A SURVEY ON A MULTI-OBJECTIVE METHODOLOGY FOR THE SELECTION AND SIZING OF WIND FARMS

D. J. C. Medina, diego76medina@yahoo.com.br
L. A. Scola, scola@ufsj.edu.br
C. C. Pellegrini, pelle@ufsj.edu.br
S. A. A. G. Cerqueira, sergioc@ufsj.edu.br
Universidade Federal de São João del-Rei, Praça Frei Orlando, 170, São João del-Rei, 36307-352

Abstract. *Among the renewable sources of energy, wind is the only one with energy prices that are currently comparable with those from fossil fuels power plants. In countries where wind is already an important fraction of the total power supplied to the electrical grid, an important obstacle to its further growth is in dealing with wind variability. Since, for locations separated by great distances, there is no synchrony between the wind speeds, it has been suggested to mitigate the wind power variability problem by spreading geographically the wind farms or, better yet, to carefully select the locations and sizes of the wind farms. In this work we present the initial results of a research that aims to develop a methodology for the selection of the location and the sizing of wind farms. A multi-objective genetic algorithm is employed to distribute a fixed number of turbines among a set of selected sites. Four objectives are considered: (i) the minimization of the power generation variability, (ii) the minimization of the mean complementary power, (iii) the minimization of the peak complementary power required and (iv) the maximization of the mean power generated. Meteorological data collected by automatic stations spread over south, south-eastern and north-eastern Brazilian states are employed. The power law is used to correct the wind speed data, collected at a height of 10 meters, for the 108 meters height typical of the class turbines studied. Further correction is done to adjust the speed for pressure and temperature, allowing the power to be obtained from manufacturer's data. The results of our experiments confirm the multi-objective nature of the problem, so that a decision taken with a single objective in mind will imply substantial compromises on the others.*

Keywords: *wind energy, geographical spread, multi-objective optimization*

1. INTRODUCTION

Climate change, natural resources scarcity. Whatever the reason, there are strong pressures for the replacement of fossil fuels for renewable energy sources. Among those sources, wind is the only one with prices that are currently comparable with those from fossil fuels power plants. It is not a coincidence therefore that it is also worldwide the fastest growing renewable energy source.

There are areas spread throughout Brazil with important wind energy potentials, according to the Brazilian Wind Potential Atlas (Amarante *et al.*, 2001). Those areas can be found in coastal areas from the south to the northeast and spread through the hinterland, as is the case of the northern and western parts of the state of Minas Gerais, as well as in mountainous areas throughout the country (see Fig. 1).

Wind is not a reliable nor a constant resource: it varies on scales ranging from fractions of seconds to multiannual. The high frequency variations (of the order of seconds or less) are small and easily absorbed by the rotors of the turbines (MacDonald, 2003). The installation of wind farms with large numbers of turbines, helping to reduce the frequency fluctuations of the order minutes (Wan and Bucaneg Jr, 2002). In countries where wind already represents a significant share of the electrical energy produced, such as Denmark, Germany, Spain and Portugal, an important obstacle to further growth of the wind's share is in dealing with wind variability (Boyle, 2007; Milligan and Factor, 2000).

On the other hand, demand in the electrical system also varies along the day, generally with a maximum at the end of the afternoon and minimum early in the morning. In order to properly consider the contribution of renewable sources to the system, one must attend to the distinction between energy and power supply. The system operator must ensure that by the end of the day not only the energy demand has been satisfied, but that at each moment throughout the day the required power has been supplied, with the necessary quality (Boyle, 2007).

Since, for locations separated by great distances, there is no synchrony between the wind speed variation, it has been suggested that an important measure to mitigate the wind power variability problem is to geographically spread the wind farms or, better yet, to carefully select the locations and sizes of the wind farms (Miranda and Dunn, 2007; Kempton *et al.*, 2010). In that selection procedure, care must be taken in the selection of a proper quality metric, for different choices (such as maximum generation energy, minimum reserve power needed to secure the attendance of charge, for example) will lead to different optimal combinations.

In a previous work (Medina *et al.*, 2010), we presented the results from a single objective optimization procedure where four different objectives were considered, one at a time. In problems where multiple, conflicting, objectives must be considered, the decision making should be made over a set of efficient solutions, *i.e.*, solutions that are not surpassed in all objectives by any other. Multi-objective problems with discrete variables, such as the number of wind turbines in a

