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Data-Driven Strategy for Three-Phase Unbalance Governance in Distribution Transformer Districts

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Abstract. Addressing the critical issue of three-phase unbalance in power systems that affect stable operation, this paper proposes a data-driven strategy for managing three-phase unbalance. By utilizing smart meter data, a voltage correlation data-driven model is employed to achieve phase identification, and a multi-time-scale prediction method is adopted to enhance accuracy. Furthermore, real-time monitoring of load phase changes is conducted through online gradient detection, and a gradient-based load phase adjustment model is constructed. Additionally, an unbalance compensation algorithm is introduced to dynamically adjust the load distribution based on real-time data. In practical application in a low-voltage area, the proposed method significantly reduced the degree of three-phase unbalance, validating its effectiveness and practicality, and providing a new solution to improve the stability and efficiency of power systems.

Key words. Three-phase unbalance, Data-Driven, Distribution Transformer Districts, Phase-identification, Multi-time-scale prediction

1. Introduction

The modern distribution network emphasizes efficiency, safety, reliability, and sustainable development, while three-phase unbalance is one of the critical factors affecting the stable operation of power systems [1,2]. By addressing three-phase unbalance, the stability of the power system can be enhanced by ensuring balanced currents and voltages, reducing fluctuations and disturbances [3,4]. The mitigation of three-phase unbalance requires real-time monitoring of the power system's operational status and adjustments based on actual conditions. This process aligns with the intelligent control philosophy of modern distribution networks, promoting their development towards greater intelligence and autonomy [5].

In low voltage regions, the preponderance of single-phase loads at end-user terminals results in three-phase unbalances in both current and voltage within power distribution lines. Consequently, the even distribution of power loads across the three phases is crucial. Nevertheless, precise phase identification techniques at the end-user level remain elusive, rendering the alleviation of three-phase unbalance a pressing issue that demands attention. There are research papers that address phase identification and the management of three-phase unbalance. A thorough literature review of the existing phase identification methods is introduced in [6]. The work in [7], a system for determining the phase of underground distribution transformers has been created to utilize fuzzy logic-based microprocessors for control. The work in [8], a bi-level optimal phase switch device placement model for mitigating three-phase unbalance is proposed, and the bi-level model is tested by an actual low-voltage area of Zhejiang province, China. In [9], the unbalance detection issue is presented as a hypothesis - related problem, and a rapid algorithm for detecting the unbalanced vector within a three-phase system is put forward. It mainly concentrates on the detection of three-phase unbalance situations, yet not comprehensively deal with the problem of alleviating three-phase unbalance [10]. Due to the complex calculation process, the method in [11] is not applicable in practical applications.

Currently, common methods for mitigating three-phase unbalance in distribution substations can be categorized into two major types based on modeling approaches: physics-based modeling methods [12-16] and data-driven approaches [17-24]. The control strategies based on physics-based modeling typically formulate the system as an optimal power flow problem. Under the premise of ensuring the safe operation of the distribution network, the objective is to minimize the degree of three-phase unbalance by optimizing the control parameters of various adjustable devices [10]. Since these problems are usually non-convex, scholars often employ heuristic algorithms such as particle swarm optimization or model simplification methods like convexification/linearization for solution. Representatively, the optimization algorithm is proposed to achieve intelligent phase-shifting of switches in [12], effectively addressing the three-phase unbalance issue in distribution networks.

Due to the traditional algorithms are prone to local optimization. An improved genetic algorithm based on the MIT-LXPM framework is proposed to implement the double-layer treatment in [13]. [14] proposes a three-stage incentive-based fair voltage control strategy to mitigate fast voltage violations in distribution networks while ensuring the benefits of both distribution system operators and PV customers. In [15], it formulates the decision-making process as a mixed-integer non-convex programming problem based on SVC model for dispatch purpose. Compared with existing work, the proposed method aims at minimizing current unbalance based on their phasor values and takes the network's operational requirements into account. A novel method to control phase-reconfiguration devices (PRDs) purely based on measurable data from PRDs is proposed in [16], followed by the optimization model that comprehensively considers operational requirements in the network. which is reformulated as an efficient solvable mixed-integer second-order cone programming based on exact reformulations or accurate linear approximations. Although the above methods can improve the degree of three-phase unbalance in distribution networks to some extent, heuristic algorithms cannot guarantee global optimality and are prone to falling into local optima. Meanwhile, model simplification methods like convexification or linearization assume global knowledge of topology, line parameters, and customer load conditions, making them difficult to apply to the actual complex systems.

In recent years, the rapid iteration and updating of data-driven methods such as machine learning and reinforcement learning have provided a new approach for the control and decision-making of various complex dynamic systems. Among these, Deep Reinforcement Learning (DRL) is an effective method for addressing the aforementioned challenges. In models involving high-dimensional state spaces, traditional reinforcement learning methods suffer from the "curse of dimensionality," which greatly limits their practical application in distribution networks. Therefore, scholars have proposed deep reinforcement learning methods to address this "curse of dimensionality". In [22], it presents an integrated method for solving related issues including user phase identification based on spectral clustering and three-phase unbalance mitigation, and a Mixed Integer Linear Programming model is then formulated.

