Optimal Energy Procurement Scheme of a DC Microgrid with Demand Response Participation

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Abstract. This paper deals with an optimal energy procurement strategy in a DC microgrid. The DC microgrid comprises renewable sources, storage systems, and demand response participators, who are players in the electricity market. The DC microgrid operator considers bids from all the market players and pursues an optimal energy procurement scheme for the DCMG. The objective is to maximize the financial benefit. Uncertainties of electrical load demand, renewable generation, and energy price of grid is incorporated through Hong's point estimate. A nested optimization problem is solved to realize the desired objective. Discrete dynamic programming is used to solve the problem of storage scheduling and optimal demand response participation. The procurement from renewable sources is determined using the particle swarm optimization method. Simulation studies on a six-bus DC microgrid test system reveal that the daily expected profit can be increased by ~31.62% using the proposed energy management scheme.

Keywords: DC Microgrid · Energy Management · Demand Response · Uncertainty modeling

1 Introduction

Increasing power requirements and climate degradation have stimulated the growth of alternative energy generation and storage options to reduce fuel consumption, operating cost, and greenhouse gas emission [1]. Utilization of small generation sources close to the customer site at the distribution level, known as distributed generation (DG), has become an attractive option for catering to the growing load demand. A microgrid (MG) comprises multiple DG units, a battery energy storage system (BESS), and controllable loads, controlled in a coordinated fashion within a defined control area [1]. Many power sources, like solar photovoltaic generators (SPG), fuel cells (FC), BESS, produce dc power at the initial stage [2]. Further, many loads (laptops, data communication centres, mobile chargers, etc.) consume DC power [2]. Therefore, DC microgrid (DCMG) has been an area of research interest in recent times. DCMG is reported to have better efficiency and lower losses than an AC MG. A DCMG may comprise non-dispatchable sources like SPG, wind power generators (WPG). Also, several controllable sources like FC, biomass units, natural gas, and microturbines may be present in a DCMG. Maximum power point tracking (MPPT) is used to control non-dispatchable units for

extracting maximum power from nature. A graded control scheme has been proposed for dispatchable sources in a DCMG [3]. A decentralized voltage control method and droop control at the primary level have been proposed for autonomous load sharing among multiple dispatchable DG units in DCMG [3]. The secondary level control restores the bus voltage to nominal values, while the tertiary level controller manages the optimal operation [3]. A bi-directional grid interlinking converter (GIC), operating in droop control mode, connects the DCMG to the upstream utility system [3, 4].

Apart from various control schemes for ensuring a stable operation, some research endeavours on the optimal management of a DCMG have also been reported. Different objectives like cost and emission minimization [4, 5], stability constrained economic functioning [6], economical operation [7], operating cost and power loss reduction [8], power loss reduction [9], etc., have been studied.

This paper proposes an optimal energy procurement strategy with the integration of a demand response program (DRP), of a grid-connected DCMG. The DRP helps customers save bills and improves operational security and reliability as it reduces the forced outages that impose financial costs and inconvenience on customers. Maximization of expected daily profit is the main objective. The uncertainties of non-dispatchable generation, electrical load demand, and price related to grid energy are modeled using Hong's 2m point estimate method (PEM). Simulation studies on a six (06) bus DCMG test system is used for validating the proposed strategy. The remaining of this paper follows the following arrangement. Section 2 deals with uncertainty modeling, while Sect. 3 discusses the objectives, constraints, and solution strategy. Section 4 discusses the simulation studies. Conclusions is presented in Sect. 5.

2   Modeling of Uncertainty

Uncertainties are associated with grid energy price, non-dispatchable (solar and wind) generation, and electrical load demand. A probabilistic approach is adopted in this paper for uncertainty modeling.

