Task Force on Modern Heuristic Optimization Test Beds
Working Group on Modern Heuristic Optimization
Intelligent Systems Subcommittee
Power System Analysis, Computing, and Economic Committee

2018 Grid Optimization Competition
Evaluating the Performance of Modern Heuristic Optimizers on Stochastic Optimization Problems applied to Smart Grids

Test bed B:
Dynamic OPF in Presence of Renewable Energy and Electric Vehicles

Problem Definition and Implementation Guidelines

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Contents

1. AIM OF THE COMPETITION [1]

The application of heuristic optimization algorithms to solve power system optimization problems is receiving a great attention due to their potential in dealing with inherent mathematical complexities of such problems including their high-dimensionality, non-linearity, non-convexity, multimodality and discontinuity of the associated search space [1]. Knowing this, the Working Group on Modern Heuristic Optimization under the IEEE PES Power System Analysis, Computing, and Economics Committee organized a special panel in the 2014 IEEE PES General Meeting, which focused on the application of these tools for solving optimal power flow (OPF) problems [1]. That was the first step towards the development of power system optimization test beds, which are aimed at ascertaining and performing comparative analysis on the general applicability and the effectiveness of emerging tools in the field of heuristic optimization [1].

Along this spirit, a new competition focusing on optimization problems related to smart grid operation was organized in 2017 [2]. A great emphasis was put on the consideration of stochastic factors linked to the deployment of renewable energy systems in the smart grid as further described in Test Bed 1 set for the 2017 competition [2]. In more details, the 2017 Test Bed 1 focused on the stochastic OPF based active-reactive power dispatch for the IEEE 57 bus system including wind, solar and small hydro power generation systems.

In a similar way to the 2017 contest, the 2018 Test Bed B competition targets a comparative assessment of the search capability of different heuristic optimization algorithms. Such a target will consider an analytical formulation of the objective function

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[1] Please note that the structure and content of this section is similar to (it is updated the new considerations for the 2018 competition): 2014 Competition Application of Modern Heuristic Optimization Algorithms for Solving Optimal Power Flow Problems by István Erlich, Kwang Y. Lee, José L. Rueda, Sebastian Wildenhues and 2017 Competition Evaluating the Performance of Modern Heuristic Optimizers on Smart Grid Operation Problems, Test Bed 1: Stochastic OPF based active-reactive power dispatch by Sergio Rivera, Andres Romero, José L. Rueda, Kwang Y. Lee, István Erlich

able to consider the stochastic behavior of the factors governing renewable energy production (Wind Speed and Solar Irradiance). Additionally, this year (2018), the Test Bed B will model electric vehicles as dispatchable units in the system under study and the model will account for the probability distribution of the possible injected power from such units (vehicle to grid) or the consumed power (vehicle battery charging). An important feature of the Test Bed B is the consideration of several time instances. In other words, the problem to be studied is not an instantaneous OPF but rather a dynamic OPF. The latter is recognized for considering the change in the network demand in the different time slots.

The assessment will be based on statistical tests performed on results submitted by interested participants. For this purpose, three encrypted files have been prepared using Matlab (version R2015a) and MATPOWER toolbox (version matpower6.0b1) in order to perform automatic evaluation of the objective function for a dynamic active-reactive power dispatch optimization problem as well as to collect and store the results automatically [1].

The objective function is modified compared to the 2014 competition. The current objective function is now targeting minimizing the expected operational cost as impacted by the uncertainty of renewable energy systems, where the expected cost value for renewable generators and the electric vehicle are given by analytical expressions (these expressions are validated with Monte-Carlo simulations in given Matlab scripts).

The problems to be solved are treated as black box tasks. Therefore, the participants are requested to exclusively work on the implementation of the particular heuristic optimization algorithm to be used, which can include any special strategy for dealing with discrete/binary optimization variables governing the tap transformers' and compensation devices' operation [1].

The encrypted files named *UC.p* and *test_bed_OPF.p* along with other exemplary Matlab m-files, which are intended for easy adaptation to any heuristic optimization algorithm, are included in the zipped folder named *test_bedB_DynamicOPF_2018.zip*. This folder also provides complete details (in MATPOWER format) of the test system (IEEE 118 buses test system). Please read carefully the instructions given in every m-file and in *readme2018TestBedB_Contest.txt* file, which provide precise indications about Matlab based procedural and implementation aspects.