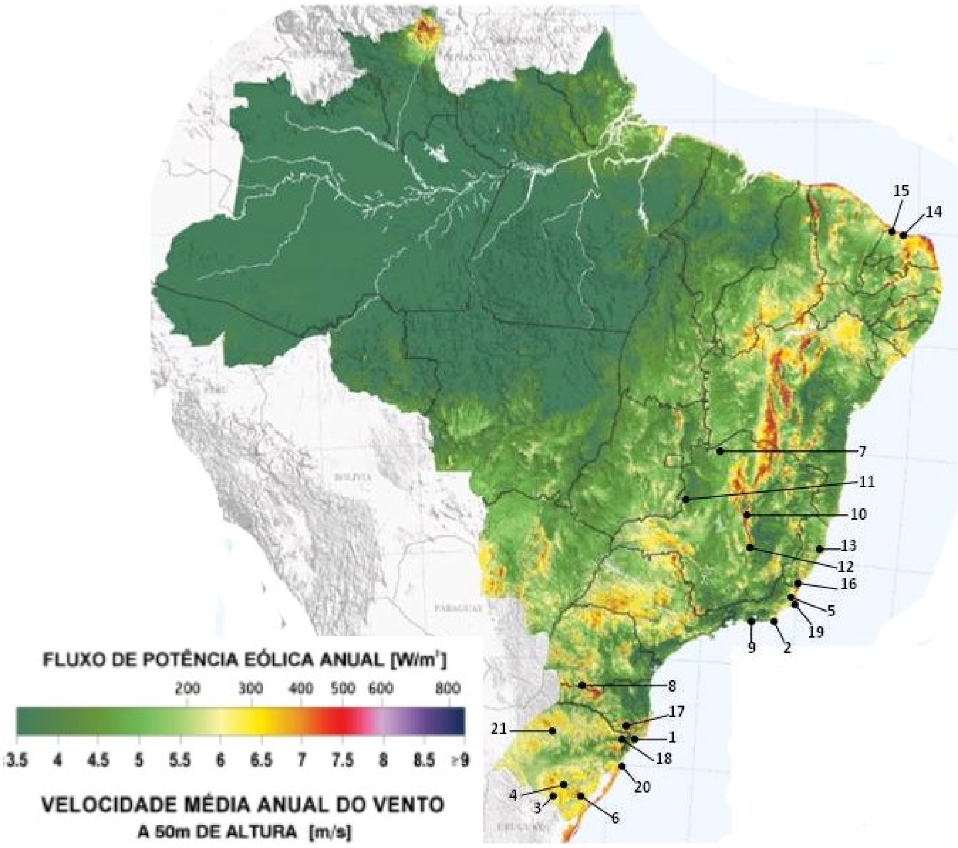

Figure 1. Brazilian wind energy potential (Amarante *et al.*, 2001). Numbers identify meteorological stations. 1. Ararangua, 2. Arraial do cabo, 3. Bage, 4. Caçapava do Sul, 5. Campos, 6. Canguçu, 7. Chapada Gaúcha, 8. Clevelândia, 9. Copacabana, 10. Diamantina, 11. Guarda Mor, 12. Ibirité, 13. Linhares, 14. Macau, 15. Mossoró, 16. Presidente Kennedy, 17. São Joaquim, 18. São José dos Ausentes, 19. São Tomé, 20. Tramandaí, 21. Cruz Alta.

farm, are dealt efficiently by evolutionary methods (Deb, 2001).

In this work, therefore, a multi-objective genetic algorithm is employed to distribute a fixed number of turbines among a fixed number of selected sites (in our experiments, 1200, 2MW class, wind turbines). The same four objectives as in the previous work are considered, now all at the same time: (i) the minimization of the power generation variability, (ii) the maximization of the mean power generated, (iii) the minimization of the mean complementary power and (iv) the minimization of the largest complementary power required. The last two objectives consider a situation in which the operator has committed to supply a fixed 15% of the nominal power of all the turbines, buying from others when the wind speed is too low.

2. METHODOLOGY

2.1 Wind Data and Wind Turbine

This work is part of a research that aims to develop a methodology for the selection of the location and the sizing of wind farms. Along with the development of the optimization procedure, a numerical atmospheric model is being employed to select sites and gather wind data. As the atmospheric simulation is yet incomplete, here the optimization procedure uses meteorological data from the National Institute of Meteorology (INMET, 2010), collected by automatic stations spread over the Brazilian South, South-Eastern and North-Eastern states.

Fifty five stations located near sites that are identified as having high potential by the Brazilian Wind Potential Atlas were studied. Of those, twenty-one were chosen (Fig. 1). The selection of the stations took into account two factors. First, the stations' locations are chosen not to provide data for wind potential but mainly for meteorological information – temperature, humidity, solar intensity and precipitation measurements are more of an issue than wind speed. Therefore, in several locations the wind speed measured does not reflect the high potential identified by the Atlas.

Second, only the automatic stations provide hourly data, suitable for the purposes of this work. Unfortunately, most of such stations in the INMET network are very recent, with a very limited set of data available, as was the case of several of the stations studied. Adding to that were maintenance problems that are reflected in the quality of the data. Some stations remain off-line for long periods, or lack part of the information required, thus reducing the amount of data available.

For the chosen sites, after discarding the incomplete sets, 14,088 out of the 18,240 possible simultaneous hourly sets of wind speed, temperature and pressure data were available during the period from 1 October 2008 to 31 October 2010.

Wind speed must receive two corrections in order for the power generation to be properly estimated. The operation in atmospheric conditions that are not the standard (15°C and 1 atm pressure) requires a correction for density. This work employs the correction velocity as proposed by Lu *et al.* (2009):

$$v_{s,c} = \left(\frac{P \cdot T}{1.225 \cdot R}\right)^{1/3} v_{s,o}, \tag{1}$$

where P and T are respectively the pressure and temperature at the turbine hub height, $v_{s,o}$ is the observed speed, $v_{s,c}$ is the speed corrected for density, and R the ideal gas constant (287.05 J/kg.K for moist air).

