Operational strategy optimisation of VRB energy storage systems considering the dynamic characteristics of VRB in active distribution networks

Jiazhi Lei1,2 | David Wenzhong Gao2 | Jinhong Liu1

1 School of Automation, Nanjing University of Science and Technology, Nanjing, China
2 Department of Electrical & Computer Engineering, University of Denver, Denver, USA

Abstract

Strategy optimisation of large-scale battery energy storage system (BESS) operation in active distribution networks (ADNs) is an actively pursued research topic concerned by electric power researchers. This study proposes a dynamic programming method (DPM)-based operational strategy optimisation of vanadium redox flow battery (VRB) ESSs for the comprehensive performance of ADNs considering the dynamic characteristics of VRB. The dynamic characteristics of VRB based on self-discharge rate, dynamic efficiencies, maximum absorption power, cycle life and apparent power are reasonably proposed to construct the operational restrictions of ESSs. VRB is safely and reasonably operated with high cycle life and ideal states by these dynamic operational restrictions. And then, DPM is used to decompose the multivariate optimisation problem into several univariate optimisation problems. Finally, different case studies showed that the developed operation strategy of VRB ESSs can greatly improve both the economy and the voltage quality of ADNs. Also, the curtailment rate of renewable energy in ADNs is greatly reduced by about 50% and VRB ESSs can get a perfect optimisation associated with a higher utilisation rate of about 0.8 and an ameliorative average efficiency of about 0.753.

1 | INTRODUCTION

Wind and photovoltaic distributed generations (DGs), as non-carbon renewable energy resources, are supported by many policies and subsidies around the world to help promote energy conservation [1, 2]. Yet, the high intermittency of these increasingly integrated renewable DGs brings many special challenges to the operation of active distribution networks (ADNs) [3]. Vanadium redox flow battery (VRB), as a large-scale energy storage medium, is an appropriate solution to facilitate the growing integration of DGs [4]. Battery energy storage systems (ESSs) are flexible in control and different operational strategies of VRB ESSs will significantly affect the operational performance of ADNs. Therefore, it is an increasingly pursued subject to realise the operational strategy optimisation of distributed VRB ESSs.

Currently, it is definite that the distributed access of VRB ESSs can help bring in more advantages on the flexible energy management of ADNs. The energy management of distributed VRB ESSs can bring many evident benefits such as electricity retail benefit, nodal voltage improvement, network loss reduction along with the reduction of greenhouse gases emission and better utilisation of renewable energy. These benefits have been partly shown in the previous literature. In [5, 6], the energy purchase cost and power losses are conducted to optimise the distributed energy management strategy in microgrids. The authors in [7] considered the battery control strategy by minimising the energy procurement and battery operation costs. In [8], the revenue from outputting energy and consuming natural gas in discharge mode of battery are modelled to determine the optimal operation strategy of BESS. In [9], costs of voltage regulation and peak demand are specially minimised to charge or discharge distributed BESSs. Clearly, these operation costs should be comprehensively considered for the day-ahead distributed BESSs operation model. Also, voltage regulation of BESSs, as a contradictory performance indicator compared with operation...
costs, should be taken into account at the same time. In addition, inappropriate operation of VRB ESSs can greatly reduce the cycle life of batteries, which leads to an unexpected high replacement cost [10, 11]. Therefore, to operate and control the distributed VRB ESSs, the multidimensional benefits of the energy storage battery associated with the performance of VRB should be optimised.

On the other hand, VRB is a complicated and variable chemical energy storage medium, which is likely to be affected by the internal parameters and the chemical reaction. For VRB, its internal operational performance, such as self-discharge rate, maximum absorption power, efficiencies and the cycle life, is constantly changing [12–15]. Therefore, the energy storage battery can no longer be simply regarded as an ideal component, and its internal operational performance parameters cannot be considered as constant values. The dynamic characteristics of VRB should be constructed first for the control of VRB ESSs. Another challenge is that the operational restrictions of VRB ESSs based on the dynamic characteristics of VRB should be fully taken into account. In [16], the remaining capacity constraint of battery energy storage was constructed for the dispatching of energy storage and wind power. In [17], efficiency constraint of battery energy storage was built for day-ahead dispatch model in smart grid. The authors in [18] considered the power and state of charge (SOC) limit constraints of battery for the operation optimisation of battery energy storage. The operational constraints involved in these studies are too simple and only limited to SOC, capacity, charging and discharging power limits. The operational constraints such as self-discharge rate, maximum absorbed power, temperature, cycle life, maximum charging and discharging time are not involved. Also, the dynamic variability of VRB’s internal operational performance parameters is not considered. These operational constraints can not only restrict or cut down the outputs of VRB but also maintain the safe or ideal operation state of VRB.

Generally, the developed mathematical strategy optimisation model is a non-linear and mixed-constrained programming problem that involves multiple decision variables and different kinds of constraints. The solution processes should cope with these multidimensional varieties of states. The traditional intelligent algorithms, such as particle swarm optimisation and genetic algorithm [19, 20], are no longer effective for these specific implications due to their limitations in dealing with the multivariate optimisation problem. Consequently, these multivariate optimisation problems should be decomposed into several univariate optimisation problems, and dynamic programming method (DPM) is suitable [21] for such process. The forecasted errors for the random outputs of DGs and load requirements are inevitable [22] and this uncertainty also should be thought over in the optimisation.

