2018 Competition on Operational Planning of Sustainable Power Systems: Testsbeds and Results

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Abstract: This paper concerns with the development of two new testbeds, the associated datasets, and the analysis of the results obtained by applying different heuristic optimization algorithms that participated in the 2018 panel and competition on "Emerging heuristic optimization algorithms for operational planning of sustainable electrical power systems". This activity was organized by the IEEE PES Working Group on Modern Heuristic Optimization (WGMHO), under the IEEE PES Analytic Methods in Power Systems (AMPS) Committee. This competition builds upon other previous competitions focused on the application of optimal power flow (OPF) to tackle schedulling problems of electrical power systems. Unlike the previous competitions, the new test beds consider more factors reflecting the stochasticity associated to renewable power generation, controllable loads, and electric vehicles. Developers of different emerging algorithms were challenged to perform algorithmic improvements and tuning within a limited computing budget. To this aim, the organizers of the competition developed and provided a set of encrypted codes for problem evaluation (i.e. calculation of objective function and constraints and saving of results). The results obtained by the best performing algorithms point out the relevance of modern heuristic optimization to tackle the complexity of stochastic OPF, without resorting to problem simplifications, and within a restricted computing budget.

Key–Words: Heuristic Optimization, Grid Optimization Competition, Optimal Power Flow, Solar Energy, Wind Energy.

1 Introduction

The variable nature of renewable energy variable generation introduces high stochasticity into the the operational planning of electrical power systems. From mathematical point of view, the different formulationa of the so-called optimal power flow (OPF), which are applied into different types of scheduling problems involved in operational planning, should account for non-linear models for power flow calculation and evaluation of technical constraints, and probabilistic models that represent the random fluctuations of renewable power generation, demand, and failures. In addition, with higher penetration of renewables, this entails performing search for optimum solutions wihtin a complex search space defined by a large number of mix-integer decision variables. Such computational complexity (i.e. multi-modality, non-convexity, discontinuity) and scalability cannot be tackled by classical optimization tools.

Heuristic optimization algorithms constitute an attractive option. Classical and emerging heuristic optimization algorithms are undergoing significant improvements to prevent stagnation and enhance the computational efficienty. However, most of these new developments have been tested in different types of theoretical optimization problems. Thus, the Working Group on Modern Heuristic Optimization (WGMHO), under the IEEE PES Analytic Methods in Power Systems (AMPS) Committee, pursues the development of different types of optimization test beds in the field of electrical power systems.

This task started in 2014 with the development of a test bed for active and reactive power dispatch based on OPF formulation with AC equations for power flow calculation and consideration of N-1 operational states. In 2017, the next step was to extend the OPF formulation into the probabilistic context to account for the stochasticity of power generation. This paper overviews the results of the work carried out for a special panel and competition organized for the 2018 IEEE PES General Meeting. Concretely, two new test beds are introduced:

Test bed 1: Stochastic OPF in Presence of Renewable Energy and Controllable Loads. The target is to miminize the total cost of the traditional generators plus an uncertainty costassociated with renewable generators. The problem evaluation (i.e., calculation of objective function and constraints) is implemented based on the active-reactive OPF formulation. The IEEE 57-bus system was selected as a case study.

Test bed 2: Dynamic OPF in Presence of Renewable Energy and Electric Vehicles. The target is to minimize the total fuel cost of traditional generators plus the expected uncertainty cost for renewableenergy generator plus the expected uncertainty cost for electric vehicles. The problem evaluation (i.e., calculation of objective function and constraints) is implemented based on the active-reactive OPF formulation. The IEEE 118-bus system was selected as a case study.

The paper also provides datasets associated to the codes implemented and provided by the authors (who chaired the panel session at the 2018 IEEE PES General Meeting) to the contestant algorithms. The developers of each algorithm had the exclusive mission of performing algoritmic modifications and tuning of the the parameters invovled in the different operations and rules of the corresponding contestant algorithm. The developers were allowed to these tasks by considering a restricted number of function evaluations, since a limited computing budget is aligned with usual practice in electrical power engineering for selection and evaluation of any type of optimization solver. It is worth mentioning that, in other fields of study, the evaluation of performance of the algorihms sometimes also involves metrics concerning the characteristic of the convergece throughout the search process. However, this is out of the scope of this paper.