Then, since wind speed is measured at a height z_s of 10 meters, it is necessary to correct it for the 108 meters height, z, typical of the class of 2 MW wind turbines. That is done using the power law (Andrews and Jellley, 2007),

$$v_z = v_{s,c}\left(\frac{z}{z_s}\right)^{\alpha_s}, \tag{2}$$

where v_z is the speed, corrected for density and height of the turbine hub and α_s is the shear coefficient. This coefficient depends strongly on the terrain and shows great diurnal variation, from 0.15 to 0.5 during the evening, depending on the atmospheric stability conditions. An approximate expression for the shear coefficient at a constant speed between 6 and 10 m/s is:

$$\alpha_s = \tfrac{1}{2}\left(z_o/10\right)^{0.2}, \tag{3}$$

where z_o is the surface roughness length, for which a value of 0.03 was used, typical of the open fields where the stations are usually installed (Andrews and Jellley, 2007).

After the wind speed is corrected, the wind turbine power output can be obtained from manufacturer's data. In this work the ENERCON E82 (Enercon, 2009) wind turbine was considered. It has a nominal power of 2.05 MW, shaft height of 108 m and rotor diameter of 82 m, with power generation cut for wind speeds greater than 28 m/s. A fitting function was obtained for the turbine power data, provided by the manufacturer's catalog (Fig. 2).

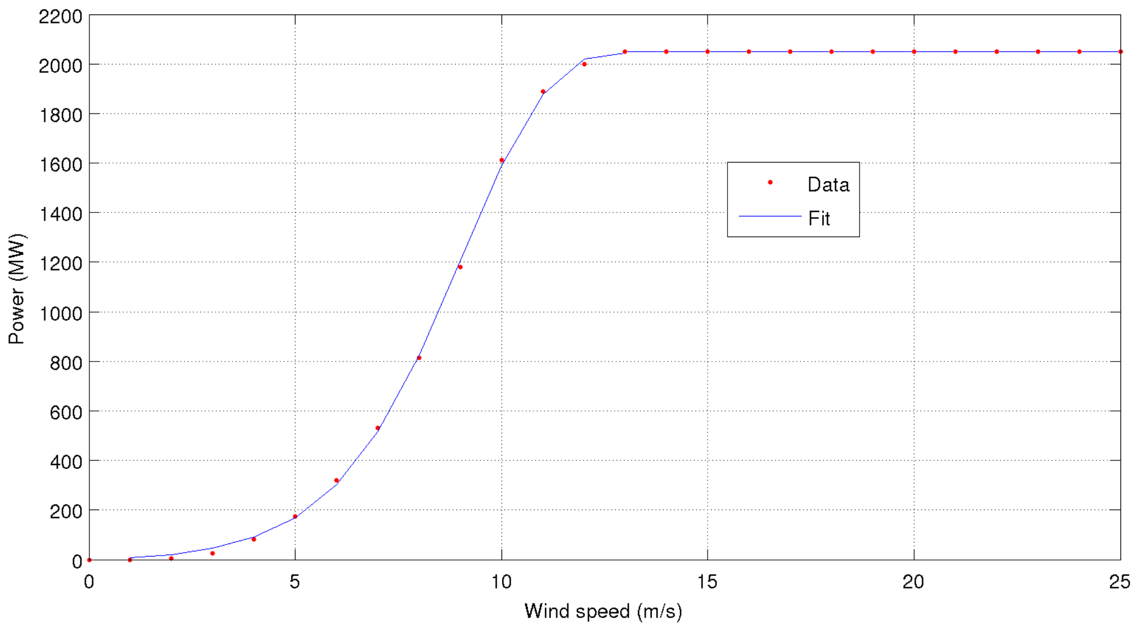

Figure 2. Power curve for the ENERCON E82 wind turbine (Enercon, 2009)

2.2 The Objective Functions

In consonance with our previous work, here four different objectives were simultaneously considered.

Minimization of the power generation variability The variability of the power produced from wind is a major problem to overcome when the share of that power in the total electrical system grows. This work employs the standard deviation as a measure of variability of a sample:

$$\min \Delta \dot{W} = \left[\frac{1}{n-1} \sum_{i=1}^{n} \left(\dot{W}_i - \bar{\dot{W}} \right)^2 \right]^{\frac{1}{2}} . \tag{4}$$

Here $\dot{W}_i$ is the power generated in the time interval i, $\bar{\dot{W}}$ is the mean power generated, n the number of intervals considered.

Minimization of the mean complementary power. There is a large difference between the selling prices of electrical energy if sold in advance and that of electricity sold in the spot market. For this objective it was assumed that the owner of the wind farms has committed to ensure a portion equivalent to 15% of total nominal power. The aim is then to minimize the total energy purchased from others to meet the times when the parks are not able to generate the necessary power. Thus,

$$\min W_c = \frac{1}{n} \sum_{i=1}^{n} \left(0.15\dot{W}_t - \dot{W}_i \right) , \tag{5}$$

where W_c is the mean complementary power and $\dot{W}_t$ is the total nominal power.

