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Demand response in the day-ahead operation of an isolated microgrid in the presence of uncertainty of wind power

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Abstract: This paper explores the utilization of demand response in the day-ahead operation of an isolated microgrid in the presence of wind units. The operation of the network with high penetration wind units (i.e. uncertainty of wind units) is modeled as a unit commitment problem. In addition, electrical power storage is modeled in a daily power curve to decrease the effect of uncertainty in the wind units. Due to avoiding large-scale complexities and the deeper study effect of demand-side management on operations, the considered network is regarded as an isolated microgrid. The demand-side management is studied as demand shifting. The simulation results and discussion show the flexibility and advantages of the proposed method.

Key words: Microgrid operation, wind power, demand response, microgrid, uncertainty

1. Introduction

1.1. Motivation

When regulating between electrical power generation and demand, consumption optimization requires changes in the load pattern. In traditional systems, electricity firms warn consumers about consumption decrease in peak times with neither encouragement nor penalty. Consumers receive their electric bill once a month or every 2 months without any kind of explanation that shows the type and times of their consumption.

Smart grids provide one mechanism using demand response and power pricing so that all consumers can participate in following the optimal load patterns. Consumers can get feedback on their usage by receiving electricity bills showing consumption value and times of load pattern correction. At the home level, consumers with installed smart counters and interfaces can monitor the status of their electrical devices.

Nowadays, demand response is used as an effective strategy in the correction of load profile. Smart counters with mutual-relation capability between customers and electricity distribution companies can inform customers of prices, warnings, and incentives.

Considering this subject, research and study of a comprehensive demand response program that maximizes users' profit in electricity markets and bidding at peak and other times could be useful.

1.2. Literature review

Probabilistic criteria to determine the units' commitment and their production level have been used for nearly 50 years [1,2,3,4,5,6,7,8]. For instance, the probabilistic basis of determining the amount of reserve based on risk analysis has been used since 1975 [8]. However, computational limits have led to oversimplifications in using

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the probabilistic criteria [2,5,6,7]. The following can be considered as reasons to increase the utilization of the probabilistic approach in operation:

- Power system restructuring [9,10,11].
- Improvement of computational tools [10,11].
- The need for more use of renewable energy for electric power generation [12].

As reasons for restructuring power systems, increasing efficiency and transparency in development and operation of power systems can be noted. Thus, use of traditional criteria for deployment of units and reserve allocation, which are more expensive and lead to reliability different than the expected value, should be reconsidered. On the other hand, due to the variable nature of renewable energies like wind and solar energy and the lack of accurate tools to forecast them, a significant amount of uncertainty is added to the system when they are used. This situation increases the necessity for proper reserve allocation in system management [13]. With new conditions in power system operation and improvement of computational tools in recent years, many efforts have been made in probabilistic determination of unit participation in electric power production in restructured power systems, and new methods have been presented [14,15,16,17]. Thus, the unit commitment problem in the case of high wind penetration is simulated and solved by considering the uncertainty of wind power production.

1.3. Contribution

In this paper, demand response in day-ahead operation of an isolated microgrid with wind production is simulated. The operation of the system considering the high wind penetration is modeled as a unit commitment problem. In order to reduce the impact of wind power's uncertainty, electrical energy stores are used. Due to avoiding the large-scale complexities and the deeper effect of demand-side management on operations, the considered network is regarded as an isolated microgrid. Additionally, the demand response is studied as demand shifting.

2. Problem modeling

2.1. Market clearing model

In this paper, a power pool-based electricity market is considered, in which producers offer their power generation levels to the local microgrid operator. In this section, the unit commitment model is simulated and the cost of electric power produced during a day is minimized. Constraints associated with this problem are load balance, production capacity of units and their ramp rates, and minimum on/off time.

In this model, the binary variables of on, off, and unit commitment and the level of power generated by units are the decision variables. The power generation output is divided into 2 parts: the first part is a parameter that represents the minimum output level, and the second is a decision variable corresponding to the output value over the minimum level for each generation unit. The last decision variable in this model is the unserved energy during each period of time. Thus, the following objective function is considered that minimizes the operation costs during a 24-h period [18]:

$$\text{Min}: \sum_{t=1}^{T}\left\{\sum_{i=1}^{N_G}\left(\begin{array}{l}\left(\pi_{i,t}\cdot P_i^{\min}+CNL_i\right)\cdot uc_{i,t}\\ +\pi_{i,t}\cdot P_{i,t}^{G}+COn_i\cdot on_{i,t}\end{array}\right)+\sum_{n=1}^{N_B}CNse\cdot nse_{n,t}\right\}, \tag{1}$$

where
t: time periods, h (alias t');
i: index of thermal generating units, running from 1 to N_G;
n: index of buses, running from 1 to N_B (alias r);
$\pi_{i,t}$: price offer submitted by unit i at period t;
$P_i^{\min}$: minimum output of generating unit i;
CNL_i : no-load cost of unit i;
$uc_{i,t}$: unit commitment binary decision variable of unit i at period t;
$P_{i,t}^G$: output power over the minimum value of unit i at period t;
COn_i : start-up cost of unit i;
$on_{i,t}$: start-up binary decision variable of unit i at period t;
$CNse$: cost of unserved energy for 1 h;
$nse_{n,t}$: unserved energy in bus n at period t.

