A Fixed-Flexible BESS Allocation Scheme for Transmission Networks Considering Uncertainties

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Abstract—Battery energy storage systems (BESSs) can play a key role in mitigating the intermittency and uncertainty associated with adding large amounts of renewable energy to the bulk power system (BPS). Two BESS technologies that have gained prominence in this regard are Lithium-ion (LI) BESS and Vanadium redox flow (VRF) BESS. This paper proposes a fixed-flexible BESS allocation scheme that exploits the complementary characteristics of LI and VRF BESSs to attain optimal techno-economic benefits in a wind-integrated BPS. Studies carried out on relatively large transmission networks demonstrate that benefits such as reduction in system operation cost, wind spillage, voltage fluctuations, and discounted payback period, can be realized by using the proposed scheme.

Index Terms—Bivariate piecewise linearization (BPL), fixed-flexible BESS, mixed integer linear program (MILP), mixture model, Vanadium redox flow (VRF), wind energy.

NOMENCLATURE

Parameters

| Symbol | Description |
|--------|-------------|
| $B_{j,k}$ | Imaginary part of admittance matrix. |
| $c_c$ | Power conditioning system (PCS) repair cost. |
| $c_{con}$ | BESS PCS investment cost. |
| $c_{em}$ | Emission cost. |
| $c_{ie}$ | BESS energy investment cost. |
| $c_{ip}$ | BESS power investment cost. |
| $c_r$ | BESS repair cost. |
| $\mathcal{CAP}_{BESS}$ | BESS capital investment. |
| $c_{pl}$ | Active power loss cost. |
| $c_{sp}$ | Wind power spillage cost. |
| $cv_j$ | Voltage deviation penalty factor for bus $j$. |
| $D_s$ | Number of days in a season. |
| $\Delta t$ | Optimization time-step size. |

| Symbol | Description |
|--------|-------------|
| $\mathcal{E}_{s,rated, fixed}$ | Fixed BESS power rating. |
| $\mathcal{PE}_{s rated, fixed}$ | Maximum BESS power rating. |
| $\mathcal{SOC}_{j min}, \mathcal{SOC}_{j max}$ | Minimum and maximum BESS SOC limits. |
| $\mathcal{SUC}_{g}, \mathcal{SDC}_{g}$ | Generator start-up and shut-down costs. |
| $\mathcal{SW}_{g max}$ | Apparent power rating of the inverter-interfaced wind resource. |
| $T_s$ | Index for time instant. |
| $\Xi_s$ | Total number of time-instants. |
| $\mathcal{Y}$ | Number of scenarios in a season. |

Variables

| Symbol | Description |
|--------|-------------|
| $\beta_{s,\psi}$ | Binary variable representing whether the BESS is charging or discharging. |
| $\mathcal{BV}_{j,t,\psi}$ | Bus voltage deviation. |
| $C_{1, BESS}$ | BESS investment cost with cost related to its PCS. |
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$C_{\text{OP,BASE}}$, $C_{\text{OP,BESS}}$, $C_{\text{R,BESS}}$, $C_{\text{TOT}}$

Network operation cost.

Daily BESS operation cost including lifetime depreciation cost.

BESS repair cost.

Total network operation, investment and repair cost for a season.

Quadratic fuel cost function for the $g$th generator.

Binary BESS siting decision variable.

Phase angle at a bus.

BESS discharge duration at a time instants.

Change in voltage magnitude at a bus.

BESS energy rating.

BESS energy stored.

Generator shut-down status.

Active power charging and discharging powers.

Active power demand at a bus.

BESS power rating.

Line active power loss.

Wind power output.

BESS’s available reactive power.

Reactive power demand at a bus.

BESS’s active power dispatch.

Wind resource’s reactive power output.

PCS power rating.

Generator start-up status.

Wind power spilled.

$LJ$ BESS model parameters

$mc_j(u)$, $md_j(v)$

Linearized slopes of the relationship between SOC and fraction of power limit available during charging and discharging.

$sc_j(u)$, $sd_j(v)$

Pieces of the piecewise linear functions for SOC level during charging and discharging.

$U, V$

Number of pieces in the piecewise linear curves between charging and discharging power limit and SOC.

$u, v$

Indices of the pieces in the piecewise linear curves between charging and discharging power limit and SOC.

$LJ$ BESS model variables

$\Delta S_{u,t}^{s,\psi}$, $\Delta S_{d,v,t}^{s,\psi}$

Components of SOC level during charging and discharging.

$F_{c_j,t}^{s,\psi}$, $F_{d_j,t}^{s,\psi}$

Fractions of the BESS power rating that can be used in period $t$ for charging and discharging.

Binary variables controlling when the LI BESS is charging and discharging.

$VRF$ BESS model parameters

$\alpha, \beta, c, d$

Per unit model coefficients representing the VRF BESS’s internal ohmic losses and parasitic losses experienced during charging and discharging.

Electrolyte temperature.

Number of segments for BESS charging power, discharging power and SOC.

Indices for the breakpoints for charging power, discharging power and SOC.

Breakpoints for BESS charging and discharging power.

Breakpoint for BESS SOC.

Binary variables corresponding to the lower-left and upper-right triangles, considering BESS charging.

Continuous variables ($\in [0,1]$) related to $(\kappa, \psi)$ and $(\lambda, \psi)$ considering BESS charging and discharging.

Binary variable corresponding to the lower-left triangle $(\lambda = 1, \ldots, \Lambda - 1; \psi = 2, \ldots, \Upsilon)$ considering BESS discharging.

Binary variable corresponding to the upper-right triangle $(\lambda = 2, \ldots, \Lambda; \psi = 1, \ldots, \Upsilon - 1)$ considering BESS discharging.

I. INTRODUCTION

O

VER the last few decades, there has been rapid growth in bulk power generation from renewable energy sources. Specifically, the global installed wind power capacity is expected to reach 850 GW by 2022 [1]. However, the intermittency and randomness of wind power can result in supply-demand imbalance, which can then lead to detrimental impacts on stability and reliability of the bulk power system (BPS). Energy storage systems (ESSs) are a viable solution in this regard because by acting as buffers, they can help manage the induced variability. However, the initial capital and maintenance costs for ESSs, such as battery ESSs (BESSs), are relatively high [2]. Therefore, it is critical to optimally size and site BESSs, especially for BPSs. Doing so will also provide additional benefits such as transmission congestion alleviation and network upgrade deferral [3].

Lithium-ion (LI) BESS is the most commonly used BESS because of its very high efficiency, high energy density, and fast response time in comparison to other (mechanical) energy storage technologies [4]–[6]. However, it possesses relatively shorter lifetime, and low discharge duration [7]. The
mathematical model of LI BESS operation is also non-linear because its charge/discharge power limits vary as a function of its state-of-charge (SOC) [8] (i.e., the non-linear functions depend on one variable). Unlike LI BESS, Vanadium redox flow (VRF) BESS has very long lifecycle because its cyclic degradation and self-discharge rates are extremely low [2]. Other favorable features of VRF BESS include [9]–[11]: the ability to completely discharge with minimal battery damage; their power and energy capacities can be scaled independently to MW and MWh levels; and the ability to discharge power for a longer duration. However, the mathematical expressions for the charging/discharging input powers and efficiencies of a VRF BESS are highly non-linear as they are functions of both the SOC as well as the charging/discharging output powers (i.e., the non-linear functions depend on two variables) [12].

