Near Optimal Control for Microgrid Energy Systems Considering Battery Lifetime Characteristics

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***Abstract*—Integration of renewable energy sources (solar, wind, hydro, etc.) in microgrid presents a great challenge to ensure power network stability and reliability due to their intermittent nature. Grid-level battery energy storage system (BESS) has been recognized as one of the promising solutions to meet this challenge as well as to participate in power system economic operation. In this paper, near optimal operation/allocation of BESS has been investigated with the consideration of lifetime characteristics. The problem is formulated as a single objective optimization to maximize the total system revenue by considering the lifetime characteristics of lead-acid batteries. Adaptive dynamic programming (ADP) is investigated to solve optimal control policy for time-dependent and finite-horizon BESS problems. A classical dynamic programming approach has also been studied to validate the proposed approach. Simulation results discuss the impact of battery lifetime characteristics on the total system revenue. The results show that the ADP can optimize the system operation under different scenarios to maximize the total system revenue.**

***Index Terms*—Near optimal control, battery energy storage system (BESS), microgrid, adaptive dynamic programming (ADP), operation optimization, state of charge (SOC), lifetime characteristics.**

I. Introduction

Participation of renewable energy sources (RESs) in microgrid is increasing day by day as an environmentally and economically beneficial solution for the future. For this reason, the power grid network experiences great challenges in transmission and distribution to meet load demand with unpredictable seasonal or daily deviations [1]. Battery energy storage system (BESS) is received as an underpinning technology to overcome these challenges [2]. Therefore, in recent years, the problem of finding optimal control policies for BESS is becoming increasingly important. Most of the time these sequential decision problems are modeled as stochastic dynamic programs, however, when state space become large, conventional techniques like backward dynamic programming, policy iteration, value iteration, etc. become computationally intractable [3]. This situation is often summarized by the phrase "curse of dimensionality" [4]. Adaptive dynamic programming (ADP) is a technique to solve these problems approximately very close to the optimal point using significantly fewer computational resources. In this paper, the ADP is investigated to solve economic optimization problem for a grid-connected microgrid system with the full consideration of the lifetime characteristics of lead-acid batteries.

An optimal energy management problem for energy storage with wind power generation is investigated under risk consideration and transaction costs of trading energy with the power grid in [5]. However, the effect of battery lifetime characteristics on the system revenue has not been addressed in [5]. In [6], a multi-objective operation optimization method is studied for standalone microgrid where a heuristic method non-dominated sorting genetic algorithm has been investigated. In [7], a method for sizing energy storage devices in microgrids is presented. The authors have studied matrix real-coded genetic algorithm to find the optimal capacities of energy storage with an objective function formulated to minimize the operation costs of the targeted microgrid. However, the effect of power fluctuation of renewable energy and the impact of lifetime characteristics of battery on the system revenue have not been considered. In [8], The authors have been reported that the effective cumulative lifetime of the lead-acid battery is associated with its operating state of charge (SOC) values. Optimal sizing and economic analysis of the BESS have discussed in different existing literature [9], [10], [11]. However, the optimal allocation of BESS considering lifetime characteristics has not been studied in those works. The finite-horizon energy storage problem is investigated and a rule-based dispatch solution is obtained in [12], yet the effect of electricity prices and the uncertainty in wind energy have not been taken into account. In [13], the storage sizing problem is studied by using deterministic price and variability in the wind energy supply. The role of BESS to reduce the total cost of the system without considering the impact of battery lifetime characteristics is discussed in [14]. A real-time BESS management algorithm for peak demand shaving in small energy communities with grid-connected photovoltaic system is proposed in [15]. In [16], a particle swarm optimization technique is investigated for the optimal operation of energy storage system in microgrid where controllable loads have used as load demand.

To find an approach that can provide optimal decision and control to address real-life problems with nonlinearities has been one of the hot and difficult topics in the control engineering field [17]. In recent years, ADP is considered as a powerful tool for solving optimal control of nonlinear systems and attracts a lot of researcher's attention [18]. The ADP has shown promising performances on various applications in the power system community. In [19], [20], [21], [22], the ADP has been implemented as an intelligent controller. In [23]-[24], The ADP has been studied for power system stability control analysis. In [25], an ADP based technique has been studied for analysing the economic operation of BESS that has formulated as an optimization problem. In [26], the ADP has been investigated for the optimal control and allocation problem of a multidimensional energy storage system.

