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Multi-Timescale Voltage Regulation for Distribution Network with High Photovoltaic Penetration via Coordinated Control of Multiple Devices

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Abstract: The high penetration of distributed photovoltaics (PV) in distribution networks (DNs) results in voltage violations, imbalances, and flickers, leading to significant disruptions in DN stability. To address this issue, this paper proposes a multi-timescale voltage regulation approach that involves the coordinated control of a step voltage regulator (SVR), switched capacitor (SC), battery energy storage system (BESS), and electric vehicle (EV) across different timescales. During the day-ahead stage, the proposed method utilizes artificial hummingbird algorithm optimization-based least squares support vector machine (AHA-LSSVM) forecasting to predict the PV output, enabling the formulation of a day-ahead schedule for SVR and SC adjustments to maintain the voltage and voltage unbalance factor (VUF) within the limits. In the intra-day stage, a novel floating voltage threshold band (FVTB) control strategy is introduced to refine the day-ahead schedule, enhancing the voltage quality while reducing the erratic operation of SVR and SC under dead band control. For real-time operation, the African vulture optimization algorithm (AVOA) is employed to optimize the BESS output for precise voltage regulation. Additionally, a novel smoothing fluctuation threshold band (SFTB) control strategy and an initiate charging and discharging strategy (ICD) for the BESS are proposed to effectively smooth voltage fluctuations and expand the BESS capacity. To enhance user-side participation and optimize the BESS capacity curtailment, some BESSs are replaced by EVs for voltage regulation. Finally, a simulation conducted on a modified IEEE 33 system validates the efficacy of the proposed voltage regulation strategy.

Keywords: multi-timescale regulation; multiple devices; coordinated control; voltage regulation; distributed photovoltaics; distribution network



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1. Introduction

In recent years, due to the increasing severity of the energy crisis and environmental pollution, more and more renewable energy resources are being sent to distribution networks (DNs) on a large scale [1–3] to realize the self-generation and self-consumption of electricity. Photovoltaics (PV), as a renewable energy resource, accounted for nearly 31% of the world's total installed renewable energy capacity in 2022, making it the second largest renewable energy resource after hydropower [4]. However, the increasing scale of grid-connected PV [5–7] brings new technical problems and challenges to the voltage control of DNs. The reverse flow caused by PV leads to the voltage violation of DNs [8,9]. The stochastic nature of PV leads to voltage fluctuation and uncontrollability [10,11]. Moreover, single-phase PV exacerbates the voltage unbalance of DNs [12,13].

A step voltage regulator (SVR) and switched capacitor (SC), as mechanical devices, mainly regulate the voltage of DNs by adjusting the tap position or changing the switching number of groups [14,15]. In [16], a proposed consensus multi-agent deep reinforcement

learning algorithm was used to determine the operation time of an SVR, on-load tap changer (OLTC), and SC to improve voltage violation and reduce line loss. In [17], a voltage control strategy based on a multi-intelligent body system (MAS) was proposed to effectively manage different types of voltage regulators to minimize voltage deviations and ensure optimal voltage regulators operation. In [18], a model-free Volt-Var control method based on a statistical analysis of measured data was proposed; it controls the voltage regulator (VR) to improve voltage violation and reduce power loss. In [19], a secure offline deep reinforcement learning algorithm was proposed by controlling the OLTC, VR, and SC to avoid voltage violations and reduce line loss and equipment wear. The above studies aimed to control mechanical voltage regulation devices to avoid voltage violation with optimal operation.

A battery energy storage system (BESS), as a power electronic switching device, is connected to a DN through a power conditioning system (PCS) [20,21], which absorbs /releases power according to the demand of the DN and realizes fast, continuous, and accurate voltage control [22,23]. In addition, in recent years, under the support and promotion of preferential policies in various countries, the global electric vehicle market has shown rapid growth, and with the rapid growth of electric vehicle (EVs) ownership, EVs as flexible energy storage devices could be involved in the voltage regulation of DNs through vehicle-to-grid (V2G) technology [24–26]. In [27], a coordinated control strategy for a BESS and OLTC was proposed by coordinating the local BESS and global OLTC to minimize voltage deviation and optimize the BESS output. In [28], a model predictive control method based on a BESS, distribution generators (DGs), and OLTC was proposed to ensure that the voltage is within the threshold while optimizing the economy of BESS utilization in voltage regulation. In [29], a two-stage optimization strategy was proposed, where the first stage achieves optimal regional division through the community-based detection particle swarm optimization (CBDPSO) algorithm, and the second stage controls the voltage within the threshold and achieves economic optimization through the coordinated control of the EVs, OLTC, SC, and VR. In [30], a strategy with a hierarchical structure was proposed to minimize the voltage unbalance and neutral current through the coordination control of the BESS, EVs, and DG in different layers. In [31], the long and short-period operation of the OLTC, DG, and BESS was proposed to maintain the voltage within the threshold and to reduce power loss and BESS cost. In [32], the coordination of the OLTC, SC, DG, and EVs was carried out to eliminate voltage deviation and voltage fluctuation. The above-related studies aimed to achieve voltage quality improvement through the coordinated control of different voltage regulation devices.

In this paper, an SVR, SC, BESS, and EVs are used as voltage regulation devices to improve the voltage quality. Multi-timescale voltage regulation via a coordinated control strategy with multiple devices is proposed to fully use the voltage regulation capability of the SVR and SC, optimize the utilization efficiency of the BESS, and promote the participation of EVs on the user's side in the electricity market. The main contributions of this paper are summarized as follows:

1. For the problem of PV forecasting accuracy, the artificial hummingbird algorithm optimization-based least squares support vector machine (AHA-LSSVM) forecasting model is proposed.
2. For the problem of frequent SVR operation with voltage dead-band control in the PV-connected DN, a novel floating voltage threshold band (FVTB) control strategy is proposed.
3. For the problem of BESS output optimization, the African vulture optimization algorithm (AVOA) is used to optimize the BESS output.
4. For the problem of frequent voltage fluctuation caused by PV, a smoothing fluctuation threshold band (SFTB) strategy is proposed.
5. For the problem of BESS capacity curtailment in voltage regulation, an initiate charging and discharging strategy (ICD) of BESS based on state of charge (SOC) management is proposed.

The structure of the rest of this paper is divided into the following sections: Section 2 illustrates the mathematical model of each regulator. Section 3 describes the proposed multi-timescale voltage regulation via a coordinated control strategy with an SVR, SC, BESS, and EVs. Section 4 performs simulations and analyzes the results. Finally, the conclusion is given in Section 5.

2. Mathematical Formulation

An SVR and SC, as traditional voltage regulation devices limited by their mechanical characteristics, cannot follow the voltage variation in PV-connected DN in real-time due to the lack of fast response capability and because the frequent exceeding of the voltage caused by PV also leads to the excessive operation of the device, which accelerates mechanical deterioration. A BESS [33,34] is capable of providing fast, continuous, and accurate voltage control for a PV-connected DN, but the cost of a BESS is high. Therefore, the application of a BESS in coordination with an SVR and SC for voltage regulation is the feasible option. Along with the implementation of the policy [35] in Henan Province, the quantity of EVs has been increased continuously, and the storage batteries contained in EVs could also be involved in voltage regulation via V2G technology. In this paper, the voltage regulation devices involved are SVR, SC, BESS, and EVs, and the mathematical model of each voltage regulation device is illustrated in this section.

2.1. SVR

An SVR, as a mechanical voltage regulation device, achieves the purpose of voltage regulation via changing the position of the tap, and an SVR as a discrete voltage regulator only regulates the voltage in three phases. The relationship between the SVR tap change and voltage variation is expressed by Equation (1) [17]:

$$\Delta V_{tap}(t) = K_{tap}(t) \Delta v_{tap} \quad (1)$$

where $\Delta V_{tap}(t)$ is the voltage variation at time t . $K_{tap}(t)$ is the SVR tap change at time t . Δv_{tap} is the voltage variation by one tap change.

The tap position constraint of the SVR is expressed by Equation (2):

$$K_{tap}^l(t) \leq K_{tap}(t) \leq K_{tap}^u(t) \quad (2)$$

$$K_{tap}^u(t) = K_{tap}^{max} - K_{tap}^{int}(t-1) \quad (3)$$

$$K_{tap}^l(t) = K_{tap}^{min} - K_{tap}^{int}(t-1) \quad (4)$$

where $K_{tap}^u(t)$ and $K_{tap}^l(t)$ are the upper and lower limits of $K_{tap}(t)$ at time t , respectively. K_{tap}^{max} and K_{tap}^{min} are the upper and lower maximum adjustable taps, respectively. $K_{tap}^{int}(t-1)$ is the tap position of the SVR at time $t-1$.

2.2. SC

An SC achieves the goal of voltage regulation by changing the number of capacitors. In terms of regulation accuracy and speed, an SC has the same problems as an SVR, but an SC can realize single-phase as well as three-phase voltage regulation, which can solve the voltage unbalance problem during the voltage regulation of a DN. Voltage variation via an SC is expressed by Equation (5) [15], where ξ denotes phase ab, phase bc, and phase ca.

$$\Delta V_{sc,i}^n(t) = C_{sc}^n(t) \cdot S_{ij}^{VQ}(\Delta Q_{sc}) \quad n \in \{\xi\} \quad (5)$$

$$\begin{cases} \begin{bmatrix} P \\ Q \end{bmatrix} = \begin{bmatrix} J_{P\theta} & J_{PV} \\ J_{Q\theta} & J_{QV} \end{bmatrix} \cdot \begin{bmatrix} \theta \\ V \end{bmatrix} \\ S_{ij}^{VQ} = \frac{\partial V_i}{\partial Q_j} = \left(J_{QV} - J_{Q\theta} \cdot J_{P\theta}^{-1} \cdot J_{PV} \right)^{-1} \end{cases} \quad (6)$$

where $\Delta V_{sc,i}^n(t)$ is the voltage variation in phase n of node i at time t . $C_{sc}^n(t)$ is the number of SCs in phase n at time t . ΔQ_{sc} is the reactive power variation caused by unit SC. S_{ij}^{VQ} is the function of reactive power and voltage. P and Q are vectors of injecting active and reactive power, respectively. θ and V are the vectors of phase angle and voltage amplitude, respectively. $J_{P\theta}$, J_{PV} , $J_{Q\theta}$, and J_{QV} are terms of the Jacobian matrix.

The constraint of the SC number, $C_{sc}^n(t)$, is expressed by Equation (7):

$$C_{sc}^{n,l}(t) \leq C_{sc}^n(t) \leq C_{sc}^{n,u}(t) \quad (7)$$

$$C_{sc}^{n,u}(t) = C_{sc}^{max} - C_{sc}^{int,n}(t-1) \quad (8)$$

$$C_{sc}^{n,l}(t) = C_{sc}^{min} - C_{sc}^{int,n}(t-1) \quad (9)$$

where $C_{sc}^{n,u}(t)$ and $C_{sc}^{n,l}(t)$ are the upper and lower limits of $C_{sc}^n(t)$ at time t , respectively. C_{sc}^{max} and C_{sc}^{min} are the upper and lower maximum adjustable numbers of $C_{sc}^n(t)$, respectively. $C_{sc}^{int,n}(t-1)$ is the number of SCs at time $t-1$.

2.3. BESS

A BESS is connected to a DN through a PCS that can realize continuous voltage regulation in each phase with high regulation accuracy and a fast response speed. The SOC is an important index of a BESS, and by the management of the SOC, the BESS could be prevented from deep charging/discharging to prolong its service life. The relationship between the SOC and the charging/discharging output of the BESS is expressed by Equation (10):

$$SOC(t+1) = SOC(t) + \sum_{n \in \{\xi\}} \frac{\int_t^{t+1} q^{ch,n}(t) \gamma_{bes}^{ch} P_{bes}^{ch,n}(t) + q^{dch,n}(t) P_{bes}^{dch,n}(t) / \gamma_{bes}^{dch} dt}{E_B} \quad (10)$$

where $SOC(t+1)$ is the SOC at time $t+1$. $SOC(t)$ is the SOC at time t . $P_{bes}^{ch,n}(t)$ and $P_{bes}^{dch,n}(t)$ are the charging and discharging outputs of the BESS in phase n at time t , respectively. γ_{bes}^{ch} and γ_{bes}^{dch} are the efficiency of charging and discharging, respectively. E_B is the capacity of the BESS. $q^{ch,n}(t)$ and $q^{dch,n}(t)$ are binary variables.

The constraints of the BESS are expressed as follows:

$$SOC^{min} \leq SOC(t) \leq SOC^{max} \quad (11)$$

$$0 < P_{bes}^{ch,n}(t) \leq P_{bes,in}^{max} \quad (12)$$

$$P_{bes,out}^{max} < P_{bes}^{dch,n}(t) < 0 \quad (13)$$

$$0 \leq q^{ch,n}(t) \leq 1 - q^{dch,n}(t) \text{ and } q^{ch,n}(t) \text{ and } q^{dch,n}(t) \in \{0,1\} \quad (14)$$

where SOC^{max} and SOC^{min} are the upper and lower limits of the SOC, respectively. $P_{bes,out}^{max}$ is the maximal discharging power. $P_{bes,in}^{max}$ is the maximal charging power.

2.4. EVs

In this paper, the EV charging model is categorized into fast charging and slow charging. According to their state at the charging station, EVs are divided into charging EVs and idle EVs. Charging EVs can be equivalent to the load that connects to the DN and does not participate in the voltage regulation in the DN, and idle EVs can be used as virtual energy storage batteries to participate in voltage regulation.

The fast charging of EVs is achieved through a three-phase connection to a DN [24,30], and the charging power $P_{ev,f}^{ch}(t)$ and discharging power $P_{ev,f}^{dch}(t)$ are expressed by Equations (15) and (16):

$$P_{ev,f}^{ch}(t) = \sum_{m=1}^M \gamma_{ev}^{ch} P_{ev,m}^{ch}(t) \quad (15)$$

$$P_{ev,f}^{dch}(t) = \sum_{m=1}^M P_{ev,m}^{dch}(t) / \gamma_{ev}^{dch} \quad (16)$$

where γ_{ev}^{ch} and γ_{ev}^{dch} are the efficiency of charging and discharging of EVs, respectively. $P_{ev,m}^{ch}(t)$ and $P_{ev,m}^{dch}(t)$ are the fast charging and fast discharging power of EV m at time t , respectively. m is the number of EVs. M is the total number of fast charging EVs at time t .