The reminder of the paper is structured as follows: Section 2 overviews the general aspects of the competion and its timeline. Sections 3 and 4 present in detail the two proposed testbeds. Section 5 shows ths adopted evaluation criteria. The best performing metaheuristic algorithms are presented and analyzed in section 6. Finally, concluding remarks are given in Section 7.

2 Competition structure and schedule

The employment of high-level optimization techniques to solve power system optimization problems is getting significant attention because of their potential to deal with inherent mathematical complexities such as high-dimensionality, non-linearity, nonconvexity, multimodality and discontinuity of the search space [1, 2].

As a result of this, the WGMHO coordinated a special panel in the 2014 IEEE PES General Meeting, which consisted of a competition focusing on the application of heuristics for solving Optimal Power Flow (OPF) problems. That was the first step towards the development of power system optimization testbeds, which are aimed at establishing and performing comparative analysis on the general applicability and effectiveness of emerging tools in the field of heuristic optimization. The next steps ware done in the competitions organised in 2017 and 2018 .

The 2018 Competition on Operational planning of sustainable power systems, proposed by WGMHO, introduced two benchmark problems (also denoted as optimization testbeds):

- Test bed 1: Stochastic OPF in Presence of Renewable Energy and Controllable Loads.
- Test bed 2: Dynamic OPF in Presence of Renewable Energy and Electric Vehicles.

The problems to be solved were treated as black box problems (inputs: decision variables, outputs: stochastic objective function, constraints value), which should be solved for different stochastic scenarios based on probability distributions of wind speed, solar irradiance and river flow over an IEEE 57 bus test system. The participants were requested to exclusively work on the implementation of the particular heuristic optimization algorithm to be used, which could include any special strategy for constraint handling, strategy for consideration of stochastic variables, or treatment of discrete/binary optimization variables related to the transformers and compensation devices [3].

The timelime of the activities carried out was as follows:

- 4 January 2018: Call for competition.
- 20 January 2018: Confirmation of participation.
- 20 March 2018: Submission of results and codes.
- 28 April 2018: Announcement of the best two ranked algorithms.
- 5-10 August 2018: Presentation of the winners at the IEEE PES General Meeting.

3 General description of Testbed 1

3.1 Target function

The target of an OPF is to allocate generator units so as to supply the demand, by minimizing the cost of the latter, while fulfilling technical constrants in the power system (associated to Nodal voltages, nodal balance power, maximum power output from slack generator, generator active power capability, among others). The search for the optimum solution can be tackled by using different mathematic tecniques and new mathematical programming tools [4].

In the test bed 1, the target is to miminize the total cost of the traditional generators plus an uncertainty cost associated with renewable generators. All generators are considered dispatchable, but owing to the volatilty of the primary source of the renewable energy based generation, they will have an uncertainty cost which is divided into over and under estimated condition, respectively. This relays on the availability of the primary energy source [5].

As the primary energy source of a renewable generator is volatile, it may be represented, in some cases, by a probability distribution function. Through such function, one can obtain one probability function of the available power [6]. Based on this function, it is possible to carry out several Monte Carlo simulation to find all possible scenarios of the available power. As indicated previously, it is considered tha there are two different cases: Under and over estimated. The steps of the simulation are summarized here, according to [6]:

i Generate a random primary energy source value (following the probability distributoin of the wind speed, solar irradiance or the river flow) of scenario j.

ii Calculate the available real power for the scenario j when renewable enery generator i is used $P_{i,j}$.

iii Verification of the underestimated $(P_{S_i} < P_{i,j})$ or overestimated $(P_{S_i} > P_{i,j})$ condition in scenario j. P_{S_i} corresponds to the decision variable describing renewable energy generator i.

iv Calculate the uncertainty cost for scenatio j:

$$[C_i, j = C_u(P_{i,j} - P_{S_i}); if; P_{S_i} < P_{i,j}] \quad (1)$$

$$[C_i, j = C_u(P_{S_i} - P_{i,j}); if \quad P_{S_i} > P_{i,j}] \quad (2)$$

v Repeat the steps i to iv N times (in the 2018 competition N is set to 2000 times).

vi Build the histogram of the uncertainty cost for the N scenarios.

vii Calculate the expected cost of the uncertainty cost function for renewable energy generator i in the considered Monte Carlo simulation.

