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Optimal Battery Sizing in Microgrids Using Probabilistic Unit Commitment

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***Abstract*—Stochastic nature of wind power can cause insufficiency of supply in electrical systems. Applying an energy storage system can alleviate the impact of wind power forecast error on power systems performance and increase system tolerance against deficiency of supply. This paper attempts to investigate a new unit commitment problem based on the cost-benefit analysis and Here-and-Now (HN) approach for optimal sizing of battery banks (BBs) in wind power integrated microgrids. To solve this problem, particle swarm optimization is used to minimize the total cost and maximize the total benefit. In this paper, twelve scenarios have been considered in the presence of BBs and without them in two operating modes: stand-alone mode and grid-connected mode. Using HN approach, the uncertainty of wind power is applied as a constraint in these operating modes. The mathematical formulations related to HN approach in microgrids and its combination by a unit commitment problem are presented in detail for optimal sizing of BBs. Simulation results show that the best sizes of BBs and the scheduling of the distributed generations would be entirely different when the accessibility of wind power is taken into consideration by applying HN approach to the proposed probabilistic unit commitment problem.**

***Index Terms*—Battery Bank, Distributed Generation, Microgrid, Unit Commitment.**

NOMENCLATURE

Abbreviations

AOTC	Annualized one-time BB cost.
BB	Battery bank.
CDF	Cumulative distribution function.
CG	Power sources which includes main grid, MTs and FC.
DG	Distributed generation.
ELD	Economic load dispatch.
ESS	Energy storage system.
FC	Fuel cell.
GCM	Grid-connected mode.
HN	Here-and-now.
MB	Market benefit.
MAPE	Mean absolute percentage error.
MG	Microgrid.
MT	Microturbine.
PSO	Particle swarm optimization.
PV	Photovoltaic panel.
PEV	Plug-in electric vehicle.
PCC	Point of common coupling.
PG	Generated power by sun.
PDF	Probability density function.
Prob	Probability of wind power.
RMSE	Root mean square error.
SAM	Stand-alone mode.
TB	Total benefit.
TC	Total cost.
TCPD	Total cost per day.
TUCC	Total unit commitment cost.
UC	Unit commitment.
Wt	Generated power by wind.
WS	Wait and See.
WT	Wind turbine.

Constants

a_n, b_n	Cost coefficients.
c	Scale factor.
C_{min}	Minimum energy stored in the BB.
C_{max}	Maximum energy stored in the BB.
$C(0)$	Initial energy inside the BB.
C_s	Initial stored energy limit of the BB.
$C(T)$	Set the same as the initial stored energy.
CR_t	Minimum spinning reserve requirement.
c_w	Wind energy cost.
c_{pv}	PV energy cost.
d_n	Startup cost.
f_n	Shutdown cost.
h_p	Wind power penetration factor.
I_{it}	Commitment state of unit i at time t.
k	Shape factor.
l	Life time (Year).
MC	Maintenance Cost.
MP_t	Market price.
n	Total number of DGs.
N_{CG}	Number of dispatchable power sources.
$P_{i,min}$	Minimum generated active power of unit i.
$P_{i,max}$	Maximum generated active power of unit i.
$P_t^{E,d}$	Discharged power by BB during the time period t.

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$P_t^{E,c}$ Charged power by BB during the time period t.
p_r Rated electrical power.
P_{dt} Power demand at hour t.
P_{st} Power loss at hour t.
$P_E^{d,max}$ Maximum discharge rate.
$P_E^{c,max}$ Maximum charge rate.
P_W Wind power.
$P10$ Reserve contribution of the 10-min quick start units.
r Interest rate.
$R10_n$ 10-min reserve capacity for n^{th} DG.
R_{nt} Spinning reserve of dispatchable DGs.
r_n Reserve cost.
t Index of hours.
T_i^{off} Minimum off time unit i.
T_i^{on} Minimum on time unit i.
V Wind speed.
v_c Cut-in wind speed.
v_r Rated wind speed.
v_f Cut-off wind speed.
$X_{i\,t}^{on}$ On time of unit i at time t.
$X_{i\,t}^{off}$ Off time of unit i at time t.
χ_h Upper bound of probability that the sum of active power not greater than P_{dt}+P_{st}.
α Factor of hourly spinning reserve to be maintained online.
σ Load forecast error factor.
η_c Charge efficiency.
η_d Discharge efficiency.

Variables

C_1, C_2 Learning factors of PSO algorithm.
$C(t)$ Energy stored in the BB at time t.
CE Size of BB.
$C_{n,t}$ Available energy stored in the n^{th} BB at time t.
G_{best} Best solution among particles till k^{th} iteration.
P_{best} Best solution of i^{th} particle till k^{th} iteration.
P_{nt} Output power of n^{th} DG at t^{th} hour.
SU_{nt} Vectors of binary integer representing unit start up status.
SD_{nt} Vectors of binary integer representing unit shutdown status.
U_{nt} Vector of binary integer representing unit status.
V_i^k, Y_i^k Velocity and position vectors of the i^{th} solution in k^{th} iteration of PSO algorithm.
ω Inertia factor of PSO algorithm.
$\bar{X}$ Vector of control variables in PSO algorithm.

