

Research Article

Multiobjective Optimization Model for Wind Power Allocation

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There is an increasing need for the injection to the grid of renewable energy; therefore, to evaluate the optimal location of new renewable generation is an important task. The primary purpose of this work is to develop a multiobjective optimization model that permits finding multiple trade-off solutions for the location of new wind power resources. It is based on the augmented ε -constrained methodology. Two competitive objectives are considered: maximization of preexisting energy injection and maximization of new wind energy injection, both embedded, in the maximization of load supply. The results show that the location of new renewable generation units affects considerably the transmission network flows, the load supply, and the preexisting energy injection. Moreover, there are diverse opportunities to benefit the preexisting generation, contrarily to the expected effect where renewable generation displaces conventional power. The proposed methodology produces a diverse range of equivalent solutions, expanding and enriching the horizon of options and giving flexibility to the decision-making process.

1. Introduction

Finding improvements in the operational conditions of a power system is an important task because many transmission networks still run inefficiently. For example, one of the current problems that most of the transmission systems face is that a great percentage of the branches are underused. In addition, for some electrical systems, the capacity to supply the load is even less than the total generation capability. Nowadays, this important fact is emphasized in power systems with high penetration of renewable resources (RR). Due to the stochastic nature of the RR, they have a significant share of unused power capacity. There are different options to increase the energy injection from renewable sources in order to exploit at a maximum the remaining renewable power capacity, for example, the addition of new transmission lines that could help delivering the extra energy, the increased participation of the consumers on the grid by using demand response programs [1, 2], the strategic location of energy storage systems that contribute to absorbing the renewable energy surpluses [3, 4], and the placement of new distributed generation that helps maximizing the load supply [5].

In addition, due to environmental concerns, the installation of distributed generation, especially renewable, is becoming a priority in many electrical systems. In those power systems where the massive integration of renewable resources is starting or planned, it is necessary to have an efficient strategy to select the best placement and proper capacity of these resources. The decision can be made based on an economic point of view (minimization of investment costs) only. However, it is better to formulate the problem as a multiobjective optimization problem to evaluate additional operational conditions of the system. The location of renewable generation constitutes a decision-making process that can be designed and influenced by different planning perspectives. For example, the placement of new wind farms, in addition to economic factors, can also take into account the minimization of wind generation intermittency [6] or the maximization of supplying load to exploit already existent generation in the grid. Formulating the problem as a multiobjective one permits placing new generation in network regions that could benefit from the injection of new energy resources and, on the other hand, helps the existent generation to increase the share on the load. Thus, evaluating

alternative sites for new generation sources is crucial and determining the optimum level of distribution of generating capacity in a multiobjective framework is more advantageous.

Multiobjective methodologies have been applied in different power system applications. Regarding generation expansion, [7] proposes the implementation of the normal boundary intersection method applied to a multiobjective generation and transmission expansion problem. The problem is modeled as a mixed-integer linear programming problem suitable for application in large-scale systems. The optimization problem is aimed at minimizing four objective functions and minimizes total costs, environmental impact, and fuel price risk while maximizing the system reliability. The study performed in [8] presents a mixed-integer linear programming model for multiyear transmission expansion planning. The study considers two objectives, the uncertain capital costs and the electricity demand, competing to occupy the permissible uncertainty budget. The authors employ the augmented ϵ -constraint method to solve the multiobjective optimization problem maximizing the robust regions against the uncertain variables centered on their forecasted values. Reference [9] represents a distant wind farm integration using a multiobjective framework. The proposed method includes two main objectives; the first one embraces the annual operational and investment costs, whereas the second one minimizes the expected not served energy. The expansion planning method uses a mixed-integer optimization problem, and a fast elitist multiobjective nondominated sorting genetic algorithm. The article [10] presents a multiobjective planning framework for the integration of stochastic and controllable distributed energy resources (DER). Multiobjective optimization is based on a strength Pareto evolutionary algorithm. The objectives are to minimize annual line losses, the annual DER dispatched energy for local ancillary services, the annual DER curtailed energy, CO₂ emissions, voltage quality index, and DER penetration level. A genetic based algorithm is presented in [11]. The model considers two objectives. The first objective is the minimization of investment cost and the second one is the maximization of system reliability. However, this work does not consider the network constraints. A linear programming based multiperiod expansion considering the transmission network is presented in [12]. Based on a weighting method, the objectives are the minimization of investment, operation and transmission costs, environmental impact, imports of fuel, and fuel prices risks. An interactive mixed-integer linear programming (MILP) approach is presented in [13]. The model considers three objective functions which quantify the total expansion cost, the environmental impact associated with the installed power, and the environmental impact associated with the energy generation. They do not consider the network. These ideas can be applied to improve the operational conditions of power systems, in particular with high penetration of RR, focusing on the system ability to supply more load. To accomplish this task, it is necessary to develop new models, evaluate different operative options, and consider extended planning strategies.

