De-risking transient stability of AC/DC power systems based on ESS integration

Liangzhong Yao1, Fubao Wu2, Gao Qiu3 ½, Junyong Liu3, Youbo Liu3, Hongfen Cui2, Bingyu Sang2, Jilei Ye2

1China Electric Power Research Institute, State Key Laboratory of New Energy Storage Operation and Control, Beijing, People’s Republic of China
2China Electric Power Research Institute, Nanjing, Jiangsu, People’s Republic of China
3Laboratory of Smart Grid Analysis, Operation and Control (Sichuan University), Chengdu, Sichuan, People’s Republic of China
E-mail: qiguaoscu@stu.scu.edu.cn

Abstract: Owing to the charging/discharging flexibility, electric storage system (ESS) is widely recognised as a promising technique that can be introduced to enhance transient stability of power systems. Here, a multi-objective ESS allocating and sizing approach is presented to de-risk the loss of stability for the AC/DC power system. The approach contains two major steps. Firstly, transient stability risk (TSR) is assessed based on the severity and probability of contingencies which is simulated according to the good point set sampling considering multiple uncertainties and probabilistic fault. In the second step, an allocating and sizing model is proposed for ESS to minimise the operational cost, while the AC/DC system is subject to the TSR. Additionally, strength Pareto evolutionary algorithm (SPEA2) is employed to solve the model, optimising ESS allocation and size as well as output of regular generators. A modified AC/DC test system is used to validate the presented approach. The results indicate that, with the appropriate planning strategy, ESS is able to significantly contribute to TSR improvement as it can assist in transient power balancing after a severe fault.

1 Introduction

In recent years, the increasing implementation of HVDC system is driving power systems to be closer to the stability boundaries, which may cause the catastrophes such as cascading failure or widespread blackout [1]. Hence, the effective measures for AC/DC power system instability prevention are desperately needed. Preventive control, as a kind of prevailing scheme, has been widely applied in transient stability assurance.

Differing from emergency control, preventive strategy emphasises on the relatively long-term risk reduction for the complete set of possible contingencies. Therefore, establishing a well-performed risk indicator is critical for assessing the control performance of launching preventive action.

The risk-based method considering the probability and severity of contingencies has been extensively utilised in AC power system security assessment and preventive control. McCalley et al. [2] presented a risk-based security index which took into account the probability and impact of instability. A linearised technique, proposed in [3], was used to determine a risk-based index for dynamic security. However, the majority of existing researches focus on decreasing transient stability risk (TSR) of the AC power system through optimising generation scheduling, without considering operation of HVDC system.

Besides generation scheduling, other transient stability enhancement techniques such as the use of ESS is becoming attractive in this decade. A number of studies have reported that the utility-scale ESS can effectively enhance the operating security of the AC power system. For example, by employing fuzzy logic controller, superconducting magnetic energy storage was applied to stabilise power system [4]. Ortega and Milano [5] presented a stochastic analysis for ESS-included transient stability, proving that ESS application can facilitate a large increase in critical clearing time. In general, a majority of these works focused on developing ESS controllers for emergency control, ignoring the optimal configuration of ESS devices and operation cost.

In this paper, a TSR indicator is first introduced to quantify the potential risk of transient instability. Additionally, the AC/DC hybrid time domain simulation (TDS) is used to measure the level of stability for the AC/DC power system, and good point set (GPS) is employed for the uncertainty scenarios production [6]. Then, a TSR mitigation model optimising both financial and dynamic security risk indicator of the AC/DC system is proposed. The model considers both generation scheduling and ESS allocation. Finally, SPEA2 is utilised to solve the multi-objective model.

The main contributions of this paper can be summarised as follows: (i) GPS-based TSR calculation method is presented to consider operation uncertainties; (ii) a multi-objective and risk-oriented ESS allocating and sizing is modelled in order to determine the most appropriate ESS configuration for de-risking the transient stability of the AC/DC power system; (iii) the comparison analysis is conducted to reveal the innovation of GPS sampling and the advantages of ESS integration.

2 GPS-based TSR calculation

An appropriate potential risk indicator is the basis for preventive control. IEEE standards define that risk is a measurement of the probability and severity of undesirable contingency, which can be calculated via combination of probability and consequence. Also, TSR calculation method includes deterministic method and uncertainty method. To quantify the operation security condition under various disturbances and analyse contingencies as comprehensive as possible, uncertainty assessment TSR calculation method is proposed which considers many stochastic scenarios under multiple uncertainties.