Minimization of the peak complementary power. Considering, as in the previous objective, a commitment of providing 15% of total nominal power, the aim here is to reduce the peak additional power needed. This is related to the size of the reserve power that is needed to ensure the demand.

$$\min \max \dot{W}_c = \max \left(0.15\dot{W}_t - \dot{W}_i \right) \quad \forall i = 1, \ldots, n \tag{6}$$

Maximizing the mean power generated. Perhaps the simplest measure of the effectiveness of a set of wind farms corresponds to the search for the increase of the total energy produced:

$$\max \bar{\dot{W}} = \frac{1}{n} \sum_{i=1}^{n} \left(\dot{W}_i \right) . \tag{7}$$

Figure 3 shows the mean and variability of the power generation for a block of 20 turbines in each of the selected locations, over the whole set of data. As could be expected, since there is a lower bound to wind speed, a clear positive correlation is observed between the two variables, with smaller powers associated with lower variability. Looking at the mean power values, there are sites were it would be unwise to install a wind farm, but were kept in the sample to preserve its diversity.

2.3 The Multiobjective Genetic Algorithm

Engineering problems are often characterized by several competing objectives, the solution of which is, in general, a set of optimal solutions, rather than a single optimal solution, as expected in a single objective one. These solutions, largerly known as Pareto optimal solutions, or efficient solutions, are such that an improvement in any objective can only be achieved at the expense of degradation in other objectives (Fonseca and Fleming, 1995b). Absent of further information, an efficient solution cannot be said to be better than any other. Over the last decades, several evolutionary methods have been proposed for the solution of multiobjective problems, notably the pioneering MOGA (Fonseca and Fleming, 1995a), the SPEA2 (Zitzler *et al.*, 2001) and, perhaps today the most popular, the NSGA-II (Deb *et al.*, 2002).

In this work the multiobjective genetic algorithm employed was the NSGA-II, with adaptations made due to the nature of the problem. The NSGA-II improves on its predecessor by incorporating a faster routine for the sorting procedure and an intrinsic elitism. As with the single objective genetic algorithm, the population in multiobjective one converges to a problem optimum through the sequential application, at each iteration, of the so-called genetic operators. Those must include selection, crossover and mutation, but can be complemented by problem-specific operators, such as the correction operator here employed.

Since the variables are the number of turbines to be installed in each proposed site, an integer encoding was employed, each individual a row vector with 21 columns, each corresponding to a selected location. A translation table was used to map the space of integer, non-negative, numbers generated by the algorithm into a space with a minimum of 20 and a maximum of 1200 turbines, with variations in blocks of 5 turbines in this range (see Fig. 4).

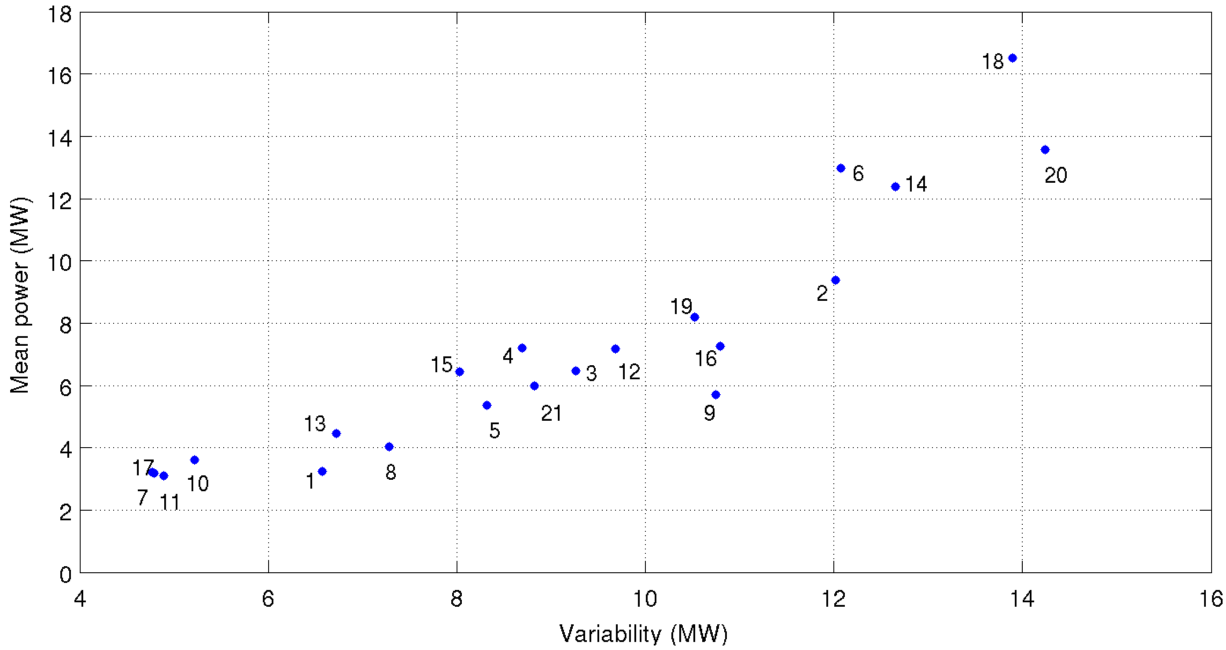

Figure 3. Mean and variability of the power generation for a block of 20 turbines in each of the selected locations.