I. INTRODUCTION

IN the future MGs will play a key role in the power systems. MGs are active distribution networks that include DGs such as: WTs, PVs, PEVs, MTs, and FCs [1], [2]. Optimal coordination and allocation of DGs with ESSs can provide several benefits for MGs. Due to the rapid depletion of fossil fuels resources, renewable energies (wind power & solar) are getting involved in the power systems, recently. They are the best choice for decreasing dependency on fossil fuels using available wind and sun. A typical MG system is shown in Fig. 1 that can operate in both SAM and GCM while the operation of MGs should be reliable and secure in both modes [3]. The objectives of energy management depend on the modes of operation: SAM or GCM. In this MG, PCC is the point in the power systems where a MG is connected to a main grid. Also the smart energy manager is the major control intermediary between the main grid and the MG. The major objectives of power system management in SAM are to sustain the frequency and voltage of MG and to minimize the total cost. Also, in GCM the main goals are commonly the maximization of the total benefit, the power factor enhancement at the PCC and the improvement of the voltage profile in the MG [4].Typically, MGs are scheduled with surplus capacity considering the local load; hence, the extra power can be injected into the main grid in order to acquire several economic benefits or store in optimal ESSs especially BBs. In addition to PEVs, ESSs especially BBs can be placed in MGs for storing the surplus energy since they can be frequently charged via utility grid or other DGs in different times based on conditions of load [5]. Therefore, BBs play an important role in this context since they are efficient to shave the peak demand, store the surplus energy and increase the reliability and security of power systems [6]. Also, they can play a key role in maintaining residential voltage profile by charging at off-peak time and discharging at the peak time [7]. The majority of the papers published on ESSs have focused on storage operation, but papers dealing with the storage sizing especially BBs are not general [8]. Because of the effective role of BBs, their sizing is necessary for enhancing the efficiency of the MGs' performance. Sizing of BBs has two main advantages. First, it can ensure that the loads are supplied in some periods of time when the main supply is insufficient. Another key aspect is to improve the financial problems from a cost-benefit point of view. In order to have a cost-effective system, one of the most important power systems' outlooks, is the selection of the optimal size of BBs. It should be noted that an improper BB sizing can lead to some problems such as poor performance of MGs in terms of total loss, total cost, supply of load and permanent damage to BB cells due to over-discharging. Since renewable energies are intermittent and their productions are stochastic, ESSs should be used to mitigate their effects and optimize the electric energy usage. A methodology has been proposed to optimally allocate ESSs in distribution systems in which the main objective is to maximize the profit of both the main grid and the DG owner [9]. In [10] the proposed approach uses a

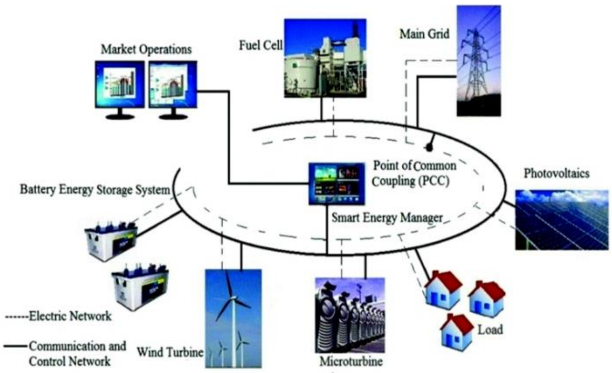

Fig.1. A simple structure of a microgrid.

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cost-benefit analysis to achieve the economic facility of the ESSs for both GCM and SAM.

Diverse methods have been proposed which consider the impact of probabilistic parameters on power systems [11]. Also, some mathematical approaches such as scenario reduction techniques [3], point estimation and nonparametric density estimators [12], Maximum Entropy and Gram-Charlier [13], Cornish-Fisher [14], Unscented Transformation [15] etc. have been recently used to reduce the time burden of Monte Carlo simulation technique. Furthermore, some computationally less intensive probabilistic methods like WS and HN are applicable for ELD models in power systems consisting of both thermal and wind turbines [16-18]. In these methods, the accessibility of stochastic wind power is considered as a constraint to ELD models. In [19] a matrix real-coded genetic algorithm has been utilized to address the optimal energy and power capacities of various ESSs. A novel approach is suggested in [20] for optimal sizing of ESSs to achieve the task of primary frequency control in a MG. Also, an approach has been introduced for the expansion and planning problem where the installation, maintenance and operating costs of the ESSs have been considered and optimized, synchronously [21]. An optimization problem has been observed for achieving the best configuration and energy split strategies of a hybrid energy storage system including a BB and a supercapacitor in [22]. Among the optimization methods, PSO is one of the strongest methods [2, 23]. A hybrid multi-objective PSO approach is suggested in [24] to minimize the power system cost and reform the system voltage profiles with the effect of uncertainties in wind power production.

On the other hand, the UC is usually defined as a scheduling of power generation over a daily period to achieve optimization of objectives while various constraints, such as minimum up/down time, ramp rates and hourly minimum spinning reserve of individual units, are considered. The UC is one of the most challenging problems in power systems' optimization which draws noticeable attentions for proposing better solutions. For instance, a hybrid PSO algorithm for security constrained UC is proposed in [25] in which the main goal is to schedule power sources that are responsible for ensuring system security. Besides, a robust UC model is presented for the security constrained UC problem in the presence of nodal net injection uncertainty in [26].

Furthermore, different researches have used ESSs in the presence of wind power. In [27, 28] discrete Fourier transform and discrete wavelet transform methods are used to size energy storage systems to mitigate wind power forecast error impacts. Also, [29] has used an ESS to overcome frequency deviation problem which let them increase the level of wind penetration. Ref. [30] expresses that since the reduction of uncertainty in the output of large wind farms by fast-acting dispatchable DGs can increase the cost of large-scale wind farms; sizing of ESSs at the wind farms output can improve the predictability of wind power and reduce the need for dispatchable DGs. In [31] the optimal sizing and management of ESSs and dynamic pricing in the presence of renewable energies are addressed as a stochastic dynamic program that attempts to minimize the long-run average cost of electricity used and investment in storage.

Considering stochastic nature of wind power which may cause forecast error, this paper uses HN approach and presents a UC problem to determine the best size of BBs for MGs in both SAM and GCM to minimize cost, maximize total benefit and increase system tolerance against deficiency of supply. In other words, a conventional UC problem with a new security constraint related to HN approach is solved to acquire the best battery size.

Similarly, the relationship between the best size of BBs and the total benefits and costs of MGs are evaluated. Simulation results show how wind power and other DGs with different availabilities affect the best size of BBs in each operating mode. Accordingly, the main contributions of this paper can be briefly expressed as follows:

- Introducing a new probabilistic UC problem in both GCM and SAM microgrids using HN approach.
- Evaluation of wind power uncertainty on BBs' size and DGs' scheduling in both GCM and SAM microgrids.
- Finding the best size of BBs in both GCM and SAM microgrids to mitigate the uncertainty of wind power.

This paper is organized as follows: In Section II, HN approach is presented. Section III introduces the modeling and formulations of the UC problem. The case study and simulation results are analyzed in Section IV. Finally, some relevant conclusions are drawn in Section V.