Motivated by the above mentioned references, we have investigated ADP for the optimal operation of BESS with the presence of wind energy, load demand and power grid. The impact of battery lifetime characteristics are also considered. The contribution of this paper is threefold, (a) the near optimal operation/allocation problem of BESS for grid-connected microgrid system is addressed considering battery lifetime characteristics, (b) the proposed ADP algorithm is evaluated for stochastic datasets and compared with traditional dynamic programming (DP), (c) real-time price data is used with different battery SOC to investigate the effect of lead-acid battery lifetime characteristics on the total system revenue.

The rest of this paper is organized as follows. The problem formulation is presented in Section II. Section III presents both DP and ADP approaches. Simulation setup and results analysis are carried out in Section IV. Finally, the conclusions are drawn in Section V.

II. Problem Formulation

A. Grid-Connected Microgrid Model and Revenue Calculation

The optimal energy storage operation and allocation problem for grid-connected microgrid system are formulated as a Markov decision process (MDP). The problem of allocating energy to a single grid-level storage device is considered over a finite horizon of time as $\tau = \{0, \Delta t, 2\Delta t, ..., T-\Delta t, T-1\}$, where $\Delta t = 1$ is the time step and $T = 25$. The benchmark problem is illustrated in Figure 1.

In the model, the microgrid is designed with an energy storage device that is connected with a wind farm and load demand as well as the main power grid. The actions are representing the flow of electricity that may flow directly from the wind farm to the storage device or it may be used to satisfy the load demand. Energy from storage may be sold to the grid at any given time and electricity from the grid may be bought to replenish the energy in storage or to satisfy the demand [26].

The following is a list of parameters used throughout the paper to characterize the storage device as,

- B^c: The energy capacity of the storage device, in MWh.

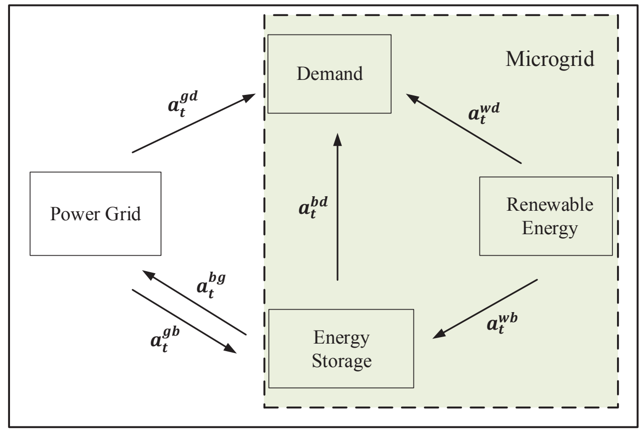

Fig. 1. The power system model diagram for grid-connected microgrid, where the solid lines represent the transferred energy among components.

- ϕ^c: The charging efficiency of the device.
- ϕ^d: The discharging efficiency of the device.
- ψ^c: The maximum charging rates of the device, in $MWh/\Delta t$.
- ψ^d: The maximum discharging rates of the device, in $MWh/\Delta t$.

The state variable of the system at any time instance t can be written as,

$$S_t = (B_t, W_t, P_t, D_t). \tag{1}$$

- B_t: The amount of energy in the storage device, in MWh.
- W_t: The net amount of wind energy available, in MWh.
- P_t: The price of electricity in the power market, in $\$/MWh$.
- D_t: The aggregate energy demand, in MWh.

To be abbreviated, let E_t= (W_t,P_t,D_t) and S_t = (B_t,E_t), where E_t is the vector which contains exogenous information and E_t is independent of B_t. Next if the exogenous information, e_{t+1}, to be the change in E_t as,

$$E_{t+1} = E_t + e_{t+1}. \tag{2}$$

where, between time t and $t+1$, e_{t+1} = (w_{t+1},p_{t+1},d_{t+1}); The exogenous information e_{t+1} is independent of S_t and a_t.

- w_{t+1}: The change in the renewable energy.
- p_{t+1}: The change in the grid electricity price.
- d_{t+1}: The change in the load demand.

At any point of time t, the decision problem is that, while anticipating the future value of storage, the energy from the following three sources must need to be combined in order to fully satisfy the demand:

- The energy currently in storage, constrained by ψ^c, ψ^d, and B_t is represented by a decision a_t^{bd}.
- The available wind energy, constrained by E_t is represented by a decision a_t^{wd}.
- The energy from the grid, at a grid price of P_t is represented by a decision a_t^{gd}.

