Intelektual Journal of Energy Harvesting and Storage
Vol. 2, No. 1, 2024, pp. 48~58
ISSN: 2963-6272, DOI: 10.11591/ehs.v2i1.pp48-58

Strategy for optimal bidding of micro-grid with demand side management for economic emission dispatch considering uncertainty and outage of renewable energy sources

Chitralekha Jena, Pampa Sinha, Lipika Nanda Arjyadhara Pradhan, Babita Panda
School of Electrical Engineering, Kalinga Institute of Industrial Technology University, Bhubaneswar, Odisha, India

Article Info

Article history:

Received May 29, 2023
Revised Apr 13, 2024
Accepted May 2, 2024

Keywords:

Distributed energy resources
demand response program
uncertainty
Micro-grid
Outage

ABSTRACT

In the restructured electricity market, microgrid (MG), with the incorporation of smart grid technologies, distributed energy recourses (DER), pumped-storage-hydraulic (PSH) unit and demand response program (DRP), is a smarter and reliable electricity provider. DER consists of gas-turbines and renewable energy sources such as photovoltaic systems and wind-turbines. Better bidding strategies, prepared by MG operators decrease the electricity cost and emission from upstream grid and conventional and renewable energy sources. But it makes inefficient due to very high intermittent nature of renewable energy and higher rate of outages. To solve these issues, this study suggests non-dominated sorting genetic algorithm-II (NSGA-II) for optimal bidding strategy considering pumped hydro energy storage and DRP based on their outage probabilities.

Corresponding Author:

Chitralekha Jena
School of Electrical Engineering, Kalinga Institute of Industrial Technology University
Patia, Bhubaneswar, Odisha 751024, India
Email: chitralekhajena@mail.com

NOMENCLATURE

PSP	: Pumped storage plant
F_C	: Cost function
F_E	: Emission function
a_{Gi}, b_{Gi}, c_{Gi}	: Cost coefficients of i th gas turbine
$\alpha_{Gi}, \beta_{Gi}, \gamma_{Gi}$	: Emission coefficients of i th gas turbine
UR_i, DR_i	: Ramp-down and ramp-up rate limits of i th gas turbine
P_{Git}	: Output power of i th gas turbine at time t
$P_{Gi}^{min}, P_{Gi}^{max}$	: Min^m and Max^m generation limits for i th gas turbine
$P_{grid,t}$	: Power procured from upstream grid at time t
$cgrid_t$	: Grid electricity price at time t
$egrid_t$	: Emission of grid power at time t
P_{wjt}	: At time t wind power available of j th wind turbine
$P_{wj}^{min}, P_{wj}^{max}$	: Min^m and Max^m generation limits for j th wind turbine
P_{wrj}	: Wind power rated of j th wind turbine
d_{wj}	: Direct cost coefficient for the j th wind turbine
v_{in}	: Cut in speed of wind
$\boldsymbol{v_{out}}$	: Cut out speed of wind

v_r	: Rated speed of wind
v_{wt}	: Forecasted speed of wind at time t
α, β	: Weibull pdfs scale factor and shape factor respectively.
μ_{Log}, σ_{Log}	: Mean and standard deviation for lognormal PDF
$\mu_{Norm}, \sigma_{Norm}$	: Mean and standard deviation for normal PDF
P_{PVkt}	: Power o/p from k th solar PV plant at time t
P_{srk}	: Equivalent rated power o/p of the PV plant
G	: Solar irradiation forecast
G_{std}	: Solar irradiation in standard environment
R_c	: Certain irradiation point.
d_{PVk}	: Direct cost co-efficient for the k th solar PV plant
u_{wj}, o_{wj}	: Penalty cost and reserve cost for the j th wind turbine
u_{PVk}, o_{PVk}	: Penalty cost and reserve cost for the k th solar PV plant
P_{ghlt}	: At time t, power generation of l th PSP
P_{phlt}	: At time t, pumping power of l th PSP
$P_{ghl}^{min}, P_{ghl}^{max}$	: Min^m and max^m generation power limits of l th PSP
$P_{phl}^{min}, P_{phl}^{max}$	: Min^m and max^m pumping power limits of l th PSP
$Q_{ghlt}(P_{ghlt})$	: At time t, discharge rate of l th PSP
$Q_{phlt}(P_{phlt})$	: At time t, pumping rate of l th PSP
$Q_{spent,TOT,l}$	: Total amount of water spent for generation of l th PSP
$Q_{pump,TOT,l}$	: Total amount of water pumped of l th PSP
$Q_{net,spent,l}$	: Net amount of water spent by l th pumped storage hydraulic unit during operation cycle
$V_{res,lt}$	: Volume of water in upper reservoir of l th PSP at time t
$V_{res,l}^{min}, V_{res,l}^{max}$	: Min^m and max^m limits of upper reservoir storage of l th PSP
$V_{res,l}^{start}, V_{res,l}^{end}$	: Specified volume of water at starting and final in upper reservoir of l th PSP
Inc^{max}	: Max^m increased load at any hour (MW)
$L_{Base,t}$	: Forecasted base load at at time t
DR_t	: Percentage of forecasted based load participated in DRP at at time t
DR^{max}	: Maximum percentage of base load that can participate in DRP
Inc_t	: Amount of increased load at time$t$
Ls_t	: Shiftable load at time t
F	: Failure rate (failure times/year)
F_{PV}, F_w	: Limit of rate of failure of solar and wind unit (failure times/hour)
$MTTR$	: Mean time to repair
MDT_i, MUT_i	: Mean down and up time of i th gas turbine
ρ	: Rate of forced outage
$\rho_{Re\,pair}, \rho_{Aging}, \rho_{Weather}$	: Forced outage rate due to repairable, aging, and weather dependent failure
ρ_{wjt}, ρ_{PVkt}	: At time t, forced outage rate of j th wind turbine and k th solar power plant
λ	: Failure probability
S_{wjt}	: '1' if j th wind power unit is scheduled on at time t and otherwise '0'.
S_{PVkt}	: '1' if k th Solar PV plant is scheduled at time t and otherwise '0'
S_{Gjt}	: '1' if ith gas turbine is scheduled on at time t and otherwise '0'
$T_{on,i,(t-1)}, T_{off,i,(t-1)}$	: On and off condition of i th gas turbine before $(t-1)$th time
t, T	: Time index and scheduling period
T_{gen}	: Set containing time intervals where PSP operate in generation mode
T_{pump}	: Set containing time intervals where PSP operate in pumping mode
N_G	: No. of thermal generating units
N_w	: No. of wind turbine
N_{PV}	: No. of solar pv plant
N_{Pump}	: No. of psp

