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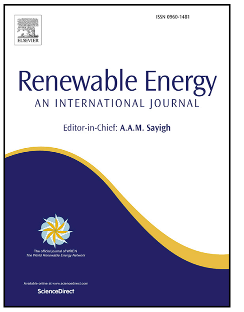

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Optimal Scheduling of Thermal-Wind-Solar Power System with Storage

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Abstract

The incorporation of renewable energy resources (RERs) into electrical grid is very challenging problem due to their intermittent nature. This paper solves an optimal scheduling problem considering the hybrid generation system. The primary components of hybrid power system include conventional thermal generators, wind farms and solar photovoltaic (PV) modules with batteries. The main critical problem in operating the wind farm or solar PV plant is that these RERs cannot be scheduled in the same manner as conventional generators, because they involve climate factors such as wind velocity and solar irradiation. This paper proposes a new strategy for the optimal scheduling problem taking into account the impact of uncertainties in wind, solar PV and load demand forecasts. The simulation results for IEEE 30 and 300 bus test systems with Genetic Algorithm (GA) and Two-Point Estimate Method (2PEM) have been obtained to test the effectiveness of the proposed optimal scheduling strategy. Results for sample systems with GA and two-point estimate based optimal power flow, and GA and Monte Carlo Simulation (MCS) have been obtained to ascertain the effectiveness of proposed method. Some of the results are also compared with the Interior Point method. From the simulation studies, it can be observed that with a marginal increase in the cost of day-ahead generation schedule, a substantial reduction in real time mean adjustment cost is obtained.

Index Terms: Energy Storage, Load Forecast Uncertainty, Optimal Scheduling, Renewable Energy Resources, Solar Energy System, Wind Energy System.

1 Introduction

The integration of stochastic weather-driven power sources has resulted in larger uncertainties that need to be met by dispatchable generation and storage. The concerns brewing up over fossil fueled generating plants and their part of play in global warming has pushed energy based research towards utilization of green energy around the globe. With the greater incorporation of renewable electricity generation like wind and solar photovoltaic (PV) power into the existing grids, research efforts must be devoted to formulate generation scheduling problems taking into account the intrinsic variability and non-dispatchable characteristics of these Renewable Energy Resources (RERs). The random nature and large scale integration of renewable sources into power system poses challenges to the system operators and/or planners. Solar irradiation and wind velocity are uncertain and their availability is irrelevant the load variation. The variability and intermittency of these resources creates important challenges to be overcome in the generation scheduling problem. This intermittent nature may have negative effects on the entire grid. One of the most viable solutions is the integration of energy storage, which mitigates against fluctuations in generation and supply. Energy storage may improve power management in the grid that include renewable energy resources. The storage devices match energy generation to consumption, facilitating a smooth and robust energy balance within the grid. However, this adds another degree of complexity to the generation scheduling.

The developments to the solar PV technology leads to lower manufacturing costs which allows the solar PV power to occupy higher percentage of electric power generation in the near future. In recent years, the grid connected solar PV system with battery storage is becoming more popular because of its impact on the peak load reduction, to reduce the fluctuations of renewable energy sources, congestion mitigation and pricing, and the commitment of expensive thermal units. The energy storage allows to store the surplus solar electricity. During the day (i.e., the solar PV system generates solar electricity), the battery storage system will ensure that surplus energy is used to charge the battery or exported to the grid. In the evening or at time of low solar PV generation, the battery system can discharge the stored electricity.

The operation of power systems has for a long time been informed by Optimal Power Flow (OPF). OPF is used to dispatch available generation in such a way that minimizes a particular objective function. OPF can fully represent the network and nodal power balance equations. It also maintains limits on bus voltage, branch power flows, and generator's active and reactive power outputs [1]-[2]. The deregulation and restructuring of power system industry along with mandates to incorporate Renewable Energy Resources (RERs) is introducing new challenges for the power system. RERs, in particular, need mitigation strategies in order to maintain reliable power on the electrical grid. The operational challenges associated with the integration of RERs can be alleviated by effectively utilizing the grid-integrated distributed energy storage [3]. The potential benefits of grid-integrated storage technologies include decreasing the need for new transmission and/or generation capacity, improving load following, providing spinning reserve, correcting frequency, voltage, and power factors, as well as the indirect environmental advantages gained through facilitating an increased penetration of RERs [3].

This paper solves an optimal scheduling problem in a hybrid power system. The primary components of the hybrid system comprises the conventional thermal generators, wind farms and solar PV plants. A set of batteries is available for the energy storage and/or discharge. The important problem in operating a wind farm or solar PV plant is that RERs cannot be scheduled in the same manner as conventional generators, because they involve climate factors eg. wind velocity and solar irradiation. The wind velocity and solar irradiation are uncertain and their availability is irrelevant to the load demand variation. The variability and intermittency of the resources are important challenges to be overcome in the generation dispatching/scheduling. Wind and solar PV power generations have very high uncertainty and variability.

Solar power is growing at a very rapid clip. Total global solar PV capacity is fast approaching the 100GW milestone, according to a new report from the International Energy Agency [4]. The report notes that even with some uncertainty present about the future state of PVs in the European and Chinese markets, that global installed capacity will almost definitely hit the 100GW milestone within the year. PV technologies instantaneously convert the irradiance into electricity, this change in irradiance causes immediate changes in power generation. For wind power technology, it is right way to classify as variable output power source instead of variable/intermittent source, because the power output does not stop and start on the basis of minute-to-minute time scale. For solar PV plants, the term variable fits well, because cloud shadowing can abruptly change the power production. On the second to minute time scale, conflicting to wind power, solar PV power can have a strong effect on the reserves. Even a clear day, without the effect of cloud shadows, for sunrise and sunset, the solar based electric power varies 80% in 1 hour, instantaneously, for all solar PV power generation in the system.

An optimal scheduling approach for the wind-solar-storage generation system considering the correlation among wind power output, solar PV power output and load demand is proposed in [5]. The optimal control/management of Microgrid's energy storage devices is addressed in [6]. The traditional OPF problem without storage is a static optimization problem as there is a need to balance generation and demand at all the times decouples the optimization in different time periods. The inclusion of storage introduces correlation and an opportunity to optimize, across the time, e.g., the cost of generation is inversely proportional to discharge [7]. In [8], an AC-OPF simulation results are used to study the effects of large-scale energy storage systems on the power system. The economic effects are also analyzed under several different operating conditions, and CO_2 emission reductions offered by the use of storage are considered.

A stochastic model of wind generation in OPF problem is addressed in [9]. The model includes error in wind power generation forecasts using probability or relative frequency histogram. A robust DC-OPF for a smart grid with high penetration of wind generation is proposed in [10]. Here, the optimal dispatch is obtained as the solution to a convex program with a suitable regularizer, which is able to mitigate the potentially high risk of inadequate wind power. In [11], a risk mitigating OPF framework to study the placement and dispatch of energy storage units in power system with wind power generators that are supplemented by conventional fast-ramping back-up generators is proposed. In [12], a probabilistic model of Security Constrained Unit Commitment (SCUC) is proposed to minimize the cost of energy, spinning reserve and possible loss of load. Reference [13] proposes a solution strategy that uses a convex optimization based relaxation to solve the optimal control problem. Reference [14] proposes the problem of coordinating wind-thermal power system using OPF model. The uncertainty caused by wind power generation has two-fold effect as wind power spillage and deficit that both of them are stated in terms of cost. These costs are considered as extra costs to manage wind intermittency.

A two-stage stochastic version of classical economic dispatch problem with AC power flow constraints, a non-convex optimization formulation that is central to power transmission and distribution over an electricity grid is proposed in [15]. Reference [16] introduces the Chance Constrained Programming (CCP) approach to OPF under uncertainty and analyze the computational complexity of the chance constrained OPF. The effectiveness of implementing a back-mapping approach and a linear approximation of the non-linear model equations to solve the formulated CCP problem is investigated in this paper. Reference [17] proposes a problem formulation which minimizes the average cost of generation over the random power injections, while specifying a mechanism by which generators compensate in real-time for renewable power fluctuations; at the same time guaranteeing low probability that any line will exceed its rating. Reference [18] builds the lowest-cost optimization model, considering the investment, operating costs of system and environmental governance as well as two operation modes, isolated and grid-connected operation, and proposes the scheduling strategy of the hybrid generation, with the aim to realize the best configuration of output power of the RERs.