Consequently, this study proposes a DPM-based operation strategy optimisation of VRB ESSs for the comprehensive performance of ADNs considering the operational restrictions of VRB. Both the total benefits or costs (associated with environmental benefit, indirect benefit, electricity retail benefit, electrical purchased cost, replacement cost of VRB ESSs, cost of curtailed renewable energy and network loss cost) and the nodal voltages regulation are maximised for the strategy optimisation. The operational restrictions including the dynamic characteristics and specific utilisation of VRB are developed to restrict the power outputs and the operational modes of VRB ESSs. Then, the developed mathematical strategy optimisation model is decomposed into several univariate optimisation problems by DPM according to the states of SOC and the corresponding solution processes are presented. Finally, the proposed method is verified by a modified IEEE 33-bus distribution network in different cases. Compared with the previous strategy optimisation of VRB ESSs, the proposed model is more reasonable in performance and effective in applications.

We organise the remainder of this study as follows: In Section 2, the modelling for ADNs, including the dynamic characteristics of VRB and the outputs of DGs, is presented. Next, the operational restrictions of ADNs is discussed in Section 3. After that, in Section 4, we develop the mathematical model for the operational strategy optimisation of VRB ESSs and the solving processes. The proposed strategy is then verified based on a modified IEEE 33-bus distribution network in two cases and comparative analysis is discussed in Section 5. Finally, conclusions are presented in Section 6.

2 | MODELLING FOR ADNs

The penetration of wind turbine generators (WTGs) and photovoltaic units in ADNs will result in a load-generation imbalance, which can lead to a load reduction or renewable power curtailment. This raises an increasing and urgent need of large-scale BESSs to cope with the uncertainties and randomness of wind or photovoltaic power generation. The operational strategies of distributed VRB ESSs are varied and independent in mutual. The dynamic characteristics of VRB associated with efficiencies and maximum absorption power are all significant parameters to influence the operational strategies. Consequently, to manage the operation of VRB ESSs in ADNs, these uncertainties and dynamic characteristics should be modelled. The distributed access of VRB ESSs to cope with the integration of WTGs and photovoltaic units in ADNs is shown in Figure 1.

2.1 | Dynamic characteristics of VRB

The chemical reaction in VRB will not stop within the battery’s life. Therefore, the self-discharge rate λ should be considered. Generally, the value of λ is associated with battery temperature $T_b$ and SOC:

$$\lambda = (g_a T_b + g_b) SOC + g_c T_d + g_d \tag{1}$$

where, $g_a$, $g_b$, $g_c$ and $g_d$ are constant coefficients that can be obtained by the tests of VRB.

To manage the operation of VRB ESSs, the dynamic characteristics of VRB should be first constructed. For a VRB, the
**FIGURE 1** Active distribution networks (ADNs) with the penetration of distributed vanadium redox flow battery (VRB) energy storage systems (ESSs)

**FIGURE 2** Maximum absorption power $P_{ab}$ influenced by parameter state of charge (SOC)

$SOC$ of VRB can be calculated as

$$SOC_t = \begin{cases} \frac{SOC_{t-1} - \int_{t-1}^{t} P_{VRB}(t) (1 - \lambda) \eta_d E_{VRB}^{\text{rated}} dt}{SOC_{t-1} - \int_{t-1}^{t} P_{VRB}(t) (1 - \lambda) \eta_c E_{VRB}^{\text{rated}} dt} & \text{discharging} \\ \frac{SOC_{t-1} + \int_{t-1}^{t} P_{VRB}(t) (1 - \lambda) \eta_c E_{VRB}^{\text{rated}} dt}{SOC_{t-1} + \int_{t-1}^{t} P_{VRB}(t) (1 - \lambda) \eta_d E_{VRB}^{\text{rated}} dt} & \text{charging} \end{cases}$$

(2)

where, $t-1$ represents the last period of $t$. For $P_{VRB}$, the plus or minus of $P_{VRB}$ is determined by the operating state of VRB. $P_{VRB} < 0$ if VRB is at charging state and $P_{VRB} > 0$ if VRB is at discharging state. In general, the dynamic efficiencies of VRB (charging efficiency $\eta_c$ and discharging efficiency $\eta_d$) are affected by many factors such as the charging or discharging current, temperature and ion concentrations. To simplify the modelling of $\eta_c$ and $\eta_d$, the dynamic efficiencies of VRB are usually considered as

$$\eta_d = \frac{P_{VRB}(\text{p.u.})}{a_d P_{VRB}(\text{p.u.}) + b_d SOC (SOC - 1) + c_d}$$

$$d_d' P_{VRB}(\text{p.u.}) + b_d' SOC + c_d'$$

$$d_d' T (SOC + b_d') + c_d'$$

$$\eta_c = \frac{(a_c SOC + b_c P_{VRB}(\text{p.u.}) + c_c SOC + d_c) P_{VRB}(\text{p.u.})}{a_c' SOC + b_c' P_{VRB}(\text{p.u.}) + c_c' SOC + d_c'}$$

$$d_c' T (SOC + b_c') + c_c'$$

(3)

where, $a_d, b_d, c_d, a_d, b_d, c_d$ and $a_d', b_d', c_d'$ are all constant coefficients. According to the values of parameters $a_d, b_d, c_d, a_d, b_d, c_d'$ and $a_d', b_d', c_d'$, the maximum absorption power $P_{ab}$ in charging and discharging state, respectively, can be obtained as shown in Figure 2.

