs for the different available active power scenarios. In this way, it is possible to get the histogram of the uncertainty cost function considering the following steps:

i) Generate a random primary energy source value (following the probability distribution of the wind speed, solar irradiance or the river flow) of scenario j. ii) Calculate the available active power of scenario j for renewable generator i (Pai_j) using the relation between the primary energy source and Pai_j. iii) Verification of the underestimated ($Psi < Pai_j$) or overestimated ($Psi > Pai_j$) condition in scenario j. Psi corresponds to the variable decision for renewable generator i. iv) Calculate the uncertainty cost for scenario j (cu and co are the penalization costs for underestimated and overestimated conditions, respectively):

$$Ci_j = cu(Pai_j - Psi) \quad if \quad Psi < Pai_j \tag{1}$$

or

$$Ci_j = co(Psi - Pai_j) \quad if \quad Psi > Pai_j \tag{2}$$

v) Repeat the steps i) to iv) N times (in this competition N is set to 5000 times). vi) Build the histogram of the uncertainty cost function for the N scenarios. vii) Calculate the expected cost of the uncertainty cost function for renewable generator i.

3.2. Test system

The IEEE 57 bus system has seven generators. In this competition, three of them are considered renewable generators, namely in the buses 2, 6 and 9.

- **Target**: Minimize the total fuel cost of traditional generators (buses: 1, 3, 8, 12) plus the expected cost of the uncertainty cost function for renewable generators (buses: 2, 6, 9).

- **Constraints**: There are 3 types of constraints:

i) Power flow constraints.

The constraints are associated with the nodal balance of power (these are equality constraints).

ii) Constraints penalized in the fitness function.

Nodal voltages for load buses (42 for the upper limits and 42 for the lower limits), allowable branch power flows (80), generator reactive power capability (7 for the upper limits and 7 for the lower limits), the maximum active power output of the slack generator (1); for normal (non-contingency) and selected N-1 conditions, that is to say, 179 for non-contingency conditions, and 178 for each N-1 condition.

iii) Minimum and maximum levels of optimization variables.

- **Optimization variables**: 31, comprising 13 continuous variables associated to generator active power outputs (6, the slack is not considered here) and generator bus voltage set-points (7), 15 discrete variables associated to stepwise adjustable on-load transformers tap positions, and 3 binary variables associated to switchable shunt compensation devices.

- **Considered contingencies (N-1 conditions)**: outages at branches 8 and 50.

- **Number of function evaluations**: 50,000.

- **Six cases** corresponding to different cases of stochastic scenarios.

3.3. Cases overview

3.3.1. Stochastic OPF for IEEE 57 bus system considering wind generators (Cases 1 and 4)

For the cases 1 and 4, it is considered that the three renewable generators are wind generators. It is well known that the wind speed probability distribution follows a Weibull distribution [12, 13]. Additionally, there is a relation between the wind speed and the available active power. In this way, it is possible to get the probability distribution of the available active power. In the competition files, there is a file (named WindStochastic.m) with the mentioned process in order to get the 5000 Monte Carlo scenarios for the available active power. Case 1 for this competition considers that each participant must use the same Monte Carlo scenarios.

For case 4, each competitor will have his own Monte Carlo scenarios generated with the WindStochastic.m. It was required that the competitors send the scenarios, in order to validate that a Weibull distribution was used for the wind speed.

3.3.2. Stochastic OPF for IEEE 57 bus system considering wind and solar generators (Cases 2 and 5)

For the cases 2 and 5, it is considered that two renewable generators are wind generators and the other a solar generator. It is well known that in several parts of the world the solar irradiance probability distribution follows a lognormal distribution [10]. Additionally, there is a relation between the solar irradiance and the available active power. In this way, it is possible to get the probability distribution of the available active power. In the competition files, there is a file (named SolarWindStochastic.m) with the mentioned process in order to get the 5000 Monte Carlo scenarios for the available active power. Case 2 for this competition considers that each participant must use the same Monte Carlo scenarios.