The competitors are provided with a main code which compiles the results and gather it in ASCII-files.

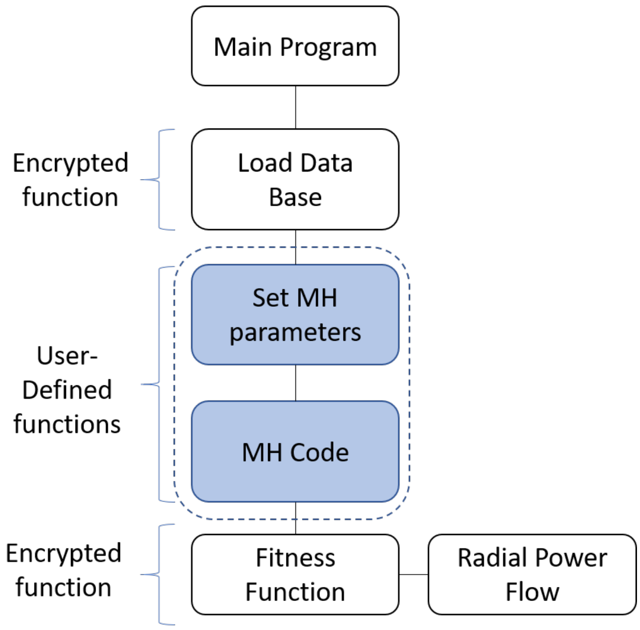

Figure 1: Flow Chart for the main code in the 2018 Competition

3.2 Uncertainty cost functions

As the available power of a renewable generator is unknown till the moment of generation, the cost of the power is calculated by using Uncertainty cost functions [7]. Such cost relies on the type of renewable energy as shown as follows.

3.2.1 Wind Study Case

In this case, it is considered that the wind follows a Rayleigh probability distribution for underestimated condition (3) and overestimated condition (4) .

$$E[C_{w,u,i}(W_{w,s,i}, W_{w,i})] = \frac{c_{w,u,i}}{2} \Big(\sqrt{2\pi}\rho\sigma(erf(\frac{W_{w,s,i} - \kappa}{\sqrt{2}\rho\sigma}) - erf(\frac{W_r - \kappa}{\sqrt{2}\rho\sigma})) + 2(W_{w,s,i} - W_r)e^{-(\frac{W_r-\kappa}{\sqrt{2}\rho\sigma})^2}\Big) + \frac{c_{w,u,i}}{2}(e^{-\frac{V_r^2}{2\sigma^2}} - e^{-\frac{V_0^2}{2\sigma^2}})(W_r - W_{w,s,i}) \quad (3)$$

$$E[C_{w,o,i}(W_{w,s,i}, W_{w,i})] = c_{w,o,i}W_{w,s,i} \cdot (1 - e^{-\frac{V_i^2}{2\sigma^2}} + e^{-\frac{V_0^2}{2\sigma^2}} + e^{-\frac{\kappa^2}{2\rho^2\sigma^2}}) - \frac{\sqrt{2\pi}c_{w,o,i}\rho\sigma}{2}\Big(erf(\frac{W_{w,s,i} - \kappa}{\sqrt{2}\rho\sigma}) - erf(\frac{-\kappa}{\sqrt{2}\rho\sigma})\Big) \quad (4)$$

3.2.2 Solar Study Case

In this case, it is considered that the solar irradiance follows a Log-Normal probability distribution. The Uncertainty Cost both in subestimated and overestimated case has 2 coditions A and B, which depends on the comparison between the available real power and reference irradiance power (underestimated (5) ans (6) or overestimated (7) and (8)):