Final results, which are automatically saved for each optimization test case over 10 independent optimization trials in formatted ASCII-files contained in a zip folder named *output_data_implementation_name.zip*, are needed for statistical tests to be performed in the competition, so this folder should be sent to srriverar@unal.edu.co, aalsumaiti@masdar.ac.ae and j.l.ruedatorres@tudelft.nl by maximum 30th March 2018 (12:00 pm EST) in accordance with the guidelines provided in this technical report. The implementation codes for each algorithm entering the competition must also be submitted along with final results for a full consideration in the evaluation. Submitted codes will be used for further tests, which are intended to crosscheck submitted results. Submitted codes will be in the public domain and no intellectual property claims should be made.

2. DEFINITION OF THE DYNAMIC OPF PROBLEM IMPLEMENTATION

2.1. Competition files structure [2][2]

The formulation of an optimal active-reactive power dispatch (OARPD) problem, i.e. [3]-[4], represents an optimization problem with an objective cost-function and constraints describing the system operation in a time instance. In this competition, six time instances are considered. Thus, the problem is recognized as a Dynamic OPF [4]. Additionally, the problem accounts for the presence of renewable energy systems and electric vehicles. In *UC.p* file, the optimization problem is implemented to calculate the objective function and the constraints for a set of decision variables. Additionally, this file has been developed for an automatic collection and storage of results in formatted ASCII-files. Moreover, there is another encrypted file called *test_bed_OPF.p* that calculates the power flow in a time instance. Such a file uses MATPOWER toolbox [5] that can be freely downloaded from http://www.pserc.cornell.edu/matpower/.

The zipped folder *test_bedB_DynamicOPF_2018.zip* contains these codes and instructions on how to use them along with an implementation example of the basic particle swarm optimization (PSO) algorithm. The code is considered as a black box, so it cannot be modified by participants.

In the zip file, there is a folder called *test_bedB_StochasticOPF_2018*. In this folder, you can find the different files of the competition. Please read the *readme2018TestBedB_Contest.txt* in order to understand the structure of competition files.

Each participant is encouraged to work exclusively on the particular optimization algorithm to be used. The use of any type of constraint handling technique is allowed, but this time the encrypted file will give only the constraints violations defined in (1). There is another encrypted file called *constraint_handling.p*. The calculations done in *UC.p* and *test_bed_OPF.p*, determines internally the set of fitness as a function of the different combinations of decision variables by using (1).

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

where ρ is a penalty factor that is set to a value of 1E+4.

The *rounding.m* file is an exemplary external function that can be employed for rounding the real numbers used to code discrete/binary optimization variables. You are allowed to modify this file to include your own rounding strategy, but the function syntax, i.e. x_out=rounding(x_in), should be kept, because it is called internally in *test_bed_OPF.p* before every function evaluation. x_in denotes one individual component in the sequence of discrete/binary variables from the vector of optimization variables to be generated using the offspring creation scheme of your optimization algorithm.

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[2] Please note that the structure and content of this subsection is similar to (it is updated the new considerations for the 2017 competition): 2014 Competition Application of Modern Heuristic Optimization Algorithms for Solving Optimal Power Flow Problems by **István Erlich, Kwang Y. Lee, José L. Rueda, Sebastian Wildenhues**

The *test_bed_OPF.p* is configured to automatically round the values corresponding to the discrete/binary coded variables to the nearest integer, so this rounding approach will be internally used regardless of whether or not your algorithm uses a rounding strategy. If a rounded variable violates its boundary, it will be automatically fixed in *test_bed_OPF.p* to the corresponding limit.

Please read the instructions given in *main_2018_TestBedB_Commented.m* to determine the indexes (elements) of the vector of optimization variables defined as discrete/binary variables. Please also refer to *main_2018_TestBedB_Commented.m* file to gather how to obtain all power system and optimization related information, e.g. location of controllable transformer and compensation devices, problem dimensionality, bounds on optimization variables, steps of discrete variables. In the *main_2018_TestBedB_Commented.m* file, it is possible to realize where the competitor can update the code in order to prematurely stop running the procedure in terms of independent trials or update the size of the population of his/her implementation.

