International Journal of Mechatronics and Applied Mechanics
2026, Issue 23, Vol. I

REAL-TIME MONITORING AND FAULT DIAGNOSIS OF DISTRIBUTION NETWORKS BASED ON SYNCHRONOUS PHASOR MEASUREMENT TECHNOLOGY

Rong Wang*, Haiying Shi, Shiyi Jing, Yan Lian, Tangqian Zhang
Xingyi Power Supply Bureau of Guizhou Power Grid Co., Ltd, Xingyi, 562400, China

Abstract - With the continuous development of modern power systems, distribution networks are becoming increasingly complex and dynamic, posing significant challenges to their safe and reliable operation. Real-time monitoring and accurate fault diagnosis have therefore become critical issues in power engineering. Based on synchronous phasor measurement technology, this study investigates a real-time monitoring and fault diagnosis framework for distribution networks and integrates intelligent computational algorithms to enhance monitoring efficiency and diagnostic performance. By utilizing synchronous phasor measurement units (PMUs), key electrical parameters-including voltage, current, and frequency-can be acquired in real time, enabling timely fault detection through advanced data analysis. In the experimental study, PMU devices were deployed to collect real-time grid data, and their measurement accuracy and response speed were evaluated in fault diagnosis scenarios. The results demonstrate that PMU-based measurements provide high precision and rapid responsiveness, significantly improving fault detection capability. Further analysis of fault occurrence frequency and system recovery time reveals that short-circuit faults are the most prevalent type, accounting for approximately 40% of all recorded faults, with a relatively short average recovery time of 15 minutes. In contrast, open-circuit faults and equipment-related faults exhibit longer recovery times, averaging 25 minutes and 30 minutes, respectively, indicating varying impacts of different fault types on system restoration. Additionally, a strong correlation between load fluctuations and voltage stability is observed; substantial load variations can lead to voltage deviations of up to 40 V, highlighting the critical influence of load dynamics on grid stability. The proposed fault diagnosis approach is further compared with several existing models in terms of diagnostic accuracy, false positive rate, and response time. The results show that the deep learning–based fault diagnosis model employed in this study outperforms other methods, achieving an accuracy of 98% and a false positive rate as low as 1%, albeit with a relatively longer response time. Overall, the findings indicate that the proposed deep learning–enabled PMU-based fault diagnosis system exhibits significant potential for intelligent and reliable distribution network management.

Keywords: Synchronous Phasor Measurement; Distribution Network; Fault Diagnosis; Deep Learning; Real-Time Monitoring.

1. Introduction

Nowadays, distribution networks are becoming increasingly complex, which makes monitoring distribution networks and diagnosing their faults more challenging [1]. Distribution networks are the final part of the power system, and their stability directly affects the power supply quality for many users. There are various uncertain factors, such as voltage changes, load variations, external interference, and equipment failures. All these situations have increased the difficulty of monitoring and fault diagnosis. Real-time monitoring of distribution networks and the rapid and accurate diagnosis of faults have become key challenges that modern power systems need to confront [2].

The phasor measurement unit, also known as PMU, is a relatively advanced technology. This technology can monitor the power system in real time by means of precise time synchronization [3]. PMU can measure synchronous voltage and current, thus collecting real-time data. Then, by analyzing these data,

dx.doi.org/10.17683/ijomam/issue23.22

potential faults or problems can be detected. In distribution networks, PMUs can enhance the accuracy of fault detection and also provide valuable support for fault diagnosis and recovery.

