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Impact of Wind Farm Integration on LMP in Deregulated Energy Markets

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Abstract: The integration of renewable energy generation affects the operating characteristics of a power system, such as electric losses, voltage profile, generation cost, system stability, and reliability of the system. The installation of renewable energy generation units in non-optimal locations may increase system losses, costs, voltage fluctuations, etc. The main hurdle in integrating renewable energy generation units with an existing electrical grid is the uncertainty of renewable sources. This paper presents the impact of wind farm integration on the system economy in a wind-integrated deregulated power market. The importance of deregulation in terms of the system generation cost, bus voltage profile, and locational marginal pricing (LMP) are also studied in this work. LMP is the main parameter responsible for handling the system economy (i.e., profit of generating units and profit of customers). Considering the variable nature of wind flow, three different real-time wind speed datasets are used to validate this work. Bus sensitivity factor (BSF) is considered for equating the optimal position of the wind farm in the integrated system. Five different optimization techniques, i.e., sequential quadratic programming (SQP), artificial bee colony (ABC) algorithms, particle swarm optimization (PSO), ant colony optimization (ACO) algorithm, and slime mold algorithm (SMA), are introduced to solve the optimal power flow problem. The SMA and ACO are used for the first time in this type of economic assessment (i.e., impact valuation of LMP) in a deregulated power system, which is the novelty of this work. The entire work is performed in a modified IEEE 30 bus test system.

Keywords: system economy; bus sensitivity factor; deregulation; wind integrated system; social benefit

Citation: Patil, G.S.; Mulla, A.; Ustun, T.S. Impact of Wind Farm Integration on LMP in Deregulated Energy Markets. *Sustainability* **2022**, *14*, 4354. https://doi.org/10.3390/su14074354

Academic Editor: Doug Arent

Received: 4 February 2022
Accepted: 1 April 2022
Published: 6 April 2022

1. Introduction

Due to continuous increments in greenhouse gases and environmental pollution, there is an ever-increasing interest in the use of renewable energy sources [1,2]. The expansion of global renewable energy generation started during the last third of the twentieth century and has been remarkably increasing year by year.

In 2009, the share of renewable energy sources was approximately 8.7% of global total energy consumption. By the end of 2019, it was found to reach 11.2% of the world's total power generation capacities [3]. It has a positive effect on employment growth in the sector every year. To adapt to the increasing penetration in grid infrastructure, renewable distributed generation requires coordinated efforts right from the planning stage to the power generation, transmission, distribution, consumption, and protection [4–7].

The uncertain nature of renewable energy generation creates many problems in system security [8]. There is a chance of grid failure if the electrical system is not handled or managed properly in the case of a renewable integrated system. During the past few years, the concept of the electrical system has changed from a regulated to a deregulated model. To date, some countries have developed their internal power structure to implement the deregulated concept properly and other countries are following the leader countries. In the

deregulated or competitive power market, several entities have performed their operation. Generation companies (GENCOs), transmission companies (TRANSCOs), distribution companies (DISCOs), retailers, independent system operator (ISO), etc. are the electricity market players. The ISO plays the most vital role in the deregulated system by controlling the entire electricity market. The prices of the electricity are also set by the ISO by optimizing the bidding values that are received from the generator side and demand side.

In the past, some research work has been carried out by several academicians in the field of renewable energy and deregulated systems [9,10]. The distribution system is a final delivery stage of a power system and it transforms the high-voltage to lower-voltage power using power transformers and directly feeds that power to different customers/consumers. Previously, distribution substations have taken that power from the transmission network of the power grid. Now, distributed generations (DGs) are becoming more popular because of the efficient utilization of energy and mitigating the global energy crisis [11]. DG is mainly of two types, i.e., non-renewable energy generation (gas turbines, coal plants, reciprocating engines) and renewable energy generation (solar PV, biomass, wind, tidal, etc.) [12,13]. The investment in renewable distributed generation (RDG) units is increasing day by day due to the reduction in gas emissions. By installing distributed generation, voltage stability, reliability, power quality, and efficiency can be improved and peak power demands, operational cost, and transmission loss can be significantly reduced in comparison to the conventional power system operation. To deliver secure, sustainable, and affordable energy, the RDG units will play an important role soon [14]. They also offer a viable alternative to sites that may not be electrified otherwise [15]. Wang et al. [16] used an analytical method to find the optimal location of DG in radial and meshed networked systems considering minimization of the system power loss. For sizing and siting of DG, both systems are essentially required for minimizing system power loss, and this is determined by using an analytical method proposed in [17]. Additionally, it is important to optimize storage systems that help increase energy security [18].

Recently, meta-heuristic algorithms have been used to optimally allocate the sizing and location of DG. In ref. [19], the artificial bee colony (ABC) algorithm was used for finding the DG unit's size, power factor, and location of the DG in the distributed network considering minimum real power loss as an objective function. Discrete particle swarm optimization (PSO) was used in [20] to solve the site and sizing problems of DG units. To determine the optimal location and size of DG in the distributed system, a modified teaching-learning-based optimization (MTLBO) algorithm was used in [21]. In ref. [22], the loss sensitivity factor and bacterial foraging optimization (BFO) algorithm were used to identify the optimal locations and size of the DG unit, respectively, considering minimization of network power losses, operational costs, and improving voltage stability. To minimize losses, the optimal location and capacity of DG were discussed by using the cuckoo search (CS) algorithm [23]. To minimize the active power loss and energy loss of distribution lines, the krill herd algorithm was used for the placement of DG by maintaining the bus voltage and voltage stability index within specified limits of the system [24]. Paper [25] proposed an ant lion optimization (ALO) algorithm for optimal location and sizing of renewable DG for various distribution systems. Wu et al. [26] deployed the optimal strategy for the optimized operation of a wind-solar-biogas integrated system. Ref. [27] displayed the optimization techniques for a solid oxide fuel cell and power to the gas integrated renewable system in a microgrid.

The literature survey shows that a limited amount of work concerning optimal sizing and placement of DGs has been reported in past years. In addition, the critical study of the literature referred to here in this aspect reveals that up until now, no one has considered the economical criterion with technical constraints for deciding on the placement of RDG units. Therefore, a comprehensive attempt has been made to study the techno-economical aspect of RDG units to cope with the competitive electricity market. Here, the total losses of the distribution network along with the overall cost factors and the profit for the investors have been investigated by using different optimization approaches. In addition, the review

of the literature highlights many aspects of power system problems but various points that need to be focused on are as follows:

- What is the economic impact of RDG units on the electricity grid?
- What is the system voltage impact of RDG units in wind-integrated systems?
- How do different optimization techniques play an important role in the economic benefit and system voltage profile of the electrical system?

These issues have not been addressed together in recent years by researchers in the field. Therefore, in this work, all these problems have been examined together by proper operation of RDG units.

In a deregulated environment, the integration of RDG units is becoming more and more popular because of their excellent eco-friendly behavior. Therefore, the research interest here is to concentrate on the "optimal operation of renewable distributed generation in a day-ahead power system". It is also emphasized in this work that the aspect of making it cost-effective is to cope with the competitive electricity market. The prime highlights of this work are as below:

- To develop a system model for optimal placement of RDG units in a competitive electricity market.
- The economic impact assessment of different wind speeds in a wind-integrated system.
- Bus sensitivity factor (BSF) has been considered for equating the optimal position of the wind farm in the integrated system.
- Comparative study of SQP, ABC, PSO, ACO, and SMA corresponding to the system profit, system generation cost, and bus voltage profile.
- The SMA and ACO have been used for the first time in this type of economic assessment (i.e., impact valuation of LMP) in a deregulated power system, which is the novelty of this work.

2. Mathematical Formulation and Optimization Techniques

The following mathematical formulations and optimization techniques are used in this paper to check the effectiveness of the proposed approach. The entire work has been performed using MATLAB software.

2.1. Wind Power Generation

Wind power generation depends on the wind speed and height of the wind turbine. For economic operation, the wind turbine height used is normally 120 m throughout the world. Therefore, the height of the wind turbine is considered as 120 m in this work. The wind speeds (km/h) at different heights are calculated using the following equation [28]:

$$\frac{WS_n}{WS_{10}} = \left(\frac{n}{10}\right)^h \quad (1)$$

Here, 'WS_n' and 'WS_{10}' are the wind speeds (km/h) at a particular height 'n' and 10 m, respectively. 'h' is the Hellman co-efficient (i.e., 1/7). The formulation of wind power generation (WPG) is as follows [28]:

$$WPG = \frac{1}{2} \cdot AD \cdot a \cdot e \cdot WS_n^3 \quad (2)$$

Here, WPG is in watts. 'AD' is air density in kg/m^3. 'a' is turbine swept area in m^2. 'e' is the efficiency of the turbine.

