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An Optimization Technique Based on Profit of Investment and Market Clearing in Wind Power Systems

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Abstract Recently, renewable energies are widely used instead of the fuel energies due to their individual potentials such as its availability, low price and environmentally friendly. One of the most important renewable energies is wind power. As a result, investment in wind power is one of the most interesting research to maximize the profit of the investment and market clearing. In this paper, bi-level optimization technique is proposed to maximize the investment problem and market clearing for the wind power at the same time and in one single problem. Then, karush–kuhn–tucker (KKT) conditions and mathematical programming with equilibrium constraints (MPEC) are applied and tried to find one level optimization problem. Due to the nonlinearity of the optimization equation, the Fortuny-Amat & McCarl (FM) linearization technique is used to linearize the model. Finally, the proposed technique is applied to the IEEE 24 buses. The result proves that the optimization analysis is very easy, fast and accurate due to the linear characteristic of the system. All the simulation results are carried out in MATLAB and GAMS softwares.

Keywords: *Optimization, renewable energies, wind power,karush–kuhn–tucker (KKT) conditions, mathematical programming Bi-level optimization*

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1. Introduction

In the recent years, the applications of the renewable energies are rapidly increased due to their availabilities and environmentally friendly [1]. As a result, investment in this kind of energy is one of the most important research area especially maximizing the profit of the investment or minimizing the cost function [2,3].

In one level optimization problem many methods are proposed such as branch and bound algorithm [4-7], linear programming [8], dynamic programming [9] and mixed-integer [10]. Also, some evolutionary algorithms suchas genetic algorithm (GA) [11], multiobjective evolutionary programming algorithm [12], refined immune algorithm [13] and particle swarm optimization (PSO) [14] are applied. However, different evolutionary methods might provide different solutions for a problem and the methods is not guarantee for all kind of problems. As a result, in some research studies, the combination of methods such as binary PSO-based dynamic multi-objective model [15] and fuzzy logic [16] are used as one-level and parallel optimization problems [17,18].

One the other hand, for market clearing some mathematical and meta-heuristics technique is proposed such as [19,20,21] are represented. In this paper, maximizing of the profit of investment and market clearing are considered as one level optimization problem. In fact, in one problem both market clearing and profit of investment are optimized and solved. As a result, at the same time, two of the most important problems of the wind power with all constraints are solved as one single problem.

At first, bi-level optimization problem as one of the robust optimization method is utilized to make a two different optimization problems as a single optimization problem. Then, the mathematical programming with equilibrium constraints (MPEC) and karush–kuhn–tucker (KKT) are defined for this problem to find an optimal solution for the problem. Then, due to the nonlinearity of the equations, the Fortuny-Amat & McCarl (FM) linearization technique is used to linearize the equations. Finally, in the GAMS software, the solution for IEEE 24 busses of the wind power systems are presented to validate the effectiveness of the proposed optimization technique.

In the next section, the bi-level optimization problem is explained. In section three, the mathematical programming with equilibrium constraints (MPEC) is represented. Section four is about the modeling of the problem. MPCC problem is described in section five and finally in the last section the simulation and results are explained.

2. Bi-level Optimization Method

Bi-level optimization methodis a type of optimization techniques which consists of upper-level and lower-level problem. In this paper, the upper-level is the profit of the investment and the lower-level is market clearing. The equations of the bi-level is:

$$\text{Minimize}_{\{y\}\cup\{y^1,\ldots,y^n\}\cup\{\lambda^1,\ldots,\lambda^n,\mu^1,\ldots,\mu^n\}} \quad f(y,y^1,\ldots,y^n,\lambda^1,\ldots,\lambda^n,\mu^1,\ldots,\mu^n) \tag{1}$$