The slow charging of EVs is carried out through a single-phase connection to a DN, and the charging power $P_{ev,s}^{ch}(t)$ and discharging power $P_{ev,s}^{dch}(t)$ are expressed by Equations (17) and (18):

$$P_{ev,s}^{ch}(t) = \sum_{h=1}^H \gamma_{ev}^{ch} P_{ev,h}^{ch}(t) \quad (17)$$

$$P_{ev,s}^{dch}(t) = \sum_{h=1}^H P_{ev,h}^{dch}(t) / \gamma_{ev}^{dch} \quad (18)$$

where $P_{ev,h}^{ch}(t)$ and $P_{ev,h}^{dch}(t)$ are the slow charging and slow discharging power of EVs h at time t , respectively. h is the number of EVs. H is the total number of slow-charging EVs at time t .

3. Novel Multi-Timescale Voltage Regulation via Coordinated Control Strategy by SVR, SC, BESS, and EVs

The uncertainty and stochasticity of PV cause fluctuations in power flow, which, in turn, lead to voltage quality degradation. The voltage regulation ability of different devices has variability on timescales, so the coordinated control of each voltage regulation device is particularly important, and this paper proposes a novel multi-timescale coordinated control strategy to realize voltage regulation in a PV-connected DN. The proposed strategy is divided into day-ahead scheduling, intra-day optimization, and real-time control. According to the characteristics of each voltage regulation device, an SC and SVR are coordinated to regulate voltage on day-ahead scheduling and intra-day optimization stages, and BESSs and EVs are coordinated to regulate voltage in the real-time control stage.

3.1. Day-Ahead Scheduling

In day-ahead scheduling, PV forecasting is utilized to obtain PV data a day ahead, and the coordinated control of an SVR and SC is formulated a day ahead to maintain the voltage and voltage unbalance factor (VUF) within the threshold. Day-ahead scheduling consists of day-ahead PV forecasting (DPVF) and day-ahead voltage regulation and voltage unbalance regulation (DVVR).

3.1.1. DPVF

As a modification of the support vector machine (SVM), an LSSVM [36,37] retains the key characteristics of an SVM while simplifying the optimization process by employing a least-squares loss function in place of the insensitive loss function used in an SVM. Additionally, the complexity of the solution is significantly reduced by replacing the inequality constraints with equation constraints.

Nonlinear mapping is applied to a training sample $\{x_\varepsilon, y_\varepsilon\}$ ($\varepsilon = 1, \dots, \uparrow$) to transform the inputs and outputs $x_\varepsilon, y_\varepsilon$ from the initial space to a high-dimensional space in order to create the optimal decision function [37].

$$y(x) = w^T \varphi(x) + b \quad (19)$$

where w represents the weight vector. $\varphi(x)$ is the mapping function for the nonlinear transformation. b is the offset.

By adhering to the risk minimization principle, the objective function is shown in Equation (20) [37].

$$\begin{cases} \min_{w,b,e} J(w,e) = \frac{1}{2}w^T w + c \sum_{\varepsilon=1}^{\downarrow} e_{\varepsilon} \\ \text{s.t. } y_{\varepsilon} = w^T \varphi(x_{\varepsilon}) + b + e_{\varepsilon} \end{cases} \quad (20)$$

where e_{ε} is the error, c is the regularization parameter, and $\downarrow$ is training samples number.

By introducing the Lagrange multiplier α_{ε} , Equation (21) is obtained.

$$L(w,b,e,\alpha) = J(w,e) - \sum_{\varepsilon=1}^{\downarrow} \alpha_{\varepsilon} \{w^T \varphi(x_{\varepsilon}) + b + e_{\varepsilon} - y_{\varepsilon}\} \quad (21)$$

The LSSVM forecasting model obtained by taking partial derivatives of w , b , e_{ε} , and α_{ε} results in Equation (21).

$$y(x) = \sum_{\varepsilon=1}^{\downarrow} \alpha_{\varepsilon} K(x, x_{\varepsilon}) + b \quad (22)$$

$K(x, x_{\varepsilon})$ is the kernel function; in this paper, we choose the radial basis kernel function (RBF), which has a simple structure and strong generalization ability, as the kernel function of LSSVM.

$$K(x, x_{\varepsilon}) = \exp\left(-\frac{\|x - x_{\varepsilon}\|^2}{2\sigma^2}\right) \quad (23)$$

where σ is the kernel parameter of the RBF.

The kernel parameter (σ) and regularization parameter (c) of the LSSVM are crucial to the degree of fit and generalization ability of the forecasting process, and the number of papers published on the preferential selection of hyperparameter values by meta-heuristic optimization algorithms has significantly improved the forecasting accuracy of LSSVMs [38–40]. The AHA is the latest proposed heuristic algorithm [41], which has the characteristics of high optimization searching accuracy, fast convergence, and robustness compared to other algorithms.

The AHA, an algorithm inspired by the foraging behaviors of hummingbirds in nature, integrates guided foraging, regional foraging, and migratory foraging patterns as well as flight skills such as axial flight, diagonal flight, and all-around flight. It also incorporates hummingbirds' foraging memory, enabling the efficient location and selection of food sources. The AHA distinguishes itself from other algorithms by demonstrating high accuracy in optimization searches, a rapid convergence speed, and robustness in various scenarios [41,42].

In this paper, the AHA-LSSVM for PV forecasting is proposed. The AHA-LSSVM takes light intensity, temperature, and humidity as inputs for PV forecasting. The two optimized parameters σ and c by AHA are substituted to LSSVM to improve the forecasting accuracy of PV. The flowchart of the AHA-LSSVM for PV forecasting is shown in Figure 1 with the following steps:

Step 1: Divide the PV data into training and testing sets and normalize them.

Step 2: Initialize the hummingbird positions (σ and c), set the AHA parameters (population size, dimension, and number of iterations), and initialize the access table.

Step 3: Introduce the hummingbird location into the LSSVM, obtain the PV forecasting value from Equation (22), and calculate the mean square error (MSE) for PV forecasting using Equation (24) with the hummingbird's fitness value f .

$$f = \frac{\sum_{r=1}^R (y_r^f - y_r^a)^2}{R} \quad (24)$$

where R is the number of training samples, y_r^a is the actual value, and y_r^f is the predicted value.

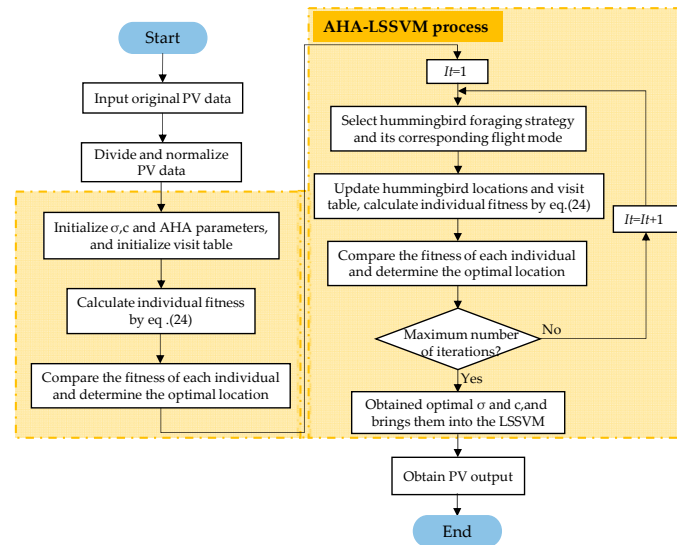


Figure 1. Flowchart of AHA-LSSVM in PV forecasting.

Step 4: Compare fitness values to obtain the optimal fitness value so far.

Step 5: Update the hummingbird position by selecting the foraging strategy and choosing flight mode in the corresponding foraging strategy [41]. Then, update the visit table.

Step 6: Repeat steps 3–5 until the maximum iteration is met and the optimal hummingbird position (σ and c) and fitness values are obtained.

Step 7: Establish the LSSVM with the optimal parameters σ and c and obtain the PV output.

3.1.2. DVVR

With the increase in PV penetration, PV stochasticity and single-phase PV connection in DN intensify voltage deterioration and voltage unbalance. Therefore, DVVR consists of the regulation voltage stage and the VUF stage.

1. Voltage Regulation

For day-ahead scheduling, the forecasting voltage is obtained by a power flow calculation according to the forecasting data in Section 3.1.1. The steps for voltage regulation are as follows:

Step 1: When the voltage satisfies Equation (25), the SVR and SC do not operate. When the voltage does not satisfy Equation (25), the voltage violation $\Delta V(t)$ to be regulated at time t is shown in Equation (26).

$$V^{\min} \leq V_i^n(t) \leq V^{\max} \quad (25)$$

$$\Delta V(t) = \begin{cases} V^{\max}(t) - V^{\max} & \text{if } V^{\max}(t) > V^{\max} \text{ and } V^{\min}(t) > V^{\min} \\ V^{\min}(t) - V^{\min} & \text{if } V^{\min}(t) < V^{\min} \text{ and } V^{\max}(t) < V^{\max} \\ \Delta V^{\text{rar}}(t) & \text{if } V^{\max}(t) > V^{\max} \text{ and } V^{\min}(t) < V^{\min} \end{cases} \quad (26)$$

$$V^{\max}(t) = \max\{V_i^n(t)\} \quad (27)$$

$$V^{\min}(t) = \min\{V_i^n(t)\} \quad (28)$$

$$\Delta V^{\text{rar}}(t) = \begin{cases} V^{\max}(t) - V^{\max} & \text{if } |\max\{V_i^n(t)\} - V^{\max}| \geq |\min\{V_i^n(t)\} - V^{\min}| \\ V^{\min}(t) - V^{\min} & \text{if } |\max\{V_i^n(t)\} - V^{\max}| < |\min\{V_i^n(t)\} - V^{\min}| \end{cases} \quad (29)$$

where $V_i^n(t)$ is the voltage of phase n of node i at time t . V^{max} and V^{min} are the upper and lower limits of the voltage, respectively. $V^{max}(t)$ and $V^{min}(t)$ are the maximum and minimum values of the voltage at time t , respectively.

Step 2: The required $K_{tap}(t)$ for voltage regulation is calculated by Equation (30), and the regulated voltage $V_{i,aft}^n(t)$ of node i in phase n is obtained by Equation (31):

$$K_{tap}(t) = - \begin{cases} \left\lceil \frac{\Delta V(t)}{\Delta v_{tap}} \right\rceil & \text{if } \Delta V(t) > 0 \\ \left\lfloor \frac{\Delta V(t)}{\Delta v_{tap}} \right\rfloor & \text{if } \Delta V(t) < 0 \end{cases} \quad (30)$$

$$V_{i,aft}^n(t) = V_i^n(t) + K_{tap}(t) \cdot \Delta v_{tap} \quad (31)$$

where $\lceil x \rceil$ is rounded up and $\lfloor x \rfloor$ is rounded down.

Step 3: When $V_{i,aft}^n(t)$ satisfies Equation (25), the regulation voltage stage is finished. If $V_{i,aft}^n(t)$ does not satisfy Equation (25), the SVR requires an SC for coordinated control, and the voltage $\Delta V_{sc-K}(t)$ regulated by the SC is derived from Equation (32).

$$\Delta V_{sc-K}(t) = \Delta V(t) + K_{tap}(t) \cdot \Delta v_{tap} \quad (32)$$

$$\Delta V_{sc}(t) = \Delta V_{sc-K}(t) \quad (33)$$

Step 4: When $\Delta V_{sc-K}(t)$ does not satisfy Equation (34), it indicates that the tap of the SVR has reached its maximum tap. Proceed to step 6.

When $\Delta V_{sc-K}(t)$ satisfies Equation (34), it indicates that the voltage cannot be completely regulated back to the threshold due to the large discrepancy in three-phase voltage, and $K_{tap}(t)$ needs to be re-determined.

$$\begin{cases} \Delta V_{sc-K}(t) < 0 & \text{if } \Delta V(t) > 0 \\ \Delta V_{sc-K}(t) > 0 & \text{if } \Delta V(t) < 0 \end{cases} \quad (34)$$

Step 5: The updated $\Delta V_{sc-K'}(t)$ regulated by SC is derived from Equation (36). When Equation (37) is satisfied, $K_{tap}(t)$ is adjusted according to Equation (40) to achieve the optimal coordination of the SVR and SC. If Equation (37) is not satisfied, the $K_{tap}(t)$ tap remains unchanged.

$$\Delta V_{sc}(t) = \Delta V_{sc-K'}(t) \quad (35)$$

$$\Delta V_{sc-K'}(t) = \Delta V(t) + k'_{tap}(t) \cdot \Delta v_{tap} \quad (36)$$

$$\begin{cases} |\Delta V_{sc-K}(t)| \geq |\Delta V_{sc-K'}(t)| \\ \varphi = 1 \end{cases} \quad (37)$$

$$\varphi = \begin{cases} 1 & \text{if } \Delta V_{sc-K'}(t) > 0 \text{ and } C_{sc}^{n,v}(t) < C_{sc}^{n,u}(t) \\ 1 & \text{if } \Delta V_{sc-K'}(t) < 0 \text{ and } C_{sc}^{n,v}(t) > C_{sc}^{n,l}(t) \\ 0 & \text{else} \end{cases} \quad (38)$$

$$k'_{tap}(t) = \begin{cases} \left\lceil \frac{(V^{min} - V^{min}(t))}{\Delta v_{tap}} \right\rceil & \text{if } \Delta V(t) > 0 \\ \left\lfloor \frac{(V^{max} - V^{max}(t))}{\Delta v_{tap}} \right\rfloor & \text{if } \Delta V(t) < 0 \end{cases} \quad (39)$$

$$K_{tap}(t) = k'_{tap}(t) \quad (40)$$

where $C_{sc}^{n,v}(t)$ is the number of required SCs for $\Delta V_{sc-K'}(t)$ regulation. φ indicates the voltage regulation capability of the SC at time, t . $k'_{tap}(t)$ is the updated tap change in the SVR at time t .

Step 6: The SC cooperates with the SVR, and the number of SCs, $C_{sc}^{n,v}(t)$, required is shown in Equation (41):

$$C_{sc}^{n,v}(t) = - \begin{cases} \left\lceil \frac{\Delta V_{sc}(t)}{S_{ij}^{VQ} \cdot \Delta Q_{sc}} \right\rceil & \text{if } \Delta V_{sc}(t) > 0 \\ \left\lfloor \frac{\Delta V_{sc}(t)}{S_{ij}^{VQ} \cdot \Delta Q_{sc}} \right\rfloor & \text{if } \Delta V_{sc}(t) < 0 \end{cases} \quad (41)$$

where $\Delta V_{sc}(t)$ is the amount of voltage violation adjusted by SC at time t .