$$
\begin{aligned}
&E[C_{_{PV},u,i}(W_{_{PV},s,i}, W_{_{PV},i}), A] = \\
&\frac{(-1)c_{_{PV},u,i}W_{_{PV},s,i}}{2}\Bigg[erf(\frac{\left(\frac{1}{2}ln(\frac{W_{Rc}G_rR_c}{W_{PVr}})-\lambda\right)}{\sqrt{2}\beta}) \\
&- erf(\frac{\left(\frac{1}{2}ln(\frac{W_{_{PV},s,i}G_rR_c}{W_{PVr}})-\lambda\right)}{\sqrt{2}\beta})\Bigg] \\
&+ \frac{c_{_{PV},u,i}W_{PVr}\cdot e^{2\lambda+2\beta^2}}{G_rR_c2} \\
&\Bigg[erf(\frac{\left(\frac{1}{2}ln(\frac{W_{Rc}G_rR_c}{W_{PVr}})-\lambda\right)}{\sqrt{2}\beta} - \sqrt{2}\beta) \\
&- erf(\frac{\left(\frac{1}{2}ln(\frac{W_{_{PV},s,i}G_rR_c}{W_{PVr}})-\lambda\right)}{\sqrt{2}\beta} - \sqrt{2}\beta)\Bigg]
\end{aligned} \tag{5}
$$

$$
\begin{aligned}
&E[C_{_{PV},u,i}(W_{_{PV},s,i}, W_{_{PV},i}), B] = \frac{c_{_{PV},u,i}W_{_{PV},s,i}}{2} \\
&\Bigg[erf\Bigg(\frac{\left(ln(\frac{W_{Rc}G_r}{W_{PVr}})-\lambda\right)}{\sqrt{2}\beta}\Bigg) \\
&- erf\Bigg(\frac{\left(ln(\frac{W_{_{PV},\infty,i}G_r}{W_{PVr}})-\lambda\right)}{\sqrt{2}\beta}\Bigg)\Bigg] \\
&+ \frac{c_{_{PV},u,i}W_{PVr}\cdot e^{\lambda+\beta^2/2}}{2\cdot G_r} \\
&\Bigg[erf\Bigg(\frac{\left(ln(\frac{W_{_{PV},\infty,i}G_r}{W_{PVr}})-\lambda\right)}{\sqrt{2}\beta} - \frac{\beta}{\sqrt{2}}\Bigg) \\
&- erf\Bigg(\frac{\left(ln(\frac{W_{Rc}G_r}{W_{PVr}})-\lambda\right)}{\sqrt{2}\beta} - \frac{\beta}{\sqrt{2}}\Bigg)\Bigg]
\end{aligned} \tag{6}
$$

$$
\begin{aligned}
&E[C_{_{PV},o,i}, (W_{_{PV},s,i}, W_{_{PV},i}), A] = \\
&\frac{-c_{_{PV},o,i}W_{_{PV},s,i}}{2}\Bigg[1 + erf(\frac{\left(\frac{1}{2}ln(\frac{W_{Rc}G_rR_c}{W_{PVr}})-\lambda\right)}{\sqrt{2}\beta})\Bigg] \\
&+ \frac{c_{_{PV},o,i}W_{PVr}\cdot e^{2\lambda+2\beta^2}}{G_rR_c2} \\
&\Bigg[erf(\frac{\left(\frac{1}{2}ln(\frac{W_{Rc}G_rR_c}{W_{PVr}})-\lambda\right)}{\sqrt{2}\beta} - \sqrt{2}\beta) + 1\Bigg]
\end{aligned} \tag{7}
$$

$$
\begin{aligned}
&E[C_{_{PV},o,i}, (W_{_{PV},s,i}, W_{_{PV},i}), B] = \frac{c_{_{PV},o,i}W_{_{PV},s,i}}{2} \\
&\Bigg[erf\Bigg(\frac{\left(ln(\frac{W_{Rc}G_r}{W_{PVr}})-\lambda\right)}{\sqrt{2}\beta}\Bigg) - erf\Bigg(\frac{\left(ln(\frac{W_{_{PV},s,i}G_r}{W_{PVr}})-\lambda\right)}{\sqrt{2}\beta}\Bigg)\Bigg] \\
&+ \frac{c_{_{PV},o,i}W_{PVr}\cdot e^{\lambda+\beta^2/2}}{2\cdot G_r} \\
&\Bigg[erf\Bigg(\frac{\left(ln(\frac{W_{_{PV},s,i}G_r}{W_{PVr}})-\lambda\right)}{\sqrt{2}\beta} - \frac{\beta}{\sqrt{2}}\Bigg) \\
&- erf\Bigg(\frac{\left(ln(\frac{W_{Rc}G_r}{W_{PVr}})-\lambda\right)}{\sqrt{2}\beta} - \frac{\beta}{\sqrt{2}}\Bigg)\Bigg]
\end{aligned} \tag{8}
$$

3.2.3 Electric Vehicle Study Case

In this case, it is considered that the solar irradiance follows a Log-Normal probability distribution.