II. Here-and-now approach

In power systems, the assessment of wind power volatility on the generated power of DGs and determination of the best size of batteries can be simultaneously fulfilled by combining HN approach and cost-benefit analysis. The HN has been introduced in [17] that presents a typical approach which considers the accessibility of probabilistic wind power with introducing parameter Prob $(P_W = 0) \leq P_a \leq 1$.

In this paper, χ_{h} denotes this parameter that is a specified threshold representing the tolerance that the total demand of MG cannot be satisfied. For example, $\chi_{\mathrm{h}} = 0.4$ shows that insufficient supply from wind power can be compensated by dispatchable DGs up to 40% of total demand. It should be noted that a large χ_{h} implies that an insufficient supply can be more tolerated by a MG.

In the following, the concept of this parameter is more elucidated for reader by providing a proper background about wind speed probability distribution.

It is illustrated that Weibull distribution is the most confirmed model. Accordingly, the CDF of wind speed is as follows.

$$Prob.(V < v) = 1 - exp\left[-\left(\frac{v}{c}\right)^k\right], (v \geq 0) \quad (1)$$

Where k and c have always positive values. Considering (1), PDF of wind speed can be written as (2).

$$f_V(v) = \frac{k}{c}\left(\frac{v}{c}\right)^{k-1} exp\left[-\left(\frac{v}{c}\right)^k\right] \tag{2}$$

Also, the output active power of a WT is calculated based on equation (3) [18].

$$P_W = \begin{cases} 0 & ; \quad V \le v_c \, or \, V \ge v_f \\ p_r & ; \quad v_r \le V \le v_f \\ p_r \times \dfrac{V - v_c}{v_r - v_c} & ; \quad v_c \le V \le v_r \end{cases} \tag{3}$$

Substituting V in equation (2) by its value obtained from equation (3) in the range of $v_c \le V \le v_r$, the PDF of P_W would be in accordance with equation (4).

$$f_{P_W}(p_w) = \frac{khv_c}{p_r c}\left[\frac{\left(1+\frac{hp_w}{p_r}\right)v_c}{c}\right]^{k-1} \times exp\left\{-\left[\frac{\left(1+\frac{hp_w}{p_r}\right)v_c}{c}\right]^k\right\} \tag{4}$$

where $h = \left({}^{v_r}/_{v_c}\right) - 1$. Based on CDF of wind speed, the probability of the points $P_W = 0$ and $P_W = p_r$ are shown in (5), (6), respectively.

$$Prob.(P_W = 0) = Prob.(V \le v_c) + Prob.\left(V \ge v_f\right) = 1 - exp\left[-\left(\frac{v_c}{c}\right)^k\right] + exp\left[-\left(\frac{v_f}{c}\right)^k\right] \tag{5}$$

$$Prob.(P_W = p_r) = Prob.\left(v_r \le V \le v_f\right) = exp\left[-\left(\frac{v_r}{c}\right)^k\right] - exp\left[-\left(\frac{v_f}{c}\right)^k\right] \tag{6}$$

$$Prob.(0 < P_W < p_r) = Prob.(v_c \le V \le v_r) = 1 - exp\left\{-\left[\frac{\left(1+\frac{hp_w}{p_r}\right)v_c}{c}\right]^k\right\} \tag{7}$$

Based on (5) to (7) the CDF of P_W can be expressed by (8) as shown in the bottom of this page. Also, in the range of $v_c \le V \le v_r$ by integrating from equation (4), the probability of wind power is as following.In power systems, the main constraint is the equality of generation and demand expressed by equation (9). In other words, the total generation of power sources, such as main grid, dispatchable DGs (MTs and FC), renewable DGs (WT and PV) and BBs should satisfy the total demand and power losses.

$$P_{Wt} + \sum_{n\epsilon CG} P_{nt} + \sum_{n\epsilon PG} P_{nt} + \sum_{n\epsilon BB} P_{nt} = P_{dt} + P_{st} \tag{9}$$

Suppose the summation of generated powers, except probabilistic wind power at t^{th} hour is named P_{Tt} (10). Therefore, according to equation (9), the prime constraint of HN approach is written by (11). Indeed, using equation (8) in sub-interval $0 \le p_w \le p_r$, the probability that wind power causes insufficiency of supply is calculated by (11).

$$P_{Tt} = \sum_{n\epsilon CG} P_{nt} + \sum_{n\epsilon PG} P_{nt} + \sum_{n\epsilon BB} P_{nt} \tag{10}$$

$$Prob.(P_{Wt} \le P_{dt} + P_{st} - P_{Tt}) = 1 + exp\left[-\left(\frac{v_f}{c}\right)^k\right] - exp\left\{-\frac{1}{p_r^k c^k}[v_c p_r + (v_r - v_c)(P_{dt} + P_{st} - P_{Tt})]^k\right\} \le \chi_h \tag{11}$$

$$h_p = \frac{c}{v_r - v_c}\left|ln\left[1 + exp\left(-\frac{v_f^k}{c^k}\right) - \chi_h\right]\right|^{1/k} - \frac{v_c}{v_r - v_c} \tag{12}$$

By extracting P_{Tt} from (11) and meanwhile defining h_p as (12), the equation (13) is concluded [17].

$$P_{Tt} \ge P_{dt} + P_{st} - p_r . h_p \tag{13}$$

Equations (11) to (13) are used to implement new constraints to the problem. According to (10), equation (11) can present as an inequality constraint meanwhile, wind power penetration factor h_p describes the contribution of the stochastic wind power to the system because h_p depends on speed parameters, i.e., c, k of wind power, and χ_h.

III. Modeling and Formulations

WTs, PVs, FCs and MTs can work together to provide the load demand in MGs. When these energy sources are abundant and available after satisfying the load demand, they can support the batteries until they are charged.

A. Unit Commitment

UC aims at obtaining the most cost-effective combination of generating units to supply forecasted load while generation and transmission constraints are met. Generally, UC is utilized for a time horizon of one day to one week and determines which generators during which hours will operate.