The aim of the work is to develop a multiobjective optimization model that permits finding multiple trade-off solutions for the location of new wind power resources. The

proposed model uses a multiobjective framework based on the augmented ϵ -constrained methodology [14, 15]. Three competitive objectives are considered: the maximization of preexisting energy injection and the maximization of new wind energy injection, both embedded in the maximization of load supply.

The paper is organized as follows: Section 2 describes and formulates the improvement of the load supplying with the placement of new wind farms under a multiobjective perspective. Section 3 presents the numerical results and the discussion about them; finally, Section 4 resumes the main conclusions of this work.

2. Load Supplying Improvement with Wind Farms Placement

The capacity of delivering energy from the generation to the load demands can be measured solving a well-structured problem [16]. The main task of this optimization problem is to stress the network to the maximum without causing line overloads. Different expansion alternatives can be compared, and as a result the system operational conditions are improved. The result of this type of problems seems to be trivial: including generation where the load is located. However, under a multiobjective perspective, the results present a more diverse spectrum of solutions, giving the decision maker (DM) a broad range of possibilities to take the final decision. Therefore, the DM can put into consideration different alternatives, equally valid, giving the same results. For example, given an expected level of load supplying, several power capacities and placements can accomplish the same goal.

2.1. Multiobjective Perspective. The aim of a Multiple-Objective Optimization Problems (MOOP) is not to find a solution but a set of solutions. The set of nondominated solutions (Pareto optimal) has the condition that none of them can be improved without deteriorating at least one of the rest.

According to [14] the methods for solving MOOP can be classified into three main categories: a priori, interactive, and generation methods. In a priori method, the DM expresses preferences before the solution process. The drawback of this methodology is that the DM needs to know and quantify the preferences beforehand accurately. In the interactive method, the DM interchanges information with the algorithm and progressively drives the search towards the preferred solution. The drawback is that the entire set of efficient solutions is never observed; therefore, the preferred solution is biased to the last solution found. In generation method, the set of efficient solutions is created before any DM decisions. The main advantage is that the DM can analyze a diverse universe of solutions and take a decision based on them.

The disadvantage of the generation method is the high computational cost that requires getting efficient solutions. The most widely used generation methods are the weighting and the ϵ -constrained methods. The weighting method optimizes the weighted sum of the objective functions. By varying the weights, it is possible to obtain different efficient solutions. In the ϵ -constrained method, one of the objective

functions is optimized using the other objective functions as constraints. The efficient solutions are obtained by parametric variation of the right-hand side of the constrained objective functions. The augmented ε -constrained method presented in [15], which is an improved version of the conventional ε -constrained method, has several advantages over the weighting method. The method can be used with multiobjective MILPs; the scaling of the objective functions is not necessary; the number of generated solutions can be user-controlled; it avoids the generation of weakly Pareto optimal solutions and accelerates the whole process by avoiding redundant iterations.

Therefore, the aim of this paper is to apply the augmented ε -constrained method to explore the different placement alternatives for new wind farm generation that lead to a more efficient exploitation of the power network and improve the energy injection of preexisting generation, while maximizing the energy injection from renewable resources.

2.2. Model Formulation. The proposed model formulation considers three objective functions: maximization of the load supplying, maximization of energy injected by preexisting generation, and maximization of energy provided by the installation of the new generation. Further details about the load supplying problem can be found in [16]. The model considers three different types of constraints: the linearized representation of the network, the limits of the preexisting generation and transmission elements, and the relationship between the wind power injection at each bus of the grid and the integer nature of the variable that represents the number of turbines to be installed. The following assumptions are considered:

- (i) There is fixed budget to install new wind generation.
- (ii) All the possible wind farm placement locations have the same capacity factor.
- (iii) All the new wind generations are installed at the same single period.
- (iv) The load participation factors are constant.
- (v) The reserve requirement for reliability is not considered.

Based on these assumptions, the proposed model formulation is as follows:

$$\max z_1 = \delta, \quad (1)$$

$$\max z_2 = \sum_b^{B_G} p_b, \quad (2)$$

$$\max z_3 = p_b^w - \sum_{i \neq b}^B p_i^w \quad \forall b, \quad (3)$$

$$-\gamma S' \Delta \theta + p + p^w = \delta \lambda, \quad (4)$$

$$|S \Delta \theta| \leq \frac{\bar{f}}{\gamma}, \quad (5)$$

$$p_b^w \leq \omega_b \text{TR} \quad \forall b, \quad (6)$$

$$\sum_b^B \omega_b \leq \Omega, \quad (7)$$

$$\omega_b \text{TR} \leq \bar{p}^w, \quad (8)$$

$$0 \leq p \leq \bar{p}, \quad (9)$$

$$\omega_b \in \mathbb{Z}. \quad (10)$$

The description of each equation is as follows.

