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Power generation planning with reserve dispatch and weather uncertainties including penetration of renewable sources

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Abstract

In this paper, a combined model for optimal power planning consisting of carbon and carbon-free sources having weather uncertainties and their corresponding costs have been presented for liberalized electricity markets. To simulate the volatility, scenarios representing different percentages of renewable penetration into the power market have been presented which take the form of stochastic linear programming model which is solved by GAMS/CPLEX. The optimal values of power generation, reserve dispatch (battery) and corresponding sales to the main stream utility market are calculated. Final computational results indicate that increasing the utilization of wind and solar power output will decrease the over-dependence on conventional thermal sources but still the proposed model cannot make the wind and solar power fully reliant for self-sufficient autonomous mode and the significance of conventional sources can not be ignored for the near future. The proposed model can address the energy sustainability and renewable integration issues.

Keywords: Optimization, power planning, distributed energy resources, weather uncertainties, battery reserves

1. Introduction

The renewables participating in real time market that are sold today make up as a 10 percent of the volume of total energy. We need to accept the open secret that the profit of non-renewables decreases sharply with increase in renewable penetration. In the renewable sources' case, the standard paradigm is "grid takes all the renewable." Therefore, fitting renewables into current deregulated markets may have significant financial implications. In 2018, about 17 percent of total U.S. electricity generation was from renewable energy sources. The U.S. Energy Information Administration (EIA) forecasts that utility-scale renewable fuels, including wind, solar, and hydro power, will collectively produce 18 percent of U.S. electricity in 2019 and 19 percent in 2020. So, we are looking forward to a 20-50 percent renewable penetration in the next two decades. If non-renewable sources are forced to incorporate the cost of renewable generation's irregularity, they rapidly become non-competitive, leading to political friction and lobbying. Energy Reliability Council of Texas (ERCOT) had more than 78,000 MW of generating capacity to meet demand but warned low reserves could force it to issue alerts urging customers to conserve energy. The planning reserve margin for this summer was a historically low 7.4 percent because several generators have been retired even though demand is rising. The reserve margin is the difference between total generation available and forecast peak demand, with the difference expressed as a percentage of peak demand. The variable demand is one of the key factors. Distributed Energy Resources (DERs), as an innovative way for electric power delivery, plays an important role in providing utility services to prosumer communities in both commercial and residential areas. A prosumer is someone who both produces and consumes energy- a shift made possible, in part, due to the rise of new connected technologies and the steady increase of more renewable power like solar and wind onto our electric grid. For the timely meeting of demand growth in the most economic and reliable manner, power distribution