2. Voltage Unbalance Regulation

In this paper, the definition of the VUF is quoted from the IEC standard [43] and is expressed by the amplitude of the negative-sequence voltage $\dot{V}_2$ and positive-sequence voltage $\dot{V}_1$, as shown in Equation (42):

$$\text{VUF}(\%) = \frac{|\dot{V}_2|}{|\dot{V}_1|} \cdot 100\% \quad (42)$$

$$\dot{V}_1 = \frac{\dot{V}_a + a\dot{V}_b + a^2\dot{V}_c}{3} \quad (43)$$

$$\dot{V}_2 = \frac{\dot{V}_a + a^2\dot{V}_b + a\dot{V}_c}{3} \quad (44)$$

where $\dot{V}_a$, $\dot{V}_b$, and $\dot{V}_c$ are the positive sequence component, negative sequence component, and zero sequence component, respectively. a is $\angle 120^\circ$.

According to the national standard GB/T15543-2008, the operation of a power system requires that the voltage unbalance at the point of common coupling should not exceed 2% and should not be more than 4% temporarily. The constraint of the voltage unbalance factor VUF(t) at time t is expressed by Equation (45):

$$\text{VUF}(t) \leq \text{VUF}_{\lim} \quad (45)$$

where $\text{VUF}_{\lim}$ is the VUF limit.

When the voltage unbalance factor exceeds the limit, $C_{sc}^{n,f}(t)$ required for VUF suppression is calculated according to Equation (41). The total number of SCs required at time t is expressed by Equation (46):

$$C_{sc}^n(t) = C_{sc}^{n,v}(t) + C_{sc}^{n,f}(t) \quad (46)$$

The flowchart for DVVR is shown in Figure 2. The sampling time is t , and the maximum sampling time is $t_{\max}$.

3.2. Intra-Day Optimization—FVTB

Due to the high stochastic and intermittent characteristics of the PV output, the intra-day PV output would deviate from the day-ahead forecasting, and the day-ahead scheduling of the SVR and SC would probably cause voltage deterioration. Therefore, the updated operation of SVR and SC is inevitable.

For the problem of frequent voltage violation caused by grid-connected PV, an SVR adopts dead-band control [27,28,44], which usually leads to an increase in the SVR operation times, resulting in mechanical degradation and service life reduction. In this paper, the concept of FVTB in the short term is proposed in intra-day optimization to achieve the update of SVR and SC operations, which reduces SVR operation times, balances the operation of the SVR and SC, and improves the voltage quality.

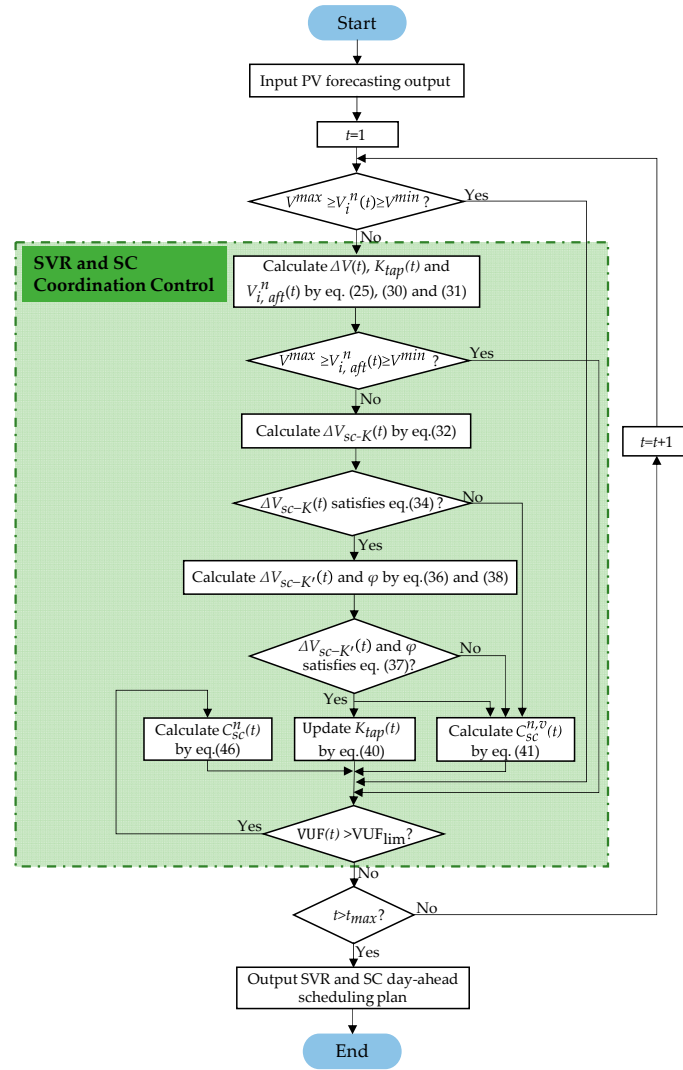


Figure 2. Flowchart of DVVR.

3.2.1. FVTB Update

In intra-day optimization, an autoregressive integrated moving average model (ARIMA) is adopted for short-term prediction. FVTB is defined by the following steps:

- During time $t - w$ to time t , the voltage at w sampling points is fitted and then used as ARIMA input to predict the voltage at time $t + 1$.
- For node i , the maximum voltage deviation and the average voltage $V_{avg,i}^n(t)$ are calculated separately during time $t - w$ to time t . The upper and lower limits of the FVTB and the floating margin $\Delta\eta(t - 1)$ are shown in Equations (47)–(49):

$$V_{vb}^{max}(t + 1) = \max\{V_{vb,i}^{pre,n}(t + 1)\} + \Delta\eta(t + 1) \quad (47)$$

$$V_{vb}^{min}(t + 1) = \min\{V_{vb,i}^{pre,n}(t + 1)\} - \Delta\eta(t + 1) \quad (48)$$

$$\Delta\eta(t + 1) = \max\left\{V_{avg,i}^n(t) \cdot \max\left\{\frac{|V_i^n(t - g) - V_i^n(t - g - 1)|}{V^{std}}\right\}, g \in (0, 1, \dots, w)\right\} \quad (49)$$

$$V_{avg,i}^n(t) = \frac{\sum_{g=0}^w V_i^n(t - g)}{w} \quad (50)$$

where $V_{vb,i}^{pre,n}(t+1)$ is the ARMLA-predicted voltage of node i in phase n at time $t+1$. $V_{vb}^{max}(t+1)$ and $V_{vb}^{min}(t+1)$ are the upper and lower limits of FVTB at time $t+1$, respectively. $V_i^n(t-g)$ is the voltage of node i in phase n at time $t-g$. $V_i^n(t-g-1)$ is the voltage of node i in phase n at time $t-g-1$. V^{std} is the rated voltage.

- During the period of PV with a stable output or no output, voltage fluctuation is relatively in a low range. $\Delta\eta(t+1)$ in Equation (49) is relatively small, which leads to a narrow FVTB, causing the unnecessary operation of the SVR and SC. To avoid this, when the floating margin is less than $k_{int}\Delta v_{tap}$, the upper and lower limits of the FVTB are updated, as shown in Equations (51) and (52):

$$V_{vb}^{max}(t+1) = \max\{V_{vb,i}^{pre,n}(t+1)\} + k_{int}\Delta v_{tap} \quad (51)$$

$$V_{vb}^{min}(t+1) = \min\{V_{vb,i}^{pre,n}(t+1)\} - k_{int}\Delta v_{tap} \quad (52)$$

where k_{int} is a constant.

- If the FVTB exceeds the voltage threshold, the FVTB is updated by Equation (53):

$$\begin{cases} V_{vb}^{max}(t+1) = V^{max} & \text{if } V_{vb}^{max}(t+1) > V^{max} \\ V_{vb}^{min}(t+1) = V^{min} & \text{if } V_{vb}^{min}(t+1) < V^{min} \end{cases} \quad (53)$$

The flowchart of FVTB updating is shown in Figure 3.

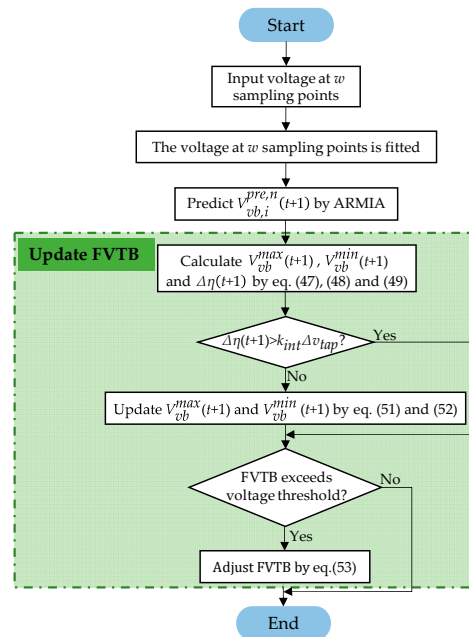


Figure 3. Flowchart of FVTB.

3.2.2. FVTB Control via SVR and SC Cooperation

In the intra-day stage, the operations of the SVR and SC implemented in day-ahead scheduling are utilized to obtain the voltage and VUF at time t . The operations of the SVR and SC under the FVTB are structured for voltage and VUF control.

1. Voltage Regulation

When the voltage satisfies Equation (54), the SVR and SC remain unchanged; otherwise, the voltage adjustment $\Delta V_{int}(t)$ to be regulated at time t is shown in Equation (55). $k_{tap,int}(t)$ and $C_{sc,int}^n(t)$ for SVR and SC adjustments at time t using the procedure described

in the voltage-regulated section are shown in Section 3.1.2. $V_{i,int}^n(t)$ is the voltage calculated based on day-ahead SVR and SC operations.

$$V_{vb}^{min}(t) \leq V_{i,int}^n(t) \leq V_{vb}^{max}(t) \quad (54)$$

$$\Delta V_{int}(t) = \begin{cases} V_{int}^{max}(t) - V_{vb}^{max}(t) & \text{if } V_{int}^{max}(t) > V_{vb}^{max}(t) \text{ and } V_{int}^{min}(t) > V_{vb}^{min}(t) \\ V_{int}^{min}(t) - V_{vb}^{min}(t) & \text{if } V_{int}^{min}(t) < V_{vb}^{min}(t) \text{ and } V_{int}^{max}(t) < V_{vb}^{max}(t) \\ \Delta V_{int}^{var}(t) & \text{if } V_{int}^{max}(t) > V_{vb}^{max}(t) \text{ and } V_{int}^{min}(t) < V_{vb}^{min}(t) \end{cases} \quad (55)$$

$$V_{int}^{max}(t) = \max\{V_{i,int}^n(t)\} \quad (56)$$

$$V_{int}^{min}(t) = \min\{V_{i,int}^n(t)\} \quad (57)$$

$$\Delta V_{int}^{var}(t) = \begin{cases} V_{int}^{max}(t) - V_{vb}^{max}(t) & \text{if } |V_{int}^{max}(t) - V_{vb}^{max}(t)| \geq |V_{int}^{min}(t) - V_{vb}^{min}(t)| \\ V_{int}^{min}(t) - V_{vb}^{min}(t) & \text{if } |V_{int}^{max}(t) - V_{vb}^{max}(t)| < |V_{int}^{min}(t) - V_{vb}^{min}(t)| \end{cases} \quad (58)$$

where $V_{i,int}^n(t)$ is the voltage of phase n of node i at time t . $V_{int}^{max}(t)$ and $V_{int}^{min}(t)$ are the maximum and minimum values of voltage at time t , respectively.

2. Voltage Unbalance Regulation

If $VUF_{int}(t)$, the value of the VUF, exceeds the limit, $C_{sc,int}^{n,u}(t)$ for SC adjustments at time t should refer to the voltage unbalance regulation procedure in Section 3.1.2. The flowchart of FVTB control via SVR and SC cooperation is shown in Figure 4.

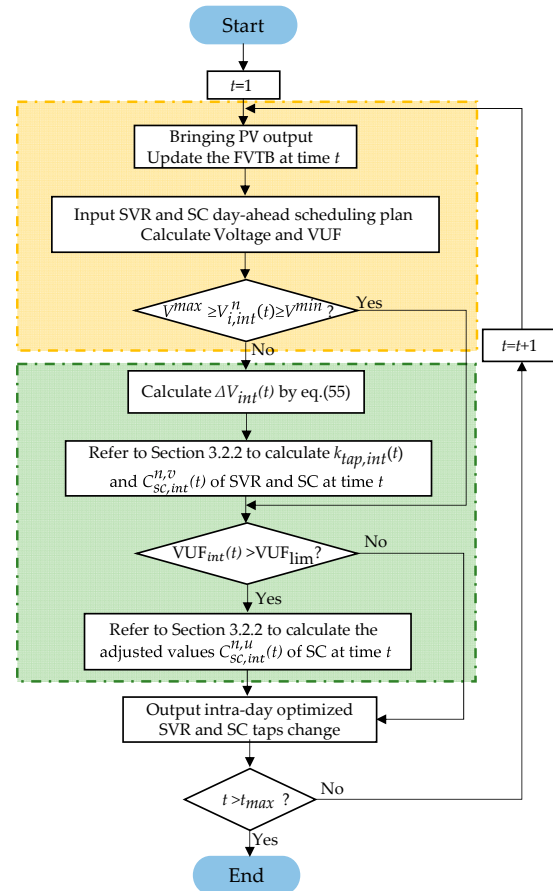


Figure 4. Flowchart of FVTB control via SVR and SC cooperation.

3.3. Real-Time Control

Considering the problem of the insufficient voltage regulating capability of the SVR and SC in a PV-connected DN, this paper adopts a BESS and EVs to achieve real-time improvement in the voltage through coordinated control with an SVR and SC. Real-time control consists of the real-time voltage regulation/voltage unbalance regulation (RVVR) mode and the voltage fluctuation suppression-initiated charging and discharging (SVF-ICD) mode, and the flowchart is shown in Figure 5.

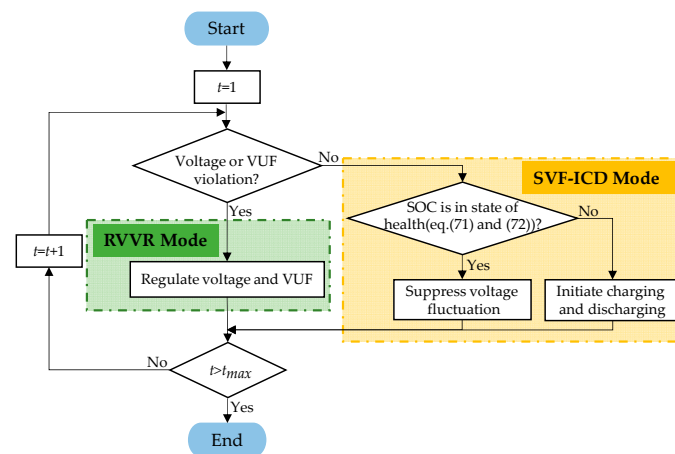


Figure 5. Flowchart of real-time control.

