

Optimal Economic Operation and Battery Sizing for Microgrid Energy Management Systems Considering Demand Response

Mehdi Mohammadjafari¹, Reza Ebrahimi^{1,*},Vahid Parvin Darabad²

¹ Department of Electrical Engineering, Gorgan Branch, Islamic Azad University, Gorgan, Iran, ² Department of Electrical Engineering, Faculty of Engineering, Golestan University, Gorgan, Iran [m.mohammadjafari@gorganiau.ac.ir,](mailto:m.mohammadjafari@gorganiau.ac.ir) [r.ebrahimi@gorganiau.ac.ir,](mailto:r.ebrahimi@gorganiau.ac.ir) v.parvin@gu.ac.ir

Abstract

Microgrids (MGs) contain a diverse mix of energy resources to provide safe and secure power to the consumers. Batteries are utilized in MGs for further energy security assurance as well as cost minimization. In this paper, an efficient approach is introduced for simultaneous energy management and optimal battery sizing to accomplish economic MG operation. Also, demand response programs are employed to further reduce MG operation costs (OCs) and strike a balance between supply and demand. The objectives sought in this context are the optimal values for DG generation levels, level of consumer participation and the respective incentive payments, battery charge and discharge levels and the amount of power exchange with upstream network within a 24-hour scheduling cycle so as to minimize OCs and maximize MG operator's (MGO) profit as a result of demand response. In order to address the hybrid energy management system (EMS) and battery sizing problem, the proposed model is solved using whale optimization algorithm (WOA) in MATLAB software for a grid-connected MG. The results indicate that battery charge and discharge is significantly lowered through optimal battery sizing incorporated into the proposed approach.

Keywords: Microgrid, Energy management system, Battery sizing, Demand response Article history: Received 05-July-2020; Revised 05-July-2020; Accepted 03-September-2020. © 2019 IAUCTB-IJSEE Science. All rights reserved

1. Introduction

Currently, distribution grids are undergoing substantial change due to increasing MGs. Characterized by high flexibility and autonomous operation, MGs improve the economic operation, reliability and environmental conditions. MGs provide a controllable infrastructure for integration of distributed energy resources (DERs) such as wind turbines (WT), photovoltaic generation (PV) and energy storage systems (ESS) into the main grid [1]. When MGs comprise several resources, their operators need an efficient control strategy for their stable and economic operation.

Through resource data processing and power exchange planning, EMS can guarantee stable energy supply for the consumer and economic operation for MG [2]. Therefore, different optimization techniques and planning strategies are

considered to yield the best efficiency when incorporated into EMS schemes. These include game theory techniques [3], Mixed integer linear programming (MILP) [4] and Mixed Integer Nonlinear Programming [5]. In case of large-scale nonlinear problems, optimization techniques such as SIPSO [6] and Gravitational Search Algorithm [7] yield better energy management results. Some research works have also drawn comparisons between Genetic Algorithm (GA), Simulated Annealing (SA), Coco Search Algorithm (CSA), Particle Swarm Optimization (PSO) and Internal Search Algorithm (ISA) as applied to EMS, though not considering batteries [8].

Demand response (DR) is an efficient tool to achieve optimal energy management and increased efficiency of energy grids [9]. Recently, several research works have been dedicated to improved DR implementation and their role in balancing the energy supply and demand when DERs are used as energy resources. This can bring several operational and economic benefits for MGs [10]. The combined EMS-DR approach is a powerful tool for MG economic optimization. The combined EMS-DR planning model has been solved using GA [11], WOA [12], Differential Evolution (DE) and modified PSO (MPSO) [13] leading to improved EMS application within MGs. However, ESS, despite being utilized in the studies, have not been addressed in adequate detail.

PV and WT integration in the MG leads to lower costs and emissions. However, their operational limitations pose different challenges to the operators. These challenges can be partly overcome by utilizing batteries. Thus, renewable energy resources (RESs) and ESS are utilized and modeled simultaneously within MGs [14]. Among different storage technologies, battery energy storage systems (BESSs) are more attractive thanks to their high power and energy density [15]. These technical advantages along with fast energy transfer capabilities, makes batteries a highly viable solution for MG as well as power system applications. A thorough comparison is carried out in [16] between different battery technologies and their application. Economic energy planning combined with optimal battery sizing is an interesting problem for small towns, villages and MGs. Battery storage performance and planning within MGs has gained significant research interest but its optimal sizing to achieve an economic grid is still underway. Different approaches and techniques have been introduced for determining optimal battery size [17- 20]. Also, based on the planning and operational objectives, some researches may exclude the batteries' capital costs and installation costs [21, 22].