A comprehensive review of various aspects of hybrid renewable energy system including the pre-feasibility analysis, optimum sizing, modeling, control aspects and reliability issues is presented in [19]. A short-term optimal operation scheduling of a power generation company with integrated wind and storage is presented in [20]. An optimal day-ahead scheduling approach for the integrated urban energy system is introduced in [21], which considers the reconfigurable capability of an electric distribution network. Reference [22] proposes a novel interval optimization based day-ahead scheduling model considering renewable energy generation uncertainties for the distribution management systems. A new risk-constrained two-stage stochastic programming model to make optimal decisions on energy storage and thermal units in a transmission constrained hybrid wind-thermal power system to control the risk of the operator decisions is presented in [23]. Reference [24] proposes a model to minimise the hybrid system's operation cost while finding the optimal power flow considering the intermittent solar and wind resources, the battery state of charge and the fluctuating load demand. Reference [25] proposes the optimal scheduling strategy taking into account the impact of uncertainties in wind, solar PV, and load forecasts, and provides the best-fit day-ahead schedule by minimizing both day-ahead and real-time adjustment costs including the revenue from renewable energy certificates.

From the above literature review, it can be observed that there is no optimal scheduling approach, which will handle the uncertainties in wind, solar PV and load demand including battery storage mechanism. In view of the uncertainties involved in wind power, solar PV power generation and load demand forecast, day-ahead (DA) scheduling strategies need to adapt to these requirements approximately. In this regard, some attempts have been made in the literature, but a methodology which can clearly reflect the cost implications of the differences in the DA schedule, and the real-time (RT) dispatch is required. This paper is aimed at bridging this gap. In the proposed optimal scheduling strategy, the uncertainties in wind, solar PV power generation and/or load demands are handled by the power system operator (SO) using the anticipated real time (RT) adjustment bids. Since, the market clearing is a multi-settlement process: day-ahead and real time, a strategy is proposed that provides the 'best-fit' day-ahead schedule, which minimizes the twin (both day-ahead and real time adjustment) costs, under all possible scenarios in real time. This two stage optimization strategy consists of a genetic algorithm (GA) based day-ahead optimum scheduling and a two-point estimate based probabilistic real time optimal power flow (RT-OPF). The former generates sample schedules with respect to which, the latter provides mean adjustment costs. Our proposed model characterizes the structure of optimal power generation and charge/discharge schedule.

The remainder of the paper is organized as follows: Section 2 presents the problem formulation and the proposed solution methodology for optimal scheduling with Renewable Energy Resources (RERs) including storage. Section 3 presents the uncertainty modeling of wind energy system. Section 4 describes the solar energy system, and the uncertainty modeling of solar energy system and load demand. Section 5 presents the simulation results and discussion. Finally, the contributions with concluding remarks are presented in Section 6.

2 Optimal Scheduling with RERs and Storage: Problem Formulation

In this paper, an optimal scheduling problem is formulated and solved considering the thermal-wind-solar hybrid generation system. The primary components considered for the hybrid power system are conventional thermal generators, wind farms and solar PV modules with batteries. The problem proposed in this paper is suitable for the large grid. The optimal scheduling with RERs and storage is very important for the optimal operation and planning of power systems to address the variability and uncertainty associated with increasing renewable power generation. The output of solar PV array/wind turbine is predicted according to the weather forecast. As the input energy of wind power generation (wind) and solar power generation (sun) is uncertain, the output of these resources is also uncertain. Normally, the probability distribution function is used to model the related uncertainty.

In this paper, it is considered that wind and solar PV power generations can be scheduled/dispatched, and can bid in the electricity market. However, the system operator should consider appropriate amount of spinning reserves in the operational plan. The required amount of spinning/non-spinning reserves can be calculated using Probability Density Function (PDF) of wind and solar PV power generation [26]-[28]. This paper presents the optimal scheduling strategy of wind and solar PV power generators in the OPF module. In this paper, an optimal scheduling strategy for the integrated operation of thermal, wind power and solar PV modules in the centralized power market is proposed. The objective function is formulated as,

Minimize,

$$\sum_{i=1}^{N_G} C_{Gi}(P_{Gi}) + \sum_{j=1}^{N_W} C_{Wj}(P_{Wj}) + \sum_{k=1}^{N_S} C_{Sk}(P_{Sk}) + \sum_{i=1}^{N_G} C_{RTi}(\widetilde{P_{Dev,i}}) \tag{1}$$

where N_G, N_W and N_S are the number of thermal, wind and solar PV generators, respectively. The terms in the objective function (i.e., Eq. (1)) are described next:

The first term in Eq. (1) is the fuel cost of conventional thermal generators, and it is expressed as,

$$C_{Gi}(P_{Gi}) = a_i + b_i P_{Gi} + c_i P_{Gi}^2 \tag{2}$$

where P_{Gi} is the scheduled power output from i^{th} conventional thermal generator in MWs, $C_{Gi}(P_{Gi})$ is the fuel cost function of conventional thermal generators, and a_i, b_i, and c_i are the fuel cost coefficients of i^{th} conventional thermal generating unit.

In the objective function (i.e., Eq. (1)), the second term is the direct cost given to wind plant owner for the scheduled wind power. In the case where the wind/solar PV plants are owned by the system operator, the cost function may not exist as the wind/solar PV power requires no fuel, unless the system operator wants to assign some payback cost to the initial outlay for the wind/solar PV plants or unless the system operator wants to assign this as a maintenance and renewal cost [29]. But, in a non-utility owned wind/solar PV plants, the wind/solar PV generation will have a cost that must be based on the special contractual agreements. The output of the wind/solar PV generator is constrained by an upper and lower limit, decided by the system operator based on the agreements for the optimal operation of the system [30]. For simplicity, this can be considered to be proportional to the scheduled wind/solar PV power or totally neglected [9], [31]. Therefore, the cost is neglected in the system-operator-owned wind/solar PV plants, and considered to be proportional to the scheduled wind/solar PV power for the non-utility-owned wind/solar PV plants. In this paper, a linear cost function is used for the scheduled wind power [32]-[33], and it is expressed as,

$$C_{Wj}(P_{Wj}) = d_j P_{Wj} \tag{3}$$

where P_{Wj} is the scheduled wind power generation from j^{th} wind farm in MWs, $C_{Wj}(P_{Wj})$ is the cost function of wind energy generator, and d_j is the direct cost coefficient of j^{th} wind farm/generator.

The third term is the direct cost for the scheduled solar PV power. As explained earlier, a linear cost function is used for the scheduled solar PV power, and it is expressed as [34],

$$C_{Sk}(P_{Sk}) = t_k P_{Sk} \tag{4}$$

where P_{Sk} is the power output from k^{th} solar PV plant (MW), and t_k is the direct cost coefficient of k^{th} solar PV plant.

The fourth term in Eq. (1) is the mean adjustment cost (MAC), which accounts the cost due to uncertain nature of wind, solar PV power and load demand. In real time (RT), thermal generators deviate from their day-ahead (DA) schedules due to uncertain nature of wind velocity, solar irradiation and load demand forecast. This deviation power is the difference between day-ahead scheduled power (P_{Gi}^{DA}), and uncertain real time power ($\widetilde{P_{Gi}^{RT}}$). A quadratic real time adjustment cost function is used to calculate the mean adjustment cost (MAC), and is given by

$$\begin{aligned} C_{RTi}(\widetilde{P_{Dev,i}}) &= C_{RTi}(|P_{Gi}^{DA} - \widetilde{P_{Gi}^{RT}}|) \\ &= x_i + y_i\widetilde{P_{Dev,i}} + z_i\widetilde{P_{Dev,i}}^2 \end{aligned} \tag{5}$$

where $P_{Dev,i}$ is the deviation power from i^{th} conventional thermal generator. x_i, y_i and z_i are the cost coefficients of i^{th} conventional thermal generator in real-time.