The initial population was randomly generated, but making sure that the sum of the number of turbines distributed between the stations was equal to a pre-established amount. On the remaining of the subsection, the genetic operators employed are briefly discussed.

Selection. Selection followed the standard procedure of the NSGA-II algorithm, with the sorting by dominance and crowding distance of a double-sized population, formed by the joining of the new and the old generations. Roulette was then employed to select the parents for crossover.

Crossover. After preliminary experiments, the crossover probability was set at 90%, slight larger than in Deb *et al.* (2002). At a difference with the standard, two distinct integer crossover operators were employed, chosen at random with equal probability. Both operate over the line segment connecting the two parents, extended by 20% on each side, then rounded for the nearest integer. The first one employs a uniform distribution to select the point over the segment (Cerqueira *et al.*, 2008). The second operator, derived from the polarized real operator (Ramos *et al.*, 2003), uses a squared uniform distribution, with a larger probability of generating an individual in the vicinity of the highest ranking parent.

Mutation. The mutation probability was set to 30% per individual, which is similar to the mutation probability per individual for a simulated binary crossover, employed by Deb *et al.* (2002). The problem-specific mutation operation, here employed, consists of the exchange of the number of turbines between two randomly chosen stations of the individual.

Correction Operator. To ensure a fixed number of turbines on each individual, a check routine was set up at the end of the crossover operation, adding up the number of turbines of all stations of the individual and comparing it with the established value. Individuals that failed the check had attributed to each station a fitness value, corresponding to the

1	0
2	20
3	25
$\vdots$	$\vdots$
i	$20 + 5i$
$\vdots$	$\vdots$
237	1195
238	1200

Figure 4. Translation table: left, the variables of the genetic algorithms; right, the corresponding number of turbines

number of turbines. If a shortage of turbines was detected, new ones were interactively added to sites selected by roulette, based on their fitness value, with higher probability for sites with a smaller number of turbines. If an excess was detected, turbines were taken from sites with a greater number, also selected by roulette according to its fitness.

3. RESULTS

In all experiments, a total of 1,200 turbines, with a total nominal power of 2,460 MW, were distributed between the 21 sites that could receive from no turbines, to any multiple of 5 between 20 and 1,200 turbines.

In order to better define a curve in a four dimensional space, a population of 500 individuals was used in all experiments. Preliminary experiments indicated that with such a population, the genetic algorithm needed some 10,000 generations to attain stagnation of the Pareto front. A quantitative comparison of the efficient solutions sets with a large number of objectives (greater than two) is still a difficult proposition and, therefore, we did not attempt to perform such an analysis of the 30 experiments whose results are presented here. On the other hand, a comparison of the extreme solutions, the best results found for each of the four objectives, indicates a convergence.

The overall best results for the extreme solutions are presented in Tab. 1. Each line represents an extreme solution, for a given objective, and each column the values of each objective for that solution. Regular numbers are for the best extreme solution, in all experiments, for each objective. Numbers in superscript are the standard deviation of the extreme solutions in all experiments.

Table 1. Values of the objective functions and standard deviation for the best solutions for the extreme solutions (in MW)

	1	2	3	4
1. Smallest Variability	$171.9^{1.43}$	$147.9^{8.84}$	$364.9^{1.40}$	$252.6^{11.6}$
2. Smallest Mean Complementary Power	$411.3^{25.5}$	$28.1^{0.77}$	$367.3^{2.90}$	$750.0^{28.9}$
3. Smallest Peak Complementary Power	$296.1^{26.9}$	$44.0^{7.22}$	$348.5^{0.65}$	$538.5^{47.4}$
4. Largest Mean Generated Power	$819.5^{1.83}$	$71.7^{0.38}$	$369.0^{0.00}$	$979.1^{0.63}$

The conflicting nature of the objectives is confirmed by the range of the results in Tab. 1. For illustration, in order to achieve the smallest variability, mean generate power is reduced to about a quarter of its maximum attainable value and mean complementary power is increased fivefold. Only for the peak complementary power are the values close, but that is related to the characteristics of the sample, which contained only a limited number of sites with high mean wind speeds.

The small standard deviation values indicate that there was a good convergence, in all experiments, in the value found for the extreme objectives. There was some variation in the solutions, though, as demonstrates the deviations in the other objectives. That seems particularly important for the extreme solutions for the mean complementary power and peak complementary power objectives.

The distribution of the turbines between the sites is shown in 5. The solution that minimizes variability spreads the turbines over a large number of sites, taking advantage of the asynchrony of the winds. Four sites stand out getting most of the turbines, São Joaquim, Chapada Gaúcha, Guarda Mor and Diamantina, places that have smaller wind power potential (see Fig. 3), hence smaller variations in wind velocity.

The opposite happens when the objective is to minimize the average complementary power, with sites of greater wind potential, and greater variability in power generation, receiving a larger number of turbines. Among them, the four largest wind potentials of the sample: Macau, Canguçu, São José dos Ausentes and Tramandaí, the latter three cities in the state of Rio Grande do Sul. The other, Macau, not only possesses the third largest wind power in the sample, as is located hundreds of miles away from the other three, in the state of Rio Grande do Norte.