- Underestimated condition.

$$
\begin{aligned}
&E[C_{e,u,i}(P_{e,i}, P_{e,s,i})] = \\
&\frac{c_{e,u,i}}{2}(\mu - P_{e,s,i})\Big(1 + erf\Big(\frac{\mu - P_{e,s,i}}{\sqrt{2}\phi}\Big)\Big) \\
&+ \frac{c_{e,u,i}\cdot\phi}{\sqrt{2\pi}}\cdot e^{-(\frac{\mu-P_{e,s,i}}{\sqrt{2}\phi})^2}
\end{aligned} \tag{9}
$$

- Overestimated condition.

$$
\begin{aligned}
&E[C_{e,o,i}(P_{e,i}, P_{e,s,i})] = \frac{c_{e,o,i}}{2}(P_{e,s,i} - \mu) \\
&\Big(erf\Big(\frac{\mu}{\sqrt{2}\phi}\Big) - erf\Big(\frac{\mu - P_{e,s,i}}{\sqrt{2}\phi}\Big)\Big) \\
&+ \frac{c_{e,o,i}\phi}{\sqrt{2\pi}}\cdot\Big(e^{-(\frac{P_{e,s,i}-\mu}{\sqrt{2}\phi})^2} - e^{-(\frac{\mu}{\sqrt{2}\phi})^2}\Big)
\end{aligned} \tag{10}
$$

3.3 Multiple set of Monte Carlo simulations and controllable load consideration

In the 2018 competition multiple set of Monte Carlo simulation are considered i.e. the uncertainty cost is made up of several scenarios of primary energy, and a set of the same decision variables will result in a different expected value.

Controllable loads (CL) are an effective way of reducing stress on the power system and peak shifting in areas with heavy load [8]. So, they are included in the 2018 competition, in a way of ”capacity block adjustment method”, which means that a compensation price is given for the total load that is interrumped by

Table 1: Compensation price per interrupted capacity block

Block #	Power interrumped	Prices
Block I	(80%-95%)*P_{IL}	C1
Block II	(65%-80%)*P_{IL}	C2
Block III	(50%-65%)*P_{IL}	C3

the optimization algorithm. In table 1 the compensation ranges are shown, here P_{IL} refers to the actual demand of the interrumpible load.

This is seen in the optimization problem, as one term which is added to the objective function. Such term is the multiplication of the compensation price (C_j) by the difference between the actual demand and the demand dispatched by the optimization algorithm.

3.4 Test bed 1 and the IEEE 57 bus system

The IEEE 57 bus system has 7 generators. In test bed 1, three of this generators are assigned as reneweables energy based generation located at buses 2, 6 and 9. From the total 42 loads in IEEE 57, 4 are considered controllable in test bed 1, that is, the ones at buses 8, 12, 18 and 47. The objective function, the constrains, and the optimization variables are explained as follows [6]:

- **Constrains:**
  0 Power flow constrains: Related to nodal balance of power (equality constrains).
  1 Constrains penalized in fitness function.
    - Nodal voltages for load buses (42+42).
    - Allowable branch power flows (80).
    - Generator reactive power capability (7+7).
    - Maximum reactive power output of 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.
  2 Mimimum and maximum level of optimization variable (2x35).
- **Optimization varibles:** 35 variables, comprising 13 continuous variables related to generator's actve power outputs (6, the slack is not considered here, since the injected power is given by the power flow) and generator's bus voltage set-points (7), 15 discrete variables related to stepwise adjustable on-load transformer's tap positions, 3 binary variables related to switchble shunt compensation devices and 4 controllable loads.
- **Considered contingencies (N-1 Conditions):** Outages at branches 8 and 50.
- **Number of function evaluations:** 30000.
- **Cases:** Five case studies of different combinations of renewable energy based generators.

3.5 Cases overview

For the 2018 competition, there are 5 cases studies. Each one with a different mix of renewable generators and controllable loads. Competitors had to select the case in the provided ".main" file. The cases are briefly described as follows [6]:

3.5.1 Case study 1: Stochastic OPF for IEEE 57 bus system considering wind energy:

- **Wind generators:** Three wind generators with Weibull probability distribution function, at buses 2, 6 and 9.
- **Solar PV generation:** 0.
- **Small-hydro generator:** 0.
- **Controllable load**: At buses 8, 12, 18 and 47.