The development of computers is particularly rapid, which makes the application of synchronous phasor measurement in distribution networks possible [4]. With modern computing technology, phasor data can be processed and analyzed in real time. With the help of intelligent algorithms, rapid network status assessment can be achieved, and fault diagnosis can also be carried out quickly. Data transmission has been improved, and distributed computing has also been enhanced [5]. This makes real-time monitoring more efficient and flexible. By integrating big data, fault diagnosis and monitoring will become more intelligent and accurate. At the same time, it can also increase the degree of automation, enabling faster fault recovery

This article mainly focuses on how synchronous phasor measurement enhances the real-time monitoring and fault diagnosis capabilities of distribution networks when combined with computer technology. Specifically, the primary innovation of this study lies in the novel integration of high-frequency PMU data streams with a tailored deep learning architecture, providing a highly automated, low-latency framework for precise fault classification. This article will first explain some basic knowledge of synchronous phasor measurement and its benefits for real-time monitoring. Then, it will introduce how to create an effective fault diagnosis system and address the challenges faced in data processing and algorithm optimization.

2. Theoretical Basis and Related Research

2.1 Basic Theory of Synchronous Phasor

Phasor measurement unit technology is a real-time monitoring technology for power systems that relies on time synchronization. Its core principle is to use high-precision synchronous clocks to conduct phasor measurements on signals such as voltage and current in the power grid, providing key data that can reflect the operating status of the power grid [6,7]. Synchronous phasors are actually the detailed representation of data at a specific time. Just like a waveform. Phasor measurement technology operates based on some key principles, including the use of synchronous clocks and data transmission mechanisms. These principles enable PMUs to accurately measure the state of the power grid and ultimately achieve real-time monitoring of the power grid. By applying these concepts, PMUs can precisely track the state of the power system. And this precise tracking is extremely crucial for the efficient management and fault detection of the power system.

Synchronous phasor measurement employs high-precision clocks from the Global Positioning System (GPS). The PMU device is synchronized with the GNSS/Beidou clock to ensure that the time at each measurement point is synchronized, allowing us to accurately capture the phase difference and amplitude of voltage and current within a millisecond time range [8,9]. With this synchronization, data from multiple PMUs can be integrated into one, ensuring data consistency. Data consistency is crucial for effective monitoring and fault diagnosis. The generated data can reflect the real-time changes in the power system, such as voltage fluctuations and power flow changes, thus enabling accurate monitoring of the distribution network.

Synchronous phasor measurement encompasses aspects such as data acquisition, transmission, processing, and analysis [10]. The data from PMU devices is sent out in real time via high-speed networks and can be updated promptly. Computer technology plays a crucial role in processing large amounts of real-time data. By leveraging the powerful computing capabilities of computers, Applying operations such as the Fast Fourier Transform (FFT) to phasor data to extract key parameters, such as voltage bias and phase difference, is helpful for fault detection and potential problem prediction [11].

The application of intelligent algorithms has greatly enhanced the use of synchronous phasor measurement in fault diagnosis. Unlike traditional models that rely on static data, modern methods utilize big data and machine learning to establish fault diagnosis models by analyzing historical data. Algorithms based on deep learning can combine synchronous phasor data for pattern recognition [12]. It can also predict faults in the power system, thus enabling more accurate diagnosis of the types and locations of distribution network faults. These intelligent diagnostic methods have significantly enhanced the automation level of power grid fault diagnosis and also shortened the time required for fault recovery.

2.2 Present Situation of Real-Time Monitoring of Distribution Network Based on Synchronous Phasor Measurement

In recent years, with the increasing complexity of power systems, the distribution network, as the terminal part, has an increasing demand real-time monitoring and fault diagnosis [13]. Traditional monitoring methods of distribution networks mainly rely on physical equipment and static data acquisition, but these methods have some problems, such as poor real-time performance, long response time, and insufficient fault diagnosis accuracy. Synchronous phasor measurement (PMU) technology has gradually become an important technical means for real-time monitoring of the distribution network due to its high performance [14]. Through accurate synchronization of the synchronous clock, PMU can synchronously obtain the phasor information of voltage, current, and other signals of the power grid at each monitoring point, thus providing reliable basic data for real-time monitoring of the distribution network.