The cycle life $\kappa$ of VRB is also dynamic and it is associated with battery temperature $T_a$ and discharge depth $D_{DL}$:

$$\kappa = \frac{1}{(k_1 T_a + k_2) N_{DL} (D_{DL})}$$

(5)

where $k_1$ and $k_2$ are constant coefficients. $N_{DL}$ represents the polynomial relationship that can be found in [12].
2.2 Outputs of DGs

Based on the historical data of wind speed or illumination intensity, wind speed $v$, and illumination intensity $I_m$ can be forecasted by autoregressive moving average (ARMA) model:

$$
\begin{align*}
\ell_t &= \mu + \sigma \cdot \ell_{t-1} \\
I_m &= \mu + \sigma \cdot I_{m-1}
\end{align*}
$$

where $\ell_t$ and $I_m$ are time series, which can be obtained by the auto-regressive parameter and moving average parameters of ARMA model.

According to the forecasted value of $v$ and $I_m$, the outputs of WTGs $P_{w}$ and photovoltaic units $P_{r}$ can be, respectively, calculated by

$$
P_w = \begin{cases} 
P_N (a_1 v^3 + a_2 v^2 + a_3 v + a_4), & v < v_{in} \\
P_N, & v_{in} \leq v < v_{N} \\
0, & v \geq v_{N}
\end{cases}
$$

$$
P_r = \begin{cases} 
P_{r,i}, & 0 \leq I \leq I_r \\
P_{r,i}, & I > I_r
\end{cases}
$$

where $a_1, a_2, a_3, a_4$ are parameters associated with WTGs data. $P_N$ is the rated power of WTGs and $P_{r,i}$ is the rated power of photovoltaic units. $I_r$ represents the rated illumination intensity of photovoltaic units.

2.3 Load requirements

Generally, the load requirements are random and vary with many factors such as air temperature $T_{\text{air}}$, humidity $H_{\text{air}}$, wind speed $v$ and air pressure $P_{\text{a}}$. The date of $T_{\text{air}}, H_{\text{air}}, v$, and $P_{\text{a}}$ can be obtained from meteorological data.

To forecast the value of load requirements, convolutional neural networks (CNN) as an artificial intelligence algorithm can provide an excellent tool [24]:

$$
P_{L,k}(t) = C(g_{L,k}, T_{\text{air}}, H_{\text{air}}, v, P_{a}), \quad k = 1, 2, \ldots, N_L
$$

where $N_L$ is the number of load nodes, $P_{L,k}$ is the load requirement at node $k$ and $g_{L,k}$ is the historical load requirement at node $k$. Load forecasting by CNN is not discussed in this study.

3 OPERATIONAL RESTRICTIONS FOR ADNs

In this section, the operational restrictions of ADNs are introduced by the corresponding mathematical expressions, especially the dynamic restrictions of distributed VRB ESSs.

3.1 Constraint restrictions of ADNs

For ADNs, the node constraints of power flow balance should be first satisfied:

$$
\begin{align*}
V_i' &= \sum_{j=1}^{N} V_j' \left( G_{ij} \cos \theta_{ij} + B_{ij} \sin \theta_{ij} \right) = P_{L,i} + P_{VRB,i} + P_{W,i} - P_{R,i} \\
V_i' &= \sum_{j=1}^{N} V_j' \left( G_{ij} \sin \theta_{ij} - B_{ij} \cos \theta_{ij} \right) = Q_{L,i} + Q_{VRB,i} + Q_{W,i} - Q_{R,i}
\end{align*}
$$

where $V_i'$ and $V_j'$ are, respectively, the voltage at node $i$ and node $j$, $P_{W,i}$, $P_{VRB,i}$, $Q_{W,i}$ and $Q_{VRB,i}$ are, respectively, the active and reactive power of WTG and photovoltaic units at node $i$, $P_{R,i}$ and $Q_{R,i}$ are, respectively, the active and reactive power of VRB ESS at node $i$. $P_{L,i}$ and $Q_{L,i}$ are, respectively, the active and reactive power of loads at node $i$. $G_{ij}$ and $B_{ij}$ are the real part and imaginary part of the admittance between nodes $i$ and $j$. $\theta_{ij}$ is the phase angle between nodes $i$ and $j$. $N$ represents the number of nodes.

For each node, the voltage magnitude should be limited within a certain range for the power quality of ADNs:

$$
V_{i,\text{min}} \leq V_i' \leq V_{i,\text{max}}
$$

For each branch of nodes $i$ and $j$, the current magnitude should be limited for avoiding cable overheating:

$$
I_{ij}' \leq I_{ij,\text{max}}
$$

The apparent power magnitude for each branch should also be limited within an upper value for the security of ADNs:

$$
S_{ij}' \leq S_{ij,\text{max}}
$$

For the outputs of DGs, these active and reactive power should satisfy the upper and lower limits:

$$
\begin{align*}
0 \leq P_{W,i} &\leq P_{W,i,\text{max}}, \quad 0 \leq Q_{W,i} \leq Q_{W,i,\text{max}} \\
0 \leq P_{VRB,i} &\leq P_{VRB,i,\text{max}}, \quad 0 \leq Q_{VRB,i} \leq Q_{VRB,i,\text{max}}
\end{align*}
$$