Subject to:

$$h\left(y,y^1,\ldots,y^n,\lambda^1,\ldots,\lambda^n,\mu^1,\ldots,\mu^n\right)=0 \tag{2}$$

$$g\left(y,y^1,\ldots,y^n,\lambda^1,\ldots,\lambda^n,\mu^1,\ldots,\mu^n\right)\le 0 \tag{3}$$

$$\begin{cases}\text{Minimize}_{y^1} f^1\left(y,y^1,\ldots,y^n\right)\\ \text{subject to:}\\ h^1(y,y^1,\ldots,y^n)=0(\lambda^1)\\ g^1\left(y,y^1,\ldots,y^n\right)\le 0\left(\mu^1\right)\end{cases} \tag{4}$$

$$\begin{cases}\text{Minimize}_{y^i} f^i\left(y,y^1,\ldots,y^n\right)\\ \text{subject to:}\\ h^i(y,y^1,\ldots,y^n)=0(\lambda^i)\\ g^i\left(y,y^1,\ldots,y^n\right)\le 0\left(\mu^i\right)\end{cases} \tag{5}$$

$$\begin{cases}\text{Minimize}_{y^n} f^n\left(y,y^1,\ldots,y^n\right)\\ \text{subject to:}\\ h^n(y,y^1,\ldots,y^n)=0(\lambda^n)\\ g^n\left(y,y^1,\ldots,y^n\right)\le 0\left(\mu^n\right)\end{cases} \tag{6}$$

where, (1-3) are the upper-level optimization problem and (3-6) are the lower-level optimization problems. The functions f , h and g are the upper level objective function, constraints of equality and inequality, respectively. And, the functions f^i, h^i and g^i are the lower level objective functions, constraints of equality and inequality, respectively.

Furthermore, the Lagrange coefficients of the lower level optimization problems are (λ^i,μ^i). It is clear that in order to solve such a problem, first the lower-level constraints should be satisfied.

3. Mathematical Programming with Equilibrium Constraints (MPEC)

The bi-level optimization method with two level optimization problems is called mathematical programming with equilibrium constraints (MPEC), if the lower-level optimization problem consists of a set of equilibrium condition. The equations for MPEC are as following:

$$\text{Minimize}_{\{v\}\cup\{v^1,v^2,\lambda^1,\lambda^2,\mu^1,\mu^2\}} f(v,v^1,x^2,\lambda^1,\lambda^2,\mu^1,\mu^2) \tag{7}$$

Subject to:

$$h\left(v,v^1,v^2,\lambda^1,\lambda^2,\mu^1,\mu^2\right)=0 \tag{8}$$

$$g\left(v,v^1,v^2,\lambda^1,\lambda^2,\mu^1,\mu^2\right)\le 0 \tag{9}$$

$$\begin{cases}\text{Minimize}_{v^1} f^1\left(v,v^1,v^2\right)\\ \text{subject to:}\\ h^1(v,v^1,v^2)=0(\lambda^1)\\ g^1\left(v,v^1,v^2\right)\le 0(\mu^1)\end{cases} \tag{10}$$

$$\begin{cases}\text{Minimize}_{v^2} f^2\left(v,v^1,v^2\right)\\ \text{subject to:}\\ h^2(v,v^1,v^2)=0(\lambda^2)\\ g^2\left(v,v^1,v^2\right)\le 0(\mu^2)\end{cases} \tag{11}$$

It should be noted that the vector v^2 is the optimization variable for *2nd* constraint problem. It should be noted that it depends on the variables of the upper and lower level optimizations. Furthermore, the upper-level optimization problem depends on all optimal variables v,v^1,v^2 and Lagrangian coefficients of the lower-level problem ($\mu^1,\mu^2,\lambda^1,\lambda^2$). All of the constraints of the upper and lower levels should be satisfied to find an optimal and global result.

4. Modeling Investment in Wind Power as an Optimization Problem

The two-level optimization problem which is required for the bi-level optimization technique is:

$$\min \sum_n C_n^w X_n^w - \sum_d N_d^H \left[\sum_n \lambda_{n,d}\, p_{n,d}^w\right] \tag{12}$$

Subject to:

$$p_{n,d}^w \le K_{n,d}^w X_n^w \forall n,\forall d \tag{13}$$

$$0 \le X_n^w \le X_n^{w,\max} \forall n \tag{14}$$

$$\sum_n C_n^w X_n^w \le C^{w,\max} \tag{15}$$

$$\left\{\min \sum_g Cost_g\, p_{g,d}\right. \tag{16}$$

Subject to:

$$-\pi \le \delta_{n,d} \le \pi : \xi_{n,d}^{down}, \xi_{n,d}^{up} \forall n \setminus ref \tag{17}$$

$$P_g^{\min} \le P_{g,d} \le P_g^{\max} : \mu_{g,d}^{down}, \mu_{g,d}^{up} \forall g \quad (18)$$