2.2. Bus Sensitivity Factor (BSF)

The BSF is the ratio of change in the active power flow in the congested line connected between buses i and j (ΔP_{ij}) to the injected active power change in the m-th bus (ΔP_m) at a time 't'. The BSF value for the m-th bus is defined as [29]:

$$BSF_m^t = \frac{\Delta P_{ij}^t}{\Delta P_m^t} \quad \forall t = 1 : T \tag{3}$$

2.3. Sequential Quadratic Programming (SQP)

Sequential quadratic programming (SQP) is one of the most effective methods to obtain the solution if the problem is related to nonlinearity. This method generates step-by-step problem formulation and solution by using the quadratic sub-problem process. The line search process and trust-region framework process are used in this method. The SQP method is suitable for solving small problems as well as large problems with a significant number of nonlinearities. The SQP method is the parallel process of Newton's method for unconstrained optimization, by which it finds a step away from the current point by minimizing a quadratic model of the problem.

Step-by-step process of SQP:

1. **Step 1:** Initializing variables.
2. **Step 2:** Define the search direction of the variables for taken objectives.
3. **Step 3:** Define and solve quadratic programming sub-problems.
4. **Step 4:** Check the optimum result: **If yes**, then go to the next step. **Otherwise**, change search size and repeat from Step 2.
5. **Step 5:** Finally, obtain the solution.

2.4. Artificial Bee Colony (ABC) Algorithm

Encouraged by the activities of honey bees, the ABC algorithm was proposed by Karaboga in 2005 [30]. A swarm (a large or dense group of honey bees) can productively complete jobs through a complete social connection. Three kinds of bees are used in this algorithm, i.e., employed bees, onlooker bees, and scout bees. The main job for the employed bees is to search for sources of food from the pre-specified food source and share the information about food with the onlooker bees. The best quality food source is selected by onlooker bees. The scout bees are the part of the employed bees that always try to search for new quality food sources [31]. In this algorithm, the employed bees are associated with the first half of the swarm and the second half is connected with onlooker bees. The number of results is equal to the number of employed or onlooker bees [32].

Step-by-step process of ABC algorithm:

1. **Step 1:** Initialize algorithm parameters and food sources.
2. **Step 2:** Define the phase of working bees.
3. **Step 3:** Calculate fitness to evaluate the source quality.
4. **Step 4:** Onlooker bee phase for generating new sources.
5. **Step 5:** Check the trial limit. **If yes**, then abandon unproductive food sources and generate new ones. **Otherwise,** save local and global best solution sets.
6. **Step 6:** Check for stop criteria met. **If yes**, then go directly to the end. **Otherwise**, increase the iteration and continue the process from Step 2.
7. **Step 7:** Stop the process when the maximum iteration has been reached.

2.5. Slime Mold Algorithm (SMA)

The slime mold algorithm (SMA) was designed by Shimin Li in 2020 [33]. It is a population-based optimization technique that works depending on the swinging style of slime-mold in nature. The slime mold refers to the Physarumpolycephalum. The name "slime mold" comes from the concept of fungus. Like other heuristic optimization techniques, some basic stages are performed here to obtain the optimal result, i.e., ini-

tialization, calculation of fitness functions, calculation of weight, position updating, and fitness findings.

Step-by-step process of SMA:

1. **Step 1:** Initialize algorithm parameters and population size.
2. **Step 2:** Read the objective function.
3. **Step 3:** Initialize the slime mold position.
4. **Step 4:** Calculate the objective function values of all slime mold.
5. **Step 5:** Sort and update the objective function values.
6. **Step 6:** Update the best positions and objective function value.
7. **Step 7:** Check for stop criteria met. **If yes**, then go directly to the end. **Otherwise,** increase the iteration and continue the process from Step 4.
8. **Step 8:** Stop the process when the maximum iteration has been reached.

2.6. Ant Colony Optimization (ACO)

ACO is a population-based metaheuristic optimization method that is used to discover estimated resolutions to hard optimization problems. In the ACO method, a set of software mediators (artificial ants) tries to explore the noble solutions to a given optimization problem. This optimization technique was developed by Marco Dorigo in the year 1992.

Step-by-step process of ACO algorithm:

1. **Step 1:** Initialize algorithm parameters, variables, and population size.
2. **Step 2:** Randomly locate ant.
3. **Step 3:** Each ant randomly chooses a path.
4. **Step 4:** Update the pheromone trail.
5. **Step 5:** Complete pheromone evaporation.
6. **Step 6:** Check the evaluation stop condition. **If yes**, then go directly to the end. **Otherwise,** continue the search process and repeat from Step 3.
7. **Step 7:** Stop the process when the maximum iteration has been reached.

2.7. Particle Swarm Optimization (PSO)

PSO is one of the bio-inspired optimization techniques and it is a simple method to examine for an optimal resolution in the solution space. PSO was invented by Eberhart and Kennedy in 1995 and Shi and Eberhart in 1998. It is a metaheuristic method like the simulated annealing technique. The method includes taking a set of candidate resolutions (particles) with arbitrary initial locations, and the particles are agreed to travel around the space to search for the finest solution. The directions and velocities allied with the particles are directed to the best position for distinct particles and the best recognized overall location.

Step-by-step process of PSO algorithm:

1. **Step 1:** Initialize algorithm parameters and particle swarm.
2. **Step 2:** Calculate the fitness of a particle.
3. **Step 3:** Individual extreme value and global extreme value of renewal particle.
4. **Step 4:** Update particle velocity and position.
5. **Step 5:** Check the evaluation stop condition. **If yes**, then go directly to the end. **Otherwise,** continue the search process and repeat from Step 2.
6. **Step 6:** Stop the process when the maximum iteration has been reached.

2.8. Controlling Parameters of Optimization Techniques

The controlling parameters of different optimization techniques that have used in this work are as follows:

ABC:

Number of onlooker bees	: 30
Number of employed bees	: 15
Number of scout bees	: 1
Number of iterations	: 300

SMA:	
Population size	: 30
Exploration capability	: 0.05
Exploitation capability	: 0.05
Number of iterations	: 300
ACO:	
Number of ants	: 30
Elicitation factor	: 0.5
Expected heuristic factor	: 3
Evaporation coefficient	: 0.5
Number of iterations	: 300
PSO:	
Swarm size	: 30
Constriction factor	: 0.45
Cognitive learning factor	: 0.85
Social learning factor	: 1.5
Number of iterations	: 300

3. Objective Functions

The main objective of this work is to assess the economic effect of wind farm integration in a day-ahead electricity market. The economic assessment of an electrical system is divided into two parts, i.e., generation cost of power generation companies and the profit of the customers (i.e., social welfare or social benefit). In the deregulated electrical system, it is desirable that the profit of the power producer must be minimized by a certain amount and that benefit given to the customer by increasing the social benefits. This happens due to the competitiveness among the market players in the deregulated power system. The mathematical expressions of the objective function (F) and social benefits (SB) are as follows:

$$\text{MinF} = \sum_{i=1}^{Ng} C_i(P_{gi}) - \sum_{j=1}^{Nd} B_j\left(P_{dj}\right) \quad (4)$$

$$\text{MaxSB} = \sum_{j=1}^{Nd} B_j\left(P_{dj}\right) - \sum_{i=1}^{Ng} C_i(P_{gi}) \quad (5)$$

Here, F is the combination of generator side bidding cost ($C_i(P_{gi})$) and benefit to the consumer ($B_j(P_{dj})$). N_g and N_d are the numbers of generators and loads, respectively. From Equations (4) and (5), it is clear that social benefit is the reciprocal of the objective function. The main objective of this work is to maximize the social benefit, so the objective function (F) must be minimized to fulfill the system requirements. The equation of the supplier's profit is:

$$P(m,t) = TRC(m,t) - TGC(m,t) \quad (6)$$

Here, 'P(m,t)', 'TRC(m,t)', and 'TGC(m,t)' are the system profit, total revenue, and total generation cost of the m-th unit at the time 't', respectively.

$$TRC(m,t) = \sum_{i=1}^{Ng} P_g(i,t) \cdot LMP(i,t) \quad (7)$$

Here, 'Pg(i,t)' and 'LMP(i,t)' are the generated power and locational marginal price at the i-th unit at the time 't'.

$$TGC(m,t) = GC_{Th}(m,t) + GC_W(m,t) \quad (8)$$

$$GC_{Th}(m,t) = \sum_{i=1}^{Ng} \left(a_m + b_m \cdot P_g(i,t) + c_m \cdot P_g(i,t)^2\right) \quad (9)$$

Here, GC_{Th} and GC_W are the thermal and wind power generation costs. 'a_m', 'b_m', and 'c_m' are the cost co-efficients of thermal generators. To solve the optimal power flow problem, several constraints need to be considered. The constraints are divided into two parts, i.e., equality and inequality constraints.