Since the techno-economic benefits offered by VRF BESS (very long lifecycle and low self-discharge) complement those offered by the more widely used LI BESS (very high efficiency and high energy density), in this paper, we propose the usage of a novel mixed BESS allocation scheme for transmission networks that have high penetration of wind energy. Since wind power and load profiles vary significantly throughout the year, the BESS requirements computed for one season may not be sufficient for a different season. This problem is addressed by placing fixed LI BESSs at strategic locations throughout the year, while strategically placed flexible VRF BESSs are made to operate only during certain seasons (in which more violations in operational constraints due to variations in wind and load are observed). LI BESS is selected to operate in the regular charge/discharge cycle across all seasons of the year (as the fixed BESS) to utilize its higher round trip efficiency. VRF BESS is used as the flexible BESS because it undergoes self-discharge at an extremely low rate [12] while possessing a quick response time (in the order of milliseconds) [4]–[6]. We also design a unique scenario generation methodology where seasonal variations of wind and load are expressed by using Weibull mixture and Gaussian mixture models, respectively.

The rest of the paper is structured as follows. Section II describes the related work and the key contributions of this paper. Section III presents the proposed scenario-based problem formulation for fixed-flexible BESS allocation. Section IV presents the results of various case studies using the proposed scheme considering growth in wind penetration and system load in relatively large transmission networks. Section V discusses the utility of the proposed BESS allocation scheme and compares it with existing optimization techniques. Lastly, Section VI contains the concluding comments and future research work.

II. RELATED WORK AND SALIENT CONTRIBUTIONS

In recent years, considerable research has been carried out on optimizing the size and location of BESSs in power networks. References [13]–[17] used metaheuristic techniques such as genetic algorithm and particle swarm optimization for BESS allocation. However, such techniques often suffer from difficulties in parameter selection, low convergence rates, and premature convergence [18]. Dynamic programming (DP), which was used in [19], [20] can be computationally inefficient for large networks (see Section V-B for performance comparison with the proposed approach).

BESS allocation in transmission networks satisfying constraints such as generation cost minimization, storage portfolio optimization, or transmission expansion investment consideration were explored in [21]–[30]. However, [13]–[17] and [19]–[29] modeled BESSs considering only their active power capabilities; in the proposed study, both the active and reactive power capabilities of BESSs are modeled. Several recent articles have also modeled optimal siting/sizing of LI and VRF BESSs in microgrids and distribution networks ([16], [17], [19], [20], [31], [32]). It is important to study the problem of optimally allocating BESSs (especially VRF BESSs) in large transmission networks, because several VRF BESSs have been (will be) deployed at the transmission level (in the near future) [9]–[11], [33]. Moreover, distribution-level BESS allocation strategies may not be directly applicable to the transmission-level because, in contrast to radial distribution grids, power flows in meshed transmission grids can change in multiple ways in response to changes in outputs of renewable resource and loads [21]. Therefore, finding optimal BESS locations and capacities for grid applications such as congestion mitigation is a more complex problem for meshed transmission networks.

Another important limitation identified in many prior research works was the assumption of generic storage models that did not account for the non-linearities associated with the BESS technologies. For example, [13]–[16] and [21]–[30] assumed that the charge/discharge limits and the efficiencies of the BESSs are constants. However, the mathematical expressions for the operations of LI BESS and VRF BESS are non-linear as explained in Section I ([8], [12], [34]). Therefore, to get most accurate results, the non-linear characteristics of BESSs must be considered in the analysis. It must be pointed out here that some researchers have considered non-linear BESS models in control applications and SOC estimation [35]–[39]. However, such a study has not been carried out for optimal BESS allocation in the BPS.

The main contributions of this paper are:

1) Design of a techno-economically viable fixed-flexible BESS allocation scheme for relatively large transmission networks considering two different BESS technologies that provide complementary benefits.

2) Modeling of (VRF and LI) BESS, tap-changing under load (TCUL) transformers, and wind energy resources with both active and reactive power capabilities. BESS degradation cost and self-discharge are also considered in the optimization model.

3) Development of linearized models of VRF and LI BESS by bivariate piecewise linearization (BPL) of the highly non-linear VRF BESS model, and by creating an enhanced mixed integer linear optimization model of the LI BESS.
4) Quantification of the uncertainty associated with wind power and system load using mixture models and submodular scenario reduction (SSR).

III. SCENARIO-BASED PROBLEM FORMULATION FOR FIXED AND FLEXIBLE BESS ALLOCATION

A. Wind Power Output and Load Scenario Generation

Realistic and efficient generation of scenarios for uncertain load and wind power output is a key step prior to formulating and solving large-scale power system planning problems. It was shown in [40] that Gaussian mixture models (GMMs) give a good representation of system load. Similarly, the Weibull distribution was found to be a good model for wind [15]. Ref. [41] presented a novel data-driven approach that learnt the spatial and temporal correlations between system loads from real load data, and used the learnt models to generate new synthetic load data that possessed characteristics similar to the real load. In this sub-section, we employ the approach developed in [41] to capture seasonal variations in both system load as well as wind power outputs.

The proposed algorithm for scenario generation is called ScenGenRed and is described below. Wind power output and system load data at an interval of five minutes for twelve years (2007–2018) from Bonneville Power Administration (BPA) [42] was collected initially. The data for the first 9 years (called \( D_{train} = \{ LW_1; LW_2; \ldots; LW_{D_{train}} \} \)) was used for training, while the data for the remaining 3 years (called \( D_{test} = \{ LW_1; LW_2; \ldots; LW_{D_{test}} \} \)) was used for testing. \( LW \) is a \( 1 \times T_s \) matrix consisting of load/wind power values.

The temporal behavior of load/wind power was learnt by identifying the first \( f \) basis vectors of \( D_{train} \) using singular value decomposition (SVD). We form \( U^f \) with the first \( f \) columns of \( U \), \( \Sigma^f \) with the first \( f \) columns and rows of \( \Sigma \), and \( V^f \) with first \( f \) columns of \( V \). The synthetic load/wind profiles were generated by taking linear combinations of first \( f \) rows of \( V^T \). The resultant matrix \( D_{train} \) is a low-rank approximation of \( D_{train} \). The required number of basis vectors is selected based on the following criterion: the sum of squares of first \( f \) singular values should be at least equal to 95\% of the sum of squares of all singular values. Based on this criterion, a suitable value of \( f \) was found to be 12 for load and 45 for wind power output for the summer season. In a similar manner, appropriate values of \( f \) were determined for load and wind power outputs for the other seasons. \( Par \in R^{N_{load}\times f} \) and \( EM \) refers to expectation-maximization [43] which was used to determine the mixture model parameters. A 3-component GMM for load and a 2-component Weibull mixture model (WMM) for wind power output were found to accurately represent the probability distributions of the coefficients in the \( f \) columns of \( U \).

The spatial correlation was modeled by \( D \in R^{N_{LW} \times N_{LW}} \), where each entry, \( D(i, j) \), is a function of the minimum number of branches between buses \( i \) and \( j \) [41]. The new dataset with both spatial and temporal correlations modeled, is denoted by

\[
Scen \in R^{B \times T_s \times N_{LW}}, \quad \text{where} \quad Un^f \quad \text{is a coefficient matrix randomly sampled from the distributions learnt from the columns of} \quad U, \quad \text{and} \quad G \quad \text{is composed of normally distributed random noise}.
\]

To improve the computational performance and validity of the results, SSR [44] was used to identify distinct scenarios that are likely-to-occur. SSR is an accelerated greedy algorithm which maximizes a specific submodular function, \( SF \), where \( W \in R^3 \) is a similarity matrix consisting of weights for each generated scenario pair, and \( \lambda \) is a parameter controlling similarity scaling. The outputs of the SSR is the reduced scenario-set generated for each load/wind bus, denoted by \( R \), and the associated probability, \( p \). Note that the probabilities of the original scenario set \( (q) \) are redistributed amongst the \( R \) scenarios.

The testing dataset, \( D_{test} \), was utilized to ensure that the actual and generated wind/load profiles have similar shapes. It is observed from Figs. 1 and 2 that the general shapes of actual load/wind power output curves and generated load/wind power output curves for the summer season are nearly the same. Similar results were also obtained for the other seasons for both system load as well as wind power outputs.