At present, some progress has been made in the application research of synchronous phasor measurement technology in distribution networks at home and abroad. Many distribution networks have begun to deploy PMU equipment and realize the comprehensive control of the operation status of the power grid by building real-time monitoring systems. By continuously collecting synchronous phasor data, these systems can effectively monitor key parameters of the power grid, such as voltage, frequency, and power flow, so as to discover unstable factors or potential faults in the system in time [15, 16]. When a voltage fluctuation, load change, or equipment failure occurs in the distribution network, PMU can quickly capture the change of power grid status, provide real-time data support for the dispatching center, and help dispatchers quickly determine and locate the fault location.

The application of synchronous phasor measurement technology in the current distribution network still faces some challenges, especially in data processing and analysis. Compared with the transmission network, the structure of the distribution network is more complex and widely distributed, which leads to the difficulty of processing and transmitting synchronous phasor data [17]. A large amount of data collected by PMU equipment in different places needs to be transmitted in real time through a computer network, and the real-time processing and analysis of this data depend on an efficient computing platform. The real-time monitoring system of modern distribution networks relies on powerful computing capabilities and adopts technologies such as distributed computing and cloud computing to ensure fast processing and accurate analysis of data. Combining big data technology, distribution networks can achieve the storage, processing, massive, providing technical support for the safety and reliability of distribution network operation [18,19].

The introduction of computer-based intelligent algorithms has significantly promoted the application of synchronous phasor measurement technology in fault diagnosis of distribution networks. The fault diagnosis system can analyze historical synchronous phasor data. In this way, when a fault occurs, it can quickly identify the fault and determine its location. The machine learning algorithm will learn the normal operation status of the power grid from the training data. Once an abnormal situation occurs, a fault warning will be issued [20, 21]. These technologies have enhanced the degree of automation in fault diagnosis, improved the accuracy and reliability of diagnosis, and at the same time reduced manual intervention, accelerating the speed of fault recovery. With the emergence of advanced algorithms such as deep learning, the fault prediction and diagnosis of distribution networks have become more intelligent and accurate, and the effect of real-time monitoring has also been improved.

3. Establishment of Distribution Network Model Based on Synchronous Phasor Measurement

3.1 Model Framework and Its Design

This study proposes a model for real-time monitoring and fault diagnosis of distribution networks using PMU technology [22]. It combines computer technology with the accuracy of synchronous phasor measurement, using distributed computing and intelligent algorithms for fault detection [23]. The model includes data collection, transmission, processing, fault diagnosis, and recovery control during operation, all of which are supported by advanced technology and can be smoothly integrated. The synchronous phasor calculation formula is shown in equation (1).

$$P = \frac{1}{N}\sum_{k=1}^{N} V_k e^{-j\omega t_k} \tag{1}$$

Among them, P represents the synchronous phasor, N represents the total number of data points, V_k represents the voltage value of the k sampling point, ω represents the angular frequency of the signal, and t_k represents the timestamp of the k sampling point. The fault diagnosis model formula is shown in (2).

$$F = arg\,\underset{f}{min}\left(\sum_{i=1}^{M}\left(\square\, d_i - d_f\, \square^2\right)\right) \tag{2}$$

Where F represents the diagnosis result, f represents the failure mode, M represents the number of sample data points, d_i represents the observation data of the i sample, and d_f represents the standard data matching the failure mode f. At the level of data acquisition, PMU equipment collects the voltage and current phasor data of each monitoring point in the distribution network in real time by synchronizing with GPS [24, 25]. The collected data is efficiently transmitted through the computer network to ensure that the data remains highly consistent with the operating status of the power grid in time. Then, the data transmission layer transmits the collected synchronous phasor data to the central monitoring system in real time through high-speed communication technology. Here, computer networks and distributed computing technology ensure the rapidity and accuracy of data transmission, and avoid the distortion of monitoring data caused by delay or packet loss. The PMU equipment data acquisition and transmission flow chart is shown in Figure 1.

