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 A:
Stochastic OPF in Presence of Renewable Energy and Controllable Loads

Problem Definition and Implementation Guidelines

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1. AIM OF THE COMPETITION [1]

The application of heuristic optimization algorithms to solve power system optimization problems is receiving great attention due to their effectiveness in solving problems with inherent mathematical complexities such as high-dimensionality, non-linearity, non-convexity, multimodality and discontinuity of the 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 competition panel in the 2014 IEEE PES General Meeting. The competition focused on the application of these heuristic tools for solving optimal power flow (OPF) problems [1]. Such competition motivated the developer to create power system optimization test beds considering renewable penetration and its stochastic behavior (see IEEE 2017 competition) [2]. Such test beds are beneficial for ascertaining and performing comparative analysis on the general applicability and effectiveness of emerging heuristic optimization tools contrasted with analytical optimization [1], [2].

Along this spirit, a new competition focused on optimization problems related to smart grid operation was organized in 2017 [2]. More specifically, integrating high penetration renewable energy systems into the grid poses many challenges as such systems are uncertain in terms of their generation. As a result, a special emphasis on the stochastic factors associated with such systems' deployment into the grid was taken into account when developing the test bed 1 of the 2017 competition [2]. In more details, the test bed focused on the stochastic OPF based active-reactive power dispatch including renewable energy systems (wind, solar PV and small hydro power), and the evaluation of implemented IEEE 57-bus system power system problems (i.e. calculation of objective function and value subject to a set of constraints)

Following the 2017 contest, the 2018 Test Bed A competition aims to perform a comparative assessment of the search capability of different heuristic optimization algorithms, considering the stochastic behavior of the objective function for the same set of decision variables (please see subsection 2.1.3). Additionally, this year (2018) will consider controllable loads as dispatchable units in the model.

The assessment will be based on statistical tests performed on results submitted by interested participants. For this purpose, an encrypted file has been prepared based on functionalities in Matlab (version: R2015a) and MATPOWER toolbox (version: matpower6.0b1) in order to perform automatic evaluation of active-reactive power dispatch optimization problem as well as to collect and store automatically the results [1]. In this year's competition, the objective function is modified with respect to the 2014 and 2017 competition. It is now a stochastic variable defined in terms of a minimization of an expected operational cost as impacted by the power generation uncertainty from renewable energy systems (detailed explanation can be found in subsection 2.1.2).

[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

The problems to be solved are 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 are requested to exclusively work on 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 [1].

What is provided in this competition?

The competitors will have access to the followings:

1. An encrypted file named *test_bed_OPF.p* along with other exemplary Matlab m-files, which are intended for an easy adaptation to any heuristic optimization algorithm, included in the zipped folder named *test_bedA_OPF_2018.zip*.
2. Complete details (in MATPOWER format) and updated diagram (in Microsoft Visio format) of the IEEE 57 bus test system are provided in subfolders named *input_data*, and *Docs* in the zipped folder, respectively.

Please read carefully the instructions given in every m-file and in *readme2018TestBedA_Contest.txt* file, which provide precise indications about Matlab based procedural and implementation aspects.

Anticipated Deliverables:

Final results, which are automatically saved for each optimization test case over 12 independent optimization trials in formatted ASCII-files contained in a zipped folder named *output_data_ScenarioType_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 implemented codes for each algorithm entering the competition must also be submitted along with final results for full consideration in the evaluation. The submitted codes will be used for further tests, which are intended to crosscheck the submitted results. The submitted codes will be in the public domain and no intellectual property claims should be made.

2. DEFINITION OF THE STOCHASTIC OPTIMIZATION PROBLEM IMPLEMENTATION (STOCHASTIC OPF)

2.1. Competition files structure [2][2]

The formulation of optimal active-reactive power dispatch (OARPD) problem, i.e. [3]-[4], represents an optimization problem with an objective cost-function and system operational constraints. The calculation of the objective function and the constraints for

[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**

a set of decision variables is implemented in the encrypted file *test_bed_OPF.p*. Additionally, *test_bed_OPF.p* has been developed for automatic collection and storage of results in formatted ASCII-files in a similar way of the 2014 and 2017 contests [1]-[2]. It uses functions for modeling the power flow calculation available in MATPOWER toolbox [5], which can be freely downloaded from http://www.pserc.cornell.edu/matpower/.

Moreover, the zipped folder *test_bedA_StochasticOPF_2018.zip* contains this code (*test_bed_OPF.p*) along with instructions (in each code and in the readme file) on how to use it as well as an implementation example with a 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_bedA_StochasticOPF_2018*. In this folder you can find different files of the competition. Please read the notepad file: *readme2018TestBedA_Contest.txt* in order to understand the structure of the 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. An exemplary routine for constraint handling is provided in the file *constraint_handling.m*. As per this file, this routine does not affect any calculation done in the file *test_bed_OPF.p*, which internally calculates the set of fitness as a function of the different combinations of decision variables by using (1).

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

where ρ is a penalty factor that is set to a value of 1E+7.