A Deep Reinforcement Learning (DRL) algorithm based on the Soft Actor-Critic (SAC) network is presented in [23], which is used to optimize the offline strategy for voltage control in distribution networks. Compared to physics-based modeling approaches, it can achieve lower network losses. Given the stated background and numerous smart meter data available nowadays [24], a practical integrated method for user phase identification and three-phase unbalance control is proposed in this work. Firstly, voltage amplitude data collected by the Power User Electricity Data Acquisition System (PUEEDAS) is utilized to identify the phase information of the users. Based on this, an intelligent algorithm model for mitigating three-phase unbalance has been established. Finally, the practical application of this method in a low-voltage area in a certain location is introduced, and the relevant validation is presented.

2. Phase Identification of Load in the Substation Area Based on Data Driven

Phase identification of load in the substation area based on data driven is a progressive process. It progressively achieves a comprehensive understanding of load phase characteristics through data analysis, dynamic prediction, and integrated recognition as shown in Figure 1. First, the voltage correlation data-driven model serves as the foundation of the entire process. It establishes a dynamic relationship model between voltage and load power, quantifies the impact of voltage on the load, and provides key features and data support for subsequent phase prediction.

Based on the correlation information between voltage and load extracted from this model, multi-time-scale load phase prediction is carried out. Short-term prediction captures instantaneous fluctuations, medium-term prediction identifies periodic variations, and long-term prediction reveals long-term trends. This process establishes comprehensive time-scale coverage for identifying the dynamic characteristics of the load.

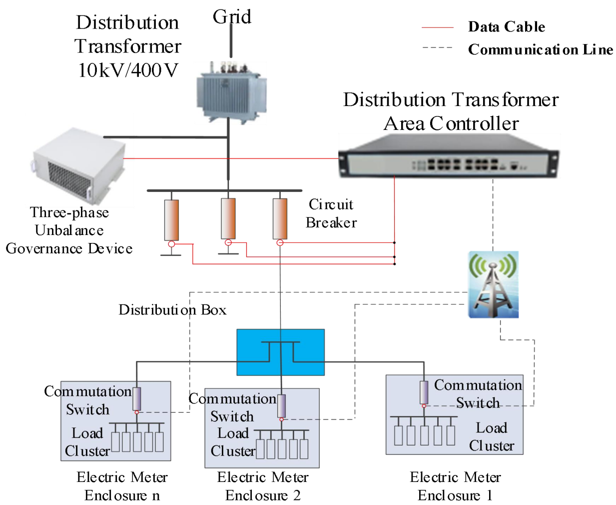


Figure 1. Clustered phase-shifting control architecture for distribution transformer load areas

Finally, in multi-time-scale phase prediction and identification, the prediction results from different time scales are integrated, and feature extraction techniques such as wavelet transform are applied to further analyze the phase variation characteristics of the load. The final phase identification results are then generated through phase angle calculation.

A. Data-Driven Model of Voltage Correlation

To achieve accurate prediction and identification of load phase, establishing a voltage correlation data-driven model is a core prerequisite. By analyzing the dynamic relationship between historical voltage and load power in the distribution transformer area, the impact of voltage changes on load power is quantified. This provides essential data support and feature information for subsequent multi-time-scale load prediction and phase identification.

Specifically, a mathematical model describing the relationship between voltage $V(t)$ and load power $P(t)$ is constructed using historical voltage data $V(t)$ and corresponding load power data $P(t)$. The model is expressed in the form of linear regression as follows:

$$P(t)=\beta_0+\beta_1 V(t)+\beta_2 V(t-1)+\beta_3 V(t-2)+...+\beta_n V(t-n)+\varepsilon(t) \quad (1)$$

Here, $\beta=\left[\beta_0,\beta_1,\cdots,\beta_n\right]^{\mathrm{T}}$ represents the regression coefficients, indicating the influence of current and historical voltage on load power. $\varepsilon(t)$ is the error term, used to represent the unexplained random fluctuations, which are assumed to follow a normal distribution $\varepsilon(t)\sim N\left(0,\sigma^2\right)$.

β is expressed as follows:

$$\beta=(\mathbf{X}^{\mathrm{T}}\mathbf{X})^{-1}\mathbf{X}^{\mathrm{T}}y \quad (2)$$

Where A is the historical voltage data matrix, B is the historical load power matrix, expressed as follows:

$$X=\begin{bmatrix} 1\ V_1(t)V_1(t-1)\cdots V_1(t-n) \\ 1\ V_2(t)V_2(t-1)\cdots V_2(t-n) \\ \vdots\ \ \vdots\ \ \ \vdots\ \ \ \ddots\ \ \vdots \\ 1\ V_N(t)V_N(t-1)\cdots V_N(t-n) \end{bmatrix} \quad (3)$$

$$y=\begin{bmatrix} P_1(t) \\ P_2(t-1) \\ \vdots \\ P_N(t-n) \end{bmatrix} \quad (4)$$

To establish a high-precision voltage correlation model, data collection and preprocessing must first be conducted. This includes obtaining voltage and load power data at different time points from smart meters or distribution transformer area monitoring devices. At the same time, outliers and missing values are cleaned and processed to ensure the completeness and consistency of the data. During the model construction phase, the model parameters β are fitted using the least squares method, and the model's performance is evaluated.

