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Data-Model Hybrid-Driven Adaptive Voltage Control for Active Distribution Networks

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Abstract: The increasing integration of renewable energy resources in active distribution networks (ADNs) aggravates voltage deviations. Fluctuations among distributed generators (DGs) and the absence of accurate network parameters hinder the performance of model-based voltage control method. How to utilize the advantages of measurement-based data-driven method combined with model-based method has become the key to effectively addressing voltage issues. This paper proposes a data-model hybrid-driven adaptive voltage control method for ADNs. A data-model hybrid-driven adaptive voltage control framework containing two hybrid modes is established with the consideration of measurement configuration. In the data-model correction mode, the performance of data-driven control is improved by prior physical knowledge in adequate measurement area. In the data-model coordination mode, the inter-area coordination realizes the complementarity of the regulating ability between the areas with adequate measurement and those without. Finally, analysis and verification are performed based on the modified IEEE 33-node distribution network. The results demonstrate that the proposed hybrid-driven voltage control method has superiority in adaptability to DG fluctuations and strategy interpretability, which obtains satisfied voltage control performance.

Key words: Active distribution networks (ADNs); distributed generators (DGs); data-model hybrid-driven; adaptive voltage control; inter-area coordination

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Nomenclature

Sets		$\mathbf{x}_r[t], \mathbf{y}_r[t]$	Expanded control strategy/objective in area r at instant t
Λ	Set of typical scenarios	$\hat{Q}_r[t]$	Reactive power demand of area r at instant t
Ω_s, Ω_r	Sets of nodes in area s and r	$\mathbf{U}_s[t], \mathbf{U}_r[t]$	Voltage of area s/r at instant t
Ω_b	Set of all branches	$P_{ij}[t], Q_{ij}[t]$	Active/reactive power flow of branch ij at instant t
Indices		$I_{ij}[t]$	Current magnitude of branch ij at instant t
i, j	Indices of nodes	$U_i[t]$	Voltage of node i at instant t
t	Index of control instant	$P_i^{\text{DG}}[t], Q_i^{\text{DG}}[t]$	Active/ reactive power injection by DG of node i at instant t
l	Index of boundary branches	$P_i^{\text{load}}[t], Q_i^{\text{load}}[t]$	Active/reactive power consumption of node i at instant t
s, r	Indices of areas	$P_i[t], Q_i[t]$	Total active/reactive power injection of node i at instant t
m, n	Indices of boundary nodes	Parameters	
Variables		μ, η, λ, ρ	Weight factors of parameter estimation in data-driven method
$\hat{\mathbf{Y}}_r[t], \hat{\mathbf{y}}_r[t]$	Estimation of control objective and expanded control objective of area r at instant t	$T, \Delta t$	Total control duration and control horizon
$\mathbf{X}_r[t], \mathbf{Y}_r[t]$	Control strategy/objective of area r at instant t	$N_\Lambda, N_t, N_{\text{node}}$	Numbers of typical scenarios, control horizons and nodes
$\Phi_r[t], \hat{\Phi}_r[t]$	Pseudo-Jacobi matrix and its estimation at instant t in data-model correction mode	N_s	Number of nodes in area s
$\mathbf{P}^{\text{DG}}[t]$	Active power output of DGs at instant t	$\mathbf{y}_r^{\text{ref}}, \mathbf{y}_r^{\text{ref}}$	Reference of control objective and expanded control objective of area r
$\omega_s[t], \omega_r[t]$	Boundary information that area s/r receives at instant t	$\mathbf{U}_s^{\text{ref}}, \mathbf{U}_r^{\text{ref}}$	Voltage reference of area s/r
$\hat{P}_{s,l}[t], \hat{Q}_{s,l}[t]$	Measurement value of active/reactive power of branch l in area s at instant t	$\mathbf{S}^{\text{DG}}$	Vector of DG converter capacity

$\hat{P}_{r,l}[t], \hat{Q}_{r,l}[t]$	Measurement value of active/reactive power of branch l in area r at instant t	Resistance and reactance of branch ij
$\hat{U}_{s,n}[t], \hat{U}_{r,n}[t]$	Measurement of boundary voltage of node n in area s/r at instant t	Upper/lower limit of nodal voltage
$\omega_s[t], \omega_r[t]$	Auxiliary iterative variables of area s/r at instant t	Upper limit of branch current magnitude
$\Psi_r[t], \hat{\Psi}_r[t]$	Pseudo-Jacobi matrix and its estimation at instant t in data-model coordination mode	Upper/lower limit of reactive power compensation of DGs of node i
$X_s[t]$	Control strategy in area s at instant t	DG converter capacity of node i

1. Introduction

Currently, the integration of renewable energy resources is significantly increased in active distribution networks (ADNs) [1], which results in the complexity of energy management. Especially, intermittent distributed generators (DGs) [2] frequently cause rapid fluctuations in power flow and severe voltage violations [3]. It is necessary to restrict voltage in the secure interval and minimize voltage deviation to provide high-quality power supply [4].

Various model-based methods have been proposed to cope with voltage control issues in ADNs, which have shown excellent performance and can be divided into three categories: centralized control, distributed control, and local control. A centralized voltage regulation method was proposed in [5] to coordinate soft open points (SOPs) and DG converters. The centralized control method aims at global optimization [6] but suffers from heavy computational and communication burdens [7]. Distributed control divides distribution networks into sub-networks and solves voltage issues through regional collaboration with multiple iterations to obtain acceptable optimal solutions [8]. Zuo et al. [9] presented a distributed coordinative optimization control method to reduce voltage fluctuation in multi-energy systems. Local control is applied to get a promising performance without reliance on

adequate communication resources [10]. Li et al. [11] proposed an automatic self-adaptive local voltage control to response to time-varying changes in network with high penetration of DGs. However, local control may suffer from voltage oscillations owing to the interaction between multiple local controllers [12].

The operation of ADNs involves various uncertainties including fluctuations in DG output [13] and complex weather patterns [14]. Moreover, accurate network parameters are difficult to obtain in practical applications. Model-based method is difficult to cope with these issues. The increasing implementation of information technologies provides promising opportunities for the application of data-driven method. Data-driven methods can statistically depict complex systems without relying on accurate network parameters and can effectively adapt to the various uncertainties in ADNs.

Data-driven method based on machine learning exploits massive multi-source historical data to generate the nonlinear input-output relationships of ADNs through training. Liu et al. [15] proposed a novel deep reinforcement learning method with offline and online stages, which promoted the safety and efficiency of voltage control performance. In [16], an emotional deep learning programming voltage controller was designed to cope with emergency faults. In [17], a deep convolution neural network was presented to obtain the optimal control curve. Pei et al. [18] proposed a voltage control method based on multi-task reinforcement learning, which had excellent robustness with different topologies of distribution networks.

In contrast to the data-driven methods based on machine learning, data-driven methods based on online feedback can adaptively exploit measurement data without training process. Model-free adaptive control (MFAC) is a dynamic linearization method proposed to address the problems of nonlinear systems. Linear time-varying method based on MFAC can eliminate discrete-time nonlinear parameters while achieving adaptive control performance. In [19], a

framework based on MFAC was proposed, considering the coordination of various regulation devices. Gao et al. [20] proposed a data-driven multi-mode adaptive control method to meet diverse operational requirements of ADNs, which was robust against bad data and measuring errors. Moreover, MFAC was exploited in [21] to cope with voltage issues of transmission grids and to get satisfied control performance.

However, data-driven method relies on the initial value for iteration and measurement configuration. Strategies generated by data-driven methods may diverge from the practical operation of ADNs. Moreover, uneven measurement configuration leads to that data-driven method is infeasible in some areas. Neither data-driven method nor model-based method alone can adequately adapt to the practical operation of ADNs.

Table 1 Comparison of literature on voltage control

References	Method mechanism	Without relying on accurate network parameters	Without training process	Without impact of Initial strategy on performance	Inter-area coordination
[5], [6], [7]	Model-based method	\	✓	✓	\
[8], [9], [11], [12]	Model-based method	\	✓	✓	✓
[15], [16]	Data-driven method	✓	\	✓	\
[19], [21]	Data-driven method	✓	✓	\	\
The proposed method	Data-model hybrid-driven method	✓	✓	✓	✓

Data-model hybrid-driven method combines the advantages of model-based method and data-driven method to improve operational performance of ADNs. A data-driven method was adopted in [22] for rapid error correction of a model-based method, creating an integrated method to improve the accuracy. Zhang et al [23] combined bi-level co-optimization method with re-routing clustering method to get optimal restoration scheme with lower computational complexity. In [24], an accurate physical model was employed to generate reference experiences for multi-agent deep reinforcement learning algorithm, which obtained satisfied convergence and control performance. Chen et al [25] modified the power flow model with data-driven method to improve convergence and calculation efficiency.