Additional allocation decisions are a_t^{bg}, the amount of storage energy to sell to the grid at price P_t; a_t^{wb}, amount of wind energy to transfer to the energy storage; and a_t^{gb}, the amount of energy to buy from the grid and store. These allocation decisions are summarized by the six-dimensional, nonnegative decision vector as,

$$a_t = (a_t^{wd}, a_t^{gd}, a_t^{bd}, a_t^{wb}, a_t^{gb}, a_t^{bg})^{\tau} \geq 0, a_t \in \chi_t \qquad (3)$$

where, $t \in \tau$, χ_t represents feasible action space.

And the constraints are as follows:

$$a_t^{wd} + \phi^d a_t^{bd} + a_t^{gd} = D_t. \qquad (4)$$

$$a_t^{bd} + a_t^{bg} \leq B_t. \qquad (5)$$

$$a_t^{wb} + a_t^{gb} \leq B^c - B_t, \qquad (6)$$

$$a_t^{wb} + a_t^{wd} \leq W_t. \qquad (7)$$

$$a_t^{wb} + a_t^{gb} \leq \psi^c. \qquad (8)$$

$$a_t^{bd} + a_t^{bg} \leq \psi^d. \qquad (9)$$

The equation (4) is for fully satisfying the demand; (5) and (6) are storage capacity constraints; (7) represents that the maximum amount of energy used from wind is bounded by W_t; and finally, (8) and (9) constrain the decisions to within the storage transfer rates.

Let η=(0, 0, -1, ϕ^c, ϕ^c, -ϕ^d) be a vector containing the flow coefficients for a decision a_t with respect to the storage device. Then, the transition function can be written as,

$$B_{t+1} = B_t + a_t \eta^T. \qquad (10)$$

The contribution function $R(S_t, a_t)$ is the revenue of the system from being in the state S_t and making the decision a_t at time t as,

$$R(S_t, a_t) = P_t(D_t + \phi^d a_t^{bg} - a_t^{gb} - a_t^{gd}). \qquad (11)$$

B. Energy Storage Life Loss Cost

The life loss level of batteries can be measured by using the effective cumulative Ah throughput as [6],

$$L_{loss} = \frac{A_c}{A_{total}}. \qquad (12)$$

where, L_{loss} is the life loss of batteries that depends on both state variable (S_t) and decision vector (a_t), A_c is the effective cumulative Ah throughput in a certain period of time. A_{total} is the total cumulative Ah throughput in life cycle. A lead-acid battery size of QAh will deliver $390Q$ effective Ah over its lifetime [8].

Based on the manufacturers' data, it is recommended that, the battery should operate within a certain range of state of charge (SOC) as,

$$SOC_{min} \leq SOC \leq SOC_{max} \qquad (13)$$

where, SOC_{min} is the SOC lower limit and SOC_{max} is the SOC upper limit.

The operational strategy of the system for controlling energy storage life loss cost is illustrated in Figure 2. According to Figure 2, if battery SOC is less than the SOC_{min} then energy is brought from the power grid to fulfill the demand as well as to charge the battery with subject to equations (4) to (9). Again if battery SOC is greater than the set-up SOC (SOC_{stp}) then the energy transferred from the battery to demand and to grid subject to equations (4) to (9).

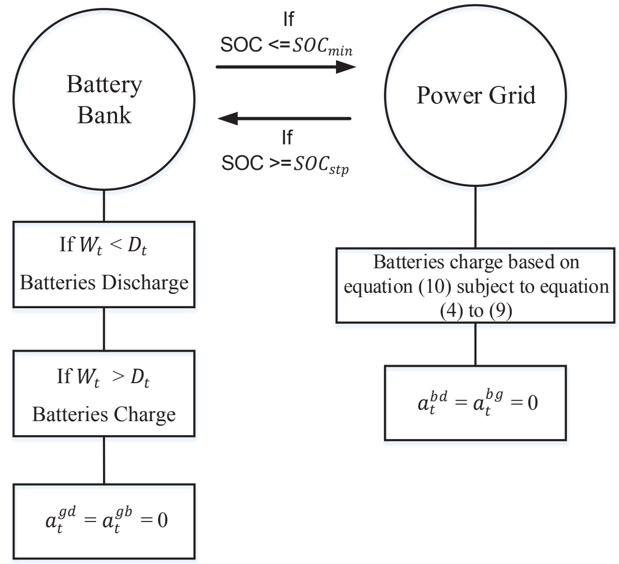

Fig. 2. Schematic diagram of the energy storage system operation strategy.