By analyzing the regression coefficients in the model, the sensitivity of load power to voltage changes at a specific time point can be determined. This dynamic characteristic directly influences the phase behavior of the load. In addition, the model's output provides critical input features for subsequent steps, such as the current voltage, lagged values of historical voltage, and their impact on the load.

B. Multi-Time-Scale Phase Prediction and Identification

By integrating short-, medium-, and long-term prediction results and applying wavelet transform, a comprehensive dynamic analysis of load phase is performed. This process integrates the applications of the previous two steps, unifying phase variation information across different time scales and generating phase identification results that can be directly utilized for grid management and planning.

1) Integration of Multi-Time-Scale Prediction Results

Short-term prediction results capture the instantaneous fluctuation characteristics of load power, while medium-term and long-term prediction results reveal periodic and trend variations, respectively. To integrate short-, medium-, and long-term prediction results effectively, a weighted fusion method is employed. This method combines predictions from different time scales based on their importance in specific application scenarios, as shown below:

$$P_{combined}(t)=\omega_s P_{short}(t)+\omega_m P_{mid}(t)+\omega_l P_{long}(t) \quad (5)$$

Here, ω_s , ω_m , ω_l represent the weights for short-term, medium-term, and long-term predictions, respectively.

2) Phase Angle Calculation and Characteristic Analysis

Based on the integrated prediction results, the phase angle of the load is further calculated to analyze its dynamic characteristics. The phase angle is a key indicator describing the relationship between load voltage and power, expressed as follows:

$$\theta_n=\omega_s\left(P_n(t+k|t)-P_n(t)\right)+\omega_l\left(P_n(t+l|t)-P_n(t)\right)+\omega_m\left(P_n(t+m|t)-P_n(t)\right) \quad (6)$$

Here, $P(t)$ represents the active power of the load, θ represents the phase angle of the load and k , l , and m represent phase A, phase B, and phase C, respectively.

3) Temporal Feature Extraction of Power

In order to comprehensively analyze the dynamic changes of load phase, the load power data is decomposed into different time scales to extract short-term, medium-term, and long-term characteristic signals. The transformation formula is as follows:

$$P_{\psi}(a,b)=\frac{1}{\sqrt{|a|}}\int_{-\infty}^{\infty} f(t)P\left(\frac{t-b}{a}\right)\mathrm{d}t \quad (7)$$

Here, $P_{\psi}(a,b)$ represents the load power signal, $f(t)$ is the wavelet coefficient at scale a and position b.

By integrating the analysis results of prediction consolidation, phase angle calculation, and multi-time-scale feature extraction, comprehensive load phase identification results are generated. The specific outputs include real-time phase variations, periodic phase changes, and long-term trend variations.

3. Online Gradient Detection of Load Phase Based on Data-Driven

A. Unbalance of Active Power

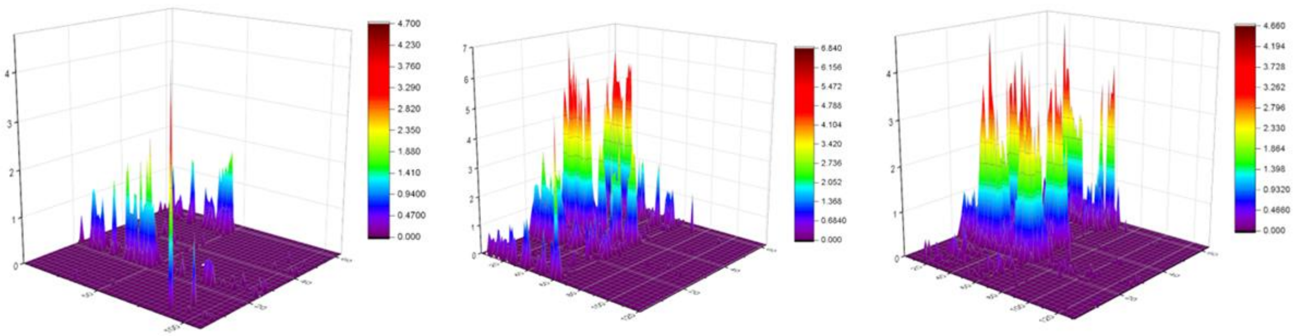
The unbalance of load phase power gradient is primarily quantified by calculating the deviation of the three-phase power from the average power. For active power, the unbalance $U(t)$ is defined as:

$$U(t)=\frac{1}{3}\sum_{i=1}^{3}\frac{\left|P_i(t)-\bar{P}(t)\right|}{\bar{P}(t)} \quad (8)$$

Here, $P_i(t)$ is the active power of phase i at time t , and $\bar{P}(t)$ is the average active power of the three phases, defined as follows:

$$\bar{P}(t)=\frac{P_a(t)+P_b(t)+P_c(t)}{3} \quad (9)$$

The online gradient detection of load phase is designed for real-time monitoring of the dynamic changes in load phase. By calculating the power gradient and evaluating the unbalance level, this method can promptly identify anomalies or optimize load distribution, as shown in Figure 2.