As shown in Table 1, voltage control for ADNs has been extensively studied. The model-based method relies on accurate network parameters, which may be difficult to obtain in practice application. The data-driven method based on reinforcement learning needs to be retrained when network topology changes. Moreover, the data-driven method based on measurement feedback may have impacts on networks. Considering the uneven measurement configuration, how to utilize the advantages of measurement-based data-driven method combined with model-based method has become the key to effectively addressing voltage issues. The detailed research gaps can be summarized as follows:

- 1) Data-driven method only relies on the measurement data to address control issues for ADNs, which may lack interpretability and reasonableness with physical layer. As for online feedback-based data-driven method, bad initial values may cause an impact on networks and affect the algorithm convergence.

- 2) Uneven measurement configuration poses the challenge that data-driven method is infeasible in some areas. The coordination between data-driven method and model-based

method can be further investigated to promote the complementarity of regulatory ability between areas with adequate measurements and those without.

To address these issues, this paper proposes a data-model hybrid-driven adaptive voltage control method for ADNs. The main contributions of this study are as follows:

1) The data-model hybrid-driven adaptive voltage control framework is established for ADNs incorporating two data-model hybrid modes. It combines the adaptability of the data-driven method and the interpretability of the model-based method to improve the voltage profiles of ADNs.

2) The data-model correction mode is proposed for the adequate measurement area with the integration of prior physical knowledge. The interpretability of data-driven method is improved and the impact on networks caused by unreasonable strategies is alleviated.

3) The inter-area data-model coordination mode is proposed to cope with the uneven measurement configuration in ADNs. With boundary information interaction, the data-model coordination mode can promote the complementarity of regulatory ability between areas with adequate measurements and those without.

The remainder of this paper is organized as follows. Section 2 elaborates on a data-model hybrid-driven adaptive control framework for ADNs. A data-model correction mode is proposed in Section 3, and a data-model coordination mode is proposed in Section 4. Case studies using the modified IEEE 33-node system are presented in Section 5 and the conclusions and future work are presented in Section 6.

2. Data-model hybrid-driven adaptive control framework for ADNs

Fig. 1 shows the framework of data-model hybrid-driven adaptive control for ADNs which contains two hybrid modes.

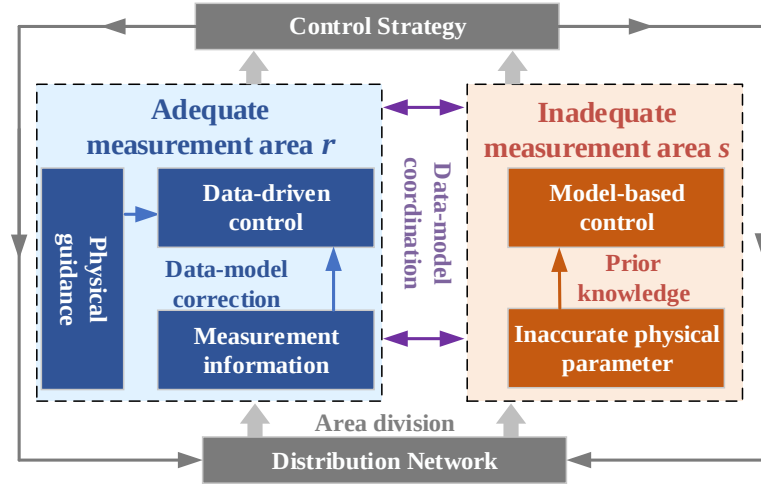


Fig. 1. Framework of data-model hybrid-driven adaptive control for ADNs.

In practical application, based on the measurement configuration, the ADN can be divided into areas with adequate measurement and those without. In adequate measurement areas, measurement devices can provide adequate measurement data for data-driven control. In inadequate measurement areas, data-driven control is infeasible due to lack of measurement data while model-based method with inaccurate network parameters is an alternative solution for voltage issues. Note that the ADN is divided into two areas in Fig. 1, but the proposed method is applicable to multiple-area division of ADNs.

As for the data-model correction mode, physical guidance is incorporated to correct the data-driven method based on measurement information in adequate measurement area. The physical guidance is considered with two aspects: a) The initial values of iterative variables in data-driven method are generated by inaccurate physical model. b) The objective function and the constraints of data-driven method are corrected based on prior physical knowledge. The interpretability of data-driven method can be improved by the data-model correction mode so that the impact on networks caused by unreasonable strategies can be alleviated.

As for the data-model coordination mode, boundary information interaction is utilized to coordinate data-driven method and model-based method. Regulatory resources in different areas are exploited to promote the inter-area complementarity capacity for voltage issues.

In general, the data-model hybrid-driven control framework for ADNs combines the advantages of data-driven methods and model-based methods. In this framework, data-driven method is exploited to response to rapid DG fluctuations without relying on accurate network parameters. Prior knowledge of model-based method is embedded into data-driven method to improve control performance. Moreover, the coordination of data-driven method and model-based method is adopted to cope with uneven measurement configuration.

3. Data-model hybrid-driven correction mode

A data-driven method is adopted in adequate measurement area r without relying on accurate network parameters, as detailed in the Appendix. However, separation from the physical layer of ADNs severely limits the practical application of data-driven method. In particular, unreasonable control strategy may affect the convergence of data-driven method and cause impacts on networks. To address these problems, a data-model correction mode is proposed to improve the interpretability of data-driven method through exploiting the prior knowledge of model-based method.

3.1. Adaptive control with initial value correction

At the start of iteration, the initial values of control strategy and pseudo-Jacobi matrix (PJM) should be set according to the iterative formulas in Appendix. In this sub-section, the initial control strategy is generated by the inaccurate physical model to alleviate the impact on networks. Then, the initial PJM is precalculated based on historical data, which can effectively improve the control performance of data-driven method.

1) Correction of initial control strategy

The initial control strategy $\mathbf{X}_r[t_0]$ can be generated by DistFlow model [26]. The objective function is the weighted sum of network loss and voltage deviation.

$$\min f = \alpha_1 f_{\text{loss}} + \alpha_2 f_u \quad (1. a)$$

$$f_{\text{loss}} = \sum_{ij \in \Omega_b} r_{ij} I_{ij}[t_0]^2 \quad (1. b)$$

$$f_u = \sum_{i=1}^{N_N} |U_i[t_0]^2 - 1| \quad (1. c)$$

where f_{loss} denotes the network loss. f_u denotes the voltage deviation. α_1 and α_2 denote the weight coefficients of objective function f . t_0 denotes the initial control instant.

Remark 1: The weighted sum method [27] is applied to the multi-objective optimization problem. The scaled coefficients have been determined by analytic hierarchy process (AHP) in [28], which can be adjusted by the distribution system operators. In addition, the sum of weight coefficients equals 1.

The power flow constraints of ADNs are described as follows.

$$\sum_{ji \in \Omega_b} (P_{ji}[t_0] - r_{ji} I_{ji}[t_0]^2) + P_i[t_0] = \sum_{ik \in \Omega_b} P_{ik}[t_0] \quad (2. a)$$

$$\sum_{ji \in \Omega_b} (Q_{ji}[t_0] - x_{ji} I_{ji}[t_0]^2) + Q_i[t_0] = \sum_{ik \in \Omega_b} Q_{ik}[t_0] \quad (2. b)$$

$$U_i[t_0]^2 - U_j[t_0]^2 + (r_{ij}^2 + x_{ij}^2) I_{ij}[t_0]^2 - 2(r_{ij} P_{ij}[t_0] + x_{ij} Q_{ij}[t_0]) = 0 \quad (2. c)$$

$$P_i[t_0] = P_i^{\text{DG}}[t_0] - P_i^{\text{load}}[t_0] \quad (2. d)$$

$$Q_i[t_0] = Q_i^{\text{DG}}[t_0] - Q_i^{\text{load}}[t_0] \quad (2. e)$$

$$(P_{ij}[t_0]^2 + Q_{ij}[t_0]^2) = U_i[t_0]^2 I_{ij}[t_0]^2 \quad (2. f)$$

The operational constraints and DG constraints are described as follows.

$$(\underline{U})^2 \leq U_i[t_0]^2 \leq (\bar{U})^2 \quad (3. a)$$

$$I_{ij}[t_0]^2 \leq (\bar{I})^2 \quad (3. b)$$

$$\underline{Q}_i^{\text{DG}} \leq Q_i^{\text{DG}}[t_0] \leq \bar{Q}_i^{\text{DG}} \quad (3. c)$$

$$\sqrt{P_i^{\text{DG}}[t_0]^2 + Q_i^{\text{DG}}[t_0]^2} \leq S_i^{\text{DG}} \quad (3. d)$$

The quadratic terms $U_i[t_0]^2$ and $I_{ij}[t_0]^2$ are substituted by variables $v_i[t_0]$ and $l_{ij}[t_0]$, as shown in the following constraints.