Economic operation has a high priority in MG planning and operation and therefore has turned into a major research area. Accordingly, optimal EMS scheme is studied for both supply and demand sides. In the demand side, DR is also included in the studies leading to EMS-DR program within MGs. However, few researchers have considered battery capacity sizing along with EMS-DR. This unexplored area can provide further advantages in economic operation of MGs. In this paper, optimal battery sizing problem is considered besides EMS-DR in order to minimize the OCs. In addition, optimal battery size can increase the longevity of energy storage system. In fact, simultaneous optimization of EMS-DR and battery storage size is crucial for minimizing total OCs. The approach considered in this paper attempts, in the first place, to approximate an optimal size for batteries and then

achieves an exact battery sizing. Given the obtained exact optimal battery size, EMS-DR problem is then solved for minimum OC and maximized MGO profit using WOA technique.

The paper sections are organized as follows. In section 2, the mathematical model of the considered problem is presented and in section 3, the WOA technique is explained as the solution algorithm. Numerical results and their validation for optimal MG operation are demonstrated in section 4 and, finally, section 5 draws the conclusions.

2. Problem Modeling

The MG model considered in this study encompasses controllable loads, DGs, RESs (PV and WT) as well as batteries connected to the utility grid. Obviously, all elements should be individually modeled along with their respective technical characteristics and constraints. Generation and DR model along with the objective functions and related constraints are given in sections 2.1 to 2.4, respectively.

A) Generation model

DG generation cost is represented by a secondorder function as (1) [23]:

$$
CF_{i,t} = a_i (P_{i,t})^2 + b_i P_{i,t}
$$
 (1)

Where a_i and b_i are fuel cost coefficients, $P_{i,t}$ is the generated power by DGs, and $CF_{i,t}$ is the fuel cost in \$.

Based on the available resources and the energy prices, the MGO can decide whether to sell / buy energy to / from the utility grid. The exchanged power with the grid for each hourly interval is expressed as (2):

$$
P_{utility,t} = \sum_{t=1}^{T} (P_{b,t} b_t^{u} - P_{s,t} (1 - b_t^{u})) \quad : \quad b_t^{u} \in [0,1]
$$
 (2)

Where $P_{b,t}$ and $P_{s,t}$ are, respectively, the purchased and sold power from/to the utility grid. $P_{utility, t}$ is the amount of power exchanged with the utility grid and b_t^u is a binary variable indicating whether the MG sells or buys energy to/from the grid at each interval. Positive exchange with the grid denote the sale and purchase of energy by the MG, respectively.

The cost of power exchange with the utility grid is obtained by (3):

$$
CU_t = \sum_{t=1}^{T} (\gamma_{b,t} P_{b,t} b_t^{u} - \gamma_{s,t} P_{s,t} (1 - b_t^{u})) : b_t^{u} \in [0,1]
$$
 (3)

Where $\gamma_{b,t}$ is the buying price and $\gamma_{s,t}$ is the selling price of energy by the MG. CU_t is the cost of power exchange with the utility grid which can be positive or negative based on the sold or purchased power by the MG. Also, the output power of the battery as another generation resource is formulated as (4):

$$
P_{batt,t} = \sum_{t=1}^{T} \left(P_{dist} b_t^{batt} - P_{ch,t} \left(1 - b_t^{batt} \right) \right) : b_t^{bat} \in [0,1]
$$
 (4)

Where $P_{dis,t}$ and $P_{ch,t}$ are the discharge and charging power of the battery. b_t^{batt} is the indication variable to distinguish between charge and discharge mode of the battery for each interval. $P_{batt,t}$ represents the battery power and when positive (negative), indicates a discharge (charge) by the battery. Taking into account the battery capital cost, the total cost of utilizing the battery at hour t is obtained by (5):

$$
CB_t = \sum_{t=1}^{T} C_{ope} \cdot \left(P_{dist} b_t^{batt} - P_{ch,t} (1 - b_t^{batt}) \right) + TCPD
$$

$$
\vdots \quad b_t^{bat} \in [0,1]
$$
 (5)

$$
TCPD = \frac{1}{365} \left(\frac{r \cdot (1+r)^{Lt}}{(1+r)^{Lt} - 1} \right) \cdot C_{cap} \cdot C_{batt}
$$
 (6)

Where C_{ope} denotes the cost of battery operation in both charge and discharge modes, r is the interest rate for the battery's capital cost, Lt is the battery lifetime, C_{cap} is the battery capital cost, C_{batt} is the battery capacity, TCPD is battery's total cost per day and CB_t is the resulting total battery cost.