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planning (PDP)is necessary to design the distribution system. The distribution planning is characterized by the high penetration of distributed generation (DG) technologies, including storage, and the participation of the consumers in the form of active demand, encouraged by national and regional policies worldwide [1]. The weather uncertainties affect the power generation capabilities. The dependence of weather (wind and sunshine) is very important for renewable generation which forms an indispensable component of DERs. Wind and solar power generation play a pivotal role in dealing with the challenges of balancing supply and demand in any electricity system, given the uncertainty associated with the wind farm power output [2]. The effect of renewable resources penetration and surplus power generation issues have been investigated and three strategies to solve the surplus power generation problem have been proposed [3]. Keeping in mind that ignoring the flexible operation characteristics can underestimate total emission reduction cost, a power generation expansion planning model incorporating renewable integration costs is proposed [4]. For scheduled planning of renewable systems with storage, a financial optimal schedule with the incorporation of uncertainty information is proposed that combines a machine learning approach [5]. Uncertainties for renewables include the difficulties in ensuring reserves [6]. The other uncertainties of load prediction, distributed generation, and interruptible load can be considered as an interval-based optimization in the environmental and economic dispatch model [7]. To minimize the total operating costs of generators and spinning reserves under renewable obligation while maximizing renewable penetration, a stochastic multi-objective economic dispatch model is proposed under renewable obligation policy framework [8]. To focus on the short-term system operations in the planning models integrating variable renewables, specially the constraints of flexible generation, interregional transmission as well as energy storage and demand side response, the combination requirement for resolution and planning horizon to match constraints and time steps in models have been presented [9]. Computational issues arising in the implementation of the framework to validate the numerical weather prediction model using real wind-speed data obtained from a set of meteorological stations are key factors in power generation planning [10]. The solar energy, especially during the summer seasons, can provide a carbon free source of energy considering the existing global climate crisis. The inclination towards DERs has become a compulsory part of European Energy policy. One of the Â Ɇuropean Electricity Grid initiatives is to transmit and distribute up to 35 percent of electricity from dispersed and concentrated renewable sources by 2020 in preparation for the planned decarbonization of electricity production by 2050 [11].Thus, there is a need for transforming the existing power generation to renewable, distributed generation implicates an increase in complexity for the control of the overall system [12]. More precisely saying, the optimal power generation must combine the integration of DERs with provision of ancillary services acting as battery reserves. The present energy support system cannot be completely dependent on DERs taking into account weather uncertainties. The main reason behind its lack of complete independence is volatility in sunshine and wind speeds which automatically induces the need of battery reserves. Energy storage plants utilizing batteries and thyristor power converters promise both operational and economic advantages for load-frequency-control and instantaneous reserve operation [13]. Battery storage systems act as a promising and cost efficient alternative where continuously growing number of renewable sources starts compromising the stability of electrical grids as contradictory to fossil fuel power plants, energy production of wind and solar energy is fluctuating [14]. Therefore, the optimal power planning incorporates the DERs and battery reserves to avoid any black outs due to the weather uncertainties. Besides the continuously changing weather, the high costs of Battery reserves also add to the concern that what should be the optimal power planning scheme. Considering all these factors in mind, we develop a mathematical model having the weather uncertainties and cost of power generation, selling price of the power and battery reserves and optimize that linear stochastic model to find the optimal power planning scheme.

2 Nomenclature

Let us define the Nomenclature:

x_1: power generation units scheduled from wind source

x_2: power generation units scheduled from solar source
x_3: power generation units scheduled from conventional source
G_1: generation from wind source in MW per unit
G_2: generation from solar source in MW per unit
G_3: generation from conventional energy source in MW per unit
C_1: generation costs for wind source in USD per unit
C_2: generation costs for solar source in USD per unit
C_3: generation costs for conventional energy source in USD per unit
M_1: minimum generation requirements for wind source in MW
M_2: minimum generation requirements for solar source in MW
y_1: battery reserves for wind source in MW
y_2: battery reserves for solar source in MW
B_1: battery costs for wind source in USD per MW
B_2: battery costs for solar source in USD per MW
S_1: selling costs for wind power in USD per MW
S_2: selling costs for solar power in USD per MW
S_3: selling costs for conventional energy power above L MW in USD per MW
S_4: selling costs for conventional energy power below L MW in USD per MW ($S_4 > S_3$)
w_1: maximum power sold from wind source in MW
w_2: maximum power sold from solar source in MW
w_3: maximum power sold from conventional energy source in MW at favorable price
w_4: maximum power sold from conventional energy source in MW at reduced price
$j = 1$: index representing above average output (surplus) scenario
$j = 2$: index representing average output scenario
$j = 3$: index representing below average output (deficit) scenario

3. Model and Method Description

In this section, we present the concept of the state of art of the system which is developed into stochastic linear program to determine the optimal power planning scheme. The role of DERs plays a significant role in the model proposed. The optimal power planning revolves between conventional and carbon free sources based on different constraints. After an analytical model is developed, we test it with different case studies having uncertainties in wind and sunshine. The objective of this model is find an optimal power planning scheme with efforts to diversify energy mix through greater integration of renewable energy via DERs keeping weather uncertainties and their effects on power generation in mind

We consider a utility environment which has "D" generating units which we have to allocate among conventional, wind and solar energy sources of power. It becomes a power planning scenario where we have to device a decision making of ' how much to allocate and to which one ?' First we discuss our model in ideal conditions with no weather uncertainty and later, we will introduce weather volatility to our scenario which are stochastic in nature. Based on weather uncertainty, we try to extend to a stochastic scheduled power planning model. With "D" generating units to be optimally scheduled among conventional and DERs , "L" be the limit on generation of conventional sources of energy (CE) which comprise of natural gas fired power plants, coal power plants, nuclear power plants in order to prevent negative energy pricing. In other words, this limit on generations acts as a production quota. Negative prices are a price signal on the power wholesale market that occurs when a high inflexible power generation meets low demand. Inflexible power sources can't be shut down and restarted in a quick and cost-efficient manner. Renewables do count in, as they are dependent on external factors such as wind and sunshine. Therefore, it becomes imperative to establish constraints on the power surplus coming from conventional energy sources. In order to make our model more dynamic, we consider battery reserves in the power planning scheme.