Equality Constraints

$$\sum_{i=1}^{Ng} P_{gi} + WGP - P_{loss} - P_L = 0 \quad (10)$$

$$P_{loss} = \sum_{j=1}^{N_{TL}} G_J \left[|V_i|^2 + |V_j|^2 - 2|V_i||V_j| \cos(\delta_i - \delta_j) \right] \quad (11)$$

$$P_i - \sum_{k=1}^{N_b} |V_i V_k Y_{ik}| \cos(\theta_{ik} - \delta_i + \delta_k) = 0 \quad (12)$$

$$Q_i + \sum_{k=1}^{N_b} |V_i V_k Y_{ik}| \sin(\theta_{ik} - \delta_i + \delta_k) = 0 \quad (13)$$

Inequality Constraints

$$V_i^{min} \leq V_i \leq V_i^{max} \qquad i = 1, 2, 3 \ldots N_b \quad (14)$$

$$\varnothing_i^{min} \leq \varnothing_i \leq \varnothing_i^{max} \qquad i = 1, 2, 3 \ldots N_b \quad (15)$$

$$TL_l \leq TL_l^{max} \qquad l = 1, 2, 3 \ldots N_{TL} \quad (16)$$

$$P_{gi}^{min} \leq P_{gi} \leq P_{gi}^{max} \qquad i = 1, 2, 3 \ldots N_b \quad (17)$$

$$Q_{gi}^{min} \leq Q_{gi} \leq Q_{gi}^{max} \qquad i = 1, 2, 3 \ldots N_b \quad (18)$$

Here, WGP is wind-generated power. P_{loss} and P_L are the transmission load and power demand. N_{TL} and N_b are the number of transmission lines and the number of buses in the system. V_i, V_j, δ_i, and δ_j are the voltage magnitude and voltage angle at the buses i and j. In the inequality function, the upper and lower limit of the voltage magnitude (V_i), voltage angle (ϕ_i), transmission line flow (TL_l), real power generation (P_{gi}), and reactive power generation (Q_{gi}) have been considered.

The indicating block diagram of the presented approach is shown in Figure 1.

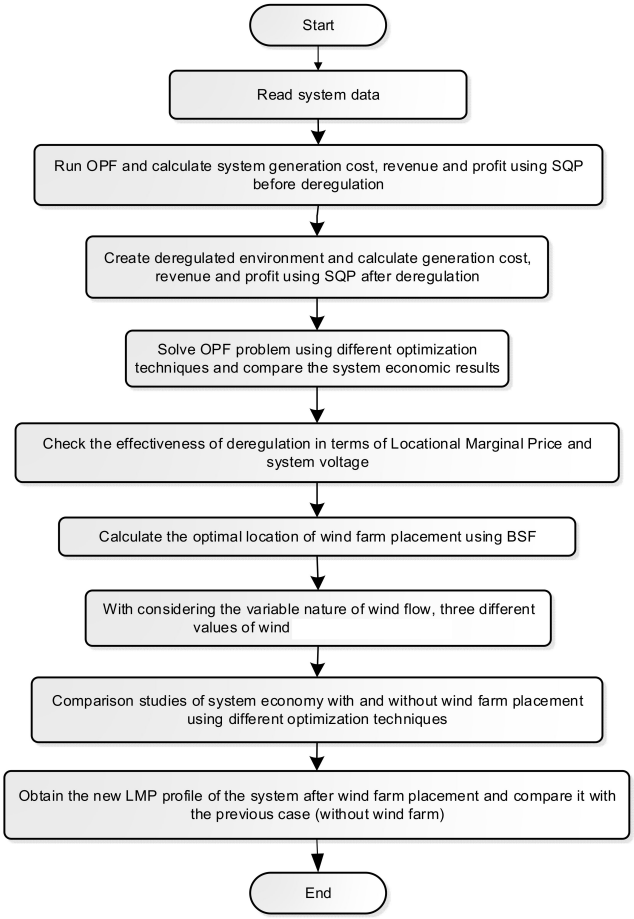


Figure 1. Indicating block diagram of the presented approach.

4. Results and Discussions

A modified IEEE 30-bus test system was used in this work to check the efficiency of the proposed concept. The initial system data were taken from [34], IEEE 30-bus system. This system has 30 buses, 6 generators, 19 loads, and 41 transmission lines. Bus no. 1 was considered as the slack bus and the system MVA limit was taken as 100 MVA. The modified IEEE 30 bus test system was adapted from [35,36] and is shown in Figure 2. The step-by-step workflow of this work is as follows:

Step 1: Check the effect of deregulation in system generation cost, profit, bus voltage, and LMP of a thermal power plant using SQP (without considering the wind farm).

Step 2: Comparative study of generation cost, profit, bus voltage, and LMP of a thermal power plant using SQP, ACO, PSO, ABC, and SMA optimization techniques (without considering the wind farm).

Step 3: Finding the optimal position of the wind farm using BSF.

Step 4: Placement of wind farm in the system and checking all economic parameters, system voltages, and LMPs after and before the wind farm placement using SQP, ACO, PSO, ABC, and SMA.

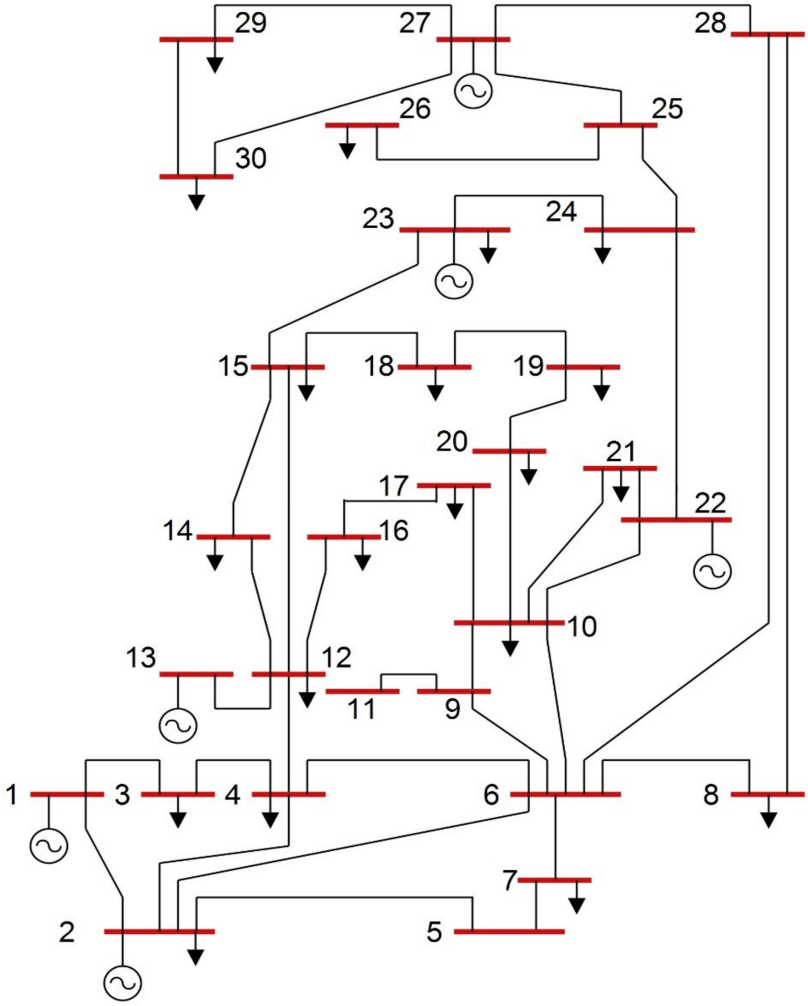


Figure 2. Single line diagram of modified IEEE 30-bus system [35,36].