The first and second terms in (5) represent the battery operation and financing costs, respectively. In our proposed approach, the optimal size of the battery is obtained by minimizing the total OC of the MG. The optimal battery sizing also takes account of the related constraints as outlined later.

B) Demand response model

Electricity consumers gain income out of DR incentives and endure costs of reduced power. Thus, their benefit can be expressed by (7):

$$
BC_{j,t} = RC_{j,t} - CC_{j,t} \tag{7}
$$

Where $BC_{j,t}$ is the customers' benefit function, $RC_{j,t}$ is the incentive payment they receive and $CC_{j,t}$ is their cost functions corresponding to their dissatisfaction with the reduced power. Thus, it would be rational for the consumers to participate in DR program when $BC_{i,t} \geq 0$ which guarantees the minimum benefits for consumers.

The consumers' cost function is a second-order function as (8) [12]:

$$
CC_{j,t} = k_{1,j} PC_{j,t}^2 + k_{2,j} PC_{j,t} - k_{2,j} PC_{j,t} \theta_{j,t}
$$
\n(8)

Where $k_{2,j}$, $k_{1,j}$ are both the coefficients of the cost function. $PC_{j,t}$ is the amount of reduced power and $\theta_{j,t}$ represents the level of customer dissatisfaction ranging from 0 to 1.

Accordingly, the MGO's benefit function to be maximized is given by (9) [24]:

$$
max\,BU = \sum_{t=1}^{T} \sum_{j=1}^{J} (\lambda_{j,t} PC_{j,t} - RC_{j,t})
$$
\n(9)

Where BU is the MGO's benefit function and $\lambda_{j,t}$ is the cost of not supplying power to a customer. In some circumstances, power transfer to distant regions and loads becomes costly for the MGO. This is defined as the "value of power interruptibility". In (9), the first term is the MGO's revenue from not supplying power to a particular customer $(PC_{j,t})$. The second term is the MGO's cost paid in the form of incentives to the customers.

The supply-demand balance may not be reached even after incorporating DR programs and customer load reduction $(PC_{j,t}^{pro})$. For these cases it is proposed to impose mandatory curtailments $(PC_{j,t}^{mand})$ accompanied by much higher incentive payments. Thus, the customers will gain higher revenues in peak periods in exchange for power reductions beyond $PC_{j,t}^{pro}$. The curtailment in excess of $PC_{j,t}^{pro}$ is formulated as (10) [12]: ${P}{C_{j,t}}^{mand}$

$$
= \begin{cases} \sum_{j=1}^{J} \sum_{t=1}^{T} (PC_{j,t}^{opt} - PC_{j,t}^{pre}) : & if (PC_{j,t}^{opt} > PC_{j,t}^{pre}) \\ 0 & : if (PC_{j,t}^{opt} \le PC_{j,t}^{pre}) \end{cases}
$$
(10)

Where $PC_{j,t}^{opt}$ is the optimal power reduction of the customers. The paid penalty to the customers related to $PC_{j,t}^{mand}$ is expressed as (11):

$$
CCM_{j,t} = \begin{cases} \mu \ CC_{j,t} (PC_{j,t}^{meand}) : & if \ (PC_{j,t}^{opt} > PC_{j,t}^{pro}) \\ 0 & : if \ (PC_{j,t}^{opt} \le PC_{j,t}^{pro}) \end{cases}
$$
 (11)

Where μ is the penalty payment coefficient and $CCM_{j,t}$ is the incentive payment for mandatory power curtailment.