1. INTRODUCTION

Microgrid (MG) is the core component of a smart grid by providing efficient energy system with enhanced power quality, reliability and economy to grid-independent end user sites. MGs continue to operate with improved integration of recent smart grid technologies, disseminated conventional and renewable energy sources, competent pumped-storage-hydraulic (PSH) unit and boost customer participation through demand side management [1], [2]. Thus, MG can purchase power from upstream grid, distributed energy sources with the advantage of time-varying electricity prices to meet its demand. But, the variability and intermittency of renewable energy sources and their outages are the main factors which challenge the MG operators to buy electricity at a price variable from a day-ahead market so that cost and emission are optimized simultaneously. Hence, to bid for electricity in the day-ahead market, MG should plan an optimal bidding strategy to buy power from upstream grid with demand response program (DRP) taking into consideration the uncertainty and outages of the sources of renewable energy.

To reduce price of energy in the electricity market which is deregulated and to enhance the reliability of the power system, MG operators give emphasis to the best bidding policy and this has been discussed in the literature [3]–[11]. Lim and Kim [3], a distributed load-shedding scheme-based bidding strategy is designed to maximize the profits of power consumers through q-learning algorithm. Optimal bidding scheme for MG has been structured using stochastic programming in [4] for power scheduling and profit maximization, and two-stage stochastic programming in [5]. A bi-level programming based energy bidding strategy for MG has been proffered in [4] in which stochastic model of uncertain renewable energy sources and loads are considered. Another stochastic optimal bidding strategy is framed in [6] and solved utilizing mixed-integer linear programming (MILP). Ferruzzi *et al.* [7], a risk management based day-ahead bidding strategy for grid-tied residential MG has been proposed. Robust optimization based day-ahead bidding approach has been employed in [8] for maximizing the profit from joint energy and spinning reserve market. Nguyen and Le [9], DRP is introduced in bidding operation of MG to facilitate customers with active participation with MG aggregator and system operator. A hierarchical market model has been design in [10], where MG aggregator involves small-scale MGs in DRP assisted real-time balancing bidding. Another DRP aided short-term bidding framework for MG has been represented in [11] as robust optimization based best cost model.

The gas turbine discharges many pollutants like (SOx), (NOx), and (CO2) into the ambiance for electric utilities, ambiance in reducing greenhouse gasses is one of the important confronts. Clean Air Act in 1990 was intended for reducing greenhouse gasses and acid rain. So for that ,the gas turbine must decrease its sulfur oxides (SOx) and (NOx) level of emission [12]. Today's civilization wants safe and sufficient electricity not only cost-effective, but with minimum stratum of greenhouse gasses.

A variety of tactics are suggested to decrease the ambience greenhouse gasses [13]. Dispatching considering emission is preferable among these. The qualms related to renewable energy resources (RER) is modelled based on historical data and forecast results [6], [14]. Again, the bidding strategies in [9]–[11] incorporate DRP to only relief load during peak load or expensive periods. However, DRP incorporation during outages of distributed energy resources (DERs) can greatly secure the MG reliability and operation costs.

Taking into account the aforementioned facts, this paper proposes a day-ahead optimal bidding strategy for MG based on economic environmental dispatch (EED) with DRP considering outages of intermittent renewable energy sources [15]. The probabilities of uncertainties of renewable energy sources are determined using various well established probability distribution functions (PDF), viz., lognormal PDF (LPDF) for solar photovoltaic (PV) units, weibull PDF (WPDF) for wind turbine (WT) units [15]. All the uncertain scenarios are mapped non-repeatedly within the forecasted upper and lower boundaries [16]. Moreover, penalty cost for underestimation and reserve cost for overestimation of RER outputs is imposed to main cost to encourage MG to decide accurate power generation dispatch during bidding [15]. Along with the intermittent nature of RERs, remoteness and harsh operating circumstances of RER plants make it more prone to forced outages. It is observed that, the outage probabilities of RER units also trail some specific mathematical formulations/PDFs depending upon different types of failures, viz, repairable failure, aging failure and weather dependent failure [17]–[19] discusses economic dispatch problem using different computational intelligent techniques. Considering the uncertainty and outage modeling of RERs, the MG operator performs the EED to settle the optimal power dispatch schedules of generators and pumped-storage-hydraulic (PSH) unit and electricity purchasing in day-ahead market to facilitate its bidding optimization. Here, NSGA-II is suggested to solve EED problem.

2. PROBLEM FORMULATION

The proposed MG is considered to be grid connected and consists of gas turbines (GTs), solar PV plant, wind power generating units, pumped-storage-hydraulic (PSH) unit and loads. Day-ahead whether data and electricity prices are assumed to be known from historical data and other factors. In order to formulate the bidding strategy, the MG operator has to decide the energy procurement level from upstream grid and GTs, solar PV plant, wind turbine and PSH generation amount to optimize total cost and emission simultaneously while considering associated constraints. The subsequent objective functions with constraints were taken for description in the problem formulation with outage probabilities and demand side management of RER units.

2.1. Uncertainty modelling

2.1.1. Distribution of probability of solar power plant and wind turbine

Due to the uncertainty and intermittency, the solar power plant and wind turbine are difficult part to integrate into an MG even if it is important. The underestimation of renewable power results wastage of surplus energy while the overestimation leads to large reserve capacity margin which imbalances the steady state security of the MG, if demand arises, both add together to the total generation and operation costs of MG in energy bidding planning. So, many researchers have exercised different uncertainty modelling to evaluate penalty cost for underestimation and reserve cost for overestimation like lognormal, weibull, beta, and gumbel probability distribution functions (PDFs), by lognormal and weibull PDFs it is found that solar irradiation and speed of wind to be well trailed respectively as in (1) and (2) [15], [17].

$$f_G(G) = \frac{1}{G\times\sigma_{Log}\times\sqrt{2\times\Pi}} \times e^{-\left\{\frac{-\left(\ln G-\mu_{Log}\right)^2}{2\times{\mu_{Log}}^2}\right\}} \text{ for } G > 0 \tag{1}$$

$$f_v(v) = \left(\frac{\beta}{\alpha}\right) \times \left(\frac{v}{\alpha}\right)^{(\beta-1)} \times e^{-\left(\frac{b}{\alpha}\right)^{\beta}} \text{ for } 0 < v < \infty \tag{2}$$