- **Without Wind Farm Placement**

The entire work was performed in the day-ahead electricity market environment. In this type of electricity environment, the power producers submit their optimal bid for power generation to the system operator (ISO); at the same time, the customer also submits their bid to the ISO for their power consumption. In this situation, the ISO performs the

optimal problem solution and fixes the price of the power at an optimal value (LMP), which gives benefit to both the power producer and customer.

It is obvious from the concept of deregulation that the profit of power producers may be reduced due to the competition in the electricity market as well as due to the increment of social benefits. For checking the effect of deregulation in the electrical system, demand-side bidding was performed in this work. Bus nos. 7 and 19 of the modified IEEE 30-bus system were considered for the demand-side bidding. Table 1 shows the effect of deregulation on system generation cost, profit, and revenue of a thermal power plant using SQP (without considering wind farms).

Table 1. Comparison of system economy before and after deregulation (without wind placement).

Details	Before Deregulation	After Deregulation
Generation Cost ($/h)	800.65	705.35
Revenue ($/h)	997.5582	844.2577
Profit ($/h)	196.9082	138.9077

From Table 1, it can be seen that the system generation cost has been reduced by a large amount after deregulation. At the same time, supplier profit has been reduced to 138.9077 $/h from 196.9082 $/h. This is due to the maximization of social benefits. In the entire work, profit is considered as the supplier-side profit. Therefore, if profit is minimized then the social benefit will maximize, which is the main motto of deregulation. Figures 3 and 4 show the impact of deregulation on system voltage profiles and LMP, respectively.

The voltage profile of the system is improved after the implementation of a deregulated power environment, which can be seen in Figure 3. Here, maximum bus voltages are trying to reach the optimal voltage value to maintain the system stability. The LMP value is decreasing for all buses after deregulation, which gives benefit to the customers.

In the modified IEEE 30-bus test system, there are six generators in operation. To examine the usefulness of different types of optimization techniques, a comparative study was performed by considering five optimization techniques (i.e., SQP, ACO, PSO, ABC, and SMA). Table 2 shows the power generation quantity for different generators with all taken optimization techniques. The best optimization techniques always provide an idea about the lowest quantity of power generation. If the system is properly or optimally scheduled, then the system loss is automatically reduced and, as a result, power generation requirement is also minimized. Table 2 indicates that the SMA provides the best power scheduling among all the considered optimization techniques.

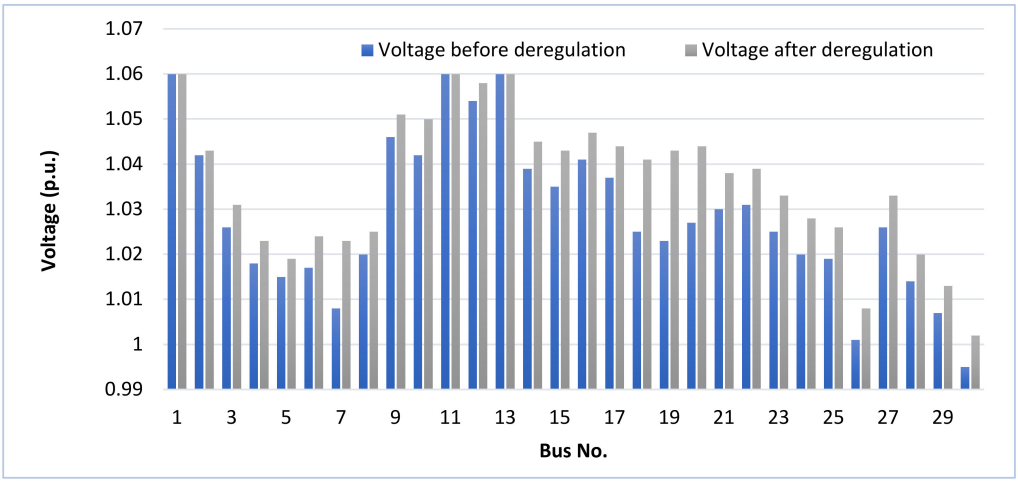


Figure 3. Comparison of system voltage profile (without wind placement).

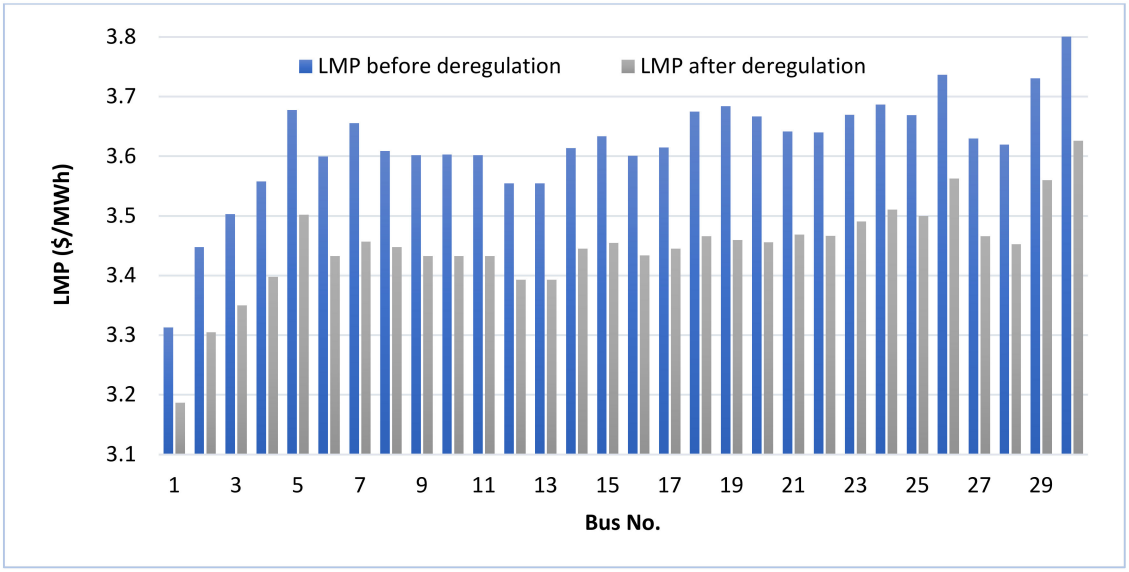


Figure 4. Comparison of LMP (without wind placement).

Table 2. Generation power with different optimization techniques (without wind placement).

Generator No.	Generated Power Using SQP (MW)	Generated Power Using ACO (MW)	Generated Power Using PSO (MW)	Generated Power Using ABC (MW)	Generated Power Using SMA (MW)
G_1	160.426	160.362	160.058	159.7948	159.3126
G_2	44.429	44.368	44.435	44.3208	44.114
G_5	20.016	20.006	20.021	20.0297	20.06
G_8	12.891	12.561	12.361	12.225	11.3111
G_{11}	10	10.238	10.213	10.1599	10.0467
G_{13}	12	12	12	12	12

Table 3 depicts the comparison in system economy with the different optimization techniques. It is observed that the system generation cost is reduced using the metaheuristic optimization techniques compared with SQP. The system generation cost is 705.35 $/h using SQP, whereas it is reduced to 688.301 $/h and 688.1534 $/h using ABC and SMA. The supplier profit is also increased using ABC and SMA. We can conclude from the results obtained in Table 3 that when the system is mathematically validated before the practical operation, then power generator scheduling must be performed by the concept of the SMA algorithm. This will provide more stability to the system economically.

Table 3. Comparison of system economy with optimization techniques (without wind placement).

Details	Using SQP	Using ACO	Using PSO	Using ABC	Using SMA
Generation Cost ($/h)	705.35	700.69	693.35	688.301	688.1534
Revenue ($/h)	844.2577	862.3889	861.321	860.1158	843.5408
Profit ($/h)	138.9077	161.6989	167.971	171.8148	155.3874

This work was performed by considering the deregulated power environment. The profit shown in Table 3 is the profit of the generation companies. From the objective function, it is clear that social benefit is maximized when GENCOS profit is minimized. Therefore, SMA provides the best social welfare as compared to the other techniques. Figures 5–8 display the impact of optimization techniques on system voltage profiles and LMP. After the application of ABC and SMA, the system voltage, as well as LMP, are improved for the entire system.