The constraints of this model are:

$$\begin{aligned}&\sum_{\substack{i=1\\ i:(i,n)\in M_G}}^{N_G}\left(P_i^{\min}\cdot uc_{i,t}+P_{i,t}^G\right)-\left(\sum_{\substack{j=1\\ j:(j,n)\in M_D}}^{N_D}P_{j,t}^D-nse_{n,t}\right),\\&+\sum_{\substack{q=1\\ q:(q,n)\in M_W}}^{N_W}\left(P_{q,t}^W-S_{q,t}^W\right)-\sum_{\substack{r=1\\ r:(n,r)\in\Lambda}}^{N_B}f_{n,r,t}=0,\forall n,\forall t\end{aligned} \tag{2}$$

$$f_{n,r,t}=B_{n,r}\left(\delta_{n,t}-\delta_{r,t}\right),\forall\left(n,r\right)\in\Lambda,\forall t, \tag{3}$$

$$-\bar{f}_{n,r}\le f_{n,r,t}\le\bar{f}_{n,r},\forall\left(n,r\right)\in\Lambda,\forall t, \tag{4}$$

$$0\le P_{i,t}^G\le\left(P_i^{\max}-P_i^{\min}\right)\cdot uc_{i,t},\forall i,\forall t, \tag{5}$$

$$P_{i,t}^G-P_{i,t-1}^G\le RUp_i,\forall i,\forall t, \tag{6}$$

$$P_{i,t-1}^G-P_{i,t}^G\le RDo_i,\forall i,\forall t, \tag{7}$$

$$0\le S_{q,t}^W\le P_{q,t}^W,\forall q,\forall t, \tag{8}$$

$$\sum_{t'=1}^{T}on_{i,t'}\le uc_{i,t}\text{if }\left\{\left(t\ge t'-MOn_i+1\right)\text{ and t}\ge t'\right\},\forall i,\forall t, \tag{9}$$

$$\sum_{t'=1}^{T}off_{i,t'}\le 1-uc_{i,t},\text{ if}\left\{\left(t\ge t'-MOff_i+1\right)\text{ and t}\ge t'\right\},\forall i,\forall t, \tag{10}$$

$$uc_{i,t}-uc_{i,t-1}=on_{i,t}-off_{i,t},\forall i,\forall t, \tag{11}$$

$$\left\{uc_{i,t},on_{i,t},off_{i,t}\right\}\in\left\{0,1\right\},\forall i,\forall t, \tag{12}$$

where
M_G : mapping of the set of generators into the set of buses;
j: index of consumers running from 1 to N_D;

M_D : mapping of the set of consumers into the set of buses;
$P^D_{j,t}$: power consumed by load j at period t;
q: index of wind units running from 1 to N_W;
M_W : mapping of the set of wind units into the set of buses;
$P^W_{q,t}$: power produced by wind unit q at period t;
$S^W_{q,t}$: power production spilled from wind unit q at period t;
Λ : set of transmission lines;
$f_{n,r,t}$: power flow through line n–r at period t;
$\bar{f}_{n,r}$: maximum capacity of line n–r;
$B_{n,r}$: absolute value of the imaginary part of the admittance of line n–r;
$\delta_{n,t}$: voltage angle at bus n at period t;
$P_i^{\max}$: maximum capacity of generating unit i;
RUp_i : upward ramp of unit i;
RDo_i : downward ramp of unit i;
MOn_i : minimum on time of unit i;
$MOff_i$: minimum off time of unit i.

Eq. (2) represents the power balance in each bus over time. Constraints (3) and (4) compute and limit the power flow through the lines. Constraint (5) limits the maximum output of generating units, and Constraints (6) and (7) are the upward and downward ramp rate constraints, respectively. The maximum spillage of wind power is restricted by Constraint (8). Minimum on/off time of units is satisfied with Constraints (9) and (10), and (11) relates the state of each unit in each hour with the preceding one. Finally, (12) forces the unit commitment on and off decision variables to take binary values.

2.2. Demand response model as load shifting

The aim of load shifting is to reduce consumption levels during peak hours and move them to off-peak hours. This leads to flattening the demand profile and therefore lower total operation costs. In this paper, the load-shifting decision is made based on total daily operation cost. In this way, consumer behavior is modeled as a centralized decision-making process. This is similar to the event that occurs during the system operator decision-making process in optimizing the operation costs. Thus, the following equations are added to the model stated in Section 2.

$$P^D_{j,t} = Dref_{j,t} + DR^{up}_{j,t} - DR^{do}_{j,t}, \forall j, \forall t, \tag{13}$$

where:
$Dref_{j,t}$: demand submitted by load j at period t without demand response;
$DR^{up}_{j,t}$: demand increase for load j at period t due to demand response;
$DR^{do}_{j,t}$: demand decrease for load j at period t due to demand response.

Constraints of the maximum shiftable load from one hour to another hour are as follows:

$$0 \le DR^{do}_{j,t} \le B^{do}_{j,t}.Dref_{j,t}, \forall j, \forall t, \tag{14}$$

$$0 \le DR^{up}_{j,t} \le B^{up}_{j,t}.Dref_{j,t}, \forall j, \forall t, \tag{15}$$

where $B_{j,t}^{do}$ and $B_{j,t}^{up}$ are the coefficients that represent the maximum variation downward or upward in the jth consumer demand level at period t due to participation in demand response, respectively, and are numbers between 0 and 1.