2.1 Equality and Inequality Constraints

The equality and inequality constraints for the above problem are presented next:

2.1.1 Nodal Power Balance Constraints

The power balance constraints include active and reactive power balances. The power flow equations reflect the physics of the power system as well as the desired voltage set points throughout the system. The physics of the power system are enforced through the power flow equations which require the net injection of active and reactive power at each bus sum to zero. The sum of power generated by conventional thermal generators, wind farms and solar PV modules is equal to the sum of the total demand and losses in the system.

$$P_i = V_i \sum_{j=1}^{n} [V_j[G_{ij}cos(\delta_i - \delta_j) + B_{ij}sin(\delta_i - \delta_i)]] - P_{Gi} - P_{Di} \tag{6}$$

$$Q_i = V_i \sum_{j=1}^{n} [V_j[G_{ij}sin(\delta_i - \delta_j) - B_{ij}cos(\delta_i - \delta_i)]] - Q_{Gi} - Q_{Di} \tag{7}$$

where

$$P_{Gi} = \sum_{j=1}^{N_G} P_{Gj} + \sum_{k=1}^{N_W} P_{Wk} + \sum_{l=1}^{N_S} P_{Sl} \quad (8)$$

P_{Di} and Q_{Di} are the load active and reactive power, respectively. $Y_{ij} = G_{ij} + jB_{ij}$ is the ij^{th} entry of the nodal admittance matrix. G_{ij} and B_{ij} are the transfer conductance and susceptance between bus i and bus j, respectively.

2.1.2 Generator Constraints

The power output of each thermal generator is restricted by their minimum, maximum limits and generator rate constraints (GRC).

$$max[P_{Gi}^{min}, P_{Gi}^{0} - R_{Gi}^{down}] \leq P_{Gi} \leq min[P_{Gi}^{max}, P_{Gi}^{0} + R_{Gi}^{up}] \quad (9)$$

The power output of each wind generator is restricted by,

$$0 \leq P_{wj} \leq P_{rj} \qquad j = 1, 2, ..., N_W \quad (10)$$

where P_{rj} is submitted as part of the wind producer energy offer. In DA scheduling, the wind power (P_{wj}) varies in the following range

$$0 \leq P_{wj} \leq P_{wf,j} \qquad j = 1, 2, ..., N_W \quad (11)$$

where $P_{wf,j}$ is the forecasted wind power from j^{th} wind generator, which is obtained from the forecasted wind speed.

The maximum penetration of solar PV to system is given by,

$$|P_{Sk}| \leq P_{Sk}^{max} \qquad k = 1, 2, ..., N_S \quad (12)$$

where P_S (MW) is the solar PV active power generation (unknown), and P_S^{max} (MW) is the available maximum active power generation (known) subject to solar irradiation and temperature. P_S can be positive or negative. A positive P_S indicates that power flow from the PV plant to the utility/grid. A negative P_S indicates that power flow from the grid to the solar energy system, this is due to the charging of the batteries during the off-peak period.

Generator voltage magnitudes (V_G), generator reactive power (Q_G) are restricted by their lower and upper limits [35]-[38], and they are represented by

$$V_{Gi}^{min} \leq V_{Gi} \leq V_{Gi}^{max} \qquad i\epsilon(N_G + N_W + N_S) \quad (13)$$

$$Q_{Gi}^{min} \leq Q_{Gi} \leq Q_{Gi}^{max} \qquad i\epsilon(N_G + N_W + N_S) \quad (14)$$

2.1.3 Security Constraints

These constraints include the limits on load bus voltage magnitudes (V_{Di}), line flow limits (S_{ij}) and transformer tap (TT_t) constraints [39].

$$V_{Di}^{min} \leq V_{Di} \leq V_{Di}^{max} \qquad i = 1, 2, ..., N_l \tag{15}$$

$$|S_{ij}| \leq S_{ij}^{max} \tag{16}$$

$$TT_t^{min} \leq TT_t \leq TT_t^{max} \qquad t = 1, 2, ..., N_T \tag{17}$$

where N_l is the number of load demands, S_{ij} is MVA (mega-volt ampere) flow and S_{ij}^{max} is the maximum thermal limit of line between bus i and bus j. TT_t is transformer tap settings and N_T is number of transformer taps.

2.2 Proposed Solution Methodology

For a specified day-ahead (DA) schedule, one can not know what exactly the actual real time (RT) conditions would be. In order to accommodate these changes, a real time optimal power flow (RT-OPF) problem is solved by using adjustment bids supplied by the market participants. However, while optimizing the DA schedule, one does not know, what will be the RT condition. Hence, a probabilistic OPF (P-OPF) with the uncertainty data given, appears to be a good option. The difference in the DA and RT schedules can be used to evaluate the mean adjustment cost (MAC). The proposed solution approach/procedure is shown in Figure 1. This figure depicts the two stage optimal scheduling strategy including day-ahead optimal power flow (DA-OPF) and probabilistic RT-OPF. The MAC is calculated using probabilistic RT-OPF. This probabilistic RT-OPF is solved inside the DA-OPF module. The inputs to the proposed optimal scheduling module are the system/network data and forecasts data of wind power, solar PV power and load demand. From Figure 1, it can be observed that the day-ahead schedules can be observed from Genetic Algorithm (GA) and the real time (RT) schedules can be determined by using Two-point estimate based RT-OPF. By using these DA and RT schedules, the MAC can be calculated. Then the objective function is formulated using the generation costs of thermal generators, wind farms, solar PV plants and the MAC. In order to determine the optimal decision variables, to optimize an objective function and to satisfy the constraints, the variables are to be represented in the binary strings. The description about representation and encoding of chromosome (i.e., overview of GA) is presented in [40]. The fitness function evaluation is presented in [41].

Corresponding to a given DA generation schedule, the MAC is evaluated over the uncertainty range of wind, solar PV and load demand forecast using P-OPF. Therefore, obtaining the analytical expression of this cost, in terms of the DA schedule variables, is difficult. Because of this, it is difficult to use the gradient based optimization techniques to solve this problem.

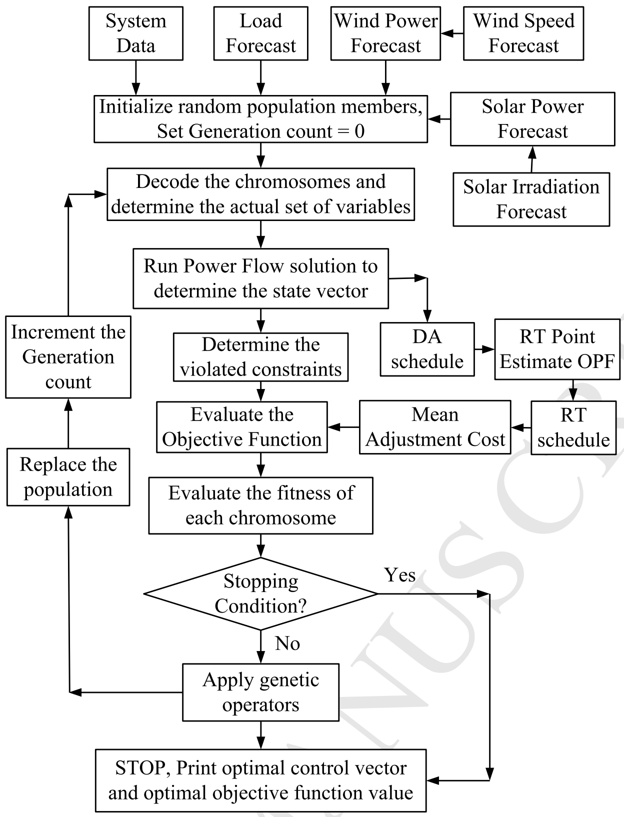

Figure 1: Flow Chart of Solution Procedure for Optimal Scheduling with RERs and Storage.