B. Problem Formulation

In this sub-section, we utilize scenarios of wind power output and system load generated in Section III-A to develop the

![Fig. 1. Comparison of two different but typical load profiles obtained during the summer season; the top row depicts actual load profiles while the bottom row depicts generated load profiles.](image1)

![Fig. 2. Comparison of two different but typical wind power output profiles obtained during the summer season; the top row depicts actual wind power output profiles while the bottom row depicts generated wind power profiles.](image2)
ScenGenRed: Algorithm for Wind Power/System Load Scenario Generation for a Season.

\[ \text{Input } [D_{train}]: \text{Training dataset of wind power output/system load profiles with 5-minute time resolution, } D_{train} \in \mathbb{R}^{(D_a \times V_t) \times T_s}. \]
\[ \text{Input } c: \text{Number of components in the mixture model for a column of } U. \]
\[ \text{Input } B: \text{Initial number of wind power/load scenarios for each bus connected with a wind resource/load.} \]
\[ \text{Input } K: \text{Number of scenarios in reduced scenario-set.} \]
\[ \text{Output } [R]: \text{Reduced set of daily scenarios of wind power output/system load.} \]
\[ \text{Output } [p]: \text{Set of probabilities of scenarios in } [R]. \]

\[
\begin{align*}
&1: \text{Initialize } U \leftarrow 0, \Sigma \leftarrow 0, V \leftarrow 0, W^i_{j,k} \leftarrow 0 \\
&2: \langle U, \Sigma, V^T \rangle \leftarrow SVD(D_{train}) \\
&3: D_{train} = U^T \times \Sigma^T \times V^T \\
&4: \text{for } i = 1, \ldots, f \text{ do} \\
&5: \text{for } j = 1, \ldots, B \text{ do} \\
&6: S_{\text{Scen}i} = [D][U_{\text{f}}(\text{random}(\text{Par}))][\Sigma^f][V^T] + [G] \\
&7: \text{end for} \\
&8: S_{\text{Scen}i} = \left[ D \left[ U_{\text{f}}(\text{random}(\text{Par})) \right] \left[ \Sigma^f \right] \left[ V^T \right] + [G] \right] \\
&9: \text{end for} \\
&10: \text{for } i = 1, \ldots, N_{\text{LW}} \text{ do} \\
&11: \text{for } j = 1, \ldots, B \text{ do} \\
&12: \text{for } k = 1, \ldots, B \text{ do} \\
&13: W^i_{j,k} := \exp \left( -\frac{\|S_{\text{Scen}i}^{\text{[last]}} - S_{\text{Scen}i}^{\text{[first]}}\|^2}{2} \right) \\
&14: \text{end for} \\
&15: \text{end for} \\
&16: \text{end for} \\
&17: \text{for } j = 1, \ldots, B \text{ do} \\
&18: R^j := S_{\text{F}} \left( S_{\text{Scen}}^{\text{[last]}}, \left[ 1, \ldots, B \right], \left[ 1, \ldots, B \right], K \right) \\
&19: \text{end for} \\
&20: \text{for } i = 1, \ldots, N_{\text{LW}} \text{ do} \\
&21: \text{for } j = 1, \ldots, K \text{ do} \\
&22: p_{i,j} \leftarrow q_{i,j} + \sum_{k \in \text{Scen}} q_{i,k}, \text{ where} \\
&23: \text{Scen} \leftarrow \{ k \in \text{Scen} \mid R : j = \arg\max_{j \in B} W^i_{j,k} \} \\
&24: \text{end for} \\
&25: \text{return } R, p
\end{align*}
\]

FixedFlexibleBEASSAllocation: Algorithm for Fixed-Flexible BESS Allocation.

\[ \text{Input } [SP]: \text{Season-wise sets of system parameters and initial variable values} \]
\[ \text{Output } [A]: \text{Optimal values of system variables, including settings of TCUL transformers and sites and sizes of fixed and/or flexible BESSs for all seasons.} \]

\[
\begin{align*}
&1: \text{Initialize } A_{TS, s, k} \leftarrow 0, A_{BAlloc, s} \leftarrow 0, \\
&\text{Viol}_{TS, s} \leftarrow 0, \text{OpCost}_{TS, s} \leftarrow 0, \text{Viol}_{BAlloc} \leftarrow 0, \\
&\text{OpCost}_{BAlloc} \leftarrow 0, S \leftarrow \{\text{Winter}(1), \text{Spring}(2), \text{Summer}(3), \text{Fall}(4)\} \\
&2: \text{for } s = 1, \ldots, S \text{ do} \\
&3: A_{TS, s} := TS(s) \\
&4: A_{BAlloc, s} := BAlloc(s) \\
&5: \text{Viol}_{TS} \leftarrow \text{Viol}_{TS, s} + \text{Viol}(A_{TS, s}) \\
&6: \text{OpCost}_{TS} \leftarrow \text{OpCost}_{TS, s} + \text{OpCost}(A_{TS, s}) \\
&7: \text{Viol}_{BAlloc} \leftarrow \text{Viol}_{BAlloc} + \text{Viol}(A_{BAlloc, s}) \\
&8: \text{OpCost}_{BAlloc} \leftarrow \text{OpCost}_{BAlloc} + \text{OpCost}(A_{BAlloc, s}) \\
&9: \text{end for} \\
&10: \text{if } \text{Viol}_{TS} = 0 \& \text{Viol}_{BAlloc} = 0 \text{ then} \\
&11: \text{if } \text{OpCost}_{TS} - \text{OpCost}_{BAlloc} \leq 0 \text{ then} \\
&12: A := A_{TS} \\
&13: \text{else} \\
&14: A := A_{BAlloc} \\
&15: \text{end if} \\
&16: \text{else} \\
&17: A := A_{BAlloc} \\
&18: \text{end if} \\
&19: \text{return } A
\end{align*}
\]

In (1), the value of \( cv_j \) for \( j \in \{1, \ldots, N\} \) is set such that the minimization of voltage deviations does not dominate the minimization of other cost components in (1). The constraints imposed on \( C^{\text{OP,BASE}} \) are as follows.

Second dimension represents the number of variables in the system (e.g., BESS energy capacity, BESS power capacity, TCUL transformer setting, etc.), and the third dimension represents the number of seasons (represented by \( s \)). \( \text{Viol} \) and \( \text{OpCost} \) determine the season-wise power/voltage limit violations and system operation cost, respectively, and are obtained from \( A_{TS} \) and \( A_{BAlloc} \).
1) Power Balance Constraint:
\[
\sum_{g=1}^{N_g} P_{G,s,t}^g + \sum_{g=1}^{N_g} (P_{W,s,t}^g - W_P S_{P,s,t}^g) = \sum_{j=1}^{N} P_{D,j,t}^s + \sum_{l=1}^{N_l} P_{S,t}^{r,l}, \forall t, \psi. \tag{2}
\]

2) Linearized Power Flow Constraints:
\[
PG_{j,t}^s + PW_{j,t}^s - W S_{P,s,t}^g - PD_{j,t}^s = \sum_{k=1}^{N} \left\{ \left( 1 + \Delta V_{j,t}^s + \Delta V_{k,t}^s \right) G_{j,k} + \left( s_{j,t} - \delta_{k,t} \right) B_{j,k} \right\}, \forall j, t, \psi. \tag{3}
\]
\[
QG_{j,t}^s + QW_{j,t}^s - QD_{j,t}^s = \sum_{k=1}^{N} \left\{ \left( s_{j,t} - \delta_{k,t} \right) B_{j,k} \right\}, \forall j, t, \psi. \tag{4}
\]