After intra-day optimization, when entering real-time control, the BESS and EVs are utilized for fast and precise regulation. When the voltage or VUF exceeds the limit, the BESS turns into RVVR mode to control the voltage and VUF within thresholds. When the voltage and VUF are within the threshold, the BESS turns into SVF-ICD mode. In SVF-ICD mode, when the SOC is in a healthy state, the voltage fluctuation is suppressed by the BESS; when the SOC is in a deep charging/discharging state, it transfers to ICD to bring the SOC back to a healthy state.

3.3.1. RVVR Mode

In RVVR mode, a meta-heuristic optimization algorithm is employed for the optimization of a BESS output to achieve accurate voltage regulation. The AVOA is a novel meta-heuristic optimization algorithm inspired by the foraging and hunting behaviors of African vulture populations. It has the advantages of strong optimization-seeking ability and fast convergence speed [45–47]. The AVOA is adopted to find the optimal output of the BESS to deal with the voltage and VUF violation problem. At the same time, this paper tries to replace part of the BESS by using EV batteries as a means to curtail the capacity of the BESS. Considering regulating the voltage/VUF back to the threshold as soon as possible, a fast-charging EV is utilized to replace part of the BESS after the optimization of the AVOA.

The flowchart of the AVOA [46] search for the BESS output is shown in Figure 6 with the following steps:

Step 1: Determine whether the voltage and VUF satisfy Equations (25) and (45); if not, the BESS output for the voltage and VUF regulation is optimized using the AVOA.

Step 2: Check whether the voltage satisfies Equation (25); if not, determine the variable dimension based on the parameter $\omega(t)$, and if yes, go to step 9.

$$\omega(t) = \sum_{n \in \{\xi\}} \beta^n \quad (59)$$

$$\beta^n = \begin{cases} 1 & \text{if } V_{i,real}^n(t) > V^{max} \text{ or } V_{i,real}^n(t) < V^{min} \\ 0 & \text{if } V^{min} \leq V_{i,real}^n(t) \leq V^{max} \end{cases} \quad (60)$$

where β^n is the number of voltage violations. $V_{i,real}^n(t)$ is the voltage in the real-time stage of time t in phase n .

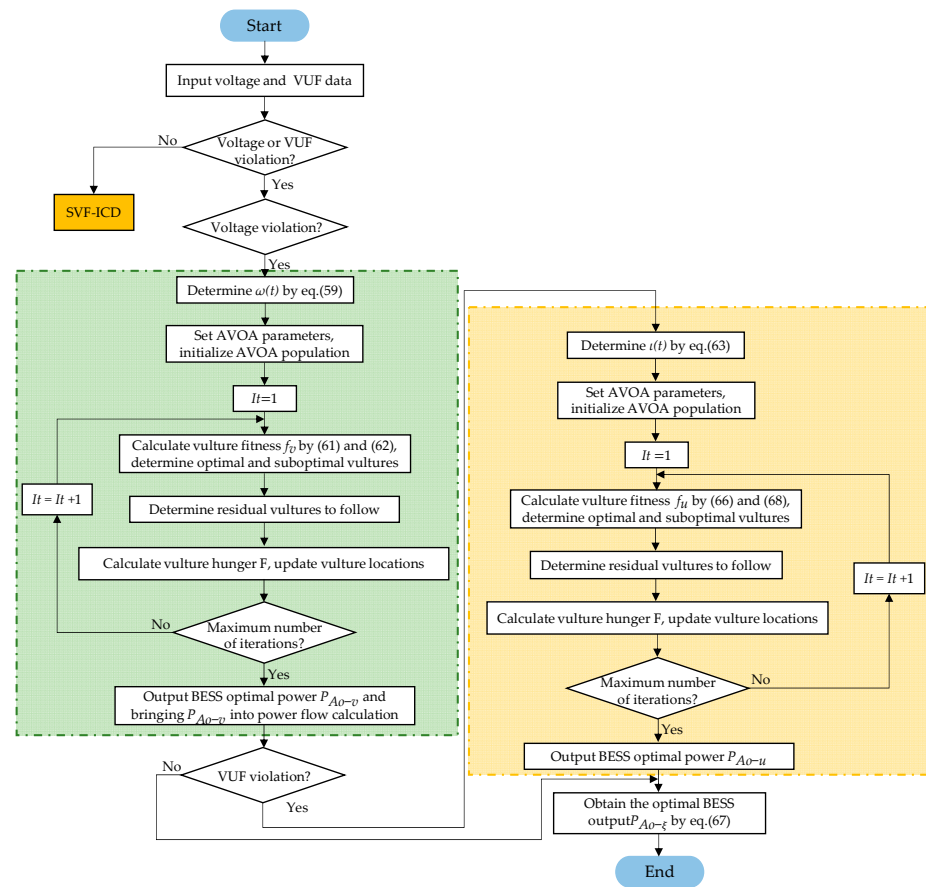


Figure 6. Flowchart of AVOA for BESS output.

Step 3: Determine the variable dimensions according to step 2, and set the upper and lower boundaries, the number of iterations, and population parameters to randomly initialize the vulture positions.

Step 4: Calculate the vulture fitness f_v according to Equation (61) and determine the optimal and sub-optimal vultures.

$$f_v = \begin{cases} V_{avoa}^{max} - V_{avoa}^{max}(t) & \text{if } V_{i,real}^n(t) > V^{max} \\ V_{avoa}^{min}(t) - V^{min} & \text{if } V_{i,real}^n(t) < V^{min} \end{cases} \quad (61)$$

where $V_{avoa}^{max}(t)$ and $V_{avoa}^{min}(t)$ are the maximum and minimum values of the voltage after bringing in the vulture position, respectively.

If the voltage after bringing in the vulture position does not satisfy Equation (25), f_v is updated by Equation (62).

$$f_v = f_v + o \quad (62)$$

where o is the penalty.

Step 5: Determine the residual vultures to follow by using roulette wheel selection [45].

Step 6: Calculate the vulture hunger, F , select the exploration stage based on hunger, and choose the foraging strategy in that stage [45] and update the vulture location.

Step 7: Repeat steps 4–6 until the maximum iteration is met, and output the optimal vulture position, that is, the optimal output P_{A0-v} of the BESS in voltage control.

Step 8: Include P_{A0-v} in the power flow calculation and verify whether the voltage complies with Equation (45); if not, proceed to step 9, and if yes, proceed to step 15.

Step 9: If the VUF exceeds the limit, when $\iota(t)$ is 1, the phase to be adjusted is $V^{max}(t)$, and when $\iota(t)$ is 0, the phase to be adjusted is $V^{min}(t)$.

$$\iota(t) = \begin{cases} 1 & \text{if } \Delta V_{st}^{max}(t) \geq \Delta V_{st}^{min}(t) \\ 0 & \text{if } \Delta V_{st}^{min}(t) < \Delta V_{st}^{max}(t) \end{cases} \quad (63)$$

$$\Delta V_{st}^{max}(t) = V^{max}(t) - V^{std} \quad (64)$$

$$\Delta V_{st}^{min}(t) = V^{std} - V^{min}(t) \quad (65)$$

where $\Delta V_{st}^{max}(t)$ and $\Delta V_{st}^{min}(t)$ are the amounts of voltage deviation from the rated voltage, respectively.

Step 10: Determine the variable dimensions according to step 9, and set the upper and lower boundaries, the number of iterations, and other population parameters to randomly initialize the vulture positions.

Step 11: Calculate the vulture fitness f_u according to Equation (66) and determine the optimal and sub-optimal vultures.

$$f_u = \text{VUF}_{\text{lim}} - \text{VUF}_{\text{avoa}}^{max}(t) \quad (66)$$

$$\text{VUF}_{\text{avoa}}^{max}(t) = \max\{\text{VUF}(t)\} \quad (67)$$

where $\text{VUF}_{\text{avoa}}^{max}(t)$ represents the maximum values of the VUF after bringing in the vulture position.

If the voltage after bringing in the vulture position does not satisfy Equation (45), f_u is updated by Equation (68).

$$f_u = f_u + o \quad (68)$$

Step 12: Determine the residual vultures to follow by using roulette wheel selection [45].

Step 13: Calculate the vulture hunger, F , select the exploration stage based on hunger, and choose the foraging strategy in that stage [45] and update the vulture location.

Step 14: Repeat steps 4–6 until the maximum iteration is met, and output the optimal vulture position, that is, the optimal output P_{A0-u} of the BESS in voltage control.

Step 15: Obtain the optimal BESS output $P_{A0-\xi}$.

$$P_{A0-\xi} = P_{A0-v} + P_{A0-u} \quad (69)$$

3.3.2. SVF-ICD Mode

1. Suppress Voltage Fluctuation (SVF)

The stochasticity of PV leads to frequent fluctuations in the voltage in the DN, which influences its stable operation. In this paper, when the voltage and VUF are within the threshold and the SOC is in a healthy state, the BESS switches into SVF mode to suppress voltage fluctuation to further improve voltage quality.

Voltage fluctuation is mainly caused by the PV output, the voltage fluctuation suppression period is chosen to be T_{svf} , and the constraint is shown in Equation (70):

$$T_s \leq T_{svf} \leq T_e \quad (70)$$

where T_{svf} is the time for voltage fluctuation suppression. T_s is the start time of the PV output. T_e is the end time of the PV output.

Before the peak time of the PV output, the BESS is in a charging state and the SOC is at a relatively high level. After the peak time, the PV output decreases, and the BESS is in a discharging state with a relatively low level of SOC. To ensure the available ca-

capacity of the BESS, the SOC is constrained depending on the PV peak time, as shown in Equations (71) and (72).

$$SOC_l(t) = \begin{cases} l_1\% & \text{if } t \leq T_p \\ l_2\% & \text{if } t > T_p \end{cases} \quad (71)$$

$$SOC_u(t) = \begin{cases} u_1\% & \text{if } t \leq T_p \\ u_2\% & \text{if } t > T_p \end{cases} \quad (72)$$

$$l_1\% < l_2\% \quad (73)$$

$$u_1\% < u_2\% \quad (74)$$

where $l_1\%$ and $l_2\%$ are the lower limits of the SOC before and after the peak time of PV, respectively. $u_1\%$ and $u_2\%$ are the upper limits of the SOC before and after the peak time of PV, respectively. T_p is the peak time of the PV output. $SOC_u(t)$ and $SOC_l(t)$ are the upper and lower limits of the SOC at time t , respectively.

- SFTB

In this paper, voltage fluctuation suppression is realized by SFTB for each phase. Compared to FVTB, the SFTB threshold band is updated with an extended period, and Equations (75)–(77) show the upper and lower SFTB limits and floating margins for each phase.

$$V_{sf}^{max,n}(t+1) = V_{sf}^{pre,n}(t+1) + \Delta\eta_s^n(t+1) \quad (75)$$

$$V_{sf}^{min,n}(t+1) = V_{sf}^{pre,n}(t+1) - \Delta\eta_s^n(t+1) \quad (76)$$

$$\Delta\eta_s^n(t+1) = V_{avg}^n(t) \cdot \frac{\sum_{\phi=0}^d \frac{|V^n(t-\phi) - V^n(t-\phi-1)|}{V^{std}}}{d} \quad (77)$$

$$V_{avg}^n(t) = \frac{\sum_{\phi=0}^d V^n(t-\phi)}{d} \quad (78)$$

where $V_{sf}^{pre,n}(t+1)$ is the ARIMA-predicted voltage of phase n at time $t+1$. $V_{sf}^{max,n}(t+1)$ and $V_{sf}^{min,n}(t+1)$ are the upper and lower limits of phase n at time $t+1$, respectively. $V^n(t-\phi)$ is the voltage at time $t-\phi$ of phase n . $V^n(t-\phi-1)$ is the voltage at time $t-\phi-1$ of phase n . $\Delta\eta_s^n(t+1)$ is the floating margin of phase n at time $t+1$. d is the number of sampling times.

When the upper and lower limits exceed the voltage threshold, the update is carried out, as shown in Equation (79):

$$\begin{cases} V_{sf}^{max,n}(t+1) = V^{max} & \text{if } V_{sf}^{max,n}(t+1) > V^{max} \\ V_{sf}^{min,n}(t+1) = V^{min} & \text{if } V_{sf}^{min,n}(t+1) < V^{min} \end{cases} \quad (79)$$

The flowchart of voltage fluctuation suppression is shown in Figure 7. Voltage fluctuation suppression is implemented based on whether the voltage, VUF, and SOC are in the SVF range at time t . The BESS output constraints are shown in Equations (12) and (13). Considering the BESS capacity curtailment, EVs are used to replace part of the BESS's capacity to realize voltage regulation with demand response. Meanwhile, to avoid fast charging damage to the EV battery, this paper selects slow-charging EVs as the primary elements in SVF mode.

2. ICD

There is an inverse relationship between the depth of discharge of the BESS and its life cycle [48–50]. To optimize the life cycle of the BESS, deep charging/discharging is improved by suppressing the voltage fluctuation selectively via ICD. To ensure SVF, according to the

severity of deep charging/discharging, ICD is subdivided into normal mode (NICD) and emergency mode (EICD), as shown in Figure 8.

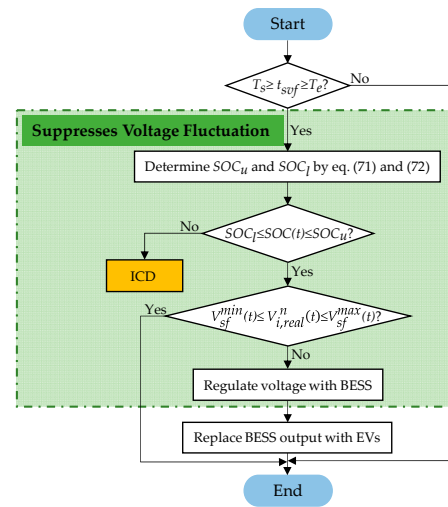


Figure 7. Flowchart of suppressed voltage fluctuation.

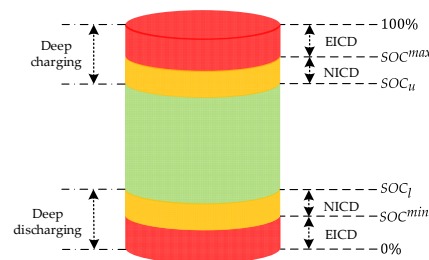


Figure 8. State of BESS.