Equation (1) is first objective function and represents the maximization of the load supplying in the power system. Equation (2) is second objective function and represents the maximization of the energy injection from the preexisting generation. Equation (3) is third objective function and represents the maximization of the energy injection from the new generation to be installed. Equation (4) is linear power flow. Equation (5) represents branch flow limits. Equation (6) is maximum bound for wind generation and establishes the relationship between the wind power injection by bus, continuous variable, and the integer number of turbines. Equation (7) is maximum number of turbines to be installed. Equation (8) is maximum power of wind generation to be installed. Equation (9) represents power limits of preexisting generation. Equation (10) represents integer nature of installed turbines.

This set of equations form a MILP problem which combined with the multiobjective ε -constrained method can jointly be solved with any general-purpose solver that deals with MILP models. It is important to note that the model can be easily extended to consider multiperiod planning framework, nonconstant load participation factors, and different wind capacity factors at each location of the grid.

3. Numerical Results

This section illustrates the proposed methodology using practical examples. We assume that the decision variables of the problem become more important than the objective values, because the objective functions z_2 and z_3 mimic a competitive electricity market environment. Therefore, we do not produce graphics representing Pareto frontiers; instead, we put the emphasis in representative variables of the problem.

The model represented by (1)–(10) and the algorithm described by [15] are implemented in GAMS, using GUROBI as the numerical solver [17]; the stop criteria are based on the gap which is set to zero.

First, the method is explained using a small example to illustrate the methodology practically. The system data is shown in Figure 1. The planned new wind generation is set to 100 turbines, each one with a 2 MW capacity. This power is allowed to be installed equally in all the buses, except for the cases indicated with “*” where only that bus is allowed.

3.1. Base Case. First, the problem formulated in [16] is solved; this case represents the benchmark for the multiobjective case.

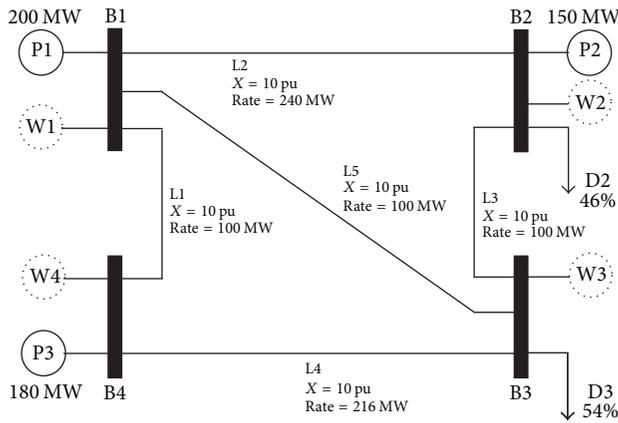


FIGURE 1: Four-bus one-line diagram.

Table 1 presents the obtained results. To analyze the behavior of the load considering different wind farm rates scenarios, the index δ was iteratively calculated for different farm rate levels, ranking from 20 MW to 200 MW, with a 20 MW step. Please note that repeated results were not included in the table. The first four cases described in the table were constructed allowing, at each bus and sequentially, incorporating the total available wind power of each MW step. The last case allowed the incorporation of the total available MW at all buses.

From the results presented in Table 1 it can be inferred that the worst location to install new wind power is Bus 1; none of the rate levels can change the δ level (actually, this is the reference case; i.e., δ is the same as the case without new wind farms). At Bus 2, the first rate level improves 2.74% the δ compared to the reference case; then δ continues improving steadily with the increasing of the rate levels reaching a final improvement of 27.4% in the final level. At Bus 3, the first rate level produces a slightly higher improvement of 5.5% on δ compared to Bus 2 case; then δ continues improving linearly with the increasing of the rate levels until it reaches the highest possible δ level. Please, note that this value is the maximum power available. At Bus 4, the behavior is similar to Bus 2 case, until half of the rate levels; after that, the network becomes saturated and the maximum possible improvement is 16.5% compared to the reference case. Finally, the last simulation with all the buses allowed incorporating 200 MW of wind power, which does not show any difference with respect to Bus 3 case.

3.2. Multiobjective Case. Similar to the previous case, all the buses are allowed to incorporate up to 200 MW of wind power.

Figure 2 shows the relation between the different wind farm configurations and the capacity to supply load. The axis description is as follows; *number of turbines* represents the number of wind turbines installed in the corresponding system bus, and *Delta* represents the corresponding load supplying value. Figure 3 shows the relation between the power injected by the existent generation and the capacity to supply load. Here the axis is *Generation Power* which

represents the power injected at the corresponding system bus. Both figures have a direct relation.

From these figures, it is possible to infer that for the reference case δ is 474 MW red dot in Figure 2. For this point, no wind power was incorporated, and the power from the existent generation was 144, 150, and 180 MW, respectively. For the same value of $\delta = 474$ MW, there are three more cases which incorporate wind power at Bus 1. For this last situation, the existent generation necessarily needs to reduce its injection, as can be confirmed with these powers being 44, 150, and 180 MW, respectively.