3) Wind Energy Resource Constraints:
Wind spillage: \( 0 \leq W S_{P,g,t}^s \leq P_{W,g,t}^s, \forall g, t, \psi. \) \tag{5a}
Reactive power: \( \left( P_{W,g,t}^s \right)^2 + \left( Q_{W,g,t}^s \right)^2 \leq \left( S_{W,g}^\text{max} \right)^2, \forall g, t, \psi. \) \tag{5b}
Reactive power limits: \( -S_{W,g}^\text{max} \leq Q_{W,g,t}^s \leq S_{W,g}^\text{max}, \forall g, t, \psi. \) \tag{5c}

4) Slack Bus Initialization:
\[
\Delta V_{1,t}^s = 0, \delta_{1,t} = 0, \forall t, \psi. \tag{6}
\]

5) Voltage Deviation Limits at Other Buses:
\[
\Delta V_{j,t}^\text{min} \leq \Delta V_{j,t}^s \leq \Delta V_{j,t}^\text{max}, \forall t, j \in \{2, \ldots, N\}, \psi. \tag{7}
\]

We have also modeled the piecewise linearization of the cost function \( CG_{s,t}^r \), constraints on conventional generation operation (e.g., unit commitment), linearized power flow, and TCU transformer branch power flow. The linearized power flow equations are derived from the original non-linear formulations. Appropriate linear approximations (considering the products of bus voltage magnitudes, and the sine and cosine of the phase angle differences across lines) are applied to the original non-linear active and reactive power flow equations to obtain a more accurate estimate of bus voltage magnitude [45]. The linearized active power loss equations are derived by performing piecewise linearization of the original non-convex network loss equations [46].

The fixed LI BESS allocation problem formulation for a season in \( BAlloc \) is described by (2)–(42), while the flexible VRF BESS allocation problem formulation for a season in \( BAlloc \) is described by (2)–(61). The objective function of \( BAlloc \) is shown in (8).

Min: \( C_T^s = C_{OP,BASE}^s + C_{OP,BESS}^s + C_{I,BESS}^s + C_{R,BESS}^s \)
\[
C_{OP,BESS}^s = \sum_{\psi=1}^{N_s} p_{s,\psi}^s \frac{\sum_{t=1}^{T_s} \sum_{c=1}^{N_c} \left( \frac{\text{CAP}_{BESS}}{E_{S_j}^{s,rated}} \cdot LC \right) \left( P_{d,j,t}^s \Delta t + P_{c,j,t}^s \Delta t + ES_j^{s,\psi} \cdot \eta_{LL} \right) \right]}{D_{s} \left[ (1+r)^{N_y} \right] - 1} \right]}{c_{ic} \sum_{j=1}^{N} E_{S_j}^{s,rated}} + c_{ip} \sum_{j=1}^{N} \left( P_{E_j}^{s,rated} \right) + c_{con} \sum_{j=1}^{N} \left( S_{P_j}^{max} \right) \]  

In \( BAlloc \), we modify constraints (2), (3), and (4) by including the terms \( \sum_{j=1}^{N} (\delta_{j,t}^s - \delta_{j,t}^r) \), \( \sum_{j=1}^{N} (\delta_{j,t}^s - \delta_{j,t}^r) \) and \( Qd_{j,t}^s \), respectively, on their left hand sides (LHSS); where \( Qd_{j,t}^s \) refers to the BESS’s reactive power dispatch. The other constraints related to both LI and VRF BESS modeling are shown in (12)–(31).

6) BESS Operational Constraints:
\[
\sum_{j=1}^{N} P_{c,j,t}^{s,\psi} \leq \sum_{j=1}^{N} W S_{P,j,t}^g, \forall j, t, \psi. \]  
\[
0 \leq \eta_{j,t}^{s,\psi} \leq \frac{1}{1 - \beta_{j,t}^{s,\psi}} \]  
\[
0 \leq \frac{P_{d,j,t}^{s,\psi}}{\eta_{j,t}^{s,\psi}} \leq \beta_{j,t}^{s,\psi} \]  
\[
0 \leq \frac{P_{E_j}^{s,rated}}{d_j^s \text{BESS}} \leq \beta_{j,t}^{s,\psi} P_{E_j}^{s,rated}, \forall j \in \{1, \ldots, N\}, t, \psi. \]  
\[
D_{T,j,t}^s = DT_{j,t}^s + \frac{1}{12} \beta_{j,t}^{s,\psi}, \forall j \in \{1, \ldots, N\}, \psi. \]  
\[
D_{T,j,t}^s = DT_{j,t}^s + \frac{1}{12} \beta_{j,t}^{s,\psi}, \forall j \in \{1, \ldots, N\}, t \geq 2, \psi. \]  
\[
D_{T,j,t}^s \leq DT_{j,t}^{max}, \forall j \in \{1, \ldots, N\}, t, \psi. \]
\[ N \sum_{j=1}^{N} P_{d_j, t}^{s, \psi} = \begin{cases} \sum_{g=1}^{N_g} \left( PG_{g, t}^{s, \psi} + PW_{g, t}^{s, \psi} - WPS_{g, t}^{s, \psi} \right) - \sum_{j=1}^{N} PD_{j, t}^{s, \psi} - \frac{\sum_{i=1}^{N_l} P_{l_i, t}^{s, \psi}}{} \right), \forall t, \psi. & (19) \\
 \text{if } \sum_{g=1}^{N_g} \left( PG_{g, t}^{s, \psi} + PW_{g, t}^{s, \psi} - WPS_{g, t}^{s, \psi} \right) - \sum_{j=1}^{N} PD_{j, t}^{s, \psi} + \frac{\sum_{i=1}^{N_l} P_{l_i, t}^{s, \psi}}{} \right), \forall t, \psi. \\
 \end{cases} \]

\[ \sum_{j=1}^{N} P_{c_j, t}^{s, \psi} = \begin{cases} \sum_{g=1}^{N_g} \left( PG_{g, t}^{s, \psi} + PW_{g, t}^{s, \psi} - WPS_{g, t}^{s, \psi} \right) - \sum_{j=1}^{N} PD_{j, t}^{s, \psi} - \frac{\sum_{i=1}^{N_l} P_{l_i, t}^{s, \psi}}{} \right), \forall t, \psi. & (20) \\
 \text{if } \sum_{g=1}^{N_g} \left( PG_{g, t}^{s, \psi} + PW_{g, t}^{s, \psi} - WPS_{g, t}^{s, \psi} \right) + \sum_{j=1}^{N} PD_{j, t}^{s, \psi} + \frac{\sum_{i=1}^{N_l} P_{l_i, t}^{s, \psi}}{} \right), \forall t, \psi. \\
 \end{cases} \]

\[ ES_{j, t}^{s, \psi} - (1 - \alpha) ES_{j, t}^{s, \psi} - \frac{P_{c_j, t}^{s, \psi}}{\eta_{j, t}^{c}} \Delta t \]

\[ SOC_{j, t}^{\min} \leq SOC_{j, t}^{s, \psi} \leq SOC_{j, t}^{\max}, \forall j \in \{1, \ldots, N\}, t, \psi. \]

\[ \sum_{j=1}^{N} SOC_{j, t}^{s, \psi} ES_{j, t}^{s, \psi} \geq E_{\text{res}}, \forall \psi, t. \]

7) BESS Reactive Power Capability Modeling:

\[ (Pd_{j, t}^{s, \psi})^2 + \left( Qdis_{j, t}^{s, \psi} \right)^2 \leq (SP_{j}^{\max})^2, (PC_{j, t}^{s, \psi})^2 \]

\[ + \left( Qdis_{j, t}^{s, \psi} \right)^2 \leq (SP_{j}^{\max})^2, \forall j, t, \psi. \]

\[ Pd_{j, t}^{s, \psi}, PC_{j, t}^{s, \psi} \geq 0, \forall j, t, \psi. \]

\[ - SP_{j}^{\max} \leq Qdis_{j, t}^{s, \psi} \leq SP_{j}^{\max}, \forall j, t, \psi. \]

\[ SP_{j}^{s, \psi} = \begin{cases} \sqrt{(Pd_{j, t}^{s, \psi})^2 + \left( Qdis_{j, t}^{s, \psi} \right)^2}, \forall j, \psi, t \in T_{\text{on-peak}} \\\n \sqrt{(PC_{j, t}^{s, \psi})^2 + \left( Qdis_{j, t}^{s, \psi} \right)^2}, \forall j, \psi, t \in T_{\text{off-peak}}. \end{cases} \]