$$\sum_{ji \in \Omega_b} (P_{ji}[t_0] - r_{ji} l_{ji}[t_0]) + P_i[t_0] = \sum_{ik \in \Omega_b} P_{ik}[t_0] \quad (4. a)$$

$$\sum_{ji \in \Omega_b} (Q_{ji}[t_0] - x_{ji} l_{ji}[t_0]) + Q_i[t_0] = \sum_{ik \in \Omega_b} Q_{ik}[t_0] \quad (4. b)$$

$$v_i[t_0] - v_j[t_0] + (r_{ij}^2 + x_{ij}^2) l_{ij}[t_0] - 2(r_{ij} P_{ij}[t_0] + x_{ij} Q_{ij}[t_0]) = 0 \quad (4. c)$$

$$(\underline{U})^2 \leq v_i[t_0] \leq (\bar{U})^2 \quad (4. d)$$

$$l_{ij}[t_0] \leq (\bar{I})^2 \quad (4. e)$$

Constraint (2. f) is relaxed into the following quadratic cone constraint in (5).

$$\left\| \begin{bmatrix} 2P_{ij}[t_0] \\ 2Q_{ij}[t_0] \\ l_{ij}[t_0] - v_i[t_0] \end{bmatrix} \right\|_2 \leq l_{ij}[t_0] + v_i[t_0] \quad (5)$$

The inaccurate physical model can be summarized in (6), which is established to generate the initial control strategy for DG converters.

$$\begin{aligned} \min f &= \alpha_1 f_{\text{loss}} + \alpha_2 f_u \\ \text{s. t. } &(4. a) - (4. e), (5) \end{aligned} \quad (6)$$

In this paper, the control strategy consists of reactive power compensation of controllable DG converters in area r . Moreover, the above inaccurate physical model can be also utilized to calculate the power flow in the generation of the initial PJM. Note that the optimal solution of the DistFlow model can be guaranteed by using the second-order cone programming (SOCP) method.

2) Correction of initial PJM

The initial PJM can be obtained by calculating the sensitivity based on the DistFlow model and is formulated as (7).

$$\hat{\Phi}_r[t_0] = \frac{1}{N_\Lambda} \sum_{\zeta \in \Lambda} \partial Y_r(\zeta) / \partial X_r(\zeta) \quad (7)$$

where $Y_r(\zeta)$ and $X_r(\zeta)$ denote the control objective and control strategy of area r in typical scenario ζ . For the voltage issues of ADNs, control objective denotes nodal voltage and control strategy denotes the reactive power compensation of DG converters. A detailed implementation of (7) is shown as follows.

Step 1: Use (6) as the inaccurate power flow calculation model.

Step 2: Input different historical DG operational data into the inaccurate physical model and calculate the corresponding value of nodal voltages.

Step 3: Calculate the variation in nodal voltages and generate the initial PJM.

Based on (7), prior physical knowledge is introduced into data-driven method. Correction of the initial PJM can accelerate the convergence of the data-driven method. The iterative formula of $\hat{\Phi}_r[t]$ is modified as (8. a). e is a sufficiently small positive number.

$$\hat{\Phi}_r[t] = \hat{\Phi}_r[t - \Delta t] + \frac{\eta(\Delta Y_r[t] - \hat{\Phi}_r[t - \Delta t]\Delta X_r^T[t - \Delta t])}{\mu + \|\Delta X_r[t - \Delta t]\|_2^2} \quad (8. a)$$

$$\hat{\Phi}_r[t] = \hat{\Phi}_r[t_0], \text{ if } \|\hat{\Phi}_r[t]\|_2 \leq e \text{ or } \text{sign}(\hat{\Phi}_r[t]) \neq \text{sign}(\hat{\Phi}_r[t_0]) \quad (8. b)$$

3.2. Adaptive control with knowledge guidance

In this sub-section, data-driven method is further modified with knowledge guidance. Specifically, the objective function is regulated with time-varying weight factor and necessary constraints are supplemented in data-driven method.

1) Guidance of the objective function

To effectively reduce the deviation of control objective, time-varying weight factor is set as shown in (9).

$$J(X_r[t]) = \min (\sigma[t]\|Y_r^{\text{ref}} - Y_r[t] - \hat{\Phi}_r[t]\Delta X_r[t]\|_2^2 + \lambda\|\Delta X_r[t - \Delta t]\|_2^2) \quad (9)$$

where $\sigma[t]$ denotes the time-varying weight factor at instant t . At each control instant, $\sigma[t]$ is determined by voltage violations in ADNs. When the nodal voltages are outside the optimization interval, the value of $\sigma[t]$ is adjusted to guide the data-driven method to reduce voltage violations efficiently. The modified iterative formula of $X_r[t]$ is shown in (10).

$$X_r[t] = X_r[t - \Delta t] + \frac{\rho\sigma[t]\hat{\Phi}_r^T[t](Y_r^{\text{ref}} - Y_r[t])}{\lambda + \|\hat{\Phi}_r^T[t]\|_F^2} \quad (10)$$

2) Correction of the data-driven method constraints

Considering the capacity of DG converters, constraints of $\mathbf{X}_r[t]$ are shown in (11).

$$\begin{aligned} \mathbf{X}_r[t] &= \sqrt{(\mathbf{S}^{\text{DG}})^2 - (\mathbf{P}^{\text{DG}}[t])^2}, \text{ if } \mathbf{X}_r[t] > \sqrt{(\mathbf{S}^{\text{DG}})^2 - (\mathbf{P}^{\text{DG}}[t])^2} \\ \mathbf{X}_r[t] &= -\sqrt{(\mathbf{S}^{\text{DG}})^2 - (\mathbf{P}^{\text{DG}}[t])^2}, \text{ if } \mathbf{X}_r[t] < -\sqrt{(\mathbf{S}^{\text{DG}})^2 - (\mathbf{P}^{\text{DG}}[t])^2} \end{aligned} \quad (11)$$

In summary, the proposed data-model correction mode incorporates prior knowledge in data-driven method of area r , which has two advantages. a) Initial values of data-driven method are corrected by model-based method and the impact on network is alleviated. b) The data-driven method is modified by the time-varying factor and necessary constraints so that its interpretability is improved.

4. Data-model hybrid-driven coordination mode

Considering uneven measurement configuration in ADNs, data-driven method is only applicable to areas with adequate measurements. However, data-driven method is infeasible in areas with inadequate measurements while model-based method using inaccurate network parameters is an alternative to cope with voltage issues. In this section, a data-model coordination mode is proposed to coordinate data-driven method and model-based method in each area, which can exploit the inter-area complementary capacity of regulation resources through boundary information interaction.

4.1. Inaccurate model-based control of area s

Based on inaccurate network parameters, a physical model is established in area s to generate control strategy $\mathbf{X}_s[t]$. The objective function is described in (12. a). In addition, the weight coefficients of (12. a) can be determined by AHP.

$$g = \min(\beta_1 g_1 + \beta_2 g_2 + \beta_3 g_3 + \beta_4 g_4) \quad (12. a)$$

where $\beta_1, \beta_2, \beta_3$ and β_4 denote weight factors.

g_1 and g_2 respectively denote network loss and voltage deviation of ADNs.

$$g_1 = \sum_{ij \in \Omega_b} r_{ij} I_{ij}[t]^2 \quad (12. b)$$

$$g_2 = \sum_{i=1}^{N_N} |U_i[t]^2 - 1| \quad (12. c)$$

As for (12. d), objective function g_3 denotes the iterative error of the boundary information in inadequate measurement area s . It makes the boundary information in area s converge to the same value with that of area r .

$$g_3 = |\omega_s[t] - \varpi_s[t]| \quad (12. d)$$

Objective function g_4 in (12. e) denotes the inter-area power transfer deviation. Note that in this paper, DG converters are regulated to cope with voltage issues so that g_4 actually denotes inter-area reactive power transfer deviation.

$$g_4 = |\hat{Q}_r[t - \Delta t] - \hat{Q}_{s,l}[t]| \quad (12. e)$$

Auxiliary variations $\varpi_s[t]$ and $\varpi_r[t]$ are formulated in (13) for inter-area boundary information iteration.

$$\begin{aligned} \varpi_s[t] &= \varpi_s[t - \Delta t] + \omega_r[t - \Delta t] - (\omega_s[t - \Delta t] + \omega_r[t - \Delta t])/2 \\ \varpi_r[t] &= \varpi_r[t - \Delta t] + \omega_s[t - \Delta t] - (\omega_r[t - \Delta t] + \omega_s[t - \Delta t])/2 \end{aligned} \quad (13)$$

Boundary information $\omega_s[t]$ and $\omega_r[t]$ consist of power flow variables of boundary nodes and branches, which are expressed as follows.