The effective cumulative Ah throughput A_c depends on the operating SOC and the actual Ah throughput $A_c^{'}$. It can be expressed as,

$$A_c = \lambda_{soc} A_c'. \qquad (14)$$

where λ_{soc} is the effective weighting factor. In this paper $SOC_{min}$is set to 0.5 and when SOC is greater than 0.5, the effective weighting factor is approximately linear with SOC, which can be expressed as,

$$\lambda_{soc} = m * SOC + n. \qquad (15)$$

In the equation, m and n are the two empirical parameters and their values can be determined from Figure 3.

The actual Ah throughput $A_c^{'}$ is the sum of total energy discharge from the battery at any given time 't' as,

$$A_c^{'} = a_t^{bd} + a_t^{bg} \qquad (16)$$

Figure 3 shows the relation between the operating SOC values and the effective cumulative lifetime for lead-acid battery. For instance, when battery SOC is 0.5, removing 1 Ah from the battery is equivalent to removing 1.3 Ah from the total cumulative lifetime. However, when battery SOC is 0.5, removing 1 Ah from the battery will result in only 0.55 Ah being removed from the total cumulative lifetime. This relation shows that the lead-acid batteries should be operated at high SOC to increase their lifetime.

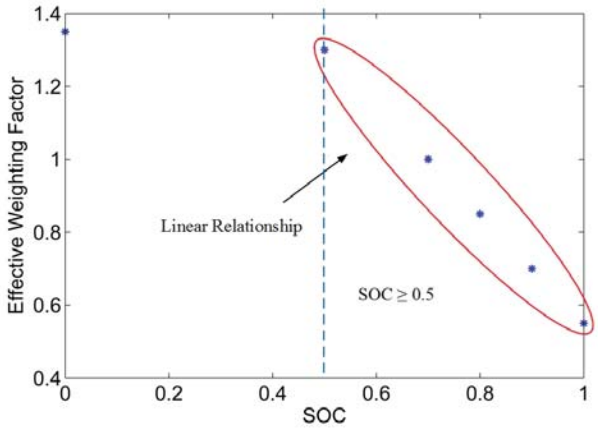

Fig. 3. Relationship between effective weighting factor and the SOC of lead-acid battery.

Finally, the life loss cost C_{bl} for a certain duration can be written as,

$$C_{bl} = L_{loss} I_{init-bat}. \tag{17}$$

where, $I_{init-bat}$ is the initial investment cost of batteries which is assumed as $\$30,000$.

C. Objective Function

In this paper, the main objective is to maximize the total profit over time with the consideration of battery life loss cost. Both equation (11) and (17) are used to obtain the net revenue of the system at time t as,

$$R_{net}(S_t, a_t) = \max_{a_t \in \chi_t} [R(S_t, a_t) - C_{bl}]. \tag{18}$$

The goal is to maximize the total system revenue as well as to minimize the battery life loss cost. The optimal control policy of ADP is used to select an action that will maximize the system revenue and minimize battery life loss cost. The total system revenue function over a finite horizon of time can be expressed as,

$$V = \max_{a_t \in \chi_t} \sum_{t=0}^{T-1} R_{net}(S_t, a_t) \tag{19}$$

The life loss cost depends on the SOC level of the battery. To minimize the battery life loss cost, the SOC of the battery needs to set up as high as possible.

III. Proposed ADP Approach

A. Dynamic Programming Approach

In terms of revenue, the optimal solution of stochastic problems can be obtained for problems that have denumerable and relatively small state (S_t), decision (χ_t) and outcome spaces (W_t). In these case, Bellman's optimality equation can be expressed as,

$$V_t^*(S_t) = \max_{a_t \in \chi_t} [R_{net}(S_t, a_t) + \sum_{s'=1}^{|S_t|} P_t(s'|S_t, a_t) V_{t+\Delta t}^*(s')], \tag{20}$$

where, $P_t(s'|S_t, a_t)$ is the conditional transition probability of going from state S_t to state s' for the decision a_t, and where $V_{T+\Delta t}^* = 0$. After solving (20), the model can be simulated as a MDP by following the optimal policy, π^*, that is defined by the optimal value functions $(V_t^*)_{t\epsilon\tau}$.

The MDP can be simulated for a given sample path ω by solving the decision as,

$$\begin{aligned} X_t^{\pi}(S_t(\omega)) = arg \max_{a_t \in \chi_t} [R_{net}(S_t(\omega), a_t) \\ + \sum_{s'=1}^{|S_t(\omega)|} P_t(s'|S_t(\omega), a_t) v], \end{aligned} \tag{21}$$

where, $v = V_{t+\Delta t}^*(s'|S_t(\omega), a_t)$ and $S_{t+1}(\omega) = S^M(S_t(\omega), X_t^{\pi}(S_t(\omega)), W_{t+1}(\omega))$.