Equation (12) ensures that the total BESS discharging power is limited by the total wind power spilled. Equations (13) and (14) ensure that the charging/discharging powers of BESS remain within the rated BESS power capacity limit of the buses where they are placed. Equations (13) and (14) also ensure that in any time-instant, the BESS does not charge and discharge simultaneously. For each time-instant, we ensure that the VRF BESS’s charging/discharging powers lie within the maximum VRF BESS absorption power [20]. The BESS can operate in a discharging mode only for a certain maximum time-period; this is described by (16)–(18). Equations (19) and (20) control the total BESS power capacity present in the system at a time-instant based on whether the BESS operates in discharging or charging mode. Equation (21) controls the energy stored in the BESS at a given time-instant; we also account for the different self-discharge rates of BESSs. Equations (22)–(25) denote the energy and SOC-related limits, while (26) is the emergency reserve capacity constraint. The active and reactive power control capabilities of BESSs is described in (27)–(31). Any BESS primarily consists of a power conditioning system (PCS) and a storage unit [47], which makes it possible to independently and rapidly control both active and reactive power in all four quadrants.

8) Enhanced LI BESS Model: Apart from the operational constraints for LI BESS shown in (12)–(31), other constraints related to its enhanced mixed integer linear program (MILP) representation are based on model MI of [8]. In that model, the BESS’s charging/discharging power limits varied as functions of its SOC and were not treated as constants. The non-linear variation of LI BESS’s power limit with SOC is shown in Fig. 3, which was obtained in [8] by modeling the physical behavior of an actual LI BESS. The LI BESS’s optimization model is formulated in (32)–(42).
\[
\sum_{v=1}^{V} \Delta S d_{v,t}^{s,\psi} m d_{j} (v) = F d_{j,t}^{s,\psi}, \forall j, \psi, t.
\] (33)

\[
\sum_{u=1}^{U} \Delta S c_{u,t}^{s,\psi} = S O C_{j,t}^{s,\psi}, \sum_{v=1}^{V} \Delta S d_{v,t}^{s,\psi} = S O C_{j,t}^{s,\psi}, \forall j, \psi, t.
\] (34)

\[
\Delta S c_{u,t}^{s,\psi} \leq sc_{j} (u) z c_{u,t}^{s,\psi}, \Delta S d_{v,t}^{s,\psi} \leq sd_{j} (v) z d_{v,t}^{s,\psi}, \forall u, v, j, \psi, t.
\] (35)

\[
\Delta S c_{u-1,t}^{s,\psi} \geq sc_{j} (u - 1) z c_{u-1,t}^{s,\psi}, \forall j, \psi, t, u \geq 2.
\] (36)

\[
\Delta S d_{v-1,t}^{s,\psi} \geq sd_{j} (v - 1) z d_{v-1,t}^{s,\psi}, \forall j, \psi, t, v \geq 2.
\] (37)

\[
0 \leq P d_{j,t}^{s,\psi} \leq P E_{j,t}^{s,\text{rated}} F c_{j,t}^{s,\psi}, \forall j, \psi, t.
\] (38)

\[
0 \leq P c_{j,t}^{s,\psi} \leq P E_{j,t}^{s,\text{rated}} F d_{j,t}^{s,\psi}, \forall j, \psi, t.
\] (39)

\[
F c_{j,t}^{s,\psi}, F d_{j,t}^{s,\psi} \geq 0, \forall j, \psi, t.
\] (40)

\[
\Delta S c_{u,t}^{s,\psi}, \Delta S d_{v,t}^{s,\psi} \geq 0, \forall u, v, j, \psi, t.
\] (41)

\[
z c_{u,t}^{s,\psi}, z d_{v,t}^{s,\psi} \in \{0, 1\}, \forall u, v, j, \psi, t.
\] (42)

Equations (32)–(37) describe the piecewise linear functions for charging and discharging of the LI BESS. We partition the non-linear curve into \(U\) pieces for charging and \(V\) pieces for discharging. Equations (32) and (33) calculate the fractions of charging and discharging limits available given the components of SOC level and linearized slopes \(mc_{j}(u)\) and \(md_{j}(v)\). Equation (34) ensures that the SOC components of the piecewise linear function adds up to the SOC level at time \(t\). Equation (35) ensures that the SOC components of the piecewise linear functions remain less than or equal to \(sc_{j}(u)\) for charging and \(sd_{j}(v)\) for discharging if the particular piece is active; binary variables \(zc_{u,t}^{s,\psi}\) and \(zd_{v,t}^{s,\psi}\) are 1 for charging and discharging, respectively.

\[
\eta_{j,t}^{d} = \frac{P d_{j,t}^{s,\psi} \left( a_{d}^{p} P d_{j,t}^{s,\psi} + b_{d}^{p} S O C_{j,t}^{s,\psi} + c_{d}^{p} \right)}{a_{d}^{p} P d_{j,t}^{s,\psi} + b_{d}^{p} S O C_{j,t}^{s,\psi} + c_{d}^{p}} \left( S O C_{j,t}^{s,\psi} - 1 \right) + c_{d}^{p} \left\{ \Gamma \left( a_{d}^{v} S O C_{j,t}^{s,\psi} + b_{d}^{v} \right) + c_{d}^{v} \right\} \quad \forall j, \psi, t \in T_{\text{on-peak}}.
\] (43)

\[
\eta_{j,t}^{c} = \frac{\left\{ \left( a_{c}^{p} S O C_{j,t}^{s,\psi} + b_{c}^{p} \right) P c_{j,t}^{s,\psi} + c_{c}^{p} S O C_{j,t}^{s,\psi} + d_{c}^{p} \right\} \left\{ \Gamma \left( a_{c}^{v} S O C_{j,t}^{s,\psi} + b_{c}^{v} \right) + c_{c}^{v} \right\}}{a_{c}^{p} P c_{j,t}^{s,\psi} + b_{c}^{p} S O C_{j,t}^{s,\psi} + c_{c}^{p} S O C_{j,t}^{s,\psi} + d_{c}^{p}} \quad \forall j, \psi, t \in T_{\text{off-peak}}.
\] (44)

\[
\eta_{j,t}^{c} P c_{j,t}^{s,\psi} = \left\{ \left( a_{c}^{p} S O C_{j,t}^{s,\psi} + b_{c}^{p} \right) P c_{j,t}^{s,\psi} + c_{c}^{p} S O C_{j,t}^{s,\psi} + d_{c}^{p} \right\} \left\{ \Gamma \left( a_{c}^{v} S O C_{j,t}^{s,\psi} + b_{c}^{v} \right) + c_{c}^{v} \right\}
\] (45)

\[
\frac{P d_{j,t}^{s,\psi}}{\eta_{j,t}^{d}} = \frac{F d_{j,t}^{s,\psi} \left( P d_{j,t}^{s,\psi}, S O C_{j,t}^{s,\psi} \right)}{a_{d}^{p} P d_{j,t}^{s,\psi} + b_{d}^{p} S O C_{j,t}^{s,\psi} + c_{d}^{p} \left( S O C_{j,t}^{s,\psi} - 1 \right) + c_{d}^{p} \left\{ \Gamma \left( a_{d}^{v} S O C_{j,t}^{s,\psi} + b_{d}^{v} \right) + c_{d}^{v} \right\}}.
\] (46)
applicable for functions such as $F_1$ and $F_2$, we propose the usage of BPL [48] in this paper. The concept of BPL is explained in Appendix A. Accordingly, the set of equations for BPL of functions $F_1$ and $F_2$ are shown in (47)–(53) and (54)–(60), respectively.