$$-P_l^{\max} \le P_{l,d} \le P_l^{\max} : \vartheta_{l,d}^{down}, \vartheta_{l,d}^{up} \forall l \quad (19)$$

$$-\sum_l AL_{l,n} P_{l,d} + p_{n,d}^{w} + \sum_g AN_{g,n} P_{g,d} - D_{n,d} = 0 : \lambda_{n,d} \forall n \quad (20)$$

$$\sum_n AL_{l,n} B_l \delta_n - P_{l,d} = 0 : \beta_{l,d} \forall l \quad (21)$$

$$\left.\delta_{n,d} = 0 : \xi_d^1 \forall n : ref .\right\} \forall d \quad (22)$$

where $C_n^{w,\max}$ is the maximum power generation capacity of the n^{th}plant, $X_n^{w,\max}$ is the maximum capacity of wind power in bus n, $p_{n,d}^{w}$ is the power generation of the wind unit which is connected to the bus n in day d, $K_{n,d}^{w}$ is the wind power capacity factor at bus n in day d, N_d^H Wind power generation coefficient in day d, $D_{n,d}$ is the Demand load from bus n in day d, p is the power flow and δ is the voltage angle. Also, equations (12-15) are the upper-level optimization problem and the (16-22) are the lower-level optimization problems. The constraints of the upper-level problem depend on (13-15) and the lower level constraints [22-29]. The equality and inequality constraints Lagrangian coefficient vectorsfor lower-level optimization are:

$$\bar{\lambda} = \{\lambda_{n,d}, \beta_{l,d}, \xi_d^1\} \quad (23)$$

$$\bar{\mu} = \{\xi_{n,d}^{down}, \xi_{n,d}^{up}, \mu_{g,d}^{down}, \mu_{g,d}^{up}, \vartheta_{l,d}^{down}, \vartheta_{l,d}^{up}\} \quad (24)$$

The Lagrangian coefficient vectors of the inequality constraints are in (24-29).

5. Changing the Wind Power Investment Problem to MPCC problem

Based on these assumptions, the Lagrangian function in everyday is.

$$\begin{aligned}
\mathcal{L} = & \sum_g Cost_g\, p_{g,d} + \sum_{n,n\neq ref} \xi_{n,d}^{down}\left(-\delta_{n,d} - \pi\right) \\
& + \sum_{n,n\neq ref} \xi_{n,d}^{up}\left(\delta_{n,d} - \pi\right) + \sum_g \mu_{g,d}^{down}\left(p_g^{\min} - p_{g,d}\right) \\
& + \sum_g \mu_{g,d}^{up}\left(p_{g,d} - p_g^{\max}\right) + \sum_l \vartheta_{l,d}^{down}\left(-p_{l,d} - p_l^{\max}\right) \\
& + \sum_l \vartheta_{l,d}^{up}\left(p_{l,d} - p_l^{\max}\right) - \sum_l \beta_{l,d}\left(\sum_n AL_{l,n} B_l \delta_{n,d} - p_{l,d}\right) \\
& - \sum_n \lambda_{n,d}\left(-\sum_l AL_{l,n}\, p_{l,d} + \sum_g AN_{g,n}\, p_{g,d} + p_{n,d}^{w} - D_{n,d}\right) \\
& - \xi_d^1 \delta_{ref.,d}
\end{aligned} \quad (25)$$

Then, the derivative of the Lagrangian function with respect to all of the variables should be zero to satisfy the KKT condition. So, the derivative of the Lagrangian function are [30-35]:

$$\begin{aligned}
& \frac{\partial \mathcal{L}}{\partial p_{g,d}} = 0 \Rightarrow \\
& Cost_g - \mu_{g,d}^{down} + \mu_{g,d}^{up} - \sum_n \lambda_{n,d} AN_{g,n} = 0 \forall g, \forall d
\end{aligned} \quad (26)$$

$$\begin{aligned}
& \frac{\partial \mathcal{L}}{\partial \delta_{n,d}} = 0 \Rightarrow \\
& -\xi_{n,d}^{down} + \xi_{n,d}^{up} - \sum_l \beta_{l,d} AL_{l,n} B_l = 0 \forall n \setminus ref, \forall d
\end{aligned} \quad (27)$$

$$\frac{\partial \mathcal{L}}{\partial p_{l,d}} = 0 \Rightarrow -\vartheta_{l,d}^{down} + \vartheta_{l,d}^{up} + \beta_{l,d} = 0 \forall l, \forall d \quad (28)$$

$$\frac{\partial \mathcal{L}}{\partial \delta_{ref.,d}} = 0 \Rightarrow \xi_d^1 = 0 \quad (29)$$

Now, due to the nonlinearity of equations, the FM technique is used to linearize the equations.