For stochastic transition from S_t to s', a statistical estimate of the value of the optimal policy can be calculated as,

$$\overline{V} = \frac{1}{K} \sum_{k=1}^{K} \sum_{t\epsilon\tau} R_{net}(S_t(\omega^k), X_t^{\pi}(S_t(\omega^k))). \tag{22}$$

where, K = 256 different sample paths, $\{\omega^1, ..., \omega^K\}$.

The effective cumulative Ah throughput in a certain period of time A_c is simulated for K different sample paths, $\{\omega^1, ..., \omega^K\}$ and then a statistical estimate of battery life loss is obtained as,

$$\bar{L}_{loss} = \frac{\frac{1}{K}\sum_{k=1}^{K}\sum_{t\epsilon\tau} A_c(\omega^k)}{A_{total}}. \tag{23}$$

Then, the battery life loss cost is calculated using equation (17).

B. Proposed Adaptive Dynamic Programming Approach

The revenue that is obtained at time t can be expressed as Bellman's optimality equation by using the available information of contribution/ revenue function in section II as,

$$V_t^*(S_t) = \max_{a_t \in \chi_t} [R_{net}(S_t, a_t) + E(V_{t+1}^*(S_{t+1})|S_t)]. \tag{24}$$

where S_{t+1} depends on both states (S_t) and a_t. Moreover, the boundary conditions are $R_T^*(S_T) = 0$ and $t \leq T$.

It is often troublesome to deal with an expectation operator due to the high dimension of the state space. Here, post-decision formulation of Bellman's equation is used to overcome this problem as,

$$V_t^*(S_t) = \max_{a_t \in \chi_t} [R_{net}(S_t, a_t) + V_t^a(S_t^a)]. \tag{25}$$

where, the expectation operator $E(V_{t+1}^*(S_{t+1}|S_t)$ is replaced by the post-decision value function $V_t^a(S_t^a)$. The post-decision state S_t^a is the state instantly after the current decision a_t is made, but before the arrival of any new information [3].

For calculating battery life loss, the actual Ah throughput A_c' is obtained from the status of the state variable B_t in equation 1 for each period of time. During simulation, battery SOC is kept in a certain range and the effective weighting factor is determined from Fig. Then the battery life is calculated as,

$$L_{loss} = \frac{\frac{1}{I}\sum_{i=1}^{I}\sum_{t\epsilon\tau} A_c}{A_{total}}. \quad (26)$$

where, i is the number of iterations and I is the maximum number of iterations. Then equation (17) is used to get the battery life loss cost.

In this paper, ADP is presented as a version of approximate value iteration (AVI). The main advantage of ADP is the rate of convergence [27]. By taking advantage of AVI, ADP can solve optimal benchmark problems within a relatively small number of iterations.

IV. Simulation Setup and Results Analysis

A. Simulation Setup

In this section, the numerical simulation results are shown for maximizing net system revenue. The optimal benchmark problem is presented for stochastic time-dependent problems for single energy storage system in the presence of exogenous information such as wind, prices, and demand. The objective function is validated for several stochastic benchmark problems to test the sensitivity of the ADP algorithm to the BESS parameters in the allocation of storage energy. The system is also tested by setting different battery SOC level to analyze how battery SOC affects the net system revenue. The system is also validated for real-time market price. The lead acid battery parameters are presented in Table I.

TABLE I
BATTERY PARAMETERS

Battery	Lead-Acid
Type	2V/1000 Ah
Capacity	30 MWh
Cycle Life	1000 @ 50% DOD
Charging and Discharging Efficiencies (ϕ^c and ϕ^d)	80%
Charging and Discharging Rates (ψ^c and ψ^d)	8 MWh/Δt

The other major parameters like maximum and minimum values of wind energy, load demand, and grid price are summarized in Table II.

TABLE II
THE SYSTEM PARAMETERS

Name	Wind Energy (MWh)	Load Demand (MWh)	Grid Price ($/MWh)
Maximum value	7	7	70
Minimum value	1	1	30

The stochastic load demand is assumed as that in [28],

$$D_{t+1} = min\{max\{D_t + \Phi^D_{t+1}, D_{min}\}, D_{max}\} \quad (27)$$

where, Φ^D_{t+1} is pseudonormally $N(0, 2^2)$ discretized over $\{0, \pm1, \pm2\}$, in order to model the seasonality that often remains in observed energy demand. And, the load demand D_t is assumed as,

$$D_t = \lfloor 3 - 4sin(2\pi(t + 1)/T)\rfloor \quad (28)$$

where, $\lfloor . \rfloor$ represents the floor function.