Voltage gradient of phase A　　Voltage gradient of phase B　　Voltage gradient of phase C

Figure 2. Three-phase voltage gradient in the transformer district.

B. Power Gradient Model for Load Phase

The core of the power gradient model is to calculate the rate of change of load power $P(t)$ and phase angle $\theta(t)$ with respect to time, which respectively describes the dynamic behavior of the load and its phase response characteristics.

For active power $P(t)$, its gradient can be expressed as:

$$\frac{dP(t)}{dt}=\frac{P(t+\Delta t)-P(t)}{\Delta t} \quad (10)$$

In order to further analyze the phase characteristics, the phase angle change rate is introduced, and its formula is:

$$GradP=\frac{\theta_n(t_s+\Delta t)-\theta_n(t_s)}{\Delta t} \quad (11)$$

C. Optimization of Load Phase Power Unbalance Based on Data Driven

In the analysis above, the load power unbalance and power gradient were obtained. To achieve rapid optimization of power imbalance, this paper adopts a combination of load phase switching based on gradient descent method and power electronic equipment control, which can also reduce the number of load phase switching times. Firstly, the gradient descent method is used to optimize the load power imbalance degree to $\alpha \cdot U(t_0)$, and then further optimization is carried out using power electronic devices. In the above, α is the adjustment coefficient and it takes values between $0 \sim 1$, and its value depends on the current load capacity and the specific power electronic device capacity. $U(t_0)$ represents the initial imbalance degree at time t_0.

1) Theoretical Design of Gradient Descent Method

To optimize the power unbalance, the optimization objective function is set as power imbalance $U(t)$, with the optimization objective of $\alpha \cdot U(t_0)$ .At the same time, the number of load switching times is added as a constraint condition.

(1) Optimization Objective

The optimization objective function is as follows:

$$\min U(t)=\frac{1}{3}\sum_{i=1}^{3}\frac{\left|P_i(t)-\bar{P}(t)\right|}{\bar{P}(t)} \quad (12)$$

The optimization objective is as follows:

$$U(t)\le \alpha \cdot U(t_0) \quad (13)$$

The additional constraint is that during the optimization process, the number of adjustments to the power distribution $P_i(t)$ should be minimized.

(2) Gradient Calculation Based on Gradient Descent Method

Utilizing the power gradient model, for each adjustment of $U(t)$, optimize power allocation through a load switching strategy. The gradient direction of each phase power is as follows:

$$\frac{\partial U(t)}{\partial P_i(t)}=\frac{1}{3\bar{P}(t)}sign\left(P_i(t)-\bar{P}(t)\right) \quad (14)$$

According to the principle of gradient descent, the power is adjusted in each iteration as follows:

$$P_i^{(k+1)}=P_i^{(k)}(t)-\eta\cdot\frac{\partial U(t)}{\partial P_i(t)} \quad (15)$$

Among them, η is the learning rate.

(3) Control of the Number of Load Switching Operations

To reduce the number of load switching operations, constraints are introduced into the power allocation during the optimization process. The load switching function is as follows:

$$S(t)=\left\|\left(\left|P_i^{(k+1)}-P_i^{(k)}(t)\right|>\Delta P_{\min}\right)\right. \quad (16)$$

In the formula, $\|(\cdot)$ represents an indicator function. When the load variation $\left|P_i^{(k+1)}-P_i^{(k)}(t)\right|$ exceeds the set minimum value $\Delta P_{\min}$, it is counted as one switch.

2) Implementation of Power Imbalance Optimization Algorithm

Step1: Initialization

(1) Allocation of initial power: $P_a^{(0)}$, $P_b^{(0)}$, $P_c^{(0)}$;

(2) Calculate initial unbalance:

$$U(t_0)=\frac{1}{3}\sum_{i=1}^{3}\frac{\left|P_i^{(0)}(t)-\bar{P}(t)\right|}{\bar{P}(t)} \quad (17)$$

(3) Set learning rate η, switching threshold $\Delta P_{\min}$, and target:

$$U_{target}(t)\le \alpha \cdot U(t_0) \quad (18)$$

Step2: Optimization Process of Gradient Descent

(1) Calculate the gradient for the power $P_i(t)$ of each phase (Formula 14).

(2) Adjust power allocation $P_i(t)$ that has the greatest impact on $U(t)$ based on the priority of sorting according to the absolute value of the gradient;

(3) Load Adjustment:

IUpdate the value of power (Formula 15):

II If the adjustment amount $\left|P_i^{(k+1)}-P_i^{(k)}(t)\right|$ is greater than $\Delta P_{\min}$, record the load switching once.

(4) Recalculate Unbalance:

$$U(t_{k+1})=\frac{1}{3}\sum_{i=1}^{3}\frac{\left|P_i^{(k)}(t)-\bar{P}^{(k)}(t)\right|}{\bar{P}^{(k)}(t)} \quad (19)$$

(5) Check the Convergence Condition.

If $U(t)$ is less than U_{target} and the condition for minimizing the number of load switching times is met, terminate.

D. Comparison of Different Optimization Algorithms

From the table, it can be seen that the gradient descent method exhibits a significant advantage in terms of time complexity. Specifically, the time complexity of the gradient descent method is relatively low, which implies that it may be more efficient when dealing with large-scale datasets.