Among all the length of δ axis, there were three worst cases, $\delta = 200$ MW, they were obtained incorporating the total wind power at Buses 1, 2, and 4, respectively, and the power injected from the existent generation was set aside. In the opposite, there were three best cases regarding δ (730 MW); these case were obtained incorporating three different wind power configurations at Bus 3. These configurations are 2 turbines at Bus 2 and 98 turbines at Bus 3; 100 turbines at Bus 3; and 1 turbine at Bus 1 and 99 at Bus 3. It should be noted that the existing generation, for all these three configurations, is at the maximum level. The zone for maximum generation is shown in Figure 4 as three green bars.

Figure 4 shows the evolution of the frontier of nondominated solutions for 60 grid points. Axis labeled *Delta* represents the corresponding load supplying capability, and the horizontal axis contains the frontier points. The red-colored areas represent efficient solutions regarding equal capacity to supply load with different wind farm configurations. These sets of efficient solutions are defined as *isotelos* and represent *identical-goal* solutions in terms of δ ; that is, δ is constant within an *isotelo*. The zones colored in red in Figure 4 are comprised of 5 or more equivalent solutions. It is important to note that every horizontal section of the frontier corresponds to an *isotelo*, but only the most representatives were colored.

Graphics like Figure 4 are very useful to easily detect constant zones of equivalent solutions that provide different alternatives for the decision-making process. Regarding the first *isotelo*, the first red-colored zone tells that this is the biggest set of 20 equivalent solutions. Depending on the aimed goal for the δ value, it could be worth analyzing more deeply this *isotelo* in particular.

Figures 5 and 6 describe with more detail the set of 20 equivalent solutions. Figure 5 illustrates the different wind turbine configurations at each bus and for each equivalent solution. Note that δ remains constant. Figure 6 illustrates the behavior for the power injected from the existent generation.

Analyzing and comparing these two figures the DM can opt for different alternatives depending on the particular placement scenario for new generation. For example, if the placement scenario consists of the installation of the total 100 turbines, then the DM can select the first two solutions, with configurations formed by 58 turbines at Bus 1, 17 at Bus 3, and 25 at Bus 4 or 58 turbines at Bus 1, 25 at Bus 2, and 17 at Bus 3, respectively. As another example, if the placement scenario consists of obtaining the same δ value but with minimum investment cost, the DM can opt for the last two solutions, with configurations formed by 8 turbines in Bus 1, 25 in Bus 2, and 17 in Bus 3 or 8 turbines in Bus 1, 17 in Bus 3, and 25 in Bus

TABLE I: Base Case load supplying results: wind farm at each bus (*).

Bus	1*		2		3		4		δ
MW available	P1	W1	P2	W2	P3	W3	W4	[MW]	
20	144	0	150	—	180	—	—	474	
200	144	0	150	—	180	—	—	474	
Bus	1		2*		3		4		δ
MW available	P1	W1	P2	W2	P3	W3	W4	[MW]	
20	137	—	150	20	180	—	—	487	
40	130	—	150	40	180	—	—	500	
60	123	—	150	60	180	—	—	513	
80	116	—	150	80	180	—	—	526	
100	109	—	150	100	180	—	—	539	
120	102	—	150	120	180	—	—	552	
140	95	—	150	140	180	—	—	565	
160	88	—	150	160	180	—	—	578	
180	81	—	150	180	180	—	—	591	
200	74	—	150	200	180	—	—	604	
Bus	1		2		3*		4		δ
MW available	P1	W1	P2	W2	P3	W3	W4	[MW]	
20	150	—	150	—	180	20	—	500	
40	156	—	150	—	180	40	—	526	
60	162	—	150	—	180	60	—	552	
80	168	—	150	—	180	80	—	578	
100	174	—	150	—	180	100	—	604	
120	180	—	150	—	180	120	—	630	
140	186	—	150	—	180	140	—	656	
160	192	—	150	—	180	160	—	682	
180	198	—	150	—	180	180	—	708	
200	200	—	150	—	180	200	—	730	
Bus	1		2		3		4*		δ
MW available	P1	W1	P2	W2	P3	W3	W4	[MW]	
Idem Bus 2									
120	102	—	150	—	180	—	120	552	
⋮									
200	102	—	150	—	180	—	120	552	
Bus	1*		2*		3*		4*		δ
MW available	P1	W1	P2	W2	P3	W3	W4	[MW]	
20	150	0	150	0	180	20	0	500	
40	156	0	150	0	180	40	0	526	
60	162	0	150	0	180	60	0	552	
80	168	0	150	0	180	80	0	578	
100	174	0	150	0	180	100	0	604	
120	180	0	150	0	180	120	0	630	
140	186	0	150	0	180	140	0	656	
160	192	0	150	0	180	160	0	682	
180	198	0	150	0	180	180	0	708	
200	200	0	150	0	180	200	0	730	

4, respectively. These two equivalent solutions are cheaper, regarding investment costs, because these two options consist of 50 turbines. Besides, these last two options can be preferred among the others because the existing generation P1 is less

impaired. In this regard, in Figure 6 it can be observed that the existing generations P2 and P3 are not affected by the diverse set of equivalent solutions. In contrast, the influence over P1 generation is evident in the graphics.