The first-order Markov chain is investigated to model the stochastic wind power supply and w^W_t i.i.d random variables that can be either uniformly or pseudonormally distributed as,

$$W_{t+1} = min\{max\{W_t + w_{t+1}, W_{min}\}, W_{max}\} \quad (29)$$

For the grid price process P_t, three types of stochastic processes are tested, they are 1st-order Markov chain, 1st-order Markov chain plus jump, and sinusoidal. Similar to wind process, p^P_t random variables can be either uniformly or pseudonormally distributed as,

$$P_{t+1} = min\{max\{P_t + p_{t+1}, P_{min}\}, P_{max}\} \quad (30)$$

Simulation results are presented in following subsections. All the simulations are conducted in $MATLAB$ 2014a environment.

B. Stochastic Experiment Study

The complex stochastic benchmark problems for validating the system are presented in Table III. In Table III, for wind energy and grid price, two different probability distribution functions are used where U and N functions are defined as uniform and pseudonormal distribution respectively. These two probability distribution functions are acted as a noise to make the system stochastic [26]. For all test problems, SOC_{stp} is kept the same as 0.5. The statistical estimate of dynamic programming is treated as optimal value of the system and compared with the proposed ADP. The percentage of optimality of the proposed algorithm is calculated as,

$$\%\ of\ optimality = \frac{V^{1000}}{\overline{V}} \times 100\% \quad (31)$$

where, the objective value given by the algorithm after 1000 iterations, V^{1000}, is compared to the statistically estimated optimal value given by DP, $\overline{V}$ in equation (22).

TABLE III
STOCHASTIC TEST PROBLEMS

No.	W.E.	Price Process	p^P_t
1	$U(-1, 1)$	$1stMC + Jump$	$N(0, 5.0^2)$
2	$U(-1, 1)$	$1stMC + Jump$	$N(0, 1.0^2)$
3	$N(0, 1.0^2)$	$1stMC + Jump$	$N(0, 5.0^2)$
4	$N(0, 3.0^2)$	$1stMC + Jump$	$N(0, 2.5^2)$
5	$N(0, 0.5^2)$	$1st - MC$	$N(0, 1.0^2)$
6	$N(0, 1.0^2)$	$1st - MC$	$N(0, 1.0^2)$
7	$N(0, 0.5^2)$	$1st - MC$	$N(0, 5.0^2)$
8	$U(-1, 1)$	$Sinusoidal$	$N(0, 25.0^2)$
9	$N(0, 0.5^2)$	$Sinusoidal$	$N(0, 25.0^2)$
10	$N(0, 1.0^2)$	$Sinusoidal$	$N(0, 25.0^2)$

The stochastic benchmark problems in Table III are used to compare our results with DP. The results are shown in Table IV. For example, in test problem 4 from Table III, the pseudonormal probability distribution is used for both stochastic wind energy and grid price. According to Table IV, the net total system revenue for problem 4 is found as \$ 3793.37 where the optimal value is obtained from DP as \$ 3855.44 and then the percentage of optimality is calculated as 98.39 % which is very promising. The other results are also showed that the ADP can obtain at least 98% of optimality for the stochastic case study that proves that the ADP can be a powerful tool of solving optimal policies for stochastic environments.

TABLE IV
RESULTS FOR STOCHASTIC TEST PROBLEMS.

No.	R ($)	C_{bl} ($)	R_{net} ($)	Optimal Value ($)	% of opt (%)
1	4191.16	277.67	3913.49	3973.49	98.49 %
2	4188.36	302.78	3885.58	3916.52	99.21 %
3	3987.98	377.49	3610.49	3624.63	99.61 %
4	4192.31	398.94	3793.37	3855.44	98.39 %
5	4211.03	412.29	3798.74	3804.83	99.84 %
6	4038.44	321.68	3716.76	3761.52	98.81 %
7	4169.87	372.29	3797.58	3832.07	99.10 %
8	4218.64	414.06	3804.58	3842.23	99.02 %
9	4029.72	318.53	3711.19	3731.34	99.46 %
10	4174.53	376.34	3798.19	3814.21	99.58 %

C. Stochastic Experiment Study with Different Battery SOC Setup

The stochastic test problem No. 4 of Table III is used for more analysis to see the effect of Battery SOC on the total system revenue. The results are presented in Table V. The experiment is conducted for four different SOC_{stp} where the SOC_{stp} is varied form 0.55 to 0.63. According to the Table V, the higher and lower system revenues are obtained at 0.55 and 0.63 respectively. The other results show that higher SOC_{stp} of the battery may cause lower revenue of the system. However, the life loss cost of the battery decreases with the increase of battery SOC. As battery life loss cost is proportional to battery lifetime, sacrificing a small amount of revenue may increase battery lifetime as well as the consistency of the system.