Since in this model the consumer load can only be moved and not curtailed, Constraint (16) ensure that demand variations are balanced during 1 day only.

$$\sum_{t=1}^{T} DR_{j,t}^{up} = \sum_{t=1}^{T} DR_{j,t}^{do}, \forall j. \tag{16}$$

Load shifting from some hours to other hours imposes some costs on consumers. In fact, in demand-response programs, consumers agree to shift their load to other hours only when they impart from incentives. Thus, in this model, the costs of incentives are added to the objective function. The approaches for modeling of fees for costs of incentives are different. In this paper, the amount proposed in [18] for load-shifting cost is considered to be equal to the average of variable generation cost.

Thus, the cost of additional energy consumption during off-peak hours is less than the cost of producing the same amount of energy by expensive units during peak hours and is also higher than the previous cost of producing during off-peak hours. Thus, considering the cost of a transaction in objective function ensures that load shifting continues before committing the most expensive unit during off-peak periods [18].

Thus, the objective function in this section will be as follows:

$$MinOC^{DR} = OC + \sum_{t=1}^{T} \sum_{j=1}^{N_D} CTr_t \cdot DR_{j,t}^{up}, \tag{17}$$

where OC is the objective function of the previous model stated in Eq. (1) and CTr_t is the cost of transaction for increasing demand level at period t [18].

2.3. Stochastic programming of 2-stage problems

Stochastic programming problems are distinguished based on the number of stages considered. The 2-stage stochastic programming problem is one of these types of problems. In this type of stochastic problem, the decision-making process is done in 2 stages and there is a stochastic process, λ, that is shown by a set of scenarios, λ_Ω. Suppose that there are 2 vectors of decision variables, x and y, and the x decision is to be made before the realization of stochastic process λ, while the y decision is to be made after the realization of stochastic process λ. Thus, the decision variable y depends on the value of x and realization of stochastic process $\lambda(\omega)$. The general form of 2-stage stochastic linear programming is as follows:

$$Minimize_x z = c^T x + \varepsilon\{Q(\omega)\}, \tag{18}$$

$$s.t Ax = b, x \in X, \tag{19}$$

$$Q(\omega) = Minimize_y q(\omega)^T y(\omega), \tag{20}$$

$$s.t T(\omega)x + W(\omega)y(\omega) = h(\omega), \tag{21}$$

$$y(\omega) \in Y, \forall \omega \in \Omega, \tag{22}$$

where x and $y(\omega)$ are the first- and second-stage decision variables, respectively, and c, $q(\omega)$, b, $h(\omega)$, A, $T(\omega)$, and $W(\omega)$ are the vectors and matrices representing the input data. Each of these vectors and matrices can depend on the set of stochastic process realization λ_Ω or not [19].

2.4. Modeling of energy market considering wind power uncertainty

In the model proposed in this paper, the main corrective action considered to cover the uncertainty of the forecast error of power produced by wind units is the use of electrical energy storage facilities. Storage technologies such as batteries have very rapid response and are very suitable for small systems like microgrids.

In the proposed model, the variables marked with the symbol $\wedge$ are the second-stage decision variables of the 2-stage stochastic programming problem. Thus, the objective function will be as follows:

$$Min : OC \\ \sum_{t=1}^{T} \left\{ \begin{array}{l} \sum_{i=1}^{N_G} \left(\begin{array}{l} \left(\pi_{i,t} \cdot P_i^{\min} + CNL_i\right) \cdot uc_{i,t} \\ +\pi_{i,t} \cdot P_{i,t}^{G} + COn_i \cdot on_{i,t} \end{array} \right) \\ + \sum_{n=1}^{N_B} CNse \cdot nse_{n,t} + \sum_{j=1}^{N_D} CTr_t \cdot DR_{j,t}^{up} \\ + \sum_{s=1}^{N_S} prob_s \cdot \left(\begin{array}{l} \sum_{n=1}^{N_B} \left(\begin{array}{l} \left(\hat{P}_{n,t,s}^{bat,up} + \hat{P}_{n,t,s}^{bat,do}\right) \cdot Cbat \\ +CNse \cdot n\hat{s}e_{n,t,s}^{add} \end{array} \right) \\ + \sum_{j=1}^{N_D} CTr_t \cdot \left(E\hat{D}R_{j,t,s}^{up} + E\hat{D}R_{j,t,s}^{do}\right) \end{array} \right) \end{array} \right\}, \tag{23}$$

where:
s: index of scenarios running from 1 to N_S;
$prob_s$: probability of scenario s;
$\hat{P}_{n,t,s}^{bat,up}$: up-reserve of the battery being in node n at period t related to scenario s;
$\hat{P}_{n,t,s}^{bat,do}$: down-reserve of the battery being in node n at period t related to scenario s;
$Cbat$: cost per kWh of battery charging or discharging;
$n\hat{s}e_{n,t,s}^{add}$: extra unserved energy in node n at period t related to scenario s;
$E\hat{D}R_{j,t,s}^{up}$: extra demand increase for load j at period t related to scenario s;
$E\hat{D}R_{j,t,s}^{do}$: extra demand decrease for load j at period t related to scenario s.