2.1   Wind Power

Wind speed is modeled using "Weibull" distribution [10]:

$$F_{wind}(v_w) = \frac{k}{c}\left(\frac{v_w}{c}\right)^{k-1} exp\left[-\left(\frac{v_w}{c}\right)^k\right] \tag{1}$$

$F_{wind}(v_w)$ denotes the probability density function (pdf) of wind speed, v_w denotes the wind speed in m/s. k and c denote shape and scale factors, respectively. The following relation is used to compute the wind turbine power output [10].

$$\begin{aligned} PW &= 0 : v_w \langle v_{ci} \quad v_w \rangle v_{co} \\ PW &= av_w^3 - bPW_r : v_{ci} \le v_w \le v_{wr} \\ PW &= PW_r : Otherwise \end{aligned} \tag{2}$$

v_{ci}, v_{co}, and v_{wr} denote cut-in, cutout, and rated wind speeds (m/s), respectively. PW_r denotes the rated output power of a wind turbine. a and b coefficients are given as follows [10]:

$$a = \frac{PW_r}{v_{wr}^3 - v_{ci}^3}, \quad b = \frac{v_{ci}^3}{v_{wr}^3 - v_{ci}^3} \tag{3}$$

2.2 Solar Power

Solar irradiance is modeled using "Beta" distribution [10]:

$$F_{solar}(S) = \frac{\Gamma(\alpha + \beta)}{\Gamma(\alpha)\Gamma(\beta)}(S)^{\alpha-1}(1 - S)^{\beta-1} : \alpha, \beta > 0 \tag{4}$$

where pdf of solar irradiance is represented as $F_{solar}(S)$. S, α, β denotes solar irradiance (kW/m^2) and shape factors, respectively. Shape and scale parameters have the following relationships with the mean (μ_s) and standard deviation (σ_s) of pdf:

$$\beta = (1 - \mu_s)\left(\frac{\mu_s(1 + \mu_s)}{\sigma_s^2} - 1\right)\alpha = \frac{\mu_s\beta_s}{1 - \mu_s} \tag{5}$$

Power output (PS) of SPG is given as follows [10]:

$$PS = N * FF * V_s * I_s, \quad I_s = s[I_{sc} + K_I(T_c - 25)],$$
$$V_s = V_{oc} - K_V T_C, \quad T_C = T_A + S\left(\frac{N_{OT} - 20}{0.8}\right), \quad FF = \frac{V_{MPP}I_{MPP}}{V_{OC}I_{SC}} \tag{6}$$

The array comprises N numbers of PV modules. FF represents the fill factor. Cell, ambient, and nominal operating temperature (°C) are denoted as T_C, T_A, N_{OT}, respectively. K_I and K_V are the current (A/°C) and voltage (V/°C) temperature coefficients, respectively (values are taken from [10]). Open-circuit voltage and short-circuit current are given by V_{OC}, I_{SC}, respectively.

2.3 Electrical Load

With a mean of μ_l and a standard deviation of σ_l load is modeled using the normal distribution [10]:

$$PL \sim N(\mu_l, \sigma_l)$$
$$F_{load}(L) = \frac{1}{\sigma_l\sqrt{2\pi}}exp\left[-\frac{(L - \mu_l)^2}{2\sigma_l^2}\right] \tag{7}$$

where $F_{load}(L)$ represents pdf of load demand.

2.4 Grid Power Price

With a mean and a standard deviation of μ_{Pk} and σ_{Pk} price related to grid energy is modeled using the normal distribution [10]:

$$Pk^{grid} \sim N(\mu_{Pk}, \sigma_{Pk})$$

$$F_{price}\left(Pk^{grid}\right) = \frac{1}{\sigma_{Pk}\sqrt{2\pi}}exp\left[-\frac{\left(Pk^{grid} - \mu_{pk}\right)^2}{2\sigma_{pk}^2}\right] \tag{8}$$

where Pk^{grid} represents grid power price.