In this experiment study, the performance of the proposed ADP approach is also validated for different SOC_{stp} and the results show that the solution of ADP is very close to the optimal solution of DP. The percentage of optimality results are presented in Table V.

TABLE V
PERCENTAGE OF OPTIMALITY FOR STOCHASTIC PROBLEM 4 WITH DIFFERENT SOC_{stp}.

No.	SOC_{stp}	R ($)	C_{bl} ($)	R_{net} ($)	OV ($)	% of opt. (%)
1	0.55	4058.12	316.92	3741.20	3793.55	98.62%
2	0.58	3971.08	265.31	3705.77	3736.79	99.17%
3	0.60	3906.57	237.48	3669.09	3695.69	99.28%
4	0.63	3806.40	202.73	3603.67	3645.96	98.84%

D. Experiment Study with Real-time pricing

For further analysis, real-time market price is used where the wind energy output is obtained using 1^{st} order Markov chain. For real-time market price, the price data of April 1, 2016 is used [29]. The wind energy output, load demand and grid price are presented in Figure 4. The wind energy output signal is obtained using the stochastic test problem 6. Like Table V, battery SOC analysis is also conducted with this setup. The results are summarized in Table VI.

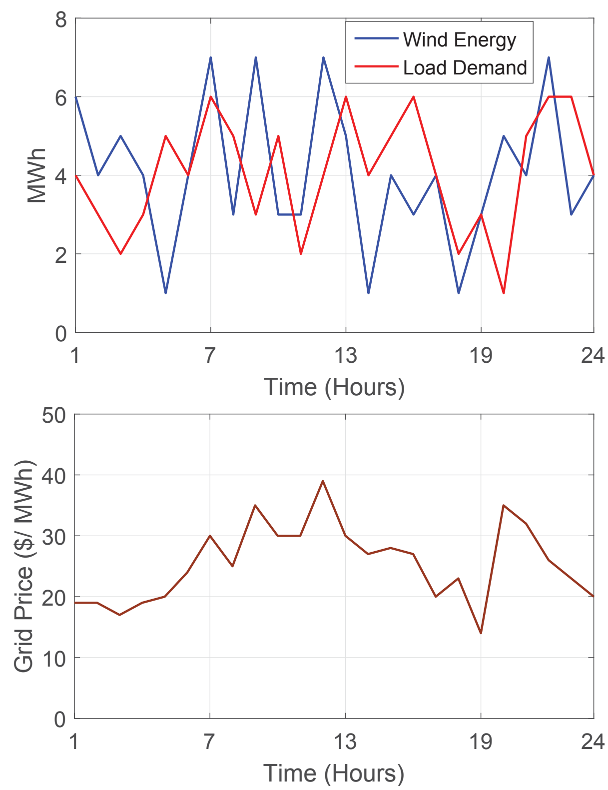

Fig. 4. Available wind energy, load demand and grid price for April 1, 2016.

TABLE VI
RESULTS OF THE TOTAL REVENUE CALCULATION FOR REAL-TIME PRICING.

No.	SOC_{stp}	R ($)	C_{bl} ($)	R_{net} ($)
1	0.55	2249.81	234.03	2015.78
2	0.60	2198.20	218.62	1979.58
3	0.63	2163.11	210.23	1952.88
4	0.65	2138.67	204.95	1933.72

In Table VI, the results are obtained for four different SOC_{stp} where the values are 0.55, 0.60, 0.63 and 0.65 respectively. According to the results, it is clear that the system revenue has an inversely proportional relationship with battery SOC. Higher SOC_{stp} of the battery can provide batteries a better condition to effectively reduce the battery life loss as well as increase the battery lifetime. The system operation profile for problem no. 2 of Table VI is presented in Figure 5 where SOC_{stp} is set to 0.6. The three different colors green, blue, and red represent the amount of energy transferring from battery to grid, battery to load demand and grid to battery respectively. The wind energy is dedicated to fulfill the load demand and after fulfilling the demand, the rest of the energy goes to charge the battery if needed. The grid energy is also available to supply the energy to the system when needed.