For case 5, each competitor will have his own Monte Carlo scenarios generated with the SolarWindStochastic.m. It was required that the competitors send the scenarios in order to validate that Weibull and lognormal distributions were used for the wind speed and solar irradiance, respectively.

3.3.3. Stochastic OPF for IEEE 57 bus system considering wind, solar and small-hydro generators (Cases 3 and 6)

For the cases 3 and 6, it is considered that at bus 2 there is a wind generator and that at buses 6 and 9 there are two generators, namely a solar generator and a small-hydro generator. It is well known that the solar irradiance probability distribution follows a lognormal distribution and the river flow follows a Gumbel distribution [14]. Additionally, there is a relation between the solar irradiance and the available active power, and between the river flow and the available active power. In this way, it is possible to get the probability distribution of the available active power. In the competition files, there is a file (named SolarWindHydroStochastic.m) with the mentioned process in order to get the 5000 Monte Carlo scenarios for the available active power. Case 3 for this competition consider that each participant must use the same Monte Carlo scenarios.

For case 6, each competitor will have his own Monte Carlo scenarios generated with the SolarWindHydroStochastic.m. It was required that the competitors send the scenarios in order to validate that Weibull, lognormal and Gumbel distributions were used for the wind speed, solar irradiance and river flow, respectively.

4. General description of Testbed 2

In testbed 2: Optimal scheduling of distributed energy resources, the optimization of two large-scale centralized Day-ahead energy resource scenarios were proposed.

4.1. Target function

The envisaged problem is a hard combinatorial Mixed-Integer Non-Linear Programming (MINLP) problem due to a high number of continuous and discrete (i.e., binary) variables and non-linear network equations. The objective of the aggregator is to maximize profits, i.e., income (In) minus operation cost (OC).

Function OC_{Total}^{Day+1}, defined in Eq. 3, represents the operation cost of the resources managed by the aggregator:

$$\text{Minimize } OC_{Total}^{Day+1} = \sum_{t=1}^{T} \left(\begin{array}{c} \sum_{I=1}^{N_I} P_{DG(I,t)} \cdot C_{DG(I,t)} + \sum_{I=1}^{N_I} P_{GCP(I,t)} \cdot C_{GCP(I,t)} + \sum_{L=1}^{N_L} P_{NSD(L,t)} \cdot C_{NSD(L,t)} + \\ \sum_{L=1}^{N_L} P_{LDR(L,t)} \cdot C_{LDR(L,t)} + \sum_{J=1}^{N_J} P_{Sup(J,t)} \cdot C_{Sup(J,t)} \\ \sum_{K=1}^{N_K} P_{Sdis(K,t)} \cdot C_{Sdis(K,t)} + \sum_{M=1}^{N_M} P_{Vdis(M,t)} \cdot C_{Vdis(M,t)} \end{array} \right) \tag{3}$$

where the first term corresponds to DG generation cost; the second term is the Generation Curtailment (GCP) cost; the third term refers to Non-Supplied Demand (NSD) penalizations; the fourth term is the cost of DR programs; the fifth term quantifies the external suppliers energy cost; and the sixth and seventh term are associated with discharging of EVs and ESSs, respectively. On the other hand, the aggregator can receive incomes (In_{Total}^{Day+1}) from four sources, as illustrated in (4):

$$\text{Maximize } In_{Total}^{Day+1} = \sum_{t=1}^{T} \left(\begin{array}{c} \sum_{L=1}^{N_L} P_{Load(L,t)} \cdot U_{Load(L,t)} + \sum_{N=1}^{N_N} P_{Sell(N,t)} \cdot U_{Sell(N,t)} + \\ \sum_{K=1}^{N_K} P_{Scha(K,t)} \cdot U_{Scha(K,t)} + \sum_{M=1}^{N_M} P_{Vcha(M,t)} \cdot U_{Vcha(M,t)} \end{array} \right) \tag{4}$$

where the first term represents the revenue from the consumer's demand; the second term is referred to profits of selling to the pool market; the third and fourth are the incomes that the aggregator perceives for charging EVs and ESS, respectively.