2.1 TSR index

There are two important factors for TSR calculation, that is, the probability and severity of contingencies. The probability of the fault occurrence is usually obtained by historical statistics. Abapour and Haghigham [7] provided general calculation formula of the probability of the fault occurrence, which is shown as follows:

\[ P_i = p_i / \sum_{i=1}^{n} p_i, \quad \forall i \in L \]  

(1)
where \( p_i \) is the average occurrence times per year of faults on line \( i \), and \( n_f \) represents the total number of lines considered in the probability analysis; \( L \) is the considered lines set.

In this paper, only two fault types are considered in the contingencies, and we assume that multi-fault is assumed to be ignored in this study.

The measure method of the severity of contingencies can be summarised into two categories, which are instability cost-based probability analysis; and fault location, and fault clearing time. Where the generators’ output is summarised into two categories, which are instability cost-based probability analysis; and fault location, and fault clearing time are generated through the uncertainty scenarios generation, including: (i) the output model comprising the probability of fault occurrence, fault type, and its sampling method. First of all, we briefly introduce GPS theory and sampling: Based on GPS theory, GPS-based generators' output and load deviations of the vector \( \theta \) are normally applied to estimate the severity of system disturbance caused by fault occurred, for example, generator rotor angles are normally applied to estimate the transient stability [8]. In this paper, a generator rotor angles-based indicator is used to measure the severity of power system

\[
\text{SEV}_i = \max \{ \theta_i - \theta_j \}/\pi, \\
\forall \epsilon \in \{\text{contingencies}\}, \forall i, j \in G
\]

where \( c \) represents fault type in the contingencies; \( \text{SEV}_c \) is the severity of fault type \( c \); \( G \) is the generator set; \( \theta \) the generator rotor angle.

Based on (1) and (2), TSR index can be calculated through the following equation

\[
\text{TSR} = \frac{\text{avg}(P \times \text{SEV})}{1}, \text{TSD} = \text{std}(P \times \text{SEV})
\]

\[
P = [P_1, \ldots, P_i, \ldots, P_n]
\]

\[
\text{SEV} = [\text{SEV}^1, \ldots, \text{SEV}^i, \ldots, \text{SEV}^n]
\]

where \( n \) is the number of sampling uncertainty scenarios; \( P \) the vector consists of the probability of fault occurrence, and \( \text{SEV} \) the vector containing the severity of faults sampled from the contingency. Notice the assumption that there are no simultaneous faults occurred on transmission lines, hence \( P \) and \( \text{SEV} \) are corresponding one by one; TSD is a statistic measuring standard deviation of the vector \( P \times \text{SEV} \) which can indicate the transient risk discreteness of the system after various contingencies occurrence.

### 2.2 GPS-based uncertainty scenarios generation

To investigate uncertainty fault scenarios of power system, a GPS-based scenarios production method is utilised, which mainly concerns the effect of the stochastic aspects on the transient stability. In this paper, three major factors are considered which affect the uncertainty scenarios generation, including: (i) the output distribution of generators, (ii) the load level, and (iii) the fault model comprising the probability of fault occurrence, fault type, fault location, and fault clearing time. Where the generators’ output distribution, load level, and fault clearing time are obtained via GPS sampling, and fault type and location are generated through probabilistic selection. First of all, we briefly introduce GPS theory and its sampling method.

2.2.1 GPS theory and sampling: Xiao et al. [9] firstly proposed GPS for placing a certain number of points evenly within a multidimensional unity space and the mechanism of GPS sampling within an S-dimensional unity space is shown below [10]:

- Let \( G \) be the unit cube in Euclidean space. If \( x \in G \), \( x = (x_1, x_2, \ldots, x_n) \), then \( x \in [0, 1]^n \) for all \( i = 1, 2, \ldots, n \).
- If a set of \( m \) points \( P_m \subseteq G \), then \( P_m = \{ (x_1^{(m)}, \ldots, x_n^{(m)}) \mid j \in [1, m], x_i^{(m)} \in [0, 1] \} \).
- Let \( \mathcal{E} = \{ r \} \) be the distribution of sample points, where \( r \) is constant only relate with \( \epsilon \) (\( \epsilon \) is a random number between 0 and 1), \( \mathcal{E} \) is called GPS, and \( r \) is good point.