2.1.2. Model of wind power

At time t, the output power [17] of j th wind turbine for a given wind speed is given as (3):

$$\begin{aligned} &P_{wjt} = 0, \text{ for } v_{wt} < v_{in} \text{ and } P_{wjt} = P_{wrj} \times \left(\frac{v_{wt}-v_{in}}{v_r-v_{in}}\right) \\ &P_{wjt} = P_{wrj} \times \left(\frac{v_{wt}-v_{in}}{v_r-v_{in}}\right), \text{ for } v_i \leq v_{wt} \leq v_r \\ &P_{wjt} = P_{wrj}, \text{ for } v_r \leq v_{wt} \leq v_{out} \end{aligned} \tag{3}$$

2.1.3. Model of solar power

At time t, the output power [20] from k th PV solar plant at time t for a given irradiation G is given by (4):

$$\begin{aligned} &P_{PVkt} = P_{srk} \times \left(\frac{G^2}{G_{std}R_c}\right), \text{ for } 0 < G < R_c \\ &P_{PVkt} = P_{srk} \left(\frac{G}{G_{std}}\right), \text{ for } G \geq R_c \end{aligned} \tag{4}$$

2.1.4. Solar power probabilities in PV power plant

Probability o PV power is equal as the value of corresponding solar power irradiation probability in (5):

$$f_{PV}(\mathrm{P}_{PV}) = f_G(G) \tag{5}$$

2.1.5. Wind turbine power probabilities

Wind power probabilities for discrete zones, i.e., for 1st and 3rd case of (3), can be calculated using (6) and (7) respectively [14].

$$f_w(P_w)|_{P_W=0} = 1 - e^{-\left(\frac{v_{in}}{\alpha}\right)^{\beta}} + e^{-\left(\frac{v_{out}}{\alpha}\right)^{\beta}} \tag{6}$$

$$f_w(P_w)|_{P_W=P_{Wr}} = -e^{-\left(\frac{v_{in}}{\alpha}\right)^{\beta}} - e^{-\left(\frac{v_{out}}{\alpha}\right)^{\beta}} \tag{7}$$

The probability for WT power in the continuous region as second case in (3) can be calculated as (8).

$$f_w(P_w) = \frac{\beta\times(v_r-v_{in})}{\alpha^{\beta}+P_{wr}} \times \left[v_{in} + \frac{P_w}{P_{wr}} \times (v_r - v_{in})\right]^{(\beta-1)} \times e^{-\left(\frac{v_{in}+\frac{P_W}{P_{Wr}}\times(v_r-v_{in})}{\alpha}\right)^{\beta}} \tag{8}$$

2.2. Modelling outage of wind turbine and solar power plant

Frequently renewable sources are facing forced outage due to harsh environmental condition, Aging, weather dependency and repairable failure are the three factors on which the forced outage modelling depends. For any power system, the repairable forced outage rate is given as (9) [15].

$$\rho_{Re\,pair} = \frac{F \times MTTR}{8760} \tag{9}$$

During the service time T, usually the component aging failure model follows the normal PDF the aging failure rate is calculated as (10).

$$\rho_{Aging} = \frac{1}{\sigma_{Norm} \times \sqrt{2 \times \Pi}} \times e^{-\frac{(T-\mu_{Norm})^2}{2 \times \sigma_{Norm}{}^2}} \tag{10}$$

For a time period of? t, by exponential distribution as (11), the weather dependent failure model is modelled as follows:

$$\rho_{Weather} = 1 - e^{-\lambda \times \Delta t} \tag{11}$$

hence, multi-factor independent outage is involved; using the union set concept, the outage rate can be evaluated. For any renewable unit the the forced outage rate can be given by (12).

$$\rho = \rho_{Re\,pair} \cup \rho_{Aging} \cup \rho_{Weather} = \rho_{Re\,pair} + \rho_{Aging} + \rho_{Weather} - \rho_{Re\,pair} \times \rho_{Aging} - \rho_{Aging} \times \rho_{Weather} - \rho_{weather} \times \rho_{Re\,pair} - \rho_{Re\,pair} \times \rho_{Aging} \times \rho_{Weather} \tag{12}$$

2.3. Objective functions and constraints

For optimal bidding, the objective functions i.e., simultaneously total cost and emission are optimized considering every operational constraint. Total cost is the summation of energy cost purchased from grid, fuel and operation cost of gas turbines and operation cost of solar PV plants and wind turbines during entire time scale. Total emission is the summation of emission corresponding to purchased grid power and emission from gas turbines.

– Cost

Cost function of fuel of the gas turbine is expressed as a quadratic function of its power output. The operational costs of the solar PV units and WT units consist of reserve cost for overestimation direct cost, penalty cost for underestimation on dispatchable solar power and wind power respectively. The total cost is the summation of fuel cost of GT power, cost of power purchased from grid and operational cost of PV solar plant and wind turbine.

$$F_C = \sum_{t=1}^{T} \left[\sum_{i=1}^{N_G} \{(a_{Gi} + b_{Gi} \times P_{Git} + c_{Gi} \times P_{Git}^2) \times S_{Git}\} + (cgrid_t \times P_{grid,t}) + \sum_{j=1}^{N_W} \{d_{wj} \times P_{wjt} + O_{wjt}(P_{wjt}) + U_{wjt}(P_{wjt})\} \times S_{wjt} + \sum_{k=1}^{N_{PV}} \{d_{PVk} \times P_{PVkt} + O_{PVkt}(P_{PVkt}) + U_{PVkt}(P_{PVkt})\} \times S_{PVkt} \right] \tag{13}$$

where $S_{wjt} = \begin{cases} 1, \rho_{wjt} < F_w \\ 0, otherwise \end{cases}$ and $S_{PVkt} = \begin{cases} 1, \rho_{PVkt} < F_{PV} \\ 0, otherwise \end{cases}$

On dispatchable wind power, for overestimation reserve cost and for underestimation penalty cost is modelled respectively in (14)-(15).

$$O_{wjt}(P_{wjt}) = o_{wj} \times \int_{P_{wjt}^{min}}^{P_{wjt}} f_w(y) (P_{wjt} - y) \tag{14}$$

$$U_{wjt}(P_{wjt}) = u_{wj} \times \int_{P_{wjt}}^{P_{wjt}^{max}} (y - P_{wjt}) \times f_w(y) \tag{15}$$