Hence, in this paper, we used evolutionary/meta-heuristic optimization techniques to get the DA schedules.

Here, genetic algorithm (GA) is used to solve this optimal scheduling with RERs and storage problem. In the first stage i.e., in outer loop, GA is used to get the DA schedules. RT schedules are obtained by using the probabilistic Two Point Estimate Method (2PEM), which is solved in the inner loop. Using the DA schedules and RT schedules, the deviation power ($P_{Dev,i}$) is calculated. $P_{Dev,i}$ is the difference between DA scheduled power and uncertain RT power. The MAC is calculated by considering the real time adjustment bids. After calculating the MAC, the objective function is formulated and is optimized using GA [40]. The RT schedules are obtained using P-OPF to account for the uncertainties involved due to wind, solar PV power generations and load demand forecasts. Since, OPF basically being a deterministic tool, it has to run several times to encompass all possible operating conditions. More accurate Monte Carlo Simulation (MCS) methods, which will handle complex random variables, provide an alternative, but MCS is computationally more demanding. Therefore, here an efficient 2PEM based P-OPF is used.

In order to account for the uncertainties in proposed optimal scheduling problem, a two-point estimate method (2PEM) [42] is used. Both MCS and 2PEM use deterministic routines for solving the probabilistic problems; but, the latter requires a much lesser computational burden. The 2PEM overcomes difficulties associated with the lack of perfect knowledge of the probability functions of stochastic variables, since these functions are approximated using only their first few statistical moments (i.e., mean, variance, skewness, and kurtosis). Therefore, a smaller level of data is required [43]. This method needs $2m$ runs of deterministic OPF for m uncertain variables, and it does not require derivatives of the non-linear function used in the computation of probability distributions. The description of 2PEM is presented in Appendix A.

2.3 Real Time Optimal Power Flow (RT-OPF) Model

Probabilistic RT-OPF is used to calculate the mean adjustment cost (MAC), and the two-point estimate OPF is used to solve this RT-OPF problem. This two-point estimate method (2PEM) uses deterministic OPF. The deterministic and probabilistic RT-OPF models are formulated next:

2.3.1 Deterministic RT-OPF Model

In this model, the objective is to minimize the deterministic mean adjustment cost (MAC), and is formulated as,

$$minimize \quad \sum_{i=1}^{N_G} C_{RTi}(P_{Dev,i}) = \sum_{i=1}^{N_G} C_{RTi}(|P_{Gi}^{DA} - P_{Gi}^{RT}|) \tag{18}$$

Subjected to equality and inequality constraints presented in Section III-A.

2.3.2 Probabilistic RT-OPF Model

In this model, the objective is to minimize the MAC due to uncertainty in wind generation, solar PV power and load demand forecasts. For probabilistic RT-OPF, the uncertain random variable is P_{Gi}^{RT} due to uncertainties in wind generation, solar PV power and load demand at real time. Hence, Eq. (18) becomes

$$minimize \quad \sum_{i=1}^{N_G} C_{RTi}(\widetilde{P_{Dev,i}}) = \sum_{i=1}^{N_G} C_{RTi}(|P_{Gi}^{DA} - \widetilde{P_{Gi}^{RT}}|) \tag{19}$$

where $\widetilde{P_{Gi}^{RT}}$ is a random variable. Subjected to equality and inequality constraints presented in Section III-A. This problem is solved using two-point estimate OPF [44].

In real time (RT), if the scheduled wind power (P_{Wj}) varies in $\pm x\%$, then

$$P_{max}^{min} = P_{Wf,j} - \left(\frac{x}{100} \times P_{Wf,j}\right) \tag{20}$$

and

$$P_{max}^{max} = P_{Wf,j} + \left(\frac{x}{100} \times P_{Wf,j}\right) \tag{21}$$

Therefore, in real time optimal power flow (RT-OPF),

$$P_{max}^{min} \leq P_{max} \leq P_{max}^{max} \tag{22}$$

$$0 \leq P_{wj} \leq P_{max} \tag{23}$$

and the similar expressions are valid for solar PV power generation also.

In order to account for uncertainties in the day-ahead optimal scheduling, a Two-Point Estimate Method (2PEM) [42] is used. Both Monte Carlo simulation (MCS) and 2PEM use deterministic routines for solving probabilistic problems [43, 44]; however, the latter requires a much lower computational burden.

3 Wind Energy System

In order to incorporate the RERs in the optimal scheduling problem, some characterization of the uncertain nature of wind speed, solar irradiation and load demand are needed. An important barrier to the incorporation of the wind power into the electrical grid is its variability. Various probability distribution functions are proposed for the statistical analysis of recorded wind speeds. Here, Weibull Probability Density Function (PDF) is used for the wind speed and then, transformed to the corresponding wind power distribution for use in proposed optimal scheduling model. The wind power output will follow stochastic nature as compared to the wind speed [45]-[46].

For a given wind speed input, the wind power output [9], [31] is expressed as,

$$p = \begin{cases} 0 & \text{for } v < v_i \text{ and } v > v_0 \\ p_r \left(\frac{v - v_i}{v_r - v_i} \right) & \text{for } v_i \leq v \leq v_r \\ p_r & \text{for } v_r \leq v \leq v_0 \end{cases} \tag{24}$$

where p is power output of wind energy generator in MWs, v is the wind speed (in m/sec), and v_i, v_o, v_r are the cut-in, cut-out and rated wind speeds, respectively.

3.1 Uncertainty Modeling of Wind Energy System

The wind speed is modeled by using Weibull Probability Density Function (PDF), and is expressed as [31],

$$f(v) = \left(\frac{k}{c}\right)\left(\frac{v}{c}\right)^{k-1} exp\left[-\left(\frac{v}{c}\right)^{k}\right] \qquad 0 < v < \infty \tag{25}$$

For the Weibull PDF (i.e., Eq. (25)), the corresponding Cumulative Distribution Function (CDF) is expressed as [47],

$$F_V(v) = 1 - exp\left[-\left(\frac{v}{c}\right)^{k}\right] \tag{26}$$

If it is assumed that the wind speed has a given distribution, such as the Weibull, it is then necessary to convert that distribution to a wind power distribution. This transformation may be accomplished in the following manner, with V as the wind speed random variable and P as the wind power random variable. For a linear transformation, in general [31], such as that described in Eq. (24)

$$P = T(V) = aV + b \tag{27}$$

and

$$f_P(p) = f_V[T^{-1}(p)]\left[\frac{dT^{-1}(p)}{dp}\right] = f_V\left(\frac{p-b}{a}\right)\left|\frac{1}{a}\right| \tag{28}$$

The wind generation output in the continuous range ($v_i \leq v \leq v_r$) is given by [31], [47],

$$p = p_r\left(\frac{v - v_i}{v_r - v_i}\right) = \left(\frac{p_r}{v_r - v_i}\right)v - \left(\frac{v_i}{v_r - v_i}\right) \tag{29}$$

where $a = \frac{p_r}{(v_r - v_i)}$ and $b = -\frac{v_i}{(v_r - v_i)}$.

According to the theory for function of random variables, Eq. (28) will take the form,

$$f_P(p) = \frac{khv_i}{p_r c}\left[\frac{1 + \frac{hp}{p_r}v_i}{c}\right]^{(k-1)} \times exp\left[-\left(\frac{1 + \frac{hp}{p_r}v_i}{c}\right)^k\right] \tag{30}$$

where $h = \left(\frac{v_r}{v_i}\right) - 1$ is an intermediary parameter. In this paper, the wind power output in discrete range [31] is also considered. The sum of the probability of discrete and continuous function is 1.