Compared with the conventional sampling method (e.g. MC sampling), GPS has a lot of advantages shown as follows:

- i. the distribution of sample point is more uniform, which can avoid information loss;
- ii. require less sampling amounts to achieve high level of scenario uncertainty; in other words, GPS is more efficient in sampling.

Hence, GPS is applied to generate uncertainty operation condition in this paper, and the two advantages of GPS mentioned above will be proved in numerical study.

Based on GPS theory, GPS-based generators’ output and load level scenarios sampling method is proposed, which is implemented by the below equations

\[
L = L_{\text{max}} + \{ r \} \times (L_{\text{max}} - L_{\text{min}}), L \in \Omega_{m \times 1}
\]

\[
G_j = G_{j \text{max}} + \{ r \} \times (G_{j \text{max}} - G_{j \text{min}}), G_j \in \Omega_{m \times 1}, \forall j \in G
\]

where the fluctuation range of the \( j \)th generator’s output and load level are \( [G_{j \text{min}}, G_{j \text{max}}] \) and \( [L_{\text{min}}, L_{\text{max}}] \), respectively; the distribution of generators’ output is updated through (5).

2.2.2 Fault model: Fault model consists of four parts, in which fault clearing time is sampling by GPS, shown as follows:

\[
\text{FCT} = \text{FCT}_{\text{max}} + \{ r \} \times (\text{FCT}_{\text{max}} - \text{FCT}_{\text{min}}), \forall j \in G
\]

where the fluctuation range of fault clearing time is \([\text{FCT}_{\text{min}}, \text{FCT}_{\text{max}}]\).

Considering the assumption mentioned in Section 2.1, the probability of fault occurrence, fault type, and fault location are integrated into a simplified probability model. Fault setting is shown in Table 1.

### 3 TSR mitigation model

The purpose of TSR mitigation model is to minimise the system risk index and the cost of ESS capacity and generation fuel through optimising ESS capacity and location and the output of generators. Also, another TSR minimisation model without allocating ESS is used to make a comparison, in which only generation output scheduling is considered. For convenience, the TSR mitigation model and TSR minimisation model without allocating ESS are denoted as models 1 and 2, respectively. It is remarkable that models 1 and 2 are both preventive control schemes.

| Fault setting | Fault location | Fault type | Fault probability |
|---------------|----------------|------------|-------------------|
| 1             | line 3–4       | line to ground | 0.40              |
| 2             | line 3–18      | line to ground | 0.27              |
| 4             | line 4–5       | line to ground | 0.16              |
| 5             | line 1–2       | three-phase short circuit | 0.10              |
| 6             | line 2–3       | three-phase short circuit | 0.07              |
3.3 Constraints

3.3.1 Power balance constraints: The sum of total generation output and ESS output should be equal to load

$$P_{ESS} + \sum_{g=1}^{G} P_g = P_{load}$$ (12)

3.3.2 AC/DC power flow constraints: The integrated AC/DC power flow is based on AC power flow, which is extended by the DC power flow equations. Also, the AC/DC power flow constraints can be conclusively given as follows:

$$P_{AC,i} - \sum_{j=1}^{V_{AC,i}} V_{AC,i} V_{AC,j} \cos(\theta_{ij}) + B_{ij} \sin(\theta_{ij}) = 0$$

$$Q_{i} - \sum_{j=1}^{V_{AC,i}} V_{AC,i} V_{AC,j} \sin(\theta_{ij}) - B_{ij} \cos(\theta_{ij}) = 0$$ (13)

where in the AC grid, $P_{AC,i}$ is the active power injection into bus $i$ and $Q_i$ the reactive power injection; $V_{AC,i}$ and $V_{AC,j}$ are the voltage amplitudes at buses $i$ and $j$, respectively; $G_{AC,ij}$ and $B_{ij}$ are the real part of the entry $ij$ of the admittance matrix and imaginary part of that; $\theta_{ij}$ the difference of phase angles between buses $i$ and $j$. In the DC grid, $P_{DC,i}$ is the active power injection into bus $i$; $V_{DC,i}$, the voltage at bus $i$; $G_{DC,ij}$ is the entry $ij$ of the admittance matrix.

The AC/DC interface is realised by converters, however, with the limitation in space, the model of converters is detailed in [11, 12].