It is clarified that the fitness calculation performed by *test_bed_OPF.p* is exclusively intended for ascertaining the fulfillment of constraints in the competition. The values of the objective function and the fitness function are automatically recorded at a predefined rate of 100 function evaluations, i.e. power flow calculations, and stored in a formatted ASCII-file, which will be used later in algorithms' performance evaluation.

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 the file *test_bed_OPF.p* before every function evaluation. The term x_in denotes one individual component of the sequence of discrete/binary variables from the vector of optimization variables to be generated using the offspring creation scheme of your optimization algorithm.

The file *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 your algorithm uses a rounding strategy or not. If a rounded variable violates its boundary, it will be automatically fixed in the file *test_bed_OPF.p* to the corresponding limit.

Please read instructions given in *main_2018_TestBedA_Commented.m* to determine indexes (elements) of the vector of optimization variables defined as discrete/binary variables. Please also refer to *main_2018_TestBedA_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_TestBedA_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 57-bus test system is used to evaluate the stochastic optimization problem. Based on details given in [6] for system buses and branches, 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 test system characteristics is shown in Table 1, whereas descriptions of the optimization test cases to be performed for the system is given in the following subsections.

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 57 bus system	
Generators	7
Loads	42
Lines/cables	63
Transformers Stepwise	15
Transformers Fixed tap	2
Shunt compensation Binary On/Off	3

2.2. Considerations regarding Stochastic Behavior of Wind, Solar and Small-Hydro Generation.

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

In this competition, the target is to minimize the total fuel cost of the traditional generators plus the expected uncertainty cost for renewable energy generators (operational cost due to variabilities of primary energy resources). In this way, each renewable generator is considered to be a dispatchable generator; and depending on the available real power, it is considered in an underestimated or overestimated condition [8]. These conditions are understood in the following ways [8]:

- Underestimated renewable energy generation situation

In this situation, the scheduled power (Ps_i) from the renewable energy generator i is less than the available real power (Pa_i). In this case, there will be a cost for underestimating the renewable energy system generation. This cost is given by: $Cu=c_u(Pa_i-Ps_i)$. Such a cost is resonated to the unused power that is available for the system. To clarify this, only Ps_i will be used in such a situation. Although, such an unused power may be looked at as wasted power, in real power system application, such power can be stored in energy storage systems along with a consideration of any relevant cost for using the system.

- Overestimated renewable energy generation situation

The scheduled power (Ps_i) from the renewable energy generator i is greater than the available real power (Pa_i) from such a system. In this situation, there would be a cost for overestimating the generation from renewable energy and treated as penalty. This cost is given by: $Co=c_o(Ps_i-Pa_i)$. In this case, the total available power is not enough to meet the planned scheduled power in the system (Ps_i). Therefore, the network operator must turn on or request more power from an alternative energy source given in mind the related cost (c_o) in this case.

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

In order to obtain the probability distribution of the available power from the known primary energy source probability distribution, it is recommended to apply Monte-Carlo Simulations. That is to say, this probability distribution will be determined through scenarios of wind speed, solar irradiance or river flow, given by aleatory scenarios from the primary energy source probability distribution. Using the relationship between the primary energy source and the injected power in the network, it is possible to get scenarios of the available real power, and through a histogram its probability distribution. In this way, uncertainties in factors driving power generation from renewable energy systems are modeled through probability distribution functions. Then, Monte-Carlo Simulations are used to account for all possible scenarios of these uncertainty factors. After that, power generation from renewable energy systems is calculated for all generated scenarios.

Given the aforementioned underestimated and overestimated situations, the expected cost in these situations is to be calculated as a probabilistic function given the uncertainty in renewable energy sources modeled through Monte-Carlo Simulations.

The following steps summarize the approach:

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 real power for scenario j when renewable energy generator i is used (Pa_{i_j}) by using the relationship between the primary energy source and Pa_{i_j}.
iii) Verification of the underestimated ($Ps_i < Pa_{i\_j}$) or overestimated ($Ps_i > Pa_{i\_j}$) condition in scenario j. Ps_i corresponds to the decision variable describing renewable energy generator i.

iv) Calculate the uncertainty cost for scenario j:

$C_{i\_j}=c_u(Pa_{i\_j}-Ps_i)$ if $Ps_i < Pa_{i\_j}$

or

$C_{i\_j}=c_o(Ps_i-Pa_{i\_j})$ if $Ps_i > Pa_{i\_j}$

v) Repeat the steps i) to iv) N (in this 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.

2.3. Multiple Sets of Monte-Carlo Simulations and Consideration of Controllable Loads (New Considerations in the 2018 Test Bed A)

In this test bed, the objective function of the optimization problem is defined as minimizing the expected value of the operational cost impacted by uncertainty in power generation from renewable energy systems.

In this year (2018), multiple sets of Monte-Carlo Simulations will be considered. That is to say, in 2017, for the 6 proposed cases, **a set** of Monte-Carlo Simulations (MCS) was considered (only one), using the probability distribution of the primary energy resources, and the result of this MCS is a set of scenarios of available power from the renewable energy generators. In this way, a set of the same decision variables will give the same expected value since it is considered only a one set of Monte-Carlo Simulations.