$$P_{c,j,t} = \sum_{\kappa=1}^{K} \sum_{\gamma=1}^{Y} p_{c,\kappa,\gamma}^{F,j,t} \varphi_{\kappa,\gamma}^{F,j,t}, \forall j,t. \quad (47)$$

$$SOC_{j,t} = \sum_{\kappa=1}^{K} \sum_{\gamma=1}^{Y} s_{\kappa,\gamma}^{F,j,t} \varphi_{\kappa,\gamma}^{F,j,t}, \forall j,t. \quad (48)$$

$$F_{1,j,t} = \sum_{\kappa=1}^{K} \sum_{\gamma=1}^{Y} F_{1,\kappa,\gamma}^{F,j,t} \varphi_{\kappa,\gamma}^{F,j,t}, \forall j,t. \quad (49)$$

$$\sum_{\kappa=1}^{K} \sum_{\gamma=1}^{Y} (\varphi_{\kappa,\gamma}^{F,j,t} + \sigma_{\kappa,\gamma}^{F,j,t}) = 1, \forall j,t. \quad (50)$$

$$\sum_{\kappa=1}^{K} \sum_{\gamma=1}^{Y} \varphi_{\kappa,\gamma}^{F,j,t} = 1, \forall j,t. \quad (51)$$

$$\varphi_{\kappa,\gamma}^{F,j,t} \leq \varphi_{\kappa,\gamma}^{F,j,t} = 1, \forall j,t, \kappa, \gamma. \quad (52)$$

$$0 \leq \varphi_{\kappa,\gamma}^{F,j,t} \leq 1, \forall j,t, \kappa, \gamma. \quad (53)$$

$$P_{d,j,t} = \sum_{\lambda=1}^{\Lambda} \sum_{\gamma=1}^{Y} p_{d,\lambda,\gamma}^{F,j,t} \varphi_{\lambda,\gamma}^{F,j,t}, \forall j,t. \quad (54)$$

$$SOC_{j,t} = \sum_{\lambda=1}^{\Lambda} \sum_{\gamma=1}^{Y} s_{\lambda,\gamma}^{F,j,t} \varphi_{\lambda,\gamma}^{F,j,t}, \forall j,t. \quad (55)$$

$$F_{2,j,t} = \sum_{\lambda=1}^{\Lambda} \sum_{\gamma=1}^{Y} F_{2,\lambda,\gamma}^{F,j,t} \varphi_{\lambda,\gamma}^{F,j,t}, \forall j,t. \quad (56)$$

$$\sum_{\lambda=1}^{\Lambda} \sum_{\gamma=1}^{Y} (\varphi_{\lambda,\gamma}^{F,j,t} + \varphi_{\lambda,\gamma}^{F,j,t}) = 1, \forall j,t. \quad (57)$$

$$\sum_{\lambda=1}^{\Lambda} \sum_{\gamma=1}^{Y} \varphi_{\lambda,\gamma}^{F,j,t} = 1, \forall j,t. \quad (58)$$
that are common to all seasons and then placed the maximum BESS capacity at the selected buses (boldfaced and underlined in Table I), across all seasons. After determining the fixed LI BESS locations and capacities, $B_{Alloc}$ checks whether flexible VRF BESS is needed. It is observed in Table II that only the summer and spring seasons required flexible VRF BESSs, with a total capacity of 7.12 MW. The CPU time for generating the BESS allocation results is $\sim 0.5$ hours.

Next, we compare the proposed fixed-flexible allocation scheme to a scheme where the allocation of a single-technology BESS (such as LI BESS) is carried out on an annual basis. For this fixed BESS allocation scheme (referred to as Scheme (b) henceforth), the wind power outputs and system loads are generated for the entire year, and the TCUL transformer settings and BESS allocation determined accordingly. From the results summarized in Table III, it is realized that the BESS capacity required using the proposed approach ($10.79 + 7.54 + 7.12 = 25.45$ MW) is less than what is required using Scheme (b) ($= 26.35$ MW). A more detailed techno-economic analysis of different BESS allocation schemes is provided below.

We now compare the costs associated with (1) and (8) considering four schemes, which are described as follows. Scheme (a): optimization of tap-settings of TCUL transformers using $TSet$ without any BESS allocation; Scheme (b): optimization of tap-settings of TCUL transformers using $TSet$ and fixed LI BESS allocation (note that this is the scheme described in Table III); Scheme (c): optimization of tap-settings of TCUL transformers using $TSet$ and fixed LI and flexible LI BESS allocation; Scheme (d): optimization of tap-settings of TCUL transformers using $TSet$ and fixed LI and flexible VRF BESS allocation (proposed scheme). Table IV presents a comparison across Schemes (a) to (d) with regards to network operation metrics (average/maximum bus voltage fluctuations); annual network operation costs; and BESS investment and repair costs and payback periods. Specifically, we use the discounted payback period (DPP) [51] for comparison, which is a key metric used to evaluate feasibility and profitability of an investment.

The following key observations are made from Table IV.

1) Network Operation Metrics: In Scheme (a), the average and maximum bus voltage deviations are the highest. This is because no BESSs are present in this scheme. Scheme (b) incurs lower voltage deviations than Scheme (c) as all allocated BESS units in Scheme (b) ($= 26.35$ MW) operate in the regular charge/discharge mode throughout the year and utilize their reactive power capabilities in minimizing voltage deviations; in Scheme (c), only the fixed LI portion ($10.79 + 7.54 = 18.33$ MW) operate throughout the year.

Scheme (d) uses the complementary characteristics of LI and VRF BESSs to incur voltage deviations that are nearly equal to those of Scheme (b).

2) Network Operation Costs: In Scheme (a), due to the absence of BESSs, wind spillage cost dominates the other cost components, driving the total operation cost to a relatively high value of $\sim 9.63$ M$. Schemes (b) and (c) have identical values for the first four cost components; however, because of more charge/discharge cycles, the year-round operation of BESSs in Scheme (b) results in higher BESS operation costs than Scheme (c). The network operation cost is lowest for Scheme (d) because of the extremely low self-discharge rate, higher range of charging and discharging (both in terms of power and energy), relatively longer discharge durations, and longer lifetimes of VRF BESSs operating in that scheme.

3) BESS Investment and Repair Costs and DPP: As per (10) and (11), the investment and repair costs are affected by the numbers and capacities of BESS allocated, the p.u. cost components, and the BESS lifetimes. For example, Scheme (c) results in the allocation of 18.33 MW and 8.57 MW of fixed and flexible LI BESSs, respectively, while the corresponding values for Scheme (d) are 18.33 MW and 7.12 MW, respectively. Based on the VRF and LI BESS lifetime and cost information provided in Table XII in Appendix B, it is realized that Scheme (d) results in a substantial reduction in BESS investment and
Fig. 6. Annual operation costs for System S1 with growth in wind penetration.

repair costs in comparison to Schemes (b) and (c). The DPP is dependent on the initial investment (e.g., investment cost for Schemes (b), (c) or (d)), the discount rate, and the operation cost benefits (e.g., obtained by using Schemes (b), (c) or (d) with respect to Scheme (a)). Table IV indicates that the proposed Scheme (d) generates the lowest value of DPP among the three schemes.

B. BESS Allocation Results With Growth in Wind Penetration in System S1

The next study on System S1 investigates the variation of the annual operation cost of the wind-integrated transmission network over a 20-year horizon with growth in installed wind penetration from 0% to 50% (load is assumed to grow at 1% per year over the same time period). The total operation cost for a season is the sum of costs due to conventional generation, emissions, power loss, and wind spillage (for Scheme (a)) or, the sum of costs due to conventional generation, emissions, power loss, wind spillage, and BESS operation (for Schemes (b) to (d)). The annual operation cost is the aggregate of the total operation costs across all seasons.