$$\omega_s[t] = [\hat{P}_{s,l}[t], \hat{Q}_{s,l}[t], \hat{U}_{s,n}[t]]^T \quad (14. a)$$

$$\omega_r[t] = [\hat{P}_{r,l}[t], \hat{Q}_{r,l}[t], \hat{U}_{r,n}[t]]^T \quad (14. b)$$

$$\begin{aligned} \hat{P}_{s,l}[t] &= \hat{P}_{r,l}[t - \Delta t], \hat{Q}_{s,l}[t] = \hat{Q}_{r,l}[t - \Delta t], \hat{U}_{s,n}[t] = \hat{U}_{r,n}[t - \Delta t] \\ \hat{P}_{r,l}[t] &= \hat{P}_{s,l}[t - \Delta t], \hat{Q}_{r,l}[t] = \hat{Q}_{s,l}[t - \Delta t], \hat{U}_{r,n}[t] = \hat{U}_{s,n}[t - \Delta t] \end{aligned} \quad (14. c)$$

The constraints of inaccurate model of area s are shown as follows.

$$\sum_{ji \in \Omega_b} (P_{ji}[t] - r_{ji} l_{ji}[t]) + P_i[t] = \sum_{ik \in \Omega_b} P_{ik}[t] \quad (15. a)$$

$$\sum_{ji \in \Omega_b} (Q_{ji}[t] - x_{ji} l_{ji}[t]) + Q_i[t] = \sum_{ik \in \Omega_b} Q_{ik}[t] \quad (15. b)$$

$$v_i[t] - v_j[t] + (r_{ij}^2 + x_{ij}^2) l_{ij}[t] - 2(r_{ij} P_{ij}[t] + x_{ij} Q_{ij}[t]) = 0 \quad (15. c)$$

$$(\underline{U})^2 \leq v_i[t] \leq (\bar{U})^2 \quad (15. d)$$

$$l_{ij}[t] \leq (\overline{I})^2 \quad (15. e)$$

$$\left\| \begin{array}{c} 2P_{ij}[t] \\ 2Q_{ij}[t] \\ l_{ij}[t] - v_i[t] \end{array} \right\|_2 \leq l_{ij}[t] + v_i[t] \quad (15. f)$$

$$\underline{Q}^{\text{DG}} \leq Q_i^{\text{DG}}[t] \leq \overline{Q}^{\text{DG}} \quad (15. g)$$

$$\sqrt{P_i^{\text{DG}}[t]^2 + Q_i^{\text{DG}}[t]^2} \leq S^{\text{DG}} \quad (15. h)$$

4.2. Data-model hybrid-driven control of area r

The data-model correction mode for area r without boundary information interaction is proposed in Section 3. In this sub-section, the data-model hybrid-driven control of area r is modified to coordinate with the model-based control of area s .

The objective function of the data-model hybrid-driven method in area r is the weighted sum of three parts, which is described in (16. a). In addition, the weight coefficients of (16. a) can also be determined by AHP.

$$C = \min (\gamma_1 C_1 + \gamma_2 C_2 + \gamma_3 C_3) \quad (16. a)$$

where γ_1 , γ_2 and γ_3 denote weight coefficients.

Objective function C_1 denotes voltage deviation in area r .

$$C_1 = \|\mathbf{U}_r^{\text{ref}} - \hat{\mathbf{U}}_r[t]\|_2^2 \quad (16. b)$$

Objective function C_2 denotes the iterative error of the boundary information in adequate measurement area r . It makes the boundary information in area r converge to the same value with that of area s .

$$C_2 = \|\boldsymbol{\omega}_r[t] - \boldsymbol{\varpi}_r[t]\|_2^2 \quad (16. c)$$

Objective function C_3 denotes the variation in control strategies, which can alleviate the fast fluctuations in the output of control devices.

$$C_3 = \|\Delta \mathbf{X}_r[t - \Delta t]\|_2^2 \quad (16. d)$$

The above data-driven method is solved by gradient descent method, which is similar to that described in Appendix. According to the objective function of area r , $\mathbf{y}_r[t]$ consists of nodal voltages and iterative error of boundary information, as shown in (17).

$$\mathbf{y}_r[t] = [\mathbf{U}_r[t]; \boldsymbol{\omega}_r[t] - \boldsymbol{\varpi}_r[t]] \quad (17)$$

Inter-area power transfer deviation is considered in data-model hybrid-driven control of area r so that control strategy $\mathbf{X}_r[t]$ is expanded with $\hat{Q}_r[t]$.

$$\mathbf{x}_r[t] = [\mathbf{X}_r[t]; \hat{Q}_r[t]] \quad (18)$$

The reactive power demand of area r is transferred to area s , where the control strategy is adjusted to support reactive power compensation for area r .

According to (A.2), the data-driven dynamic linearization formula of area r is given by (19).

$$\hat{\mathbf{y}}_r[t + \Delta t] = \mathbf{y}_r[t] + \boldsymbol{\Psi}[t]\Delta\mathbf{x}_r[t] \quad (19)$$

The estimation function of $\boldsymbol{\Psi}_r[t]$ can be described in (20).

$$J(\boldsymbol{\Psi}_r[t]) = \min (\|\hat{\mathbf{y}}_r[t] - \mathbf{y}_r[t]\|_2^2 + \mu\|\boldsymbol{\Psi}_r[t] - \hat{\boldsymbol{\Psi}}_r[t - \Delta t]\|_F^2) \quad (20)$$

Utilizing the gradient descent method, the iterative formulas of $\hat{\boldsymbol{\Psi}}_r[t]$ and $\mathbf{x}_r[t]$ are shown as follows.

$$\hat{\boldsymbol{\Psi}}_r[t] = \hat{\boldsymbol{\Psi}}_r[t - \Delta t] + \frac{\eta(\Delta\mathbf{y}_r[t] - \hat{\boldsymbol{\Psi}}_r[t - \Delta t]\Delta\mathbf{x}_r[t - \Delta t])\Delta\mathbf{x}_r^T[t - \Delta t]}{\mu + \|\Delta\mathbf{x}_r[t - \Delta t]\|_2^2} \quad (21)$$

$$\mathbf{x}_r[t] = \mathbf{x}_r[t - \Delta t] + \frac{\rho\theta[t]\hat{\boldsymbol{\Phi}}_r^T[t](\mathbf{y}_r^{\text{ref}} - \mathbf{y}_r[t])}{\lambda + \|\hat{\boldsymbol{\Phi}}_r^T[t]\|_F^2} \quad (22)$$

The time-varying weight factor $\theta[t]$ is also incorporated in (22) to adjust $\mathbf{x}_r[t]$ according to the deviation of control objective. In addition, the initial value of $\hat{\boldsymbol{\Psi}}_r[t]$ and $\mathbf{x}_r[t]$ is generated by the same method in Section 3.1.

4.3. Implementation of data-physical hybrid-driven control

A flowchart of the data-model hybrid-driven adaptive voltage control method for ADNs is shown in Fig. 2. First, based on the measurement configuration, ADN is divided into areas with

adequate measurements and those without. The data-driven control and model-based control for each area are respectively adopted. Then, considering that the regulation resources in different areas are uneven, the inter-area coordination with boundary information interaction is conducted to promote the complementary capacity. By utilizing the proposed data-model hybrid-driven voltage control method for ADNs, voltage violations can be effectively alleviated, and network loss can be reduced.