6. Using Fortuny-Amat & McCarl (FM) Linearization Method in MPEC

In FM technique, it is assumed that

$$A_{\min} \le a \le A_{\max} \quad (30)$$

$$B_{\min} \le b \le B_{\max} \quad (31)$$

$$a \times b = 0 \quad (32)$$

where a and b are the variables in an optimization problem. Also, A_{min} and A_{max} are the minimum and maximum values of the variable A, respectively. Also,B_{min} and B_{max} are the minimum and maximum values of the variable B, respectively. As a result, the linearization equations are,

$$A_{\min}\beta \le a \le A_{\max}\beta \quad (33)$$

$$B_{\min}(1-\beta) \le b \le B_{\max}(1-\beta) \quad (34)$$

where, β is a binary variable.According to the above definition, the followinglinear equations are obtained:

$$\begin{aligned}
& \xi_{n,d}^{down}\left(-\delta_{n,d} - \pi\right) = 0 \\
& \Rightarrow \begin{cases} -2\pi(1 - z\xi_{n,d}^{down}) \le \left(-\delta_{n,d} - \pi\right) \le 0 \\ 0 \le \xi_{n,d}^{down} \le M_{n,d}^{down} z\xi_{n,d}^{down} \end{cases} \forall n \setminus ref, \forall d
\end{aligned} \quad (35)$$

$$\begin{aligned}
& \xi_{n,d}^{up}\left(\delta_{n,d} - \pi\right) = 0 \\
& \Rightarrow \begin{cases} -2\pi(1 - z\xi_{n,d}^{up}) \le \left(\delta_{n,d} - \pi\right) \le 0 \\ 0 \le \xi_{n,d}^{up} \le M_{n,d}^{up} z\xi_{n,d}^{up} \end{cases} \forall n \setminus ref, \forall d
\end{aligned} \quad (36)$$

$$\begin{aligned}
& \mu_{g,d}^{down}\left(\mathrm{P}_g^{\min} - p_{g,d}\right) = 0 \\
& \Rightarrow \begin{cases} -2P_g^{\max}(1 - z\mu_{g,d}^{down}) \le \left(P_g^{\min} - p_{g,d}\right) \le 0 \\ 0 \le \mu_{g,d}^{down} \le M_{g,d}^{down} z\mu_{g,d}^{down} \end{cases} \forall g, \forall d
\end{aligned} \quad (37)$$

$$\mu_{g,d}^{up}\left(p_{g,d}-P_g^{\max}\right)=0$$

$$\Rightarrow\begin{cases}-2P_g^{\max}(1-z\mu_{g,d}^{up})\le\left(p_{g,d}-P_g^{\max}\right)\le 0\\ 0\le\mu_{g,d}^{up}\le M_{g,d}^{up}z\mu_{g,d}^{up}\end{cases}\forall g,\forall d \qquad (38)$$

$$\vartheta_{l,d}^{down}\left(-p_{l,d}-\mathrm{P}_l^{\max}\right)=0$$

$$\Rightarrow\begin{cases}-2P_l^{\max}(1-z\vartheta_{l,d}^{down})\le\left(-P_l^{\max}-p_{l,d}\right)\le 0\\ 0\le\vartheta_{l,d}^{down}\le M_{l,d}^{down}z\vartheta_{l,d}^{down}\end{cases}\forall l,\forall d \qquad (39)$$

$$\vartheta_{l,d}^{up}\left(P_{l,d}-\mathrm{P}_l^{\max}\right)=0$$

$$\Rightarrow\begin{cases}-2P_l^{\max}(1-z\vartheta_{l,d}^{up})\le 0\\ 0\le\vartheta_{l,d}^{up}\le M_{l,d}^{up}z\vartheta_{l,d}^{up}\end{cases}\forall l,\forall d \qquad (40)$$