Therefore, to deal with a single-objective optimization problem, it is formulated as a minimization function Z, as shown in Eq. 5:

$$\text{Minimize} \quad Z = OC_{Total}^{Day+1} - In_{Total}^{Day+1} \tag{5}$$

The minimum value of Z (hopefully negative) is the profit of the energy aggregator. The aggregator perceives profits only if Z is negative. Otherwise, if Z is a positive value will mean that operation costs are higher than incomes. Thus, profit is $P = -Z$, where P is the profit. Nevertheless, the goal in optimization terms is to obtain the minimum value of Z in the metaheuristics form.

The full mathematical model also includes network power constraints similarly to [6, 15]. The problem is mainly constrained by the network equations, namely active and reactive powers balance, voltage and angle limits, DG generation and supplier limits in each period, ESS capacity, charge and discharge rate limits, EVs capacity, EVs trips requirements, charge and discharge efficiency and rate limits. A full AC power flow is used to check the network conditions [16].

4.2. Metaheuristic method framework

In this competition, for testbed 2, the method of choice used by the participants to solve the presented problem must be a metaheuristic-based algorithm. The structure adopted in the competition is described in this document and follows the framework presented in Fig. 1.

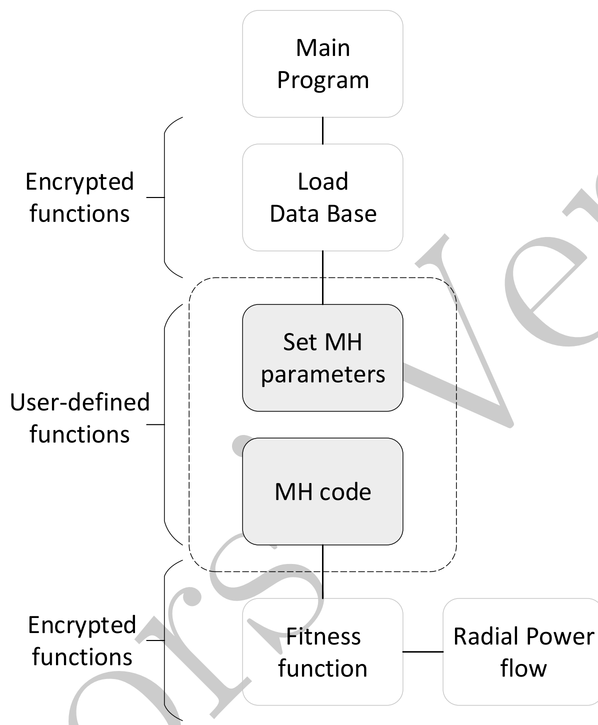

Figure 1: Required functions for the 2017 competition.

The competitors are provided with a set of encrypted functions for loading a dataset and evaluate the fitness of a solution. Additionally, the set of functions includes as an example the metaheuristic differential search algorithm [17] implemented and adapted to solve the energy resource management. The competitors should then replace the blocks "Set MH parameters" and "MH code" to test their metaheuristics.

4.3. Solution encoding

The competitors should encode the solutions as vectors $\vec{x} = (x_1; x_2; ...; x_D)$. Such vectors must contain sufficient information to evaluate the encrypted fitness function, i.e., continuous variables corresponding to active and reactive power of DG and charge and discharge values for EVs and ESS; and also DG units binary variables indicating a connection ('1' value) or a disconnection ('0' value) of the corresponding unit.

The number of variables for a solution in the implemented codes is case-study dependent. However, the variables should follow a given order, shown in Fig. 2, to respect the fitness function and given bounds. The variables are grouped into eight categories repeated for each period (i.e., 24 periods in the proposed competition), giving as a total the dimension of the problem $D = 49,848$ for case study 1 and $D = 154,800$ for case study 2. A solution matrix with N solutions (i.e., SM^{NXD}) is also represented in Fig. 2.