Since the UC problem deals with the limits such as the minimum spinning reserve, the units' minimum ON/OFF time, ramp rates and network security, the total UC cost (TUCC) is

$$Prob.(P_W \le p_w) = \begin{cases} 0 & (p_w < 0) \\ 1 - exp\left\{-\left[\left(1 + \dfrac{hp_w}{p_r}\right)v_c/c\right]^k\right\} + exp\left\{-\left(\left(\dfrac{v_f}{c}\right)\right)^k\right\} & (0 \le p_w \le p_r) \\ 1 & (p_w \ge p_r) \end{cases} \tag{8}$$

written as (14). In order to solve this problem, one needs to consider the constraint (13) in section II to address HN approach in the proposed unit commitment problem.

$$Min\left[TUCC = \sum_{t}\sum_{n\epsilon CG}(r_nR_{nt} + d_nSU_{nt} + f_nSD_{nt} + U_{nt}(a_n + b_nP_{nt})) + \sum_{t}(U_{nt}P_{Wt}c_w) + \sum_{t}\sum_{n\epsilon PG}(U_{nt}P_{nt}c_{pv})\right] \quad (14)$$

The hourly UC constraints in below include the unit minimum ON time limits (15), unit minimum OFF time limits (16) and unit generation limit (17).

$$[X_{i\,(t-1)}^{on} - T_i^{on}] * [I_{i\,(t-1)} - I_{it}] \geq 0 \quad (15)$$

$$[X_{i\,(t-1)}^{off} - T_i^{off}] * [I_{it} - I_{i(t-1)}] \geq 0 \quad (16)$$

$$P_{i,min} * I_{it} \leq P_{it} \leq P_{i,max} * I_{it} \qquad i = (1, \ldots, N_{CG}) \quad (17)$$

The charge and discharge equations of BBs are written in (18) and (19) [10]:

$$\text{Discharge}: C(t+1) = C(t) - \Delta t P_t^{E,d}/\eta_d \quad (18)$$

$$\text{Charge}: C(t+1) = C(t) + \Delta t P_t^{E,c}\eta_c \quad (19)$$

The following constraints should be also satisfied by BBs. They include power limits, stored energy and starting – ending limits (20-22) [10].

$$0 \leq P_t^{E,d} \leq P_E^{d,max} \quad (20)$$

$$0 \leq P_t^{E,C} \leq P_E^{c,max}$$

$$C_{min} \leq C(t) \leq C_{max} \quad (21)$$

$$C(0) = C(T) = C_s \quad (22)$$

In order to consider the energy balance of a BB, the stored energy inside the BB at the end of the (dis)charging period, i.e. $C(T)$, is set the same as the initial stored energy. Also, based on the equation (23), unit spinning reserve capacity is regarded as (23).

$$R_{tn} \leq min[R10_n * U_{tn}, P_n^{max} * U_{tn} - P_{nt}] \qquad \forall t, n\,\epsilon\, CG \quad (23)$$

The capacity of largest ON-status unit is in (24).

$$CR_t \geq P_{nt} \qquad \forall\, n, t\, \in CG \quad (24)$$

WhereR10 is the 10-min spinning reserve capacity.
System spinning reserve and system 10-min operating reserve are respectively shown by constraints (25) and (26) [10]. $RMSE$is installed WT capacity for the day ahead forecast and $MAPE$ is difference between the actual and forecasted radiation. Time series method and feed forward neural networks can be used to achieve the forecast wind speed and solar radiation of a day [10]. Each PV panel is rated by its DC output power under standard test conditions, and typically ranges from 100 to 320 watts. Accordingly, the maximum output power of PV and the total cost function of MTs and FC can be achieved in [32].

$$\sum_{n\epsilon CG} R_{tn} + \sum_{n\epsilon BB}\eta_d(C_{n,t} - C_{min}) \geq \alpha * CR_t + RMSE\sum_{n\epsilon WG}P_{nw} + MAPE\sum_{n\epsilon PG}P_{nt} + \sigma\sum_{i}P_{dti} \quad (25)$$

$$\sum_{n\epsilon CG} R_{tn} + \sum_{n\epsilon G10}(1 - U_{tn}) * P10_n + \sum_{n\epsilon BB}\eta_d\,(C_{n,t} - C_{min}) \geq CR_t + RMSE\sum_{n\epsilon WG}P_{nw} + MAPE\sum_{n\epsilon PG}P_{nt} + \sigma\sum_{i}P_{dti} \quad (26)$$

where, P10 is the reserve contribution of the 10-min quick start units.

BBs are the source of direct voltage and they change chemical energy to electrical energy by chemical reactions. The batteries used to store solar and wind energy are currently mainly lithium-ion batteries [33, 34]. Due to the random behavior of PVs and WTs, the optimal size of BBs constantly changes in the power systems. When the summation of PVs and WTs output powers is greater than the load demand, the BB is in charging state and vice versa.

As engineers of electrical systems should install battery banks with higher benefits and lower costs due to their very expensive and sensitive nature, reference [35] in Section V presents a cost model for a battery-cell array for various types of battery and switch faults; in other words, battery banks are designed by making the tradeoff between cost and reconfiguration ability. Also, it expresses that an effective monitoring of large number of batteries can be effectively done by combined hardware-software architecture. Sometimes, they are not selected based on cost-benefit analysis correctly; as a result, the presence of BBs can be unhelpful and expensive for MGs. The total cost of a BB is $CE(FC + l * MC)$($).Also, FC contains the purchase of batteries and their installation.

$$AOTC = \frac{r(1+r)^l}{(1+r)^l - 1}FC * CE \quad (27)$$

The total cost of a BB can be achieved by adding AOTC and the MC. Then, TCPD of BB installed in $/day is as following.

$$TCPD = \frac{1}{365}(AOTC + CE * MC) \quad (28)$$

TABLE I: THE DATAOF DGs

DG	MT1	MT2	FC
$a(\$)$	30	50	80
$b\left(\frac{\$}{Kw}\right)$	0.13	0.35	0.5
$P_n^{Min}(KW)$	100	100	100
$P_n^{Max}(KW)$	2000	1000	1000
$d\left(\frac{\$}{start}\right)$	150	30	30
T^{on}	2	0	0
T^{off}	2	0	0
r ($/KW)	0.01	0.01	0.01
P10 (KW)	0	1000	1000
R10 (KW)	2000	1000	1000

TABLE II: MARKET PRICES OF MAIN GRID

Hour	$/kWh	Hour	$/kWh
1	0.11	13	0.50
2	0.10	14	0.40
3	0.11	15	0.30
4	0.09	16	0.30
5	0.11	17	0.40
6	0.11	18	0.50
7	0.13	19	0.30
8	0.15	20	0.26
9	0.26	21	0.15
10	0.30	22	0.13
11	0.35	23	0.10
12	0.40	24	0.11

A. Grid-Connected Microgrids

MG can be connected to and disconnected from the main grid to operate in both GCM and SAM. For GCM, the main grid can be treated as a bidirectional generator which can generate positive power when the power is injected from the main grid to the MG. Negative power of main grid means the power is transferred from the MG to the main grid. The output of this bidirectional generator is limited by the capacity of the transmission line between the MG and the main grid.