Reserve cost for overestimation and penalty cost for underestimation for dispatchable solar power is modelled respectively in (16)-(17).

$$O_{PVkt}(P_{PVkt}) = o_{PVk} \times \int_{P_{PVkt}^{min}}^{P_{PVkt}} f_{PV}(x)(P_{PVkt} - x) \quad (16)$$

$$U_{PVkt}(P_{PVkt}) = u_{PVk} \times \int_{P_{PVkt}}^{P_{PVkt}^{max}} f_{PV}(x)(x - P_{PVkt}) \quad (17)$$

– Emission

The ambience green house gases such as SOx, NOx, and CO2 produced by gas turbine is modelled separately. But, for evaluation purpose, total emission of green house gases is given as sum of a quadratic function, while the total emission is the summation of emission from gas turbine and emission of power taken from upstream grid.

$$F_E = \sum_{t=1}^{T}\left[\sum_{i=1}^{N_G}\{(\alpha_{Gi} + \beta_{Gi} \times P_{Git} + \gamma_{Gi} \times P_{Git}^2) \times S_{Git}\} + \left(egrid_t \times P_{grid,t}\right)\right] \quad (18)$$

2.3.1. Power balance constraint

Limit of power balance is depicted in (19)-(20), which states that the power procured from grid, GTs, WTs, PVs, and PSH unit will be scheduled according to the load considering DRP. Assuming that, when load is curtailed due to DRP, at that time $Ls_t = 0$ and, when load is shifted to base load demand, at that time no load is curtailed.

$$P_{grid,t} + \sum_{i=1}^{N_G}(P_{Git} \times S_{Git}) + \sum_{j=1}^{N_W}\left(P_{wjt} \times S_{wjt}\right) + \sum_{k=1}^{N_{PV}}(P_{PVkt} \times S_{PVkt}) + \sum_{l=1}^{N_{pump}} P_{ghlt} = (1 - DR_t) \times L_{Base,t} + Ls_t, t \in T_{gen} \quad (19)$$

$$P_{grid,t} + \sum_{i=1}^{N_G}(P_{Git} \times S_{Git}) + \sum_{j=1}^{N_W}\left(P_{wjt} \times S_{wjt}\right) + \sum_{k=1}^{N_{PV}}(P_{PVkt} \times S_{PVkt}) - \sum_{l=1}^{N_{pump}} P_{phlt} = (1 - DR_t) \times L_{Base,t} + Ls_t, t \in T_{pump} \quad (20)$$

This power procurement from upstream grid is limited by power transfer capacity of line linking the MG to main grid as (21).

$$0 \leq P_{grid,t} \leq P_{grid}^{max} \quad (21)$$

2.3.2. Pumped-storage-hydraulic (PSH) unit constraints

$$V_{res,l(t+1)} = V_{res,lt} + Q_{phlt}\left(P_{phlt}\right), l \in N_{pump}, t \in T_{pump} \quad (22)$$

$$V_{res,l(t+1)} = V_{res,lt} - Q_{ghlt}\left(P_{ghlt}\right), l \in N_{pump}, t \in T_{gen} \quad (23)$$

$$P_{ghl}^{min} \leq P_{ghlt} \leq P_{ghl}^{max} \; l \in N_{pump}, t \in T_{gen} \quad (24)$$

$$P_{phl}^{min} \leq P_{phlt} \leq P_{phl}^{max} \; l \in N_{pump}, t \in T_{pump} \quad (25)$$

$$V_{res,l}^{min} \leq V_{res,lt} \leq V_{res,l}^{max} \; l \in N_{pump}, t \in T \quad (26)$$

In this problem, net amount of water utilized by PSH unit is equal to zero as the initial and final volume of water of the upper reservoir of the (PSH) unit are taken,

$$V_{res,l0} = V_{res,lT} = V_{res,l}^{start} = V_{res,l}^{end} \quad (27)$$

$$Q_{net,spent,l} = Q_{spent,TOT,l} - Q_{pump,TOT,l} = \sum_{t \in T_{gen}} Q_{ghlt}\left(P_{ghlt}\right) - \sum_{t \in T_{pump}} Q_{phlt}\left(P_{phlt}\right) = 0 \quad (28)$$

2.3.3. Generation limits of gas turbine

$$P_{Gi}^{min} \leq P_{Git} \leq P_{Gi}^{max}\ l \in N_G, t \in T \tag{29}$$

2.3.4. Ramp rate limits of gas turbine

$$\begin{aligned} P_{Git} - P_{Gi(t-1)} &\leq UR_i, \rightarrow i \in N_G, t \in T \\ P_{Gi(t-1)} - P_{Git} &\leq DR_i, \rightarrow i \in N_G, t \in T \end{aligned} \tag{30}$$

$$\begin{cases} \left(T_{on,i,(t-1)} - MUT_i\right) \times \left(S_{Gi(t-1)} - S_{Git}\right) \geq 0, i \in N_G, t \in T \\ \left(T_{Off,i,(t-1)} - MDT_i\right) \times \left(S_{Git} - S_{Gi(t-1)}\right) \geq 0, i \in N_G, t \in T \end{cases} \tag{31}$$

Demand side management (DSM) programs gives many merits like, boosting the power system security reducing the cost, [21]. Programs are categorized as strategic conservation demand response. Here, DSM is utilized and is modeled according to time-of-use (TOU) program [11], fixing the net amount of load demand, some percentage of load demand is shifted from peak or expensive period to off peak or cheap period. Hence, the load curve flattens and the probable operation cost trims down. Numerical model of TOU program is given by (32) and constrained by (33)-(36).

$$L_t = (1 - DR_t) \times L_{Base} + L_{st} \tag{32}$$

$$\sum_{t=1}^{T} L_{st} = \sum_{t=1}^{T} DR_t \times L_{Base,t} \tag{33}$$

$$L_{Inc_t} = Inc_t \times L_{Base,t} \tag{34}$$

$$DR_t \leq DR^{max}, t \in T \tag{35}$$

$$Inc_t \leq Inc^{max}, t \in T \tag{36}$$

3. NONDOMINATED SORTING GENETIC ALGORITHM-II

To contend with multi-objective optimization problems, Srinivas and Deb [22] ascertained nondominated sorting genetic algorithm (NSGA). Nondomination is utilized as grading criterion of solutions, and fitness distribution is utilized for diversification control in the investigated space. To fitness distribution parameters, NSGA is extremely responsive, Deb *et al*. [23] pioneered nondomoinated sorting genetic algorithm-II (NSGA-II), which gives further dependable solution quickly than its antecedent. Due to limitation in space, detailed description of NSGA-II is not mentioned here. The flow chart of NSGA-II is shown in Figure 1 (see in Appendix).