The widest distribution of the turbines is observed in the extreme solution to the objective of minimizing the peak complementary power: eighteen sites are selected, with wide geographic distribution. The opposite occurs when the objective is to maximize the average power generated, in which, as might be expected, all of the turbines are installed at the site of highest wind energy potential, São José dos Ausentes.

A plot of the instantaneous power generation for the extreme solutions over the complete data set is shown in Fig. 6. Only the solution with the smallest variability leads to a mean generated power (blue line) smaller than the target of 15% of the nominal power (red line). The different natures of the solutions are exposed, from the very low but steady power generation in Fig. 6a to the ragged lines of 6d. Non-extreme efficient solutions show intermediate behaviors, with higher mean power values associated with greater oscillations in power generation.

Graphically representing a four dimensional solution is hard to undertake. Figure 7 shows the results for the overall best solutions found in the 30 experiments, projected over the six planes defined by the four objectives. Highlighted in red are the solutions that would continue to be efficient if only the two objectives that define the plane were considered. The blue dots, though not efficient for the two objectives, are efficient for the full four objectives problem. The axis for the

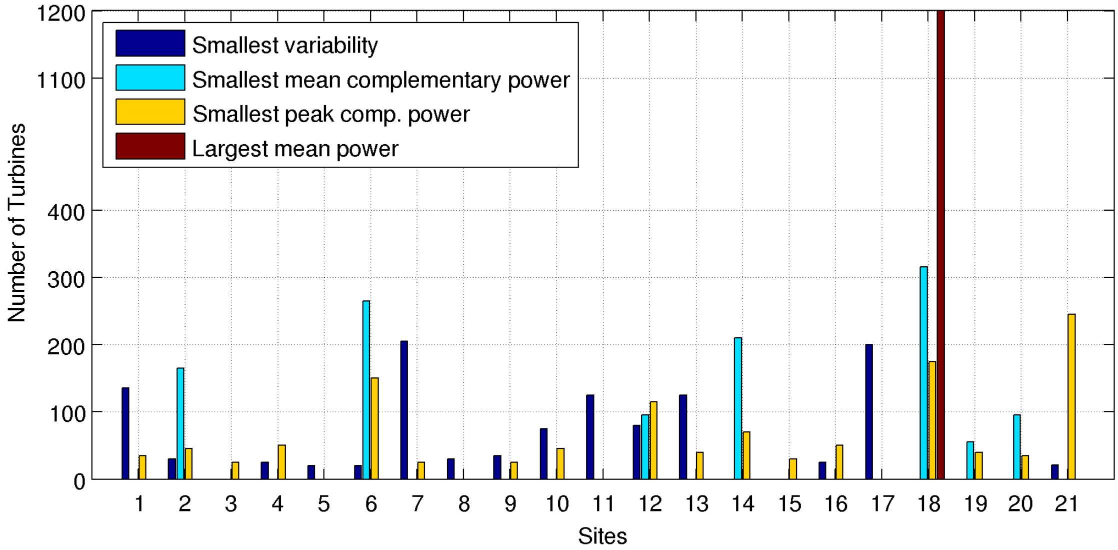

Figure 5. Turbine distribution between the sites for the extreme solutions. Numbers identify meteorological stations: 1. Ararangua, 2. Arraial do cabo, 3. Bage, 4. Caçapava do Sul, 5. Campos, 6. Canguçu, 7. Chapada Gaúcha, 8. Clevelândia, 9. Copacabana, 10. Diamantina, 11. Guarda Mor, 12. Ibirité, 13. Linhares, 14. Macau, 15. Mossoró, 16. Presidente Kennedy, 17. São Joaquim, 18. São José dos Ausentes, 19. São Tomé, 20. Tramandaí, 21. Cruz Alta.

objective of maximizing the mean power generate was reversed, to give all the plots the same two-objective minimization Pareto looks.

The left column (figures 7a, 7c and 7e) is comprised of plots in which the dots are closely packed. Only when the peak complementary power objective is one of the axis (right column, figures 7b, 7d and 7f, there is a great scatter of the results. While in the first group the two-objective Pareto is well defined, in the latter the front is defined by a smaller number of solutions (red dots). This suggests that the peak complementary power objective is harder to attain, perhaps as a consequence of the number of stations, perhaps of data set employed.

Observation of Fig. 7b confirms what was expected, that is, that the larger the production of power the larger the variability. Compromises, though, can be found in great number. Solutions lying on the right side of the set might be of more interest, for they trade a smaller amount of power for a larger reduction in variability. The large number of solutions to the two-objective problem shown in Fig. 7b, along with the fact the all other points lie close to the efficient set, might lead to the equivocal conclusion that those objectives suffice. A look to Fig. 7a and 7e shows how deceiving that is, with a large number of non-efficient solutions showing up. In those two figures, the points further away from the efficient set are in general the most efficient in the third objective. Though no solutions were found that belong to all of the three two-objectives efficient sets, there are a number of possibly interesting solutions, providing mean power above 700 MW, with variability close to 400 MW and mean complementary power close to 30 MW.