The 2018 competition consider not only a set of Monte-Carlo simulations but also multiple stochastic sets of MCS. In this way, a set of the same decision variables will give a different expected value since it is considered stochastic sets of Monte-Carlo Simulations.

Controllable loads (CLs) or interruptible loads are a very flexible solutions to adjust the load curve of any system, and to take advantage of the active participation of large consumption centers [9]. CLs are one of the main forms of peak demand change solutions. They are vital elements that can be adjusted during hours of high electricity demand. In more details, they are controllable to reduce the electrical stress on the system.

In this test bed, the model of compensation is used based on the "capacity block adjustment method", which establishes compensation prices according to capacity blocks of the power interrupted, as shown in Table 2. It is important to clarify that P_{IL} refers to the actual demand of the interruptible load.

Table 2: Compensation price per interrupted capacity block

Block #	**Power interrupted**	**Compensation prices**
Block I	$(80\% – 95\%)* P_{IL}$	C_1
Block II	$(65\% – 80\%)* P_{IL}$	C_2
Block III	$(50\% – 65\%)* P_{IL}$	C_3

For each considered controllable load in the problem, an additional term is added to the objective function. This term represents the multiplication of the compensation price (Cj) by the difference between the demand of the interruptible load (P_{IL}) and the dispatched load found from the solution of the deployed heuristic algorithm to the problem under study.

3. TEST CASES FOR STOCHASTIC OPF IN PRESENCE OF RENEWABLE ENERGY AND CNTROLLABLE LOADS (IEEE 57 bus system)

The IEEE 57 bus system has 7 generators. In this test bed, three of these generators are assigned as renewable energy generators. The renewable energy generators are located at buses 2, 6 and 9. Additionally, the IEEE 57 test system has 42 loads. In the test bed, four of these loads are considered as controllable loads. Such controllable loads are located at buses 8, 12, 18 and 47.

Now, we will describe the objective function, the constraints and the optimization variables:

- **Objective Function:** Minimize the total fuel cost of traditional generators (buses: 1, 3, 8, 12) plus the expected uncertainty cost for renewable energy generators (buses: 2, 6, 9) plus the compensation cost for controllable loads (buses: 8, 12, 18, 47).

- **Constraints:**

There are 3 types of constraints:

i) Power flow constraints

Such constraints are related to nodal balance of power (these are equality constraints)

ii) Constraints penalized in the fitness function

- Nodal voltages for load buses (42 + 42)
- Allowable branch power flows (80)
- Generator reactive power capability (7 +7)
- Maximum active 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.

iii) Minimum and maximum levels of optimization variable (2 x 35)

- **Optimization variables:** 35 variables, comprising 13 continuous variables related to generator's active 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 transformers' tap positions, 3 binary variables related to switchable 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 generators (The competitor must select the case in the *main.m* file)

3.1. Case Study 1: Stochastic OPF for IEEE 57 Bus System Considering Wind Energy Generators and Controllable Loads

For this case study, the test bed accounts for three wind turbines to generate renewable energy. It is well known that the wind speed probability distribution follows a Weibull probabilistic distribution [10] - [11]. Additionally, there is a relationship between the wind speed and the power obtained from operating wind turbine as explained in the file *WindStochastic.m*.

An example of the stochastic nature of wind speed reflected into uncertain power generation as obtained from Monte-Carlo Simulations is further explained by the histogram derived from randomly generated wind speed. The latter follows Weibull probabilistic distribution as shown in Figure 1. Also, this figure shows the calculated power for the randomly generated samples of wind speed. Moreover, Figure 2 presents the uncertainty of power generation for the three wind turbines used in the test bed at bus 2, bus 6 and bus 9.

