A Fast Computation and Optimization Algorithm for Smart Grid Energy System

Avijit Das[1], Zhen Ni[1], Wei Sun[2]

1. Electrical Engineering and Computer Science Department, South Dakota State University, Brookings, SD, USA, 57007
E-mail: {avijit.das, zhen.ni}@sdstate.edu

2. Department of Electrical Engineering and Computer Science, University of Central Florida, Orlando, FL, USA, 32816
E-mail: sun@ucf.edu

Abstract: Increasing penetration of intermittent and variable renewable energy sources (RESs) has significantly complicated smart grid operations. The uncertain nature of RESs may cause increased operating costs for committing costly reserve units or penalty costs for curtailing load demands. In addition, it is often desired to control and coordinate a battery energy storage system (BESS) in an efficient and economical way, especially for islanded microgrid. To address these issues, an approximate dynamic programming (ADP) approach is proposed to investigate the optimal operation of energy systems in islanded microgrid considering stochastic wind energy and load demands. A battery control strategy is also presented to maintain the battery state of charge in a certain range which will help to increase the battery lifetime in the future. The traditional dynamic programming (DP) approach is also implemented to validate the percentage of optimality of the proposed ADP approach for stochastic case studies. The simulation results show that the proposed ADP approach can obtain competitive percentages of optimality with around 50% less computational time compared to the traditional DP approach. Again, the proposed ADP approach is also validated on a large data sample case and achieved 18.77 times faster response than the traditional DP approach.

Key Words: Near optimal control, battery energy storage system (BESS), islanded microgrid, approximate dynamic programming (ADP), dynamic programming, state of charge (SOC).

1 INTRODUCTION

Nowadays, due to the integration of different energy systems in the smart grid, the balancing between power generation and load demand becomes a critical problem. Specifically, due to the intermittent nature of renewable energy sources (RESs), power system optimization becomes significantly complicated [1]. The battery energy storage system (BESS) has been recognized as the most promising approach to overcome these challenges and to increase the efficiency of the power supply by smoothing load fluctuations. Therefore, in recent years, the goal has been to find an optimal control approach for investigating the optimal operation of energy systems in the smart grid considering stochastic RESs and load demands, as well as the battery lifetime characteristics, becomes an interesting research field.

In recent years, most of the published works focus on deterministic microgrid operations [2]-[9]. Although, stochastic optimization has been researched for bulk power systems in the literature [10]-[13]. However, stochastic optimization for the microgrid has not been well documented in the literature [14]. Again, due to the uncertain nature of RESs, the deterministic optimization may fail to ensure the power quality. Therefore, in this paper, the goal is to consider the stochastic nature of RESs and the load demand for the stochastic optimization of an islanded microgrid.

Stochastic dynamic programming (DP) approaches are generally used to solve sequential decision problems with stochastic variables. However, conventional techniques like backward dynamic programming, policy iteration, value iteration, etc., are not feasible to solve the problem with large state spaces because they are computationally intractable [15]. This scenario is known as "curse of dimensionality" [16]. In this paper, an approximate dynamic programming (ADP) is proposed to overcome these problems. The ADP approach solves the stochastic optimization problem approximately very close to the optimal point using significantly fewer computational resources [17]. In [18]-[20], the ADP has implemented as an intelligent controller to develop internal goal representation for online learning and optimization. Several existing publications have proposed the ADP approach for solving stochastic optimization problem of a grid-connected microgrid without considering the battery lifetime characteristics [21]-[23].

Motivated by the above mentioned literatures, an ADP approach is proposed to investigate the optimal operation of energy systems in an islanded microgrid. A battery control strategy is also implemented to maintain the healthy operation of BESS. The impact of battery lifetime parameters are also considered. The contribution of this paper is fourfold, (a) the energy optimization problem for islanded microgrid is formulated as a Markov decision process (MDP) considering stochastic wind energy and load demand, (b) a state of charge (SOC) based battery control strategy is proposed to increase the battery lifetime, (c) the performance of the ADP approach is compared with the traditional DP approach in terms of percentage of optimality and compu-

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tational time, (d) the performance of the ADP approach is also justified using large data samples and compared with the traditional DP approach.

The rest of this paper is organized as follows. The model description and problem formulations of the islanded microgrid is presented in Section 2. In Section 3, the proposed ADP and the DP approaches are demonstrated. Simulation setup and results analysis are carried out in Section 4. Finally, the conclusions are drawn in Section 5.