C) Object functions

Generally a fair and rational interaction is expected to be established between generation and DR within a MG. EMS and optimal economic operation is therefore employed to achieve this goal. The first objective function aims at minimizing the OC of generation sources within the MG as in (12):

$$
F_1 = \sum_{t=1}^T \left(\sum_{i=1}^t CF_{i,t} + CU_t + CB_t \right)
$$
 (12)

The second objective function tries to maximize the MGO's benefit from DR. Since the

(20)

overall objective function is a minimization problem, (9) is made negative as in (13):

$$
F_2 = \sum_{t=1}^{T} \sum_{j=1}^{J} \left(RC_{j,t} - \lambda_{j,t} PC_{j,t}^{opt} \right)
$$
 (13)

Both F_1 and F_2 objective functions are expressed in \$ but different weight factors are used in accordance with the objectives of the proposed model. Thus, using different weighting factors, the two objective functions are transformed into a single-objective function to be minimized, as (14):

$$
\min \, cost = w_1 \left(F_1 \right) + w_2 \left(F_2 \right) \tag{14}
$$

Where w_1 and w_2 are the weighting factors the sum of which is equal to unity. More often, however, they are taken equal to balance between different objectives.

D) Constraints

Different technical constraints encountered in MG operation are presented in this section. At each time interval, the total amount of non-renewable and renewable generation and the power exchange with the upstream grid as well as the battery power should equal the load demand. Otherwise, the customers implement the power reduction schemes. The loadgeneration balance constraint is expressed as (15):

$$
\sum_{i=1}^{I} P_{i,t} + P_{wind,t} + P_{pv,t} + P_{utility,t} + P_{batt,t}
$$
\n
$$
= P_{demand,t} - \sum_{j=1}^{I} PC_{j,t}^{opt}
$$
\n(15)

All generation resources should be operated within their allowable limits as (16): $DER_x^{min} \le DER_{x,t} \le DER_x^{max}$

$$
\Delta \Sigma_{\mathcal{L}} \Sigma_{\mathcal{L}} \Sigma_{\mathcal{L}} \Sigma_{\mathcal{L}} \Sigma_{\mathcal{L}} \tag{16}
$$

Where DER_x^{max} and DER_x^{min} are the maximum and minimum allowable generation limits for resource x, respectively.

For simultaneous EMS and battery sizing problem, the battery constraints should be taken into account. The battery charge should not fall below a specified level. Thus the battery state of charge (SOC) at each interval is expressed by (17) and (18) [25]:

$$
charge: SOC_{t+1} = SOC_t \cdot (1 - \xi \cdot \Delta t) + \frac{\eta_{ch} \times P_{ch,t} b_t^{batt}}{C_{batt}} \tag{17}
$$

$$
Discharge: SOC_{t+1} = SOC_t \cdot (1 - \xi \cdot \Delta t) - \frac{P_{dist}(1 - b_t^{batt})}{C_{batt} \times \eta_{dis}}
$$
(18)

Where η_{ch} and η_{dis} are the charge and discharge efficiencies, respectively. C_{batt} is the battery capacity and ξ is the battery self-discharge parameter. ξ is used in this paper for a more realistic modeling of the battery to help further reduce the overall cost.

The battery SOC limitation is expressed by (19) :

$$
SOC^{min} \leq SOC_t \leq SOC^{max} \tag{19}
$$

Equation (19) impacts the selection of minimum and maximum battery energy. Also, at each interval the battery can be charged or discharged with a certain min/max power rate, as given in (20):

 $p_{batt}^{min} \leq p_{batt,t} \leq p_{batt}^{max}$

Where p_{batt}^{max} and p_{batt}^{min} are the maximum charge and discharge level of the battery with the following conditions:

If:

 $p_{bat,t} > 0$, the battery is discharging; $p_{batt,t}$ < 0, the battery is charging; $p_{batt,t} = 0$, the battery is inactive.

3. Whale Optimization Algorithm

WOA is a nature-inspired metaheuristic algorithm imitating the humpback whale hunting strategy. Using a special hunting method called bubble-net approach, whales search for and surround their prey through creating bubbles in a spiral form (similar to digit 9). The activities of initial whale population are mainly divided into two tasks: One group is deployed for exploration of the prey while the second group tries to hunt (exploit) the detected prey. Through mathematical modeling of these two phases, an optimal value can be obtained. Further details are explained in [26].

Using the WOA technique, an overview of the EMS model can be achieved as shown in Fig. 1. Using the input data, the multi-objective function is converted into a single-objective function and the battery sizing task can be accomplished. Due to the nonlinearity of simultaneous EMS and battery sizing problem, the optimization task is performed by WOA method in MATLAB software on an example MG.