For the tie-line interactive power, the exchange power $P_{\text{grid},i}$ and $Q_{\text{grid},i}$ should satisfy the upper and lower limits due to the limited adjustment capability of the main grid:

$$
\begin{align*}
P_{\text{grid},\text{min}} \leq P_{\text{grid},i} &\leq P_{\text{grid},\text{max}} \\
Q_{\text{grid},\text{min}} \leq Q_{\text{grid},i} &\leq Q_{\text{grid},\text{max}}
\end{align*}
$$

3.2 Dynamic restrictions of distributed VRB ESSs

Due to the dynamic characteristics of VRB, the internal operational performances of VRB are constantly variable. To
guarantee the safe and reasonable operation of VRB, dynamic restrictions of distributed VRB ESSs should be satisfied.

VRB ESSs can be used for active power and reactive power regulation. The apparent power of VRB ESSs \( S_{VRB,k} \) should be restricted:

\[
|S_{VRB,k}| \leq |S_{VRB,k,\text{max}}| \tag{16}
\]

where \( S_{VRB,k} \) is the total of active power \( P_{VRB,k} \) and reactive power \( Q_{VRB,k} \).

For the SOC of VRB ESS \( k \), the upper and lower limit constraints should be satisfied:

\[
SOC_{k,\text{min}} \leq SOC_{VRB,k} \leq SOC_{k,\text{max}} \tag{17}
\]

For the output power of distributed VRB ESS \( k \), \( P_{VRB,k} \) should be less than the maximum absorption power, which can be depicted as

\[
|P_{VRB,k}| (1-\lambda) \leq P_{\text{d,k}}(SOC_{VRB,k}) \cdot P_{\text{rated}}^\text{abs} \tag{18}
\]

For the discharge depth in the \( i \)th cycle \( D_{d,i} \), the upper limit also should be satisfied:

\[
D_{d,i,k} \leq D_{d,i,k,\text{max}} \tag{19}
\]

To make sure of the long-term use of VRB, the cycle life \( \kappa \) of VRB should be set more than the minimum value:

\[
\kappa \geq \kappa_{\text{min}} \tag{20}
\]

Also, the charge and discharge time \( T \), which can be obtained by Equation (2), should be limited to the maximum charge and discharge time \( T_{\text{c,max}} \):

\[
T \leq T_{\text{c,max}} \tag{21}
\]

The restrictions of VRB ESSs are clearly shown in Figure 3.

4 | OPERATIONAL STRATEGY OPTIMISATION OF VRB ENERGY STORAGE SYSTEMS

The operational strategy of distributed VRB ESSs is used to determine the charging or discharging states of VRB ESSs and manage the outputs of VRB ESSs for the power balance of load requirements, renewable energy and power network. Distributed VRB ESSs are flexible in management, and the operational strategy of VRB ESSs should be optimised.

4.1 | Developed mathematical model

The penetration of distributed VRB ESSs can bring great benefits to ADNs such as reducing the network loss, getting environmental benefit, promoting the consumption of renewable energy and improving the node voltages. Also, ESSs can get electricity retail benefit by charging when the electricity price is low and discharging when the electricity price is high. Therefore, the developed mathematical model for the operational strategy optimisation of distributed VRB ESSs should make a comprehensive consideration of the overall benefits and maximise these benefits. The developed mathematical objective function is formulated as

\[
\begin{align*}
\max f_1 &= C_{EB} + C_{SE} + C_{OM} - C_{PE} - C_{RF} - C_{AB} - C_{let} \\
\min f_2 &= \sum_{i=1}^{N} (V_i - V_i^{\text{exp}})^2
\end{align*}
\tag{22}
\]

where \( C_{OM} \) is the operation and management cost of VRB ESSs, \( C_{EB} \) is the environmental benefit brought by VRB ESSs and DGs, \( C_{PE} \) is the electrical purchased cost from the main grid, \( C_{SE} \) is the electricity retail benefit from ADNs to the main grid.
grid, \( C_{ID} \) is the indirect benefit brought by VRB ESSs, \( C_{RP} \) is
the replacement cost of VRB ESSs, which is associated with
\( N_{rec} \). \( C_{AB} \) is the cost for the curtailed renewable energy of DGs
and \( C_{loss} \) is the network loss cost of ADNs. \( V_{i}^{exp} \) is the expected
voltage of node \( i \) (in p.u.).

For the value of \( C_{OM} \), it is associated with the output power
of VRB ESSs, which can be calculated as

\[
C_{OM}(P_{d}) = \int_{0}^{T} K_{OM}[P_{VRB,k}] dt
\]

(23)

where \( K_{OM} \) is considered as a constant coefficient.

For the values of \( C_{FE} \) and \( C_{SE} \), they are all dependent on
the exchange power between ADNs and main grid \( P_{grid,k} \), which
remain all the objective function and they need to be
simplified in the developed model.