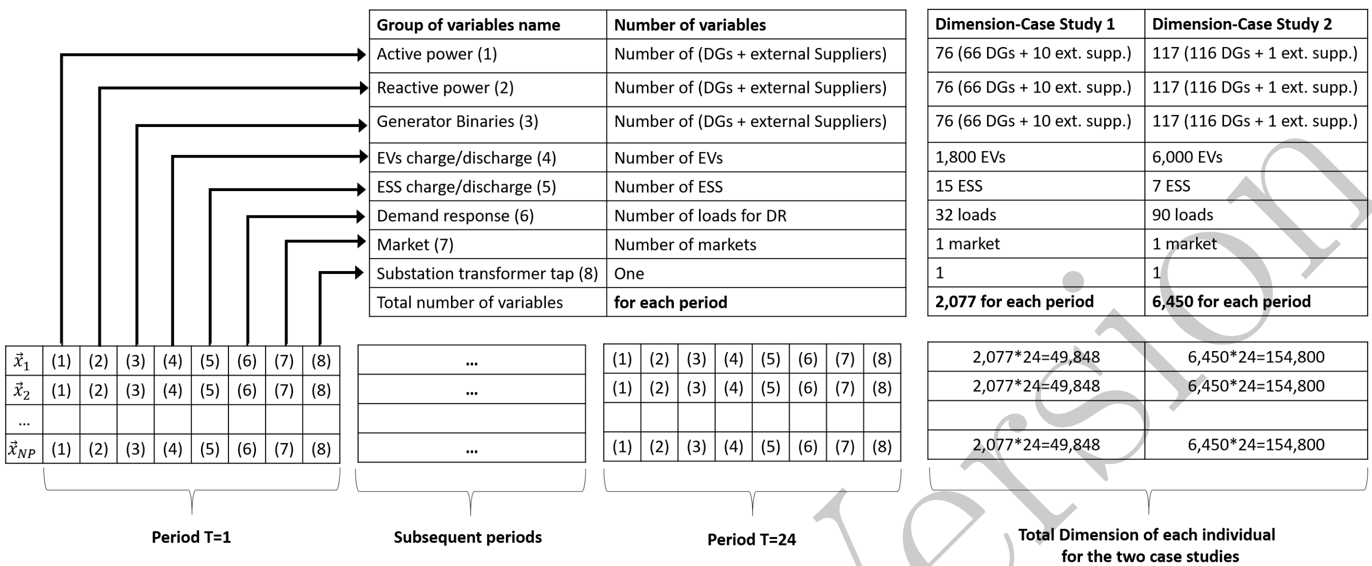

Figure 2: Groups of variables for one period that form a solution and structure of a solution Matrix. Rows correspond to solutions while each column corresponds to a set of variables.

The competitors are free to propose any search method to evolve their solutions. They are also allowed to specify any number of solutions (population size) and iterations for their proposed metaheuristics as long as they do not violate a fixed maximum number of 50,000 fitness evaluations.

4.4. Fitness function

The fitness function f (Eq. 6) considers the objective Z of the aggregator (see Eq. 5), plus the summation of the penalties found during evaluation of the solution:

$$\text{Minimize } f = Z + \rho \sum_{i=1}^{N_p} \max[0, g_i] \tag{6}$$

In this case, g_i is the value of the i-th constraint (equality and inequality), and ρ is a configurable penalty factor (high value).

4.5. Some notes on the implementation of the problem

- Internally in the fitness function, it is assumed that the charge/discharge variables for the EVs are the same, but positive is charge value and negative is discharge to save computational memory.
- The same principle described above for EV applies to the stationary storage variables.
- The market in which the aggregator participates can accept any bid amount
- Internally, the market value is positive for an offer (sale) and negative for a bid (buy).

- Direct repair of solutions is used in the fitness function.
- A maximum number of 50,000 evaluations is allowed in the competition. (Take into account that it is not the same as algorithm iterations).