2.5 Hong PEM

Transfer of uncertainties from random input variables to output variables is done using Hong's 2m point estimate method [10]. The output ($\mathbf{Z}$) is related to the input uncertain variables (r_i, $i = 1, 2, \ldots m$) by $\mathbf{F}$ (set of equations) as given below:

$$\mathbf{Z}(l, k) = \mathbf{F}(r_1, r_2, \ldots r_l, \ldots r_m) \tag{9}$$

Based on statistical information, PEM computes the K concentrations (for 2m, K = 2). The pair, constituting the location $p_{l,k}$ and weight $w_{l,k}$, forms the kth concentration $\left(p_{l,k}, w_{l,k}\right)$ for the input random variable r_l.

The location of the kth concentration for l^{th} input random variable is given as ($\forall l \in \{1, 2, \ldots m\}, \forall k \in \{1, 2\}$):

$$p_{l,k} = \mu_{rl} + \xi_{l,k}\sigma_{rl} \tag{10}$$

The standard location is given as ($\forall l \in \{1, 2, \ldots m\}, \forall k \in \{1, 2\}$):

$$\xi_{l,k} = \frac{\lambda_{l,3}}{2} + (-1)^{3-k}\sqrt{m + \left(\frac{\lambda_{l,3}}{2}\right)^2} \tag{11}$$

The weights are given as ($\forall l \in \{1, 2, \ldots m\}, \forall k \in \{1, 2\}$):

$$w_{l,k} = \frac{1}{m}(-1)^k\frac{\xi_{l,3-k}}{\xi_l} \tag{12}$$

$$\xi_l = 2\sqrt{m + \left(\frac{\lambda_{l,3}}{2}\right)^2}$$

$$(\forall l \in \{1, 2, \ldots m\}, \forall k \in \{1, 2\}) \tag{13}$$

The coefficient of skewness of r_l is given by ($\forall l \in \{1, 2, \ldots m\}$):

$$\lambda_{l,3} = \frac{M_3(r_l)}{(\sigma_{rl})^3} \tag{14}$$

The third moment of r_l is given by ($\forall l \in \{1, 2, \ldots m\}$):

$$M_3(r_l) = \int (r_l - \mu_{rl})^3 f_{pl} dr_l \tag{15}$$

The expected value of the output variable is computed as follows:

$$E(Z_i(l, k)) = \sum_{l=1}^{m} \sum_{k=1}^{2} w_{l,k} Z_i(l, k) \tag{16}$$

3 Problem Formulation

3.1 Operating Framework

The operation of the DCMG is managed by the DCMG operator (DCMGO). Renewable generators (solar and wind), BESS, demand response (DR) participants are participators in the electricity market. The participators in the electricity market submit hourly bids. The DCMGO considers hourly bids submitted by the participators in the electricity market in conjunction with the upstream grid energy price and formulates an optimal energy procurement strategy. The energy management strategy aims to maximize the expected daily profit. Electricity is sold to local customers at a flat rate. The absolute difference in income from the sale of electricity and the expenses incurred for procuring energy from different sources constitutes the profit. Therefore, coordination among various sources is essential for maximizing profit.

3.2 Objective Function

Maximization of expected daily profit is the main objective of DCMGO, as given below:

$$\sum_{t \in \Omega_t} Ex(\rho(t)) \tag{17}$$

Expectation is denoted by Ex(.), time index by t and Ω_t denotes the time indices set. The profit (ρ) for the concentration (l, k, $l \in \{1, 2, \ldots, m\}$, $k \in \{1, 2\}$) is given as follows:

$$\rho_{l,k,t} = \psi_{l,k,t}^{P} \sum_{i \in \Omega_b} PLD_{l,k,t}^{i} - (\psi_{l,k,t}^{gp} P_{l,k,t}^{grid} + \psi_{l,k,t}^{sp} \sum_{i \in \Omega_b} PSG_{l,k,t}^{i}$$
$$+ \psi_{l,k,t}^{wp} \sum_{i \in \Omega_b} PWG_{l,k,t}^{i} - \psi_{t}^{b} \sum_{i \in \Omega_b} PB_{l,k,t}^{i} + \psi_{l,k,t}^{dr} \sum_{i \in \Omega_b} (PLD_{l,k,t}^{i,0} - PLD_{l,k,t}^{i})) \tag{18}$$