The variables x_1, x_2, x_3 are the decision variables. Now we will be consider weather uncertainty in our model. There will be volatile winds and solar conditions affecting the power generation. A total of three scenarios are presented: Above average power output (surplus) under favorable weather conditions, average output and below average (deficit) representing unfavorable weather conditions. The model involves a large number of stochastic decision variables and constraints linking cost constraints and operating power units. The power planning problem is to decide the optimal power scheduling i.e. we need to determine x_1, x_2, x_3 without knowing which one of the three scenarios is going to happen with regards to battery reserves costs y_1, y_2 and selling costs S_1, S_2, S_3, S_4 . Hence, the decisions depend on the scenarios which are indexed by $j = 1,2,3$ with $j = 1$: index representing above average output (surplus) scenario

$j = 2$: index representing average output scenario

$j = 3$: index representing g below average output (deficit) scenario

We introduce corresponding new variables

$$y_{ij}, 1 \leq i \leq 2, 1 \leq j \leq 3, \qquad and \qquad z_{ij}, 1 \leq i \leq 4, 1 \leq j \leq 3$$

z_{ij} is the new variable that defines the power sold (MW) for the three scenarios. For instance, z_{31} represents the amount of power sold (MW) from conventional energy at favorable price in surplus power output scenario.

The decision variables y_{ij} and z_{ij} are referred to as decision variables. For a stochastic decision program, we denote

$$R^{n1}, x \geq 0$$

The vector of decision variables. It is subject to constraints

$$Ax \leq b$$

Where A is the coefficient matrix for the sources of power generation and b refers to the generating units. where

$$R^{m1Xn1}, b\epsilon R^{m1}$$

Are fixed matrix and vector respectively.

In Optimal power planning problem,

$$x = (x_1, x_2, x_3)^T$$

Represents the number of generating units devoted to the three different sources of energy. Here

$$m_1 = 1, \qquad A = (111), \qquad b = D$$

where m1 represents the column dimension of the coefficient matrix and n1 represents the row dimension of the coefficient matrix. We further denote by ε, a random vector whose realizations provide information on the stage decisions y which is a random vector with realizations in R_+^{n2}.

In optimal power planning problem,

$$\varepsilon = (t_1, t_2, t_3)^T \qquad with \quad t_i = t_i(s), \qquad 1 \leq i \leq 3, \qquad where \qquad s\epsilon \quad 1,2,3$$

Stands for the three possible scenarios (above average, average and below average). In other words $t_i(s)$, represents the power generation of source i under scenario s.

$$y = (y_1, y_2, y_3 = w_1, y_4 = w_2, y_5 = w_3, y_6 = w_4)^T$$

Is the random vector whose realizations

$$y_(s), s\epsilon 1,2,3$$

Are the decisions on the amount of power to have as reserve battery storage or sold at scenario s. The relationship between x and y can be expressed according to :

$$Wy = h - Tx,$$

where W is the coefficient matrix of the constraints, called as recourse matrix. $h \epsilon R^{m2}$ is a fixed vector representing the minimum requirements for generation, $W \epsilon R^{m2Xn2}$ is a fixed matrix and T is a random matrix with realizations $T(s) \epsilon R^{m2Xn1}$

W is the recourse matrix and T is referred to as the technology matrix. Altogether, the stochastic program can be reformulated as :

$$Minimize \quad c^T x + E_\varepsilon Q(x, \varepsilon)$$

subject to following constraints

$$Ax \leq b \qquad and \quad x \geq 0$$

where $c \epsilon R^{n1}$ is given and E_ε stands for expectation.