4. SIMULATION RESULTS

The proposed NSGA-II based a day-ahead optimal bidding strategy for MG based on economic environmental dispatch (EED) with DRP considering outages of intermittent renewable energy sources is performed using numerical simulation. Simulation outcomes of the test system is used to match the efficacy of the suggested NSGA-II with strength pareto evolutionary algorithm 2 (SPEA 2) [24].

The proposed grid-connected MG model has three gas turbines, one solar PV unit, one wind turbine and one PSH unit and their data are shown in Table 1, Table 2, and Table 3 respectively in the appendix. Day-ahead forecasted loads and electricity prices for 24 consecutive hours are tabulated in Table 4. 15% of 16th and 17th hour load is shifted to 5th and 6th hour and 20% of 19th hour load is shifted to 9th hour during DSM. The emission of grid power is considered 50Kg/MWh. The PSH plant has the following characteristics:

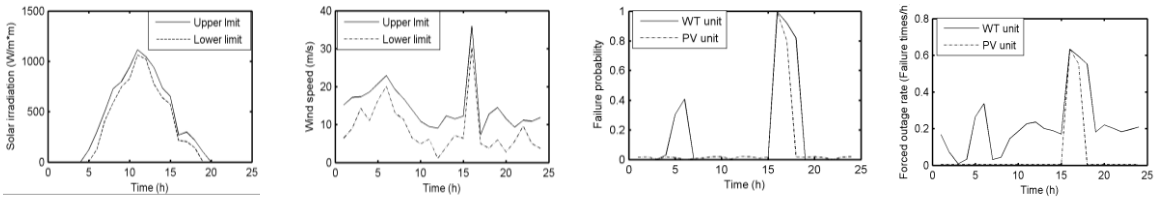
Generating mode: Q_{ght} is positive when generating, P_{ght} is positive and $0 \leq P_{ght} \leq 6$ MW, $Q_{ght}(P_{ght}) = 4 + 2P_{ght}$ acre-ft/hr. Pumping mode: Q_{pht} is negative when pumping, P_{pht} is negative and $-6\ MW < P_{pht} \leq 0\ MW, Q_{pht}(P_{pht}) = -12$acre-ft/h with $P_{pht} = -6$ MW.

Operating limitations: the pumped hydro plant will be permitted to work only at −6 MW while pumping. Reservoir starts at 160 acre-ft and must be at 160 acre-ft at the end of the 24 hours. The water inflow rate is neglected without considering spillage.

Upper and lower forecast limits of solar irradiation and velocity of wind are given in Figures 2(a) and 2(b) respectively. At 16th hour a sudden change in speed of wind is noticed in Figure 2(b). Due to this high wind speed, it results into turbulent weather condition which causes failure in renewable unit? the failure probabilities, for PV and WT units, can be fetched from weather dependent historical data which are portrayed in Figure 2(c). Forced outage rates of PV and WT units are shown in Figure 2(d) correspondingly. From Figure 2(d), it is evident that, PV unit has high failure rates at 16th and 17th hour and WT unit has high failure rates at 16th, 17th, and 18th hour. 17th or/and 18th hour is required for repairmen of PV and WT units respectively.

Total cost and emission are the two conflicting objective functions. To elucidate contradictory relationships amongst the objective functions, each objective function i.e., total cost and total emission is minimized separately by utilizing real-coded genetic algorithm (RCGA). Here, the population size, maximum number of iterations, crossover and mutation probabilities are chosen as 100, 200, 0.9, and 0.2 respectively [25].

NSGA-II has been pertained to optimize two objectives i.e., total cost and total emission objectives simultaneously. For comparison, SPEA 2 has been pertained for solving this problem. In case of NSGA-II and SPEA 2, the population size, maximum number of iterations, crossover and mutation probabilities are taken as 20, 30, 0.9, and 0.2 respectively.



(a) (b) (c) (d)

Figure 2. These figures are; (a) upper and lower forecast limits of solar irradiation, (b) upper and lower forecast limits of wind speed, (c) failure probabilities (?) for PV and WT, and (d) forced outage rates of PV and WT units

The gas turbine-wind-solar-pumped storage generations and power procured from upstream grid acquired from economic dispatch and emission dispatch are summarized in Tables 1 and 2 respectively. The gas turbine-wind-solar-pumped storage generations and power procured from upstream grid acquired from economic emission dispatch utilizing NSGA-II and SPEA 2 are summarized in Table 3 and Table 4 (see in Appendix) respectively. The total cost and total emission acquired from economic dispatch, emission dispatch and economic emission dispatch are summed up in Table 5. Figures 3(a) and 3(b) (see in appendix) reveal cost and emission convergence characteristics. Figure 3(c) (see in appendix) reveals the distribution of 20 nondominated solutions acquired in the last iteration of suggested NSGA-II and SPEA2 acquired from cost and emission objectives optimized simultaneously.