Suffixes l, k, t denotes the concentration of the lth input random variable for the kth evaluation at time t. $PLD_{l,k,t}^{i,0}/PLD_{l,k,t}^{i}$ denotes the electrical load demand at bus i before/after DR implementation. Energy drawn from grid is denoted as $P_{l,k,t}^{grid}$. $PSG_{l,k,t}^{i}/PWG_{l,k,t}^{i}$ denotes active power of SPG/WPG. Charging/Discharging power of battery is denoted as PB^i. Ω_b denotes the set of all system buses. The DCMGO sells electricity to consumers at a price of ψ^p. The price at which active power is drawn from the grid is given by ψ^{gp}. ψ^{sp}/ψ^{wp} is the bid offered for active power by SPG/WPG. ψ^b and ψ^{dr} denote bid offered by BESS and DR participants, respectively. Charging of BESS is denoted by the positive value of PB and negative denotes discharging.

3.3 Constraints

Following constraints must hold ($\forall l \in \{1, 2, \ldots, m\}$, $\forall k \in \{1, 2\}$, $\forall t \in \Omega_t$):

3.3.1 Power Balance Constraint

$$\Lambda^i P_{l,k,t}^{grid} + PSG_{l,k,t}^i + PWG_{l,k,t}^i - PB^i - PLD_{l,k,t}^i$$
$$= V_{l,k,t}^i \sum_{j \in \Omega_b} Y^{ij} V_{l,k,t}^j \quad \forall i \tag{19}$$

$\Lambda^i = 1$, if the GIC is present at bus i. Otherwise, $\Lambda^i = 0$.

3.3.2 GIC Droop Characteristic

The current injected by the GIC connected to bus i follows a droop characteristic as given below [4–6] ($\forall l \in \{1, 2, \ldots, m\}$, $\forall k \in \{1, 2\}$, $\forall t \in \Omega_t$):

$$I_{l,k,t}^i = \frac{V^{ref} - V_{l,k,t}^i}{Rd_i} \tag{20}$$

The grid injected power by the GIC at bus i is given by:

$$P_{l,k,t}^{grid} = \frac{V^{ref} - V_{l,k,t}^i}{Rd_i} V_{l,k,t}^i \tag{21}$$

3.3.3 Voltage Limits on Bus

The bus voltages ($\forall i \in \Omega_b$) must be within allowable limits ($\forall l \in \{1, 2, \ldots, m\}$, $\forall k \in \{1, 2\}$, $\forall t \in \Omega_t$):

$$V^{min} \leq V_{l,k,t}^i \leq V^{max} \tag{22}$$

V^{min}/V^{max} is the minimum/maximum allowed value of bus voltage.

3.3.4 Line Current Limits

The line current limits ($\forall j \in \Omega_l$) must not be exceeded ($\forall l \in \{1, 2, \ldots, m\}$, $\forall k \in \{1, 2\}$, $\forall t \in \Omega_t$):

$$IL_{l,k,t}^j \leq IL_{rated}^j \tag{23}$$

$IL_{l,k,t}^j$ is the current in line j. IL_{rated}^j is the current rating of line j. Ω_l denotes the set of all lines.

3.3.5 DG Unit Power Limits

$$Ex\left(PSG_t^i\right) \le Ex\left(PSG_{avl,t}^i\right) \le PSG_{rated}^i \tag{24}$$

$$Ex\left(PWG_t^i\right) \le Ex\left(PWG_{avl,t}^i\right) \le PWG_{rated}^i \tag{25}$$

$$Ex\left(P_t^{grid}\right) \le P_{rated}^{grid} \tag{26}$$

$PSG_{avl,t}^i/PWG_{avl,t}^i$ denotes the available solar/wind energy at time t at bus i. $PSG_{rated}^i/PWG_{rated}^i$ denotes power ratings of the SPG/WPG at bus i. P_{rated}^{grid} denotes the power rating of the GIC.