2 MODEL DESCRIPTION AND PROBLEM FORMULATIONS

A islanded microgrid model is investigated where the system is designed with a wind turbine, a battery bank, and a diesel generator as power supply units. Load demand is used to represent the demand unit. In the model, the diesel generator is used as the backup power source. When the SOC of the battery goes below a certain limit, the wind turbine and diesel generator units are responsible to charge the battery. The problem is formulated over a finite horizon of time as $\tau = \{0, \Delta t, 2\Delta t, ..., T-\Delta t, T-1\}$, where $\Delta t = 1$ hour is the time step and $T = 25$ hours.

At any time instance t, the state variable can be written as,

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

where, B_t, W_t, and D_t are the amount of energy in the storage device at time t, in kWh, net amount of wind power available at time t, in kW and power load demand at time t, in kW, respectively.

In the model, the transferring power from one unit to another unit is assumed as action. There are five different actions in the model and using these allocation actions, a five-dimensional, nonnegative decision vector can be defined as,

$$a_t = (a_t^{wd}, a_t^{gd}, a_t^{bd}, a_t^{wb}, a_t^{gb})^\tau \geq 0, a_t \in \chi_t, t \in \tau \tag{2}$$

where, χ_t represents feasible action space and a_t^{ij} stands energy transferred from i to j at time t. The superscript w, d, g and b represent wind power, load demand, diesel generator and battery, respectively.

2.1 BESS MODEL

The BESS is one of the major power supply units of the islanded microgrid. The battery control strategy impacts the performance of the overall system significantly.

The SOC of the BESS should be within a certain range as,

$$SOC_{min} \leq SOC \leq SOC_{max} \tag{3}$$

where, SOC_{max} and SOC_{min} are the upper limit of battery state of charge and the lower limit of battery state of charge, respectively.

The SOC of the BESS for the next time step is determined by the SOC value at present time step and the charging/discharging battery power during the present time period. The equation for determining the next hour SOC can be expressed as,

$$SOC_{t+\Delta t} = SOC_t + \frac{\phi^c(a_t^{gb} + a_t^{wb})}{B^c} - \frac{a_t^{bd}}{B^c\phi^d} \tag{4}$$

where, B^c is the energy capacity of the storage device, in kWh, ϕ^c is the charging efficiency of the device and ϕ^d is the discharging efficiency of the device.

The daily operational cost function of the battery can be expressed as,

$$C_t^{BESS} = C_w P_t^B \Delta t \tag{5}$$

For the instance t, the discharging energy from the BESS can be calculated as,

$$P_t^B = a_t^{bd}\lambda_{soc} \tag{6}$$

where, a_t^{bd} represents the amount of energy transferred from the battery to the load demand and λ_{soc} is the effective weighting factor which is determined from the battery SOC for each time period. In this paper, SOC_{min} is defined as 0.5 and from the manufactures' data, it is found that when the battery SOC is greater than 0.5, the effective weighting factor maintains an approximately linear relationship with the battery SOC as [22], [24],

$$\lambda_{soc} = p * SOC + q \tag{7}$$

In the equation, p and q are the two empirical parameters.

The equation of the battery wear cost can be written as,

$$C_w = \frac{C_i}{\phi^d B^c N_c \delta} \tag{8}$$

where, δ is the depth of discharge (DOD) of BESS and N_c is the corresponding number of life cycle at rated DOD. Since the DOD can vary in between the allowable range (0 to 50 % DOD for this study), corresponding life cycle N_c is also varied.

2.2 DIESEL GENERATOR MODEL

In the islanded microgrid, diesel generator is one of the core power supply units which is generally served as a backup energy source. The fuel consumption (L) of the diesel generator can be expressed as,

$$L_t = (L_0 \times P_{rated} + L_1 \times P_t^{gen}) \tag{9}$$

where, L_0 and L_1 are the fuel consumption curve fitting coefficients, where the values are set as 0.08415 and 0.246 respectively based on the recommended value from [25]. The actual output power of the diesel generator, P_t^{gen}, can be calculated as,

$$P_t^{gen} = a_t^{gd} + a_t^{gb} \tag{10}$$

The power limit of the diesel generator can be expressed as,

$$k_{gen} P_{rated} \leq P_t^{gen} \leq P_{rated} \tag{11}$$

where, the value of k_{gen} is set to 0.3 based on the manufacturer's suggestion [9].