These equations are the linear constraints of the problem. Due to $\lambda_{n,d}\,p_{n,d}^{w}$ was nonlinear, then the objective function of the upper-level optimization problem is nonlinear. To linearize the objective function, following equations are defined:

$$\begin{aligned}\sum_g Cost_g\,p_{g,d} &= \sum_{n\neq ref}(\xi_{n,d}^{down}+\xi_{n,d}^{up})(-\pi)\\ &+\sum_g\mu_{g,d}^{down}P_g^{\min}+\sum_g\mu_{g,d}^{up}(-P_g^{\max})\\ &+\sum_l(\vartheta_{l,d}^{down}+\vartheta_{l,d}^{up})(-P_l^{\max})+\sum_n\lambda_{n,d}(D_{n,d}-p_{n,d}^{w})\end{aligned} \qquad (41)$$

$$\begin{aligned}\sum_n\lambda_{n,d}\,p_{n,d}^{w} &= \sum_{n\neq ref}(\xi_{n,d}^{down}+\xi_{n,d}^{up})(-\pi)+\sum_g\mu_{g,d}^{down}P_g^{\min}\\ &+\sum_g\mu_{g,d}^{up}(-P_g^{\max})+\sum_l(\vartheta_{l,d}^{down}+\vartheta_{l,d}^{up})(-P_l^{\max})\\ &+\sum_n\lambda_{n,d}D_{n,d}-\sum_g Cost_g\,p_{g,d}\end{aligned} \qquad (42)$$

Based on the above equations, the optimization problem is a Mixed-integer linear programming (MILP)

7. Case Study and Results

In this section, the proposed method is applied to IEEE 24 buses. Figure 1 shows the single line diagram for IEEE 24 buses.

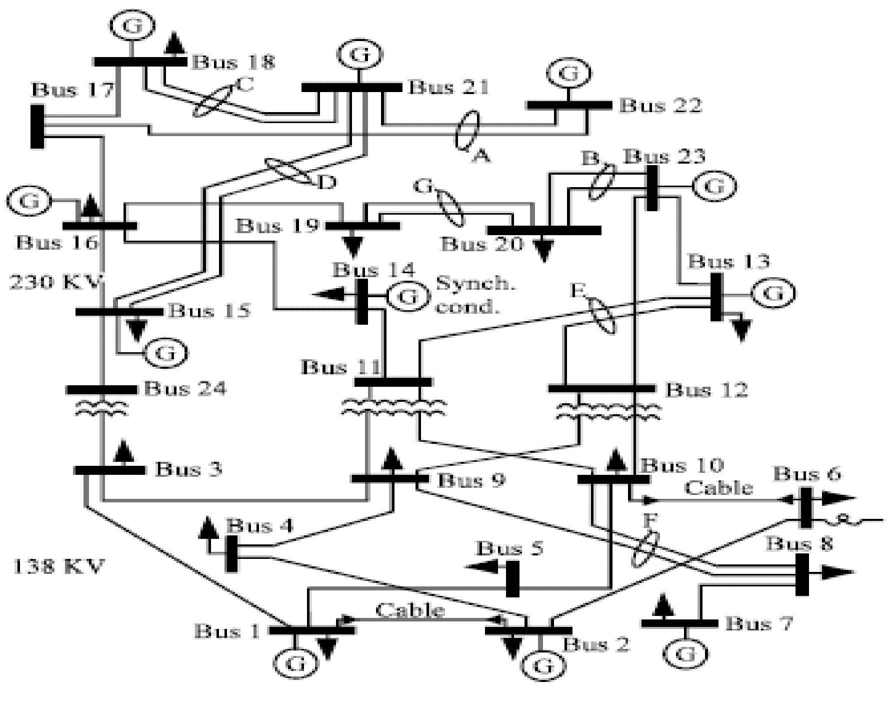

Figure 1. Single line diagram for IEEE 24 buses

Assuming that the construction cost for every power plant in each bus is $116000 and the maximum generation power in each bus is 800 MW. Moreover, in this model, the overall power wind power generation is 1600 MW. First, consider a set of four buses candidates to choose the best optimal wind power bus networks. Then, by comparing between the sets, the optimal bus for the investment in four wind generator units are selected. As a result, four scenarios for selection of the buses are defined as following

A) First Scenario

First, assuming that the candidate buses for investment are 1, 7, 13, and 15. The result of the technique is shown in Table 1.