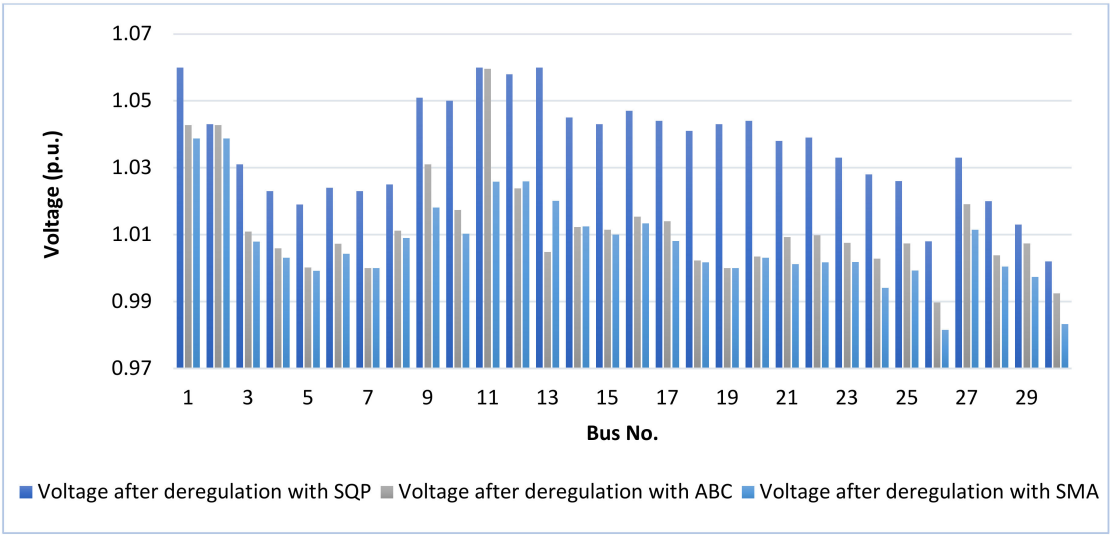


Figure 5. Voltage with different optimization techniques (without wind placement) (SQP, ABC, SMA).

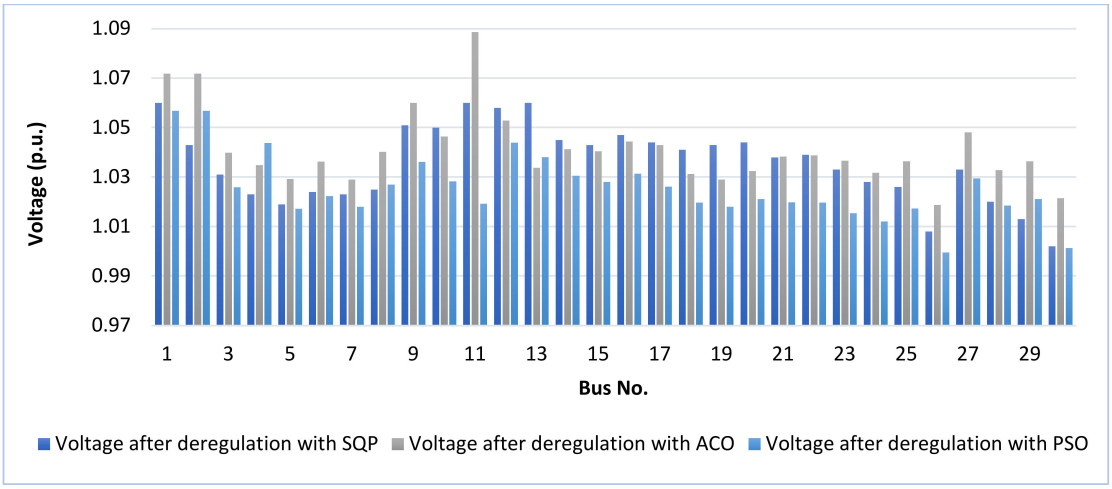


Figure 6. Voltage with different optimization techniques (without wind placement) (SQP, ACO, PSO).

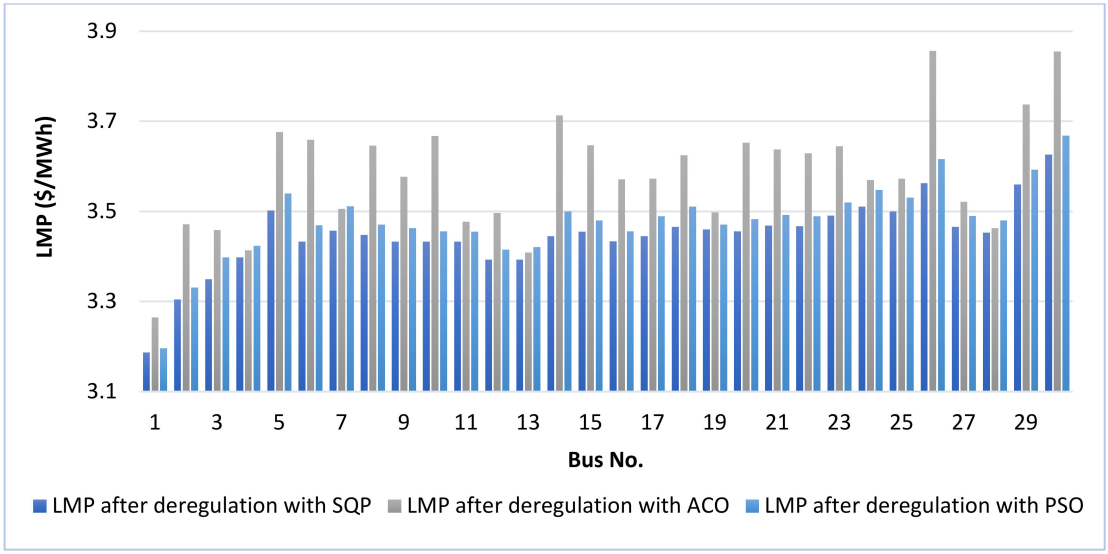


Figure 7. LMP with different optimization techniques (without wind placement) (SQP, ABC, SMA).

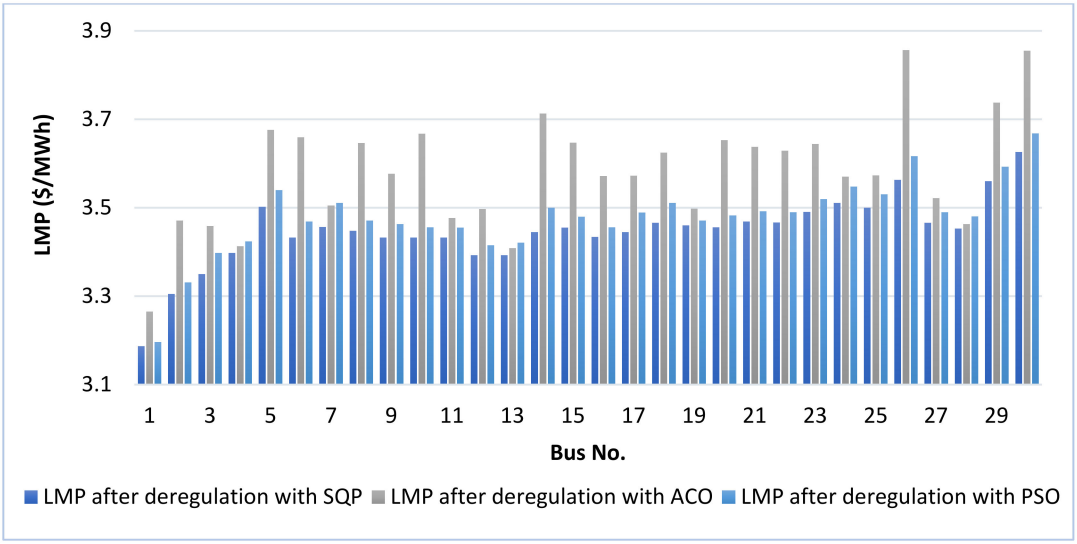


Figure 8. LMP with different optimization techniques (without wind placement) (SQP, ACO, PSO).

After the detailed study, we can conclude that the system economy, as well as system stability, can be enhanced by using the SMA and ABC optimization techniques. Therefore, in the next part of this work we have used SMA and ABC along with SQP algorithms instead of five optimization techniques. SQP is a linear optimization technique. It is considered for comparative study along with the most superior considered optimization techniques (i.e., ABC and SMA).