$$Q(x, \varepsilon) = min(q^T y)$$

such that the following constraints are satisfied

$$Wy + Tx \leq h, \quad y \geq 0$$

3.1. Scenario Description

The generation in MW per unit has been provided for conventional(carbon-inclusive) and carbon free(solar and wind) sources. The generation costs for conventional sources provide an approximate costs associated with different kinds of sources such as natural gas, nuclear, coal and other power plants. As the energy surplus is already there for conventional sources, but in order to decrease its over dependence and go towards carbon free path, we need to make sure that we do not proceed towards negative pricing of electricity. Therefore, we put a threshold cap on the selling prices for conventional sources at 18000MW. There are minimum requirements of generation expected from wind and solar sources. In the event solar and wind are not able to meet the requirements due to weather fluctuations, battery reserves are assigned with corresponding costs are assigned to each of them. As indicated, the conventional sources can generate more power per unit in comparison to solar and wind sources. Let us try to implement this model using a case study with weather volatility affecting the power planning. The power generation is sensitive to weather conditions.

Table 1. Data for optimal power planning

	Conventional	Solar	Wind
Generation (MW/unit)	60	9.0	7.5
Generations costs($/unit)	780	690	450
Reserve costs (Battery)($/MW)	-	620	714
Selling Price ($/MW)	108(under 18000 MW), 30(above 18000MW)	450	510
Minimum Requirement (MW)	-	720	600
Total Available units 1500			

We now introduce wind and solar volatility conditions affecting the total power output. Here we consider the two scenarios of surplus and deficit power output differ by a margin of 20 percent from the average. We assume that the three scenarios occur with the same probability of 1/3. Our objective is to maximize profit, we are led to the following problem.

$$A = (1,1,1), b = 1500, h = (600,720,0,-18000),$$

$$q = (714,620,-510,-450,-108,-30)^T, c = (450,690,780),$$

$$Minimize \qquad 714y_1 - 510w_1 + 620y_2 - 450w_2 - 108w_3 - 30w_4$$

This function gets incorporated to become a comprehensive objective function later. subject to

$$t_1(s)x_1 + y_1 - w_1 \geq 600,$$
$$t_2(s)x_2 + y_2 - w_2 \geq 720,$$
$$t_3(s)x_3 - w_3 - w_4 \geq 0,$$
$$w_3 \leq 18000,$$
$$y, w \geq 0,$$

In order to satisfy the constraint

$$Wy + Tx \leq h,$$

$$W = \begin{bmatrix} 1 & 0 & -1 & 0 & 0 & 0 \\ 0 & 1 & 0 & -1 & 0 & 0 \\ 0 & 0 & 0 & 0 & -1 & -1 \\ 0 & 0 & 0 & 0 & -1 & 0 \end{bmatrix}$$

W is the recourse matrix having dimensions (4X6) and

$$T(s) = \begin{bmatrix} t_1(s) & 0 & 0 \\ 0 & t_2(s) & 0 \\ 0 & 0 & t_3(s) \\ 0 & 0 & 0 \end{bmatrix}$$

On simplifying, the stochastic program becomes

$$\begin{gathered} Minimize \quad (450x_1 + 690x_2 + 780x_3 \\ -(170z_{11} - 238y_{11} + 150z_{21} - 210y_{21} + 36z_{31} + 10z_{41}) \\ -(170z_{12} - 238y_{12} + 150z_{22} - 210y_{22} + 36z_{32} + 10z_{42}) \\ -(170z_{13} - 238y_{13} + 150z_{23} - 210y_{23} + 36z_{33} + 10z_{43})) \end{gathered}$$

Subject to following constraints

$$x_1 + x_2 + x_3 \leq 1500 \tag{3.1}$$
$$9x_1 + y_{11} - z_{11} \geq 600, \tag{3.2}$$
$$10.8x_2 + y_{21} - z_{21} \geq 720, \tag{3.3}$$
$$z_{31} + z_{41} \leq 72x_3, \tag{3.4}$$
$$z_{31} \leq 18000, \tag{3.5}$$
$$7.5x_1 + y_{12} - z_{12} \geq 600, \tag{3.6}$$
$$9x_2 + y_{22} - z_{22} \geq 720, \tag{3.7}$$
$$z_{32} + z_{42} \leq 60x_3, \tag{3.8}$$
$$z_{32} \leq 18000, \tag{3.9}$$
$$6x_1 + y_{13} - z_{13} \geq 600, \tag{3.10}$$
$$7.2x_2 + y_{23} - z_{23} \geq 720, \tag{3.11}$$
$$z_{33} + z_{43} \leq 48x_3, \tag{3.12}$$
$$z_{33} \leq 18000, \tag{3.13}$$
$$x, y, z \geq 0 \tag{3.14}$$