Table 1. Optimal wind power generation in buses 1, 7, 13, 15

Bus No.	Power (MW)
1	49.82
7	443.204
13	0
15	800

In this scenario, the total power generation is 1293 MW and the total profit of the investment is 7.3 M$.

B) Second Scenario

In this scenario, assuming that the candidate buses are 3, 5, 7, and 16. Table 2 shows the results of this part, when the total wind power generation is 1281 MW and the total profit of investment is 7.27 M$. The important point is the reduction in power generation for bus 7, comparing with the previous scenario.

Table 2. Optimal wind power generation in buses 3, 5, 7,16

Bus No.	Power (MW)
3	425.226
5	0
7	55.629
16	800

C) Third Scenario

The candidate buses for this scenario are 7, 16, 21, 23. Table 3 shows the results for this scenario, when the total power generation is 1244 MW and the profit of the investment is 7.39 M$.

Table 3. Optimal wind power generation in buses 7, 16, 21, 23

Bus No.	Power (MW)
7	0
16	0
21	800
23	444.104

D) Fourth Scenario

Finally, in the last scenario, the candidate buses are 16, 17, 21, and 23. Based on Table 4, the total power generation is 1267 MW. Also, the profit of the investment is 7.41 M$.

Table 4. Optimal wind power generation in buses 7, 16, 21, 23

Bus No.	Power (MW)
16	0
17	250.378
21	800
23	217.163

The comparison between the scenarios for bus 7 is shown in Figure 2. The results prove that the maximum power generation in bus 7 is related to the first scenario. In the other word, in the first scenario, bus 7 is the better position than others.

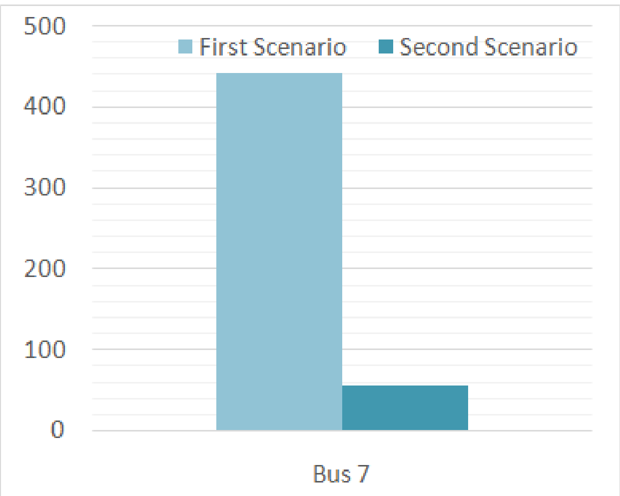

Figure 2. Comparing of wind power in various scenarios at bus 7

Also, Figure 3 shows the result of the bus 16 in all scenarios. The results prove that bus 16 is only in the second scenario has a good position to generate the wind power.

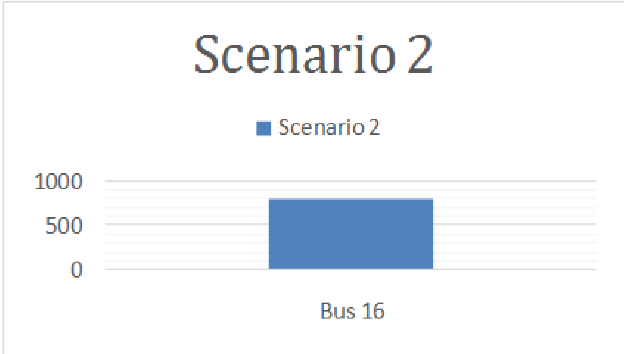

Figure 3. Comparing of wind power in various scenarios at bus 16

Figure 4, shows the comparison of the buses 21 and 23 in the third and fourth scenarios. According to the result, bus 21 has a good position for wind power generation in both scenarios. Also, bus 23 has a better position in third scenario than the forth scenario.