3.3.3 ESS power constraints:

$$P_{ESS}^{min} \leq P_{ESS} \leq P_{ESS}^{max}$$ (14)

where $P_{ESS}^{min}$ and $P_{ESS}^{max}$ are power lower and upper limit of ESS output.

3.3.4 Generation output constraints:

$$P_{g}^{min} \leq P_g \leq P_{g}^{max}, \forall g \in G$$ (15)

where $P_{g}^{min}$ and $P_{g}^{max}$ are power lower and upper limit of generation output.

3.3.5 Bus voltage constraints:

$$V_{AC,i}^{min} \leq V_{AC,i} \leq V_{AC,i}^{max}$$

$$V_{DC,i}^{min} \leq V_{DC,i} \leq V_{DC,i}^{max}$$ (16)

where $V_{AC,i}^{min}$ and $V_{AC,i}^{max}$ are the lower and upper limit of AC bus $i$ voltage; $V_{DC,i}^{min}$ and $V_{DC,i}^{max}$ the lower and upper limit of DC bus $i$ voltage.

3.3.6 Line flow constraints:

$$P_{AC,ij}^{min} \leq P_{AC,ij} \leq P_{AC,ij}^{max}$$

$$P_{DC,ij}^{min} \leq P_{DC,ij} \leq P_{DC,ij}^{max}$$ (17)

where $P_{AC,ij}^{min}$ and $P_{AC,ij}^{max}$ are the lower and upper limit of power of AC line $ij$; $P_{DC,ij}^{min}$ and $P_{DC,ij}^{max}$ the lower and upper limit of power of DC line $ij$. 

Fig. 1 TSR calculation framework

3.1 Objective function

The objective functions of TSR mitigation model contain TSR indicator, TSD indicator, and the cost of ESS and generation, which can be mathematically illustrated as follows:

$$\min F = [TSR, TSD, C_{cost}]$$

$$C_{cost} = C_{ESS} + C_{GEN}$$ (7)

where TSR and TSD are the system stability indicators; $C_{cost}$ represents the total cost of ESS and generation; $C_{ESS}$ and $C_{GEN}$ stand for ESS capacity cost and generation fuel cost, respectively. $C_{ESS}$ and $C_{GEN}$ can be calculated by (8) and (9), respectively

$$C_{GEN} = \sum_{g=1}^{G} (a_g + b_g P_g + c_g P_g^2) T$$ (8)

$$C_{ESS} = u P_{ESS} T$$ (9)

where $a_g$, $b_g$, and $c_g$ are the fuel cost coefficients of the $g$th generator which are constant; $u$ is the ESS unit capacity investment cost; $P_g$ the $g$th generation output and $T$ the simulation time of TDS. Since the simulation time of TDS is extremely small, the SOC of ESS is ignored. Moreover, the operation strategy of ESS and generation in the preventive control is pre-decided, so the ESS capacity can be simply obtained by the below equation

$$S_{ESS} = P_{ESS} T$$ (10)

3.2 Optimisation variables

Optimisation variables are usually composed of control variables (e.g. generation output etc.) and state variables (e.g. bus voltage etc.). In this paper, for allocating ESS, the optimisation variables also include ESS capacity and location. Thereby, the optimisation variables are shown as follows:

$$VAR_{opt} = [P_{ESS}, LOC_{ESS}, U, \theta, P_G]$$ (11)

where $LOC_{ESS}$ is the access location of ESS; $U$ and $\theta$ are bus voltage and phase angle; $P_G$ is the generation outputs.

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3.3.7 Constraints processing: Adding constraints to the objective functions in the form of quadratic penalty terms, which can be described in the below equation

\[ F = [\text{TSR}, \text{TSD}, C_{\text{cost}}] + \sum_{i=1}^{n_{\text{cons}}} \sum_{j=1}^{n_{\text{var},i}} (x_{i,j} - x_{i,j}^{\text{bound}})^2 \]  

(18)

where \( x_{i,j} \) stands for the \( j \)th variable in the \( i \)th constraint and \( x_{i,j}^{\text{limit}} \) represents the lower or upper bound of the variable; \( n_{\text{cons}} \) indicates the number of constraints and \( n_{\text{var},i} \) represents the number of variables in the \( i \)th constraint.