- **With Wind Farm Placement**

In the previous section, we have already seen the importance of different types of optimization techniques in the deregulated power environment. Due to the limitations in future power generation from the thermal power plant, the whole world is now going towards renewable energy sources. At present, renewable energy sources are used as the backup source but in the near future, they will be the prime power generating sources. In this section of the work, an assessment study has been performed for checking the status of the system economy as well as voltage level after the placement of the wind farm.

A factor named 'bus sensitivity factor (BSF)' has been used for finding the optimal position of wind farm placement in the system. Equation (3) depicts the mathematical equation of BSF. By using this concept, the BSF values of all buses were calculated, which are shown in Table 4.

Based on the concept of BSF, the wind farm is placed at the bus that has the lowest value of BSF. The lowest values of BSF indicate the most sensitive bus in the system. It can be observed from the table that bus no. 2 has the lowest BSF value. However, this bus already has the thermal generator, so the wind farm has been placed in the next priority bus, i.e., bus no. 3. The wind speed is variable in nature. When considering this phenomenon, three different wind speeds were used to check the performance of the presented approach. The real-time data for Silchar, Assam, India, for a particular day at midnight, 8 AM, and 4 PM were taken from [37]. Table 5 shows the real-time wind speed data and wind power calculation for all the considered periods. The operational cost of wind power generation is considered as 2 $/MWh. The wind power operational cost data were chosen after a detailed study about the recent wind investment cost in India.

Table 4. BSF calculation (without wind placement).

Bus No.	BSF	Ranking	Bus No.	BSF	Ranking
1	0.3798	30	16	−0.4181	12
2	−0.9807	1	17	−0.4359	8
3	−0.5658	2	18	−0.4265	9
4	0.0275	28	19	−0.4216	10
5	−0.3503	26	20	−0.4177	13
6	−0.1946	27	21	−0.4064	15
7	−0.3674	24	22	−0.4204	11
8	−0.3858	20	23	−0.4089	14
9	−0.4052	16	24	−0.3872	18
10	−0.3858	21	25	−0.3935	17
11	−0.466	3	26	−0.3714	23
12	−0.466	4	27	−0.3574	25
13	−0.4593	5	28	−0.3801	22
14	−0.4494	6	29	−0.3861	19
15	−0.443	7	30	0.2611	29

Table 5. Real-time wind speed data and wind power calculation.

Hour	WS at 10 m Height (km/h)	WS at 10 m Height (m/s)	WS at 120 m Height (m/s)	Wind Power with 100 Turbines (MW)	Wind Generation Cost with 100 Turbines ($/h)
12 Night	16	4.44	6.3407	6.84	13.68
8 AM	5	1.39	1.9814	1.17	2.34
4 PM	10	2.78	3.9629	9.38	18.76

In the previous section, the entire work was performed without the placement of a wind farm. Now, the wind farm has been placed at the optimal position (optimal location was calculated using the concept of BSF). Table 6 deploys the comparison result before and after wind farm placement using SQP.

Table 6. Comparison result before and after wind farm placement (using SQP).

Details	Without Wind Placement	With Wind Placement		
		At Midnight	At 8 AM	At 4 PM
Generation Cost ($/h)	705.35	676.25	683.78	672.94
Revenue ($/h)	844.2577	836.2958	842.9219	847.6913
Profit ($/h)	138.9077	160.0458	159.1419	174.7513

From Table 6, it can be seen that wind farm placement plays a vital role in a deregulated system. The system generation cost is minimum with the integration of the maximum amount of wind power in the system. This placement also affects the supplier's profit. The supplier profit is maximum with the placement of a high-value wind farm and profit is minimum without the implementation of the wind farm in the system. Figures 9–11 display the LMP after the placement of the wind farm in the system. It can be observed that the maximum amount of wind farm integration provides more economic stability to the system by all the optimization techniques. The highest amount of wind farm integration

and the application of the SMA optimization technique provide the most economic result for the wind-integrated deregulated power system.

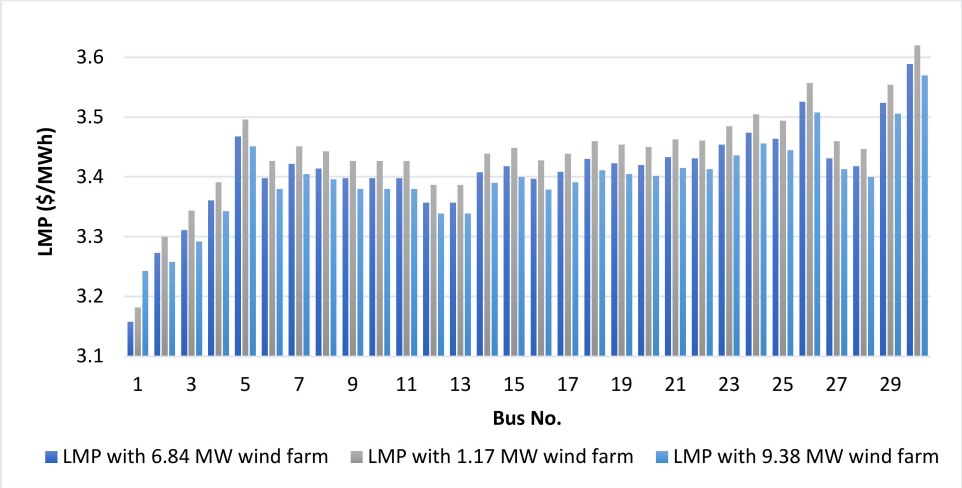


Figure 9. LMP with different values of wind power using SQP.

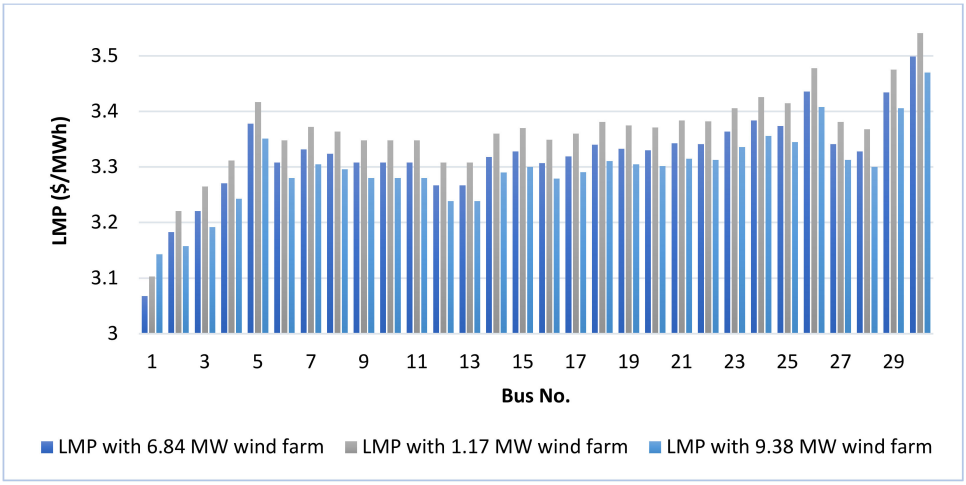


Figure 10. LMP with different values of wind power using ABC algorithm.

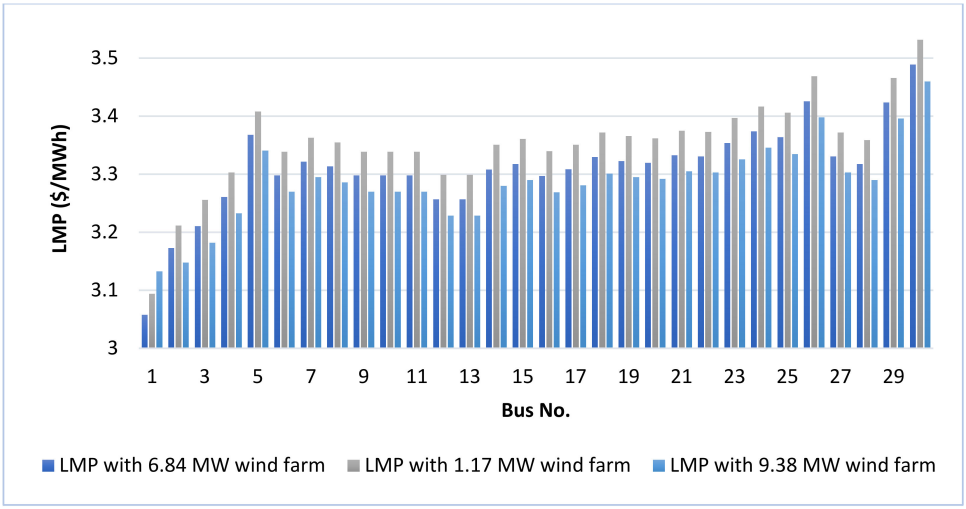


Figure 11. LMP with different values of wind power using SMA.