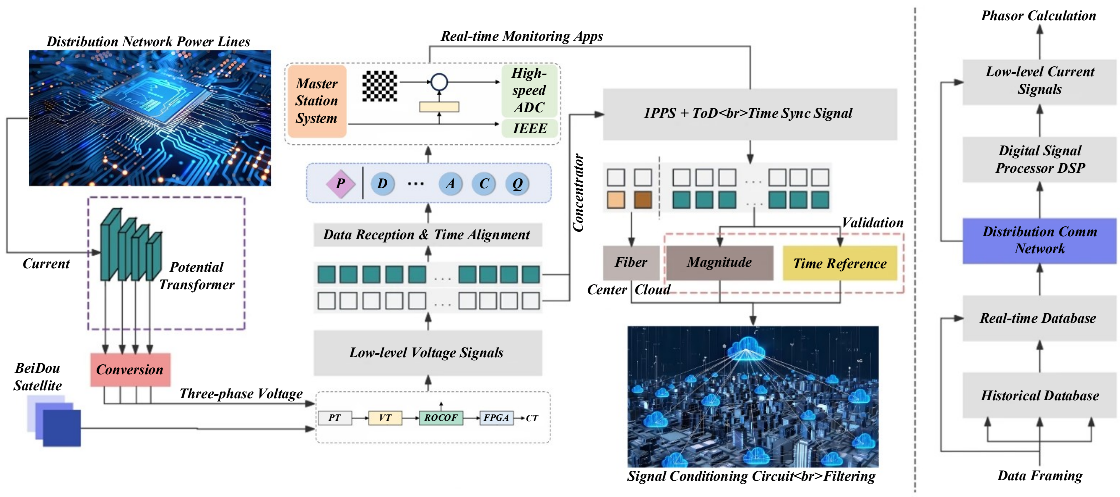

Figure 1: PMU equipment data acquisition and transmission flow chart

This flowchart shows the data acquisition and transmission process of PMU equipment. First, the PMU equipment collects the current and voltage signals of the distribution network through current sensors and potential transformers, and performs time synchronization with the help of the time synchronization signals provided by the Beidou satellite [26]. Then, the data is converted through a high-speed ADC, received and timed by the master station system, signals are conditioned and filtered, and finally transmitted to the cloud or database. The processed data is used for real-time monitoring and fault diagnosis to ensure efficient operation and accurate monitoring of the distribution network.

In the stage of data processing and analysis, computer technology plays a crucial role. By using efficient data processing platforms and real-time analysis algorithms, the real-time operational status of the distribution network can be fully displayed. This article uses mathematical algorithms such as fast Fourier transform to quickly analyze dynamic characteristic deviations, frequency fluctuations, etc., and identify potential fault risks. The fault diagnosis and recovery module uses data analysis to quickly locate faults and trigger rapid responses, and intelligent algorithms can improve system performance. This automation reduces manual intervention and accelerates fault recovery. The Fourier transform formula used for analysis is shown in equation (3).

$$X(f) = \int_{-\infty}^{\infty} x(t) e^{-j2\pi ft} dt \tag{3}$$

Where *x(f)* represents the frequency domain of the signal, *x(t)* represents the time domain signal, *f* represents the frequency, *t* represents the time, and *j* represents the imaginary unit. Voltage deviation analysis formula (4).

$$\Delta V_i = | V_i - V_{ref} | \tag{4}$$

Where ΔV_i represents the voltage deviation of the *i* node, V_i represents the actual voltage of the *i* node, and V_{ref} represents the reference voltage. This model combines synchronous phasor measurement data fusion with real-time monitoring and fault diagnosis, supplemented by intelligent algorithms. It can quickly identify and locate faults, improving the stability and reliability of the distribution network. This method is crucial for managing large-scale networks, improving the efficiency and fault recovery of modern power systems.