3.3.6 BESS Constraints

The BESS must satisfy the following constraints:

$$EB_t = EB_{t-1} + PB_t \frac{\Delta T}{\eta_{dis}}; \quad PB^t < 0 \tag{27}$$

$$EB_t = EB_{t-1} + PB_t \, \Delta T \eta_{chg}; \quad PB^t \ge 0 \tag{28}$$

$$EB^{min} \le EB_t \le EB^{max} \tag{29}$$

$$EB_0 = EB_T \tag{30}$$

$$|PB_t| \le PB^{rated} \tag{31}$$

Discharging and charging equations are given by (27) and (28), respectively. (29) states that the energy of the BESS must lie within maximum (100% SOC) and minimum (20%) limits. (30) signifies that the battery's energy content must be the same at the beginning and the end of the day. The charging/discharging power of the BESS must be within the power rating of the BESS. EB_t is the energy of the BESS at the end of the optimization interval t. η_{chg}/η_{dis} denotes the charging/discharging efficiency. EB^{min}/EB^{max} denotes the allowed minimum/maximum energy content of the BESS. PB^{rated} is the power rating of the BESS.

3.3.7   DR Constraints

$$\sum_{t \in \Omega_t} \sum_{i \in \Omega_b} (PLD_{l,k,t}^{i,0} - PLD_{l,k,t}^i) = 0 \; \forall l, k \tag{32}$$

(32) states that loads can be shifted from one period to another, but there should be no net energy curtailment in a day due to the DRP.

3.4   Solution Approach

A nested optimization problem is solved. The BESS scheduling is solved as a master problem using the discrete dynamic programming approach (DDP) [11]. DR implementation is done using a DDP approach as a slave problem. Further, the hourly optimal renewable energy procurement strategy is also solved as a slave problem using the particle swarm optimization (PSO) technique [11]. To manage inequality constraints, a penalty function approach is utilized. The equality constraint (of power flow) is met by running the power flow subroutine. A modified Newton-Raphson power flow technique is used to incorporate the droop control feature of the GIC [4, 5].

4   Result and Discussion

4.1   Test System

The proposed method is validated on a 6-bus DC MG test system [5]. Load at different buses and line parameters are taken from [4, 5]. An SPG and a WPG, each of 25 kW, are present at bus #1 and bus #6, respectively. Cut-in, cut-out, and rated speeds of the wind turbine are 3 m/s, 25 m/s, and 12 m/s, respectively. Two BESSs, with the initial SOC of each battery as 60% and each having a capacity of 100 kWh/24 kW, are present on buses #1 and #6. Charging/discharging efficiencies are taken to be 95%. Hourly solar data, wind data are adopted from [5]. Load profile on an hourly basis is adopted from [12]. Maximum curtailment of load at any hour due to the DRP is set to 10%. The optimization problem is then solved in MATLAB 2015a software.
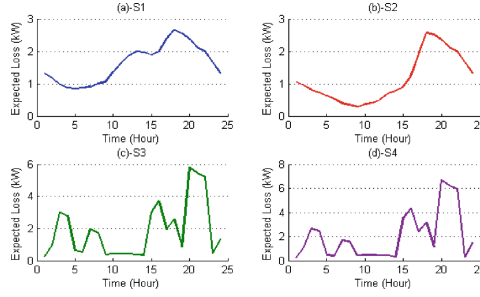
4.2   Simulation Cases and Results

Simulations are done for different scenarios. Expected profit and real power loss for different scenarios are calculated and are given in Table 1 and Fig. 1, respectively. The expected hourly real powers drawn from the grid in different scenarios are given in Fig. 2. Various scenarios are as follows:
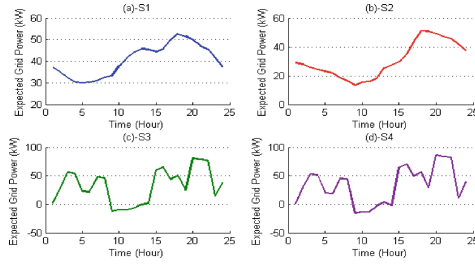
Table 1. Comparison of profit for different scenarios