Tables 7 and 8 display the comparison result before and after wind farm placement using ABC and SMA. Like the previous case, economic sustainability is enhanced in this case with the wind farm placement in an integrated deregulated system with the operation of ABC and SMA. The system generation cost approaches the minimum value with the incorporation of the maximum amount of wind power. The supplier profit is supreme with the settlement of high-value wind farms and profit is lowest without the operation of the wind farm in the system.

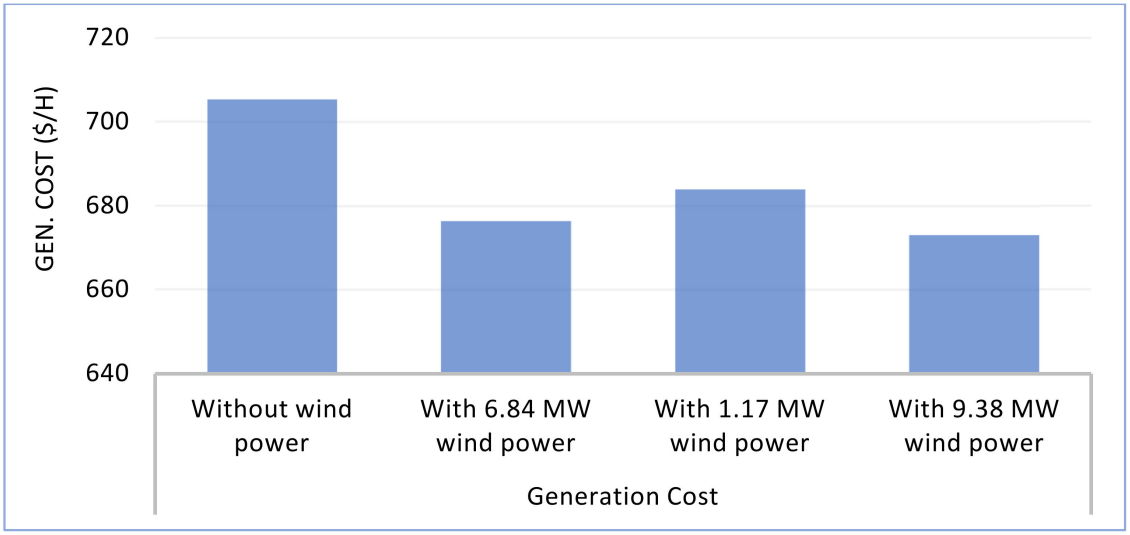
Table 7. Comparison result before and after wind farm placement (using ABC).

Details	Without Wind Placement	With Wind Placement		
		Midnight	At 8 AM	At 4 PM
Generation Cost ($/h)	688.301	679.5391	686.9457	676.021
Revenue ($/h)	860.1158	874.9061	880.2147	878.383
Profit ($/h)	171.8148	195.367	193.269	202.362

Table 8. Comparison result before and after wind farm placement (using SMA).

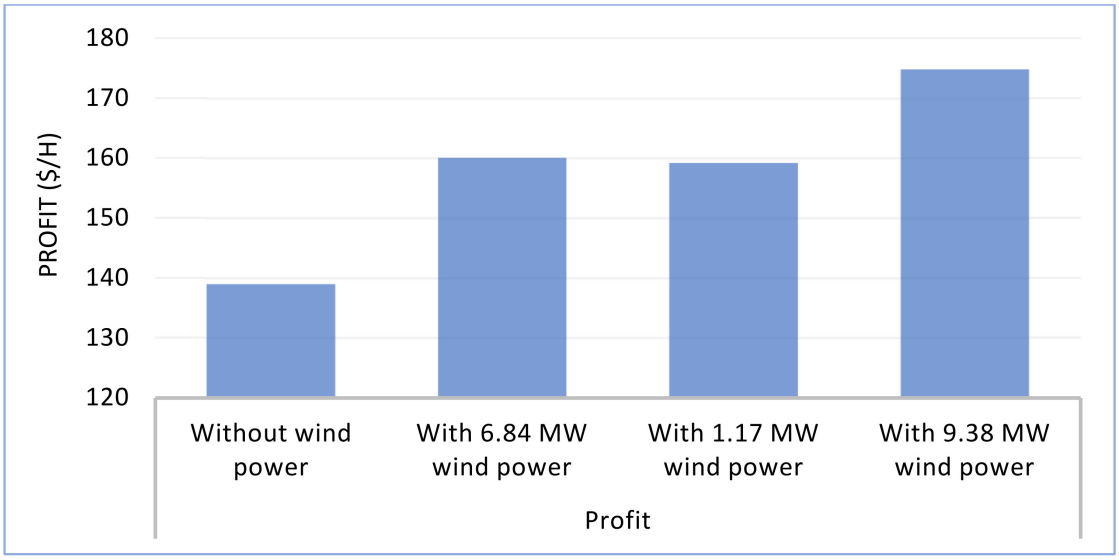
Details	Without Wind Placement	With Wind Placement		
		At Midnight	At 8 AM	At 4 PM
Generation Cost ($/h)	688.1534	679.0809	686.7302	675.7125
Revenue ($/h)	843.5408	858.4419	864.4222	864.0765
Profit ($/h)	155.3874	179.361	177.692	188.364

Figures 12–14 show the comparative results of system economy with three different optimization techniques. In the results, two cases have been displayed, i.e., without windfarm integration and with wind farm integration. After the incorporation of the wind farm, all the applied optimization techniques show better results towards the economic advancement of the system.



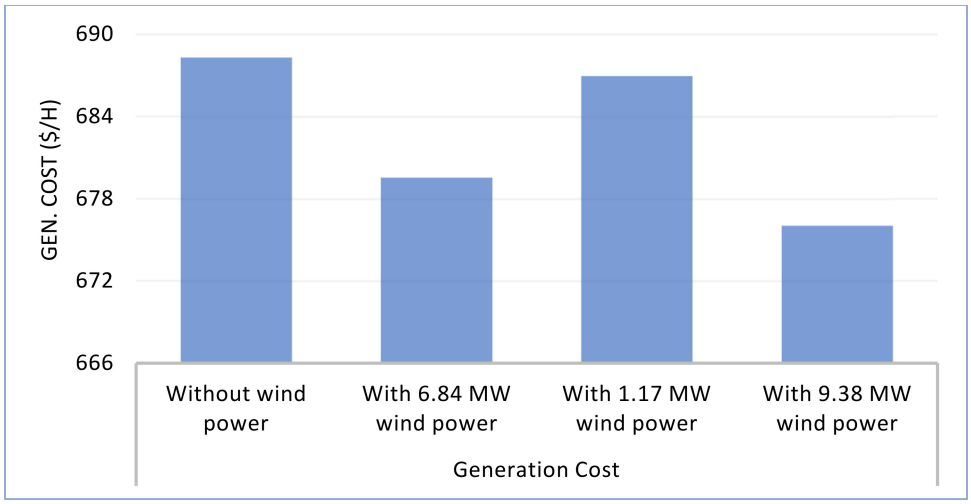
(**a**)

Figure 12. *Cont.*

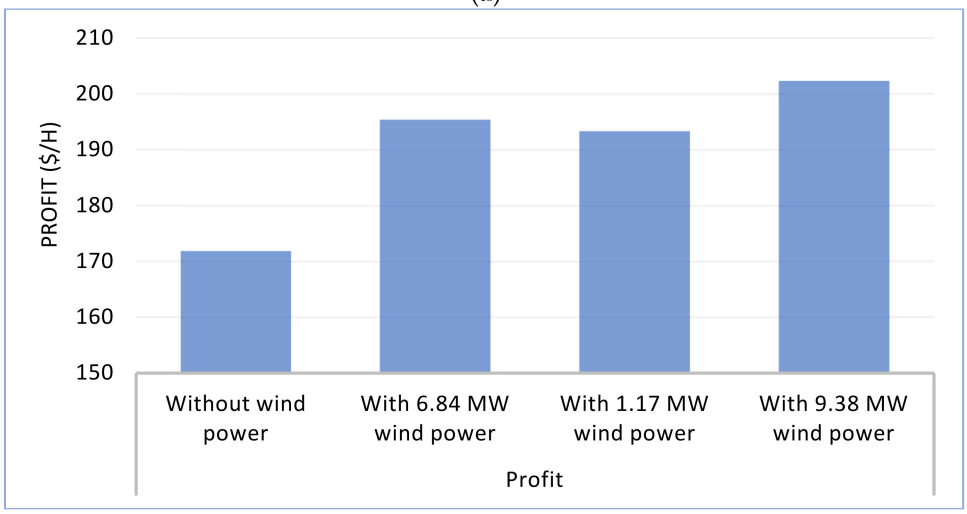


(**b**)

Figure 12. Comparison of system economy using SQP. (**a**) Generation Cost, (**b**) Profit.