- NICD

When the SOC is between SOC_u and SOC^{max} or SOC_l and SOC^{min} , as shown in Equation (80), the BESS undergoes slightly deep charging/discharging, and it is in NICD.

$$\begin{cases} SOC_l(t) \geq SOC(t) > SOC^{min} \\ SOC_u(t) \leq SOC(t) < SOC^{max} \end{cases} \quad (80)$$

According to the voltage, NICD is categorized into three modes, as shown in Equation (81):

$$Mode = \begin{cases} 1 & \text{if } \Delta V^u(t) \neq 0 \text{ and } \Delta V^l(t) \neq 0 \\ 2 & \text{if } \Delta V^u(t) = 0 \text{ and } \Delta V^l(t) = 0 \\ 3 & \text{else} \end{cases} \quad (81)$$

$$\Delta V^u(t) = \begin{cases} |V_{sf}^{max,n}(t) - V_{i,real}^n(t)| & \text{if } V_{i,real}^n(t) > V_{sf}^{max,n}(t) \\ 0 & \text{if } V_{i,real}^n(t) \leq V_{sf}^{max,n}(t) \end{cases} \quad (82)$$

$$\Delta V^l(t) = \begin{cases} |V_{i,real}^n(t) - V_{sf}^{min,n}(t)| & \text{if } V_{i,real}^n(t) < V_{sf}^{min,n}(t) \\ 0 & \text{if } V_{i,real}^n(t) \geq V_{sf}^{min,n}(t) \end{cases} \quad (83)$$

where $\Delta V^u(t)$ and $\Delta V^l(t)$ are the differences between $V_{i,real}^n(t)$ and the upper and lower limits of the SFTB at time t , respectively.

The profiles of V^{n1} and V^{n2} are used as examples to illustrate mode 1, mode 2, and mode 3.

Mode 1:

In mode 1, as shown in Figure 9, the BESS regulates $\Delta V^u(t)$ and $\Delta V^l(t)$ at the same time to suppress voltage fluctuation. In the case of deep charging, the discharging output of the BESS involved in regulating $\Delta V^l(t)$ must be larger than or equal to the charging output involved in regulating $\Delta V^u(t)$ to ensure that it does not intensify the BESS's deep charging degree. The same occurs when dealing with the case of deep discharging. The constraint of the BESS is shown in Equation (84). S_{ij}^{VP} is the function of active power and voltage according to Equation (6).

$$\begin{cases} P^l(t) \geq P^u(t) & \text{if } SOC_u \leq SOC(t) < SOC^{max} \\ P^u(t) \geq P^l(t) & \text{if } SOC_l \geq SOC(t) > SOC^{min} \end{cases} \quad (84)$$

$$P^l(t) = \sum_{n \in \{\xi\}} S_{ij}^{VP}(\Delta V^l(t)) \quad (85)$$

$$P^u(t) = \sum_{n \in \{\xi\}} S_{ij}^{VP}(\Delta V^u(t)) \quad (86)$$

where $P^u(t)$ and $P^l(t)$ are the outputs of the BESS in the regulation of $V^u(t)$ and $\Delta V^l(t)$, respectively.

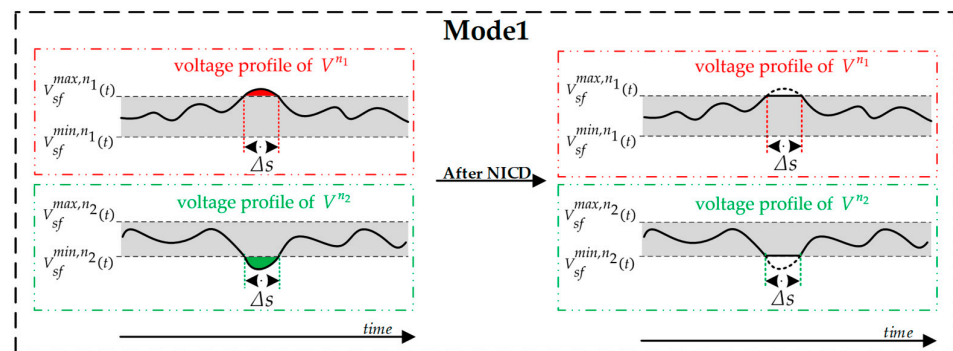


Figure 9. The principle of mode 1.

Mode 2:

In mode 2, as shown in Figure 10, the voltage is within the SFTB and the BESS is incapable of implementing NICD. The updated upper and lower limits are proposed in Equations (87) and (88). The voltage $\Delta V^u(t)$ or $\Delta V^l(t)$ is derived by narrowing the SFTB to ensure the proper implementation of NICD in the SOC adjustment. The constraint in mode 2 is the same as that in mode 1.

$$V_{sf-V}^{min,n}(t) = V_{sf}^{min,n}(t) + \Delta V_{sf}^n(t) \quad (87)$$

$$V_{sf-V}^{max,n}(t) = V_{sf}^{max,n}(t) - \Delta V_{sf}^n(t) \quad (88)$$

$$\Delta V_{sf}^n(t) = k_s (V_{sf}^{max,n}(t) - V_{sf}^{min,n}(t)) \quad (89)$$

where $V_{sf-V}^{max,n}(t)$ and $V_{sf-V}^{min,n}(t)$ are the upper and lower limits of phase n after narrowing, respectively. k_s is constant. $\Delta V_{sf}^n(t)$ is the update amount.

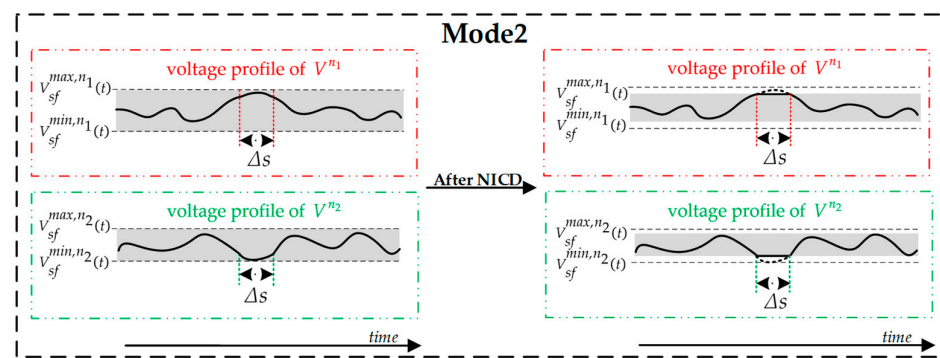


Figure 10. The principle of mode 2.

Mode 3:

In mode 3, as shown in Figure 11, for the case of deep charging, when $\Delta V^l(t)$ is not adjustable but $V^u(t)$ exists, along with the regulation of $V^u(t)$, the lower limit is updated by Equation (87) to induce the available $\Delta V^l(t)$ to discharge the BESS and realize SOC adjustment. When $\Delta V^l(t)$ exists but $V^u(t)$ is not adjustable, the BESS regulates $\Delta V^l(t)$ to suppress voltage fluctuation. The same occurs when dealing with the case of deep discharging. The power constraint in mode 3 satisfies Equation (84).

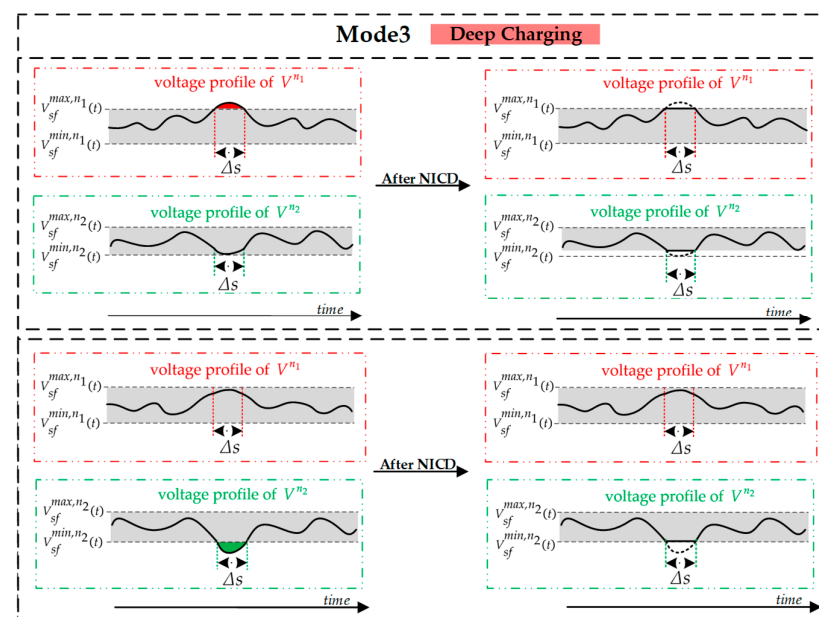


Figure 11. The principle of mode 3.

- EICD

When the SOC exceeds SOC^{max} or SOC^{min} , as shown in Equation (90), the BESS is in EICD. BESS deep charging/deep discharging is so severe that the SOC should be adjusted to return to its constraints as soon as possible.

$$\begin{cases} SOC(t) \leq SOC^{min} \\ SOC(t) \geq SOC^{max} \end{cases} \quad (90)$$

In EICD, the BESS undergoes deep charging, and $V_{sf}^{min,n}(t)$ is updated by Equation (87). The BESS performs selective voltage regulation, whereby the BESS only adjusts $\Delta V^l(t)$ and

does not deal with $V^u(t)$ to achieve the mitigation of BESS deep charging as soon as possible. The same occurs when dealing with the case of deep discharging.

In this paper, novel multi-timescale voltage regulation is proposed with a coordinated control strategy using an SVR, SC, BESS, and EVs. The framework of the proposed control strategy is shown in Figure 12. In day-ahead scheduling, AHA-LSSVM is utilized to forecast the PV output for the whole day ahead, and SVR and SC operation is formulated for day-ahead scheduling. Due to errors in PV forecasting, in intra-day optimization, the short-term voltage prediction is obtained by ARIMA, and FVTB is proposed to update day-ahead scheduling. In real-time control, a BESS cooperating with an SVR and SC is categorized into RVVR and SVF-ICD modes depending on whether the voltage and VUF are within the threshold or not. Furthermore, SVF-ICD mode is divided into an SVF and ICD according to the SOC of the BESS, and EVs are used to replace BESSs for capacity curtailment. Finally, voltage unbalance and voltage are successfully controlled by the proposed method in this paper.

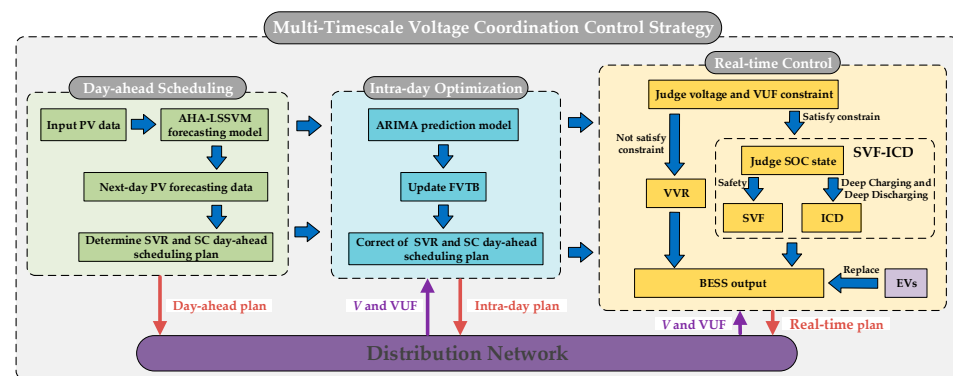


Figure 12. Framework of multi-timescale voltage coordinated control.

4. Case Study

4.1. Simulation Conditions

In this paper, a modified IEEE 33 system, as illustrated in Figure 13, is selected to verify the effectiveness of the proposed strategy. The parameters are shown in Table 1, Table 2, and Table 3, respectively.

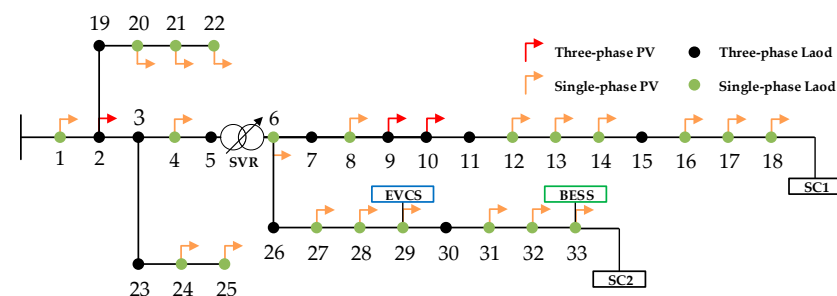


Figure 13. Modified IEEE 33 system.

4.2. Case Study and Discussion

In this paper, Monte Carlo [51,52] is used to simulate the distribution of on-station EVs in 24 h. The 2022 white paper on China's electric vehicle users' charging behavior [53] selected the main peak (nighttime) and the secondary peak (midday) to simulate the EV charging load distribution. It is assumed that 100 EVs are charged on the station throughout the day. In the main peak during nighttime, the charging start time of each EV satisfies the normal distribution $N(21, 2^2)$. In the secondary peak during midday, the charging start time of each EV satisfies the normal distribution $N(12, 2^2)$. According to [50], it is assumed

that the ratio of EVs choosing fast and slow charging is 6:4. Based on the fast/slow charging habits of EVs, it is assumed that the number of EVs choosing fast charging at midday and nighttime accounts for 80% and 20% of the total number of fast charging EVs, respectively. The number of EVs choosing slow charging at midday and nighttime accounts for 20% and 80% of the total number of slow-charging EVs, respectively. The initial SOC is assumed to obey a normal distribution of $N(0.5, 0.1^2)$. The power of EVs charging at the station is shown in Figure 14. The number of charging EVs is set to be the same as that of idle EVs.

Table 1. Parameters of distribution network.

Parameter	Value
Voltage grade (kV)	35
Total load (MW)	14.5
Total PV power (MW)	16.4
Rated voltage (pu)	1.0
Limit of node voltage (pu)	[0.95,1.05]
Voltage unbalance limit (%)	2
Voltage dead-band limit (pu)	[0.975,1.025]
Day-ahead scheduling sample interval (min)	5
Intra-day optimization sample interval (min)	1
Real-time control sample interval (s)	2
Mechanical delay (s)	8

Table 2. Parameters of voltage regulation equipment.