3.2 Data Acquisition and Real-Time Transmission Module

This module uses PMU devices with synchronous phasor technology to measure voltage and current in the distribution network. Real time data is sent to the monitoring system for accurate analysis, ensuring the reliability of the fault diagnosis system [27]. Its core is the high-precision measurement and efficient data transmission of PMU devices. Synchronous phasor measurement relies on the clock synchronization provided by GPS between each measurement point, thereby simultaneously obtaining instantaneous state information of the power grid. The flow chart of the data acquisition and real-time transmission module is shown in Figure 2.

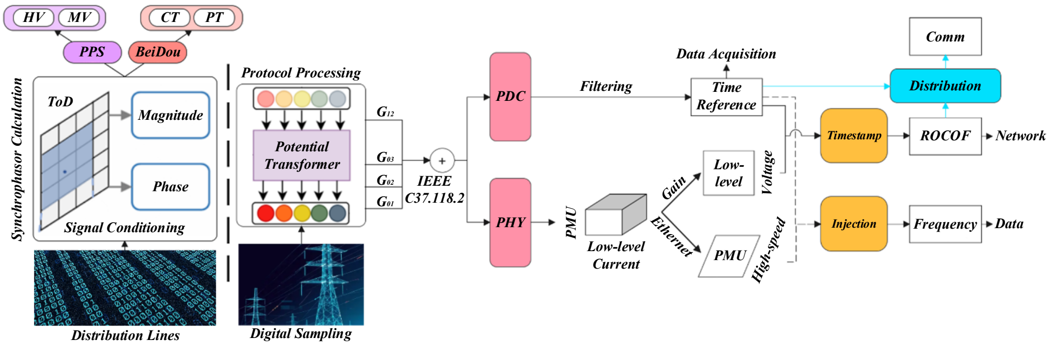

Figure 2: Flowchart of data acquisition and real-time transmission module

This flowchart shows the whole process of data acquisition and real-time transmission. The system obtains the data of the distribution network through the signal source, and performs signal conditioning and synchronous phasor calculation to generate amplitude and phase information. Then, the data is digitally sampled and protocol processed, normalized to data compliant with protocols such as IEEE 37.118. Then, the data is time-synchronized and filtered through PDC to ensure the accuracy and timing consistency of the data. The processed data is distributed through the network, and frequency and ROCOF analysis are carried out to realize real-time monitoring and fault diagnosis.

PMU equipment obtains the amplitude, phase, and frequency information of voltage and current by phasor conversion of voltage and current signals of the power grid, which are crucial for monitoring the dynamic characteristics of the power grid. The accuracy of data acquisition directly affects the accuracy of fault diagnosis and power grid condition monitoring. Each PMU device performs synchronous measurements at monitoring points and transmits the collected signals to the control center through a computer network [28]. The key to this process lies in stability of data transmission. High-precision data can be transmitted to the monitoring system promptly to avoid data inconsistency caused by delay or packet loss. The synchronous phasor conversion formula and phase difference calculation formula are shown in equations (5) and (6), respectively.

$$P = \frac{1}{N}\sum_{k=1}^{N} V_k e^{j(\theta_k)} \tag{5}$$

$$\Delta\theta = \theta_1 - \theta_2 \tag{6}$$

Among them, P represents the synchronous phasor, N represents the total number of data points, V_k represents the voltage amplitude of the k sampling point, θ_k represents the phase angle of the k sampling point, j represents the imaginary unit, $\Delta\theta$ represents the phase difference, θ_1, θ_2 represent the phase angles of the two phasors.