The first constraint above denote the maximum number of units allocated for a given scenario. The second and third constraints refer to the power generation expected from wind and solar sources in above average output scenario respectively. Then the next two constraints define the conventional generation in case of above average generation. There is also a constraint keeping a check on the negative pricing of electricity by not trying to exceed the power surplus which we will be getting from the conventional sources. Then the constraints (2.6) - (2.9)are represented for average and the constraints (2.10)-(2.13) represent the below average scenarios. The last constraint (2.14) represents the non-negativity of decision variables. This is an extensive form of the stochastic program. The reason for this notation is that it explicitly describes the second stage variables for all possible scenarios. We assume that the three scenarios occur at the same probability of 1/3. The results obtained after running the solver are discussed in next section.

Table 2. Computational results for the stochastic decision program under weather uncertainties

		Conventional	Solar	Wind
	Units	300	100	1,100
Above Average	Generation (MW)	21,600	1,080	9,900
Above Average	Battery Reserves Requires (MW)	-	-	-
Above Average	Selling (MW)	18000(favorable), 3600(unfavorable)	360	9300
Average	Generation (MW)	18,000	900	8,250
Average	Battery Reserves Requires (MW)	-	-	-
Average	Selling (MW)	18,000	180	7,650
Below Average	Generation (MW)	14,400	720	6,600
Below Average	Battery Reserves Requires (MW)	-	48	-
Below Average	Selling (MW)	14,400	-	6,000
Maximum Profit ($)	5034900			

4. Conclusions and Key Takeaways for the Least Cost Approach

As we are looking for the least costly alternative, we come up with the optimization results that the dependence on conventional sources can not be eliminated by 100 percent. The forecasted generation is 74,820 MW annual and the sales from optimal results account to 77,490 MW which is a close match. In order to close the gap, the surplus sales of conventional sources can be altered. This solution comes when we are looking for a renewable penetration of 85.57 percent (23490/27450*100). Despite the paradigm, “grid should take all the renewable”; the significance of conventional sources can’t be ignored especially in case of natural gas fired power plants because of its low cost. The cost comparisons will be affected if we lower the percentages of renewable penetration. The cases of renewable penetration at different rates can be discussed as grid taking all the renewable may not be sustainable and it has to go hand in hand with the conventional sources. The battery reserves, despite with the development of new technologies, still do not find a place in the mainstream utility generation.

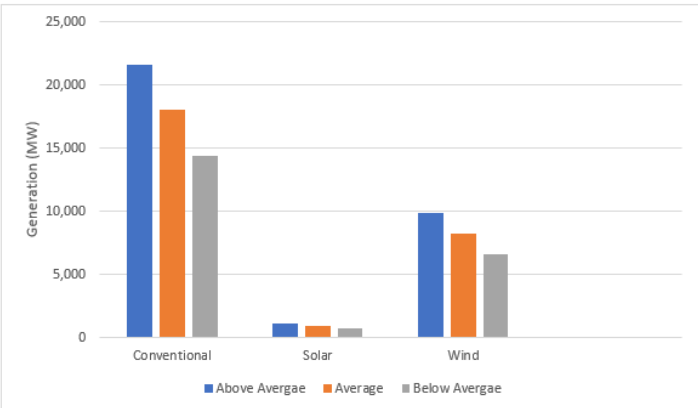

Fig. 1. Power generation planning with 85 percent of renewable penetration

No matter how favorable the weather is for DERs generation, the conventional sources are still playing the significant role in power planning policies. This is in contradiction to the scenarios that we are experiencing in European countries where DERs primarily are envisaging the energy scenario. Carbon footprints have been reducing at an enormous rate in countries like Norway.Europe is transforming its power system which is due to be carbon-free by 2050 for which the the credit must given to the policy making decisions besides technological innovations [15]. More capital should be invested in Renewable sector as speeding up the transition to renewable energy and to drive the market near zero emission requires investment in technological innovations [16]. The role of batteries is still undecided in the current power scenario. The sensitivity analysis at different percentages of renewable penetration can be carried and their respective affects can be studied in the power market. The proposed model can be used effectively in the areas of carbon management and therefore, can address the issue of global warming. By increasing the role of DERs in renewable penetration, carbon intensity (CI) values can be improvised. There is a significant room to improve especially in CI reduction.