The IEEE 118-bus test system is used to evaluate the dynamic OPF problem. Based on the details of system buses and branches as given in [6], the data of the system has been structured in MATPOWER data format. Branch thermal limits were defined based on reference values given in [7]. A summary of the characteristics of the test system is shown in Table 1. Please note that a MATPOWER folder must be in the Matlab work path since the codes use some MATPOWER functions.

Table 1: Composition of test system

IEEE 118 bus system	
Generators	54
Loads	99
Lines/cables	177
Transformers Stepwise	9
Transformers Fixed tap	0
Shunt compensation Binary On/Off	14

2.2. Considerations regarding Stochastic Behavior of Wind, Solar Generation and Electric Vehicles.

Normally, the target in the ORAPD is to minimize the total fuel cost while fulfilling constraints (nodal power balance, nodal voltages, allowable branch power flows, generators' reactive power capability, and maximum active power output of slack generator) for normal (non-contingency) and selected N-1 conditions [1].

In this test bed, the target is to minimize the total fuel cost of traditional generators plus the expected uncertainty cost of renewable energy generators. In this way, each renewable energy generator is considered to be a dispatchable generator, and depending on the available real power, it is considered either in an underestimated or overestimated condition [8]. These conditions are understood in the following ways [8]:

- Underestimated condition

The scheduled power (Ps_i) from the renewable energy generator (i) is less than the available real power (Pa_i). In this case, there would be a cost for such an underestimate given by: $Cu=c_u(Pa_i-Ps_i)$ since not all the available power for the system will be utilized. Only Ps_i will be used. It would be a kind of power wasted, but in real applications, such excess generation can be directed to an energy storage system with a related cost for using such a system.

- Overestimated condition

The scheduled power (Ps_i) from the renewable energy generator (i) is greater than the available real power (Pa_i). Therefore, there would be a cost for such an overestimate given by: $Co=c_o(Ps_i-Pa_i)$. In this case, the total available power is not enough to meet the scheduled power to the system (Ps_i). Therefore, the network operator must turn on or request more power from another energy source with a related cost (c_o).

The available real power (Pa_i) from a renewable energy generator is not known with certainty. Nevertheless, in some cases, it is possible to know the probability distribution of the primary factor (wind speed, solar irradiance, or river flow) governing energy production from the renewable energy system. In this way, considering the relationship between the primary factor and the power from such systems, it is possible to get the probability distribution of Pa_i.

There are two ways of get the expected uncertainty cost. The first way is through Monte-Carlo Simulations given by scenarios' generation based on probabilities distribution describing the primary factors governing energy generation from renewable energy systems (See Test Bed A). The second way is through analytical expressions. References [9] and [10] probed that the expected uncertainty cost of renewable energy generators and electric vehicles can be calculated through such analytical expressions. These expressions are defined as uncertainty cost functions [9]-[10].

The aspect of the analytical expressions for each case is given below. You can find the meaning of each term in [9], but for this Test Bed it is not necessary that competitors know this since it is considered as a black box problem.

WIND CASE STUDY (wind speed follows a Rayleigh probability distribution)

- Cost due to an underestimated condition:

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

- Cost due to an overestimated condition:

$$
\begin{aligned}
E\left[C_{w,o,i}\left(W_{w,s,i}, W_{w,i}\right)\right] \\
&= c_{w,o,i} W_{w,s,i} \cdot \left(1 - e^{-\frac{V_i^2}{2\sigma^2}} + e^{-\frac{V_0^2}{2\sigma^2}} + e^{-\frac{\kappa^2}{2\rho^2\sigma^2}}\right) \\
&- \frac{\sqrt{2\pi} c_{w,o,i} \rho\sigma}{2}\left(er\,f\left(\frac{W_{w,s,i} - \kappa}{\sqrt{2}\rho\sigma}\right) - er\,f\left(\frac{-\kappa}{\sqrt{2}\rho\sigma}\right)\right) \qquad (3)
\end{aligned}
$$

SOLAR STUDY CASE (solar irradiation follows a Log-normal distribution)