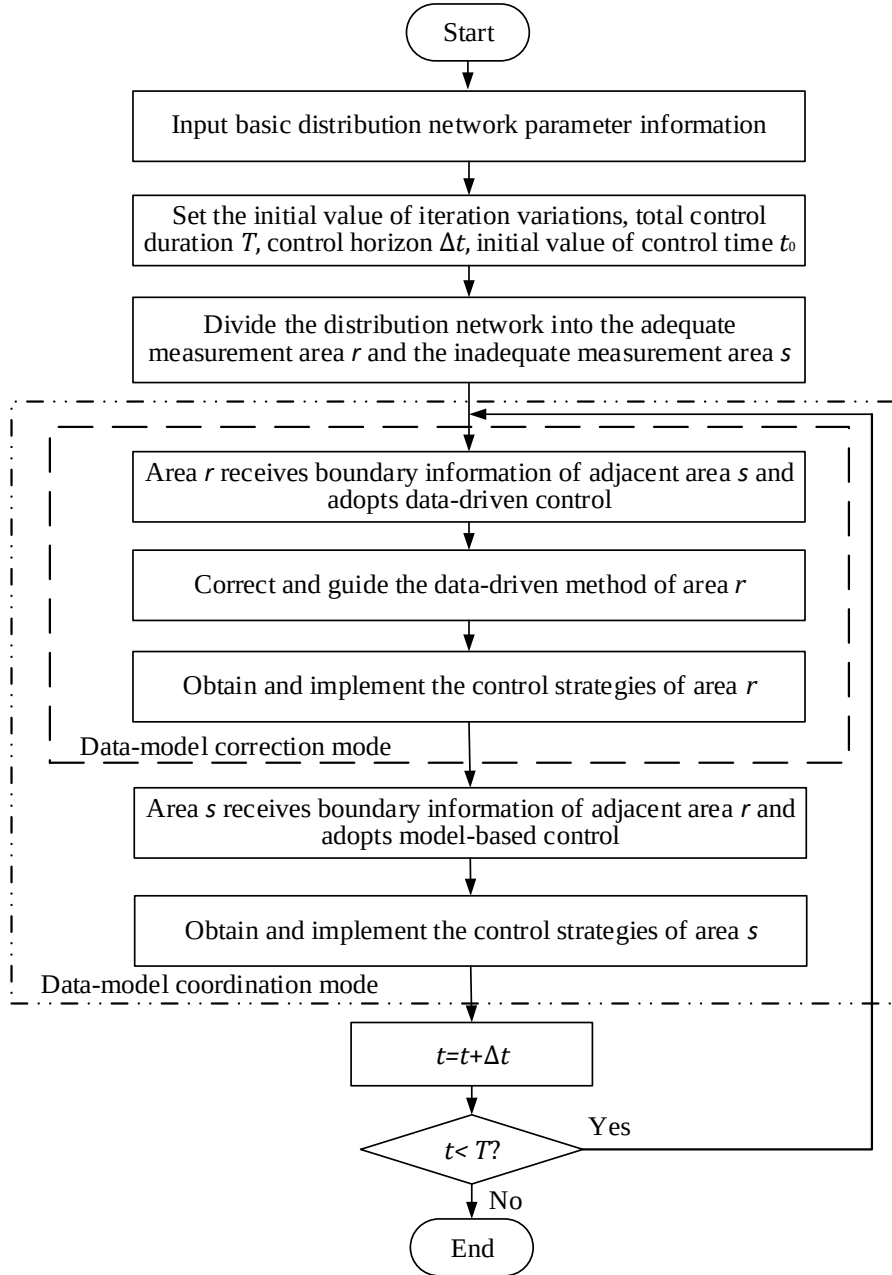


Fig. 2. Flowchart of the data-model hybrid-driven voltage control method.

Remark 2: In the proposed hybrid-driven method, the model-based method is a SOCP problem using convex relaxation, which is solved by the CPLEX solver in YALMIP. CPLEX utilizes interior-point method to solve SOCP problem [29]. The time complexity of interior-point method is $O(n^{3.5} \log(1/\epsilon))$ [30], where n is the number of decision variables and ϵ is the target precision. In contrast, the data-driven control does not contain any optimization issues and cyclic process, which only involves simple algebraic operations. Thus, the time complexity of data-driven control is $O(1)$. Considering that the model-based control method and the data-driven control method are respectively solved once in every control instant, the time complexity of the problem is $O(N_t n^{3.5} \log(1/\epsilon))$.

5. Case studies and analysis

In this section, the effectiveness of the proposed data-model hybrid-driven voltage control method is verified on the modified IEEE 33-node distribution system. The proposed method is implemented in MATLAB R2019a. The numerical experiments are conducted using an Intel Xeon CPU E5-1620 processor running at 1.60 GHz and 16 GB of RAM.

5.1. Modified IEEE 33-node distribution system

The modified IEEE 33-node distribution system includes a substation and 32 branches, of which the rated voltage level is 12.66 kV. The total active power and reactive power demands are 3715.0 kW and 2300.0 kvar. Considering the uneven configuration of measurements in practical networks, the area division for the ADN is shown in Fig. 3.

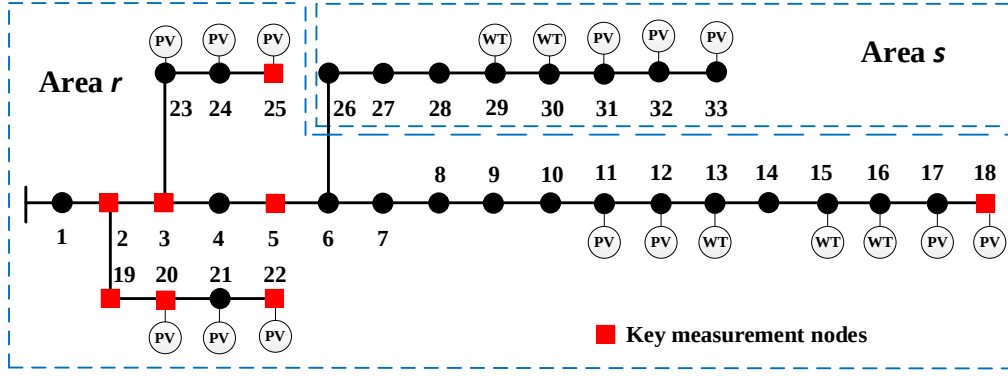


Fig. 3. Structure of the modified IEEE 33-node system.

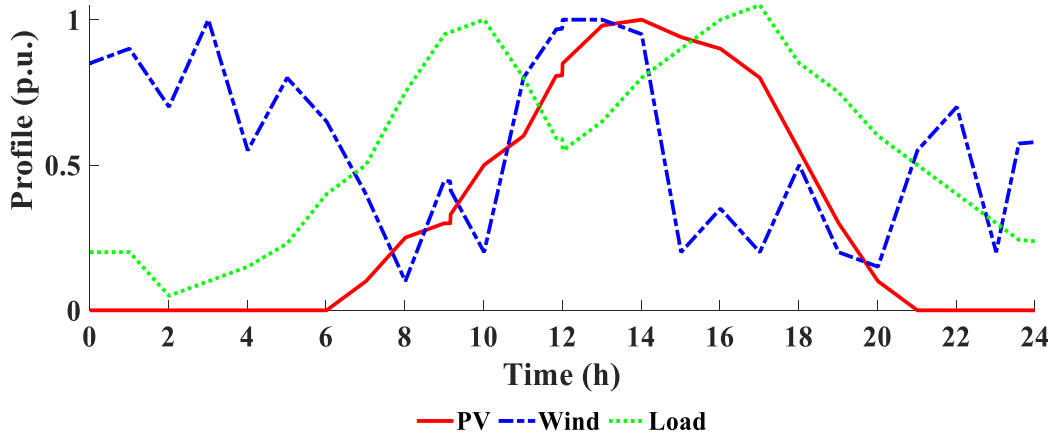


Fig. 4. Operational curves of DGs and loads.

To fully consider the proliferation of DG, five wind turbines (WTs) each with a capacity of 500 kVA are installed at Nodes 13, 15, 16, 29 and 30. Thirteen photovoltaics (PVs) each with a capacity of 100 kWp are installed at Nodes 11, 12, 17, 18, 20, 21, 22, 23, 24, 25, 31, 32 and 33. The penetration of DG reaches almost 100 %. The control horizon Δt is set to 0.5 minutes and the total control period T is set to 24 hours. In data-driven method, the weight factors λ , ρ , η and μ are set to 1.0. The voltage deviation is regulated to within 0.03 p.u. The operational curves of DGs are shown in Fig. 4.

5.2. Analysis of Data-model Hybrid-driven Control Effect

Four scenarios are set to compared with other works and verify the effectiveness of the proposed method, which are shown as follows.

Scenario I: The initial operation state of ADN is obtained without control strategy.

Scenario II: The proposed data-model hybrid-driven voltage control method is adopted.

Scenario III: The data-driven voltage control method is adopted [19].

Scenario IV: The accurate model-based method is adopted [26].

1) Results of data-model correction control

Fig. 5 shows the initial voltage control process of Node 18 at 0:00 for ten iterations. On the first iteration, the voltage in Scenario II is in the secure interval owing to adopting reasonable initial control strategy, which is corrected by the proposed data-model correction mode. In contrast, the initial abnormal voltage in Scenario III may cause an impact on the network.

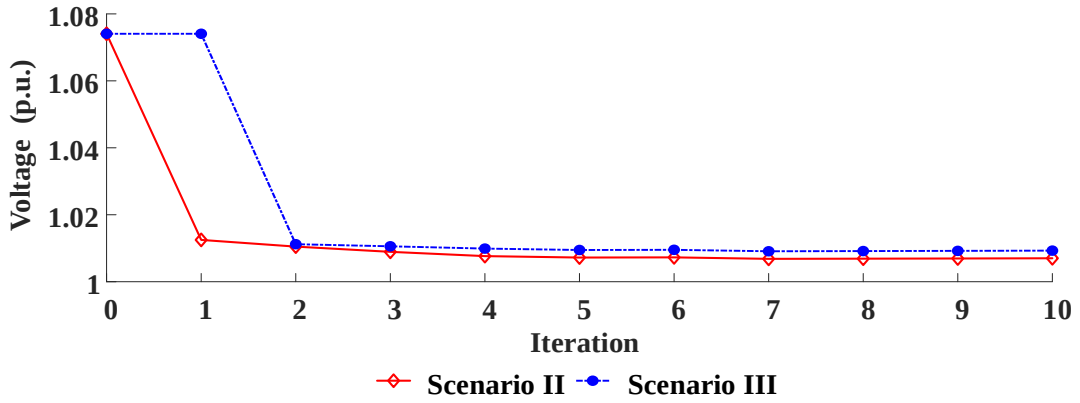


Fig. 5. The voltage control process of Node 18 at 0:00.