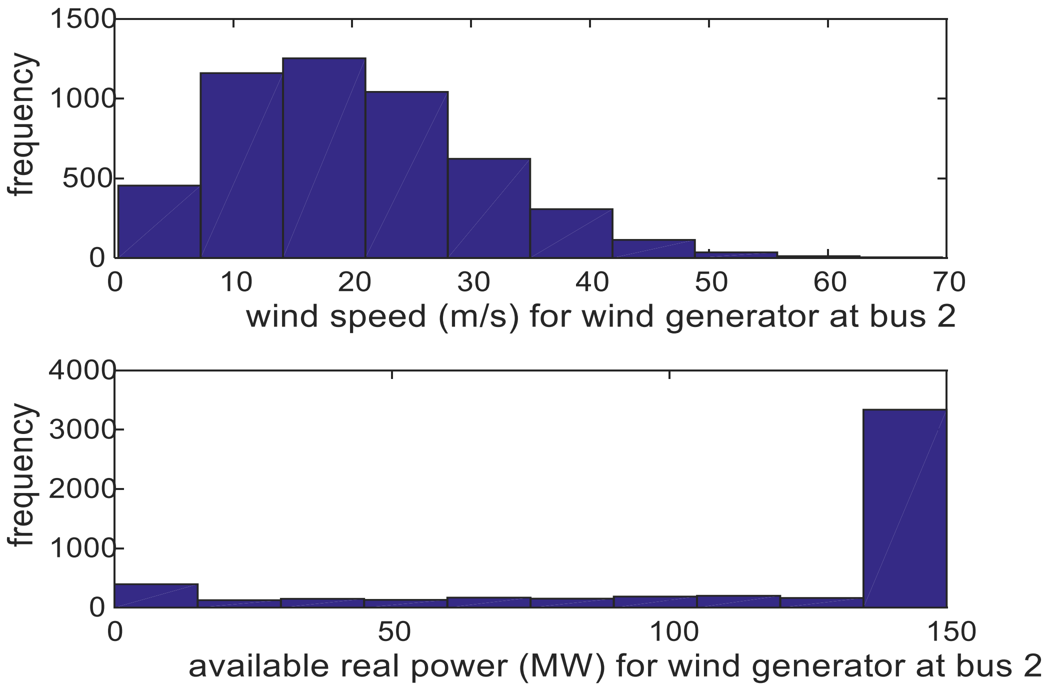

Figure 1. Wind Generator at bus 2.

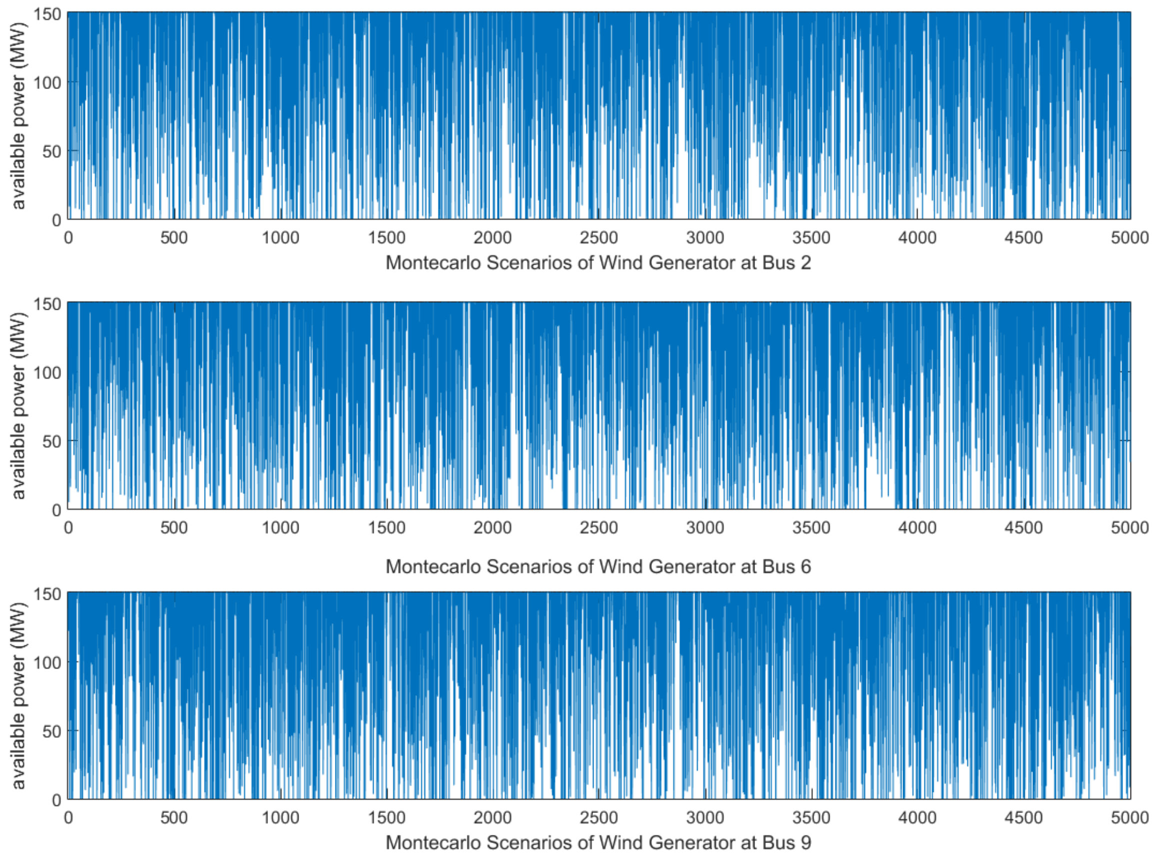

Figure 2. Montecarlo Scenarios of Wind Generators for case 1.

In order to run the case 1, please uncomment line 69 in the file *main.m* (`%ScenarioType=1; % UNCOMMENT FOR CASE 1`). Please note that every time that you call the encrypted file (*test_bed_OPF.m*) in your implementation (for instance line 68 and line 101 in *psopt.m* file), there would be a different set of Monte-Carlo Simulations given by the stochastic process of the primary energy resource (in this case wind speed).

3.2. Case Study 2: Stochastic OPF for IEEE 57 Bus System Considering Wind and Solar Energy Generators and Controllable Loads

In this case study, the test bed accounts for three renewable energy generators (2 wind and 1 solar PV). It is well known that in several parts of the world that the solar irradiance probability distribution follows a lognormal distribution [8], [12]. Additionally, there is a relationship between the solar irradiance and the power produced from the solar PV system. Therefore, by modeling the probabilistic nature of solar irradiance through such a probability distribution function, it is possible to derive the power produced from the solar PV system.