As can be seen in Eq. (23), the corrective actions considered include up/down-reserve of batteries, shedding the amount of consumer demand in addition to the planned amount $nse_{n,t}$, extra shifting of consumer demand, and wind power spillage. Thus, the 2-stage stochastic programming problem has 4 main decision variables of the second stage, which are up/down-reserve of batteries, extra load shedding, extra demand shifting, and wind power spillage. In addition to Constraints (2) to (16), which should be considered in the model, the other constraint of this model is:

$$\sum_{\substack{i=1 \\ i:(i,n)\in M_G}}^{N_G} \hat{P}_{i,t,s}^{G} + \left(\hat{P}_{n,t,s}^{bat,up} - \hat{P}_{n,t,s}^{bat,do}\right) - \left(\sum_{\substack{j=1 \\ j:(j,n)\in M_D}}^{N_D} \hat{P}_{j,t,s}^{D} - nse_{n,t} - n\hat{s}e_{n,t,s}^{add} \right) \\ + \sum_{\substack{q=1 \\ q:(q,n)\in M_W}}^{N_W} \left(\bar{P}_{q,t,s}^{W} - \hat{S}_{q,t,s}^{W}\right) - \sum_{\substack{r=1 \\ r:(n,r)\in \Lambda}}^{N_B} \hat{f}_{n,r,t,s} = 0, \forall n, \forall t, \forall s \tag{24}$$

where:
$\hat{P}_{i,t,s}^{G}$: power produced by plant i at period t related to scenario s;

$\bar{P}^{W}_{q,t,s}$: power produced by wind unit q at period t related to scenario s;

$\hat{S}^{W}_{q,t,s}$: power production spilled from wind unit q at period t related to scenario s;

$\hat{f}_{n,r,t,s}$: power flow through line n-r at period t related to scenario s.

Eq. (24) shows the load balance in each scenario. Since the change in output power of thermal plants is not considered as a corrective action, the second-stage variable of power produced by these units, $\hat{P}^{G}_{i,t,s}$, must be equal to the corresponding variable in the first stage and in fact equal to the scheduled value. This assumption is due to the fact that the corrective actions should not result in a change in the values programmed. Thus, the following constraint limits the amount of power generated by thermal units:

$$\hat{P}^{G}_{i,t,s} = P_i^{\min} \cdot uc_{i,t} + P^{G}_{i,t}, \forall i, \forall t, \forall s. \tag{25}$$

Constraints (26) and (27) are added to the model to calculate and limit the power flow through the lines in each of the scenarios.

$$\hat{f}_{n,r,t,s} = B_{n,r}\left(\hat{\delta}_{n,t,s} - \hat{\delta}_{r,t,s}\right), \forall (n,r) \in \Lambda, \forall t, \forall s, \tag{26}$$

$$-\bar{f}_{n,r} \le \hat{f}_{n,r,t,s} \le \bar{f}_{n,r}, \forall (n,r) \in \Lambda, \forall t, \forall s, \tag{27}$$

where $\hat{\delta}_{n,t,s}$ is the angle of voltage at node n at period t related to scenario s.

The following constraint limits the maximum spillage of wind power in each scenario.

$$0 \le \hat{S}^{W}_{q,t,s} \le \bar{P}^{W}_{q,t,s}, \forall q, \forall t, \forall s. \tag{28}$$

The charging and discharging of the batteries as downward and upward reserve can be modeled as follows:

$$0 \le \hat{P}^{bat,up}_{n,t,s} \le C^{bat}_{n} \cdot u^{bat,dch}_{n,t,s} \cdot \eta^{dch}_{n}, \forall n, \forall t, \forall s, \tag{29}$$

$$0 \le \hat{P}^{bat,do}_{n,t,s} \le C^{bat}_{n} \cdot u^{bat,ch}_{n,t,s} \cdot \frac{1}{\eta^{ch}_{n}}, \forall n, \forall t, \forall s, \tag{30}$$

$$u^{bat,dch}_{n,t,s} + u^{bat,ch}_{n,t,s} \le 1, \forall n, \forall t, \forall s, \tag{31}$$

$$S\hat{O}C^{bat}_{n,t,s} = S\hat{O}C^{bat}_{n,t-1,s} - \frac{1}{C^{bat}_{n}}\left(\tfrac{1}{\eta^{dch}_{n}} \times \hat{P}^{bat,up}_{n,t,s} - \eta^{ch}_{n} \times \hat{P}^{bat,do}_{n,t,s} \right), \forall n, \forall t, \forall s, \tag{32}$$

$$0 \le S\hat{O}C^{bat}_{n,t,s} \le 1, \forall n, \forall t, \forall s, \tag{33}$$

$$\hat{P}^{D}_{j,t,s} = P^{D}_{j,t} + E\hat{D}R^{up}_{j,t,s} - E\hat{D}R^{do}_{j,t,s}, \forall j, \forall t, \forall s, \tag{34}$$

$$0 \le E\hat{D}R^{up}_{j,t,s} \le B^{'up}_{j,t}.DR^{up}_{j,t}, \forall j, \forall t, \forall s, \tag{35}$$

$$0 \le E\hat{D}R^{do}_{j,t,s} \le B^{'do}_{j,t}.DR^{do}_{j,t}, \forall j, \forall t, \forall s, \tag{36}$$

where:

C^{bat}_{n} : capacity of the battery in the node n;

$u^{bat,ch}_{n,t,s}$: binary variable showing the charging state of battery in node n at period t related to scenario s;

$u_{n,t,s}^{bat,dch}$: binary variable showing the discharging state of battery in node n at period t related to scenario s;

η_n^{ch} : charge efficiency of the battery in node n;

η_n^{dch} : discharge efficiency of the battery in node n;

$S\hat{O}C_{n,t,s}^{bat}$: state of charge of the battery in node n at period t related to scenario s;

$\hat{P}_{j,t,s}^{D}$: power consumed by load j at period t related to scenario s;

$B_{j,t}^{'up}$: coefficient of maximum extra increase in jth consumer demand level at period t;

$B_{j,t}^{'do}$: coefficient of maximum extra decrease in jth consumer demand level at period t.

Constraints (29) and (30) limit the up/down-reserve of the batteries, Constraint (31) restricts the charge or discharge state of batteries in each hour, and Constraints (32) and (33) are applied to calculate the amount of energy remaining in the battery and limit its level. Eq. (24) is the load balance constraint in the case of uncertainty in which the amount of power consumed by each consumer is calculated according to Eq. (34) and replaced. Constraints (35) and (36) have been considered for limiting the maximum amount of increase or decrease in conditions of randomness. The amount of the extra load increase or decrease is a percentage of the load increase or decrease planned in first-stage decision making.

3. Numerical studies and simulation

In this section, the model presented in the previous section is simulated on a microgrid system and the results are discussed and analyzed. First, the studied microgrid is introduced, and then the effects of demand-response programs and wind power production on the operation of the system will be studied with and without considering storage.

3.1. Case study

The test system is a low-voltage microgrid that has 3 feeders to supply the electrical energy requirements of residential, industrial, and commercial sections ....[20]. There are 3 wind units and 5 microturbines to produce the required electrical energy in this system (Figure 1). Additionally, typical load curves for each feeder of the network and rate of forecasted production of wind turbines are shown in Figures 2 and 3. It is assumed that all of the generating units work at unity power factor and no reactive power is generated or absorbed. The purchased energy costs from the wind units is assumed to be zero, reflecting their operating costs [21,22]. Other characteristics of the generating units are listed in Tables 1 and 2.

Table 1. Generating unit characteristics.

Unit ID	Unit name	Min capacity (kW)	Max capacity (kW)	Min on time (h)	Min off time (h)	Start-up cost (c$)	No load cost (c$/h)
1	MT 1	50	1000	2	2	200	1700
2	MT 2	35	700	3	3	260	2200
3	MT 3	40	800	2	2	180	1140
4	MT 4	60	1200	4	4	280	1860
5	MT 5	30	600	1	1	220	1320

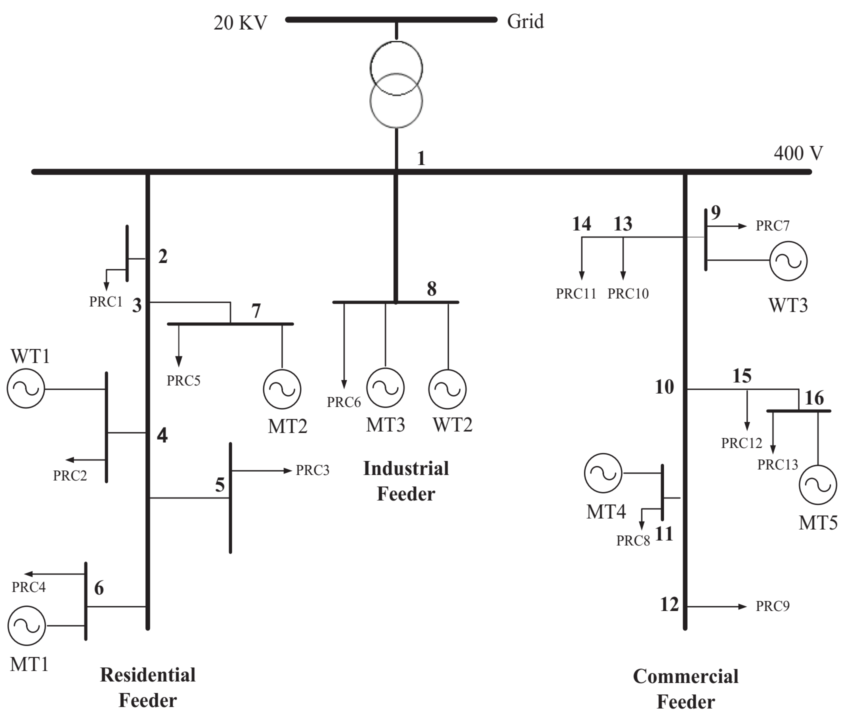

Figure 1. The case study low-voltage microgrid.