- Cost due to an underestimated condition (there are two conditions A and B depending on the comparison between the available real power and a reference irradiance value):

$$
E\left[C_{PV,u,i}\left(W_{PV,s,i}, W_{PV,i}\right), A\right] = \frac{(-1) c_{PV,u,i} W_{PV,s,i}}{2}\left[er\,f\left(\frac{\left(\frac{1}{2} ln\left(\frac{W_{R_C} G_r R_C}{W_{PV_r}}\right) - \lambda\right)}{\sqrt{2}\beta}\right) - er\,f\left(\frac{\left(\frac{1}{2} ln\left(\frac{W_{PV,s,i} G_r R_C}{W_{PV_r}}\right) - \lambda\right)}{\sqrt{2}\beta}\right)\right] + \frac{c_{PV,u,i} W_{PV_r} \cdot e^{2\lambda + 2\beta^2}}{2 G_r R_C}\left[er\,f\left(\frac{\left(\frac{1}{2} ln\left(\frac{W_{R_C} G_r R_C}{W_{PV_r}}\right) - \lambda\right)}{\sqrt{2}\beta} - \sqrt{2}\beta\right) - er\,f\left(\frac{\left(\frac{1}{2} ln\left(\frac{W_{PV,s,i} G_r R_C}{W_{PV_r}}\right) - \lambda\right)}{\sqrt{2}\beta} - \sqrt{2}\beta\right)\right] \qquad (4)
$$

$$
E\left[C_{PV,u,i}\left(W_{PV,s,i}, W_{PV,i}\right), B\right] = \frac{c_{PV,u,i} W_{PV,s,i}}{2}\left[er\,f\left(\frac{\left(ln\left(\frac{W_{R_C} G_r}{W_{PV_r}}\right) - \lambda\right)}{\sqrt{2}\beta}\right) - er\,f\left(\frac{\left(ln\left(\frac{W_{PV,\infty,i} G_r}{W_{PV_r}}\right) - \lambda\right)}{\sqrt{2}\beta}\right)\right] + \frac{c_{PV,u,i} W_{PV_r} \cdot e^{\lambda + \beta^2/2}}{2 G_r}\left[er\,f\left(\frac{\left(ln\left(\frac{W_{PV,\infty,i} G_r}{W_{PV_r}}\right) - \lambda\right)}{\sqrt{2}\beta} - \frac{\beta}{\sqrt{2}}\right) - er\,f\left(\frac{\left(ln\left(\frac{W_{R_C} G_r}{W_{PV_r}}\right) - \lambda\right)}{\sqrt{2}\beta} - \frac{\beta}{\sqrt{2}}\right)\right] \qquad (5)
$$

- Cost due to an overestimated condition (there are two conditions A and B depending on the comparison between the available real power and a reference irradiance value):

$$E\left[C_{PV,o,i}\left(W_{PV,s,i},W_{PV,i}\right),A\right] = \frac{-c_{PV,o,i}W_{PV,s,i}}{2}\left[1+erf\left(\frac{\left(\frac{1}{2}ln\left(\frac{W_{R_c}G_rR_c}{W_{PV_r}}\right)-\lambda\right)}{\sqrt{2}\beta}\right)\right] + \frac{c_{PV,o,i}W_{PV_r}\cdot e^{2\lambda+2\beta^2}}{2G_rR_c}\left[erf\left(\frac{\left(\frac{1}{2}ln\left(\frac{W_{R_c}G_rR_c}{W_{PV_r}}\right)-\lambda\right)}{\sqrt{2}\beta}-\sqrt{2}\beta\right)+1\right] \quad (6)$$

$$E\left[C_{PV,o,i}\left(W_{PV,s,i},W_{PV,i}\right),B\right] = \frac{c_{PV,o,i}W_{PV,s,i}}{2}\left[erf\left(\frac{\left(ln\left(\frac{W_{R_c}G_r}{W_{PV_r}}\right)-\lambda\right)}{\sqrt{2}\beta}\right)-erf\left(\frac{\left(ln\left(\frac{W_{PV,s,i}G_r}{W_{PV_r}}\right)-\lambda\right)}{\sqrt{2}\beta}\right)\right] + \frac{c_{PV,o,i}W_{PV_r}\cdot e^{\lambda+\beta^2/2}}{2G_r}\left[erf\left(\frac{\left(ln\left(\frac{W_{PV,s,i}G_r}{W_{PV_r}}\right)-\lambda\right)}{\sqrt{2}\beta}-\frac{\beta}{\sqrt{2}}\right)-erf\left(\frac{\left(ln\left(\frac{W_{R_c}G_r}{W_{PV_r}}\right)-\lambda\right)}{\sqrt{2}\beta}-\frac{\beta}{\sqrt{2}}\right)\right] \quad (7)$$