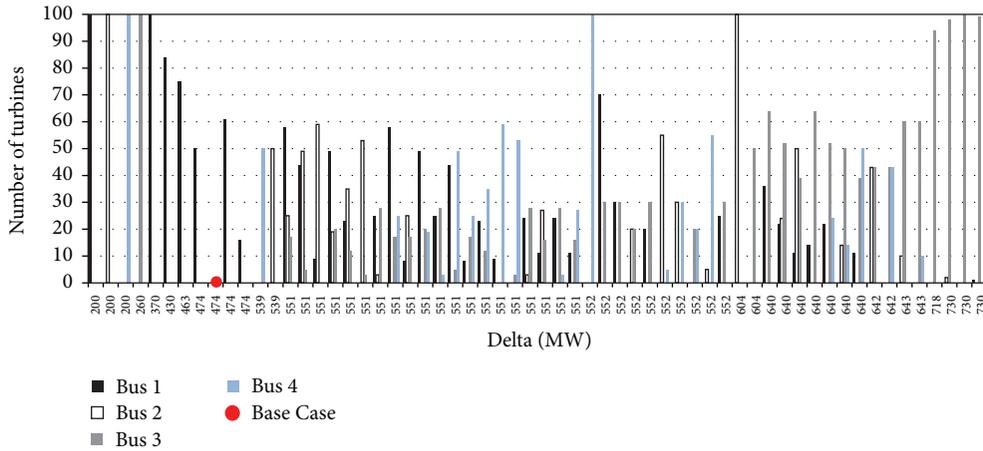


FIGURE 2: Wind turbines versus Delta, 60 frontier points.

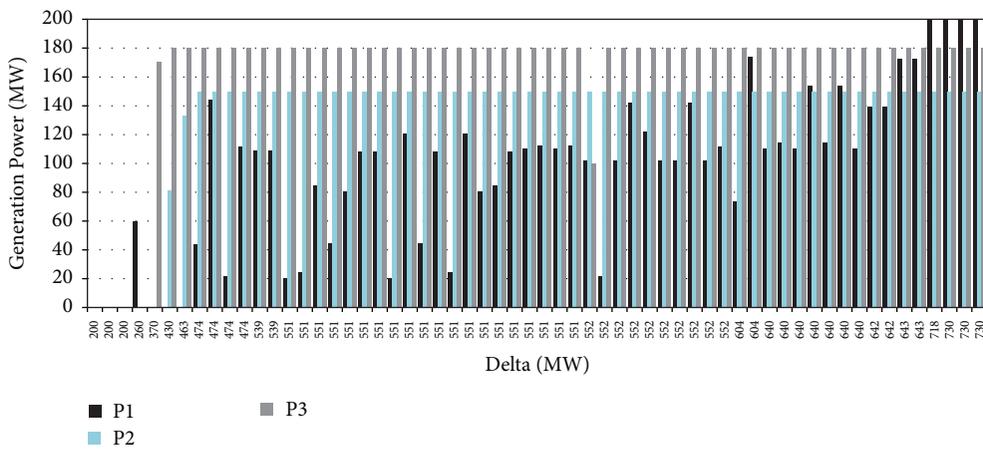


FIGURE 3: Power generation versus Delta, 60 frontier points.

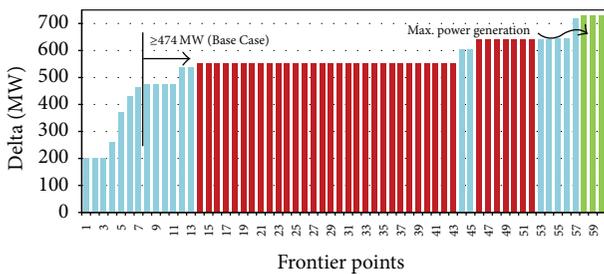


FIGURE 4: Delta versus frontier points. Red isotelos ≥ 5 .

It is also interesting to analyze what happened with the existing generation increasing δ from the reference case (474 MW) and wind power incorporation. From Figure 3, it can be inferred that visible changes of the energy injected by P2 and P3 with δ changes do not exist. These patterns are nearly identical to the ones reflected in Table 1. On the other hand, the changes of energy injected by P1 with respect to the changes of δ are very noisy, reinforcing the best feature