Table 1. Comparison of Different Optimization Algorithms.

Algorithm	Time complexity	Time complexity concrete value
Gradient descent	$O(n\cdot d)$	1.5×10^5
LSTM	$O(m\cdot p2)$	3.63×10^6
CNN-LSTM	$O(k\cdot m\cdot p2)$	2.3232×10^8
CNN-LSTM-AM	$O(k\cdot m\cdot p2)$	2.3232×10^8

4. Switching of Load Phases Based on Data-Driven

A. Load Phase Adjustment Model under the Gradient Model

By calculating the gradient changes of load power and imbalance degree, the optimal load adjustment amount $\Delta P_i(t)$ is determined, and the adjustment formula is:

$$P_{adjusti}(t)=P_i(t)+\Delta P_i(t) \quad (20)$$

Where $P_{adjusti}(t)$ is the power of the *i*-th phase after adjustment; $P_i(t)$ is the power of phase *i* before adjustment; $\Delta P_i(t)$ is the adjustment amount, representing the power transferred or introduced from the *i*-th phase.

The calculation formula for adjustment amount $\Delta P_i(t)$ is as follows:

$$\Delta P_i(t)=-\alpha\frac{\partial U(t)}{\partial P_i(t)} \quad (21)$$

Among them, ∂ is the adjustment parameter used to control the adjustment force, and $U(t)$ is as shown in the previous text.

B. Multi-Time Scale Load Phase Adjustment Strategy

By combining short-term, medium long-term, and long-term load analysis, dynamically optimizing load phase allocation and reducing three-phase imbalance $U(t)$, the adjustment formula is as follows:

$$P_{adjust}(t)=\omega_s\Delta P_{short}(t)+\omega_m\Delta P_{mid}(t+k)+\omega_l\Delta P_{long}(t) \quad (22)$$

Here, ω_s, ω_m, ω_l represent the weights for short-term, medium-term, and long-term adjustment amount respectively.

And $\Delta P_{short}(t)$, $\Delta P_{mid}(t+k)$ and $\Delta P_{long}(t)$ are short-term, medium-term, and long-term adjustment amount respectively,the expression formulas are as follows:

$$\Delta P_{short}(t)=-k_s\left(P_i(t)-\bar{P}(t)\right) \quad (23)$$

$$\Delta P_{mid}(t+k)=-k_m\int_t^{t+k}\left(P_i(\tau)-\bar{P}(\tau)\right)d\tau \quad (24)$$

$$\Delta P_{long}(t)=-k_l\left(T_i(t)-\bar{T}(t)\right) \quad (25)$$

Among them, k_s, k_m and k_l are the short-term, medium long-term, and long-term adjustment coefficients, respectively, and $T_i(t)$ is the long-term trend component, $\bar{T}(t)$ is the average of the long-term trend of the three phases.

5. Unbalance Compensation Algorithm Based on Unbalance Range

A. Unbalance Range for Power Unbalance Based on Data-Driven

In three-phase power systems, load power unbalances can lead to increased equipment losses, intensified voltage fluctuations, and even potential power quality issues.

This paper employs real-time calculation and analysis methods based on load data to evaluate the uniformity of three-phase load distribution in the power grid, identify unbalance issues, and provide decision-making support for subsequent compensation strategies. Power unbalance not only requires instantaneous detection but also needs to track its dynamic variation over time. To this end, the time rate of change of unbalance is introduced with the following formula:

$$\frac{dU(t)}{dt}=\frac{\partial U(t)}{\partial P_a(t)}\frac{dP_a(t)}{dt}+\frac{\partial U(t)}{\partial P_b(t)}\frac{dP_b(t)}{dt}+\frac{\partial U(t)}{\partial P_c(t)}\frac{dP_c(t)}{dt} \quad (26)$$

Using the formula above, the variation trend of the unbalance can be dynamically tracked, allowing for the early identification of potential worsening unbalance situations.

B. Unbalance Compensation Strategy Based on Data-Driven

By introducing or removing a compensation amount $\Delta P_{comp}(t)$ for each phase load, the load distribution is dynamically adjusted to reduce power differences among the three phases and achieve load balance. The compensation formula is as follows:

$$\Delta P_{comp,i}(t)=-\beta U(t)\times sign\left(P_i(t)-\bar{P}(t)\right) \quad (27)$$

Here, $\Delta P_{comp,i}(t)$ is the compensation amount, β is the compensation coefficient, used to control the intensity of the compensation, and $sign\left(P_i(t)-\bar{P}(t)\right)$ indicates the direction of deviation of phase power from the average power.