5. Senstivity Analysis

Conventional sources such as natural gas and nuclear energy are still very significant in the current power generation scenario.The model and associated conclusions discussed above rely heavily on the need of DERs. Wind farms are coming out as a reliable carbon free alternative. But the findings do not undermine the importance of conventional sources. We can extend this model with different margins for the power surplus and deficits. A sample case study above helps in deciding the optimal power planning under different levels of penetration of renewable energy. This model can be further extender on a wide range of data having different probabilities of weather conditions.

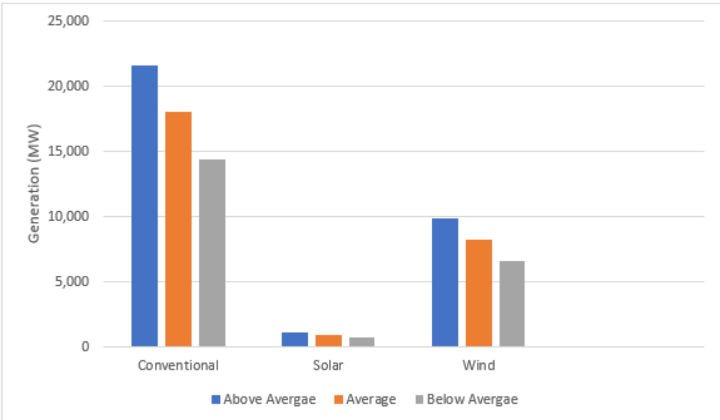

Fig. 2. Power generation planning with 85 percent of renewable penetration

We are looking for the least costly alternatives, we come up with the optimization results that the dependence on conventional sources can not be eliminated by 100 percent. The forecasted generation is 74,820 MW annual and the sales from optimal results account to 77,490 MW which is a close match. In order to close the gap, the surplus sales of conventional sources can be altered. This solution comes when we are looking for a renewable penetration of 85.57 percent (23490/27450*100). Despite the paradigm, "grid should take all the renewable"; the significance of conventional sources can't be ignored especially in case of natural gas fired power plants because of its low-cost reasons.

For renewable penetration of around 70 percent, we look for (18,792/27,450*100 MW) among the carbon free sources and a penetration of 25.12 percent (18,792/74,820*100 MW) to the total power forecasted. For a renewable penetration of around 60 percent, we look for (16,443/27,450*100 MW) among the carbon free sources and a penetration of 21.97 percent (16,470/74,820*100 MW) to the total power forecasted. For a renewable penetration of around 50 percent, we look for (14,094/27,450*100

MW) among the carbon free sources and a penetration of 18.83 percent (14,094/74,820*100 MW) to the total power forecasted. For a renewable penetration of around 40 percent, we look for (11,745/27,450*100 MW) among the carbon free sources and a penetration of 15.70 percent (11,745/74,820*100 MW) to the total power forecasted. The 3-D bubble charts are being drawn for wind and solar power reflecting their sales at different percentages of penetration.