Fig. 6 shows the reactive power compensation process of DG converter of Node 18 at 0:00. The red solid line and the blue dotted line respectively denote the reactive power compensation profiles of DG converter of Node 18 in Scenarios II and III. According to the data-model correction mode in Scenario II, the initial control strategy of DG converter of Node 18 is generated by inaccurate physical model. As shown in Fig. 6, the initial reactive power compensation of DG converter is -79.9 kvar in Scenario II and that of Scenario III is set to 0 kvar, where the negative value means that the DG converter absorbs reactive power from the network. Obviously, the initial value in Scenario II is closer to the stable value of -100 kvar. Compared with Scenario III, the impact in the first iteration is significantly alleviated. Moreover,

no active power is generated by PVs at 0:00, and all the capacity of PV converters is utilized to regulate voltage in ADNs.

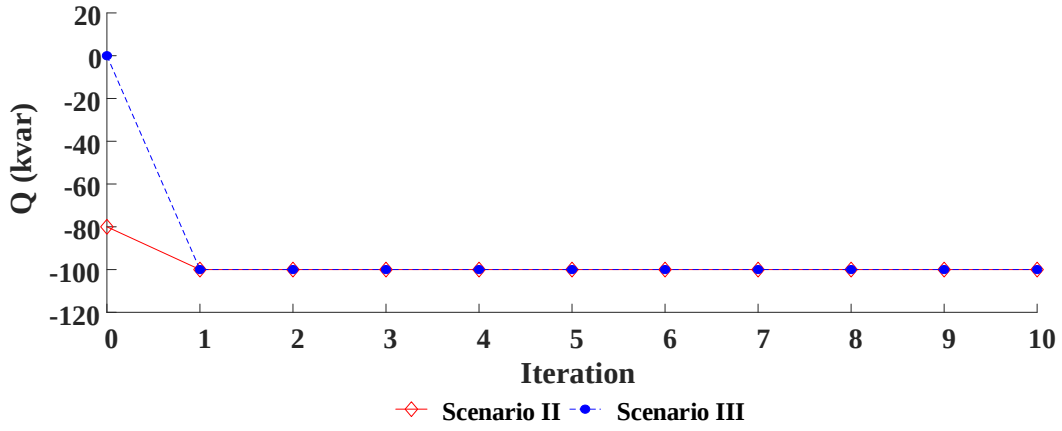


Fig. 6. Reactive power compensation process of DG converter of Node 18 at 0:00.

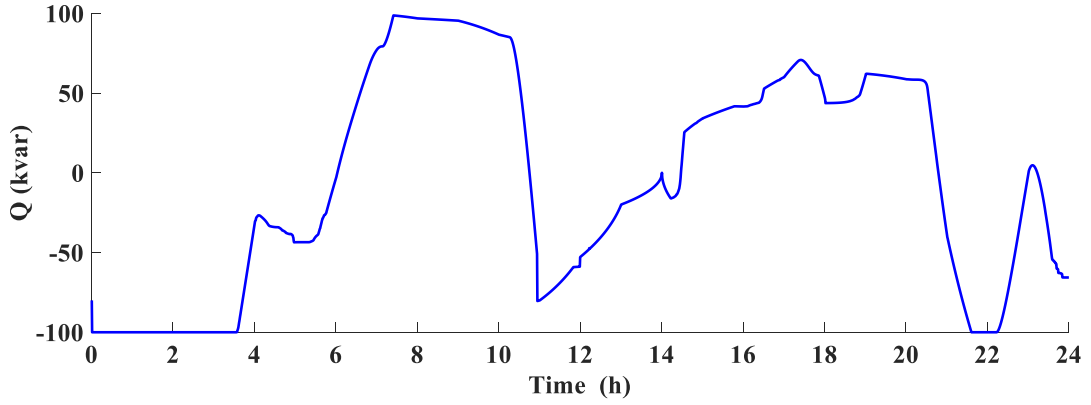


Fig. 7. Daily reactive power compensation of DG converter at Node 18 in Scenario II.

Fig. 7 shows the daily reactive power compensation of the DG converter at Node 18 in Scenario II. During the light-load periods, e.g., 0:00-3:00, the voltage of Node 18 exceeds the upper limit owing to the active power output of WTs. In Scenario II, the DG converter of Node 18 absorbs reactive power from the network to reduce voltage deviation. During heavy-load periods, e.g., 7:30- 10:00, the DG converter of Node 18 provides reactive power compensation to ensure that voltage does not fall below the lower limit. Moreover, guidance with prior knowledge prevents unreasonable control strategies and ensures the secure operation of ADNs.

2) Results of data-model coordination control

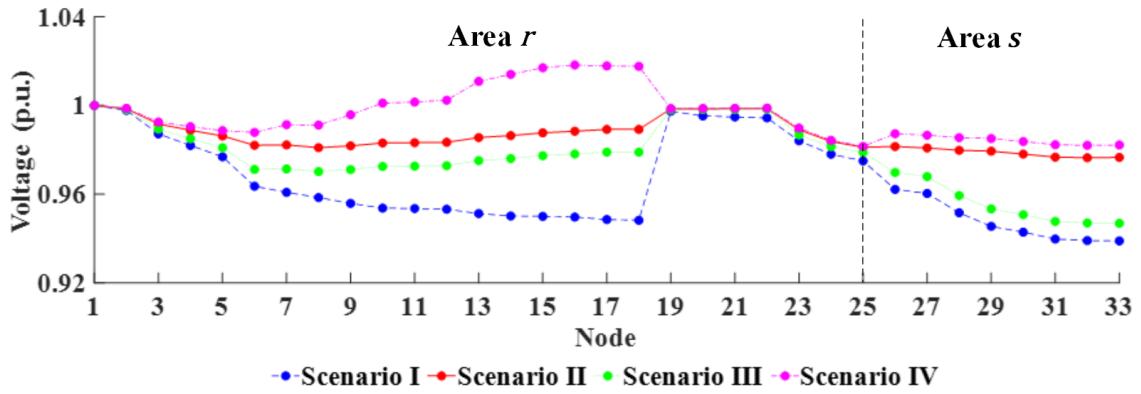
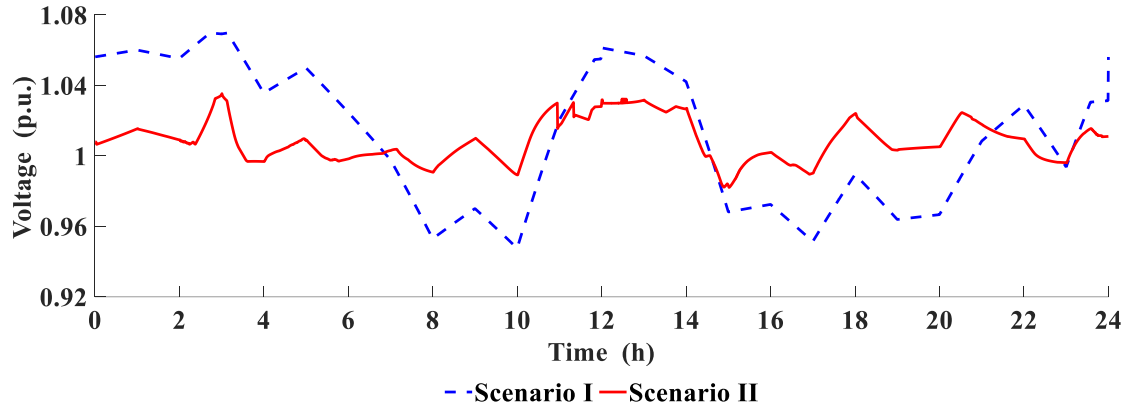


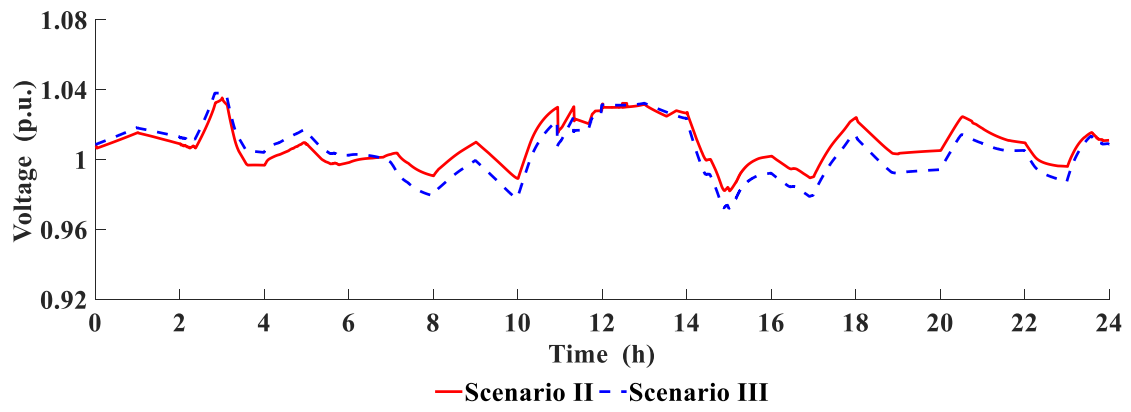
Fig. 8. Voltage distribution of each node in the four scenarios at 10:00.