3.4 Optimisation algorithm

The TSR mitigation model is a dynamic, non-linear, multi-objective optimisation problem, and it is hard to get the optimal solution by traditional mathematical optimisation algorithm. Multi-objective evolutionary algorithms (MOEAs) have been widely employed in such applications and obtained very good results; hence, SPEA2 belonging to MOEAs is applied to solve the TSR mitigation model in this paper. The implementation program of SPEA2 is detailed in [13, 14].

After solving the TSR mitigation model through SPEA2, a set of Pareto optimal solution can be found, then we need an effective method to select optimal solution according to preference information. In this paper, technique for order performance by similarity to ideal solution (TOPSIS) is adopted to choose the optimal solution from Pareto solution set, and the procedure of TOPSIS is detailed in [15]. In addition, the weights of objective functions TSR, TSD, and \( C_{\text{cost}} \) are 0.5, 0.3, and 0.2, respectively, and the weight value indicates that TSR is the most important target in optimisation, successively followed by TSD and \( C_{\text{cost}} \).

4 Results

The modified IEEE 39 system shown in Fig. 2 was used as the test system; the reference power of which was 100 MW. Line 4–14 was replaced by HVDC transmission line and its rated voltage and power were 500 and 500 MW, respectively. It was assumed that the reactive power reserve of the system is sufficient. The \( N-1 \) contingency was shown in Table 2. Where the zero-sequence and negative-sequence impedance used for line to ground fault TDS were both 0.4 p.u.

4.1 GPS and random sampling comparison

The distribution of 500 generators’ output scenarios by GPS and MC sampling is shown in Figs. 3a and b, respectively, where only two-dimensional space is represented. It is obvious that the distribution of MC scenarios is non-uniform, meaning that scenarios generated by MC inevitably lack a lot of knowledge. For example, the space within black circle labelled in Fig. 3a contains no scenarios, while the space within black circle labelled in Fig. 3b is filled with scenarios. This drawback may lead inaccuracy of TSR computing when MC is applied.

| Number | Variables and solutions of TOPSIS selected Pareto sets | ESS output, p.u. | ESS location | C_{\text{cost}}, $ | TSR | TSD |
|--------|------------------------------------------------------|----------------|--------------|----------------|-----|-----|
| 1      |                                                      | 11.772         | 4            | 7.662          | 0.0421 | 0.0184 |
| 2      |                                                      | 11.821         | 4            | 7.611          | 0.0424 | 0.0210 |
| 3      |                                                      | 11.824         | 4            | 7.592          | 0.0432 | 0.0227 |
| 4      |                                                      | 11.824         | 4            | 7.373          | 0.0458 | 0.0226 |
| 5      |                                                      | 11.822         | 4            | 7.344          | 0.0463 | 0.0245 |
| 6      |                                                      | 11.627         | 4            | 7.706          | 0.0488 | 0.0249 |
| 7      |                                                      | 6.128          | 4            | 7.575          | 0.0567 | 0.0197 |
| 8      |                                                      | 6.125          | 4            | 6.642          | 0.0577 | 0.0215 |
| 9      |                                                      | 11.621         | 4            | 7.707          | 0.0508 | 0.0261 |
| 10     |                                                      | 11.779         | 4            | 7.319          | 0.0564 | 0.0249 |
Moreover, to quantificationally compare sampling performance between GPS and MC, information entropy (IE) is performed to measure the coverage level of scenarios in sampling space, e.g. the higher IE, the higher the coverage level. IE is calculated by the below equation

\[
\text{Ent}(x) = -\sum_{s=1}^{S} \text{Pro}(x) \log \text{Pro}(x) \quad \forall x \in \Psi
\]  

(19)

where \( S \) is the number of segmentations that divides the vector \( x \) evenly; \( \text{Pro}(x) \) denotes the probability of \( x \) occurring in the segment \( s \). \( \Psi \) is the sampling space, expressed as a matrix, consisting of multi-vectors.

With gradually increasing sampling scenarios and calculating IE of two sampling methods step by step, Fig. 4 can be obtained. As is shown in Fig. 4, GPS is stabilised at top coverage level after the number of sampling scenarios increased to 500, and the highest IE of GPS is 3.3219. However, MC can hard reach its top coverage level steadily, and more scenarios are needed to attain high IE when MC is applied. Moreover, the highest IE of MC is 3.3214, less than that of GPS. In a word, GPS outperforms MC, and the global optimisation ability and computational efficiency of SPEA2 can be indirectly improved by GPS.