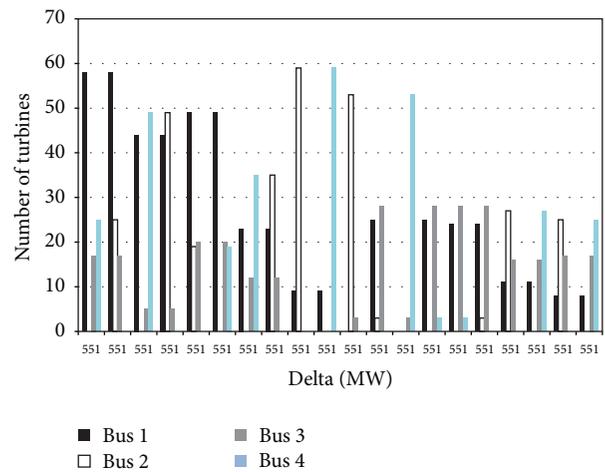


FIGURE 5: Wind turbines versus Delta 551 MW.

of multiobjective optimization, which is the “diversity.” The pattern for P1 in Table 1 shows a similar but smoother behavior, that is, less diversity of solutions.

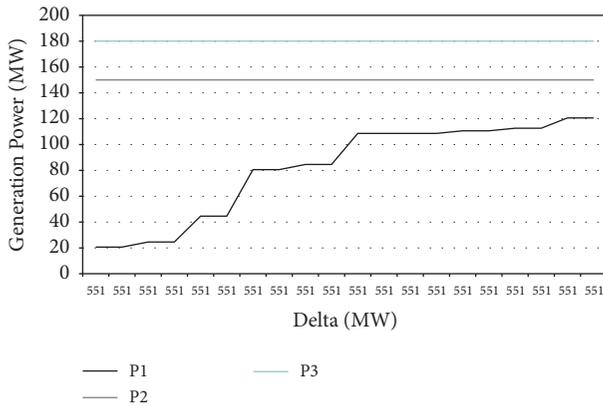


FIGURE 6: Power generation versus Delta 551 MW.

To Summarize, in general, it can be stated that the load supplying capability can be highly influenced by the placement of new generation. For some cases, the load supply is deteriorated compared to the case without the inclusion of the new generation, and for some cases, the existing generation is benefited by the incorporation of new generation, increasing their load shares. A remarkable feature of the multiobjective analysis is the universe of solutions that offers, giving some space to find clusters of solutions with the same load supply value but with different power configurations.

Specifically for this system it is important to remark some interesting results. The installation of the total available wind power at Bus 1, 2, or 4 drastically deteriorated the initial load supply value from 474 MW to 200 MW, which represents a decrease of 57.8%. The first case where the load supply level was improved is related to the installation of 50 turbines at Bus 4, an increase of 13.7%. In the base case, the total available generation could only be dispatched to a 90% of its total capacity. However, with the inclusion of new wind power in specific places the total existing generation capacity can be exploited. This case can be seen in the three last cases illustrated by Figures 2 and 3. In these cases the load supply value was improved from 474 MW to 730 MW, representing an increase of 54%. Perhaps the most important conclusion is that this solution does not rely on the trivial solution “generation where the load is” because the multiobjective methodology offers the opportunity to find different equivalent solutions. The variety of solutions for the best load supply value (730 MW) is not as much as could be expected for large real-case power systems. Besides, depending on the aimed goals for the load supply, it is very valuable to have sets of equivalent solutions like the constant patterns showed in Figure 4 because they permit evaluating different trade-offs between cases. There were two of these big groups of equivalent solutions, red-colored in Figure 4, with 20 and 7 solutions, respectively.

3.3. Further Results. In this section, we present the multi-objective results for a real-case power system. The system diagram and data are described in Figure 7. The corresponding demand participations are given in Table 2. Due to

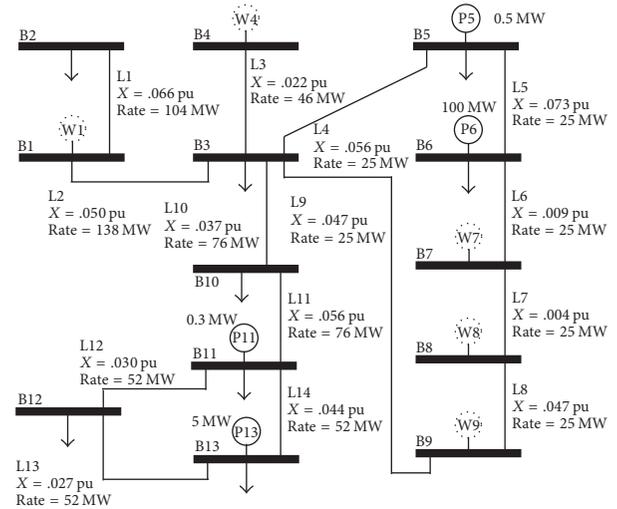


FIGURE 7: Large power system diagram.

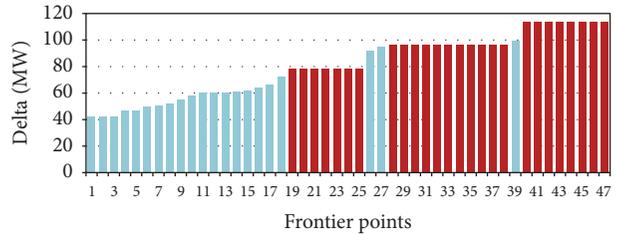


FIGURE 8: Delta versus frontier points. Red isoteles ≥ 5 .