The SOC status of the battery is shown in Figure 6. From Figure 6, it is clear that whenever battery SOC goes below the SOC_{min} level, the control policy of ADP charge the battery from the grid up to the operator defined SOC_{stp} level. In general case, the system has the tendency to discharge

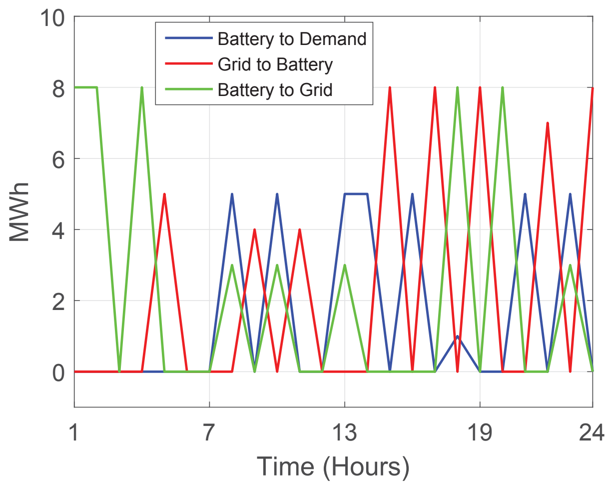

Fig. 5. System operation profile under the operation strategy of No.2 from Table VI.

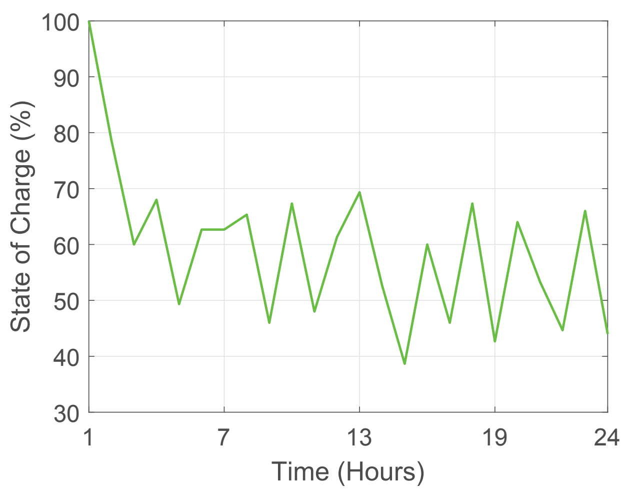

Fig. 6. Battery SOC changing over time under the operation strategy of No.2 from Table VI.

the battery at its maximum discharging rate to maximize the system revenue. However, when battery SOC is reached at equal or lower state of SOC_{stp}, the system is stopped selling energy to the grid to keep the battery SOC close to SOC_{min} to maintain the healthy operation of battery. In some critical situations like time period 14, the load demand, the available wind energy and the battery SOC were 4 MWh, 1 MWh and 0.53 respectively. In this situation, the control policy has no way to fulfill the demand without compromising the healthy operation of BESS. In this case, the system has transferred energy from the BESS to fulfill the load demand and stopped selling energy to the grid. When the system has more than enough energy after fulfilling the demand, that storage energy is used to sell to the grid to get the revenue. However, if the storage does not have enough energy to get charged from the wind energy, the system buys that energy from the grid to keep battery SOC above the defined level as well as to reduce battery life loss cost.

V. Conclusion

In this paper, near optimal operation of energy storage system is discussed with the presence of wind energy, load demand and power grid by considering lifetime characteristics. The problem is formulated as a MDP, and the near optimal policy is simulated by proposed ADP. To verify the performance of the proposed algorithm, DP is used to statistically estimate the optimal value of the total system revenue and compared with the proposed ADP approach. The proposed ADP approach successfully approximated the solution that was very close to the optimal solution of DP. Simulation studies have been carried out for three cases: ten different stochastic test problems were investigated and validated with DP, one stochastic test problem is used by varying battery SOC_{stp} to see the effect of battery SOC on the total system revenue and for further analysis real-time pricing is also used. The simulation results show that ADP is a powerful tool for the power system optimization problem that can provide sequential optimal decision and control to address optimal operation of BESS.

In future work, the proposed ADP can be compared with the other existing approaches to investigate the performance of the algorithm for power system optimization problems. Another interesting direction is to investigate the proposed ADP approach for different real-time BESSs for the comparative study.

Acknowledgement

This work was supported by the National Aeronautics and Space Administration (NASA) under award No. NNX15AK54A.

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