C. Consideration of Power Unbalance and Three-Phase Unbalance Compensation Design

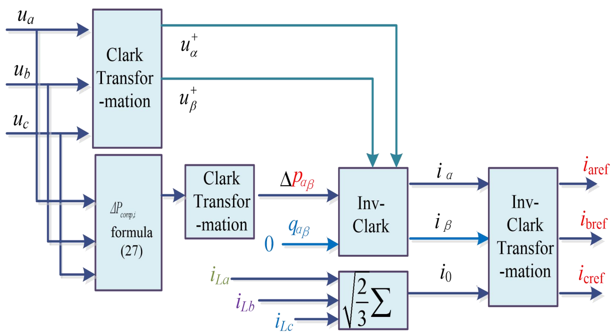


Figure 3. The Proposed Three-Phase Unbalance Compensation Process for Power Unbalance

The three-phase voltages u_a , u_b , u_c and the corresponding phase currents i_{La}, i_{Lb}, i_{Lc} of the four-wire system output of the distribution transformer in the distribution network are collected. According to Equation (20), the three-phase unbalanced power Δp_a , Δp_b and Δp_c is obtained. Through the Clark transformation, the unbalanced power in the $\alpha-\beta$ coordinate system is derived, and the unbalanced compensation current is obtained by applying the inverse Clark transformation to the unbalanced power, as shown in Figure 3.

To further process and compensate for this unbalance, the unbalanced powers are transformed into the $\alpha-\beta$ coordinate system using the Clark transformation. Unlike conventional current and voltage Unbalance compensation methods, the power imbalance detection and compensation integrates the advantages of phase shifting and capacity compensation. By ensuring infrequent phase reversals, it guarantees the frequency stability of the power transmission system, while dynamic capacity compensation in real-time achieves optimized governance of three-phase unbalance. Once the unbalanced powers are in the $\alpha-\beta$ coordinate system, the unbalanced compensation currents can be derived by applying the inverse Clark transformation to these powers. This inverse transformation converts the unbalanced powers back into the three-phase system, bu t in a form that represents the currents needed to balance the system. By following these steps, the distribution network can be maintained in a balanced state, ensuring optimal performance and minimizing potential issues related to unbalance.

6. Strategy of Data-Drive Three-Phase Unbalance Compensation

To address the issue of three-phase unbalance in power systems, we propose a data-driven strategy for managing three-phase unbalance, shown as in Figure 4. The detailed procedure of this strategy is as follows:

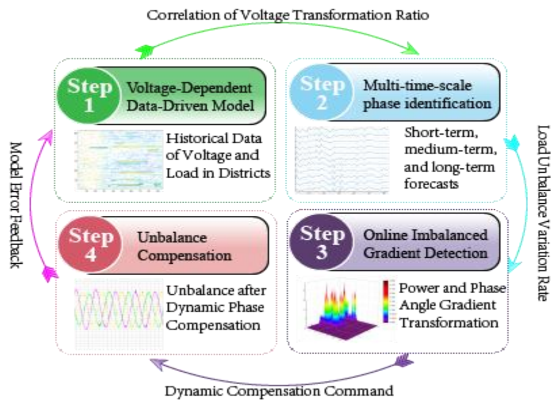


Figure 4. Clustered phase-shifting control architecture for distribution transformer load areas

Step 1: Data Collection and Preprocessing

First, real-time data on voltage, current, and other relevant parameters are collected from the power system using smart meters and other devices. Subsequently, the collected data undergo preprocessing, including data cleaning, noise reduction, and other steps to ensure the accuracy and reliability of the data.

Step 2: Data-Driven Phase Identification

Using the preprocessed data, a voltage correlation-based data-driven model is constructed for phase identification. This model accurately determines the phase affiliation of each user by comparing the correlations in voltage data. Additionally, short-term, medium-term, and long-term prediction methods, combined with techniques such as wavelet transformation, are employed to predict and identify phases across multiple time scales, providing a solid foundation for subsequent management efforts.

Step 3: Online Gradient Detection and Optimal Load Distribution

By calculating the gradient changes in load power and phase angle, the dynamic changes in load phase are monitored in real-time. Upon detecting any changes in load phase, a gradient-based load phase adjustment model is immediately triggered. This model dynamically adjusts the load distribution based on real-time monitoring data, redistributing unbalanced loads to other phases to optimize overall load distribution.

Step 4: Application of Unbalance Compensation Algorithms

Building on real-time monitoring and optimization, an unbalance compensation algorithm is introduced. This algorithm detects power unbalance in real-time based on live data and dynamically adjusts the load distribution according to the detected level of unbalance. The algorithm provides specific compensation formulas and strategies. Achieving three-phase load balance by adjusting the load quantities of each phase.

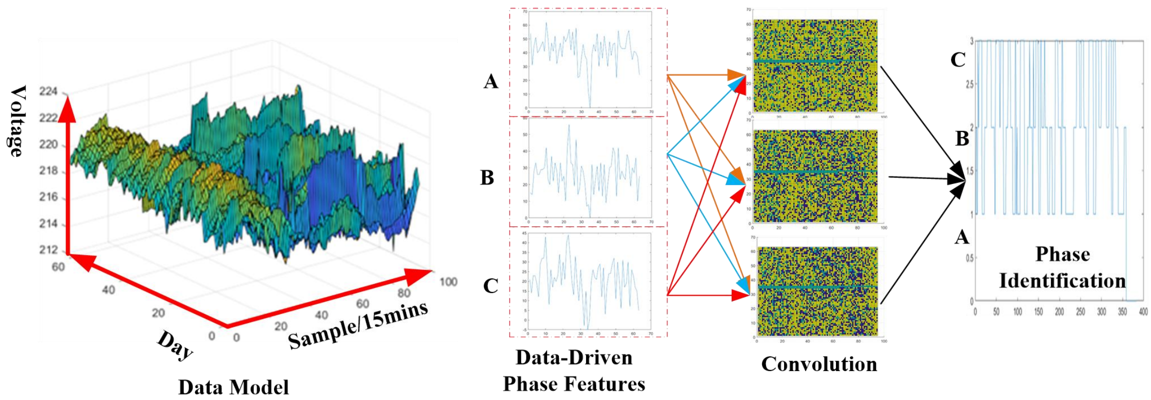


Figure 5. Examples and results of phase identification for transformer district load