We first describe the variation in annual operation cost with increase in wind penetration considering Scheme (a), which is represented by the black curve in Fig. 6. We see that the operation cost gradually increases with increase in wind penetration. This is because in absence of BESSs, the increase in cost is proportional to the amount of wind power that is spilled. For Scheme (b), which is represented by the green curve, we see that the operation cost gradually decreases with increase in wind penetration. There are two reasons why this happens. First, due to the presence of fixed LI BESSs, there is a substantial decrease in costs due to wind spillage, which then brings down the annual operation cost. Second, the optimally allocated fixed LI BESSs (which may be located close to certain load buses) can charge during off-peak periods and discharge during peak-load periods and serve the peak demand instead of conventional generating units. The ability of the BESSs to serve loads located close to them during peak-load periods brings about a reduction in transmission line losses, and thereby lowers the cost of conventional generation and associated emissions. The reasons behind the reductions in network operation costs across Schemes (b) through (d) was described through Table IV, for a specific wind penetration level (50%); the same rationales hold true for other wind penetration levels as well. Schemes (c) and (d) are represented in Fig. 6 by the red and blue curves, respectively.

Further, the first four cost values in Fig. 6 indicate that there is no requirement of BESS investment till a wind penetration level of ~4% is reached. This means that the existing TCUL transformers in System S1 are able to mitigate the power limit violations and voltage fluctuations that occur for wind penetration levels between 0% and 4%. Thus, it becomes clear from Fig. 6 that by using the proposed scheme, the annual operation costs benefits (that is, the difference between the costs shown by the black curve and the blue curve) increase considerably with increase in wind penetration.

C. Application to a Relatively Large Test System (System S2)

The proposed BESS allocation technique is applied to System S2 (IEEE 300-bus system) to validate its performance on relatively large systems. The scenario-based problem for fixed LI and flexible VRF BESS allocation is implemented in a manner similar to what was done for System S1 in Sections IV-A and IV-B. Wind generation resources are placed on buses 80, 88, 125, 128, 156, 199, 222, 246, 248, 7049, and 9001 to make wind penetration levels between 0% and 50% (~54,143 MW). Season-wise scenarios of wind power output and system load are generated in a manner similar to those generated for System S1. By using the proposed BESS allocation scheme, we obtained fourteen fixed LI BESS locations (shown in Table V), with a total fixed BESS capacity of ~1.130 MW. In summer and spring, twelve additional buses are selected for flexible VRF BESS placement (shown in Table VI), with a total capacity of ~635 MW. The CPU time for generating the BESS allocation results is ~6 hours.

Next, we conducted studies similar to those shown in Table IV, for System S2. The results comparing the different schemes for System S2 are shown in Table VII. By applying the proposed Scheme (d) to System S2, the average and maximum bus voltage deviation values were found to be 0.021 p.u. and 0.03 p.u., respectively. The BESS investment and repair costs were approximately 532 MS and 87 MS, respectively. With 50% wind penetration, the annual operation cost is ~313 MS, if Scheme (a) is used, while the operational benefit is ~70 MS, if Scheme (d) is employed. The DPP for Scheme (d) was 9.23 years, which was
TABLE VII
SYSTEM S2: COMPARISON OF FOUR SYSTEM PLANNING SCHEMES

| Scheme (a) | Scheme (b) | Scheme (c) | Scheme (d) |
|------------|------------|------------|------------|
| Avg. voltage deviation | 0.038 | 0.019 | 0.026 | 0.021 |
| Max. voltage deviation | 0.057 | 0.028 | 0.043 | 0.030 |

Network operation metrics (p.u.)

Conventional generation
| Scheme (d) | 121.37 | 117.15 | 117.15 | 113.51 |
| Emission | 9.36 | 8.56 | 8.56 | 8.30 |
| Wind spillage | 134.36 | 34.25 | 34.25 | 33.19 |
| Active power loss | 47.53 | 23.98 | 23.98 | 23.24 |
| BESS operation | - | 68.71 | 65.03 | 61.41 |

Network operation costs (M$)

BESS investment and repair costs and DPP
- Investment (M$) | - | 598.73 | 598.21 | 532.20 |
- Repair (M$) | - | 89.29 | 89.02 | 86.85 |
- DPP (years) | - | 14.21 | 12.89 | 9.23 |

TABLE VIII
SYSTEM S2: PERFORMANCE COMPARISON OF THE PROPOSED BESS ALLOCATION SCHEME

| Scheme (d) | Scheme (e) |
|------------|------------|
| Avg. voltage deviation | 0.021 | 0.016 |
| Max. voltage deviation | 0.030 | 0.025 |

Network operation metrics (p.u.)

Conventional generation
| Scheme (e) | 113.51 | 113.51 |
| Emission | 8.30 | 8.30 |
| Wind spillage | 33.19 | 33.19 |
| Active power loss | 23.24 | 23.24 |
| BESS operation | 61.41 | 63.87 |

Network operation costs (M$)

BESS investment and repair costs and DPP
- Investment (M$) | 532.20 | 532.69 |
- Repair (M$) | 86.85 | 87.05 |
- DPP (years) | 9.23 | 9.73 |

lower than the DPPs for Scheme (b) (14.21 years) and Scheme (c) (12.89 years).

V. DISCUSSIONS

A. Utility of Proposed Fixed-Flexible BESS Allocation Scheme

In order to demonstrate the utility of the fixed-flexible scheme (Scheme (d)), we compare it with a scheme where both types of BESSs (LI and VRF) are available throughout the year; we call this new scheme, Scheme (e). Note that unlike Scheme (b) where only one type of battery technology (LI BESS) was used, Scheme (e) optimally allocates both LI as well as VRF BESSs. The comparison was done for System S2, in terms of network operation metrics, network operation costs, BESS investment and repair costs, and DPP, and the results obtained are shown in Table VIII.

Table VIII shows that Scheme (e) incurs lower voltage deviations than Scheme (d) because all allocated VRF and LI BESS units in Scheme (e) operate in the regular charge/discharge mode throughout the year and utilize their reactive power capabilities in minimizing voltage deviations; in Scheme (d), the fixed LI BESSs operate throughout the year while the flexible VRF BESSs operate only during certain seasons. However, note that although the voltage deviations in Scheme (d) are somewhat higher than Scheme (e), they are still within tolerable limits. Schemes (d) and (e) have identical values for the first four network operation cost components; however, because of higher number of charge/discharge cycles, the year-round operation of both LI and VRF BESSs in Scheme (e) results in higher BESS operation costs than Scheme (d). For similar reasons, the BESS investment and repair costs and DPP are higher for Scheme (e) than Scheme (d). Thus, Table VIII proves the techno-economic advantage of the proposed fixed-flexible scheme over a scheme where both types of BESSs are available throughout the year.

This analysis also confirms that the proposed scheme accentuates the advantages of both the well-established LI BESS technology and the upcoming VRF BESS technology. With regards to the flexible mode of operation of the proposed scheme, when the VRF BESS is not in use, it can be kept in a standby/sleep mode [52]. The advantage of doing so is two-fold: (1) as VRF BESS has an extremely low self-discharge rate, keeping it in a standby/sleep mode will not reduce its life by a significant amount, and (2) at the time of need, due to its quick response time, VRF BESS can quickly switch to the usual charge/discharge mode and provide ancillary service.