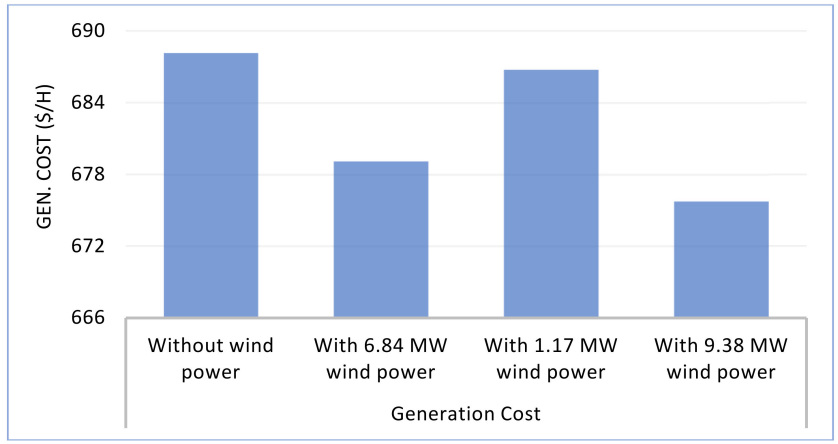


(**a**)

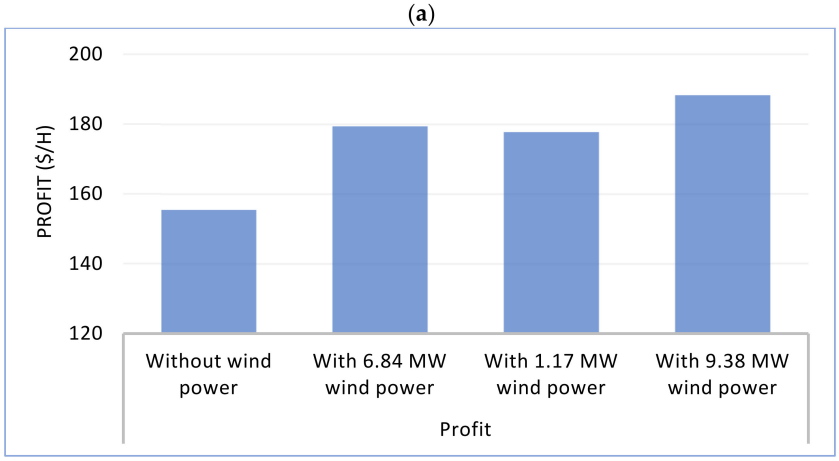


(**b**)

Figure 13. Comparison of system economy using ABC. (**a**) Generation Cost, (**b**) Profit.



(**a**)



(**b**)

Figure 14. Comparison of system economy using SMA. (**a**) Generation Cost, (**b**) Profit.

Our main objective is to minimize the system generation cost, which can be achieved by using the SMA. When the generation cost is minimized then social welfare is automatically maximized. From this study, we observed that the maximum amount of wind farm integration along with the optimal concept of SMA provides the highest social welfare and minimum system generation cost. The convergence plots of ABC and SMA with two different situations (i.e., without wind farm and with a maximum capacity of wind farm) are depicted in Figures 15 and 16.

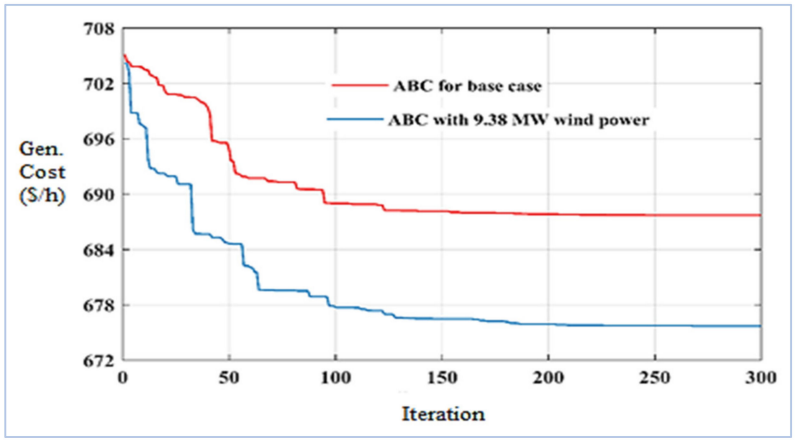


Figure 15. Convergence plot with ABC algorithm.

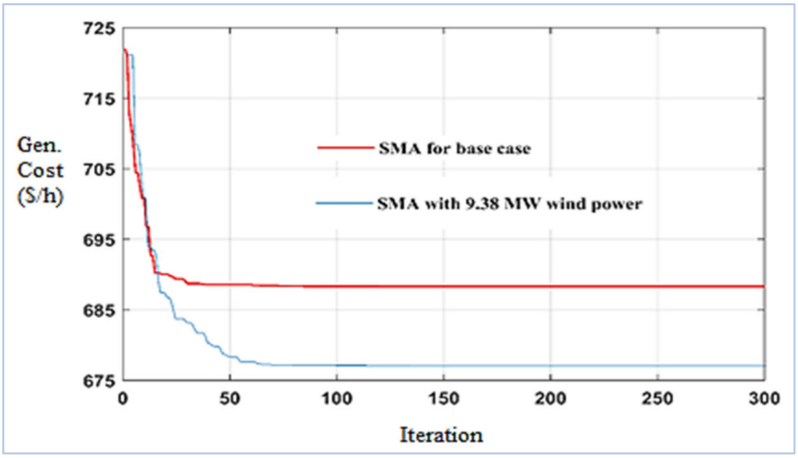


Figure 16. Convergence plot with SMA.

5. Conclusions

The modernization of technology in all aspects throughout the world has forced the electrical sector to consider the economical sustainability of the system. This situation creates an environment in the electricity market where power suppliers and power consumers both obtain benefits. Renewable energy integration in the deregulated power sector is challenging work for the market controller. In this paper we have provided a detailed study about the economic impact of wind farm integration in a deregulated power system. It was observed that the system will be more stable in an economic manner after wind farm placement with the maximum capacity, i.e., system generation cost is minimized with a high amount of wind farm placement. The profit of the generation companies and customers is directly linked to the system generation cost. Therefore, the profit will maximize with the minimization of system generation cost. Among all the applied optimization techniques, SMA gives the best result in this work in terms of system economy. The generation cost has been considered as the combination of both thermal power plants and wind power plants. The same concept has also been used for the revenue. The SMA has been used for the first time in this type of economic assessment (i.e., impact valuation of LMP) in a deregulated power system, which is the novelty of this work. The economic improvement studies in this work will encourage energy sector personnel to invest in and install more renewable energy sources.

Author Contributions: Conceptualization, G.S.P. and A.M.; methodology, G.S.P., A.M. and T.S.U.; software, G.S.P.; validation, G.S.P., A.M. and T.S.U.; formal analysis, T.S.U.; investigation, G.S.P.; resources, G.S.P., A.M. and T.S.U.; data curation, T.S.U.; writing—original draft preparation, G.S.P.; writing—review and editing, T.S.U.; visualization, G.S.P., A.M. and T.S.U.; supervision, G.S.P.; project administration, G.S.P., A.M. and T.S.U.; funding acquisition, T.S.U. All authors have read and agreed to the published version of the manuscript.

Funding: There was no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

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