Scenario	S1	S2	S3	S4
Profit ($)	46.97	52.82	59.68	61.82
% Profit w.r.t S1	-	12.45	27.06	31.62

Fig. 1. Expected hourly power loss (kW)

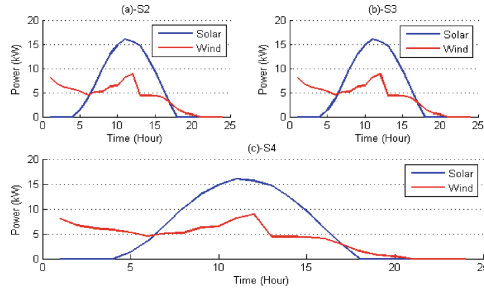**Fig. 2.** Expected hourly real power drawn from grid

Scenario #S1: This is the base case, in which renewable sources (SPG and WPG), BESS, and DR are not considered. The daily expected profit for S1 is $46.97. The expected daily real power drawn from the grid is 972.11 kWh, and the expected daily loss is 38.81 kWh. All the other scenarios are compared with S1.
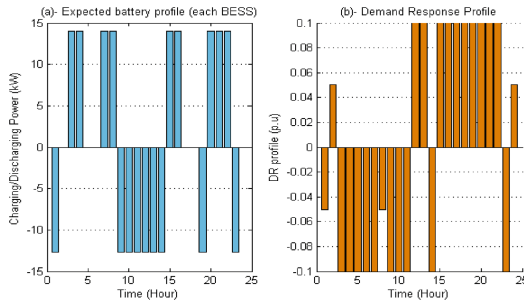
Scenario #S2: In this scenario, only renewable sources are considered while BESS and DR are not considered. The expected hourly real powers procured from SPG and WPG are given in Fig. 3(a). The daily expected real power drawn from the grid is 734.12 kWh, and the daily expected loss is 27.13 kWh. The expected daily profit is $52.82 (12.45% higher than S1).

Scenario #S3: In this scenario, renewable sources and BESS are considered, while DR is not considered. The expected hourly battery profile is given in Fig. 4(a), in which charging is denoted by positive value and discharging by negative value. The expected hourly real powers procured from SPG and WPG are given in Fig. 3(b). The daily expected real power drawn from the grid is 776.29 kWh, and the daily expected loss is 44.65 kWh. The expected daily profit is $59.68 (27.06% higher than S1).

Scenario #S4: In this scenario, renewable sources, BESS, and DR are considered. The expected DR profile is given in Fig. 4(b). The expected hourly real power generated from SPG and WPG are given in Fig. 3(c). The daily expected real power drawn from the grid is 791.64 kWh, and the daily expected loss is 48.52 kWh. The expected daily profit is $61.82 (31.62% higher than S1).

Fig. 3. Expected hourly real power generated from solar and wind.

Fig. 4. Expected BESS and DR profile

5   Conclusions

This paper proposes an energy management scheme for a DCMG comprising SPG, WPG, BESS, and DR participants. SPG, WPG, BESS, and DR participants are independent entities participating in the electricity market. The DCMGO uses an optimal energy procurement scheme for a financially viable system operation. Hong's point estimate method incorporates uncertainties of electrical load demand, price related to grid power, and renewable generation into the optimization problem. The optimization problem is then solved using the PSO technique for a modified six bus DCMG. Simulation results are then framed for different scenarios, which indicates that with the incorporation of only renewable generation, the percentage profit is 12.45%. Further addition of BESS (using DDP) into the system improves the profit by 27.06%. Incorporating DR and BESS into the system improves percentage profit by 31.62%. Thus, the proposed energy management methodology effectively maximizes the profit of a DCMG.

Authors' Contributions.   Abhishek Singh: Simulation, Writing. Avirup Maulik: Conceptualization, Simulation, Writing.

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