The file *SolarWindStochastic.m,* considers a set of Monte-Carlo simulations for the solar irradiance following the lognormal probabilistic distribution and calculates the power generated from the solar PV for every randomly generated sample from such a distribution.

An example of the stochastic nature of solar irradiance reflected into uncertain power generation as obtained from Monte-Carlo Simulations is further demonstrated by histograms shown in Figure 3. Such histograms are derived from randomly generated solar irradiance following lognormal probabilistic distribution and then calculating the corresponding power to be produced from the solar PV system. Moreover, Figure 4 presents the uncertainty of power generation accounting for the presence of both wind turbines at bus 2 and bus 9 and solar PV systems at bus 6 of the test bed.

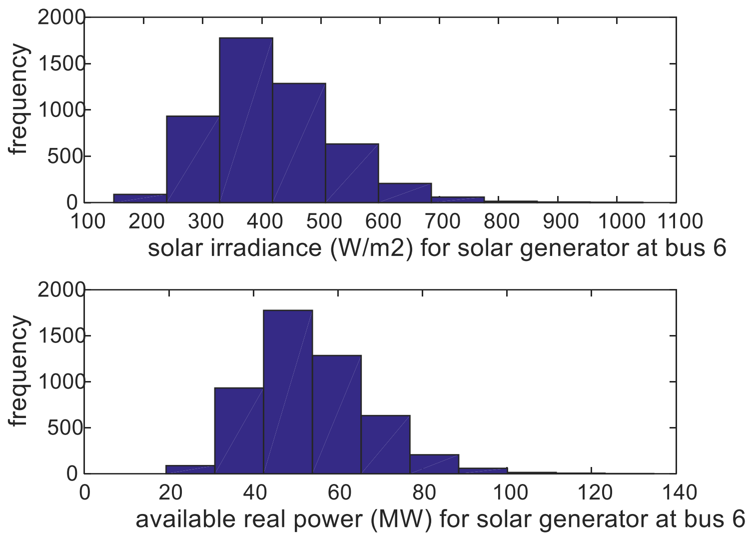

Figure 3. Solar energy generator at bus 6.

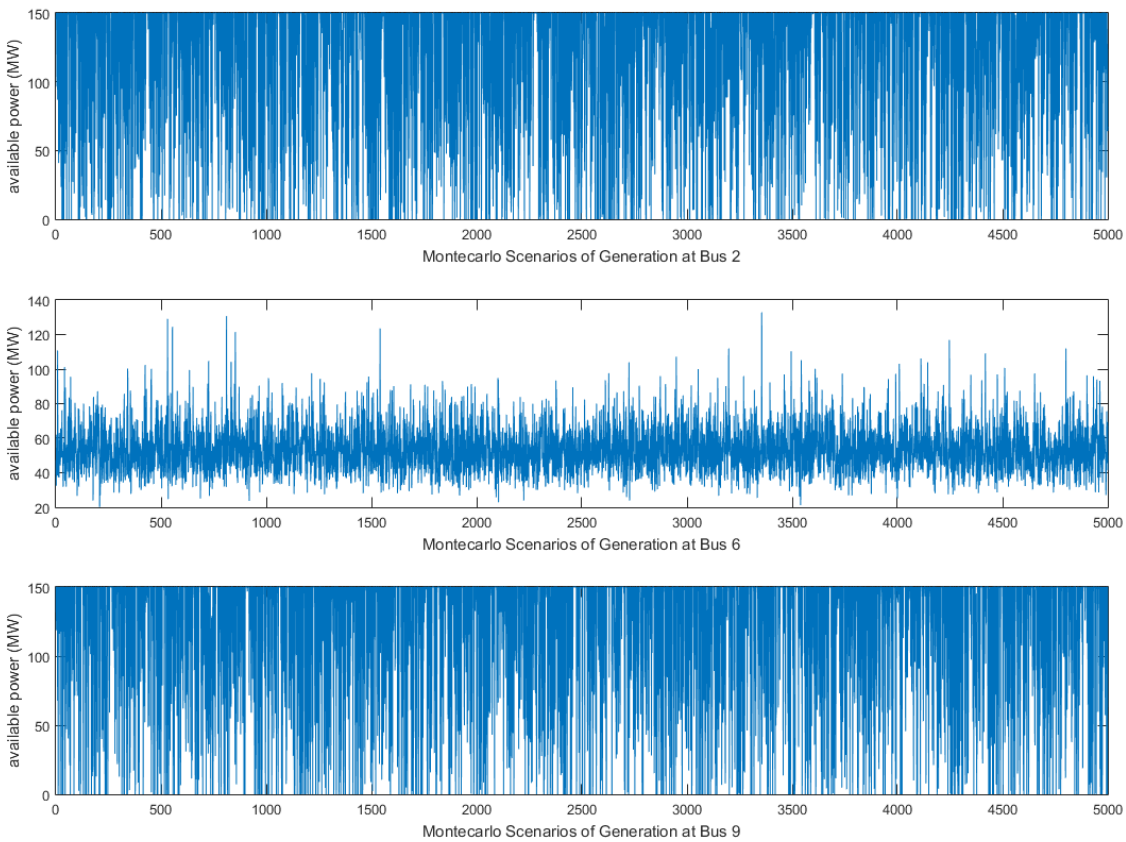

Figure 4. Monte-Carlo scenarios related to wind and solar energy generators modeling for case 2.