The daily operational cost function of diesel generator can be calculated as,

$$C_t^{gen} = C_t^{die-fuel} + C_{die-om} + C_{die-loss} \tag{12}$$

where, $C_t^{die-fuel}$, C_{die-om} and $C_{die-loss}$ is the fuel cost, operation and maintenance cost, and life loss cost of the diesel generator, in \$, respectively. The fuel cost of the diesel generator $C_t^{die-fuel}$, can be expressed as,

$$C_t^{die-fuel} = F \times L_t \tag{13}$$

where, F represents the fuel price, in $\$/L$.

2.3 THE STOCHASTIC WIND ENERGY AND LOAD DEMAND AND TRANSITION FUNCTION

The stochastic wind power is modeled using a bounded 1st-order Markov chain as,

$$W_{t+1} = min\{max\{W_t + w_{t+1}, W_{min}\}, W_{max}\} \tag{14}$$

where, $W_{min} \leq W_t \leq W_{max}$ and w_{t+1} i.i.d random variables that can be either uniformly or pseudonormally distributed.
The stochastic load demand can be written as,

$$D_{t+1} = min\{max\{D_t + \Phi_{t+1}^D, D_{min}\}, D_{max}\} \tag{15}$$

where, Φ_{t+1}^D i.i.d random variables that are pseudonormally $N(0, 2^2)$ discretized over noise $\{0, \pm 1, \pm 2\}$.
For the transition function of exogenous information, let E_t= (W_t,D_t) and S_t = (B_t,E_t), where E_t is the vector of exogenous information and E_t is independent of B_t. The next-hour exogenous information can be written as,

$$E_{t+1} = E_t + e_{t+1} \tag{16}$$

where, e_{t+1} = (w_{t+1},d_{t+1}); The next-hour exogenous information e_{t+1} is independent of S_t and a_t.

2.4 THE BATTERY CONTROL STRATEGY

A battery control strategy is presented in Figure 1. According to the control strategy, the battery SOC is measured and monitored by the energy management system. In the model, there is a parameter named set-up SOC (SOC_{stp}) which is defined by the operator. When the battery SOC is greater than SOC_{stp}, the BESS serves as the power supply unit with the wind energy and the decisions of the diesel generators are assumed as 0. At this time, the batteries can be in charge, discharge, or standby mode depending on wind power generation and load demand. If the battery SOC is below or equal to its lower limit SOC_{min}, the diesel generator starts as the backup power supply unit, while the lead-acid batteries turn into the charging process and the decision of the battery is defined as 0. When the SOC rises above SOC_{stp}, the diesel generator stops and the lead-acid batteries serve as the power supply units again. When the SOC of the BESS is in-between SOC_{stp} and SOC_{min}, then both the BESS and diesel generator serve as the power supply units. When battery SOC becomes equal or less than SOC_{min}, then only diesel generator operates with wind turbine as power supply units to fulfill the demand and to charge the battery.

2.5 THE OBJECTIVE FUNCTION AND CONSTRAINTS

For the cost function, the daily operational cost of diesel generator and BESS are combined with two weights. The

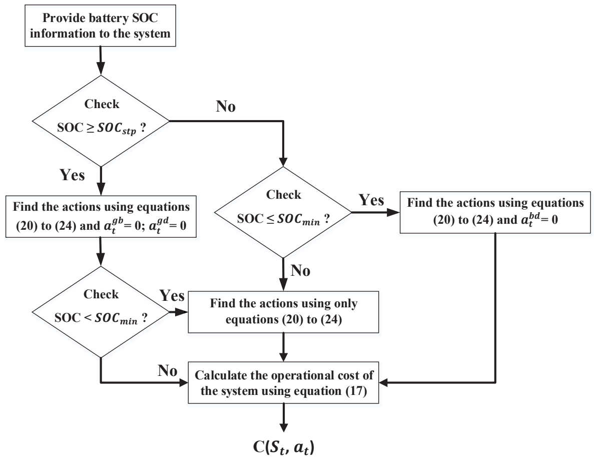

Figure 1: The proposed battery control strategy algorithm for battery SOC.