Considering distributed generator data in Table I and the market price in Table II for the grid-connected MG, the market benefit (MB) which should be maximized can be formulated as (29). Therefore, considering TCPD of BB for grid-connected MGs, the objective function will change to maximizing the total benefit (TB) in (30).

$$MB = \sum_t \left(MP_t \times \sum_{n\epsilon CG} P_{nt} \right) - TUCC \tag{29}$$

$$TB = MB - TCPD \tag{30}$$

TUCC includes the FC and MTs costs (start-up cost, online spinning reserve cost, and generating energy cost) and renewable energy cost (wind and PV energy cost). To obtain the best size of BB, the main problem is to maximize TB in (30) for the grid-connected MG.

B. Stand Alone Microgrids

SAM occur when a DG or a group of DGs continue to energize a portion of the power system that has been separated from the main grid. However the implementation of DGs can increase reliability of the power system in case of utility outage or when a MG needs to be independent and is called intentional islanding. The best size can then be found at the minimum cost point of (31) for the stand-alone MG [10].

$$TC = TCPD + TUCC \tag{31}$$

TC contains TCPD and TUCC, and its best value is achieved by a balance between TUCC and TCPD. The flowchart of the proposed optimization problem is shown in Fig. 2 that is used to find the best size of BBs in each predetermined value of χ_h.

Based on this algorithm, the following steps are drawn briefly:

1) Calculate $\chi_{h\,max}$ and BB_{min}.
2) Calculate h_p in (12) and P_{Tt} in (13).
3) Solve the objective functions for BB (Minimize the total cost or maximize the total benefit).
4) If BB<BB_{max} , update BB. Otherwise, find TC_{min} or TB_{max} and relevant BB size.
5) If $\chi_h \geq \chi_{h\,min}$, update χ_h and go to step 1 for calculate BB_{min} otherwise, this algorithm will stop.

where, BB_{max}andBB_{min} are maximum and minimum size of batteries considered for applying the proposed algorithm, $\chi_{h\,max}$ and $\chi_{h\,min}$ are maximum and minimum tolerance threshold of MG. In addition, $\Delta BB$and $\Delta\chi_h$are certain steps to increase the size of BBs in the range of $[BB_{min}, BB_{max}]$ and decrease tolerance threshold of MG in the range of $[\chi_{h\,min}, \chi_{h\,max}]$. Consequently, for every value of χ_h, the proposed optimization is run to dispatch DGs optimally in order to have an optimal size for the installed BB and the best values for objective functions.

Following steps should be proceeded to solve the proposed optimization problem.

Step 1: Generate $Y_{M\times N}$ for the first iteration, where M is the number of PSO solutions (i.e. i=1:100), and N is the number of particles which depends to operating mode of MG. Matrix $Y(i,:) = \bar{X}_{1\times n}$ which contains active power of DGs (i.e. FC, MT, BB and main grid)is all control variables for one solution.

$$\bar{X}_{1\times n} = [\bar{P}_{DG}^1, \bar{P}_{DG}^2, \dots, \bar{P}_{DG}^{N_{DG}}]_{1\times n} \tag{32}$$

$$\bar{P}_{DG}^i = [P_{DG,1}^i, \dots, P_{DG,T}^i] \tag{33}$$

Step 2: For each solution, calculate related objective function (i.e. total cost in SAM or total benefit in GCM) and then its normalized value based on corresponding fuzzy membership function.

Step 3: Find the minimum amount of objective function in SAM or maximum amount in GCM to find P_{best} and G_{best} for k^{th} iteration.

Step 4: Calculate $Y_{M\times N}$ for k^{th} iteration using equations (34) and (35).

$$V_i^{k+1} = \omega.V_i^k + C_1 \times rand_1(\cdot) \times (P_{best,i}^k - Y_i^k) + C_2 \times rand_2(\cdot) \times (G_{best,i}^k - Y_i^k) \tag{34}$$

$$Y_i^{k+1} = Y_i^k + V_i^{k+1} \tag{35}$$

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Step 5: Go to the step 2.

Where, V_i^{k+1} and X_i^{k+1} are the velocity and position of the i^{th} solution in (k+1)th iteration. $rand_1(\cdot)$and$rand_2(\cdot)$ are random numbers in the range [0, 1]. $C_1 = C_2 = 2$are the learning factors and ω is the inertia or momentum weight factor[2].

IV. Case Study

As in any research area, in the microgrids, it is important to allow the reproduction of one's results. The only way of doing that is using public domain data sets. We followed the same strategy and considered Fig.1as the test case of the paper. It is noted that the proposed method is tested on the real typical microgrid network. Each microgrid includes different modules and one of them is the microgrid central control (MGCC) module which includes energy management section. In other words, the proposed method takes the advantage of probabilistic unit commitment to determine optimal battery sizing from the microgrid operation point of view.

This section tries to determine the best size of a BB for the GCM and SAM of the MG that is shown in Fig.1. The MG is connected with the main grid at PCC, and it can buy power from the power market during the peak load period and sell power to the power market during the low load period.

The capacity of power transaction between the MG and the main grid is 1000 kW. The parameters of the WT and PV are: $k = 2,\ c = 15,\ P_r = 1$ MW, $v_c = 3m/s$,$v_r = 12m/s$, $v_f = 20\ m/s$, η = 15.7 %, S = 7000 m^2 and MC= 2000$.The load forecast error factor σ =3%, r =6 %, $RMSE$ =13% and $MAPE$ =8.96%. The maximum dis(charge) limits are set as 50% of its full capacity that means the BB can be (dis)charged in 2 hours. As it is shown in Fig. 2, the proposed algorithm starts with a high value forχ_h. For instance, in this paper HN approach is firstly performed with χ_h= 0.5. In other words, insufficient supply from wind power can be compensated by dispatchable DGs up to 50% of total demand. Then, χ_h = 0.4 and χ_h = 0.3 are chosen to address stricter conditions for the MG.