3.5.2 Case study 2: Stochastic OPF for IEEE 57 bus system considering wind energy, solar energy:

- **Wind generators:** Two wind generators with Weibull probability distribution function, at buses 2, 9.
- **Solar PV generation:** One solar PV generator with log-normal probability distribution function, at bus 6.
- **Small-hydro generator:** 0.
- **Controllable load**: At buses 8, 12, 18 and 47.

3.5.3 Case study 3: Stochastic OPF for IEEE 57 bus system considering wind energy, solar energy and Small-hydro and controllable loads:

- **Wind generators:** One wind generators with Weibull probability distribution function, at bus 3.
- **Solar PV generation:** One solar PV generator with log-normal probability distribution function, at bus 6.
- **Small-hydro generator:** One Small-hydro generator with Gumbel probability distribution function, at bus 9.
- **Controllable load**: At buses 8, 12, 18 and 47.

3.5.4 Case study 3: Stochastic OPF for IEEE 57 bus system considering wind energy, solar energy and Small-hydro and controllable loads:

- **Wind generators:** One wind generators with Weibull probability distribution function, at bus 3.
- **Solar PV generation:** One solar PV generator with log-normal probability distribution function, at bus 6.
- **Small-hydro generator:** One Small-hydro generator with Gumbel probability distribution function, at bus 9.
- **Controllable load**: At buses 8, 12, 18 and 47.

3.5.5 Case study 4: OPF using an Analytical Uncertainty Cost function for IEEE 57 bus system. Considering wind generators and Controllable loads

In this case study, analytical cost functions are used to calculate the expected uncertainty cost, as it is proved in [7]. The expression for wind energy is named "Wind Uncertainty Cost Function", taking into account the Weibull distribution. So, the competitors have to use such equation and obtain the scheduled power, which depends on the decision variable.

3.5.6 Case study 5: OPF using an Analytical Uncertainty Cost function for IEEE 57 bus system. Considering wind and solar generators and Controllable loads

In this case study, analytical cost functions are used to calculate the expected uncertainty cost, as it is proved in [7]. The expression for wind energy is named "Wind Uncertainty Cost Function", taking into account the Weibull distribution. The expression for solar generation is named "Solar Uncertainty Cost Function", and takes into account the log-normal distribution. So, the competitors have to use such equations and obtain the scheduled power, which depends on the decision variables.

4 General description of Testbed 2

In this test bed, electric vehicles are included as dispatchable units, besides test bed 2 takes into account several time instances. The electric vehicles have associated a normal probability distribution function [7], so as to determine wether they act as a generator (vehicle to grid) or as load (vehicle battery charging).

This test bed is a active-reactive power dispatch problem, that has an cost-function contrains describing the system in a time instance. In the 2018 competition six time instances, so test bed is a dynamic OPF [6].

4.1 Test bed 2 and the IEEE 118 bus system

The IEEE 118 bus system has 54 generators, and, in this test bed, 4 generators are considered as renewables (2 wind and 2 solar PV). Also, there are 4 electric vehicles and 6 time instances [3].

- **Objective:** Minimize the total fuel cost of traditional generators plus the expected uncertainty cost for renewable energy generator plus the expected uncertainty cost for electric vehicles.
- **Optimization variables:** 6x130, where 130 encompasses 107 continuous variables decribing generator active power outputs (53, the slack generator is not considered here, sice the injected power is given by the power flow calculation) and generator bus voltage set-points, 54), 9 discrete variables related to stepwise adjustable onload transformer's tap positions, 14 binaty variables linked to switchable shunt compensation devices.
- **Constrains:** There are 3 types of constrains:

  i Power flow constrains These are related to nodal balance of power (equality constraints). Each time instance in the dynamic OPF, has a different demand condition.

  ii Constrains penalized in the fitness function.
    - Nodal voltages for load buses: 6x(99+99).
    - Allowable branch power flows: 6x(186).
    - Generator reactive power capabitility: 6x(54+54).
    - Maximum active power output of a slack generator: 6x(1).