In order to run the case 2, please uncomment line 71 in the file *main.m* (`%ScenarioType=2; % UNCOMMENT FOR CASE 2`). Please note that every time that you call the encrypted file (*test_bed_OPF.m*) in your implementation (for instance line 68 and line 101 in *psopt.m* file), there would be a different set of Monte-Carlo Simulations given by the stochastic process of the primary energy resource (in this case wind speed and solar irradiance).

3.3. Case Study 3: Stochastic OPF for IEEE 57 Bus System Considering Wind, Solar and Small-Hydro Generators and Controllable loads

For case study 3 of this test bed, it is considered that there is a wind energy generator at bus and there are two generators, a solar generator and a small-hydro generator at bus 6 and 9. The uncertainty in wind speed and solar irradiance governing power production from their systems would be modelled using the appropriate probabilistic distributions explained earlier in case study 1 and case study 2. Since the river flow is the main factor governing the power production from the hydro power generator, the probabilistic distribution describing the uncertainty in such a flow is modelled using a gumbel probabilistic distribution [13]-[14]. The file *SolarWindHydroStochastic.m* uses Monte-Carlo Simulations to generate random samples of wind speed, solar irradiance, and river flow following the appropriate probabilistic distributions describing their uncertainty. The file also calculates the corresponding power from such resources' systems as per the sampled data. This is further explained by Figure 5 and Figure 6.

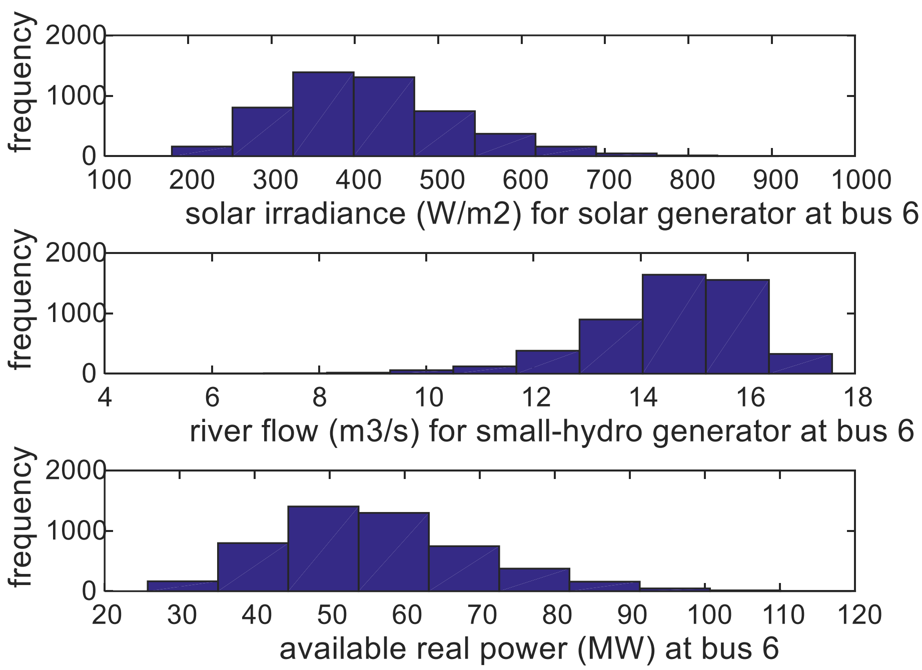

Figure 5. Solar and Small-Hydro Generators at bus 6.