In this paper, according to tables III and IV, twelve scenarios have been presented with different values forχ_h; six scenarios for GCM and six scenarios for SAM. In each MG operating mode, there are two diverse cases; with BB and without BB. To optimize the proposed probabilistic UC problem the PSO algorithm has been applied [2-3, 18].

Case 1: Grid- Connected Mode

In GCM, by maximizing TB and solving UC problem, simulation results clearly show the effect of batteries on TB. For χ_h = 0.5, 0.4 and 0.3 the maximum value of TB would acquire with the best sizes of 400, 800 and 1100 kWh which lead to $5810, $5205 and $4851, respectively while without BB, TB will decrease to $ 4337, $ 4268 and $ 4145 respectively.

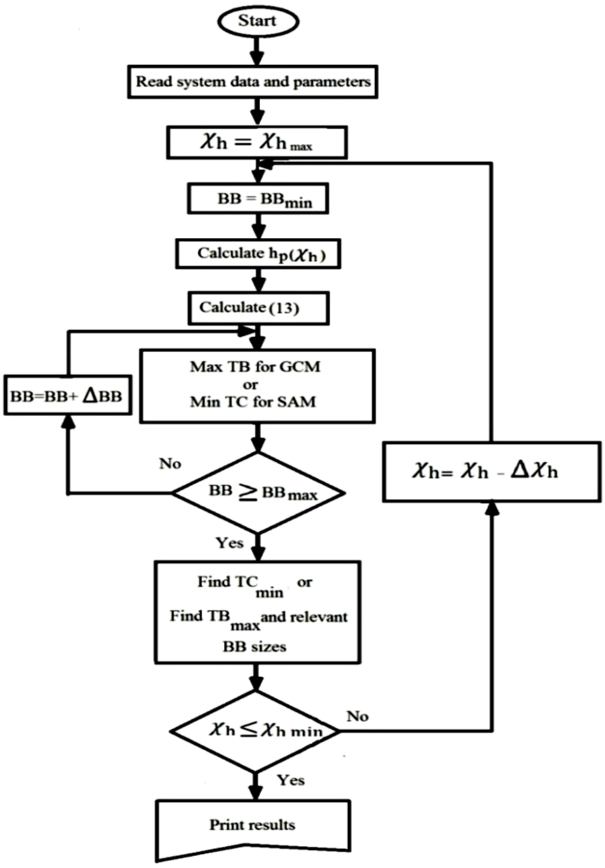
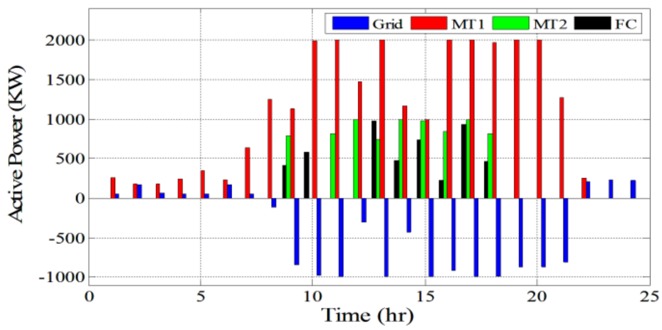
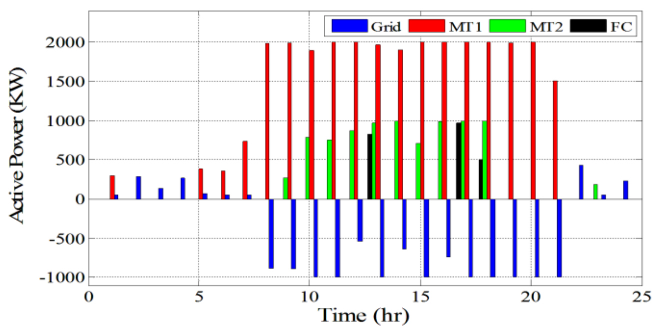


Fig. 2.The flowchart of the proposed problem.

It can be seen that as much as power supply conditions in MG become stricter, the best size of BB needs to be larger. It is seen that by installing the best BB, MG gains more benefit than when BB is not installed; $1473 for 400kWh, $937 for 800kWh and $706 for 1100kWh batteries.



(a)



(b)

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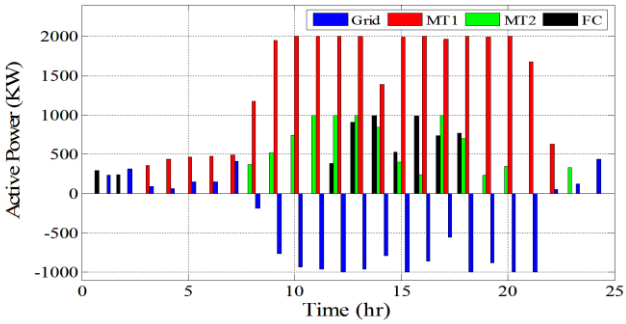

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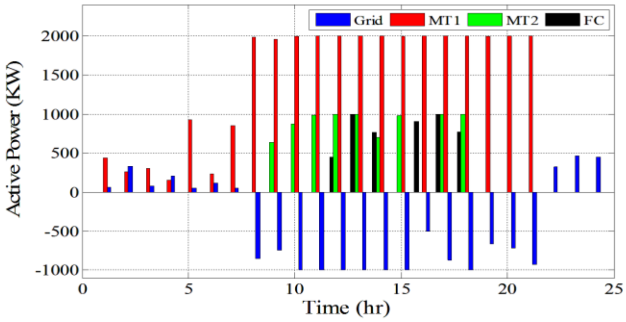