  The penalization is done for for normal (non-contigngency) and selected N-1 conditions i.e. 493 constraints for non-contingency conditions, and 492 constraints for each N-1 condition in each time instance.

  Additionally, ramp constrints are considered, i.e. the generation change between two instances must not be greater than a limit (the number of constraints in this case would be 5x53, 5 because there are 6 time instances, and 53 because there are 53 location varibales related with active power generation). The total number of constrains is: (6x493)+(6x492)+(5x53).

iii Minimum and maximum levels on optimization variables (6x130x2).

- **Considered contingencies (N-1 conditions):** Outage of branches 21, 50, and 48.
- **Number of function evaluations:** 9000 power flows, for 6 time instances.

5 Evaluation guidelines

The ranking is calculated based on statistics of the best fitness value f_{best} for every case and test bed. The evaluation is carried out from 31 runs considered for the competition. In this way, the succes of single case (or scenario) is given by [6]:

$$Score = mean(f_{best}) \tag{11}$$

Where mean stands for mean value of the total number of scenarios. The ranking is based on the increased order of the $Total_{score}$ as shown in equation (12).

$$Total_{score} = \sum_{i=1}^{N_{scenario}} score_i \tag{12}$$

The ranking is based on increasing order of each participant, as it was done on the 2017 competition [9]. As it can be seen from equation (12), the Total score does not take into consideration the time spent for the algorithm, but a convergence signal may be used also for evaluation in future competitions. In this competition, this is not relevant.

The participants received one encrypted file called "$test\ bed\ OPF.p$" which automatically calculates the fitness function for a set of decision variables, by using equation (13).

$$fitness(decision\ variables) : objective\ function + \rho \sum_{i=1}^{constraints} max[0, constraints\ violation]^2 \tag{13}$$

Where ρ is a penalty factor that is 1E+7 for test bed 1 and 1E+4 for test bed 2.

6 Competition results and meta-heuristics

This section shows the results of the 2018 competition for test bed 1 and 2. The contestant algorithms are shown in Table 2.

6.1 Test bed 1: Competition results

Table 3 shown the official results of the 2018 competition for test bed 1, and its statistic parameters.

6.2 Test bed 2: Competition results

6.3 Overview of best performing methods

In this section the the best ranked methods are briefly overiewed.

6.3.1 CE+EPSO

CE + EPSO is the combination of two optimization methods: Cross-Entropy (CE) and Evolutionary Particle Swarm Optimization (EPSO) [6]. The CE is an optimization method used to solve well-known probabilistic problems, it is used because it provides a fast way of deriving, by using updating/learning rules and simulation theory. CE method involves the following two phases [10]:

- Generate a random data sample (trajectories, vectors, etc) according to a mechanims.
- Update the parameter so that the next sample performs better.

EPSO is one meta-heuristic optimization method, it is an hybrid between Evolutionary Strategies (ES) and Particle Swarm Optimization (PSO) proposed by Vladimiro Miranda, the algorithm consists in the following steps [3]:

- Replication: each individual is replicated r times.
- Mutation: the r clones have their weights w mutated.
- Recombination: the r+1 individuals generate one offspring.
- Evaluation: each offspring has its fitness evaluated.
- Selection: the best particle out of the r+1 survives to be part of a new generation.

6.3.2 Entropy Enhanced Covariance Matriz Adaptation Evolution Strategy (EE-CMAES)

This is a combination of two optimization methods: Entropy Enhanced (EE) and Covariance Matriz Adaptation Evolution Strategy (CMAES). EE is a heuristic method for solving optimization problems, and involves two phases [11].

- Generation of a sample of random data according to a specified random mechanism.
- Updating the parameters of the random mechanism, typically parameters of pdfs, on the basis of the data, to produce a better sample in the next iteration.