7. Experimental Case Study Analysis

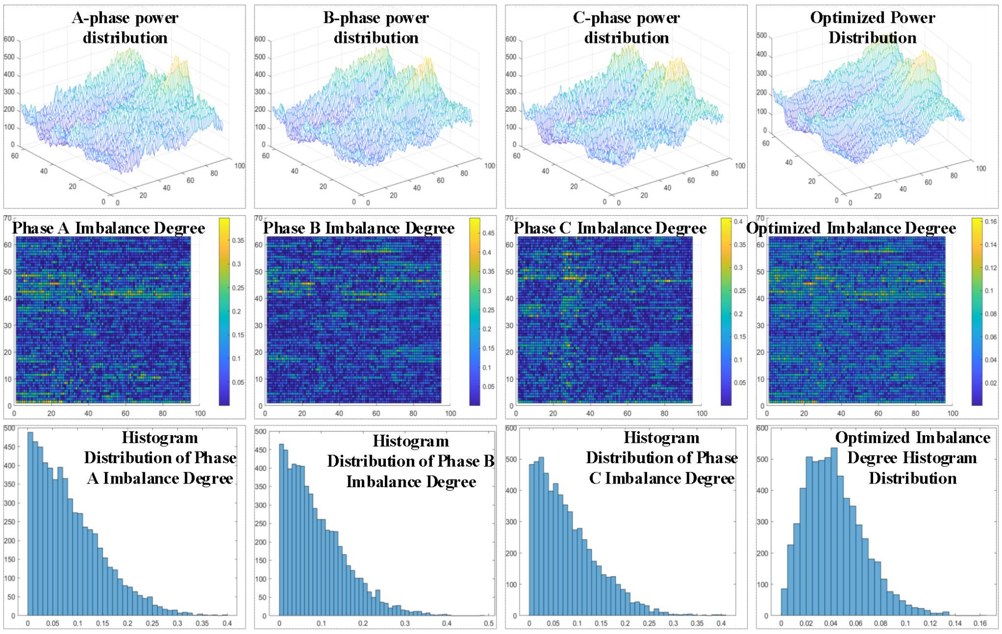
Verification and analysis of three-phase unbalance mitigation strategies in the 400V distribution area of Jin Yun Lane. The study object is a distribution area containing 358 single-phase loads, with the three-phase unbalance degree of the transformer ranging from 15.8% to 26%. The verification and analysis steps are as follows: First, the phase identification of single-phase loads is verified; Second, the load power gradient is validated; Third, analyze the unbalanced phase adjustment; Finally, the coordinated mitigation strategy of the unbalance mitigation device is verified.

A. Phase Identification Analysis of 358 Single-Phase Loads in a Distribution Area

As shown in Figure 5, the demonstration validation platform confirms that the voltage fluctuation range in the distribution area is between 213V and 224V. The voltage waveforms of the three phases (A, B, and C) at the voltage outlet of the distribution area were collected. Through data-driven model training, the characteristics of the three-phase data were obtained: the characteristic values of phase A fluctuate between 30 and 55, those of phase B between 15 and 40, and those of phase C between 5 and 30. The data-driven model-generated data characteristics exhibit significant phase differences. Subsequently, the convolution processing of the characteristic fluctuation values with the single-phase load data characteristics yields the target identification data characteristics. The target characteristic values are within a 5% identification margin of the phase characteristic values, leading to the identification results. Through phase A identification, 108 single-phase users were identified; through phase B identification, 120 single-phase users were identified; and through phase C identification, 130 single-phase users were identified. On-site verification of phase identification revealed that 5 users (2 in phase B and 3 in phase C) were incorrectly identified, primarily due to the similarity in the fluctuation of the data characteristic markings. Therefore, the phase identification accuracy is 98.6%.

B. Load Phase Voltage Gradient

As shown in Figure 6, the demonstration verification platform confirms that the three-phase power ranges from 0 to 400W, with a three-phase unbalance degree spanning from 5% to 35%. The unbalance degree of Phase A load ranges from 5% to 35%, with an unbalance probability of 63.62%, and the probability of optimizing to a 10% unbalance degree through gradient optimization is 35.4%. The unbalance degree of Phase B load ranges from 5% to 40%, with an unbalance probability of 64.78%, and the probability of optimizing to a 10% unbalance degree through gradient optimization is 37.65%. The unbalance degree of Phase C load ranges from 5% to 30%, with an unbalance probability of 61.64%, and the probability of optimizing to a 10% unbalance degree through gradient optimization is 32.14%. The unbalance degree of the three-phase load is time-varying. For a 1600KVA distribution transformer, the cost of compensation capacity at a maximum of 40% is relatively high. By optimizing the three-phase power gradient, with a target of 10% unbalance, the phase of critical load users is adjusted through phase-switching switches to achieve an optimized three-phase unbalance degree with a probability of 40.92% within the range of 5% to 10%. This phase optimization ensures that users remain on the same phase for 5 hours, preventing oscillation risks associated with frequent phase switching.