For the value of \( C_{EB} \), it depends on the greenhouse gases
(such as CO\(_2\), SO\(_2\) and NO\(_x\)) emission due to the reduction of
\( P_{grid,k} \) in ADNs. Generally, the value of \( C_{EB} \) can be depicted as

\[
C_{EB} = \sum_{j=1}^{N} \left( \int_{0}^{T} (P_{grid,k} - P_{grid,k}^{\min}) dt \right) \zeta_{grid,k,j}
\]

(26)

where \( j \) is the variety of greenhouse gases. Clearly, \( N=3 \) as only
three greenhouse gases are considered in this study. \( P_{grid,k}^{\min} \),
represents the initial exchange power between ADNs and the main
grid when distributed VRB ESSs are not installed. \( \zeta_{grid,k,j} \) is the
density of greenhouse gas \( j \) when generating unit electricity. \( \eta_{grid,j} \)
is the environmental pollution price in unit for greenhouse gas 4.2 Simplifying of the developed mathematical model

In the developed mathematical model, two objective functions
are used. Therefore, the solution set of Equation (22) is variable.
Also, \( f_1 \) and \( f_2 \) are different in dimension. It is not
tuitive to judge the advantages or disadvantages of the operational
strategy of VRB ESSs by \( f_1 \) and \( f_2 \). To simplify the developed
mathematical model, we set \( f_1 \) as the objective function and \( f_2 \)
as a variable constraint. The developed mathematical model is
simplified as

\[
\begin{cases}
\max f_1 = C_{EB} + C_{FE} + C_{ID} - C_{OM} - C_{RP} - C_{AB} - C_{loss} \\
s.t. f_2 = \sum_{i=1}^{N} (V_i - V_{i}^{exp})^2 \leq \delta \\
\text{Other constraints}
\end{cases}
\]

(32)

where \( \delta \) is a variable parameter. Other constraints include
the operational restrictions of ADNs that are depicted as Equations (10)–(21).
4.3 Solving processes

For the model of Equation (32), the decision variables are the outputs of distributed VRB ESSs in the time interval. In this study, the real-time operation interval is set as 15 min. Therefore, the decision variables can be depicted as

\[
P_{VRB,k}^t = \left[ P_{VRB,k}^1, P_{VRB,k}^2, \ldots, P_{VRB,k}^{Q_t} \right], \quad Q = 96 \tag{33} \]

Clearly, the developed model is a non-linear and mixed-constrained programming problem, which involves multiple decision variables and constraints. The traditional mathematical programming methods are not suitable. DPM can decompose a multivariate optimisation problem into several univariate optimisation problems by the transition of stage states [25]. Therefore, DPM is used to solve Equation (32) in this study. The designed solving processes of DPM are illustrated in Figure 4.

In Figure 4, the calculation of \(SOC(k+1)\) can be realised by Equation (1), \(X\) represents the upper and lower limit of \(SOC\), which is shown by Equation (15). \(\Omega\) represents the constraints in Equation (32).

For DPM, it begins at period \(N-1\) and recurses by layers until the endpoint, which can be depicted as

\[
f_{N-1}[SOC(k)] = \max_{P_{VRB,k} \in \Omega} f_{N-1}[SOC(k)]
= \max_{P_{VRB,k} \in \Omega} \left\{ J_{N-1}[SOC(k), N] + L[SOC(k), P_{VRB,k}^t, k] \right\}
\]

s.t.

\[
\begin{align*}
SOC(k+1) &= f[SOC(k), P_{VRB,k}^t, k] \\
SOC(k) &\in X \in R^u \\
P_{VRB,k}^t &\in \Omega \in R^a
\end{align*} \tag{34}
\]

In the univariate optimisation problems, the previous optimisation consequent of \(P_{VRB,k}^t\) is used as the initial value of the next univariate optimisation problem. Because of the existence of forecasted error in DGs and load requirements, a certain margin should be reserved in the power balance for satisfying load requirements. In addition, the responding speed of VRB ESSs are not timely, and this also needs a certain margin in power balance:

\[
\begin{align*}
\left| P_{PV,i}^t + P_{PV,i}^p + P_{VRB,k}^t + P_{grid,i}^t - P_{grid,i}^t - P_{init,i} \right| > \varepsilon_1 \\
\left| Q_{PV,i}^t + Q_{PV,i}^p + Q_{VRB,k}^t + Q_{grid,i}^t - Q_{grid,i}^t - Q_{init,i} \right| > \varepsilon_2
\end{align*} \tag{35}
\]

where \(\varepsilon_1\) and \(\varepsilon_2\) are, respectively, the margin of active and reactive powers.

5 CASE STUDY

5.1 Input data

To verify the effectiveness of the proposed mathematical model for the operational strategy optimisation of VRB ESSs, a modified IEEE 33-bus distribution network is applied as shown in Figure 5.

The capacity of this distribution system is 3715+j2300 kVA. In the modified IEEE 33-bus distribution network, VRB ESS 1, VRB ESS 2 and VRB ESS 3 are, respectively, installed at nodes 1, 9 and 15. The capacity of VRB ESS 1, 2 and 3 are all 100 kWh. Nodes 7 and 19 are used as installation nodes for WTGs. Nodes 14 and 30 are used as installation nodes for photovoltaic units. In all the case studies, the base capacity is 1 MVA. The upper and lower voltage bound for nodes voltage are, respectively, 1.05 and 0.95 p.u. All these case studies were performed by MATLAB R2019a on a PC with Intel Core i7-9750H (2.60 GHz) and 16-GB RAM.