4.6. Scenarios overview

Two case studies, i.e., a 12.66 kV 33-bus and a 30 kV 180-bus distribution network, are considered to test the competitors' algorithms.[2]

4.6.1. Scenario 1: 33-bus network

The 33-bus network scenario adapted from [20] includes 67 DGs (with a large wind unit), ten external suppliers, 15 ESS and 1800 EVs with V2G capabilities. External suppliers are modeled as a substation connected to the main grid in bus 33. Demand Response (DR) with Direct Load Control (DLC) is considered, setting DLC contracts to 0.02 m.u./kWh (m.u.: monetary units). The consumers receive this benefit for each unit of energy reduced, instead of paying the aggregator contracted supply price of 0.14 m.u./kWh. The selling energy price is set to 0.14 m.u./kWh as well. A fleet of 1800 EVs with V2G capabilities is considered with a total energy demand predicted for trips of 13.77 MWh and a total of 2553 trips. The discharging cost for EVs and ESS is set to 0.19 m.u./kWh. The charging/discharging efficiency is set to 70% for EVs and 90% for ESS.

Solving an instance of scenario 1, the 33-bus network, using traditional tools (GAMS/MINLP) takes about 19 hours in a state-of-the-art workstation (Intel(R) Xeon(R) CPU- E5-2620 v2 @ 2.10GHz with 16 GB RAM). The optimal value found with a MINLP was 5667 of profits (i.e., a fitness of -5667) [15].

4.6.2. Scenario 2: 180-bus network

For this case study, a 6,000 EVs fleet with total energy demand predicted of 34.26 MWh, corresponding on average to 5.7 kWh per vehicle, and a total of 10,137 trips was considered. The discharging cost for the EVs was set to 0.19 m.u./kWh. For the ESS, the discharging cost (that also includes battery degradation cost) was set to 0.18 m.u./kWh. Charging/discharging efficiency for both, EVs and ESS, was set to 90%. External suppliers contracts are considered with a minimum purchase of 2 MW in the considered time horizon and a maximum capacity of 10 MW. Total forecast load without considering EVs, ESS and DR program was 243.36 MWh.

As reference, GAMS/MINLP takes more than 168 hours to solve scenario 2 (i.e., 180-bus network) in a state-of-the-art workstation (Intel(R) Xeon(R) CPU- E5-2620 v2 @ 2.10GHz with 16 GB RAM). The optimal value found with a MINLP was 3365 of profits (i.e., a fitness value of -3365) [21].

5. Evaluation guidelines

A ranking index is established, which accounts for the statistics of the best fitness value f_{best} obtained for each problem within the specified maximum number of function evaluations in each of the 31 runs considered for the

[2] Both networks represent an SG operated by an aggregator with projections of DG and V2G penetration levels for the year 2040. The considered prices and capacities of DG take into account the observations made in [18]. The scenarios of EVs were developed using the tool presented in [19].

competition. Thus, the success achieved for a single case (denoted as a scenario in testbed 2) is quantified as:

$$Score_i = mean(f_{best-i}) \tag{7}$$

where *mean* stands for the mean value of the 31 trials, and i denotes the scenario (e.g., $i = 1$ corresponds to scenario 1: 33-bus network).

The total score is calculated as the sum of the individual scores corresponding to the total number of scenarios ($N_{Scenarios}$) belonging to the corresponding testbed 2, that is:

$$Total_{score} = \sum_{i=1}^{N_{Scenarios}} Score_i \tag{8}$$

The ranking is based on increasing order of $Total_{score}$. Note that execution time was not taken into account in this competition due to differences in the computer where the algorithms were running. In next competitions, a measure of the convergence might be included in the criterion for selection of the winners.

6. Competition results and metaheuristics

In this section, we provide the official ranking of the competition for both testbeds. Nearly 30 participants registered for this competition from which 14 teams finally submitted results (nine for testbed 1 and five for testbed 2).

Table 1 presents the official ranking for testbed 1 and testbed 2 respectively. This table also summarizes the metaheuristics proposed by the participants and the winning methods.