4 Solar Energy System

For the generation scheduling and dispatch, electric power utilities are interested in the availability of solar PV power on an hourly basis. The hourly meteorological data are required to simulate the performance of solar energy. The actual size of the battery depends on amount of peak shaving desired.

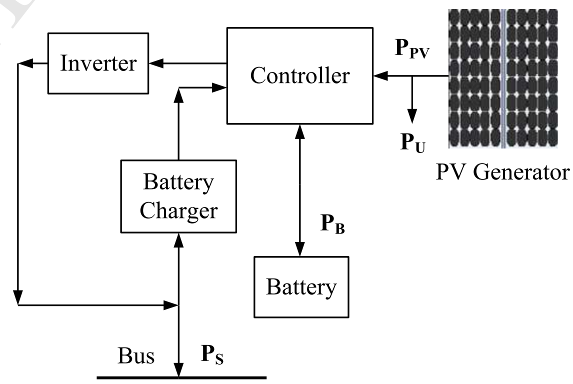

Figure 2: Solar Energy System Connected to Solar PV System With Battery Storage.

In the presence of battery storage, the power output of solar PV cell (P_{PV}) and the power output of solar energy system (P_S) are different. The power balance in solar energy system is represented as [48],

$$P_S = P_{PV}(G) + P_B - P_U \tag{31}$$

In this paper, we assume that there is no spillage power (P_U(MW)) from PV. We also ignore the effect of spillage power of the aggregated battery. The solar PV power output can be controlled by the power tracking control scheme or to be charged into the batteries. Hence, the maximum penetration of solar PV to system is given by [48]-[49],

$$|P_S| \leq P_S^{max} \tag{32}$$

In this paper, it is assumed that the battery voltage keeps constant during the scheduling period (i.e., 1 hour). The maximum charge and discharge capacity of battery is represented by Eq. (33). However, this limit depends on the rating of the battery. P_B is the power charge/discharge to/from battery (MW). P_B is positive for discharging and negative for charging.

$$\underline{P_B} \leq P_B \leq \overline{P_B} \tag{33}$$

where $\overline{P_B}$ is the aggregated discharging power limit (positive) for all batteries (MW), and $\underline{P_B}$ is the aggregated charging power limit (negative) of all batteries (MW). In this paper, we ignore the effect of spillage power of the aggregated battery.

If C_{init} and C are aggregated battery state of charge of all batteries (kAh) at the beginning and the end of the scheduling period (say 1 hour). The contribution of solar PV module to the grid during interval 'Δt' (1 hour) is [48],

$$P_S = P_{PV}(G) + \frac{(C_{init} - C)V_B}{\eta_B \Delta t} - P_U \tag{34}$$

where V_B is battery voltage, η_B is the efficiency during the charging period (75%), and $P_{PV}(\cdot)$ is the solar irradiation to energy conversion function of the solar PV generator or power output from solar PV cell [48], and is given by

$$P_{PV}(G) = \begin{cases} P_{sr}\left(\frac{G^2}{G_{std}R_c}\right) & \text{for } 0 < G < R_c \\ P_{sr}\left(\frac{G}{G_{std}}\right) & \text{for } G > R_c \end{cases} \tag{35}$$

In this paper, it is assumed that the solar PV cell temperature is ignored. Where,

G : Solar irradiation forecast in W/m^2.

G_{std} : In the standard environment, the solar irradiation is set as 1000 W/m^2.

R_c : A certain irradiation point set as 150 W/m^2.

P_{sr} : Rated equivalent power output of the solar PV generator.

P_B : Power charge/discharge to/from the battery.

4.1 Uncertainty Modeling of Solar PV System

The power output of solar PV generator is mainly depends on irradiance. The distribution of hourly irradiance at a particular location usually follows a bi-modal distribution, which can be considered as a linear combination of two uni-modal distributions. The uni-modal distribution functions can be modeled by Weibull, Beta and Log-normal PDFs. In this paper, the Weibull probability distribution function is used and it is expressed as,

$$f_G(G) = \omega \left(\frac{k_1}{c_1}\right) \left(\frac{G}{c_1}\right)^{k_1-1} exp\left[-\left(\frac{G}{c_1}\right)^{k_1}\right]$$
$$+(1-\omega) \left(\frac{k_2}{c_2}\right) \left(\frac{G}{c_2}\right)^{k_2-1} exp\left[-\left(\frac{G}{c_2}\right)^{k_2}\right] \quad 0 < G < \infty \tag{36}$$

where ω is weight parameter in the range between 0 and 1 ($0 < \omega < 1$). k_1, k_2 and c_1, c_2 are the shape and scale factors, respectively.

4.2 Normal Distribution for Load Demand Uncertainty

The future system load demand is uncertain at any given period of time. Normally used two probability density functions (PDFs) for modeling load demand uncertainty are Normal and Uniform PDFs. In this paper, Normal PDF is used to model the load distribution. The PDF of normal distribution for uncertain load 'l' is given by [50],

$$f_l(l) = \frac{1}{\sigma_L\sqrt{2\Pi}} \times exp\left[-\left(\frac{(l-\mu_L)^2}{2\sigma_L^2}\right)\right] \tag{37}$$

where μ_L and σ_L are the mean and standard deviation of the uncertain load, respectively.

5 Simulation Results and Discussion

IEEE 30 and 300 bus test systems [51] are used to establish the effectiveness of the proposed optimal scheduling approach considering the Renewable Energy Resources (RERs) and storage.

5.1 Results for IEEE 30 Bus System

The original IEEE 30 bus test system is modified to include the RERs. The modified IEEE 30 bus system consists of 6 generators, among them 4 are considered as conventional thermal generators located at the buses 1, 2, 5 and 8; and 2 are considered to be RERs, located at the buses 11 and 13. A wind energy system is assumed at bus 11, and a solar energy system is assumed at bus 13. The cost coefficients and generator power limits data of thermal, wind and solar PV generators have been presented in Appendix B.

In IEEE 30 bus system, the maximum power limit of wind energy generator is considered as 45MW. Here, we have assumed the forecasted wind velocity as 10m/sec. For a given wind speed forecast, the wind power output is determined using Eq. (24). Therefore, the wind power output is 35MW i.e., from the system optimization point of view, the scheduled wind power generation can go any where from 0 to 35MW, provided if there is no uncertainty in the wind generation. Suppose, if we consider the uncertainty in wind power generation, then the maximum power generation limits are differed by uncertainty margin (using Eq. (22)). For the Two Point Estimate Method (2PEM), the samples are generated between P_{max}^{min} and P_{max}^{max}, which will follow Weibull PDF. Weibull PDF is assumed to represent the wind speed, and then it is transformed to the corresponding wind power distribution, which can be used in the proposed optimal scheduling problem.

The maximum power generation limit of solar PV system is considered as 40MW. Here, we have assumed the forecasted irradiation as 500 W/m^2. For a given solar irradiation forecast, the solar PV power output is calculated using Eq. (35). Therefore, the solar PV power output (i.e., $P_{PV}(G)$) is 20MW. Bi-modal distribution function is used to represent the uncertainty in solar PV power generation. The minimum and maximum limits of State of Charge (SOC) of the battery are considered as 5kAh and 15kAh, respectively. The initial SOC is assumed to be 10kAh. The efficiency of the battery and inverter are 75% and 95%, respectively. The uncertainty levels of wind, solar PV power and load demand forecasts depends on the historical data and their probability analysis (i.e., mean, standard deviation, etc). In this paper, we have considered ±20% and ±30% uncertainty for wind and solar PV plants; and ±5% uncertainty for load demands based on the historical wind speed, solar irradiation and load demand data given in [52].