TABLE 2: Large system: demand participation data.

Bus	2	3	5	6	10	11	12	13
[%]	2.56	2.56	7.93	15.34	15.34	17.90	25.57	12.79

environmental constraints, the new wind capacity cannot be located at a load bus, but one bus further. Therefore, Buses 1, 4, 7, 8, and 9 are allowed to incorporate up to 50 MW of wind capacity, which can be arranged with 25 turbines of 2 MW each.

Figure 8 presents the evolution of δ with the frontier points. Frontier point number 16 is the base value for $\delta = 64.3$ MW (red dot in Figure 9, no wind power). It is important to remark that all the combinations of wind turbines installations, as shown in Figure 9, were formed by the total of 25 turbines available. Therefore, there were 15 combinations of turbine installations that decrease the capacity of the network to supply the load. Only after point 16, δ increased, reaching its maximum at 114.1 MW, representing a 77.4% increment. In Figure 8 the three most important *isoteles* are colored. They were formed by 5 or more equivalent solutions. Note that for the best δ value there are 8 different combinations of turbine installation that are equivalent, confirming that the number of equivalent solutions increases with the size of the power system.

Figures 9 and 10 show the patterns for turbines installation and wind generation with increasing δ , respectively. For

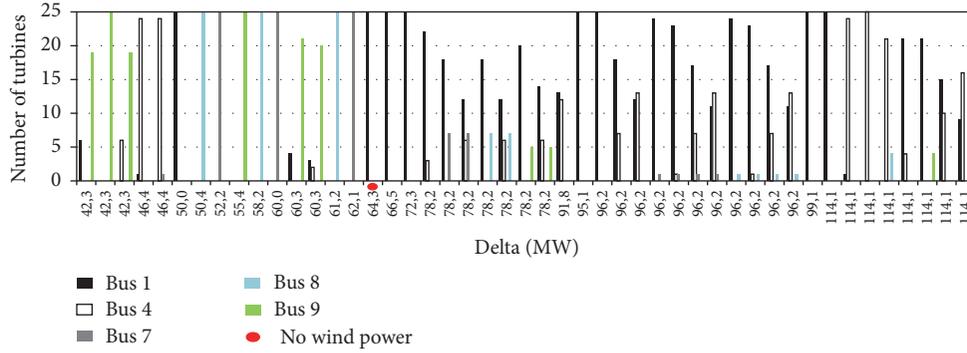


FIGURE 9: Turbines versus Delta.

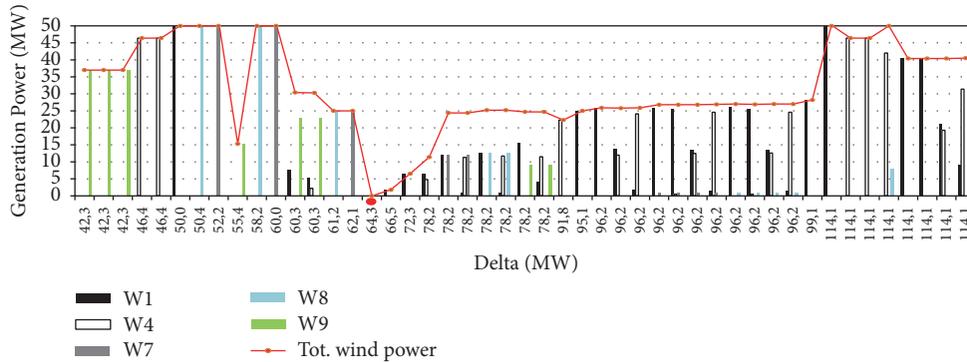


FIGURE 10: Wind generation versus Delta.

TABLE 3: Combination of turbine placements for $\delta = 114.1$ MW.

W1	W4	W7	W8	W9
25	—	—	—	—
1	24	—	—	—
—	25	—	—	—
—	21	—	4	—
21	4	—	—	—
21	—	—	—	4
15	10	—	—	—
9	16	—	—	—

the maximum $\delta = 114.1$ MW there are 8 different possible combinations of turbines; this is described in Table 3. These combinations are mainly formed by turbine placement at Buses 1 and 4. For the maximum δ , the first and fourth combinations illustrated in Figure 10 presented maximum wind generation; however, the impact on preexisting generation can be seen in Figure 11. There are also two more important trade-off zones, red-colored, with 7 and 11 equivalent combinations of turbine placements.

From Figure 11, it can be observed that the total power injected by preexisting generation is improved from the base point (red dot) to the best δ . Generations labeled P5, P11, and P13 generate constant injections. Generation P6 generates in

average more power compared to the base point. Therefore, the wind generation never reduces the injected MWs from preexisting power resources. Nevertheless, generation P6 never reaches its technical maximum power of 100 MW; the maximum generation was 67.9 MW, representing a 16.1% increment compared to the base point. Note that, due to scaling, P6 is divided by 10.