4.2 Initial operation condition TSR

To cover fault scenarios near initial operation condition as many as possible, 500 sampling scenarios were generated by GPS. Then the TSR of each scenario was calculated. Notice that some of the sampling scenarios may be non-convergence of AC/DC power flow; hence, the number of ASs is 397. TSR of each AS is shown in Fig. 5.

As shown in Fig. 5, ASs corresponding to different fault type are artificially classified into different clusters. For example, ASs in clusters 1, 2, and 3 are scenarios with faults 1, 2, and 3 occurred, respectively. In addition, TSR within each fault cluster is close, and the average TSR value of clusters 1, 2, and 3 are 0.1535, 0.1052, and 0.0494, respectively. However, compared with clusters mentioned above, the characteristic of cluster 4 is quite different: (i) the ASs in cluster 4 contain two fault types scenarios, i.e. faults 4 and 5 scenarios, (ii) TSS value of the ASs in cluster 4 is dispersive, (iii) the number of ASs in cluster 4 is much less than that in clusters 1, 2, and 3. In a word, TSR depend mainly on the TSR value of ASs in clusters 1, 2, and 3 which are high probability of fault occurrence.

4.3 TSR mitigation

Solve the TSR mitigation model with ESS integration and the generation scheduling model without ESS integration through employing SPEA2. Then the acquired optimal Pareto sets of these two models can be depicted as Figs. 6 and 7, respectively. Through TOPSIS, the selected top ten Pareto optimal solutions are determined, which are marked with red solid circles in Figs. 6 and 7.

It can be seen from Figs. 6 and 7, SPEA2 can solve the TSR mitigation model effectively and the results show a good convergence. The minimum TSR values of model 1 and comparison model 2 are 0.421 and 0.0556, respectively; thus, it is observed that model 1 can exactly mitigate TSR in the AC/DC system.

In order to show the statistics of the Pareto solution sets of the two models intuitively, box plots are drawn which are shown in Fig. 8.

From Fig. 8, it is obvious that the average value of TSR and TSD of model 1's pareto solutions is lower than that of model 2's pareto solutions, which implies that ESS can indeed improve power system transient stability.

Furthermore, Table 2 is given to investigate the effect of ESS on the TSR mitigation, and the ten optimal variables and solutions are corresponding to TOPSIS selected Pareto optimal solutions.

From Table 2, ESS locations are optimised to bus 4, which is the highest fault occurrence probability position. In other words,
the TSR mitigation model prefers to configure ESS at the weak bus, and improvement of the transient stability can be maximised. Additionally, the lower TSR value, the higher cost. Thereby, the rational allocation of ESS output and generation output for achieving dual optimal economic and transient stability is important, and the number 1 Pareto optimal solution (i.e. allocating ESS at bus 4 and configuring ESS output as 11.772 p.u.) is the most appropriate scheme; in this case, the corresponding $C_{\text{Cost}}$, TSR, and TSD are 7.662$, 0.0421, and 0.0184, respectively. It is noting that although the same ESS configuration does not mean to the same level of TSR reduction, the gap is actually quite small. For example, taking into account the second (number 2) and third (number 3) solution in Table 2, ESS are equally configured but the generation outputs are different, the optimised TSR have only a little difference. It can be therefore concluded that the impact on TSR caused by generators’ output is far less than that of ESS.

5 Conclusion and further work

This paper presents a novel risk-based preventive control methodology of ESS output, location, and generation output for AC/DC power system transient stability improvement. This paper presents a novel risk-oriented preventive control scheme for the AC/DC power system to de-risk transient instability by integrating ESS. The TSR indicator is first modelled to consider multi-uncertainties, including generation outputs, load fluctuation, and probabilistic fault modes. Afterwards, an allocating and sizing model is established for ESS to minimise the operational cost in the context of transient stability prevention. The proposed approach provides a generic tool to optimally determine the configuration of ESS that is adopted in the AC/DC hybrid power system, enabling TSR enhancement as much as possible while considering the financial cost minimisation. In the future, the precise ESS controller model will be developed to realise the dynamic scheduling and controlling strategy to stabilise the bulk power system.

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Fig. 8 Box plots on different TSR mitigation scheme
(a) The optimised TSR solutions, (b) The optimised TSD solutions