For WTGs, \(v_{in} = 15 \text{ m/s}, v_{p} = 4 \text{ m/s}, v_{w} = 20 \text{ m/s};\) the fitting coefficients \(a_1 = 0.0014848, a_2 = -0.041545, a_3 = 0.43333, a_4 = -1.1636.\) For photovoltaic units, \(I = 1000 \text{ W/m}.\) The capacity of WTG1 and WTG2 are 500 kW; the capacity of PV1 and PV2 are 400 kW. For the operational constraints, \(SOC_{max} = 1, SOC_{min} = 0.2, SV_{VRB} = 120 \text{ kVA}, P_{VRB}^{max} = 7.5 \text{ MW}, P_{grid}^{max} = 3.0 \text{ MW, } Q_{grid}^{max} = 1.5 \text{ MVAR, } Q_{grid}^{max} = 2.3 \text{ MVAR, } \lambda_c = 0.3 \text{ S/kWh, } K_{OM} = 0.0381 \text{ S/kWh.}\) For the electricity price, time-of-use (TOU) price is used, which can be referred to [26]. \(\lambda_i\) is set as 0.03 S/kWh and \(K_{OM}\) is set as 0.01 S/kWh. In case 1, \(\delta\) is set as 0.06, and in case 2, \(\delta\) is set as 0.04. To simply the optimisation, all the operational strategies of VRB ESSs are considered as the same.
5.2 | Operational strategy optimisation in case 1

According to the CNN and ARMA models, the curves of WTGs, photovoltaic units and load requirements in one day can be acquired as shown in Figures 6(a) and (b). As the real-time operation interval of VRB ESSs is set as 15 min, the predictions of WTGs, photovoltaic units and load requirements are all realised once per 15 min. Also, the curve of TOU electricity price is presented in Figure 6(a).

As shown in Figures 6(a) and (b), the power outputs of WTGs and photovoltaic units mismatch the load requirements. Therefore, VRB ESSs should be operated for supplying the load requirements or consuming renewable energy. According to the proposed mathematical model for the operational strategy optimisation of VRB ESSs and the solving processes, the operational strategy of VRB ESSs can be obtained as shown in Figure 6(b).

In Figure 6(b), the optimal outputs of VRB ESSs are presented. In the time intervals of [0:00, 5:00], [6:00, 12:15] and [23:00, 24:00], VRB ESSs are used to consume wind or photovoltaic power as VRB ESSs are set in charging state. This is a fact that renewable energy in these time intervals is abundant, and consuming renewable energy can get environmental benefits and reduce \( C_{AB} \). In the time interval of [14:15, 23:00], VRB ESSs are set in discharging state. As the electricity price in this time interval is very high, the value of \( C_{PE} \) is largely reduced. Also, indirect benefit \( C_{ID} \) can be brought with the discharging of VRB ESSs in this time interval. In addition, the value of \( P_{grid,t} \) is largely reduced as the operation of VRB ESSs. In the time interval of [1:45, 5:30], renewable energy are sufficient to supply load requirements but \( P_{grid,t} \) is more than \( P_{grid, min} \). This is a fact that the electricity price in this time interval is very low and purchasing electricity from the main grid is economical.

As shown in Figure 6(c), the increment of \( SOC \) is not linear, and this is a fact that \( P_{i,VRB} \) is not constant. Also, VRB ESSs are not fully utilised, as \( SOC \) of VRB does not reach the maximum value of one. In the time interval of [5:00, 6:00], VRB ESSs are set in the static state as the electricity price in this time interval is very low and is not economical to discharge VRB ESSs. In [12:15, 14:15], VRB ESSs are also set into the static state. This is a fact that photovoltaic power is adequate in this time interval and renewable power is prior to VRB ESSs. The dynamic efficiencies of VRB is relatively low in the time intervals of [4:30, 5:00] and [6:00, 12:15]. This is a fact that \( P_{i,VRB} \) in these time intervals are very low. The average efficiency of VRB is about 0.753, and this significantly explained the optimal operation performance of VRB ESSs.

The permeability rate of renewable energy is about 22.76%. With the optimal operation of VRB ESSs, the curtailment rate of renewable energy is reduced from 8.26% to 4.08%, which is due to the charging of VRB ESSs when renewable energy is sufficient. In time intervals of [0:00, 1:45] and [5:45, 7:15], the abandonment of renewable energy exist, and this is due to the maximum absorption power restriction of Equation (18).

In Figure 6(d), \( P_{i,VRB} \) and maximum absorption power \( P_{ab,t} \) are shown. Clearly, \( P_{i,VRB} \) is restricted by \( P_{ab,t} \) in the time intervals of [0:00, 2:15], [10:30, 11:45] and [12:15, 22:45]. This restriction guaranteed the safe operation of VRB ESSs.

In Figure 7(a), the costs of each part in \( f_1 \) are shown. With the optimal operational strategy of VRB ESSs, the value of \( f_1 \) is increased from about –141.085 to 15.323 $ although \( C_{OM} \) and \( C_{RP} \) are added. The economy of ADNs is largely improved.
When VRB ESSs are not operated, $C_{PE}$ and $C_{AB}$ are, respectively, 92.152 and 45.601 $. With the operational strategy of VRB ESSs, $C_{PE}$ and $C_{AB}$ are, respectively, reduced to 45.018 and 22.530 $. Also, $C_{EB}$ and $C_{ID}$ are, respectively, increased to 32.642 and 91.921 $.