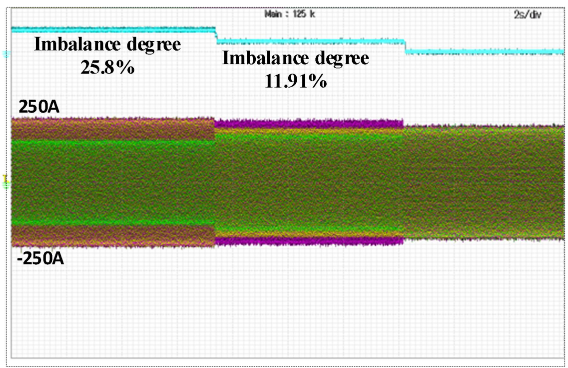


(a) Unbalance Degree of Phase A (b) Unbalance Degree of Phase B (c) Unbalance Degree of Phase C (d) Optimized Imbalance Degree

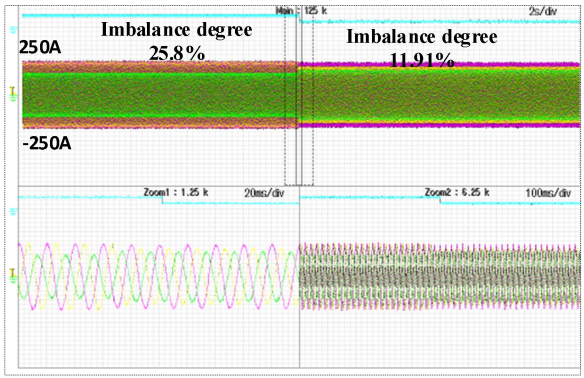
Figure 6. Gradient of three-phase voltage variation in transformer district load.

C. Verification of Unbalanced Coordination Governance Strategies

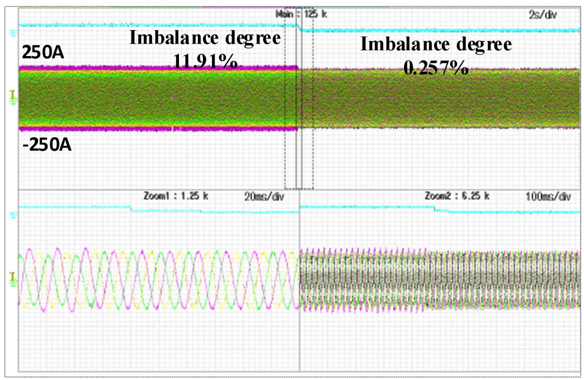
At the transformer outlet of the distribution station area, a three-phase unbalance compensation device with 15% capacity is installed. As shown in Figure 6, gradient optimization phase adjustment is performed under a scenario with an unbalance degree of 25.8%. Before phase adjustment, the currents in phases A, B, and C are 250A, 166.6A, and 250A, respectively, with a three-phase unbalance degree of 25.8%. After gradient optimization phase adjustment, the currents in phases A, B, and C are 214A, 192.5A, and 242A, respectively, with a three-phase unbalance degree of 11.91%. Finally, the auxiliary compensation device is used for compensation, resulting in currents of 216.5A, 217A, and 217.5A in phases A, B, and C, respectively, with a three-phase unbalance degree of 0.257%. Data analysis shows that the strategy of power gradient optimization and auxiliary compensation has a good effect on three-phase unbalance management, with lower costs, thus validating the effectiveness of the proposed method and strategy.



(a) Power Gradient Commutation and Auxiliary Compensation



(b) Power Gradient Commutation from25.8% to 11.91%



(c) Auxiliary Compensation from11.91% to 0.257%

Figure 7. Case study of unbalanced feeder zone auxiliary device governance.

8. Conclusion

This paper proposes a data-driven three-phase unbalance management strategy for distribution network transformer districts, leveraging intelligent algorithms and real-time data analysis to effectively address the issue of three-phase unbalance. The following is a summary of the contributions and innovations of this study:

1) By integrating data-driven methods with deep reinforcement learning and other intelligent algorithms, the traditional "curse of dimensionality" problem associated with high-dimensional state spaces in physical modeling is resolved. A phase identification method based on voltage correlation data-driven models is proposed, which accurately identifies user load phases by analyzing the dynamic relationship between voltage and load power.

2) An innovative multi-time-scale load phase adjustment strategy is introduced, combining short-term, medium-term, and long-term adjustments to comprehensively analyze the dynamic characteristics of load phase changes and perform intelligent adjustments accordingly.

3) A real-time online gradient detection technique is proposed, which can rapidly respond to load changes and adjust load distribution in a timely manner, effectively avoiding the lag issues inherent in traditional methods and significantly reducing three-phase unbalance.

4) The effectiveness and practicality of the proposed method are validated through real-world application cases, providing a new solution for three-phase unbalance management with significant engineering application value.

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