In recent years, MATLAB software has been used successfully for solving the power system optimization problems [53]-[58]. In this paper, all the optimization programs are coded in MATLAB and are implemented on a PC-Core 2 Quad Computer with 8GB of RAM. The simulation results for different case studies on IEEE 30 bus system are presented next:

5.1.1 Study 1: Optimizing total cost minimization objective function with no uncertainties in wind, solar PV power generations, and load demand forecasts

Generally, the cost of wind and solar PV power generations are lesser than the conventional thermal generation costs. Therefore, they tends to schedule to their maximum forecasted power output. However, for security reasons the OPF program can curtail their power output. This case does not consider any uncertainties in wind, solar PV power generations and demand forecasts. In this case, the total cost minimization objective function consists only first 3 terms of Equation (1), i.e., costs due to conventional thermal generators, wind farms and solar PV plants. The scheduled power outputs of wind farm and solar PV plant located at buses 11 and 13 are 34.6752MW and 20.9207MW, respectively. Figure 3 depicts the optimum generation schedules for Studies 1, 2, 3 and 4. The power generated from the solar PV system (i.e., 20.9207MW) is the sum of power generated from solar PV generator (i.e., 17.9468MW) and the aggregated battery (i.e., 2.9739MW). Here, the optimum generation cost obtained is 1961.5150$\$/hr$, and the convergence time required is 30.1652sec.

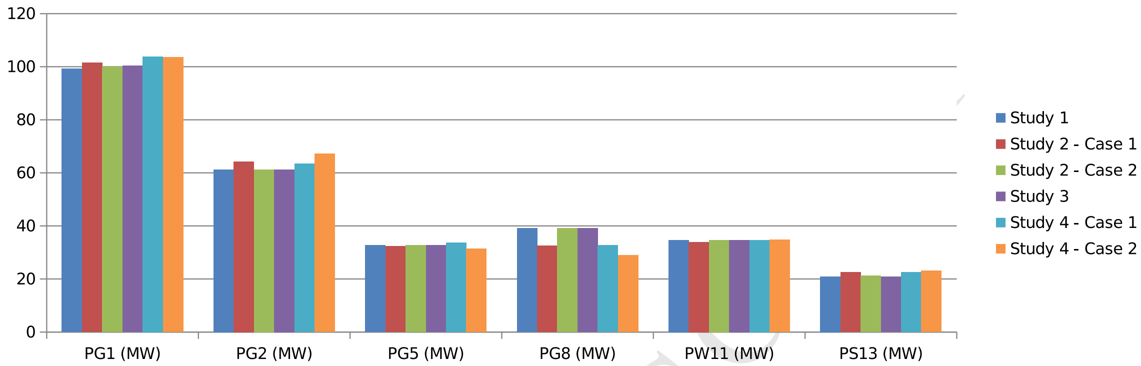

Figure 3: Optimum Generation Schedules for Studies 1, 2, 3 and 4.

5.1.2 Study 2: Optimizing total cost minimization objective function considering uncertainties in wind and solar PV power generations

In this case, the objective function include all the four terms of objective function (Eq. (1)), i.e., cost of thermal generators, direct cost of wind energy generators, solar PV generators and mean adjustment cost (MAC) due uncertainty in wind and solar PV power generation. Based on the level of uncertainty in wind and solar PV generations, this Study 2 has two cases. In Study 2 - Case 1, ±20% uncertainty in wind and solar PV power generations is considered, whereas in Study 2 - Case 2, ±30% uncertainty in wind and solar PV power generations is considered.

Table 1: Optimum Objective Function Values for Study 2.

Objective Function Value	**±20% uncertainty in Wind & Solar PV Power (Study 2 - Case 1)**	**±30% uncertainty in Wind & Solar PV Power (Study 2 - Case 2)**
Generation Cost ($\$/hr$)	**1970.6326**	**1971.2660**
Mean adjustment cost ($\$/hr$)	**58.0966**	**90.8192**
Total Cost ($\$/hr$)	**2028.7292**	**2062.0852**
Convergence Time (sec)	**196.0755**	**198.6129**

Table 1 presents the optimum objective function value for the total cost minimization objective with ±20% uncertainty in wind and solar PV power generation (i.e., Study 2 - Case 1). The obtained optimum scheduled power outputs for this study are depicted in Figure 3. For the wind farm located at bus 11, the scheduled wind power is 33.9060MW, and for the solar PV plant located at bus 13, the scheduled solar PV power is 22.4843MW. The scheduled power output from the solar PV module is the sum of power generated from solar PV plant (i.e., 18.2762MW) and the aggregated battery storage (i.e., 4.2081MW). In this Study 2 - Case 1, the optimum total cost obtained is 2028.7292 $\$/hr$, which includes thermal, wind and solar PV generation cost of 1970.6326 $\$/hr$ and mean adjustment cost (MAC) of 58.0966 $\$/hr$. The total cost incurred in this case is higher than cost obtained from the Study 1, due to ±20% uncertainty in wind and solar PV power generation.

The results obtained in this Study 2 - Case 1 are also validated using MCS. The mean adjustment cost obtained from MCS (10000 samples) with ±20% uncertainty in wind and solar PV power generation is 58.0893 $\$/hr$, and hence the total cost is $1970.6326 + 58.0893 = 2028.7219\$/hr$, which is approximately equal to total cost (2028.7292 $\$/hr$) obtained from the proposed approach considering two-point estimate method (2PEM).

Suppose, if we consider the schedules of Study 1 and calculating the MAC with ±20% uncertainty in wind and solar PV power generation then the obtained MAC is 109.1132 $\$/hr$ and generation cost same as Study 1, i.e., 1961.5150 $\$/hr$. Therefore, the total cost is $1961.5150 + 109.1132 = 2070.6282\$/hr$, which is higher than the cost obtained in Study 2 - Case 1, i.e., 2028.7292 $\$/hr$, even though the '*best-fit day-ahead schedule*' has a higher cost compared to that with the conventional generation schedule (i.e., Study 1).

Table 1 also presents the optimum objective function value for total cost minimization objective with ±30% uncertainty in wind and solar PV power generation (i.e., Study 2 - Case 2). For the wind farm located at bus 11, the scheduled wind power is 34.6752MW, and for the solar PV plant located at bus 13 the scheduled solar power is 21.1806MW. As explained earlier, the scheduled power output from the solar PV module is the sum of the power generated from solar PV plant and storage battery. In this case, the optimum total cost incurred is 2062.0852 $\$/hr$, which includes thermal, wind and solar PV generation cost of 1971.2660 $\$/hr$ and MAC of 90.8192 $\$/hr$. This is validated using the MCS. The MAC obtained from MCS (10000 samples) with ±30% uncertainty in wind and solar PV power generation is 90.7814 $\$/hr$, and hence the total cost is $1971.2660 + 90.7814 = 2062.0474\$/hr$, which is approximately equal to total cost (2062.0852 $\$/hr$) obtained from the proposed approach considering two-point estimate method (2PEM). The convergence times required for Study 2, Cases 1 and 2 using proposed approach are 196.0755sec and 198.6129sec, respectively.

Suppose, if we consider the schedules of Study 1 and calculating the MAC with ±30% uncertainty in wind and solar PV generation then the obtained MAC is 159.0319 $\$/hr$ and the generation cost is same as the Study 1, i.e., 1961.5150 $\$/hr$. Therefore, the total cost is

$1961.5150 + 159.0319 = 2120.5469\$/hr$, which is higher than the cost obtained in Study 2 - Case 2, i.e., 2062.0852 $\$/hr$, even though the '*best-fit day-ahead schedule*' has a higher cost compared to that with the conventional generation schedule (Study 1).

5.1.3 Study 3: Optimizing total cost minimization objective considering uncertainty in load demand forecasts

Table 2 presents the optimum objective function value for the total cost minimization objective with $\pm 5\%$ uncertainty in load demand forecasts (Study 3). In this paper, it is considered that wind and solar PV generators are not participating in the real time adjustment, only thermal generators will participate in real time adjustment bidding. In this Study, the amount of power generated from the wind farm is 34.6923MW, and the solar PV energy system is 20.9034MW, which is the sum of power generated from solar PV plant (i.e., 17.9468MW) and power generated from the aggregated battery (i.e., 2.9566MW). Figure 3 presents the optimum scheduled power outputs for Study 3. The convergence time required for Study 3 is 306.1037sec.