cost function can be written as,

$$C(S_t, a_t) = M_1 \times C_t^{gen} + M_2 \times C_t^{BESS} \tag{17}$$

where, M_1 and M_2 are the weights.
The goal is to minimize total cost of operation in islanded microgrid. The total system objective function over a finite horizon of time can be expressed as,

$$V = \min_{a_t \in \chi_t} \mathbb{E}[\sum_{t=0}^{T-1} C(S_t, a_t)] \tag{18}$$

where, $\mathbb{E}[.]$ is the expectation operator.
The goal is to find a set of actions (a_t) so that the total system objective function V can be minimized as,

$$a_t = arg \min_{a_t \in \chi_t} V \tag{19}$$

The set of constraints are as follows,

$$a_t^{wd} + a_t^{gd} + a_t^{bd} = D_t \tag{20}$$

$$a_t^{wb} + a_t^{wd} \leq W_t \tag{21}$$

$$a_t^{wb} + a_t^{gb} \leq min(\frac{B^c - B_t}{\Delta t}, \psi^c) \tag{22}$$

$$a_t^{gb} + a_t^{gd} \leq G_t \tag{23}$$

$$a_t^{bd} \leq min(\frac{B_t - B_{min}}{\Delta t}, \psi^d) \tag{24}$$

where, ψ^c is the maximum charging rates of the device, in $kWh/\Delta t$, ψ^d is the maximum discharging rates of the device, in $kWh/\Delta t$, B_{min} is the minimum limit of the storage device, in kWh and G_t is assumed as the available energy capacity of the diesel generator, in kW. The available energy capacity of the diesel generator depends on the fuel availability. In this paper, it is assumed that enough fuel is available to satisfy the load demand and to charge the BESS.

3 PROPOSED APPROACHES

3.1 DYNAMIC PROGRAMMING APPROACH

For finding the optimal solution of stochastic problems, Bellman's optimality equation can be expressed as [26],

$$V_t^*(S_t) = \min_{a_t \in \chi_t} [C(S_t, a_t) + \sum_{s'} P_t(s'|S_t, a_t) V_{t+\Delta t}^*(s')], \quad (25)$$

where, $P_t(s'|S_t, a_t)$ is the probability of going from state S_t to state s' for the decision a_t which is known as conditional transition probability, and where $V_{T+\Delta t}^* = 0$.
For a given sample path ω, the MDP can be simulated by solving the decision as,

$$\begin{aligned}\Pi_t^{\pi^*}(S_t(\omega)) = arg \min_{a_t \in \chi_t} [C(S_t(\omega), a_t) \\ + \sum_{s'} P_t(s'|S_t(\omega), a_t) \upsilon],\end{aligned} \quad (26)$$

where, $\upsilon = V_{t+\Delta t}^*(s'|S_t(\omega), a_t)$ and $S_{t+1}(\omega) = S^M(S_t(\omega), \Pi_t^{\pi^*}(S_t(\omega)), W_{t+1}(\omega))$. Here, $S^M(.)$ is the system model which describes how a system evolves from S_t to $S_{t+\Delta t}$ using action a_t and new exogenous information $E_{t+\Delta t}$ as, $S_{t+\Delta t} = S^M(S_t, a_t, E_{t+\Delta t})$.
A statistical estimated value of the optimal policy for the stochastic transition from the current state S_t to s' can be written as,

$$V^* = \frac{1}{K} \sum_{k=1}^{K} \sum_{t \epsilon \tau} C(S_t(\omega^k), \Pi_t^{\pi^*}(S_t(\omega^k))). \quad (27)$$

where, K is the total number of sample paths, $\{\omega^1, ..., \omega^K\}$. In this paper, this statistical estimated value is used as expected value function.

3.2 PROPOSED APPROXIMATE DYNAMIC PROGRAMMING APPROACH

The Bellman's equation can be written as an expectation form as,

$$V_t^*(S_t) = \min_{a_t \in \chi_t} [C(S_t, a_t) + \mathbb{E}\{V_{t+1}^*(S_{t+1})|S_t\}]. \quad (28)$$

where, S_{t+1} depends on both S_t and a_t. It is usually troublesome to solve the optimization program efficiently with traditional DP approaches due to the curse of dimensionality [**?**]. A post-decision formulation of Bellman's equation is formulated to overcome the problem as,

$$V_t^*(S_t) = \min_{a_t \in \chi_t} [C(S_t, a_t) + V_t^a(S_t^a)]. \quad (29)$$

where, S_t^a is called post-decision state which can be defined as the state instantly after the current decision a_t is made, but before the arrival of any new information.
The value function of the post decision state $V_t^a(S_t^a)$ can be expressed as,