Table 1. Hourly generation (MW) schedule acquired from economic dispatch

Hour	P_{G1}	P_{G2}	P_{G3}	P_w	P_{PV}	P_{gh}	P_{grid}
1	0.6298	0	1.5639	5.8212	0	-6.0000	12.9852
2	0.8553	3.0453	0.7363	3.7275	0	-6.0000	14.6356
3	0.3991	1.0051	0.8399	6.0000	0	-6.0000	16.7560
4	0.6081	1.3772	1.6879	6.0000	0	-6.0000	19.3268
5	0.4880	0.2047	1.9993	6.0000	0.1923	-6.0000	28.8158
6	1.9216	0.7481	2.7325	6.0000	0.8348	-6.0000	24.3881
7	1.5856	0.3667	0	6.0000	2.3992	-6.0000	24.6485
8	0.1625	1.9725	0.3555	5.7430	3.4953	-6.0000	22.2711
9	0.5190	1.1200	3.3573	2.9220	3.9706	2.3230	20.2882
10	0.8907	2.6495	1.5506	4.0779	4.5148	5.3246	8.9919
11	0.0170	1.4556	0.5235	2.9853	5.3980	5.2082	13.4123
12	0	0.0240	4.2554	3.2272	5.1496	1.2458	20.0979
13	0.3012	0	0.2509	3.6931	03.6931	4.1066	17.7686
14	2.2093	1.0051	0.9918	3.6435	3.4621	5.7353	26.9530
15	1.6945	1.4396	0.1913	2.0145	2.0145	2.9754	20.9221
16	0.3881	0.7093	2.4411	0	0	6.0000	22.7616
17	0.7696	1.8868	1.4992	0	0	3.1149	24.6046
18	2.2199	2.6392	1.0943	0	0.7651	6.0000	29.2816
19	3.1803	2.0358	3.7213	3.5852	0.0101	2.7308	22.7366
20	1.6180	2.9112	4.3674	3.6505	0	4.6711	26.7818
21	1.2593	2.3805	0.3604	3.8269	3.8269	-6.0000	22.1729
22	1.2593	2.3805	0.3604	3.8269	0	-6.0000	22.1729
23	1.6118	2.5635	0.8152	4.0647	0	-6.0000	24.9448
24	0.3996	0.4968	2.5094	3.3909	-6.0000	-6.0000	23.7034

Table 2. Hourly generation (MW) schedule acquired from emission dispatch

Hour	P_{G1}	P_{G2}	P_{G3}	P_w	P_{PV}	P_{gh}	P_{grid}
1	7.0000	8.0000	1.1149	4.2348	0	-6.0000	0.6503
2	6.1038	4.2514	4.4232	3.9685	0	-6.0000	4.2530
3	7.0000	4.8154	6.0059	6.0000	0	-6.0000	1.1788
4	3.9615	5.5252	10.0000	6.0000	0	-6.0000	3.5133
5	7.0000	8.0000	8.3917	6.0000	0.2820	-6.0000	8.0263
6	4.1579	7.7078	6.9339	6.0000	1.1555	-6.0000	10.6700
7	7.0000	8.0000	10.0000	6.0000	2.1760	-6.0000	1.8240
8	3.3406	4.4722	7.9446	6.0000	3.2179	-6.0000	9.0247
9	0	4.4199	6.4004	5.3569	3.9839	6.0000	8.3390
10	3.6391	8.0000	10.0000	1.7040	4.5179	0	0.1390
11	0	5.7708	8.2316	2.9397	5.4283	6.0000	0.6297
12	3.3376	8.0000	10.0000	0.1225	0.1225	6.0000	1.3240
13	5.0748	5.4475	8.7944	3.2667	4.2871	0	2.6295
14	3.3861	8.0000	10.0000	3.7343	3.6557	0	15.2239
15	7.0000	6.7643	7.0934	3.1759	2.9030	0	4.5635
16	5.1998	8.0000	10.0000	0	0	6.0000	3.1002
17	7.0000	4.2384	6.1245	0	0	6.0000	8.5121
18	6.7873	8.0000	10.0000	0	0.7848	6.0000	10.4279
19	7.0000	7.1155	7.6116	1.6464	0.0193	6.0000	8.6072
20	4.4799	8.0000	4.3326	4.3861	0	6.0000	16.8014
21	7.0000	5.7954	6.5600	3.0305	0	-6.0000	20.6140
22	5.9080	8.0000	10.0000	3.6751	0	-6.0000	2.4168
23	7.0000	4.8374	9.8673	1.3874	0	-6.0000	10.9079
24	5.4220	8.0000	9.8645	4.4821	0	-6.0000	2.7314

Table 3. Hourly generation (MW) schedule acquired from EED using NSGA-II

Hour	P_{G1}	P_{G2}	P_{G3}	P_w	P_{PV}	P_{gh}	P_{grid}
1	2.9849	3.3890	6.0376	5.3880	0	-6.0000	3.2004
2	4.3916	4.8276	4.7287	6.0000	0	-6.0000	3.0521
3	5.5260	4.2543	5.5066	6.0000	0	-6.0000	3.7130
4	3.7725	1.6378	4.6157	5.7529	0	-6.0000	13.2211
5	5.3743	2.1891	3.8308	6.0000	0.5194	-6.0000	19.7865
6	5.7943	5.9921	7.5277	6.0000	1.4583	-6.0000	9.8526
7	4.6254	6.0212	8.6737	6.0000	2.1887	-6.0000	7.4911
8	3.3167	3.9214	4.1157	6.0000	3.4748	-6.0000	13.1714
9	3.7432	5.6613	4.8407	3.9216	3.9872	2.9205	9.4256
10	1.1587	5.1351	1.8917	3.1512	4.1462	2.0266	10.4904
11	4.2170	4.1247	3.0509	2.6654	5.3866	4.0886	5.4669
12	3.3202	5.7683	6.3407	1.8956	5.1213	4.0920	7.4619
13	1.9101	5.0711	3.8029	1.1529	4.4227	5.3794	7.7608
14	4.9169	4.0195	6.3225	4.5013	3.3649	5.7586	15.1164
15	2.7623	5.6823	5.1959	1.9308	3.2481	6.0000	6.6806
16	2.1534	3.6187	6.2732	0	0	0.8184	19.4364
17	4.2556	3.8879	5.5650	0	0	5.7746	12.3919
18	4.5558	5.1500	6.5900	0	0.9406	6.0000	18.7636
19	2.7147	3.1687	5.5892	6.0000	0.1918	2.5038	17.8318
20	2.7607	4.2326	5.5113	1.8022	0	2.6334	27.0598
21	5.1978	2.3587	7.0244	1.8975	0	-6.0000	26.5216
22	2.5099	2.6826	8.4443	4.1604	0	2-6.0000	12.2028
23	1.6348	6.1588	6.7497	3.8893	0	-6.0000	15.5674
24	2.6016	4.9480	5.6753	2.3559	0	-6.0000	14.9193

Table 5. Comparison of performance

		Cost ($)	Emission (Kg)
Economic dispatch		63538	26394
Emission dispatch		217006	8910
EED	NSGA-II	130407	16098
	SPEA 2	131451	16286

5. CONCLUSION

NSGA-II based day-ahead optimal bidding strategy for MG based on economic environmental dispatch is proposed in the presence of DRP under outage conditions and uncertainties of renewable energy sources. The uncertainty related to solar and wind units are modeled using lognormal and Weibull probability distribution. TOU based DRP is used, especially considering time of outages along with time of peak loads/prices to enhance reliability of MG and reduce the cost and emission.