In Figure 7(b), the node voltages of ADNs in case 1 are presented. Clearly, with the optimal operational strategy of VRB ESSs, the node voltages of ADNs are largely improved. When VRB ESSs are not operated, $J_2$ is about 0.0767. With the operational strategy of VRB ESSs, $J_2$ is reduced to about 0.0592. VRB ESSs can be used to absorb reactive power, and this can largely make up the reactive output of renewable energy. Consequently, the node voltages of ADNs will be significantly reduced.

5.3 Operational strategy optimisation in case 2

To further verify the effectiveness of the proposed operational strategy optimisation of VRB ESSs, case 2 is applied. Figure 8 shows the costs of $J_1$ in case 2. In Figure 7(b), the node voltages of ADNs in case 2 are also presented. Compared with case 1, $J_2$ is reduced to about 0.0395, but the value of $J_1$ is cut down. In case 2, $C_{PE}$ and $C_{AB}$ are, respectively, increased to 45.724 and 22.752 $. Also, $C_{EB}$ and $C_{ID}$ are, respectively, reduced to 31.350 and 90.465 $. $C_{OM}$ and $C_{OP}$ are, respectively, added to 25.892 and 12.871 $. As VRB ESSs are more used for absorbing reactive power, the outputs of active power for BRB ESSs will slightly decrease due to the apparent power restriction of Equation (16).

As shown in Figure 8, the total benefits of ADNs with the optimal operational strategy of VRB ESSs in case 2 is reduced to about 12.273 $. Compared with case 1, $J_2$ is declined by 33.28%, and $J_1$ is declined by 19.90%. To get the best operational performance of ADNs, the value of $\delta$ should be comprehensively considered.

5.4 Comparative analysis

For the proposed mathematical model for the operational strategy optimisation of VRB ESSs, $\delta$ is a critical parameter that affects the economy of ADNs. To get more economical benefits, the value of $\delta$ should be largely reduced. Also, the operational modes of VRB ESSs are greatly restricted by $\delta$. Therefore, the influences of $\delta$ on the operational strategy of VRB and the operational performances of ADNs should be analysed. To reflect the variety of VRB ESSs’ operational strategy, the utilisation of VRB ESSs $\psi_u$ and average efficiency $\eta_{av}$ are used. To reflect the operational performances of ADNs, $J_1$ and the absorptive rate of renewable energy $\zeta$ are applied. Figure 9 shows the trends of $\psi_u$, $\eta_{av}$, $J_1$ and $\zeta$ with the growth of $\delta$. The value of $\psi_u$ is reflected by SOC of VRB.

As shown in Figure 9, the value of $\psi_u$, $\eta_{av}$, $J_1$ and $\zeta$ are all increased with the growth of $\delta$. The increased rate of $\zeta$ is slight, as consuming renewable energy can only occur in the charging time intervals of VRB ESSs. In addition, the consumption of
renewable energy will be restricted when VRB ESSs are releasing energy.

When $\delta$ is set to be less than 0.0307, this restriction of $J_2$ cannot be realised by the operation of VRB ESSs. This is a fact that the reactive power outputs of renewable energy are high enough, and the reactive power absorption capacity of VRB ESSs is limited. When $\delta$ is set to be more than 0.0767, the economical benefits of ADNs will no longer increase and this is because of the fact that reactive power is not required to be absorbed by VRB ESSs, and active power outputs of VRB ESSs are restricted.

With the growth of $\delta$, the average efficiency $\eta_{av}$ of VRB ESSs will be increased and this is because more active power is released by VRB ESSs and $P_{VRB,t}$ will be increased. Consequently, the dynamic efficiencies of VRB will increase due to Equation (3). In addition, the utilisation of VRB ESSs $\psi_u$ will also increase with the growth of $\delta$. As the value of $P_{VRB,t}$ will be added, VRB ESSs will be more utilised. Clearly, the selection of $\delta$ is complicated and it should comprehensively consider the operational requirements of ADNs. In the ADNs, power quality should be tightly guaranteed, and the value of $\delta$ should be set as a lower value.

6 CONCLUSION

This study proposed a DPM-based operation strategy optimisation model of VRB ESSs for the comprehensive performances of ADNs considering the dynamic characteristics of VRB. The developed operational strategy of VRB ESSs can greatly improve both the economy by more than 12.5 and the voltage quality of ADNs. For VRB ESSs, the power outputs and the operational modes are significantly influenced by the operation restrictions of distributed VRB ESSs developed by the dynamic characteristics and the specific utilisation of VRB that cannot be ignored. Also, the curtailment rate of renewable energy in ADNs is largely reduced by more than 50% and VRB ESSs can get a perfect optimisation associated with a higher utilisation rate of about 0.8 and an ameliorative average efficiency of more than 0.75. In addition, the economy and the voltage quality of ADNs are contradictory performance indicators. The operators should make a comprehensive consideration of the operational requirements of ADNs for the strategy optimisation of BESSs. For the limits of the proposed method and our future work, a more accurate model of VRB is needed for the dynamic characteristics research in battery energy storage application.