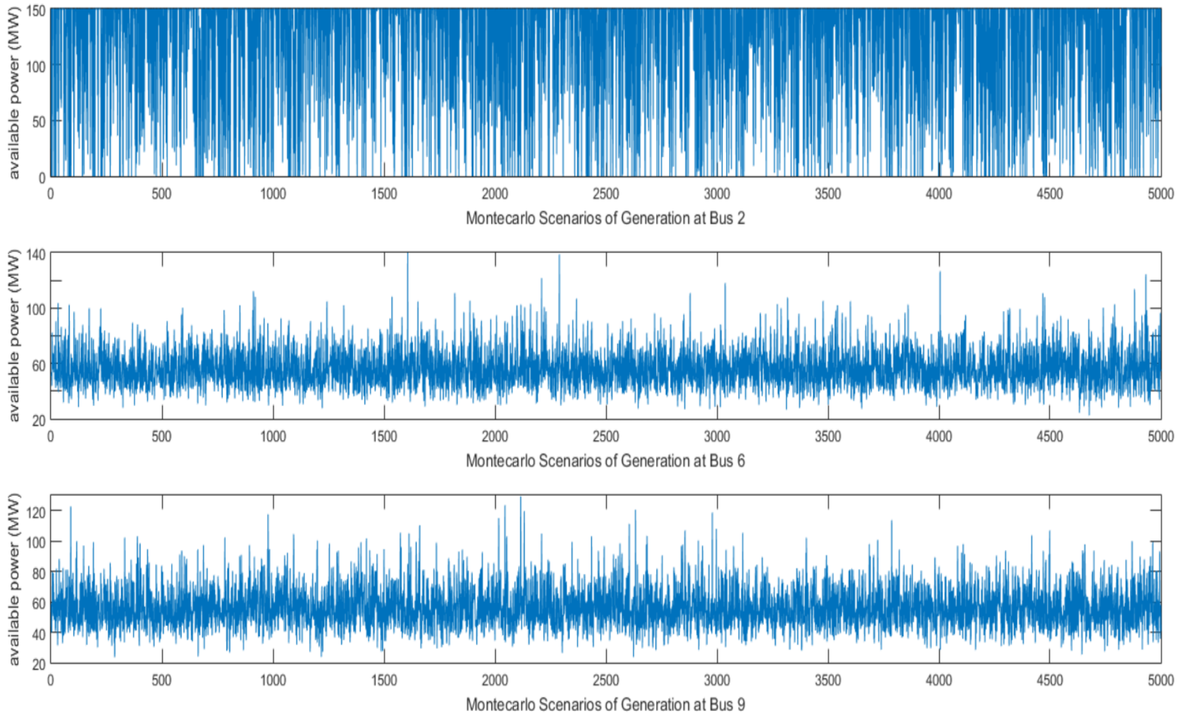

Figure 6. Montecarlo Scenarios of Wind, Solar and Small Hydro Generators for case 3.

In order to run the case 3, please uncomment the line 73 in the file *main.m* (`%ScenarioType=3; % UNCOMMENT FOR CASE 3`). Please note that every time that you call the encrypted file (*test_bed_OPF.m*) in your implementation (for instance line 68 and line 101 in *psopt.m* file), there will be a different set of Monte-Carlo Simulations given by the stochastic process of the primary energy resource (in this case wind speed, solar irradiance and river flow).

3.4. Case Study 4: OPF using an Analytical Uncertainty Cost Function for IEEE 57 bus system considering Wind generators and Controllable loads

References [15] and [16] probed that the expected uncertainty cost for wind energy generators can be calculated with an analytical expression. This expression is called "Wind Uncertainty Cost Function" [15]-[16]. The competitors can reproduce the simulation contrasting the expected uncertainty cost from Monte-Carlo Simulations and from the wind analytical uncertainty cost function. The file named *MontecarloVsAnalyticalWind.m* in the folder *StochasticTests* has the mentioned process in order to get the expected uncertainty cost.

Note that there is a different expected cost for every scheduled power (Psi corresponds to the decision variable related to the renewable energy generator i). For instance, for a 100 MW of scheduled power from wind energy generators, the results are:

ExpectedUncertaintyCost_Montecarlo = 2.0892e+04
ExpectedUncertaintyCost_Analytical = 2.0850e+04

The detailed deduction of the wind analytical expression and data demonstration can be found in [15].

In order to run case study 4, please uncomment line 75 in the file *main.m* (`%ScenarioType=4; % UNCOMMENT FOR CASE 4`). Please note that every time you call the encrypted file (*test_bed_OPF.m*) in your implementation (for instance line 68 and line 101 in *psopt.m* file), there will not but a different set of Monte-Carlo Simulations but a target function considering the wind analytical expression from [15].

3.5. Case study 5: OPF using an Analytical Uncertainty Cost Function for IEEE 57 bus system considering Wind and Solar generators (Cases 5) and Controllable loads

References [15] and [16] probed that the expected uncertainty cost for solar energy generators can be calculated with an analytical expression. This expression is called "Solar Uncertainty Cost Function" [15]-[16]. The competitors can reproduce the simulation contrasting the expected uncertainty cost from Monte-Carlo Simulations and from the solar analytical uncertainty cost function. The file named *MontecarloVsAnalyticalSolar.m* in the folder *StochasticTests* has the mentioned process in order to get the expected uncertainty cost.

Note that there is a different expected cost for every scheduled power (Psi corresponds to the decision variable describing the power from renewable energy generator i). For instance, for a 100 MW of scheduled power from solar energy generators, the results are:

ExpectedUncertaintyCost_Montecarlo = 3.2458e+04
ExpectedUncertaintyCost_Analytical = 3.2442e+04

The detailed deduction of the solar analytical expression and data demonstration can be found in [15].

In order to run case study 5, please uncomment line 77 in the file *main.m* (`%ScenarioType=5; % UNCOMMENT FOR CASE 5`). Please note that every time that you call the encrypt file (*test_bed_OPF.m*) in your implementation (for instance line 68 and line 101 in *psopt.m* file), there will not but a different set of Monte-Carlo Simulations but a target function considering the wind and solar analytical expressions from [15].

4. IMPLEMENTATION ASPECTS[3]

The *main.m* file contained in *test_bedA_OPF_2018.zip* allows selecting the case to be solved, 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

[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

main_2018_Commented.m provides a thorough description of the overall procedure and adaptation of the provided files for your implementation.