APPENDIX

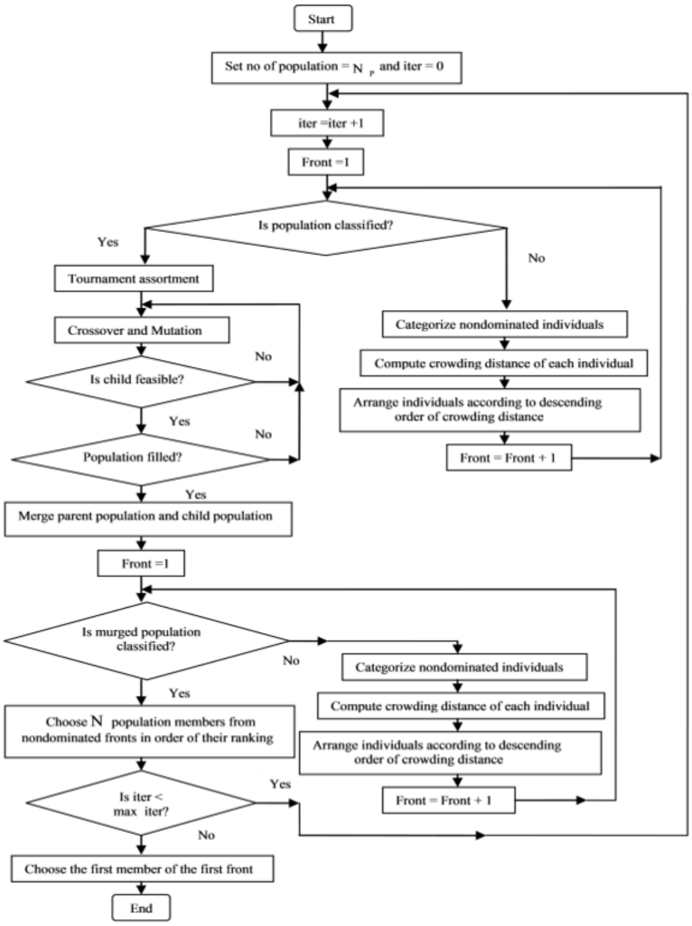


Figure 1. Flowchart of NSGA-II

Table 4. Hourly generation (MW) schedule acquired from EED using SPEA 2

Hour	P_{G1}	P_{G2}	P_{G3}	P_w	P_{PV}	P_{gh}	P_{grid}
1	2.5427	2.4507	6.7079	5.7131	0	-6.0000	3.5856
2	2.3406	1.9487	7.5644	4.2689	-6.0000	-6.0000	6.8774
3	3.6110	5.5991	7.3003	6.0000	0	-6.0000	2.4896
4	5.6085	6.2597	2.8790	6.0000	0	-6.0000	8.2528
5	1.8660	4.9910	6.7697	6.0000	0.0015	-6.0000	18.0719
6	3.7170	2.3154	2.3735	6.0000	0.8573	-6.0000	21.3618
7	3.2606	3.4488	2.3018	6.0000	2.5002	-6.0000	17.4885
8	1.7427	3.0117	6.5092	4.7685	3.6194	-6.0000	14.3486
9	1.9691	5.7996	5.8071	2.1872	3.8808	3.2319	11.6242
10	4.1763	2.8650	3.5324	3.1975	4.6041	5.6938	3.9310
11	3.1729	2.3437	2.6837	2.1978	5.4940	3.1735	9.9344
12	3.3695	2.3701	6.5418	1.8983	5.2217	4.8002	9.7984
13	5.3372	5.0548	4.4428	3.7490	4.6394	1.9723	4.3045
14	2.9497	2.6122	6.3042	3.9209	3.5155	4.8144	19.8830
15	2.3080	3.0905	6.2872	3.6466	2.8986	0.3914	12.8777
16	5.2098	4.5483	5.9327	0	0	6.0000	10.6092
17	2.3849	6.6198	7.9512	0	0	2.6639	12.2552
18	2.2529	7.4168	7.7712	0	0.8893	4.4687	19.2011
19	4.1608	5.2687	6.5545	3.5303	0.0175	5.6991	12.7692
20	4.4487	6.6452	7.5509	2.5236	0	5.0874	17.7442
21	2.3126	3.4898	7.9173	2.0801	0	-6.0000	27.2002
22	5.0339	5.1311	7.5146	3.8693	0	-6.0000	8.4510
23	2.8586	2.4976	8.0536	3.7064	0	-6.0000	16.8838
24	1.8391	3.8461	6.1609	4.2228	0	-6.0000	14.4311

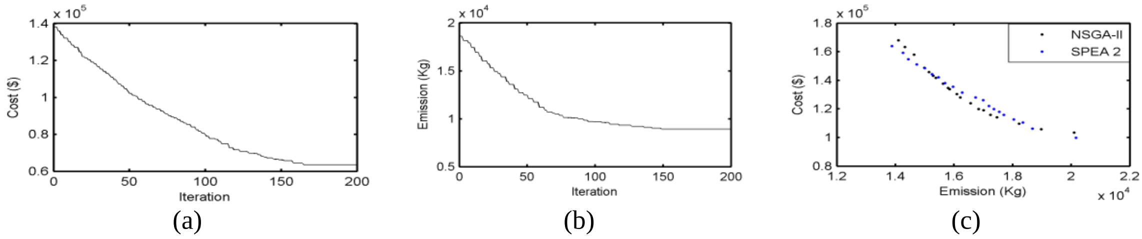


Figure 3. These figures are; (a) Cost convergence characteristic, and (b) Emission convergence characteristic and (c) Pareto-optimal front acquired from the last iteration

REFERENCES

[1] M. Smith and D. Ton, "Key connections: The U.S. department of energy?s microgrid initiative," *IEEE Power and Energy Magazine*, vol. 11, no. 4, pp. 22–27, Jul. 2013, doi: 10.1109/MPE.2013.2258276.

[2] D. Zhang, S. Li, P. Zeng, and C. Zang, "Optimal microgrid control and power-flow study with different bidding policies by using powerworld simulator," *IEEE Transactions on Sustainable Energy*, vol. 5, no. 1, pp. 282–292, Jan. 2014, doi: 10.1109/TSTE.2013.2281811.