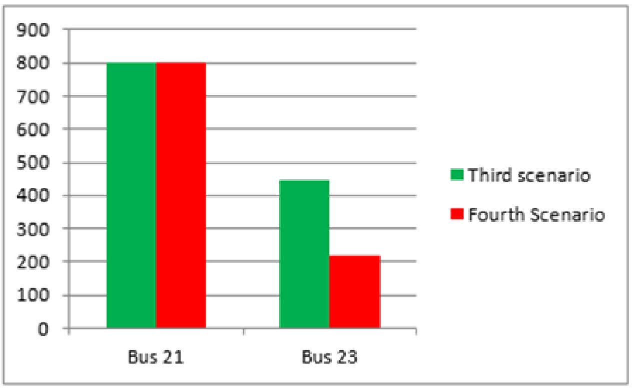

Figure 4. Comparing of wind power in scenarios 3 and 4 at buses 21 and 23

Now, the network is divided into four area to determine the final optimal selection of the buses for the optimization of wind power and maximize the profit of the investment. As a result, four areas are defined as below,

1) First Area

Buses 1 to 6 are the selected buses for this area. Table 5 shows the results of selected buses.

Table 5. Optimal wind power generation in buses 1 to 6

Bus No.	Power (MW)	Profit of investment (M$)
2	47.491	7.334
3	599.554	
4	333.472	
6	278.153	

In this area, the buses 2,3,4 and 6 are the best-selected candidates and the profit of investment is 7.334 M$.

2) Second Area

The selected buses for this area are 7 to 12. The result proves that the buses 10 and 11 are in the best position for the investment. Also, the profit of investment is 7.408. Table 6 shows the result of this area.

Table 6. Optimal wind power generation in buses 7 to 12

Bus No.	Power (MW)	Profit of investment (M$)
10	458.671	7.408
11	800	

3) Third Area

The selected buses for this area are 13 to 18. Table 7 shows the results of this area.

Table 7. Optimal wind power generation in buses 13 to 18

Bus No.	Power (MW)	Profit of investment (M$)
13	535.28	7.404
17	741.934	

Based on the result, the buses 13 and 17 have the best position for the investment in this area.

4) Fourth Area

The selected buses in this area are 19 to 24. The results are shown in Table 8. Based on the results, buses 21 and 23 have the best positions for the investment. Moreover, the profit of the investment is 7.261 M$.

Table 8. Optimal wind power generation in buses 19 to 24

Bus No.	Power (MW)	Profit of investment (M$)
19	501.99	7.26
24	800	

Now, if all bus candidates obtained in different parts are put together and considered them as candidate for the construction of wind power plant, it can be seen that the results are same with the results of the four scenarios. In fact, the buses 17, 21 and 23 are the best candidate for the investment and maximizingthe profit of the investment. Figure 5 shows the difference in the profit of the investment before and after optimization technique.

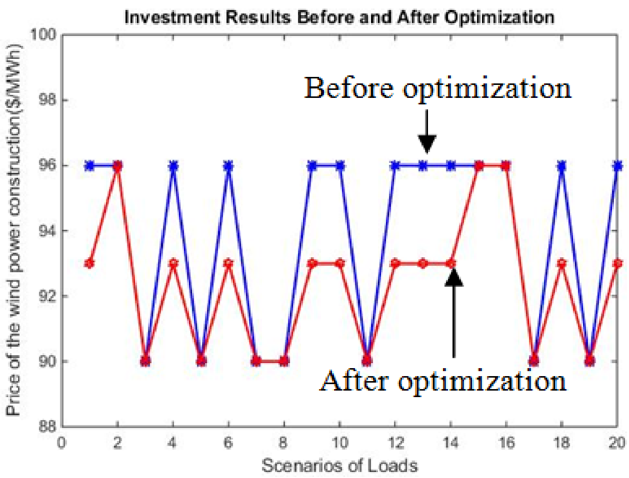

Figure 5. Comparison of investment results before and after optimization.

8. Conclusion

In this research study, two of the most important optimization problems which are profit of the investment and market clearing are analyzed at the same time. In fact, two optimization problems are converted to one single problem by bi-level technique. Then, the results converted to MPEC to find an optimal solution and grantee the global solution. Finally, due to nonlinearity of equations, FM technique is used to linearize the single optimization problem.

In the second part, the proposed method is applied to IEEE 24 buses to analyze the wind power behavior on the profit of the investment and market clearing. The results are shown the accurate results regarding the proposed technique. Optimization is one of the most important research studies in many fields. As a result, the proposed technique can be used in many other fields such as cyber-physical systems, smart grids and energy management.

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