The optimum total cost obtained in this case is 2014.8244 $\$/hr$, which includes the conventional thermal, wind and solar PV power generation cost of 1973.0461 $\$/hr$, and the mean adjustment cost (MAC) of 41.7783 $\$/hr$.

Table 2: Optimum Objective Function Value for Study 3.

Generation Cost ($\$/hr$)	**1973.0461**
Mean adjustment cost ($\$/hr$)	**41.7783**
Total Cost ($\$/hr$)	**2014.8244**
Convergence Time (sec)	**306.1037**

5.1.4 Study 4: Optimizing total cost minimization objective considering uncertainties in wind, solar PV power generations, and load demand forecasts

In this Study, the total cost minimization objective function is optimized considering the uncertainties in wind, solar PV powers and load demand forecasts. Table 3 shows the optimum objective function value for the total cost minimization objective considering $\pm 20\%$ uncertainties in wind and solar PV power generations, and $\pm 5\%$ uncertainty in load demand forecast (i.e., Study 4 - Case 1). Figure 3 shows the optimum generation schedules for Study 4. In this Study 4 - Case 1, the amount of power scheduled from the wind farm is 34.6581MW and the scheduled power from the solar PV system is 22.5471MW, which is the sum of solar PV plant (i.e., 18.6659MW) and the aggregated battery (3.8812MW). The generation (i.e., thermal, wind and solar PV) cost incurred in this case is $1996.9450\$/hr$, and the MAC obtained is

102.5603$\$/hr$. Therefore, the total cost (i.e., generation cost and MAC) is 2099.5053$\$/hr$.

Table 3: Optimum Objective Function Values for Study 4.

Objective Function Value	**±20% uncertainty in Wind, Solar Power & ±5% uncertainty in load forecasts (Study 4 -Case 1)**	**±30% uncertainty in Wind, Solar Power & ±5% uncertainty in load forecasts (Study 4 - Case 2)**
Generation Cost ($\$/hr$)	**1996.9450**	**2002.0178**
Mean adjustment cost ($\$/hr$)	**102.5603**	**144.1052**
Total Cost ($\$/hr$)	**2099.5053**	**2146.1230**
Convergence Time (sec)	**419.4672**	**423.6104**

Table 3 also presents the optimum objective function value for the total cost minimization objective function considering ±30% uncertainties in wind and solar PV generations, and ±5% uncertainty in load demand forecasts (Study 4 - Case 2). The total cost incurred in this case is 2146.1230$\$/hr$, which is the sum of generation cost (i.e., 2002.0178$\$/hr$) and the MAC (i.e., 144.1052$\$/hr$). The total cost incurred in this case is higher than all other cases studied due to the higher uncertainty levels in wind speed and solar irradiation forecasts. The convergence times required for Study 4, Cases 1 and 2 using proposed approach are 419.4672sec and 423.6104sec, respectively.

5.2 Performing Simulation Studies on IEEE 30 Bus System Using Interior Point Method for Studies 1 and 2

In this paper, some of the case studies are also performed using Interior Point method (IPM). In Study 1, using the Interior Point Optimal Power Flow (IPOPF), the obtained optimum cost is 1965.3217$/hr which is higher than the cost obtained from the proposed approach (i.e., 1961.5150$/hr). In Study 2 - Case 1, the optimum total cost is 2034.7297$/hr which is the sum of generation cost of 1975.7031$/hr and the MAC of 59.0266$/hr; and this cost is higher than the cost obtained from the proposed approach (i.e., 2028.7292$/hr). But, the convergence time required for Study 2 - Case 1 using IPOPF is 42.9025sec, which is less compared to the proposed approach (i.e., 196.0755sec).

From these results, it can be observed that the total cost obtained from the proposed approach is better than the value obtained from the IPOPF, however the convergence time is

Table 4: Optimum Objective Function Values for Studies 1 and 2 using Interior Point Method.

Objective Function Value	Study 1	Study 2-Case 1	Study 2-Case 2
Generation Cost ($/hr)	**1965.3217**	**1975.7031**	**1976.5112**
Mean adjustment cost ($/$hr$)	——	**59.0266**	**92.2048**
Total Cost ($/hr)	**1965.3217**	**2034.7297**	**2062.0852**
Convergence Time (s)	**5.1366**	**42.9025**	**43.1317**

less for Interior Point method.

5.3 Results for IEEE 300 Bus System

The original IEEE 300 bus system [51] is modified to include the RERs, i.e., wind farms and solar PV plants. The modified IEEE 300 bus system consists of 69 generators, of which 57 are conventional thermal generators, 6 are assumed to be wind farms and remaining 6 are assumed to be solar PV plants. The wind farms are located at buses 8, 55, 80, 104, 128 and 150; whereas solar PV plants are located at buses 199, 222, 256, 267, 294 and 296. The rated capacity of each wind farm and solar PV plant are assumed to be 250MW. The simulation results for different case studies on IEEE 300 bus system are presented next:

5.3.1 Study 1: Optimizing total cost minimization objective with no uncertainties in wind, solar PV power generations, and load demand forecasts

Table 5 presents the objective function value for Study 1. As mentioned earlier, this Study does not consider any uncertainties in wind, solar PV power generation and load demand forecast. In this Study, the total cost minimization objective function consists only first three terms of Eq. (1). The optimum total cost obtained in this Study is 805814.6118$/hr, which is the sum of thermal power generation cost (771324.8599$/hr) and wind and solar PV power generation cost (34489.7519$/hr).

Table 5: Objective Function Value for Study 1 (for IEEE 300 Bus System)

Cost of Thermal Power Generation ($/$hr$)	**771324.8599**
Cost of Wind and Solar Power Generation ($/$hr$)	**34489.7519**
Total Cost ($/$hr$)	**805814.6118**

5.3.2 Study 2: Optimizing total cost minimization objective considering uncertainties in wind and solar PV power generations

Table 6 presents the optimum objective function value for the total cost minimization objective with ±20% uncertainty in wind and solar PV power generation. In this Study, the objective function consists of all the four terms of Eq. (1). As the forecasted wind velocity assumed for the wind generators is 10m/sec, the day-ahead schedules of wind farms are between (0-200)MW. Here, ±20% uncertainty in wind power generation is considered, hence in RT, the maximum schedules of wind generators are uncertain in (160-240)MW range using Eq. (22). As mentioned earlier, the maximum power generation limit of solar PV system is 250MW. In this paper, we assumed that the forecasted solar irradiation is 500 W/m^2. Hence, by using Eq. (35), the obtained solar PV power output is 125MW. The optimum total cost obtained in this study using the proposed optimal scheduling approach is 828150.6154\$/hr, which includes the thermal, wind and solar power generation cost of 806912.0544\$/hr and MAC of 21238.5610\$/hr. The total cost obtained in this Study is higher than the total cost obtained from Study 1, due to ±20% uncertainty in wind and solar PV power generations.

Table 6: Objective Function Value for Study 2 (for IEEE 300 Bus System).

Generation Cost ($\$/hr$)	**806912.0544**
Mean Adjustment Cost ($\$/hr$)	**21238.5610**
Total Cost ($\$/hr$)	**828150.6154**

As discussed earlier, whether we consider the uncertainty in day-ahead schedule or not, the conditions in real time will always be different, requiring a real time adjustment OPF, and the associated adjustment cost. Since, at the day-ahead stage the real time picture is unknown, only a mean adjustment cost (MAC) can be evaluated. Hence, the conventional day-ahead scheduling (considering the schedules from Study 1) has the MAC of 43852.9917 \$/hr. The total cost of two-stage optimal scheduling will then be 805814.6118+43852.9917 = 849667.6035\$/hr. This is greater than the total cost obtained from the proposed optimal scheduling approach 806912.0544 + 21238.5610 = 828150.6154\$/hr. Hence, although the 'best-fit day-ahead schedule' has a slightly higher generation cost compared to that with the conventional schedule, it has much lesser mean adjustment cost compared to that with the latter, giving overall savings.