For this particular example, there are 15 combinations of turbine placements that decrease the capacity of the system to supply load. On the opposite, 31 combinations increase the capacity. There are three important trade-off zones with 7, 11, and 8 equivalent turbine placement solutions. Regarding load supply, Buses 1 and 4 seem to be the best placement locations for turbines and Bus 9 is the worst. For the maximum δ , there exist 8 different turbine configurations, these alternatives being very valuable for a DM that has the option to decide among different locations, maximum wind generation, minimum impact on preexisting generation, or diversification of wind patterns. This variety of solutions is what strongly support the utilization of multiobjective methodologies for a decision-making process.

4. Conclusion

In this work a MILP model has been proposed that permits evaluating different goals for the placement of new wind generation resources. It can help any DM to design a proper

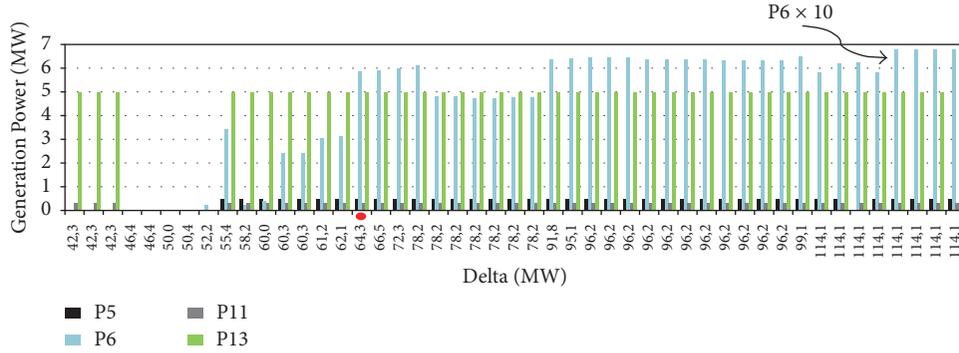


FIGURE 11: Preexisting generation versus Delta.

policy about the incorporation of renewable but also distributed resources.

Results demonstrate that exists a diverse range of equivalent solutions. These solutions contribute to a decision-making process because they expand the horizon of options. Also it was found that the load supplying capability can be highly influenced by the placement of new generation. Results show that there are cases where the load supply is deteriorated with the inclusion of the new generation and cases where it is improved. Moreover, there are situations that benefit the preexisting generation.

The methodology presented in this work opens a diverse range of possibilities for further improvements, for example, to evaluate further objective functions like investment costs, wind capacity factors, wind intermittency, environment impact, reliability goals, or ancillary services. One the most remarkable features of the multiobjective methodology presented in this paper is the fact that the competing objectives should not necessarily need to be in monetary terms.

Nomenclature

B : Set of buses
 B_G : Set of buses with preexisting generation
 b : Bus index
 δ : Load supplying capability
 z_1 : Maximization of δ
 z_2 : Maximization of energy injection from preexisting generation
 z_3 : Maximization of wind energy injection in bus b
 p_b : MW bus injection
 ω_b : Integer number of wind turbines by bus
 p_b^w : Wind power bus injection
 p : Generation vector
 p^w : Wind generation vector
 f : Branch flow vector
 $\Delta\theta$: Bus voltage angle difference vector
 λ : Load participation factors vector
 \bar{f} : Max flow limits vector
 \bar{p} : Generation max bounds vector
 \bar{p}^w : Max wind generation to be installed
 Ω : Max number of turbines to be installed
 γ : Branch susceptances matrix

S : Branch-bus incidence matrix ($'$ is transpose)

TR : Turbine rates.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

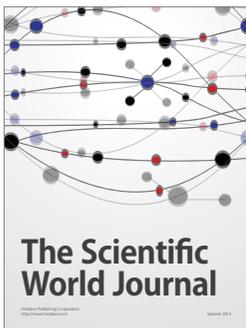
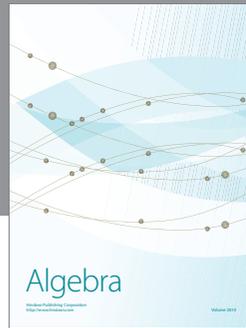
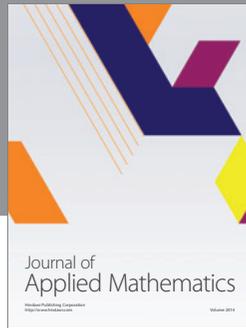
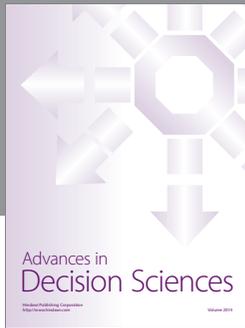
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