[3] Y. Lim and H.-M. Kim, "Strategic bidding using reinforcement learning for load shedding in microgrids," *Computers & Electrical Engineering*, vol. 40, no. 5, pp. 1439–1446, Jul. 2014, doi: 10.1016/j.compeleceng.2013.12.013.

[4] H. Shayeghi and B. Sobhani, "Integrated offering strategy for profit enhancement of distributed resources and demand response in microgrids considering system uncertainties," *Energy Conversion and Management*, vol. 87, pp. 765–777, Nov. 2014, doi: 10.1016/j.enconman.2014.07.068.

[5] D. T. Nguyen and L. B. Le, "Optimal bidding strategy for microgrids considering renewable energy and building thermal dynamics," *IEEE Transactions on Smart Grid*, vol. 5, no. 4, pp. 1608–1620, Jul. 2014, doi: 10.1109/TSG.2014.2313612.

[6] G. Liu, Y. Xu, and K. Tomsovic, "Bidding strategy for microgrid in day-ahead market based on hybrid stochastic/robust optimization," *IEEE Transactions on Smart Grid*, vol. 7, no. 1, pp. 227–237, Jan. 2016, doi: 10.1109/TSG.2015.2476669.

[7] G. Ferruzzi, G. Cervone, L. Delle Monache, G. Graditi, and F. Jacobone, "Optimal bidding in a day-ahead energy market for micro grid under uncertainty in renewable energy production," *Energy*, vol. 106, pp. 194–202, Jul. 2016, doi: 10.1016/j.energy.2016.02.166.

[8] J. Wang *et al.*, "Optimal bidding strategy for microgrids in joint energy and ancillary service markets considering flexible ramping products," *Applied Energy*, vol. 205, pp. 294–303, Nov. 2017, doi: 10.1016/j.apenergy.2017.07.047.

[9] D. T. Nguyen and L. B. Le, "Risk-constrained profit maximization for microgrid aggregators with demand response," *IEEE Transactions on Smart Grid*, vol. 6, no. 1, pp. 135–146, Jan. 2015, doi: 10.1109/TSG.2014.2346024.

[10] W. Pei, Y. Du, W. Deng, K. Sheng, H. Xiao, and H. Qu, "Optimal bidding strategy and intramarket mechanism of microgrid aggregator in real-time balancing market," *IEEE Transactions on Industrial Informatics*, vol. 12, no. 2, pp. 587–596, Apr. 2016, doi: 10.1109/TII.2016.2522641.

[11] A. Mehdizadeh and N. Taghizadegan, "Robust optimisation approach for bidding strategy of renewable generation-based microgrid under demand side management," *IET Renewable Power Generation*, vol. 11, no. 11, pp. 1446–1455, Sep. 2017, doi: 10.1049/iet-rpg.2017.0076.

[12] K. D. Le *et al.*, "Potential impacts of clean air regulations on system operations," *IEEE Transactions on Power Systems*, vol. 10, no. 2, pp. 647–656, May 1995, doi: 10.1109/59.387899.

[13] J. H. Talaq, F. El-Hawary, and M. E. El-Hawary, "A summary of environmental/economic dispatch algorithms," *IEEE Transactions on Power Systems*, vol. 9, no. 3, pp. 1508–1516, 1994, doi: 10.1109/59.336110.

[14] S. Surender Reddy, P. R. Bijwe, and A. R. Abhyankar, "Real-time economic dispatch considering renewable power generation variability and uncertainty over scheduling period," *IEEE Systems Journal*, vol. 9, no. 4, pp. 1440–1451, Dec. 2015, doi: 10.1109/JSYST.2014.2325967.

[15] W. Li, *Riskn assessment of power systems: models, methods, and applications*. Wiley, 2004. doi: 10.1002/0471707724.

[16] J. V Seguro and T. W. Lambert, "Modern estimation of the parameters of the Weibull wind speed distribution for wind energy analysis," *Journal of Wind Engineering and Industrial Aerodynamics*, vol. 85, no. 1, pp. 75–84, Mar. 2000, doi: 10.1016/S0167-6105(99)00122-1.

[17] J. Hetzer, D. C. Yu, and K. Bhattarai, "An economic dispatch model incorporating wind power," *IEEE Transactions on Energy Conversion*, vol. 23, no. 2, pp. 603–611, Jun. 2008, doi: 10.1109/TEC.2007.914171.

[18] C. Jena, M. Basu, and C. K. Panigrahi, "Differential evolution with Gaussian mutation for combined heat and power economic dispatch," *Soft Computing*, vol. 20, no. 2, pp. 681–688, Feb. 2016, doi: 10.1007/s00500-014-1531-2.

[19] C. Jena, S. S. Mishra, and B. Panda, "Group search optimization technique for multi-area economic dispatch," in *Information and Decision Sciences*, 2018, pp. 217–225. doi: 10.1007/978-981-10-7563-6_23.

[20] R.-H. Liang and J.-H. Liao, "A fuzzy-optimization approach for generation scheduling with wind and solar energy systems," *IEEE Transactions on Power Systems*, vol. 22, no. 4, pp. 1665–1674, Nov. 2007, doi: 10.1109/TPWRS.2007.907527.

[21] A. Yousefi, H. H.-C. Iu, T. Fernando, and H. Trinh, "An approach for wind power integration using demand side resources," *IEEE Transactions on Sustainable Energy*, vol. 4, no. 4, pp. 917–924, Oct. 2013, doi: 10.1109/TSTE.2013.2256474.

[22] N. Srinivas and K. Deb, "Muiltiobjective optimization using nondominated sorting in genetic algorithms," *Evolutionary Computation*, vol. 2, no. 3, pp. 221–248, Sep. 1994, doi: 10.1162/evco.1994.2.3.221.

[23] K. Deb, A. Pratap, S. Agarwal, and T. Meyarivan, "A fast and elitist multiobjective genetic algorithm: NSGA-II," *IEEE Transactions on Evolutionary Computation*, vol. 6, no. 2, pp. 182–197, Apr. 2002, doi: 10.1109/4235.996017.

[24] E. Zitzler, M. Laumanns, and L. Thiele, *SPEA2: improving the strength pareto evolutionary algorithm*. ETH Zurich, Computer Engineering and Networks Laboratory, 2001.

[25] K. Deb and R. B. Agrawal, "Simulated binary crossover for continuous search space," *Complex Systems*, vol. 6, pp. 115–148, 1995.