B. Comparing Performance With Dynamic Programming (DP)

The utilization of DP for optimal BESS allocation and operation was described in [19], [20] as a sequential decision making problem. The main goal of this sub-section is to apply DP to solve the FixedFlexibleBESSAllocation algorithm described in this paper and compare results with the proposed approach (which uses the branch-and-cut algorithm [53]). The comparison will be done in terms of solution quality and computational performance. One can observe from Table IX that the annual operation costs obtained by using the DP approach are slightly higher than those obtained by the proposed approach for both Systems S1 and S2. The differences in computational performance of DP and the proposed approach are considerably more prominent. For System S2, the CPU time for generating the solution is ∼74 hours, which is approximately 12 times the CPU time of the proposed approach. The results obtained in Table IX show the superiority of the proposed approach with regards to DP.

C. Comparing Performance of Proposed Algorithm With and Without Bivariate Piecewise Linearization (BPL)

The FixedFlexibleBESSAllocation algorithm can be implemented without using the BPL formulation for VRF BESS. However, the main drawback of doing so is that instead of a MILP, one has to now solve a mixed integer non-linear program (MINLP). In this sub-section, the MINLP version of FixedFlexibleBESSAllocation algorithm is solved using KNITRO [54]. The comparison of the two solutions (MILP vs. MINLP) from a
computational performance and quality viewpoint is described in Tables X and XI. From the tables, it is observed that for both the systems, the annual operation costs obtained using KNITRO (for solving the MINLP problems) are significantly higher than those obtained using the BPL-based MILP (proposed approach). This is because KNITRO can ensure optimal solutions only if the objective function and all constraints are convex; otherwise it gives a sub-optimal solution that is obtained using heuristic methods [54]. The difference in computational performance of KNITRO and the proposed approach is also significant. For System S2, the CPU time for generating the MINLP solution is ~21 hours, which is approximately 3.5 times the CPU time of the proposed approach. The results summarized in Tables X and XI clearly show the advantage of performing BPL.

VI. CONCLUSION

This paper developed a novel scenario-based approach for optimal allocation of fixed and flexible BESSs in relatively large wind-integrated transmission networks. Historical wind power output and load data, mixtures of probability distributions and SSR were used to generate realistic scenarios of wind power output and system load. Next, a novel approach to allocate fixed LI and flexible VRF BESSs was presented. The fixed LI BESS was operated throughout the year, while the flexible VRF BESS was operated only during specific seasons that encountered relatively higher violations in system operational limits. Detailed technology-specific BESS models were created, and the BESS allocation framework was linearized to ensure near-global optimality and scalability.

The proposed strategy of fixed and flexible BESS allocation resulted in both technical (in terms of minimization of emissions, network losses, voltage fluctuations, and wind power spillage) as well as economic (in terms of reduction of network operation, and BESS costs, and discounted payback period) benefits with regards to four other BESS allocation schemes. The proposed framework utilized the complementary benefits of LI and VRF BESS technologies, primarily, the higher efficiency of LI BESS and the very low rates of cyclic degradation and self-discharge of VRF BESS, to attain the desired objectives. Future extension of this research work will involve the development of a comprehensive and computationally efficient framework for co-optimized allocation of fixed and flexible BESSs in realistic transmission & distribution (T&D) networks considering renewable energy and load-induced uncertainties.

APPENDIX A

The concept of bivariate piecewise linearization (BPL) [48] is illustrated using a bivariate non-linear function $f(v_1, v_2)$, shown along the Z-axis in Fig. 7; that is, $f$ is a function of two variables, namely, $v_1$ (along X-axis) and $v_2$ (along Y-axis). We first divide the X-axis into $M - 1$ segments using breakpoints $\{v_1^1, v_1^2, \ldots, v_1^M\}$, and the Y-axis into $N - 1$ segments using breakpoints $\{v_2^1, v_2^2, \ldots, v_2^N\}$; note that $v_1^1$ and $v_1^M$ ($v_2^1$ and $v_2^N$) are the minimum and maximum values of $v_1$ ($v_2$). The breakpoints on the axes partition the bivariate non-linear function domain into several rectangles. Consider the rectangle defined by vertices $(v_1^m, v_2^n), (v_1^{m+1}, v_2^n), (v_1^m, v_2^{n+1})$, and $(v_1^{m+1}, v_2^{n+1})$. This rectangle is composed of a lower-left triangle and an upper-right triangle having vertices $(v_1^m, v_2^n), (v_1^{m+1}, v_2^{n+1})$, and $(v_1^m, v_2^{n+1})$, $(v_1^{m+1}, v_2^n)$, and $(v_1^{m+1}, v_2^{n+1})$, $(v_1^m, v_2^{n+1})$, respectively; both triangles are separated by the diagonal of the rectangle denoted by $(v_1^{m, n})$ and $(v_1^{m+1, n+1})$. We also associate a continuous variable, $c^{m, n} \in [0, 1]$ for every $(m, n)$ and two binary variables, $b_1^{m, n}$ and $b_2^{m, n}$, that control whether the lower-left or the upper-right triangle is chosen for linearizing function $f$. The following equations can now be written.

$$v_1 = \sum_{m=1}^{M} \sum_{n=1}^{N} v_1^m c^{m, n}, v_2 = \sum_{m=1}^{M} \sum_{n=1}^{N} v_2^n c^{m, n} \quad (A1)$$

$$\bar{f} = \sum_{m=1}^{M} \sum_{n=1}^{N} f(v_1^m, v_2^n) c^{m, n} \quad (A2)$$

$$\sum_{m=1}^{M} \sum_{n=1}^{N} (b_1^{m, n} + b_2^{m, n}) = 1 \quad (A3)$$

![Table X](image)

Table X: Performance Assessment of the Proposed Scheme With and Without Bivariate Piecewise Linearization: Operation Cost

| System | Annual operation cost (MS) |
|--------|----------------------------|
| Without BPL (KNITRO) | With BPL (GUROBI) |
| S1     | 10.07                      | 7.43           |
| S2     | 335.51                     | 239.65         |

![Table XI](image)

Table XI: Performance Assessment of the Proposed Scheme With and Without Bivariate Piecewise Linearization: Solution Time

| System | Solution time (hours) |
|--------|-----------------------|
| Without BPL (KNITRO) | With BPL (GUROBI) |
| S1     | 1.25                  | 0.56           |
| S2     | 20.93                 | 5.98          |

![Fig. 7](image)
TABLE XII

| Parameter       | Unit | Value |
|-----------------|------|-------|
| $LC$            | Cycles | VRF: 12,000; LL: 2,000 [2] |
| $SOC_{min}$     | %    | VRF: 0 [2]; LL: 20 [4] |
| $SOC_{max}$     | %    | VRF: 100 [2]; LL: 80 [4] |
| $D_{T}^N$       | Hours | VRF: 8; LL: 4 [4] |
| $P_{e}$         | $$/kW | 11 [4] |
| $m$             | %/month | VRF: 0; LL: 10 [12] |
| $c_{pm}$        | $$/MWh | 20.14 [55] |
| $c_{pc}$        | $$/MWh | 42.58 [56] |
| $c_{pv}$        | $$/MWh | 100 [57] |
| $c_{e}$         | $$/kWh | VRF: 150; LL: 300 [5] |
| $c_{p}$         | $$/kW | 2 [5] |
| $c_{pm}$        | $$/kW | 150 [5] |
| $c_{pv}$        | $$/kWh | VRF: 600; LL: 900 [6] |

We use (A1) to uniquely represent a given point, $(v_1, v_2)$, while being weighted by the corresponding variables $c_{m,n}$. The bivariate non-linear function $f$ can now be approximated by a linear function $\tilde{f}$ in (A2), which is essentially convex combinations of $f$ calculated at the vertices of the triangle that contains the point $(v_1, v_2)$, as linear combinations of the vertex coordinates weighted by the corresponding variables $c_{m,n}$. Equation (A3) ensures that in any solution only one of the triangles is chosen. Equations (A4)–(A6) ensure that in any solution, at most three of the continuous variables $c_{m,n}$ take non-zero values. This completes the BPL of function $f$.

APPENDIX B

The values of key parameters used in this paper are shown in Table XII.

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