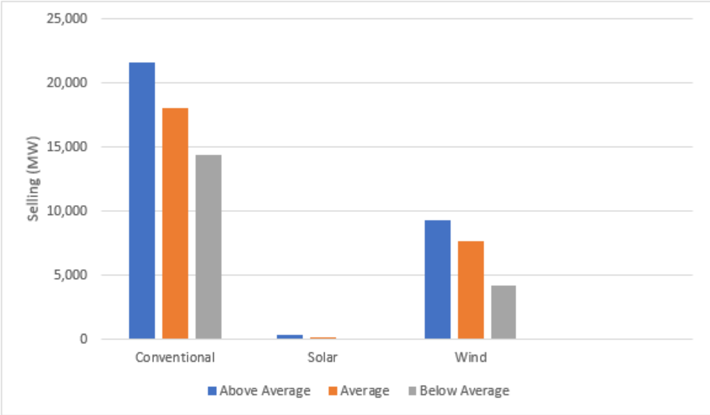

Fig. 3. Power selling with 85 percent of renewable penetration

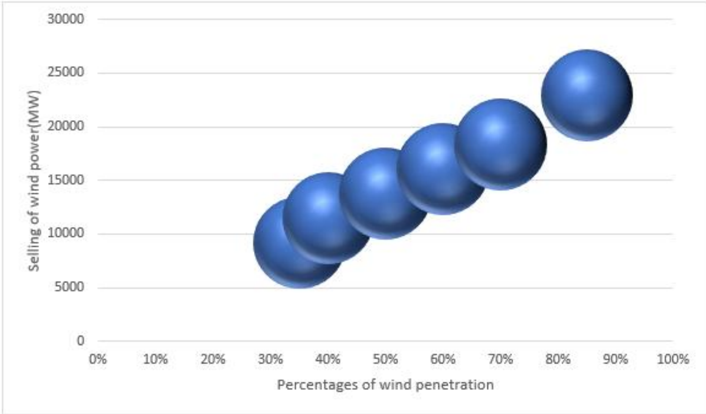

Fig. 4. 3-D bubble plot at different percentages of wind penetration

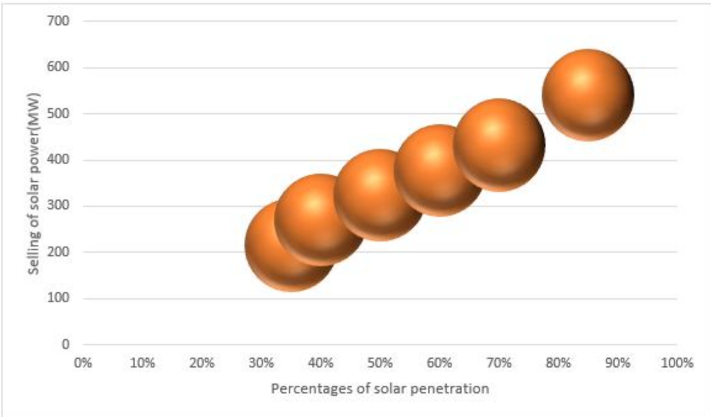

Fig. 5. 3-D bubble plot at different percentages of solar penetration

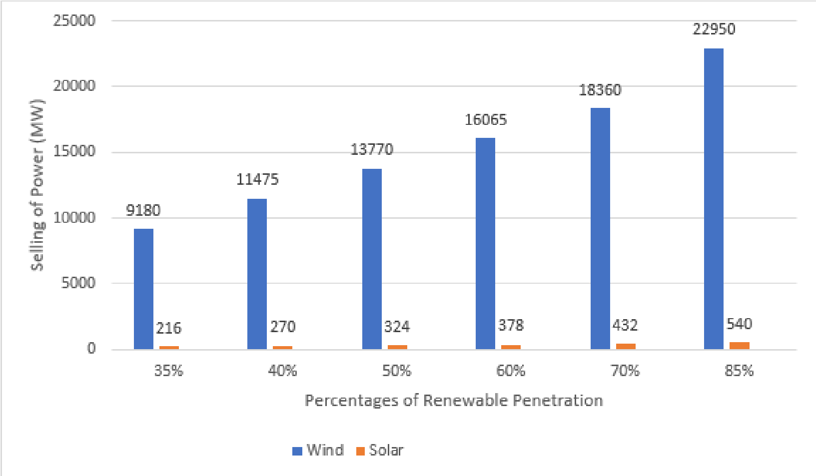

Fig. 6. Sensitivity analysis at different percentages of renewable penetration

The sensitivity analysis can be visualized with the help of x-y scatter plot as well.