4. Simulation results

This section presents simulation results and analysis for the proposed approach on a MG with controllable loads. A large scale MG with large consumers (equivalent to aggregated loads) is studied which consists of 10 DG units and a WT unit, one PV unit, one battery set and seven customers.

EISSN: 2345-6221

Fig. 1. Proposed flowchart for simultaneous EMS and battery sizing optimization problem

WT and PV data are taken from [27] and their OCs are assumed zero. Maximum power rating for PV and WT are 150MW and 165MW, respectively. DG units are always on and no startup costs are considered for them. Also, DG cost function coefficients are taken from [24].

Maximum traded power between MG and the main grid is assumed 150 MW and the MGO's daily budget is taken as \$150000. It is assumed that the MGO knows the customers' cost function coefficients $(k_{1,j}$ a $k_{2,j})$. The MGO has also received the hourly energy reduction bids from the customers ($PC_{j,t}^{pro}$) to derive the customer priority $(\theta_{i,t})$. This way, a more accurate DRP can be implemented and realistic incentives can be paid [12]. The hourly values of power interruptibility for the seven customers are adopted from [24]. All customers have bid their highest offer for t=21. In order to determine the incentive payments for $PC_{j,t}^{mand}$, the value of μ is calculated based on the mutual contracts between MGO and the customers which is assumed 2 have. The total daily demand of the MG is 40911MWh and two peak periods, namely during hours 12 and 20 occur [24].

MGs as well as power systems may utilize a big battery set with high capacity [28]. Therefore, in this paper a single large battery set is considered. Battery-related parameters are given in Table 1. The battery is assumed to charge/discharge within two hours.

Simultaneous EMS and battery sizing is a complex optimization problem for which WOA technique is employed. The output of WOA should determine the most economical power supply conditions alongside the optimal battery size. Parameters in WOA are randomly initialized. The number of search agents is considered 200 with a maximum iteration of 500. Given the MG scale, the maximum and minimum battery capacity is assumed as known, meaning that the search space of WOA is predetermined. The whales are randomly initialized within the search space. Through the evaluation of objective functions for each whale, the best results are updated. This process is maintained until the stopping criterion, i.e. maximum number of iterations, is reached.

Fig. 2. Optimal value of energy capacity using MG OC for different battery sizes.

The trade-off approach can also approximate the battery capacity [17]. Fig. 2 illustrates the optimal battery sizing using the MG OC minimization. The range of optimum battery capacity is determined by the trade-off method. Considering the MG scale, the battery sizing is initially carried out for a capacity of 10 to 200 MWh. Based on the trade-off method this is narrowed to 145-175MWh (see Fig. 2). Selection of a higher or lower battery capacity range will incur extra OCs though the MGO may be willing to consider that option as well. Using very large battery capacity is counter-intuitively not desirable in all cases. In very high capacities, abrupt charge and discharge of the

battery may result in higher OCs. Therefore an optimum point should be sought for the battery capacity in MGs as well as for other power networks.

Table 2 presents a comparison of the resulted battery capacity using trade-off method versus the proposed sizing approach. As mentioned, using the trade-off method, the optimal range of the battery capacity was obtained between 145 and 175 MWh. Considering initial SOCs of 30%, 60% and 90%, the trade-off method yields optimal capacities of 170, 160 and 150 MWh, respectively. Although fairly acceptable, the results can be more exactly and optimally determined using the proposed sizing method. Using the proposed method, optimal capacities of 165.29, 154.02 and 149.75 MWh are obtained for initial SOC levels of 30%, 60% and 90%, respectively.