Device	Location	Parameter	Value
BESS	Bus 33	Capacity (kWh)	350
		Power limit (kW)	[−200, 200]
		Charging/discharging efficiency (%)	100
		SOC limit (%)	[20, 80]
		Initial SOC (%)	50
EVCS	Bus 29	Fast-charging power (kW)	60
		Slow-charging power (kW)	7
		Charging/discharging efficiency (%)	90
SVR	Bus 5–Bus 6	Tap range	[−5, 5]
		Per tap (%)	2
SC1	Bus 18	Capacitor number range	[0, 7]
		Per capacitor (kVar)	25
SC2	Bus 31	Capacitor number range	[0, 7]
		Per capacitor (kVar)	25

Table 3. Parameter settings.

Parameter	Value
Sampling points w	5
Constant k_{int}	0.4
PV output start T_s time (h)	6:52
PV output end T_e time (h)	18:42
PV output peak time T_p (h)	12:00
Lower limit of SOC l_1 before T_p (%)	0.3
Lower limit of SOC l_2 after T_p (%)	0.4
Upper limit of SOC u_1 before T_p (%)	0.65
Upper limit of SOC u_2 after T_p (%)	0.75
Sampling points d	5
Constant k_s	0.1
Penalty value o	100

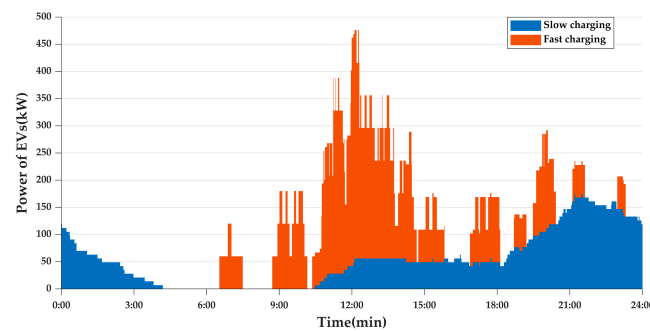


Figure 14. The power of charging EVs on the station.

In this paper, the forecasting results of AHA-LSSVM are compared with LSSVM and BP to verify the feasibility and validity of AHA-LSSVM, and the results are shown in Figure 15 with cloudy weather as an example.

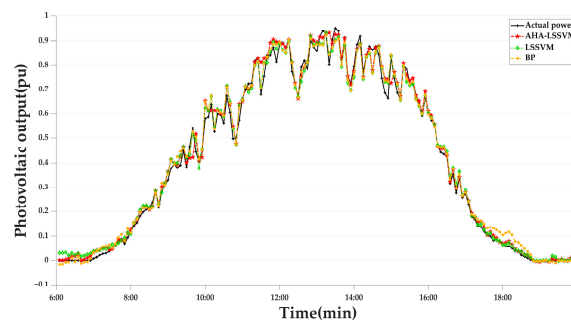


Figure 15. Comparison of PV forecasting.

All three models, namely, the AHA-LSSVM, LSSVM, and BP, have a good performance in PV forecasting. The mean absolute error (MAE) and root mean square error (RMSE) of the PV output of each model are given in Table 4. In Table 4, the RMSE of the LSSVM is reduced by 5.8%, and the MAE is reduced by 3.8% compared with BP. The RMSE of the AHA-LSSVM is reduced by 12.7% compared with BP and 7.3% compared with the LSSVM, and the MAE is reduced by 18.8% compared with BP and 15.3% compared with the LSSVM. The increase in predictive accuracy achieved by the LSSVM over BP is relatively subtle (MAE reduction of 0.08%). In contrast, the enhancement in predictive accuracy realized by the AHA-LSSVM compared to the LSSVM is remarkably substantial (MAE reduction by 0.32%), signifying a threefold improvement. The results show that the accuracy of the LSSVM in PV forecasting is better than that of BP, and the improved AHA-LSSVM in PV forecasting has much better accuracy regarding forecasting results compared to the LSSVM.

Table 4. Differences in MAE and RMSE.

	BP	LSSVM	AHA-LSSVM
$E_{RMSE}(\%)$	2.77	2.61	2.42
$E_{MAE}(\%)$	2.13	2.05	1.73

Eleven cases involved in three timescales are designed to analyze and verify the feasibility and effectiveness of the proposed multi-timescale voltage regulation via a coordinated control strategy, as shown in Table 5.

In the day-ahead stage, the time interval is 5 min. In Case 1-1, the PV output by the AHA-LSSVM is used to obtain the day-ahead voltage and VUF. In Case 1-2, the voltage and VUF of Case 1-1 are adjusted by the proposed day-ahead coordinated control of the SVR and SC to verify the effectiveness.

Table 5. Case study.

		SVR	SC	BESS	EVs
Case 1: Day-ahead scheduling	Case 1-1				
	Case 1-2	✓	✓		
Case 2: Intra-day optimization	Case 2-1	✓	✓		
	Case 2-2	✓	✓		
	Case 2-3	✓	✓		
Case 3: Real-time control	Case 3-1	✓	✓		
	Case 3-2	✓	✓	VVR	
	Case 3-3	✓	✓	VVR	
	Case 3-4	✓	✓	VVR	SVF
	Case 3-5	✓	✓	VVR	SVF ICD
	Case 3-6	✓	✓	VVR	SVF ICD ✓

✓: Involved.

In the intra-day stage, the time interval is 1 min. Case 2-1 applies the coordinated control in Case 1-2 to the intra-day stage to verify its effectiveness. Case 2-2 and Case 2-3 use dead-band control and FVTB control to modify the control strategy in Case 1-2, respectively. The effectiveness of the proposed FVTB control strategy is verified.

In real-time control, the time interval is 2 s. Case 3-1 implements the control strategy of Case 2-3 to verify the effectiveness of intra-day scheduling in the real-time stage. BESS participates in voltage regulation in Case 3-2 for real-time control. Case 3-3 uses AVOA to optimize the BESS output to achieve accurate voltage regulation as well as reduce the BESS output for capacity curtailment. Case 3-4 implements a strategy to suppress voltage fluctuations. Case 3-5 implements the ICD strategy to mitigate BESS deep charging/discharging as well as curtail the BESS capacity. Case 3-6 further optimizes Case 3-5 by replacing part of the BESS with EVs.

- Case 1-1: Without Voltage Control

In Case 1-1, the forecasting output of PV is brought into power flow calculation to obtain the voltages at nodes 18 and 33, as shown in Figure 16a,b. The maximum VUF at node 33 is shown in Figure 16c.

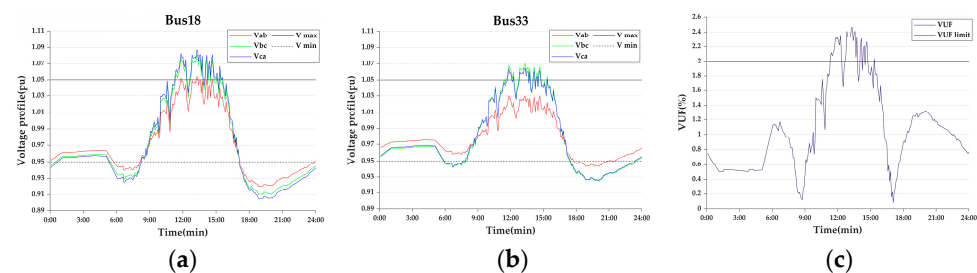


Figure 16. Voltage and VUF profiles in Case 1-1. (a) Voltage profile of node 18; (b) voltage profile of node 33; (c) VUF profile of node 33.

In Figure 16a,b, the voltage exceeds the lower limit during the 5:00–8:30 and 17:00–1:00 periods when there is no PV output or less PV output, which is about 43.8% of the whole day's length. Particularly during the 19:00–20:30 period, with regular loads and demands for charging EVs, the voltage exceeds the lower limit to 0.905 pu.

With the increase in the PV output, the voltage exceeds the upper limit frequently during the 11:00–16:00 period, which is about 15.6% of the whole day's length. During the peak period of PV output (13:00–14:00), the voltage exceeds the upper limit by up to 1.087 pu.

From Figure 16c, with single-phase load and single-phase PV, the degree of voltage unbalance increases and exceeds the limit during the 11:00–15:30 period, which accounts for about 11.5% of the whole day's length, and the VUF reaches a maximum of 2.47%.

- Case 1-2: Day-Ahead Scheduling

As shown in Figure 17a,b, neglecting the mechanical delays of the SVR and SC, the day-ahead scheduling strategy regulates the voltage within the threshold. The VUF is smaller than 2% throughout the day, as shown in Figure 17c. It indicates the effectiveness of the day-ahead scheduling strategy proposed in this paper.

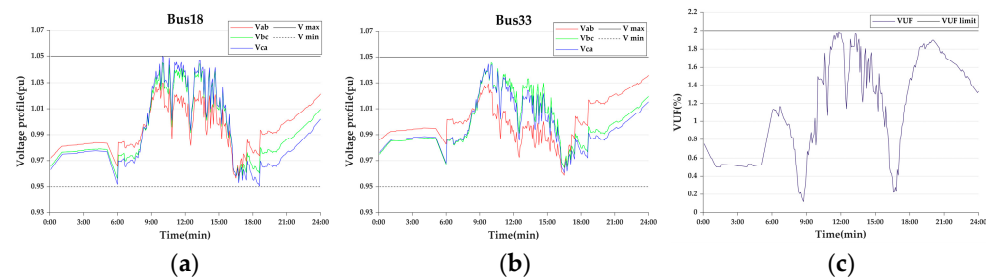


Figure 17. Voltage and VUF profiles in Case 1-2. (a) Voltage profile of node 18; (b) voltage profile of node 33; (c) VUF profile of node 33.

In Figure 18a,b, the SVR and SC operations are in accordance with the day-ahead scheduling strategy. When the voltage exceeds the limit, the SVR operates first to adjust the voltage amplitude. When the SVR cannot adjust the voltage back to the threshold or the VUF is larger than 2%, the SC participates in regulation for coordinated control. In Figure 18b, before 11:15, the VUF is within the threshold, and only the SVR operates for voltage regulation. After 11:15, the VUF is larger than 2%, SC2 at node 33 operates to provide reactive power to suppress the VUF, and it reaches 75 kVar at 12:15. SC2 at node 33 perfectly regulates the VUF back to its limit, and therefore, SC1 has no operation. The proposed day-ahead scheduling strategy successfully regulates the voltage and VUF within the threshold.

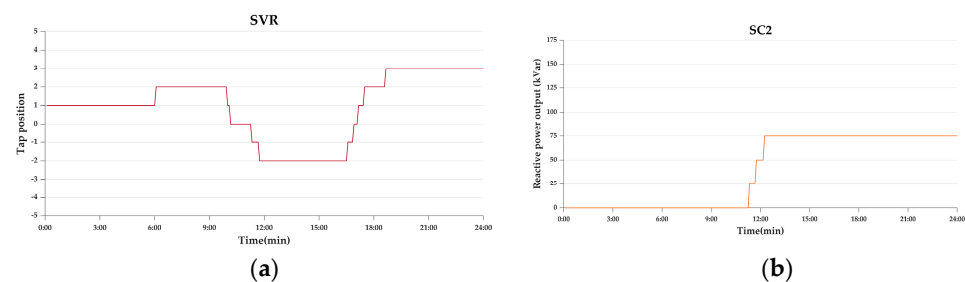


Figure 18. Operation of SVR and SC in Case 1-2. (a) SVR operation; (b) SC2 operation.

- Case 2-1: Intra-Day Optimization Control

In Case 2-1, as seen in Figure 19a,b, the voltage exceeds the upper/lower limits during the 9:30–11:30 and 16:30–19:00 periods, respectively. The voltage violation accounts for 3% of the whole day's length. In Figure 19c, the VUF also frequently exceeds the limit during the 11:00–12:30 period. This is because there is an error in the intra-day PV output compared with day-ahead forecasting, and it is impossible to control the voltage and VUF well within the thresholds when executing the day-ahead scheduling plan in intra-day optimization. Therefore, intra-day optimization is required.

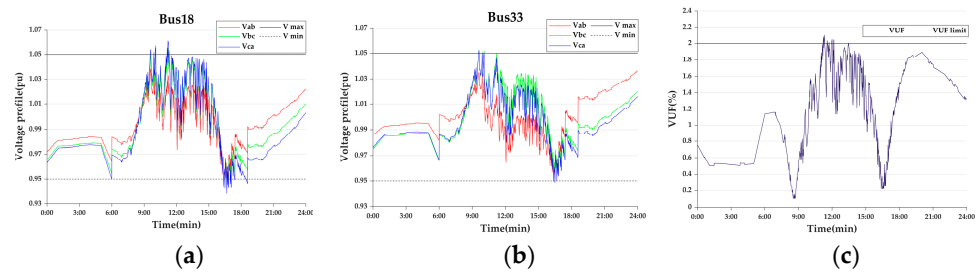


Figure 19. Voltage and VUF profiles in Case 2-1. (a) Voltage profile of node 18; (b) voltage profile of node 33; (c) VUF profile of node 33.

- Case 2-2: Dead-Band Control

The voltage and VUF profiles with voltage dead-band control are shown in Figure 20.

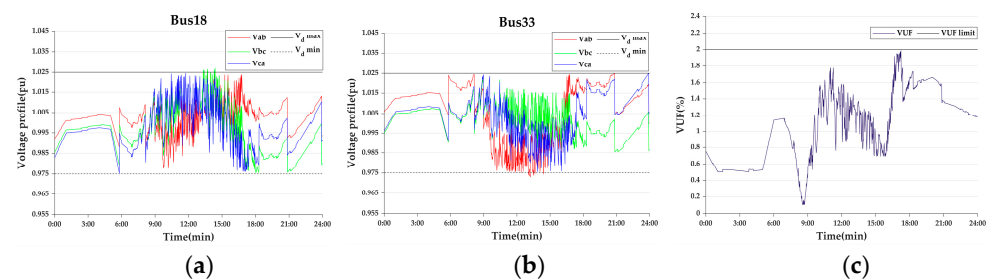


Figure 20. Voltage and VUF profiles in Case 2-2. (a) Voltage profile of node 18; (b) voltage profile of node 33; (c) VUF profile of node 33.