Fig. 8 shows the nodal voltage profiles of the four scenarios at 10:00. The nodal voltages in Scenario II remain within the desired range and control performance in Scenario II is approximate to that of Scenario IV. It is demonstrated that the proposed method effectively reduces the voltage deviation of ADNs with uneven measurement configuration.

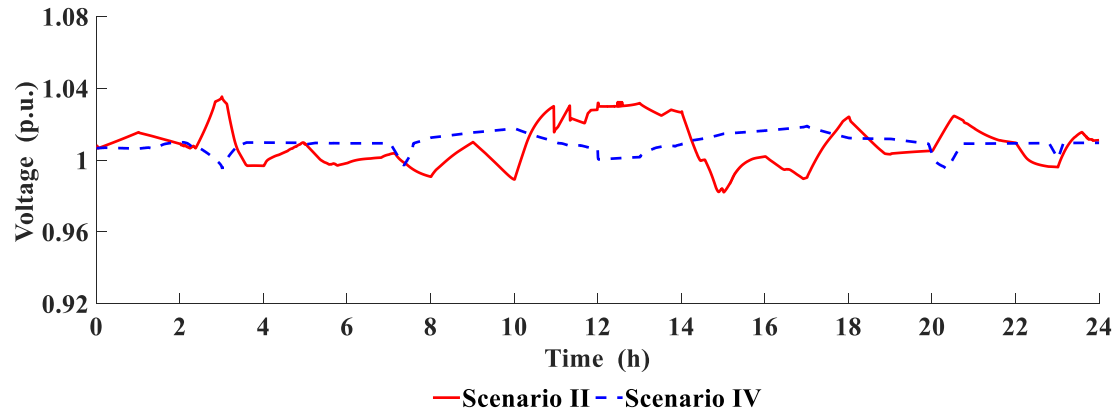
Fig. 9 shows the daily voltage profiles of Node 18 in the four scenarios. The comparisons of daily maximum and minimum voltage profiles are shown in Fig. 10 (a). Compared to the initial operation state in Scenario I, it shows that the proposed method in Scenario II can effectively alleviate the voltage violation. It can be observed in Fig. 10 (b) that compared with the data-driven control method in Scenario III, the proposed method fully exploits the regulating capacity of resources in each area to cope with voltage violation. Fig. 10 (c) illustrates that the voltage control performance of the proposed method is approximate to that of the model-based method using accurate network parameters in Scenario IV.



(a)



(b)



(c)

Fig. 9. (a) Voltage profiles of Node 18 in Scenarios I and II. (b) Voltage profiles of Node 18 in Scenarios II and III. (c) Voltage profiles of Node 18 in Scenarios II and IV.

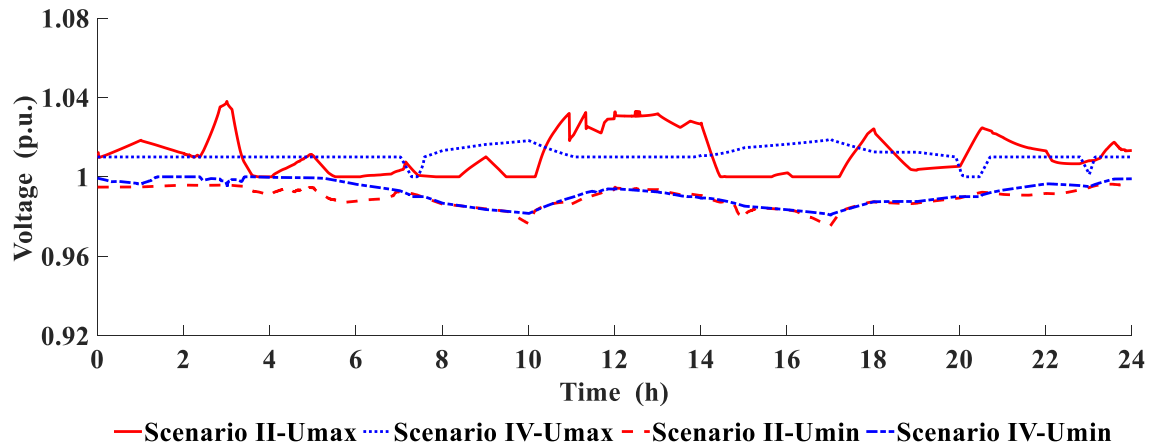
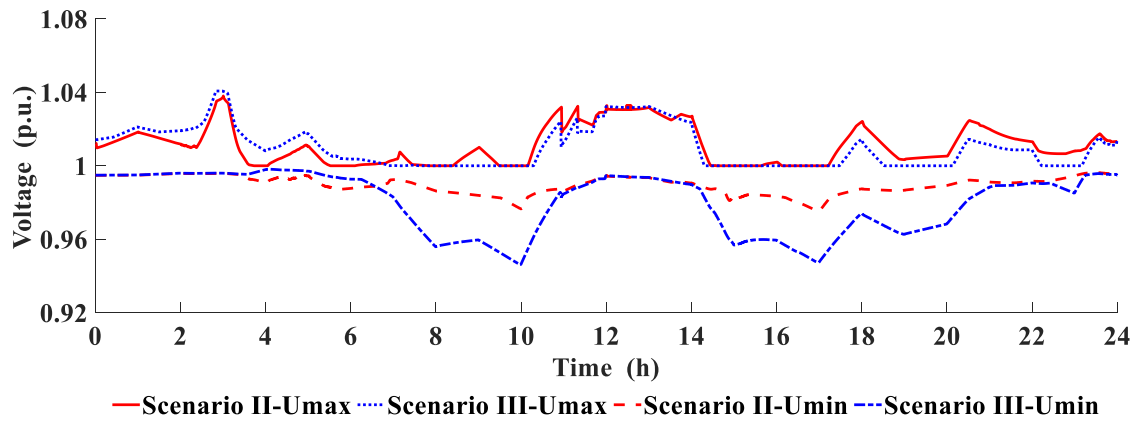
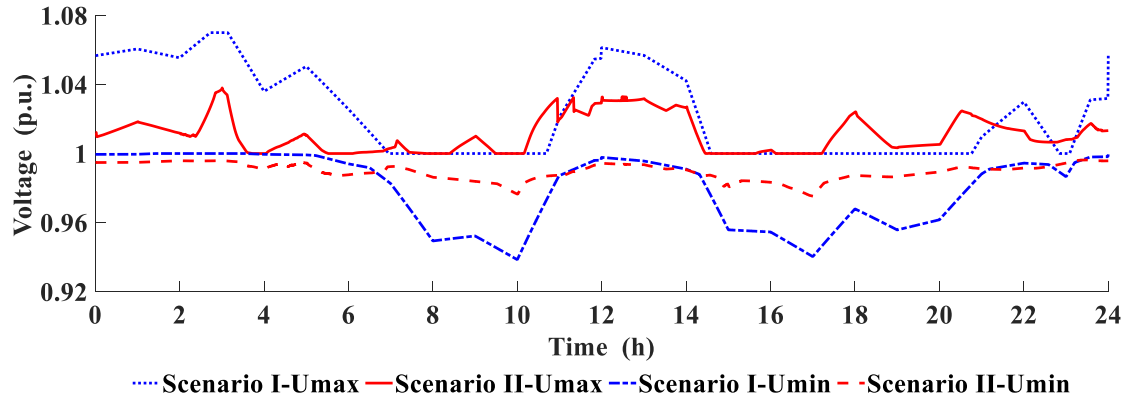


Fig. 10. (a) Comparison of daily voltage profiles in Scenarios I and II. (b) Comparison of daily voltage profiles in Scenarios II and III. (c) Comparison of daily voltage profiles in Scenarios II and IV.