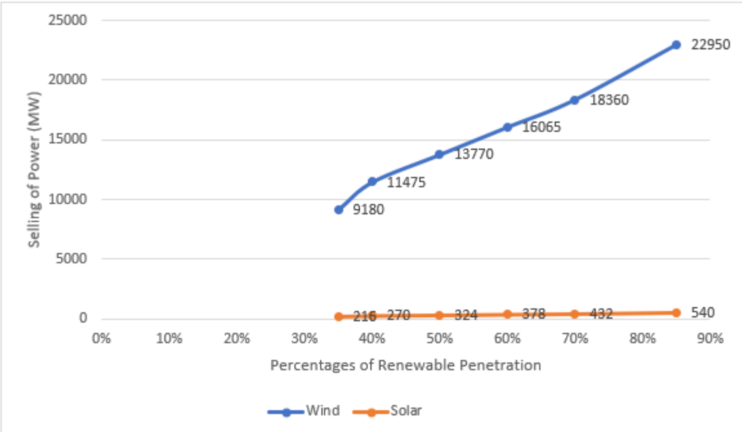

Fig. 7. X-Y scatter plot at different percentages of renewable penetration

Table 3. Computational results for the stochastic decision program under weather uncertainties-35 percent exclusive renewable penetration

			Conventional	Solar	Wind
		Units	300	100	1,100
Above Average		Generation(MW)	21,600	1,080	9,900
Above Average		Battery Resreves Requires (MW)	-	-	-
Above Average		Selling (MW)	18,000(favorable) 3,600(surplus)	144	3,720
Average		Generation(MW)	18,000	900	8,250
Average		Battery Resreves Requires (MW)	-	-	-
Average		Selling (MW)	18,000	72	3,060
Below Average		Generation(MW)	14,400	720	6,600
Below Average		Battery Resreves Requires (MW)	-	-	-
Below Average		Selling (MW)	14,400	-	2,400

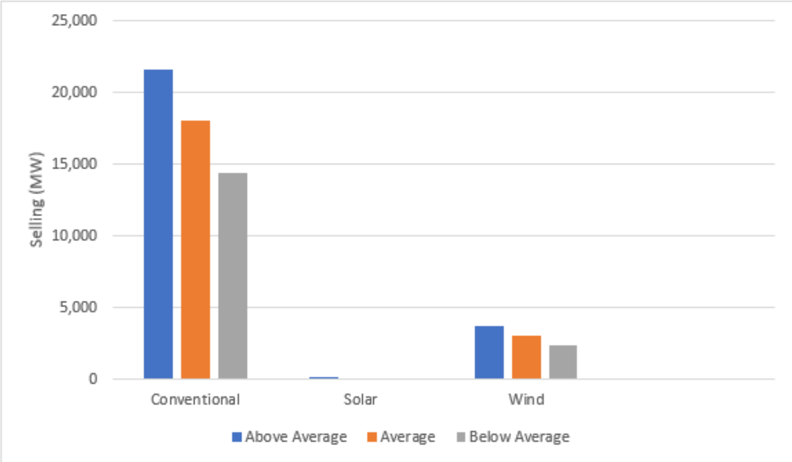

Fig. 8. Power selling with 35 percent of renewable penetration

For a renewable penetration of around 35 percent, we look for (9,396/27,450*100 MW) among the carbon free sources and a penetration of 12.56 percent (9,396/74,820*100 MW) to the total power forecasted.

This model can be used to investigate the effects of large penetrations of offshore wind power into a large electric system using realistic wind power forecast errors and a complete model of unit commitment, economic dispatch, and power flow. Moreover, the clustering of wind farms on large scale can ameliorate the issue of wind variability and predictability. But the costs associated with it might lead to a trade off between conventional and DERs. This lays stress on the need of more integration of DERs in conventional power market. National Renewable Energy Laboratory(NREL) is analyzing offshore wind energy needs and developing computer-aided engineering tools to support distributed and small wind development. At the micro-grid level, wind power can act as a reliable and economic viable source at selected locations which can be investigated further. Different levels od renewable penetration can be studied to analyze the generational and economical aspects of DERs into the power market. The proposed model can also play a significant role in carbon solutions evaluation with focus in renewable integration as renewable integration using DERs offers the larger regional benefit at various levels given energy usage. The model, besides addressing the emissions reductions, can be instrumental in optimizing carbon and climate policies along with the regulatory index. In a gist, technology, policy, infrastructure and supply chain transfers need to go hand in hand to design optimal power framework that are compatible and stable with risk-return environment. Therefore, more efforts are needed to be made to decouple economic growth from carbon emissions.

Conflict of Interest

The authors declare no conflict of interest.

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