Table 1: Official ranking for the IEEE PES WGMHO - 2017 Competition on Smart Grid Operation Problems

Team	Algorithm	Position		
		Testbed 1	Testbed 2	Overall
UNESP-LaPSEE (Brazil)	Variable Neighborhood Search (VSN)	2	1	1
INESC TEC-CEFET MG (Portugal-Brazil)	Cross-Entropy Method and Evolutionary PSO (CEEPSO)	1	3	2
CHARUSAT (India)	Chaotic Differential Evolution with PSO (Chaotic-DEEPSO)	3	4	3
CHARUSAT (India)	Levy Differential Evolution with PSO (Levy-DEEPSO)	4	5	4
UNAL (Colombia)	Chaotic Biogeography-based Optimization (CBBO)	N/A	2	5
UFMG (Brazil)	Hybrid Differential Evolution (HDE)	5	N/A	6
NTU-EEE (Singapore)	Differential Evolution (DE)	6	N/A	7
CHARUSAT (India)	Biogeography-Based Optimization (BBO)	7	N/A	8
UB-UTD (USA)	Mixed-Discrete PSO with explicit diversity preservation (MDPSO)	8	N/A	9
CHARUSAT (India)	Artificial Bee Colony (ABC)	9	N/A	10

In next subsection, we provide the scores achieved by all the teams and summarize the winner methods.

6.1. Testbed 1: Competition results and metaheuristics

The best three teams out of the nine participants are summarized in the following paragraphs (see Tables 1 and 2).

First place: The winner of the testbed 1 was INESC TEC-CEFET MG (Portugal-Brazil). They use a combination of a Cross-Entropy Method and Evolutionary Particle Swarm Optimization (CEEPSO). PSO is one of the most popular and successful evolutionary algorithms, with a large number of variants to improve its performance [22, 23]. In this occasion, the PSO algorithm was enhanced by combining it with a method based on cross-entropy. Cross-entropy method was inspired in an algorithm for estimating probabilities of rare events in complex stochastic networks. Soon after, the method was adapted to solve combinatorial optimization problems as well [24]. The combination of these two techniques in the proposed CEEPSO showed promising results getting profits for both case studies in this competition. Further research can be done to improve the performance of the algorithm.

Second place: The second place was UNESP-LaPSEE (Brazil) using a metaheuristic based on Variable Neighborhood Search algorithm (VNS) [25]. VNS is a metaheuristic used for solving combinatorial and global optimization problems. The basic idea of VNS consists in exploring distant neighborhoods from the incumbent solution and moving from there to a new neighborhood only if an improvement is achieved. A local search method is applied iteratively to find locally optimal solutions from the neighborhood. The method only requires one individual to perform the search and proved to be very useful in solving the six cases of testbed 1.

Third place: CHARUSAT (India) participated with two different versions of Differential Evolution with Particle Swarm Optimization (DEEPSO) [26]. In the first variant, named as Chaos-DEEPSO (third place in the competition), DEEPSO search is enhanced by using some principles of Chaotic search [27]. DEEPSO use Chaos to avoid local convergence and obtain more diversity. Further study is required to adopt diversity techniques into the scope of energy resource management problems and in that way, explore their capabilities to get better results.

As additional information, the times reported for the participants were on average 850 seconds to find a solution in each case and run.

6.2. Testbed 2: Competition results and metaheuristics

In this section, we present the three best teams out of five that finally submitted results for testbed 2 (see Table 1 and 3).

First place: The winner of the 2017 competition, testbed 2: Optimal scheduling of distributed energy resources, was UNESP-LaPSEE (Brazil) using a metaheuristic based on Variable Neighborhood Search algorithm (VNS) [25]. VNS showed the best performance in both scenarios of testbed 2 with a very low standard deviation, which indicates the high robustness of the approach. Moreover, this method (based on VNS algorithm) uses only one individual (instead of a population) to explore the search space and find near-optimal solutions efficiently. This team got the second place in the testbed 1 as well. The description of this algorithm can be found in section 6.1.