Figures 7a, 7d, and 7f, on the left column show a more complex scene. There are many solutions that for at least one moment produced no power at all, their peak complementary power being thus equal to 15% of the total nominal power. Even for the other solutions, the best solution that was found led to a reduction of only 20,5 MW in the reserve power needed to ensure the electrical system stability. It would be expected that a larger number of sites with higher wind speeds, would lead to a more pronounced reduction.

4. CONCLUSION

We presented the first results of a research aiming at the development of a method for the selection of sites and sizing of wind farms, through multiobjective optimization. They corroborate the expected multiobjective nature of the problem, presenting a large number of compromise solutions, other than the extreme solutions found after a single objective optimization. We are currently working on the acquisition of a larger data set and also, more importantly, on the generation of data sets through numerical atmospheric simulations.

5. ACKNOWLEDGEMENTS

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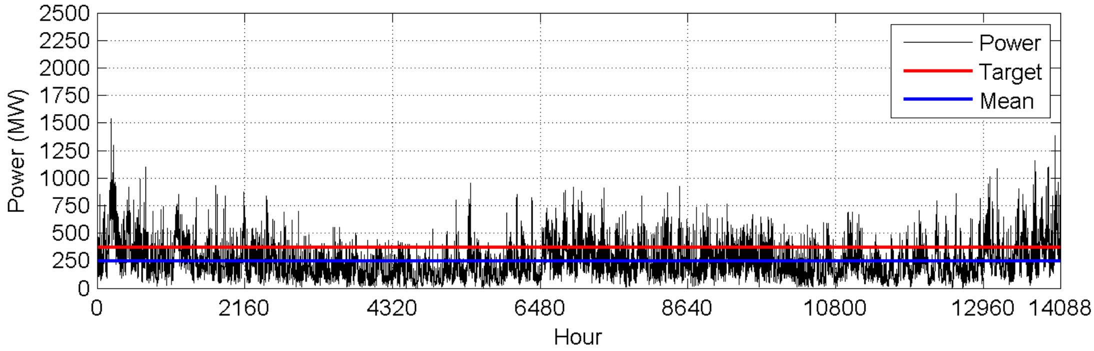
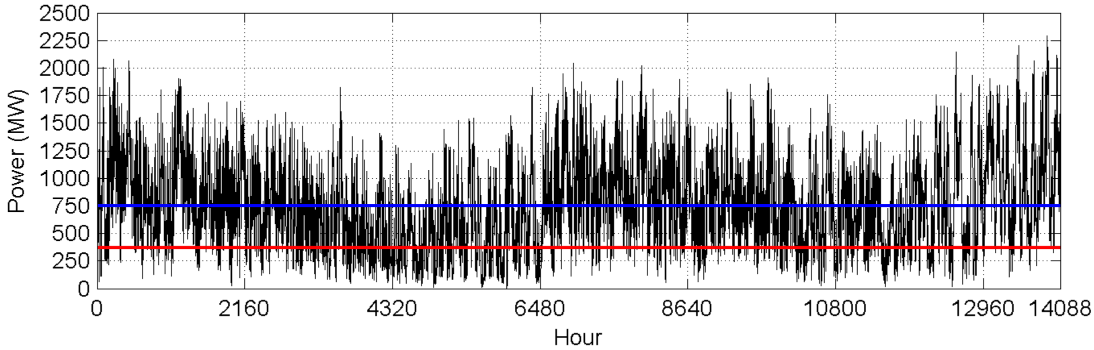
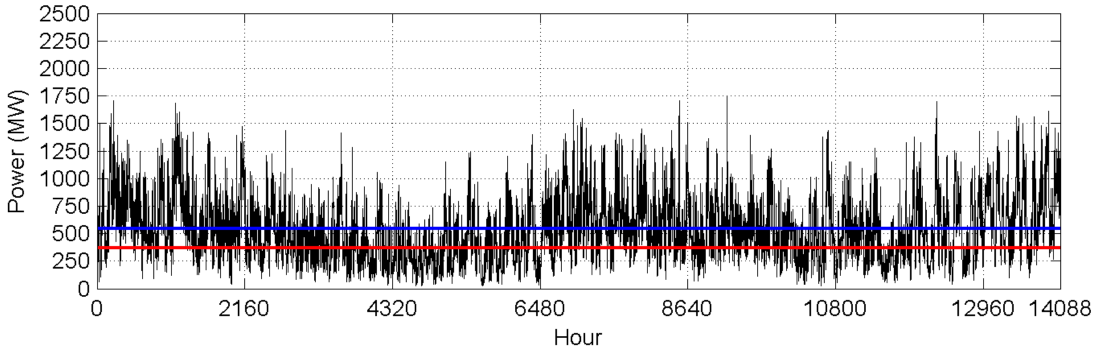