As shown in Figure 20a,b, the high penetration of PV, SVR, and SC (neglecting the mechanical delay) without soft control capability cannot eliminate the voltage violation caused by the PV output, and the voltage exceeds the dead-band at 13:00 and 14:30. The voltage violation accounts for 1.3% of the whole day's length. The VUF in Figure 20c is smaller than 2% throughout the day after dead-band control. As seen in Figure 20, dead-band control successfully regulates the voltage and VUF within the threshold [0.95, 1.05], but compared with Case 1-2, the narrow range of voltage dead-band leads to the excessive operations of the SVR and SC, as shown in Figure 21. In Figure 21, the operation numbers significantly increase for the regulation of the voltage and VUF.

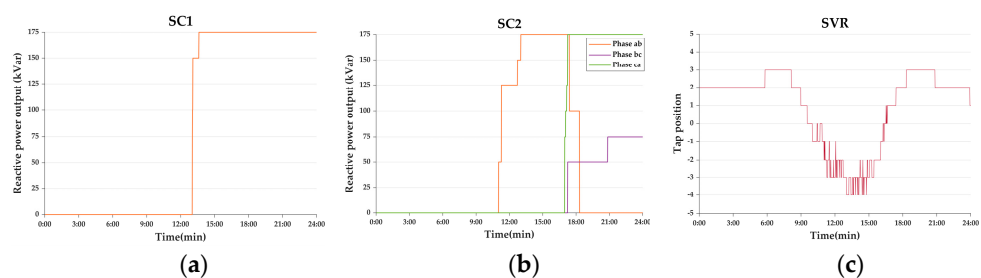


Figure 21. Operation of SVR and SC in Case 2-2. (a) SC1 operation; (b) SC2 operation; (c) SVR operation.

- Case 2-3: FVTB Control

In this paper, the FVTB control strategy is proposed as an alternative to voltage dead-band control to mitigate the frequent SVR and SC operations and alleviate the frequent voltage violations. The voltage and VUF profiles in FVTB control are shown in Figure 22.

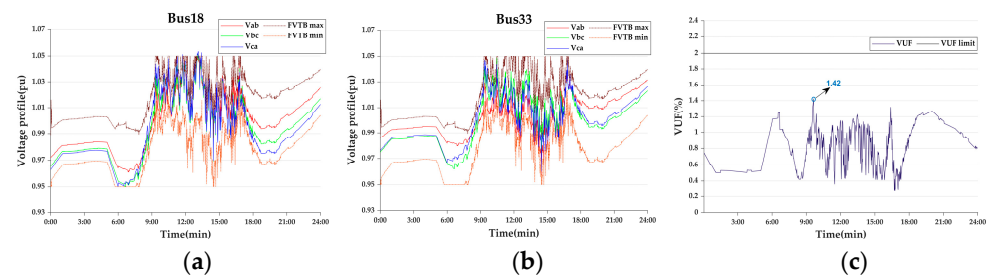


Figure 22. Voltage and VUF profiles in Case 2-3. (a) Voltage profile of node 18; (b) voltage profile of node 33; (c) VUF profile of node 33.

As seen in Figure 22a,b, the voltage is basically within the FVTB; however, like in Case 2-2, there is a voltage violation during the 11:30–13:30 period subject to SVR and SC regulation capability, but the voltage violation only accounts for 0.6% of the whole day's length, which is much smaller than that in dead-band control. As seen in Figure 22c, the VUF is controlled well within 2% for the whole day in FVTB control.

The SVR and SC operations are shown in Figure 23. In Figure 23a,b, the SC operations with FVTB control rise in comparison with dead-band control. In Figure 23c, the number of SVR operations in FVTB control is significantly reduced compared to that in dead-band control, especially during the peak period of PV output. The numbers of SVR and SC operations in voltage dead-band control and FVTB control are given in Table 6.

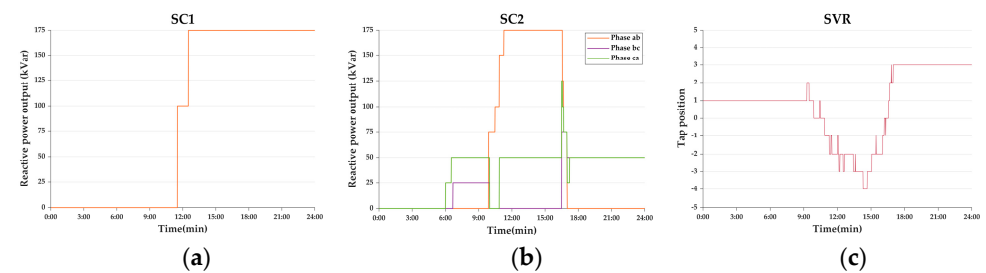


Figure 23. Operation of SVR and SC in Case 2-3. (a) SC1 operation; (b) SC2 operation; (c) SVR operation.

Table 6. Operation times of SVR and SC.

Control Type	Operation Times		
	SVR	SC1	SC2
Dead-band	78	4	12
FVTB	33	2	23

As shown in Table 6, compared to dead-band control, the number of SVR operations in FVTB control is reduced by 45 times, which is only 42.3% of that in dead-band control. The number of SC operations in FVTB control is increased to 25, improving the participation of SC. Therefore, FVTB control effectively reduces the number of SVR operations and increases SC involvement.

• Case 3-1: Only SVR, SC Control

In the real-time stage, the timescale is 2 s. After accounting for the mechanical delays of SVR and SC, the voltage and VUF curves in the real-time stage are shown in Figure 24 with intra-day scheduling in Case 2-3.

In Figure 24a,b, the voltage exceeds its limit due to the mechanical delay of SVR/SC and ultra-short-term fluctuations in PV, and it accounts for about 5.4% of the whole day's length. As shown in Figure 24c, the VUF is always smaller than 2% throughout the day. Therefore, in the real-time control stage, the SVR and SC cannot cope with the voltage

violation problem, as shown in Figure 24, and a BESS is employed for real-time operation with flexible control ability.

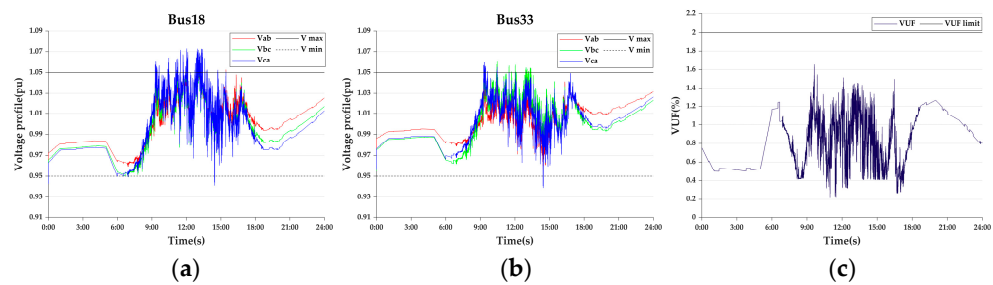


Figure 24. Voltage and VUF profiles in Case 3-1. (a) Voltage profile of node 18; (b) voltage profile of node 33; (c) VUF profile of node 33.

- Case 3-2: Coordination Control of BESS, SVR, and SC

In Figure 25, the BESS's participation in voltage regulation maintains the voltage and VUF within the thresholds throughout the day, indicating that the BESS eliminates the voltage violation caused by the mechanical delay of SVR/SC and PV fluctuation in the real-time stage, as seen in comparison with Figure 24a–c. The BESS output and SOC are given in Figure 26.

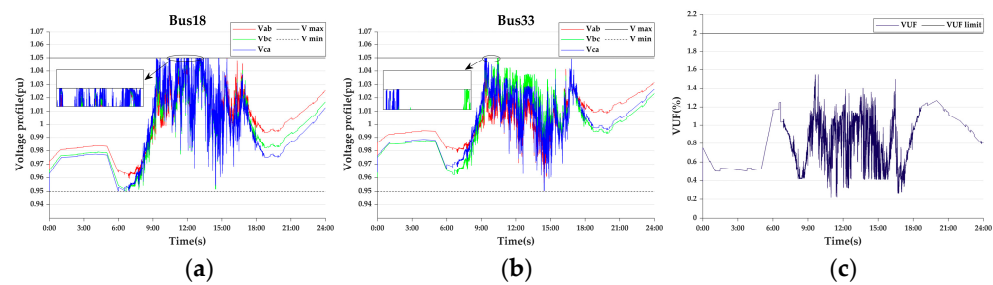


Figure 25. Voltage and VUF profiles in Case 3-2. (a) Voltage profile of node 18; (b) voltage profile of node 33; (c) VUF profile of node 33.

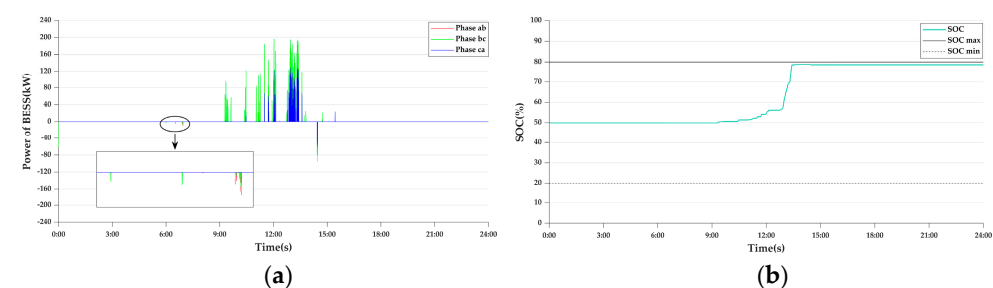


Figure 26. BESS output and SOC profile in Case 3-2. (a) BESS output; (b) SOC profile.

In Figure 26a, the maximum charging power of the BESS is close to 200 kW, and the maximum discharging power is about 100 kW. At around 6:00, the voltage slightly exceeds the lower limit due to the mechanical delay of the SVR and SC, and the BESS is capable of adjusting the voltage back to its threshold by briefly discharging. In Figure 26b, before the peak of the PV output, the SOC rises to a maximum of 78.86%. The voltage slightly exceeds the lower limit around 14:45, and the BESS discharges as the SOC decreases by 0.2%.

- Case 3-3: AVOA Optimization for BESS Output

In Figure 27, the AVOA is utilized to optimize the BESS output to achieve accurate voltage regulation and reduce the BESS output. This is in contrast to Figure 25a,b, where

the adjusted voltage does not closely track the threshold boundary due to over-regulation, resulting in an increase in the BESS output.

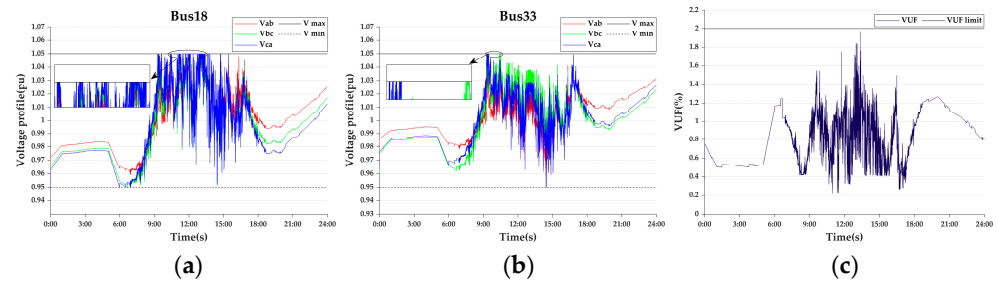


Figure 27. Voltage and VUF profiles in Case 3-3. (a) Voltage profile of node 18; (b) voltage profile of node 33; (c) VUF profile of node 33.

In Figure 27a,b, the BESS output by AVOA precisely regulates the exceeding voltage to the threshold boundary. In Figure 27c, the VUF also does not exceed the threshold. The BESS output and SOC profile by AVOA are shown in Figure 28.

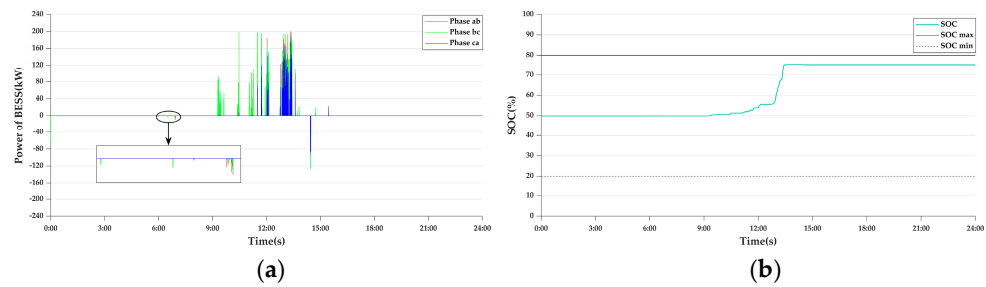


Figure 28. BESS output and SOC profile in Case 3-3. (a) BESS output; (b) SOC profile.

Figure 28a shows the BESS output by AVOA. Compared with Case 3-2, the maximum value of the SOC decreases from 78.86% to 75.54% in Figure 28b. In this paper, the BESS capacity is set to be 350 kWh, and the initial SOC is 50%; according to Equation (91), the curtailment of the BESS capacity reaches 11.51% by AVOA compared to Case 3-2.

The evaluation of the curtailment of the BESS capacity is expressed by Equation (91):

$$F_{cur} = \frac{\Delta SOC_{\Lambda-B} - \Delta SOC_{\Lambda-A}}{\Delta SOC_{\Lambda-B}} \quad (91)$$

where F_{cur} is the BESS capacity curtailment rate. $\Delta SOC_{\Lambda-B}$ and $\Delta SOC_{\Lambda-A}$ are the changes in the SOC before and after the utilization of the AVOA, respectively.

- Case 3-4: SVF

The intensity of voltage fluctuation, F_{flu} , is etched by the voltage fluctuation rate, as shown in Equation (92):

$$F_{flu} = \frac{\sum_{t=1}^{t_{max}} \sum_{i=1}^{N_{node}} \sum_{n \in \{\xi\}} \sqrt{(V_{i,real}^n(t) - V_{i,real}^n(t-1))^2}}{t_{max} \cdot N_{node} \cdot n_s} \quad (92)$$

where N_{node} is the number of nodes in DN. n_s is coefficient.

In Figure 28a, the BESS is idle most of the time, and the operation time is only about 5% of the whole day. Figure 27a,b show that the voltage fluctuation is very drastic, and F_{flu} , which is calculated according to Equation (92), reaches 12.39%. To suppress the voltage fluctuation and improve the utilization rate of the BESS, the BESS is mobilized in an idle period, and the voltage and VUF profiles are shown in Figure 29.