ELECTRIC VEHICLE CASE STUDY (availability of vehicle to grid and battery vehicle charge functionalities follow normal distributions)

- Cost due to an underestimated condition:

$$E\left[C_{e,u,i}\left(P_{e,i},P_{e,s,i}\right)\right] = \frac{c_{e,u,i}}{2}\left(\mu-P_{e,s,i}\right)\left(1+erf\left(\frac{\mu-P_{e,s,i}}{\sqrt{2}\phi}\right)\right)+\frac{c_{e,u,i}\cdot\phi}{\sqrt{2\pi}}\cdot e^{-\left(\frac{\mu-P_{e,s,i}}{\sqrt{2}\phi}\right)^2} \quad (8)$$

- Cost due to an overestimated condition:

$$E\left[C_{e,o,i}\left(P_{e,i},P_{e,s,i}\right)\right] = \frac{c_{e,o,i}}{2}\left(P_{e,s,i}-\mu\right)\left(erf\left(\frac{\mu}{\sqrt{2}\phi}\right)-erf\left(\frac{\mu-P_{e,s,i}}{\sqrt{2}\phi}\right)\right)+\frac{c_{e,u,i}\cdot\phi}{\sqrt{2\pi}}\cdot\left(e^{-\left(\frac{\mu-P_{e,s,i}}{\sqrt{2}\phi}\right)^2}-e^{-\left(\frac{\mu}{\sqrt{2}\phi}\right)^2}\right) \quad (9)$$

Competitors can reproduce the simulation contrasting the expected uncertainty cost from Monte-Carlo Simulations and from the proposed analytical uncertainty cost functions in [9]. The files named *MontecarloVsAnalyticalWind.m*, *MontecarloVsAnalyticalSolar.m* and *MontecarloVsAnalyticalEV.m*, are in the folder *StochasticTests*. These files get the expected uncertainty cost by the two mentioned ways.

Note that there is a different expected cost for every scheduled power.

The detailed deduction of the analytical expressions and the demonstration using Monte-Carlo simulations can be found in [9].

3. TEST CASE FOR DYNAMIC OPF IN PRESENCE OF RENEWABLE ENERGY AND ELECTRIC VEHICLES (IEEE 118 bus system)

The IEEE 118 bus system has 54 generators. In this test bed, four of the generators are considered renewable energy generators (two wind and two solar PV systems). Additionally, in this test bed, four electric vehicles are considered, and the problems are evaluated over six time instances. In this case, the number of decision variables and constraints will be multiplied by 6.

- **Objective:** Minimize the total fuel cost of traditional generators plus the expected uncertainty cost for renewable energy generators plus the expected uncertainty cost for electric vehicles.

- **Optimization variables:** 6 x 130, where the 130 is given for 107 continuous variables describing generator active power outputs (53, the slack is not considered here, since the injected power is given by the power flow) and generator bus voltage set-points (54), 9 discrete variables related to stepwise adjustable on-load transformers' tap positions, 14 binary variables linked to switchable shunt compensation devices.

- **Constraints:**

There are 3 types of constraints:

i) Power flow constraints

These constraints are related to nodal balance of power (these are equality constraints). The encrypted file *UC.p* calculates 6 power flows (one for each time instance); each time instance corresponds to a different network power demand condition.

ii) Constraints penalized in the fitness function

- Nodal voltages for load buses: 6 x (99 + 99)
- Allowable branch power flows: 6 x (186)
- Generator reactive power capability: 6 x (54 + 54)
- Maximum active power output of a slack generator: 6 x (1)

For normal (non-contingency) and selected N-1 conditions, that is to say 493 constraints for non-contingency conditions, and 492 constraints for each N-1 condition in each time instance.

Additionally, ramp constraints 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 5 x 53, 5 because there are 6 time instances and 53 because there are 53 decision variables related with active power generation).

In total, we have the following number of constraints:

(6 x 493) + (6 x 492) + (5 x 53)

iii) Minimum and maximum levels on optimization variables (6 x 130 x 2)

- **Considered contingencies (N-1 conditions):** outages at branches 21, 50, 16 and 48.