ACKNOWLEDGEMENT

This work was supported by The National Key R&D Program of China (2018YFB0904200)

REFERENCES

1. Damiano, G.G., et al.: Real-time control strategy of energy storage systems for renewable energy sources exploitation. IEEE Trans. Sustainable Energy 5(2), 567–576 (2014)
2. Zhang, Z., et al.: Market-oriented optimal dispatching strategy for a wind farm with a multiple stage hybrid energy storage system. CSEE J. Power Energy Syst. 4(4), 417–424 (2018)
3. Rahbar, K., Xu, J., Zhang, R.: Real-time energy storage management for renewable integration in microgrid: An off-line optimization approach. IEEE Trans. Smart Grid 6(1), 124–134 (2015)
4. Qiu, X., et al.: A field validated model of a vanadium redox flow battery for microgrids. IEEE Trans. Smart Grid 5(4), 1592–1601 (2014)
5. Shi, W., et al.: Distributed optimal energy management in microgrids. IEEE Trans. Smart Grid 6(3), 1137–1146 (2015)
6. Zhang, Y., Gatsis, N., Giannakis, G.B.: Robust energy management for microgrids with high-penetration renewables. IEEE Trans. Sustainable Energy 4(4), 944–953 (2013)
7. Zheng, Y., et al.: Optimal operation of battery energy storage system considering distribution system uncertainty. IEEE Trans. Sustainable Energy 9(3), 1051–1060 (2018)
8. Shu, Z., Jirutijaroen, P.: Optimal operation strategy of energy storage system for grid-connected wind power plants. IEEE Trans. Sustainable Energy 5(1), 190–199 (2014)
9. Jayasekara, N., Masoum, M.S., Wolfs, P.J.: Optimal operation of distributed energy storage systems to improve distribution network load and generation hosting capability. IEEE Trans. Sustainable Energy 7(1), 250–261 (2016)
10. Graber, G., et al.: Techno-economic sizing of auxiliary-battery-based substations in DC railway systems. IEEE Trans. Transp. Electrific. 4(2), 616–625 (2018)
11. Masteri, K., Venkatesh, B., Freitas, W.: A fuzzy optimization model for distribution system asset planning with energy storage. IEEE Trans. Power Syst. 33(5), 5114–5123 (2018)
12. Lei, J., et al.: Optimal allocation of a VRB energy storage system for wind power applications considering the dynamic efficiency and life of VRB in active distribution networks. IET Renewable Power Gen. 13(4), 563–571 (2019)
13. Nguyen, T.A., et al.: Performance characterization for photovoltaic vanadium redox battery microgrid systems. IEEE Trans. Sustainable Energy 5(4), 1379–1388 (2014)
14. Nguyen, T.A., Crow, M.L., Elmore, A.C.: Optimal sizing of a vanadium redox battery system for microgrid systems. IEEE Trans. Sustainable Energy 6(3), 729–737 (2015)
15. Lei, J., Gong, Q.: Operating strategy and optimal allocation of large-scale VRB energy storage system in active distribution networks for solar/wind power applications. IET Gener. Transm. Distrib. 11(9), 2403–2411 (2017)
16. Sun, Y., et al.: Stochastic scheduling of battery-based energy storage transportation system with the penetration of wind power. IEEE Trans. Sustainable Energy 8(1), 135–144 (2017)
17. Zhang, Y., Rahban, N., Chow, M.-Y.: Day-ahead smart grid cooperative distributed energy scheduling with renewable and storage integration. IEEE Trans. Sustainable Energy 7(4), 1739–1748 (2016)
18. Hisham, A., Kankar, B.: Stochastic optimal planning of battery energy storage systems for isolated microgrids. IEEE Trans. Sustainable Energy 9(1), 211–227 (2018)
19. Xu, L., et al.: An improved optimal sizing method for wind-solar-battery hybrid power system. IEEE Trans. Sustainable Energy 4(3), 774–785 (2013)
20. Mao, M., Jin, P., Hatziargyriou, N.D.: Multiagent-based hybrid energy management system for microgrids. IEEE Trans. Sustainable Energy 5(3), 938–946 (2014)
21. Zeng, P., et al.: Dynamic energy management of a microgrid using approximate dynamic programming and deep recurrent neural network learning. IEEE Trans. Smart Grid 10(4), 4435–4445 (2019)
22. Deng, Z., et al.: Multi-objective mixed-integer dynamic optimization method applied to optimal allocation of dynamic var sources of power systems. IEEE Trans. Power Syst. 33(2), 1683–1697 (2018)
23. He, G., et al.: Optimal operating strategy and revenue estimates for the arbitrage of a vanadium redox flow battery considering dynamic efficiencies and capacity loss. IET Gener. Transm. Distrib. 10(5), 1278–1285 (2016)
24. Zang, H., et al.: Hybrid method for short-term photovoltaic power forecasting based on deep convolutional neural network. IET Gener. Transm. Distrib. 12(20), 4557–4567 (2018)
25. Hargreaves, J.J., Hobbs, B.F.: Commitment and dispatch with uncertain wind generation by dynamic programming. IEEE Trans. Sustainable Energy 3(4), 724–734 (2012)
26. Celebi, E., Fuller, J.D.: Time-of-use pricing in electricity markets under different market structures. IEEE Trans. Power Syst. 27(3), 1170–1181 (2012)

How to cite this article: Lei J, Gao DW, Liu J. Operational strategy optimization of VRB energy storage systems considering the dynamic characteristics of VRB in active distribution networks. IET Renewable Power Generation. 2021;15:1058–1068. https://doi.org/10.1049/rpg2.12089