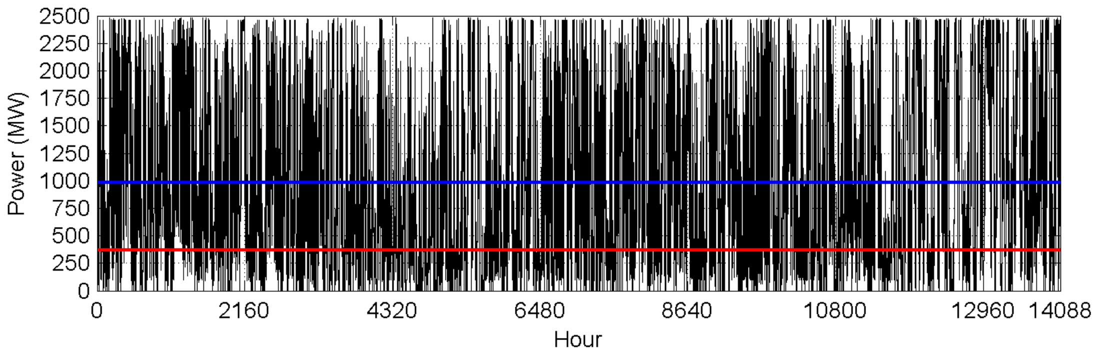
(a) Smallest variability



(b) Smallest mean complementary power



(c) Smallest peak complementary power



(d) Largest mean generated power

Figure 6. Power generation for the complete data set.

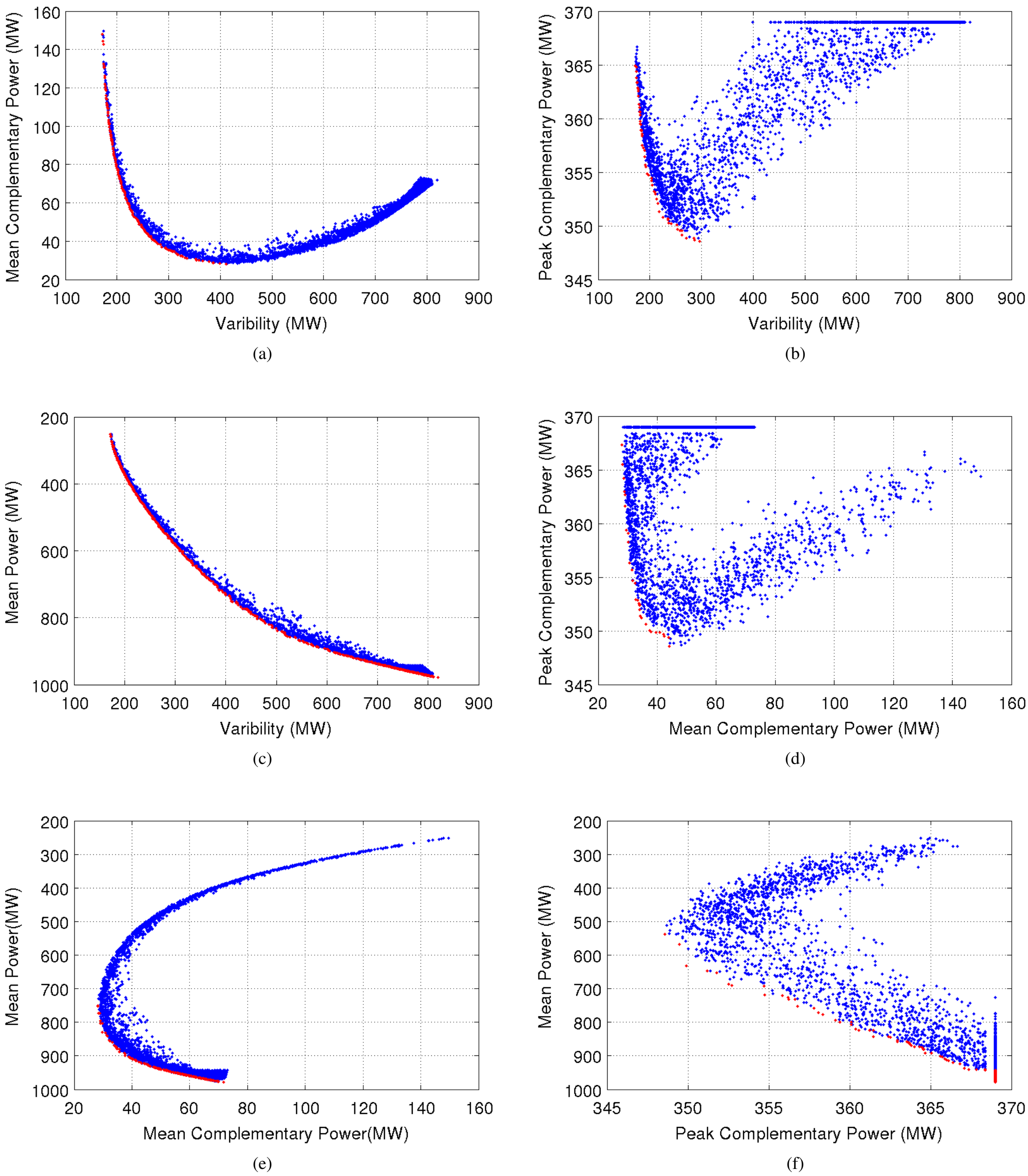


Figure 7. Projection of the overall Pareto set over the six planes

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