- **Number of function evaluations:** 90000 power flows. Please note that every time that you run the *UC.p* function, you calculate 6 (time instances) power flows for each set of decision variables.

4. IMPLEMENTATION ASPECTS[3]

The *main.m* file contained in *test_bedB_DynamicOPF_2018.zip* allows selecting the case to be solved (case 1 in this test bed), as well as calling the implementation routine written for your optimization algorithm. Please note that this year is not considered to employ a shared-memory parallel computing functionality of Matlab's Parallel Computing Toolbox. The file *main_2018_TestBedB_Commented.m* provides a thorough description of the overall procedure and the adaptation of the provided files for your implementation.

4.1. Experimental setting

- **Trials/problem:** It is fixed to 10 trials in *test_bed_OPF.p* by using field *proc.n_run*, which is declared global. For initial testing purposes, you are allowed to change the value of this variable to a lower value but please remember that 10 trials are mandatory for performance evaluation in the competition.

- **Stopping criterion:** *test_bed_OPF.p* is configured to terminate automatically an optimization trial upon completion of the maximum number of function evaluations (in this case 90000 power flows). It is possible to prematurely stop running a current trial in your implemented algorithm. Nevertheless, it is pointed out that automatic storage of intermediate results in formatted ASCII files will not be performed in this case, so you may have to add some commands to your implementation for recording the progress of objective function, fitness, constraint fulfillment, and optimization variables. Please remember that the maximum number of function evaluations established in the previous section is mandatory for performance evaluation in the competition, and only the ASCII files created automatically by *test_bed_OPF.p* should be submitted for evaluation.

[3] Please note that the structure and content of this section is similar to (it is updated the new considerations for the 2018 competition): 2014 Competition Application of Modern Heuristic Optimization Algorithms for Solving Optimal Power Flow Problems by István Erlich, Kwang Y. Lee, José L. Rueda, Sebastian Wildenhues and 2017 Competition Evaluating the Performance of Modern Heuristic Optimizers on Smart Grid Operation Problems, Test Bed 1: Stochastic OPF based active-reactive power dispatch by Sergio Rivera, Andres Romero, José L. Rueda, Kwang Y. Lee, István Erlich

- **Initialization:** uniform random initialization within the search space.

- **Encoding:** If the algorithm requires encoding, then the encoding scheme should be independent of the specific optimization tasks and governed by generic factors such as search ranges, dimensionality of the problems, etc.

- **Algorithm tuning:** The participants are allowed to tune their algorithms. Details of tuning procedure, corresponding dynamic ranges of algorithm's parameters, and final parameter values used should be provided to the organizers and thoroughly discussed in the panel as well.

4.2. Results to be submitted

UC.p performs automatic saving of results in formatted ASCII-files contained in a zipped folder named *output_data_ImplementationName.zip*. The folder is created once a scenario of a test case for an individual system is solved for the first time. Newly created results are automatically added to this folder.

Before submission of results, please check whether the folder contains a total of four files. Each of the four files should automatically be assigned names according to the following convention:

(Name of your implementation)_(Number of buses denoting the system)_2_ScenarioType_(xyz).txt where (xyz) stands for different items to be stored:

- objective: recorded objective function convergence data for each optimization trial (It is only recorded the data after the 90000 power flows).
- fitness: recorded fitness convergence data for each optimization trial. (It is only recorded the data after the 90000 power flows).
- variables: final best solution achieved by the optimization algorithm in each optimization trial
- complexity: computing time associated to each optimization trial

The file *output_data_ImplementationName.zip* together with the implementation codes of the used algorithm must be summited to srriverar@unal.edu.co, aalsumaiti@masdar.ac.ae and j.l.ruedatorres@tudelft.nl by maximum 30th March 2018 (12:00 pm EST). Details on the computing system and the programming language used should also be provided. It is discouraged to attempt deliberating manipulation of the ASCII-files, e.g. replacement of files corresponding to a given optimization test case by new ones collecting the results of the best 10 trials picked up after performing a myriad of optimization trials.

4.3. Evaluation criteria

Although the submitted results will be mainly assessed in terms of the achieved final fitness values, which are automatically saved in ASCII-files by the *test_bed_OPF.p* file, the fulfillment of the established bounds for the optimization variables will also be considered. Based on these results, a ranking index will be established accounting for different problem complexities.

5. REFERENCES

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