Second place: The second place of the competition, Universidad Nacional de Colombia (UNAL), used a Biogeography-based Optimization algorithm with Chaos (CBBO) [28]. CBBO is an advanced version of the BBO algorithm proposed by Simon in [29]. BBO has some features in common with other biology-based optimization methods, such as GAs and Particle Swarm Optimization (PSO), and it is primarily inspired on mathematical equations that govern the distribution of organisms (also called biogeography) [30]. The method is combined with chaotic maps to avoid entrapment in local optima and slow convergence speed. This algorithm also presents significant running times in the competition compared to the other participants. However, such times may be caused by the implementation rather than the search method itself.

Third place: INESC TEC-CEFET MG (Portugal-Brazil) obtained the third place using a combination of a Cross-Entropy Method and Evolutionary Particle Swarm Optimization (CEEPSO). This team got the first place in the testbed 1. The description of this algorithm is presented in section 6.1.

As additional information, the times reported for the participants were on average 30 mins to find a solution for scenario 1, and 1 hour for scenario 2 of testbed 2, with the exception of the team UNAL (second place of the competition in testbed 2), that reported on average running times 7 times higher than the rest of the participants. In next competitions, a measure of the convergence might be included in the criterion for selection of the winners.

Table 2: Computed scores of 2017 competition testbed 1 for the six proposed scenarios.

Rank	Algorithm	Case 1 Score	Case 2 Score	Case 3 Score	Case 4 Score	Case 5 Score	Case 6 Score	**Total Score**
1	CEEPSO	72,686.53	72,049.53	60,286.37	71,396.14	70,572.44	60,805.33	**407,796.33**
2	VNS	72,683.97	72,045.84	60,284.28	71,943.91	70,929.22	60,461.50	**408,348.72**
3	LEVY DEEPSO	72,704.19	72,077.57	60,312.79	72,922.17	72,068.92	60,639.53	**410,725.17**
4	CHAOS DEEPSO	72,693.44	72,064.91	60,299.35	72,910.90	71,700.94	61,292.59	**410,962.14**
5	HDE	75,311.72	73,020.86	61,663.61	73,475.22	72,300.21	62,075.09	**417,846.70**
6	DE	87,802.77	74,019.41	62,164.47	87,042.36	72,698.79	62,543.84	**446,271.65**
7	BBO	81,104.44	77,475.82	66,137.55	80,505.27	77,939.38	67,192.12	**450,354.58**
8	MD-PSO	88,224.25	73,670.62	73,533.97	86,723.85	72,968.03	64,497.51	**459,618.23**
9	ABC	86,550.74	88,612.14	89,244.22	85,615.52	70,488.93	82,821.91	**503,333.46**

7. Conclusions and final remarks

This paper described the structure, dataset, and results of the IEEE PES WGMHO 2017 competition[3]. The framework was developed in MATLAB©, and provides a platform for an easy test of metaheuristics even after this competition. We encourage other researchers to use the datasets and framework to propose new search methods to solve these problems efficiently.

In this competition, the participants were able to propose different metaheuristics and explore the convergence capabilities and quality of solutions of metaheuristics solving the stochastic optimal power flow for six cases considering uncertainty (testbed 1) and the day-ahead ERM problem in two different large-scale scenarios without uncertainty (testbed 2). The results allowed us to identify robust metaheuristics that performed quite well in two distinct smart grid problems, namely CEEPSO, VNS, Chaotic-DEEPSO, and Levy-DEEPSO. Despite the fact that CBBO (UNAL team) is well ranked, it did not participate in testbed 1. Among the robust algorithms, VNS and CEEPSO are suggested in this research to be the most effective approaches for the proposed problems.

The authors believe that this kind of work contributes to bridging the gap between theory and real-world application of evolutionary computation. The developed testbeds constitute a unique and valuable platform to test new algorithms and to compare their performance against the best algorithms identified in the competition. This is very important to ascertain the effectiveness of new algorithms to tackle real-world smart grid optimization problems 1) considering high uncertainty and 2) large-scale number of optimization variables. This competition was very important as a learning

[3] The complete dataset, instructions and results can be found in: http://sites.ieee.org/psace-mho/2017-smart-grid-operation-problems-competition-panel/

Table 3: Computed scores of 2017 competition testbed 2 for the two proposed scenarios.