In the CEMAES, there are 2 principles [11]:

Table 2: Participants in the 2018 IEEE PES WGMHO competition on operational planning of sustainable electrical power systems

Team	Algorithm
1	Improved Chaotic Differential Evolutionary Particle Swarm Optimization (ICDEPSO)
2	Entropy Enhanced Covariance Matriz Adaptation Evolution Strategy (EECMAES)
3	Shrinking Net Algorithm (SNA)
4	CE+EPSO
5	Artificial Bee Colony (ABC)

Table 3: Official ranking for the IEEE PES WGMHO Emerging heuristic optimization algorithms for operational planning of sustainable electrical power systems - Test bed 1

Number	Algorithm	Case 1 Score	Case 2 Score	Case 3 Score	Case 4 Score	Case 5 Score	Total Score	Ranking
1	ICDEPSO	84,565.0	71,132.5	58,129.5	88,367.1	71,953.3	374,147.6	3
2	EECMAES	81,382.6	68,519.1	56,032.9	84,348.3	71,033.3	361,316.3	2
3	SNA	85,649.2	71,037.0	59,203.5	86,354.0	73,984.2	376,228.177	4
4	CE+EPSO	81,077.0	68,473.4	55,935.6	84,442.9	71,065.9	360,994.9	1
5	ABC	141,249.2	119,775.0	136,899.9	121,928.2	112,077.1	631,929.7	5

- Maximum-likelihood principle, based on the idea of increasing the probability of successful candidate solutions and search steps.
- Two path of the time evolution of the distribution mean of the strategy are recorded, called search or evolution paths.

6.3.3 Improved Chaotic Differential Evolutionary Particle Swarm Optimization (ICDEPSO)

This method combines Improved Chaotic Differential (ICD) and the EPSO method shown in section 6.3.2. Evolutionary algorithms relies on the random secuence of variations operators. Recently chaotic sequences have been used in heuristic algoritms, producing good results [12]. This is because the algorithm can escape from local mimimum points.

7 Conclusions and final remarks

This paper described two new testbeds concerning the optimal schedulling (active-reactive power dispatch) of generation in power systems dominated by renewables, and with the presence of controllable loads and electric vehicles. These test beds were used in the 2018 IEEE PES WGMHO panel and competition on Emerging heuristic optimization algorithms for operational planning of sustainable electrical power systems. The test beds were coded in Matlab based on a open source tool for power flow calculation. Algorithm developers can easily use these codes to testing their new developments. Like in the competition, the codes shall be treated as black-box, and the challenge is to beat the best performing algorithms within the same restricted computing budget. Remarkably, CE+EPSO was found to be successful in solving both test beds (i.e. different OPF formulations and operational scenarios). This finding is an important step in the ambition of achieving powerful algorithms to support power system operational planning in real practice. The WGMHO will continue its mission of developing more test beds. The next stage is the development of problems in the field of power system planning.

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Competitor Number	Algorithm	Case 1 Score	Case 1 Best fitness	Case 1 Worst fitness	Case 1 Std	Total Score	Ranking
1	ICDEPSO	NA	NA	NA	NA	NA	NA
2	EECMAES	NA	NA	NA	NA	NA	NA
3	SNA	1,518,786.29	1,171,878.10	1,878,123.10	227,650.99	1,518,786.29	2
4	CE+EPSO	789,719.58	773,193.77	823,684.44	15,618.73	789,719.55	1
5	ABC	NA	NA	NA	NA	NA	NA

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- CE+EPSO and ICDE+EPSO. Developers: Leonel Carvalho. INESC TEC, Porto, Portugal. Vladimiro Miranda. INESC TEC, Porto, Portugal and Faculty of Engineering of the University of Porto FEUP, Porto, Portugal. Armando Leite da Silva. Pontifcia Universidade Catlica do Rio de Janeiro PUC Rio, Rio de Janeiro, Brazil. Carolina Marcelino. COPPE/Federal University of Rio de Janeiro, Rio de Janeiro, Brazil. Elizabeth Wanner. School of Engineering and Applied Sciences, Birmingham, UK and Centro Federal de Educao de Minas Gerais CEFET-MG, Minas Gerais, Brazil.
- Entropy Enhanced Covariance Matrix Adaptation Evolution Strategy. Developers: Kartik Pandya. Dept. of Electrical Eng., CSPIT, Charusat, Changa, India. Jigar Sarda. Dept. of Electrical Eng., CSPIT, Charusat, Changa, India.
- Shrinking Net Algorithm. Developers: Chengchen Qian. Stated Grid Shanghai Municipal Electrical Power Company, China. Haoming Liu. College of Energy and Electrical Engineering, Hohai University, China. Yunhe Hou. Department of Electric and Electronics Engineering, the University of Hongkong, China.

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