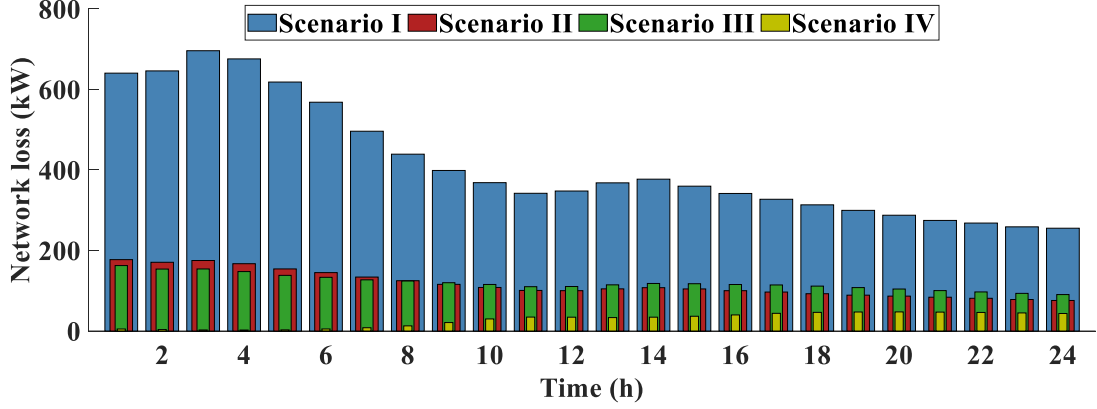


Fig. 11. Daily network loss of the four scenarios

To quantify the voltage regulation result, voltage deviation index (VDI) is defined in (23).

$$VDI = \sum_{t \in T} \sum_{i \in \Omega_s \cup \Omega_r} |U_i^{\text{ref}} - U_i[t]| / (N_{\text{node}} * N_t) \quad (23)$$

Fig. 11 shows the daily network loss of the four scenarios and the operational results for the four scenarios are listed in Table 2. The voltage data in Table 2 further proves the effectiveness of the proposed method. The voltage deviation in Scenario II is significantly reduced and compared with Scenarios I and III respectively, the VDI of Scenario II is reduced by 63.04 % and 37.61 %. Moreover, Compared with Scenario I, the daily network loss is significantly reduced by 72.17 % in Scenario II.

Table 2 Operation results of the four scenarios

Scenario	Minimum voltage (p.u.)	Maximum voltage (p.u.)	VDI (p.u.)	Network loss (kW)
I	0.9385	1.0753	0.0184	415.4
II	0.9753	1.0380	0.0068	115.6
III	0.9461	1.0407	0.0109	120.0
IV	0.9807	1.0191	0.0052	28.1

In summary, it is demonstrated that the proposed data-model hybrid-driven adaptive voltage control method for ADNs promotes voltage control performance and reduces network loss, which can facilitate the cleaner and more sustainable production of ADNs. The data-model correction mode improves the interpretability of the data-driven method and alleviates the

impact on ADNs caused by unreasonable control strategies. The data-model coordination mode adequately invokes the regulation resource in each area to effectively reduce voltage deviations considering uneven measurement configuration in ADNs.

6. Conclusion

This study proposes a data-model hybrid-driven adaptive voltage control method, which contains data-model correction mode and data-model coordination mode. DG converters are regulated to cope with the voltage issues of ADNs without reliance on accurate network parameters. Case studies with different scenarios are conducted to verify the effectiveness of the proposed method. The results show that the proposed method can combine the adaptability of data-driven method and the interpretability of model-based method to improve the voltage profiles of ADNs. Specifically, the data-model correction mode improves the interpretability of data-driven method with the prior physical knowledge, which alleviates the impact on the network caused by unreasonable strategies. The data-model coordination mode promotes the inter-area complementary capacity through boundary information interaction.

However, several issues warrant further investigation. Limited by the capacity of DG converters, it is necessary to incorporate the traditional discrete voltage regulation devices, such as on-load tap changer (OLTC). A coordinated voltage control strategy is expected to be designed, which can alleviate the voltage fluctuation on multiple time-scales. Moreover, the measurement data quality has a significant impact on the voltage control performance. The bad-data checking and identification are expected to further improve the adaptability of data-model hybrid-driven method in practical ADNs.

Appendix

According to the area division of ADNs based on measurement configuration, data-driven method is only applicable to adequate measurement area r . The data-driven control for ADNs can be briefly described as follows, utilizing real-time measurement information.

$$\mathbf{Y}_r[t + \Delta t] = F(\mathbf{Y}_r[t], \dots, \mathbf{Y}_r[t - N_Y \Delta t], \mathbf{X}_r[t], \dots, \mathbf{X}_r[t - N_X \Delta t]) \quad (\text{A. 1})$$

where F denotes the input-output coupling relationship in control process. N_Y and N_X are time factors. For voltage control in ADNs, $\mathbf{X}_r[t]$ denotes the reactive power compensation of DG converters and $\mathbf{Y}_r[t]$ denotes the nodal voltage of ADNs.

The dynamic linearization of (A.1) is implemented at each control instant, as shown in (A. 2).

$$\hat{\mathbf{Y}}_r[t + \Delta t] = \mathbf{Y}_r[t] + \boldsymbol{\Phi}_r[t] \Delta \mathbf{X}_r[t] \quad (\text{A. 2})$$

$\boldsymbol{\Phi}_r[t]$ describes the real-time input-output relationship of ADNs in area r . (A. 2) shows that PJM refers to the time-varying input-output sensitivity of ADNs. Control objective at instant $t + \Delta t$ can be estimated by the linearization at instant t . In addition, the dynamic linearization of relies on the following assumptions.

Assumption (1): The controlled system satisfies the Lipschitz condition in (A. 3). For $\forall t_1, t_2$, the Lipschitz condition is shown as follows. a is a constant.

$$\|\mathbf{Y}_r[t_1] - \mathbf{Y}_r[t_2]\|_2 \leq a \|\mathbf{X}_r[t_1 - \Delta t] - \mathbf{X}_r[t_2 - \Delta t]\|_2 \quad (\text{A. 3})$$

Assumption (2): The partial derivative of F is continuous for the input $\mathbf{X}_r[t]$.

In the normal operation of ADNs, Assumptions (1) and (2) are both reasonable. Assumption (1) means that if the variation rate of input is bounded, the variation rate of output is also finite. Specifically, normal control strategy can not lead to the status infinity of ADNs, considering the system stability. Thus, Assumption (1) is satisfied. Assumption (2) describes the typical condition for the normal operation of ADNs. Therefore, Assumption (2) is also satisfied. The detailed proof process can refer to Ref. [19].

To calculate the estimation of control objective at instant t , $\Phi_r[t]$ and $X[t]$ must be obtained. The unknown F in (A. 1) results in that $\Phi_r[t]$ cannot be solved accurately. To reduce the deviation of control objective, $\Phi_r[t]$ can be estimated by the following parameter estimation function.

$$J(\Phi_r[t]) = \min (\|\hat{Y}_r[t] - Y_r[t]\|_2^2 + \mu \|\Phi_r[t] - \hat{\Phi}_r[t - \Delta t]\|_F^2) \quad (\text{A. 4})$$

where $\|\hat{Y}_r[t] - Y_r[t]\|_2^2$ is introduced to improve the estimation accuracy of $\Phi_r[t]$. $\mu \|\Phi_r[t] - \hat{\Phi}_r[t - \Delta t]\|_F^2$ is introduced to reduce fluctuations in the parameter estimation.

The gradient descent method is used to solve (A. 4) and the iterative estimation formula for PJM is shown in (A. 5).

$$\hat{\Phi}_r[t] = \hat{\Phi}_r[t - \Delta t] + \frac{\eta(\Delta Y_r[t] - \hat{\Phi}_r[t - \Delta t] \Delta X_r[t - \Delta t]) \Delta X_r^T[t - \Delta t]}{\mu + \|\Delta X_r[t - \Delta t]\|_2^2} \quad (\text{A. 5})$$

The deviation of control objective and the variation of control strategy should be considered when estimating. The objective function of the control process is expressed in (A. 6).

$$J(X_r[t]) = \min (\|Y_r^{\text{ref}} - Y_r[t] - \Phi_r[t] \Delta X_r[t]\|_2^2 + \lambda \|X_r[t] - X_r[t - \Delta t]\|_2^2) \quad (\text{A. 6})$$

where $\|Y_r^{\text{ref}} - Y_r[t] - \Phi_r[t] \Delta X_r[t]\|_2^2$ is to improve the estimation accuracy of $X_r[t]$. $\lambda \|X_r[t] - X_r[t - \Delta t]\|_2^2$ is to reduce fluctuations in control strategy and effectively alleviate the impact on networks.

Similarly, (A. 6) can be solved using the gradient descent method. The iterative estimation equation is described in (A. 7).

$$X_r[t] = X_r[t - \Delta t] + \frac{\rho \hat{\Phi}_r^T[t] (Y_r^{\text{ref}} - Y_r[t])}{\lambda + \|\hat{\Phi}_r[t]\|_F^2} \quad (\text{A. 7})$$

The iterative estimation equations at instant t contain the operational information of ADNs at instant $t - \Delta t$. Therefore, real-time feedback must be realized to adjust the data-driven method dynamically.

Credit authorship contribution statement

Chenhai Li: Data curation, Writing - original draft. **Jinli Zhao:** Conceptualization, Methodology. **Haoran Ji:** Writing - review & editing. **Shiyuan Gao:** Investigation, Software. **Hao Yu:** Formal analysis. **Jianzhong Wu:** Validation, Supervision. **Peng Li:** Project administration.

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