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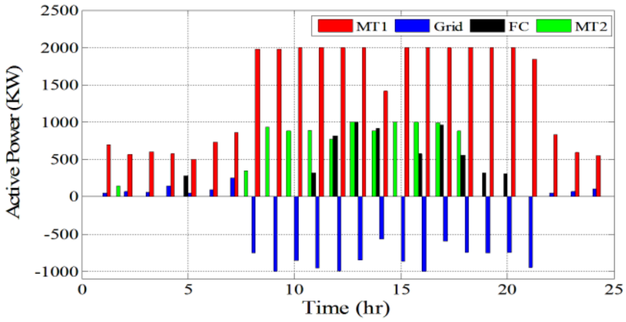
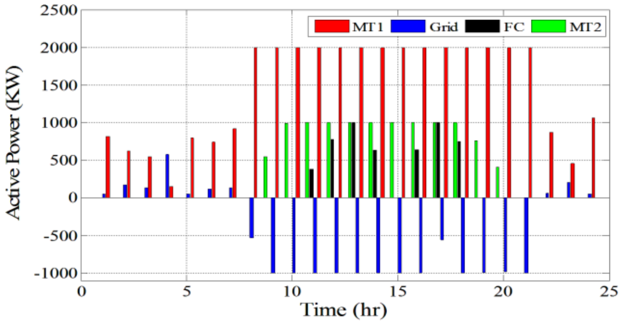


(e)



(f)

Fig. 3.Unit commitment for (a) χ_h= 0.5, No BB; (b) χ_h= 0.5, BB= 400; (c) χ_h = 0.4, No BB; (d) χ_h= 0.4, BB= 800, (e) χ_h= 0.3, No BB; (f) χ_h= 0.3, BB = 1100.

Therefore, these quantitative results declare that the value of TB is entirely different when an optimal BB is used in MG. Indeed, TB increases by 33.97 % for χ_h = 0.5, 21.95 % for χ_h = 0.4 and 18.22 % for χ_h = 0.3, respectively.

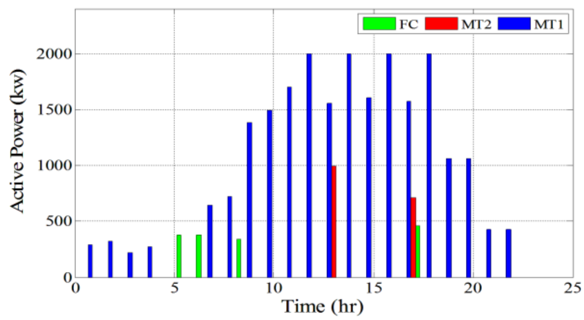
The output active power of DGs and the main gird are shown in Figs.3 (a) to (f). In these figures, it is shown that grid-connected MG can buy power from the main grid during the low price period and sell power to the main grid during the high price period. This is true for both MGs; without BB and with optimal sizes of BB. DGs can be shut down during some hours to save cost under the same system constraints.

The fuel cell is shut down in the 9th, 10th, 14th, 15th and16th hour when 400kWh BB is installed in the MG. Because of low price in the first six hours, DGs produce low active power and in the8th hour they produce high active power lightly and sell to main grid.

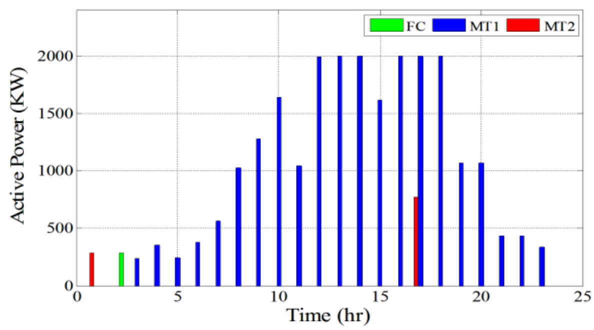
Case 2: *Stand Alone Mode*

In SAM, the aim is to minimize TC. By leading MG towards stricter conditions (i.e. from χ_h = 0.5 to 0.3) TC and the best size of BBs increases. Hence, the best size of BB can be found at 1400 kWh for χ_h = 0.5, 1500 kWh for χ_h = 0.4 and 1600kWh for χ_h = 0.3. Thus, TC would be minimum with values of \$7252, \$7893 and \$9256 for χ_h= 0.5, 0.4 and 0.3, respectively. TCs are \$7497, \$8906 and \$9747 for χ_h= 0.5, 0.4 and 0.3 without installation of BBs. It is seen, with installing an optimal BB, MG gains more benefit than when BB is not installed; \$245 for 1400kWh, \$1013 for 1500kWh and \$ 491 for 1100kWh batteries. The outputs of DGs in both operating modes of MG are shown in Figs. 4 (a) to (f). Therefore, these quantitative results declare that the value of TC is entirely different when an optimal BB is used in MG. Indeed, TC decreases by 3.4 %, 12.8 % and 5.5% for χ_h= 0.5, 0.4 and 0.3 respectively. DGs can be shut down during some hours to save cost under the same system constraints. This is true in both operating modes.

The FC is shut down in the 5th, 6th, 7th, and17th, hour when1400Kwh BB is installed in the MG, and also the FC is



(a)