Rank	Algorithm	Scenario 1 (33-bus)				Scenario 2 (180-bus)				**Total score**
		Score	Best fitness	Worst fitness	Std	Score	Best fitness	Worst fitness	Std	
1	VNS	-5595.98	-5597.27	-5594.51	0.86	-3054.00	-3060.56	-3045.90	3.68	**-8649.99**
2	CBBO	-5387.60	-5399.60	-5378.53	4.96	-2652.86	-2680.75	-2640.87	9.89	**-8040.46**
3	CEEPSO	-5185.26	-5216.82	-5128.71	20.48	-2550.12	-2566.78	-2519.15	17.08	**-7735.38**
4	CHAOS-DEEPSO	-4655.81	-5015.34	-3993.63	205.71	-2500.55	-2558.72	-2480.92	22.86	**-7156.36**
5	LEVY-DEEPSO	-4538.08	-4986.48	-4191.09	204.58	-2494.26	-2554.99	-2478.44	20.31	**-7032.34**

step for preparing the next set of the competitions. Regarding the tested smart grid problems, it would be interesting to incorporate uncertainty in testbed 2 (which is a crucial aspect when considering renewables and EVs) to assess the robustness of different approaches under different circumstances. Another thing that would be interesting to include in future competitions is considering the evaluation of the convergence rate of the proposed metaheuristics.

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Nomenclature

Indices:

t	period
I	DG units
L	loads
J	external suppliers
K	ESS
M	EVs
N	energy buyers

Parameters:

T	number of periods
N_I	number of DG
N_L	number of loads
N_J	number of external suppliers
N_K	number of ESS
N_M	number of EVs
N_N	number of energy buyers
$C_{DG(I,t)}$	generation cost of DG I in period t (m.u.)
$C_{GCP(I,t)}$	generation curtailment power cost of DG I in period t (m.u.)
$C_{NSD(L,t)}$	non-supplied demand cost of load L in period t (m.u.)
$C_{LDR(L,t)}$	demand response program cost of load L in period t (m.u.)
$C_{Sup(J,t)}$	energy price of external supplier J in period t (m.u.)
$C_{Sdis(K,t)}$	discharging cost of ESS K in period t (m.u.)
$C_{Vdis(M,t)}$	discharging cost of EV M in period t (m.u.)
$U_{Load(L,t)}$	electricity retail price of load L in period t (m.u./kWh)
$U_{Sell(N,t)}$	electricity sell price to market N in period t (m.u./kWh)
$U_{Scha(K,t)}$	charging price of ESS K in period t (m.u./kWh)
$U_{Vcha(M,t)}$	charging price of EV M in period t (m.u./kWh)
$P_{Load(L,t)}$	day-ahead active power forecast of load L in period t (kW)

Variables:

OC_{Total}^{Day+1}	total day-ahead operation cost (m.u.)
In_{Total}^{Day+1}	total day-ahead income (m.u.)
$P_{DG(I,t)}$	active power generation of DG I in period t (kW)
$P_{GCP(I,t)}$	generation curtailment power of DG I in period t (kW)
$P_{NSD(L,t)}$	non-supplied demand power of load L in period t (kW)
$P_{LDR(L,t)}$	active power reduction of load L in period t (kW)
$P_{Sup(J,t)}$	active power flow in the branch connecting to external supplier J in period t (kW)
$P_{Sdis(K,t)}$	Power discharge of ESS K in period t (kW)
$P_{Vdis(M,t)}$	Power discharge cost of EV M in period t (kW.)
$P_{Sell(N,t)}$	electricity sell price to market N in period t (kW)
$P_{Scha(K,t)}$	Power charge of ESS K in period t (kW)
$P_{Vcha(M,t)}$	Power charge of EV M in period t (kW)

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