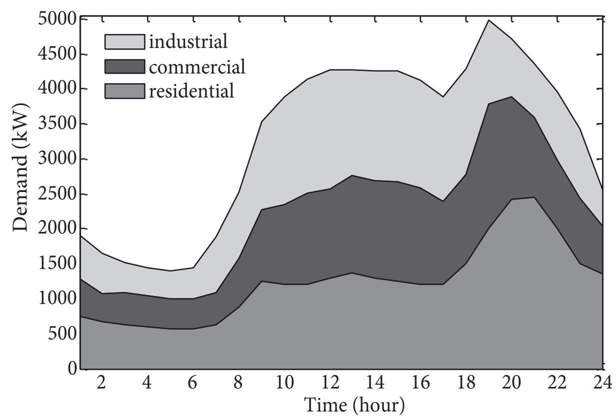

Figure 2. Typical load curve for each feeder of the network.

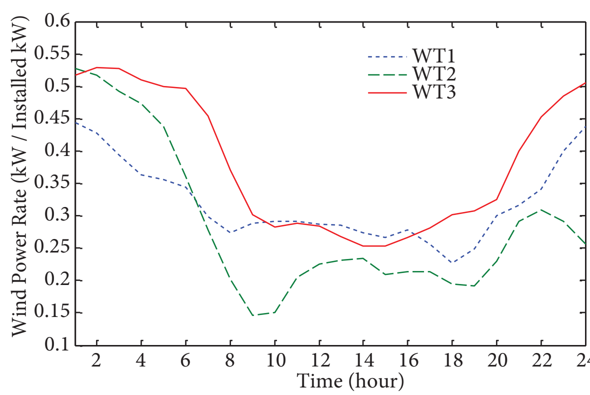

Figure 3. Rate of forecasted production of wind turbines (WTs).

The installed capacity of the wind units is considered equal. Hourly cost of load shifting CTr_t equals the average of variable generation cost, and the cost of load shedding $CNse$ is considered to be 8 times the cost of hourly load shifting. To cover the stochastic nature of wind power in operating the system, batteries are used with a storage capacity of 50 kWh at nodes 2, 4, and 8 and 100 kWh at nodes 9 and 11 to 16. The charge and discharge efficiency of all of the batteries is assumed to be 85%, and their charging or discharging cost is considered to be 0.04 $/kWh. It is assumed that the batteries can charge or discharge completely during 1 h. In order to model the impact of the uncertainty of wind production power, 10% error has been applied to the initial rate of forecasted production of the wind turbines and 100 scenarios have been randomly generated from a normal distribution. In the next stage, 100 scenarios are reduced to 20 scenarios by the SCENRED tool of GAMS optimization software. All of the models are solved using Cplex.12 under GAMS 23.0. In a 2-stage stochastic linear programming problem, it is possible to reduce a large scenario set to a simpler one that is close to the original if measured by a so-called probability distance. Under mild conditions in the problem data, it can be shown that the optimal value of the simpler problem (the one involving the reduced scenario set) is close to the value of the solution to the original problem (the one considering the original scenario set) if the scenario sets are sufficiently close in terms of such a probability distance [19].

Table 2. Daily prices of generating units (c$/kWh).

Unit	t 1	t 2	t 3	t 4	t 5	t 6	t 7	t 8	t 9	t 10	t 11	t 12
MT 1	7.33	6.7	5.74	4.98	4.26	5.75	7.57	10.35	11.98	12.92	12.76	14.26
MT 2	7.42	4.69	4.91	4.56	5.2	6.5	6.77	11.53	13.36	11.93	14.9	13.87
MT 3	7.17	5.4	6.22	4.99	5.9	5.05	7.14	9.04	11.75	12.54	14.91	16.41
MT 4	6.78	5.92	6	5.89	4.9	5.85	6.83	10.91	13.22	12.51	14.73	15.9
MT 5	7.31	6.06	7.25	4.71	4.07	5.02	6.23	10.2	12.45	13.04	15.11	15.58
Unit	t 13	t 14	t 15	t 16	t 17	t 18	t 19	t 20	t 21	t 22	t 23	t 24
MT 1	12.77	12.72	10.93	11.32	11.12	23.23	18.22	16.13	10.82	10.18	9.09	9.19
MT 2	14.97	12.63	12.8	10.21	11.65	19.54	14.09	12.32	12.38	9.61	8.29	8.12
MT 3	13.39	12.19	11.9	11.52	11.13	20.79	18.4	12.32	12.55	9.03	8.77	8.82
MT 4	13.12	14.86	10.33	9.88	9.08	21.46	19.2	13.56	12.71	9.84	9.6	8.76
MT 5	13.98	14.92	12.35	9.3	8.44	21.44	14.42	13.76	11.71	11.82	9.27	8.23

3.2. Results

In this section, the model of microgrid operation is simulated and the results are presented considering the wind power uncertainty with and without the use of electrical energy storage. In fact, the storage is used in order to cover the random volatility in wind power production. This is done by storing the excess energy in periods of low energy consumption and releasing it during peak times. All of the simulation results are shown in 20 different modes of operation including 4 modes of installed wind power capacity and 5 modes from different percentages of consumer participation in demand response. These modes are shown in Tables 3 and 4.

Table 3. Different percentages of consumer participation (B).

DR	DR1	DR2	DR3	DR4	DR5
B (%)	0	10	20	30	40

Table 4. Different capacities of installed wind power (WP).