4.1. Experimental Settings

- **Trials/problem:** It is fixed to 12 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 12 trials are mandatory for performance evaluation in the competition.

- **Stop criterion:** *test_bed_OPF.p* is configured to terminate automatically an optimization trial upon completion of the maximum number of function evaluations. 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.

- **Initialization:** A random uniform 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 on the uniform tuning procedure, the 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

The file *test_bed_OPF.p* performs automatic saving of results in formatted ASCII-files contained in a zipped folder named *output_data_ScenarioType_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 for each case study (1 to 5) contains a total of 4 files. Each of the 4 associated 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. The convergence data is recorded after the first and after every 100 function evaluations.

- fitness: recorded fitness convergence data for each optimization trial. The convergence data is recorded after the first and after every 100 function evaluations.
- variables: final best solution achieved by the optimization algorithm in each optimization trial
- complexity: computing time associated with each optimization trial

The file *output_data_ScenarioType_ImplementationName.zip* together with the implementation codes of the algorithm being used must be summited to srriverar@unal.edu.co, aalsumaiti@masdar.ac.ae and j.l.ruedatorres@tudelft.nl by maximum March 30th, 2018 (12:00 pm EST), indicating in the email title "Test Bed A, IEEE 2018 Competition". Moreover, 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 the files corresponding to a given optimization test case by new ones collecting the results of the best 12 trials picked up after performing a myriad of optimization trials.

4.3. Evaluation Criteria

Although 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, which accounts for different problem complexities, will be established.

5. REFERENCES

[1]. 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.
Available online: http://sites.ieee.org/psace-mho/panels-and-competitions-2014-opf-problems/

[2]. 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
Available online: http://sites.ieee.org/psace-mho/2017-smart-grid-operation-problems-competition-panel/

[3]. Saraswat, and A. Saini, "Optimal reactive power dispatch by an improved real coded genetic algorithm with PCA mutation," 2nd International Conference on Sustainable Energy and Intelligent Systems, pp. 310-315, July 2011.

[4]. C.-M. Huang, S.-J. Chen, Y.-C. Huang, and H.-T. Yang, "Comparative study of evolutionary computation methods for active-reactive power dispatch," IET Generation, Transmission & Distribution, vol.6, no.7, pp. 636- 645, July 2012.

[5]. R. D. Zimmerman, C. E. Murillo-Sánchez, and R. J. Thomas, "MATPOWER: Steady-State Operations, Planning and Analysis Tools for Power Systems Research and Education," IEEE Transactions on Power Systems, vol. 26, no. 1, pp. 12-19, Feb. 2011.

[6]. http://www.ee.washington.edu/research/pstca/. Last accessed on August 15, 2013.

[7]. Y.H. Song, and X.F. Wang, Operation of Market-Oriented Power Systems. Springer Verlag: London, pp. 146, 2003. ISBN 978-1-85233-670-7.

[8]. S. S. Reddy, P. R. Bijwe, and A. R. Abhyankar, "Real-Time Economic Dispatch Considering Renewable Power Generation Variability and Uncertainty Over Scheduling Period," IEEE Systems Journal, vol. 9, pp. 1440-1451, 2015.

[9]. Yao, S., Liu, H., Lu, D., & Yuan, X. "Time-Space Characteristic of Interruptible Load on Dispatch Solution," Internacional Federation of Automatic Control, 48(28), 1355-1358, 2015. http://www.sciencedirect.com/science/article/pii/S2405896315029444

[10]. T. P. Chang, "Performance comparison of six numerical methods in estimating Weibull parameters for wind energy application," Applied Energy, vol. 88, pp. 272-282, Jan. 2011.

[11]. T. Arslan, Y. M. Bulut, and A. Altın Yavuz, "Comparative study of numerical methods for

determining Weibull parameters for wind energy potential," Renewable and Sustainable Energy Reviews, vol. 40, pp. 820-825, Dec. 2014.
[12]. T. P. Chang, "Investigation on frequency distribution of global radiation using different probability density functions, Int. J. Appl. Sci. Eng, vol. 8, no. 2, 99–107, 2010.
[13].P. Cabus, "River flow prediction through rainfall–runoff modelling with a probability-distributed model (PDM) in Flanders, Belgium," Agricultural Water Management, vol. 95, no. 7, pp. 859-868, 2008.
[14].N. Mujere, "Flood Frequency Analysis Using the Gumbel Distribution," International Journal on Computer Science and Engineering (IJCSE), vol. 3, no. 7, pp. 2774-2778, 2011.
[15]. J. Arévalo, F. Santos, S. Rivera, "Uncertainty cost functions for solar photovoltaic generation, wind energy generation, and plug-in electric vehicles: Mathematical expected value and verification by monte carlo simulation," International Journal of Power and Energy Conversion, in press, 2017.
http://www.inderscience.com/info/ingeneral/forthcoming.php?jcode=ijpec
[16]. S. Rivera, A. Romero, "Dispatch Modeling Incorporating Maneuver Components, Wind Power and Electric Vehicles Penetration, using Heuristic Techniques," Application of Modern Heuristic Optimization Techniques in Power and Energy Systems, ed: Wiley, in press, 2017.