$$V_t^a(S_t^a) = \mathbb{E}\{V_{t+1}^*(S_{t+1})|S_t^a\}, \quad (30)$$

$$V_{t-1}^a(S_{t-1}^a) = \mathbb{E}\{V_t^*(S_t)|S_{t-1}^a\}. \quad (31)$$

Table 1: The Proposed Algorithm

Step 0.
a. Initialize $V_t^{a,0}(s) = 0$ for each $s \epsilon S$, and $t \leq T-1$.
b. Set $V_T^{a,n}(s) = 0$ for each $s \epsilon S$, and $n \leq N$.
c. Set n=1.
d. Initialize S_0^1.
Step 1. Choose a sample path ω^n.
Step 2. For $t \leq (T-1)$:
a. Solve:
$\hat{v}_t{}^n = \min_{a_t \in \chi_t} [C(S_t^n, a_t) + V_t^{a,n-1}(S^{M,a}(S_t^n, a_t))]$.
b. If $t > 0$, update $V_{t-1}^{a,n-1}$ using,
$V_{t-1}^{a,n}(S_{t-1}^{a,n}) = (1-\alpha_{n-1}) V_{t-1}^{a,n-1}(S_{t-1}^{a,n}) + \alpha_{n-1} \hat{v}_t{}^n$.

c. Find the post-decision state:
$S_t^{a,n} = S^{M,a}(S_t^n, a_t^n)$.

d. The next pre-decision state:
$S_{t+1}^n = S^M(S_t^n, a_t^n, E_{t+1}(\omega^n))$.

Step 3. If $n < N$, increment n and return **Step 1.**

The proposed algorithm is presented in Table 1. Initially, a suitable value function approximation $V_t^a(S_t^a)$ is assumed. Then, n numbers of sample paths are chosen in $step$ 1. In $step$ $2a$, the value of being in state S_t^n is calculated and the post-decision value function approximation is updated in $step$ $2b$. In $step$ $2b$, α_{n-1} is known as a "stepsize", and generally takes on values between 0 and 1. It is often defined as "smoothing", a "linear filter" or "stochastic approximation". The post-decision state is figured out in $step$ $2c$ and the next pre-decision state is found in $step$ $2d$. Finally, in $step$ 3, if the number of iteration is less than the maximum number of iteration, the n is incremented and the system is returned to $step$ 1.

4 SIMULATION SETUP AND RESULTS ANALYSIS

In this section, the numerical and graphical simulation results are presented by investigating the proposed ADP approach where the traditional DP approach is used to validate the proposed approach. This section is parted into three sub-sections. All the simulation parameters and the information about simulation environment is presented in section 4.1, the simulation results for stochastic case study are shown in section 4.2 and the computational time analysis for large data samples are presented section 4.3.

4.1 SIMULATION SETUP

The battery parameters are summarized in Table 2. The other major parameters like maximum and minimum limits of wind energy, load demand, and power generation of diesel generator are presented in Table 3.
To validate our proposed algorithm, the percentage of optimality (%) is calculated as,

$$\% \; of \; optimality = \frac{\hat{V}}{V^*} \times 100\% \quad (32)$$

where, $\hat{V}$ is defined as the estimated value obtained from the proposed ADP approach and V^* is the optimal value obtained from the traditional DP approach.

Table 2: Battery Parameters

Battery	Lead-Acid
Type	2V/1000 Ah
Quantity	75
Capacity	150 kWh
Minimum limit	75 kWh
Cycle life	1000 @ 50% DOD
Charging and discharging efficiencies (ϕ^c and ϕ^d)	80%
Maximum charging and discharging rates (ψ^c and ψ^d)	50 kWh
Battery cost	\$80 per kWh
Installation cost	\$20 per kWh
Transportation cost	\$20 per kWh

Table 3: The System Parameters

Name	Demand (kW)	Diesel generator (kW)	Wind energy (kW)
Maximum	50	70	50
Minimum	20	21	0

Simulation results are shown in the rest of these sections. The simulations are conducted in $MATLAB$ $2015b$ environment using a computer with 3.60 GHz $Intel\ Core\ i7-4790\ CPU$ processor and 8 $GB\ RAM$.

4.2 STOCHASTIC CASE STUDY

For stochastic analysis, the noise supports are introduced to create noise that can be either uniformly or pseudonormally distributed. Though the probability distribution and noise supports are kept same for load demand at each time step, however different probability methods are used for the wind energy presented in the second column of Table 4. In Table 4, U and N functions are represented as uniform and pseudonormal probability distribution, respectively. The next-hour wind energy and load demand are obtained using the probability distribution functions [24]. For all test problems, SOC_{stp} is assumed as 0.6.

Table 4: Results for Stochastic Test Problems.