Wind Power	WP1	WP2	WP3	WP4
Installed capacity (kW)	400	800	1200	1600

The expected values of spilled wind power in a day with and without considering storage are shown in Figures 4 and 5. This value is calculated as follows:

$$\bar{S} = \sum_{s=1}^{N_S} \sum_{t=1}^{T} \sum_{q=1}^{N_W} \left(prob_s \times \hat{S}^W_{q,t,s} \right). \tag{37}$$

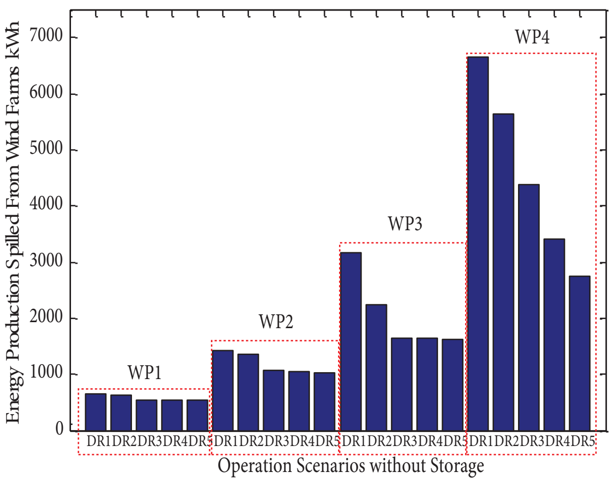

Figure 4. Expected value of spilled wind power without considering storage.

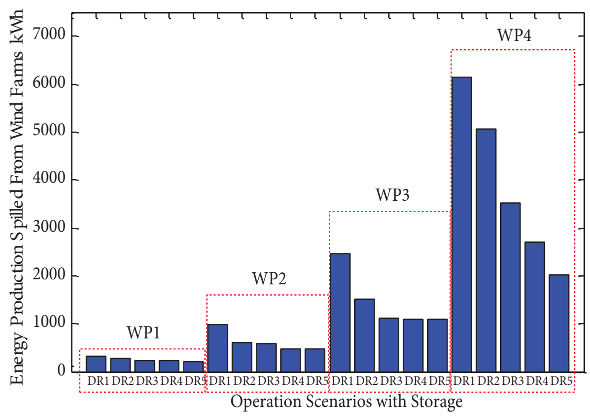

Figure 5. Expected value of spilled wind power considering storage.

As can be seen in Figures 4 and 5, storage makes a significant contribution to the reduction of wind power spillage. By comparing these figures, it can be concluded that in low wind power installation modes, the storage reduces the total wind power spillage by about 50%.

The decreasing effect of storage on reducing the wind power spillage is due to the constant capacity of installed storage when the wind power capacity increases.

The storage's impact on decreasing the wind power spillage is as down-reserve, and the extra wind power produced due to the wind power prediction error is stored in the batteries and prevents its spillage as well. Likewise, in lack of power production due to a decrease in wind power, the storage works as up-reserve and helps to satisfy the load balance constraint.

In Figures 4 and 5, the effect of demand response in decreasing the wind power spillage is clearly visible. Increasing the demand side participation up to 40% decreases spillage by 30% to 60%.

The average costs of energy supply in the operation horizon with and without considering storage are shown in Figures 6 and 7. As can be seen, the average cost is reduced when the storage is used. This reduction is due to the ability to store and release energy during off-peak and peak load hours, respectively. Furthermore, demand response and increasing the wind power capacity help reduce the average cost of the energy supply. Demand response's role in reducing the cost of operation has already been discussed in detail. Reduction in average cost caused by increasing the installed capacity of wind units arises from considering no operation cost for wind units.

In Figures 8 and 9, the expected value of additional unserved energy with and without taking storage into account is shown. This value is calculated as follows:

$$Tnse = \sum_{s=1}^{N_S} \sum_{t=1}^{T} \sum_{n=1}^{N_B} \left(prob_s \times n\hat{s}e_{n,t,s}^{add} \right). \tag{38}$$

As can be seen in these figures, of the 3 factors including demand response, storage, and increasing the wind power, 2 factors lead to a decrease and 1 leads to an increase in extra unserved energy.

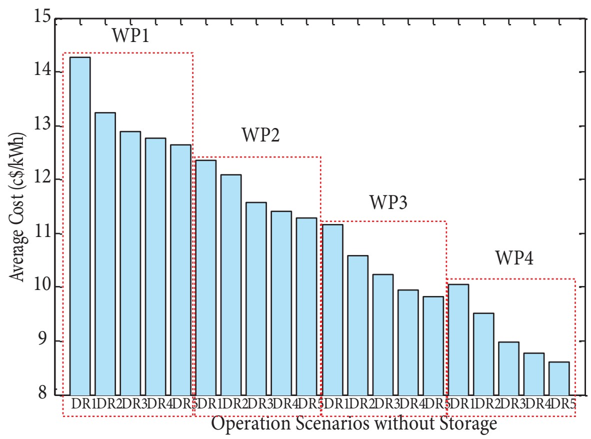

Figure 6. Average operational cost without considering storage.