Table.2. Optimal operation results for different scenarios

Without battery	With battery						
		Trade-off method			Proposed sizing method		
		Initial	<i>Initial</i>	<i>Initial</i>	Initial	<i>Initial</i>	<i>Initial</i>
		$SOC = 30\%$	$SOC=60\%$	$SOC=90%$	$SOC=30\%$	$SOC = 60\%$	$SOC=90\%$
Battery sizing (MWh)		170.00	160.00	150.00	165.29	154.02	149.75
Fuel cost (S)	770060	765920	764800	764450	766900	765780	765540
Trade cost (\$)	115340	109960	109870	107570	106830	107010	107170
OC of Battery $(\$)$	Ω	2064	1740	1442	2006	1675	1440
Customers Incentive (\$)	96215	102930	102380	104560	103920	103040	99363
Mandatory Curtailment (MWh)	281.79	563.92	576.56	574.73	572.79	570.43	558.42
Normal Curtailment (MWh)	2657.00	2667.20	2638.90	2680	2678.60	2660.80	2601.00
Diesel Generation (MWh)	35501	35337	35285	35265	35377	35326	35313
Trade with utility grid (MWh)	3098.00	3036.90	3040.10	2988.10	2975.90	2974.20	2975.60
Total OC of MG (\$)	426902	422226	421256	419879	420809	420063	419320
TCPD(S)	-	3485	3280	3075	3388	3157	3070
$OC+TCPD(S)$		425711	424536	422954	424197	423220	422389

Besides the optimal battery capacity, Table 2 also includes the MG economic operation conditions. As observed, the proposed sizing method delivers the lowest OC through determining the most optimal battery capacity. Considering different scenarios, it is realized that without the battery, DG generation level as well as power exchange with the grid are increased. The power import from the upstream to cover the demand leads to higher OCs. Also, when using the battery, the stress on the utility grid DGs is reduced and higher DR contributions are achieved. This is due to the higher flexibility offered by the batteries which helps with the realization of a smart planning scheme for critical periods and further cost reductions.

In the simulations, similar weights are allocated by the operator to each objective term. By adopting this policy, the objective functions are treated in a fair and rational manner. Thus, the planned operation scheme encompassing the optimal levels for the generation of each DER, BESS charge and discharge, exchange power with the utility grid, and $PC_{j,t}^{opt}$ is obtained. It is highly recommended to start the operation cycle with a high initial SOC so as to significantly reduce the MGs OCs. However, this may be impossible in some cases. Therefore, here the worst case results, corresponding to the lowest initial SOC $(=30\%)$, are presented.

Fig. 3. Output power from the DERs, DR and total demand (Proposed sizing method with initial SOC=30%).

Fig. 3 demonstrates the optimal level of RES generation, battery charge/discharge, power exchange with the utility grid, sum of DG generated powers, optimal power reduction by customers and the total demand. The optimal power reduction by customers $(PC_{j,t}^{opt})$ is the sum of $PC_{j,t}^{norm}$ and $PC_{j,t}^{mand}$ indicating the DR level of the MG. Power purchase from the utility grid is mainly carried out at peak periods, in particular at 12 and 20. Due to lower power consumption during hours 22 to 9 AM as well as from 14 to 19, the excess power is sold to the utility grid. The battery is charged during early hours so as to be available for the first peak period

between 11 and 12 AM. The battery is again charged during hours 14 and 15 in preparation for the second peak period. During peak hours 20 and 21, in addition to power purchase from the utility grid, the battery is also discharged to help balance the supply and demand. Thus, the battery plays a significant role in cost reductions and flexible operation of the MG. At the end of the day, the battery is again charged for the next daily cycle. A significant part of the OCs is related to DG fuel which is in turn dependent on the DG capacity and the load level. In peak periods, DGs generate their maximum power to help maintain the supply demand balance. Occasionally, a circumstance might occur when all generation resources are at their maximum generation level, the battery has been discharged and the customers have implemented $PC_{j,t}^{pro}$ of power reduction and still the supply-demand balance cannot be met. In this case, the role of mandatory reduction $PC_{j,t}^{mand}$ is highlighted. It is worthy to note that $PC_{j,t}^{mand}$ is not only important for supplydemand balance but it may also help, at times, lower the OCs. The total demand in this case study is 40911MWh and the amount of reduced power varies for different scenarios. However, an average of 7.8% optimal power reduction is witnessed across all scenarios.

The daily battery SOC is depicted in Fig. 4. For an initial SOC of 30%, the battery gets charged at 1:00 when demand is low. The minimum SOC is rarely reached and mostly witnessed at peak periods when the battery helps with the supply-demand balance. Most often, the battery is at its maximum SOC. The proposed approach prevents abrupt charge and discharge instances leading to higher battery life and avoiding extra costs. The SOC is at its highest at 24:00 guaranteeing the battery's readiness for the next daily cycle. This further demonstrates the efficiency of the proposed approach for optimal energy management.