No.	w_t^W	C^{gen} (\$)	C^{BESS} (\$)	$\hat{V}$ (\$)	% of opt. (%)
1	$U(-1,1)$	162.58	18.45	90.52	98.62 %
2	$N(0,1.0^2)$	158.36	14.01	86.19	98.02 %
3	$N(0,3.0^2)$	165.75	20.47	93.11	98.13 %
4	$N(0,0.5^2)$	164.38	21.06	92.72	99.17 %
5	$N(0,2.5^2)$	159.06	15.85	87.46	98.66 %
6	$N(0,1.5^2)$	161.14	21.53	91.34	99.05 %
7	$N(0,3.5^2)$	163.30	20.82	92.06	98.37 %
8	$N(0,4^2)$	165.46	21.58	93.52	98.45 %

The probability distribution functions for stochastic wind energy are presented in column No. 2 of Table 4. The stochastic simulation results are also shown in Table 4. According to Table 4, the daily operational cost of the system for problem 2 is obtained as \$86.19, where the optimal value is obtained from DP as \$87.93, and then the percentage of optimality is calculated as 98.02% which is very promising. The other results are also validated that the

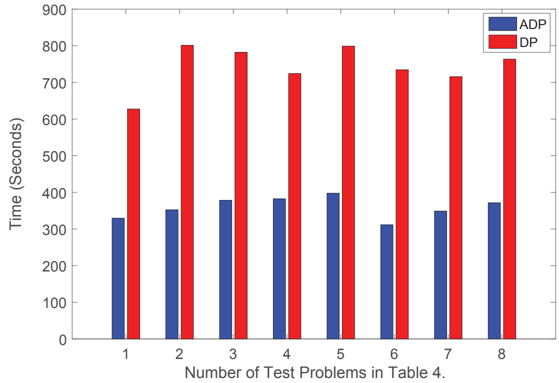

Figure 2: The computational time comparison between the DP and ADP.

ADP can obtain at least 98% of optimality for the stochastic case study. The computational time to solve the problem for the traditional DP and ADP approaches are also reported in Figure 2. For example, to solve problem No. 4, the computational time cost for the ADP and DP are obtained as 382.44 seconds and 724.41 seconds, respectively. In Figure 2, the other results are also justified that, the proposed ADP approach takes almost 50% less computational time than the traditional DP approach. The results prove that the proposed ADP approach can be a powerful tool of solving stochastic optimization problems.

4.3 COMPUTATIONAL TIME ANALYSIS

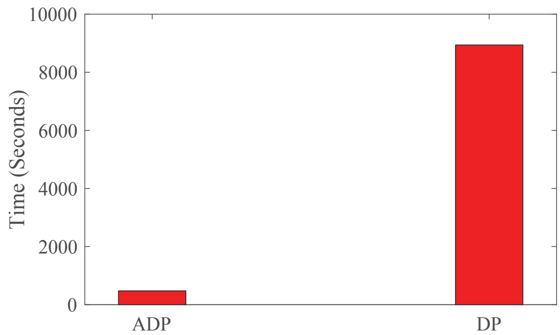

Figure 3: The computational time comparison between the DP and ADP for large data samples using test problem No. 4 of Table 4.

The performance of the proposed ADP approach is also validated using relatively large data samples where 0.5 million of data samples are taken into consideration for each time step. The stochastic test problem No. 4 of Table 4 is used for this analysis. The proposed ADP approach solved the test problem with the computational time as 476.37 seconds for 1000 iterations and the near optimal value of the daily operational cost is found as \$96.98. The statistical estimated value using the traditional DP approach is obtained as \$97.79 with the time cost as $8,940.83$ seconds which is 18.77 times higher than the proposed ADP approach in terms of computational time. The computational time comparison for this experiment is presented in Figure 3.

5 CONCLUSION

In this paper, a computationally efficient ADP approach is proposed to investigate the optimal operation of energy systems in an islanded microgrid considering the stochastic wind energy and the load demand. Simulations with different case studies are conducted to validate the effectiveness of the proposed ADP approach. The traditional DP approach is adopted to validate the proposed approach. The results showed that the proposed ADP approach can achieve at least 98 % of optimality for the stochastic case study with around 50 % less computational time. The computational time comparison is justified for large date samples where the proposed ADP approach achieved the solution approximately with 18.77 times faster than the traditional DP approach in seconds. From the simulation results, it can be concluded that the proposed ADP approach can be a powerful software for the stochastic power system optimization problems in future.

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