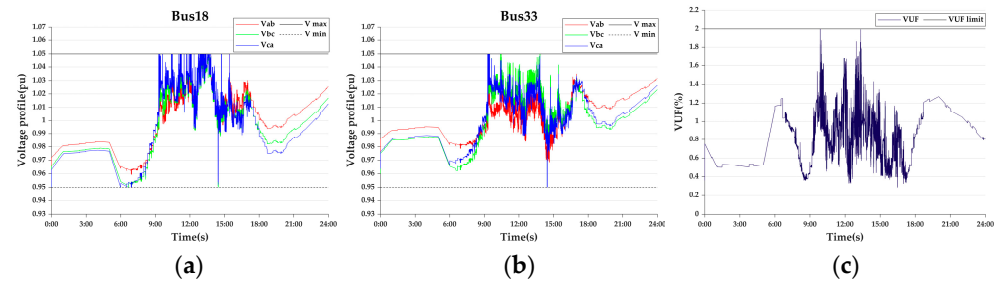


Figure 29. Voltage and VUF profiles in Case 3-4. (a) Voltage profile of node 18; (b) voltage profile of node 33; (c) VUF profile of node 33.

In Figure 29a,b, voltage fluctuation is obviously alleviated by SFTB, and F_{flu} is reduced to 7.97%, which is a 35.7% reduction in F_{flu} compared to 12.39% in Case 3-3. The voltage and VUF are within the threshold throughout the day. The comparison before and after the SVF of node 18 is taken as an example and illustrated in Figure 30.

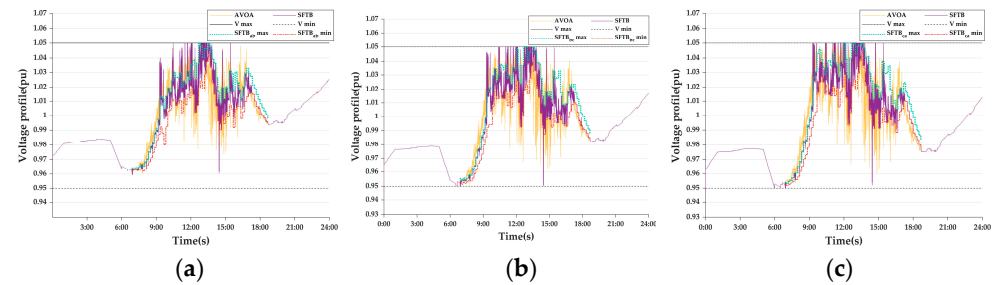


Figure 30. Voltage profiles of node 18 in Case 3-4. (a) Voltage profile in phase ab of node 18; (b) voltage profile in phase bc of node 18; (c) voltage profile in phase ca of node 18.

In Figure 30, the SFTB effectively suppresses voltage fluctuation compared to Case 3-3. During the period of voltage violation, the prior objective of the BESS is to deal with the voltage violation problem, so there are voltages that have not converged into the SFTB. The BESS output and SOC profile are shown in Figure 31.

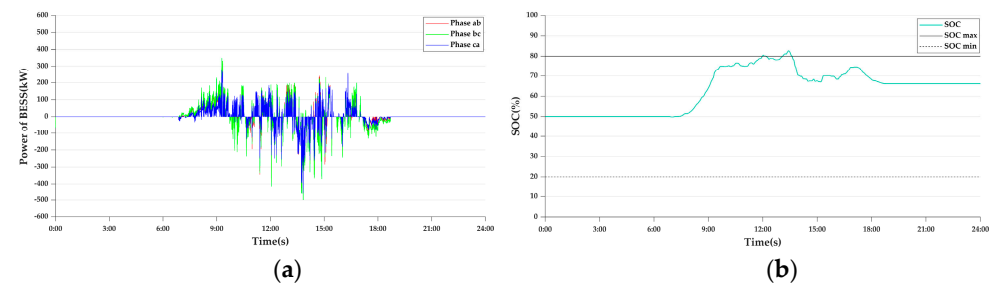


Figure 31. BESS output and SOC profile in Case 3-4. (a) BESS output; (b) SOC profile.

In Figure 31a, the BESS operation time is significantly increased, and the utilization rate is improved. Around the 19:00–6:00 period, voltage fluctuation suppression is not performed without the PV output. In Figure 31b, with the increase in the PV output, the overall voltage tends to rise and exceed the upper limit of the SFTB. The BESS adjusts the voltage by charging, which leads to the rise in the SOC to the maximum value of about 82.75% at about 13:25. After the peak time of PV, the voltage tends to descend and exceed the lower limit of the SFTB. The BESS adjusts the voltage by discharging, which leads to a decrease in the SOC to the minimum value of about 49.81% at about 7:00. During the 12:00–13:30 period, the SOC exceeds the upper limit, leading to the deep charging of the BESS. In Figure 31a, the maximum charging power of the BESS is close to 350 kWh, and

the maximum discharging power is about 500 kW. The calculated capacity of the BESS is 1.5 MWh.

- Case 3-5: ICD

In Case 3-4, the effectiveness of voltage fluctuation suppression is significant, and the utilization of the BESS is also improved, but the required BESS capacity and PCS are greatly increased, and the BESS also suffers from the problem of deep charging. Therefore, in this case, we propose the ICD strategy for the BESS to realize the curtailment of the BESS capacity as well as suppress the voltage fluctuation and avoid the deep charging/discharging of the BESS.

As shown in Figure 32, the voltage and VUF are within the threshold throughout the day with the ICD strategy. The voltage fluctuation is significantly diminished, and F_{flu} is reduced to 9.14%. Although the voltage suppression effect is slightly inferior compared to Case 3-4, the capacity of the BESS is reduced to 350 kWh through the ICD strategy, and the maximum output of the BESS is 200 kW, as shown in Figure 33a. The maximum SOC is about 76.93%, as shown in Figure 33b. The results verify that the ICD strategy realizes BESS capacity curtailment and solves the deep charging problem while suppressing voltage fluctuation and improving BESS utilization.

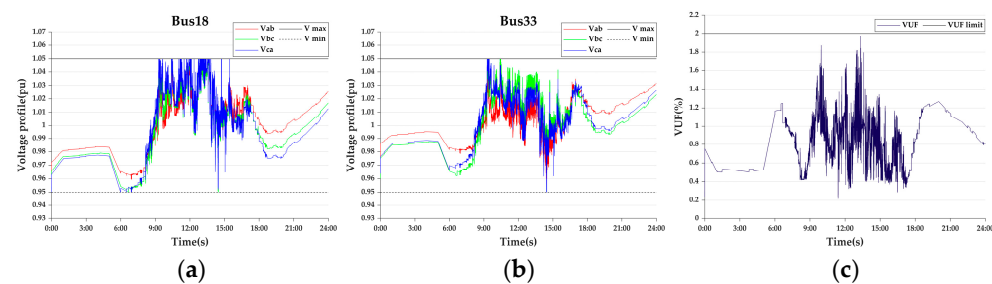


Figure 32. Voltage and VUF profiles in Case 3-5. (a) Voltage profile of node 18; (b) voltage profile of node 33; (c) VUF profile of node 33.

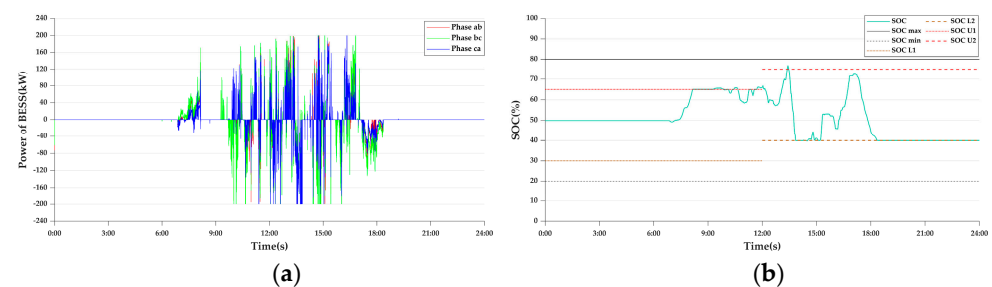


Figure 33. BESS output and SOC profile in Case 3-5. (a) BESS output; (b) SOC profile.

- Case 3-6: EV Replacement

EVs are used in this paper to replace BESSs for the further curtailment of the BESS capacity. The profiles of the voltage, VUF, BESS output, SOC variation, and EV charging/discharging power after EV replacement are shown in Figures 34 and 35.

In Figure 34a–c, the voltage and VUF are within the thresholds throughout the day. Compared to the ICD strategy, after replacing part of the BESS with EVs, the BESS output and operation period decrease, and the maximum value of the SOC decreases to 72.17%. Figure 35c shows the charging/discharging power of EVs. The BESS capacity required in Case 3-6 is scaled down by 13.09% compared to that in the ICD strategy.

The comparison of each case is shown in Table 7. The AVOA realizes the accurate output of the BESS and voltage regulation. The proposed SVF significantly moderates the voltage fluctuation. The proposed ICD realizes the great curtailment of the BESS's capacity.

Ultimately, the application of EVs further improves the curtailment of the BESS capacity with user participation in the voltage regulation of DN.

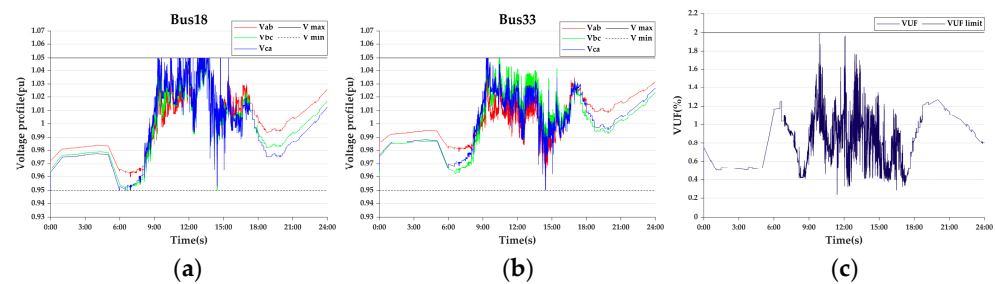


Figure 34. Voltage and VUF profiles in Case 3-6. (a) Voltage profile of node 18; (b) voltage profile of node 33; (c) VUF profile of node 33.

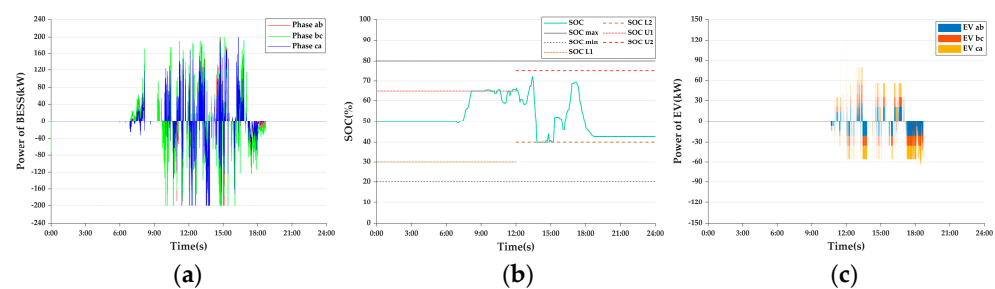


Figure 35. BESS output, SOC profile, and EVs charging/discharging power in Case 3-6. (a) BESS output; (b) SOC profile; (c) EVs charging/discharging power.

Table 7. Comparison of F_{flu} , BESS capacity, SOC, and PCS.

Case	F_{flu} (%)	BESS Capacity (kWh)	PCS (kW)	$SOC^{max}(\%)$	$SOC^{min}(\%)$
Case 3-2	12.2440	350	200	78.86	49.92
Case 3-3	12.3928	350	200	75.54	49.92
Case 3-4	7.9731	1500	500	82.75	49.81
Case 3-5	9.1439	350	200	76.93	39.73
Case 3-6	9.1498	350	200	72.17	39.84

5. Conclusions

The rapid development of PV, BESS, EVs, and their associated infrastructure is reshaping the energy landscape within DNs. Voltage control in DNs now demands more than just the simple manipulation of a single device. The efficient coordination of control strategies for both new and existing voltage regulators has emerged as a critical research focus within the realm of DN voltage control. This paper addresses this challenge specifically within DN, which exhibits a high penetration of distributed PV. To tackle the inherent stochasticity in the PV output, we introduce the AHA-LSSVM, which amalgamates the precision and resilience necessary for accurate PV forecasting. Given the unique attributes of each voltage regulation equipment, coordination among these devices is implemented across three distinct time scales, day-ahead, intra-day, and real-time, to facilitate effective voltage regulation. The management of the BESS output is optimized using the AVOA technique, and SOC management is enhanced through the introduction of the ICD, thereby increasing the available capacity of the BESS. Additionally, we propose EVs into the system to supplement BESS functionalities, thereby paving the way for a novel source–storage–load configuration for the DN.

This paper introduces the AHA-LSSVM forecasting model for PV output forecasting. The study results indicate that the AHA-LSSVM model reduces the RMSE by 12.7% and 7.3%, as well as the MAE by 18.8% and 15.3%, compared to the BP and LSSVM models.

The FVTB concept is proposed for liberating the SVR from frequent operations and balancing the number of SVR and SC operations, as Figures 21 and 23 illustrate, and the number of SVR operations under FVTB control accounts for only 42.3% of the number of dead-band voltage control operations.

By applying the AVOA to optimize the BESS output, the findings indicate a reduction of 11.5% in the necessary BESS capacity for voltage regulation. By introducing the ICD strategy in the SFTB for BESS, this study demonstrates a substantial decrease of 76.7% in the BESS capacity, accompanied by a reduction in the maximum SOC from 82.75% to 76.93%. Additionally, utilizing EVs to replace a portion of the BESS for voltage regulation leads to a further 13.1% reduction in the BESS capacity and a decreased cost in BESS utilization.

The cooperative voltage regulation strategies of the SVR, SC, BESS, and EVs for the day-ahead, intra-day, and real-time stages fully utilize the voltage regulation capabilities of the existing regulators while promoting the use of new regulators. The results show that the voltage is well regulated to within the thresholds, while the voltage fluctuation rate is reduced by 35.7%.

Future research in dealing with distribution network voltage problems amid the rapid popularization of technologies like PV, BESS, and electric vehicles poses significant challenges. To enhance the accuracy of PV forecasting, it is important to categorize the factors influencing photovoltaic (PV) output, including irradiation and temperature, based on geographical location, usage environment, and other relevant factors. Algorithmic enhancements also play a crucial role in achieving effective voltage regulation. Moreover, further advancements in validating the proposed strategies against large-scale and real systems are imperative to enhance their practical utility. Additionally, the economic and environmental implications of these strategies require in-depth exploration. These aspects collectively represent the focus of our ongoing research.

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