Fig. 4. The value of the state of charge (SOC) of the battery for various scenarios.(Top figures for Trade-off method and bottom figures for proposed sizing method)

5. Conclusion

In this paper, a hybrid EMS-DR model including optimal battery sizing was introduced for MG economic operation. The economic operation model optimizes different related variable within a 24-hour span, including the amount of reduced power by customers, paid DR incentives, optimal power allocation to DGs, optimal battery charge and discharge and the power exchange between the utility grid and MG. A large size of the used battery set will not guarantee the minimum OCs, rather an optimum capacity should be considered in the design of a MG. Economic operation through optimal battery capacity sizing leads to a remarkable decrease in the MG OCs and lowers the costs of supplying the load power. The proposed battery sizing method was demonstrated to have a great accuracy in determining the optimal battery size for economic operation of the MG. Optimal battery capacity was obtained for different initial SOC values. According to the results, higher initial SOCs will require lower battery capacity leading to fairly lower OCs. Therefore, it is recommended to use and plan for a high initial SOC. The DR program within the proposed approach achieved an average power reduction of 7.8% indicating the advantage of integrating DR with MG EMS to achieve optimal values for both supply and demand variables along with more efficient battery sizing. As demonstrated, the proposed approach is highly proficient and accurate for application in economic operation planning within MGs as well as power systems.

References

- [1] Muhammad Sufyan, Nasrudin Abd Rahim,ChiaKwang Tan, Munir Azam Muhammad, Siti Rohani Sheikh Raihan, "Optimal sizing and energy scheduling of isolated microgrid considering the battery lifetime degradation," *plos one,* vol. 14, no. 2, 2019.
- [2] M. Elsied, A. Oukaour, H. Gualous, R. Hassan, A. Amin, "An advanced energy management of microgrid system based on genetic algorithm," in *2014 IEEE 23rd International Symposium on Industrial Electronics*, Turkey, 2014.
- [3] H. Huang, Y. Cai, H. Xu and H. Yu, "A Multiagent Minority-Game-Based Demand-Response Management of Smart Buildings Toward Peak Load Reduction," *IEEE Transactions on Computer-Aided Design of Integrated Circuits and Systems,* vol. 36, p. 573–585, 2017.
- [4] W. Lyzwa, M. Wierzbowski and B. Olek, "MILP Formulation for Energy Mix Optimization," *IEEE Transactions on Industrial Informatics,* vol. 11, p. 1166–1178, 2015.
- [5] E. D. Mehleri, H. Sarimveis, N. C. Markatos, L. G. Papageorgiou, "Optimal Design and Operation of Distributed Energy Systems," *Renewable Energy,* vol. 51, pp. 331-342, 2013.
- [6] J. Soares, M. Silva, T. Sousa, Z. Vale, H. Morais, "Distributed energy resource short-term scheduling using signaled particle swarm optimization," *Energy,* vol. 42, pp. 466-476, 2012.