In all the cases studied, it is observed that the cost of 'best-fit generation schedule' is just marginally higher than that with the conventional one. However, the difference in the mean adjustment cost between 'best-fit' generation schedule and conventional generation schedule is substantial. Therefore, implementing the 'best-fit' generation schedule will in general, be quite economical than the conventional one. From the simulation results it is also clear that as the uncertainties in wind and solar PV power generations and load demand forecasts increases, total cost will increase.

6 Conclusions

In this paper, the problem of optimal scheduling with Renewable Energy Resources and storage by taking the cognizance of uncertainties in wind, solar PV power and load demands during real time, has been tackled. The anticipated real time mean adjustment cost, that accounts for the wind, solar PV power and load demand uncertainties, is introduced to accomplish this. This mean adjustment cost is calculated considering the day-ahead schedule and various probabilistic real time operating scenarios. Since, the actual power requirement in real-time can not be known a priori, while optimizing the day-ahead schedule, only the mean adjustment cost over the uncertainty range can be obtained. The proposed scheduling methodology clearly reflects the cost implications of the differences in the day-ahead schedule and the real-time dispatch. The effectiveness of the proposed optimum scheduling approach is validated on modified IEEE 30 and 300 bus test systems. Validation of results for a few cases has also been done using Monte Carlo Simulation and Interior Point Method. Simulation results in all test cases indicate that with just a marginal increase in the cost of day-ahead generation schedule, a substantial reduction in real time mean adjustment cost is obtained. Determining the day-ahead generation schedules taking into account the unit-commitment and ancillary services is a scope for future work.

Appendix A

Uncertainty Handling using Two Point Estimate Method (2PEM) [42]-[44], [59]

This paper uses the 2PEM to model the uncertainty in power output from wind/solar power generating units and load demands. The Weibull and normal PDFs are used to model the variations of input random variables. In this method, for every uncertain variable, two deterministic values are computed, on each side of the mean. The deterministic OPF is then run for each of these values, while keeping all other uncertain variables, at their mean values.

The optimum scheduling/OPF can be seen as a multivariate non-linear function h of the form,

$$Y = h(X) \tag{38}$$

where the random input vector X can be written as,

$$X = [P_w \qquad P_S \qquad P_D] \tag{39}$$

and the output Y is adjustment cost of uncertain real time schedule with respect to a given day-ahead schedule.

It needs to be emphasized that although two-point estimate OPF procedure is general enough, we are using it for only evaluation of the mean adjustment cost (MAC). The goal is to find the PDF $f_Y(y)$ of Y, when the PDF $f_X(x)$ is known, where $x \epsilon X$ and $y \epsilon Y$. The MAC is evaluated using the following two-point estimate [44] procedure:

Step 1: Determine the number of uncertain variables m (m is total number of wind, solar PV generators and uncertain loads).

Step 2: Set $E(Y) = 0$ and $E(Y^2) = 0$.

Step 3: Set $t = 1$.

Step 4: Determine the locations of concentrations $\xi_{t,1}$, $\xi_{t,2}$ and the probabilities of concentrations $P_{t,1}$ and $P_{t,2}$.

$$\xi_{t,1} = \sqrt{m} \tag{40}$$

$$\xi_{t,2} = -\sqrt{m} \tag{41}$$

$$P_{t,1} = P_{t,2} = \frac{1}{2m} \tag{42}$$

Step 5: Determine the two concentrations $x_{t,1}$ and $x_{t,2}$

$$x_{t,1} = \mu_{X,t} + \xi_{t,1}\sigma_{X,t} \tag{43}$$

$$x_{t,2} = \mu_{X,t} + \xi_{t,2}\sigma_{X,t} \tag{44}$$

where $\mu_{X,t}$ and $\sigma_{X,t}$ are mean and standard deviation of X_t respectively.

Step 6: Run the deterministic OPF for both concentrations $x_{t,i}$, $i = 1, 2$ using

$X = [\mu_{X,1}, \mu_{X,2}, ..., x_{t,i}, ..., \mu_{X,n}]$.

Step 7: Update $E(Y)$ and $E(Y^2)$

$$E(Y) \cong \sum_{t=1}^{m}\sum_{i=1}^{2}(P_{t,i}h([\mu_{X,1}, \mu_{X,2}, ..., x_{t,i}, ..., \mu_{X,n}])) \tag{45}$$

$$E(Y^2) \cong \sum_{t=1}^{m}\sum_{i=1}^{2}(P_{t,i}h\left([\mu_{X,1}, \mu_{X,2}, ..., x_{t,i}, ..., \mu_{X,n}]\right)^2). \tag{46}$$

Step 8: Repeat steps 4 to 7 for $t = t + 1$ until the list of uncertain variables is exhausted.

Step 9: Calculate the mean and standard deviation using

$$\mu_Y = E(Y) \tag{47}$$

$$\sigma_Y = \sqrt{E(Y^2) - \mu_Y^2}. \tag{48}$$

The flow chart for handling the uncertainty using 2PEM is shown in Figure 4.

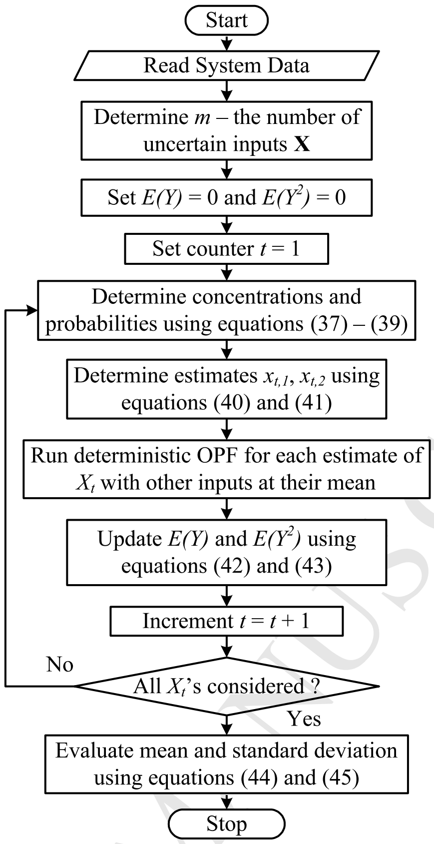

Figure 4: Flow chart for handling the uncertainty using Two-Point Estimate Method (2PEM)

Appendix B

Modified IEEE 30 Bus System Data

Tables 7 and 8 presents cost coefficients of thermal generators, wind and solar PV generators, respectively. The real time adjustment cost coefficients (x, y and z) for the thermal generators are 0 \$/hr, 5.6 \$/MWhr, and 0.01 $\$/MW^2hr$, respectively.

Table 7: Cost coefficients of thermal generators.

Gen. No.	Bus No.	a (\$/hr)	b (\$/MWhr)	c ($\$/MW^2hr$)	P_{Gi}^{min} (MW)	P_{Gi}^{max} (MW)
1	1	0	3	0.00250	50	200
2	2	0	2.75	0.00625	20	80
3	5	0	3.25	0.00834	10	35
4	8	0	3.5	0.00375	15	50

Table 8: Cost coefficients of wind and solar PV generators.

Gen No.	Bus No.	d or t ($/MWhr)	P_{Wj}^{min} or P_{Sk}^{min} (MW)	P_{Wj}^{max} or P_{Sk}^{max} (MW)
1	11	3.25	0	45
2	13	3.5	0	40

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Research Highlights

- Incorporation of renewable energy sources into grid is a challenging problem due to their intermittent nature.
- This paper solves an optimal scheduling problem considering the hybrid generation system.
- A new strategy is proposed taking into account the impact of uncertainties in wind, solar PV and load forecasts.
- Simulations are performed on IEEE 30 and 300 bus systems with Genetic Algorithm and Two-Point Estimate Method.