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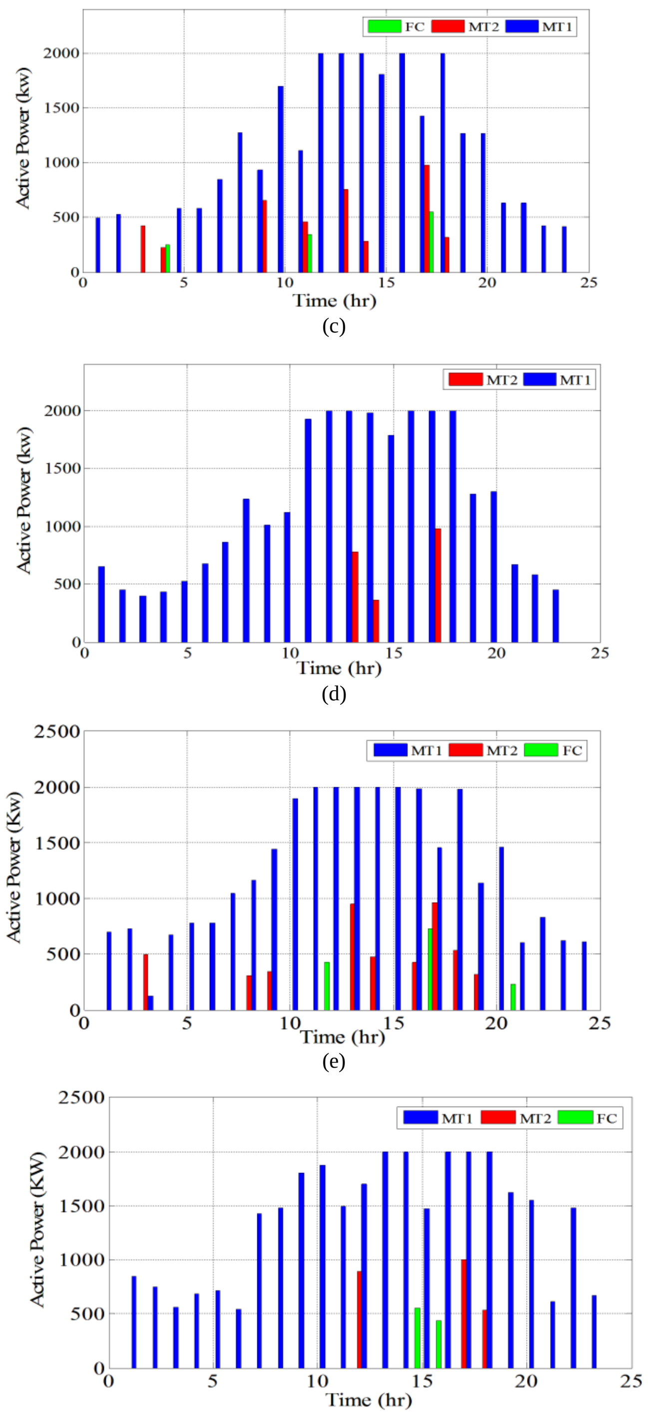

Fig. 4.Unit commitment for (a) χ_h=0.5, No BB; (b) χ_h=0.5, BB= 1400; (c) χ_h= 0.4, No BB; (d) χ_h= 0.4, BB= 1500, (e) χ_h= 0.3, No BB; (f)χ_h= 0.3, BB=1600.

shut down in the 4th, 6th, 7th, 11th, and 17th, hour when 1500Kwh BB is installed. In the first six hours, DGs produce low active power and in the 8th hour they produce high active power. Between 8th hour and 21th hour DGs produce high active power and BB is charged.

Tables III and IV and Fig. 5 show the values of TC and TB for SAM and GCM with different χ_h respectively.

In short, taking all aforementioned simulation results into account, it can be observed that by increasing parameter χ_h the parameter h_p will increase, which leads to an increase in total active power reserve of dispatchable DGs (see equation (13)). This means that insufficiency of supply which comes from wind power supply can be compensated by increasing generated active power of DGs. Then, the best size of BBs will also decrease to provide less total cost in SAM and more total benefit in GCM. The proposed algorithm has been implemented using MATLAB 7.10 and executed on a core i5 with 4 GB of memory.

V. CONCLUSION

The problem of UC and the stochastic effect of wind power can be solved using HN approach and cost-benefit analysis to determine the best size of batteries. Regarding stochastic behavior of wind power in MGs, the scheduling of DGs is done based on the maximization of MG's total benefit for GCM and minimization of MG's total cost for SAM. When MG's tolerance threshold (i.e. χ_h) changes, the maximumvalues of the total benefit and the minimum value of total cost vary while different optimal sizes for batteries are found. Also, without any batteries, total benefit/cost of MGs is less/more than that with optimal battery banks obtained by proposed approach.

In this paper, simulation results show that battery banks can increase the TB and decrease TC in the presence of stochastic DGs like WTs and PVs. Despite the fact that simulation results are case dependent, assessed cases in this paper will provide beneficial framework that can be served as useful references for other potential cases.

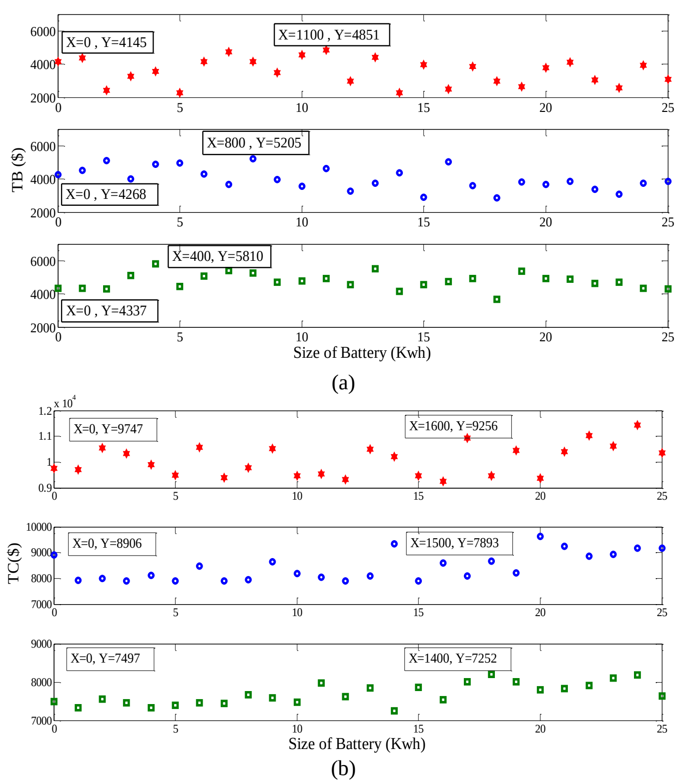

Fig.5.Total benefit (a) and total cost (b) in one day of different size of BBs with different χ_h =0.3 (red), 0.4 (blue) and 0.5 (green).

TABLE III: ALL OF SCENARIOS FOR SAM

Scenario	SAM	χ_h	TC ($)
1	With BB (1600 Kwh)	0.3	9256
2	Without BB	0.3	9747
3	With BB (1500 kwh)	0.4	7893
4	Without BB	0.4	8906
5	With BB (1400 kwh)	0.5	7252
6	Without BB	0.5	7497

TABLE IV: ALL OF SCENARIOS FOR GCM

Scenario	GCM	χ_h	TB ($)
7	With BB (1100 Kwh)	0.3	4851
8	Without BB	0.3	4145
9	With BB (800 kwh)	0.4	5205
10	Without BB	0.4	4268
11	With BB (400 kwh)	0.5	5810
12	Without BB	0.5	4337

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