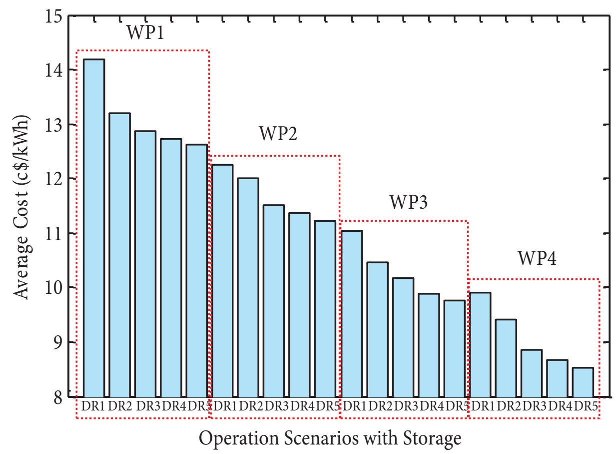

Figure 7. Average operation cost considering storage.

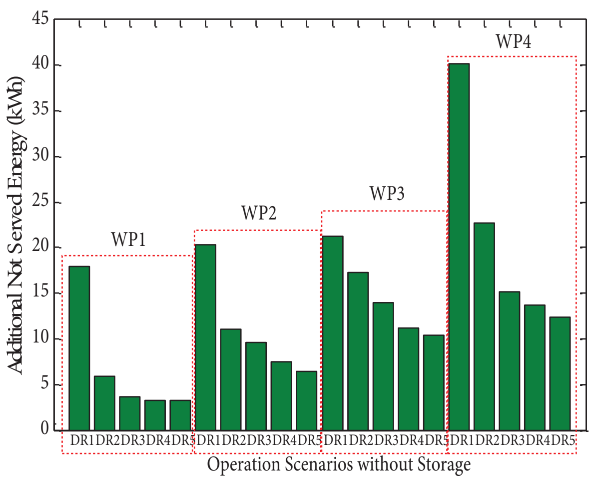

Figure 8. Expected value of extra unserved energy without considering storage.

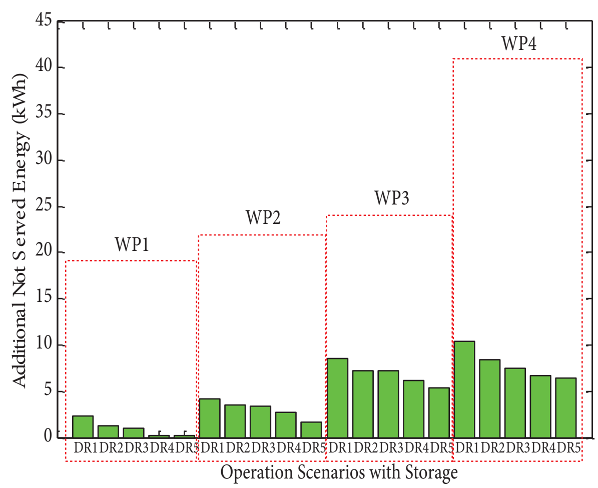

Figure 9. Expected value of extra unserved energy considering storage.

As mentioned previously, the use of demand response leads to shifting the load consumption from high-load hours to low-load ones and therefore reduces the unserved energy in peak periods and over the whole optimization period. Additionally, the use of storage makes it possible to release more energy with lower cost during peak hours. Thus, storage using a low-cost energy supply reduces the amount of unserved energy.

However, the effect of increasing the installed capacity of wind power units is not as above. In this case, the increase in range of the uncertain wind power output leads to an increase in the unserved energy and consequently the need for more regulation of energy production and consumption.

In fact, in this case, the increase in unserved energy is due to increasing the random amplitude decreases of the wind units' output. In these hours, the system needs some ancillary services such as load curtailment, release of stored energy in the batteries, and some load shedding. In other words, the role of load shedding in this case is similar to demand response and storage when the wind power decreases.

4. Conclusion

In this paper, the operation of a microgrid system was modeled as a unit commitment problem considering the high wind power penetration. Storage was used to cover the wind output fluctuations. In covering the wind output uncertainty, it was shown for this assumed case study that in critical conditions, storage such as batteries can be very suitable in microgrids. The extra wind power produced due to the wind power prediction error is stored in the batteries and its spillage is prevented, and in the absence of wind production due to the decrease of natural wind energy, the storage works as up-reserve to satisfy the load balance constraint. It is concluded that storage has a great effect on reducing the average cost and the amount of unserved energy.

In addition, increasing the wind power capacity leads to increasing the variations of output power that require more storage and extra load shedding in order to satisfy the load balance constraint. In this case, average operation costs are reduced, too. We expected this result, because of the consideration of no operational cost for the wind units. On the other hand, unserved energy will be increased due to the uncertain range of wind power output and, consequently, the system needs some ancillary services such as load curtailment, discharging of stored energy in the batteries, and extra load shedding. Therefore, high penetration of wind power in a network needs high flexibility from consumers.

Furthermore, it has been shown that the use of demand-response programs can reduce operational costs, the spillage of wind power, and unserved energy to consumers, but managing them and the costs associated with implementing them are problems that directly affect consumers. Thus, using all options and demand-side potentials to improve system performance and efficient operation requires more studies. As future work, we intend to extend the simulation algorithm to model the problem as multiobjective programming with objective functions, such as minimizing operation costs and minimizing the daily load curve deviation from its average value.

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