EISSN: 2345-6221

- [7] T. Niknam, F. Golestaneh, A. Malekpour, "Probabilistic energy and operation management of a Microgrid containing Wind-Photovoltaic-Fuel cell generation and energy storage devices based on point estimate method and self-adaptive gravitational search algorithm," *Energy,* vol. 43, pp. 427-437, 2012.
- [8] M. Mehdi.Rouholamini, "Energy management of a grid-tied residential-scale hybrid renewable generation system incorporating fuel cell and electrolyzer," *Energy and Buildings,* vol. 102, p. 406– 416, 2015.
- [9] A. Khan, S. Razzaq, A. Khan, F. Khursheed, "HEMSs and enabled demand response in electricity market: an overview," *Renew Sustain Energy Rev,* vol. 42, pp. 773-785, 2015.
- [10] H. Wu, M. Shahidehpour, A. Alabdulwahab and A. Abusorrah, "Thermal generation flexibility with ramping costs and hourly demand response in stochastic security-constrained scheduling of variable energy sources," *IEEE Trans. Power Syst,* vol. 30, pp. 2955-2964, 2015.
- [11] A. Arif, F. Javed, N. Arshad, "Integrating renewables economic dispatch with demand side management in micro-grids: a genetic algorithm-based approach," *Energy Efficien,* vol. 7, pp. 271-284, 2014.
- [12] M. Mohammadjafari, R. Ebrahimi, V. Parvin Darabad, "Optimal Energy Management of a Microgrid Incorporating a Novel Efficient Demand Response and Battery Storage System," *Journal of Electrical Engineering & Technology,* vol. 15, no. 2, pp. 571-590, 2020.
- [13] M. Sedighizadeh, M. Esmaili, A. Jamshidi, M. H. Ghaderi, "Stochastic multi-objective economic-environmental energy and reserve scheduling of microgrids considering battery energy storage system", Electrical Power and Energy Systems," *Electrical Power and Energy Systems,* vol. 106, p. 1–16, 2019.
- [14] Mohammed Atta Abdulgalil, Muhammad Khalid and Fahad Alismail, "Optimal Sizing of Battery Energy Storage for a Grid-Connected Microgrid Subjected to Wind Uncertainties," *Energies ,* vol. 12, no. 12, 2019.
- [15] Q. Fu, A. Hamidi, A. Nasiri, V. Bhavaraju, S. B. Krstic, and P. Theisen, "The Role of Energy Storage in a Microgrid Concept: Examining the opportunities and promise of microgrids," *IEEE Electrification Mag.,* vol. 1, no. 2, p. 21–29, 2013.
- [16] X. Luo, J. Wang, M. Dooner, and J. Clarke, "Overview of current development in electrical energy storage technologies and the application potential in power system operation," *Applied Energy,* vol. 137, p. 511–536, 2015.
- [17] S. Sukumar, H. Mokhlis, S. Mekhilef, K. Naidu, M. Karimi, "Mixmode energy management strategy and battery sizing for economic operation of grid-tied microgrid," *Energy,* vol. 118, p. 1322–1333, 2017.
- [18] J. P. Fossati, A. Galarza, A. Martín-Villate, L. Fontán, "A method for optimal sizing energy storage systems for microgrids," *Renewable Energy,* vol. 77, p. 539–549, 2015.
- [19] S. Sharma, S. Bhattacharjee, A. Bhattacharya, "Grey wolf optimisation for optimal sizing of battery energy storage device to minimise operation cost of microgrid," *IET Generation, Transmission & Distribution,* vol. 10, p. 625–637, 2016.
- [20] Ibrahim Alsaidan, Amin Khodaei, Wenzhong Gao , "A Comprehensive Battery Energy Storage Optimal Sizing Model for Microgrid Applications," *IEEE Transactions on Power Systems,* vol. 33, no. 4, pp. 3968 - 3980, 2018.
- [21] T. Kerdphol, Y. Qudaih, and Y. Mitani, "Battery energy storage system size optimization in microgrid using particle swarm optimization," in *IEEE PES Innovative Smart Grid Technologies, Europe*, Istanbul, Turkey , 2014.
- [22] A. Toliyat and A. Kwasinski, "Energy storage sizing for effective primary and secondary control of low-inertia microgrids," in *2015 IEEE 6th International Symposium on Power Electronics for Distributed Generation Systems (PEDG)*, Aachen, Germany , 2015.
- [23] N.I. Nwulu, X. Xia, "Multi-objective dynamic economic emission dispatch of electric power generation integrated with game theory based demand response programs," *Energy Conversion and Management,* vol. 89, pp. 963-974, 2015.
- [24] N. Nwulu, X. Xia, "Optimal dispatch for a microgrid incorporating renewables and demand response," *Renewable Energy,* vol. 101, pp. 16-28, 2017.
- [25] K. Wu, H. Zhou, "A multi-agent-based energy-coordination control system for grid-connected large-scale windphotovoltaic energy storage powergeneration units," *Solar Energy,* vol. 107, pp. 245- 259, 2014.
- [26] Seyedali. Mirjalili , Andrew. Lewis, "The Whale Optimization Algorithm," *Advances in Engineering Software,* vol. 95, pp. 51-67, 2016.
- [27] H. Tazvinga, B. Zhu, X. Xia, "Energy dispatch strategy for a photovoltaic wind diesel battery hybrid power system," *Solar Energy,* vol. 108, pp. 412-420, 2014.
- [28] M. Rahimiyan, L. Baringo and A. J. Conejo, "Energy management of a cluster of interconnected price-responsive demands," *IEEE Transactions on Power Systems,* vol. 29, pp. 645-655, 2014.