This module uses high-speed networks and distributed computing to enhance data transmission stability and efficiency. It processes data from multiple points in real-time, ensuring synchronization and reducing delays, which improves fault detection and network reliability [29]. The communication protocol and encryption protect data from loss or tampering. The formula for summarizing distributed computing data is shown in equation (7).

$$D_{agg}(t) = \sum_{i=1}^{N}\left(w_i \cdot D_i(t)\right) \tag{7}$$

Where $D_{agg}(t)$ represents the aggregated data value, $D_i(t)$ represents the data value of the i measurement point at time t, i represents the weight of the i measurement point, and N represents the number of measurement points. The data synchronization formula is shown in (8).

$$D_{shyc}(t) = D_i(t - \delta t) \tag{8}$$

Among them, $D_{sync}(t)$ represents the data value after synchronization, $D_i(t)$ represents the original data value of the i node, and δ_t represents the time synchronization error. The design advantage of the data acquisition and real-time transmission module lies in the high-precision synchronous measurement of the PMU and a powerful data transmission system, which can provide reliable real-time fault diagnosis. Compared with traditional static monitoring methods, this module has extremely high real-time and accuracy, and can capture the operation abnormalities of the power grid in time [30]. Through the high-speed transmission of a computer network, the system can collect and process a large amount of data in a very short time, which provides sufficient information support for the subsequent data analysis and fault diagnosis module.

3.3 Data Processing and Fault Diagnosis Module

The data processing and fault diagnosis module is one of the core modules of this model. Its main task is to analyze the state of the power grid by real-time processing of collected synchronous phasor data, and to achieve rapid positioning and diagnosis when faults are detected. This module uses data processing algorithms and advanced methods to analyze real-time phasor data and detect faults or anomalies in the system.

In the data processing stage of this article, efficient cleaning algorithms are used to preprocess and denoise the phasor data to ensure accuracy. The system applies methods such as Fast Fourier Transform (FFT) to analyze voltage and current signals, extracting key parameters such as frequency, amplitude, and phase. These data help detect issues such as voltage instability and frequency fluctuations, thus enabling early identification of potential faults. The formula for data denoising and cleaning is shown in equation (9).

$$x_k = H_k \cdot x + e_k \tag{9}$$

Where x_k denotes the measurement value, H_k denotes the measurement matrix, x denotes the state vector, and e_k denotes the measurement error. The load estimation formula of the distribution network is shown in (10).

$$L(t) = \sum_{k=1}^{N} \left(V_k I_k \cos(\theta_v - \theta_i) \right) \tag{10}$$

Where $L(t)$ represents the load, V_k, I_k represent the amplitudes of the voltage and current, and θ_v, θ_i represent the phase angles of the voltage and current. In the fault diagnosis stage, the system employs a deep learning-based architecture, specifically utilizing a LSTM network, to analyze the temporal sequence of the grid faults. The AI network architecture is systematically designed with an input layer corresponding to the dimensional features of the normalized PMU data, followed by two hidden LSTM layers to capture the complex temporal dependencies of the voltage and current fluctuations. A dense output layer utilizing a softmax activation function is deployed to probabilistically classify the fault types. During the training phase, the network utilizes a categorical cross-entropy loss function optimized via the Adam optimizer.

By learning from historical data, the system can identify and locate faults in real-time. It automatically classifies faults, such as voltage drops, overloads, or short circuits, and pinpoints their location within seconds. This intelligent method improves fault detection accuracy and efficiency while reducing manual intervention. The formula for fault location in the distribution network is shown in equation (11).

$$d = \frac{L_{fault}}{V} \tag{11}$$

Where d represents the fault location, L_{fault} represents the distance from the fault point to the measurement point, and V represents the voltage amplitude. This module combines big data technology and machine learning to enable intelligent fault identification and localization. Unlike traditional, error-prone models, it uses automation for accurate fault diagnosis, greatly improving efficiency and accuracy. This method allows for quick fault recovery, enhancing the stability and reliability of the distribution network.

4. Experimental Results and Analysis

The data for this experiment comes from synchronous phasor measurement devices at different nodes of the distribution network, which include voltage, current, frequency, and phase. These real-time data are sent to the processing platform through a high-speed communication network, which helps with fault diagnosis and monitoring.

The hardware of this experiment includes a synchronous phasor measurement unit, data acquisition equipment, communication equipment, and sensors in the distribution network. The phasor measurement equipment in the experiment ensured accurate collection and precise time synchronization of dynamic power grid data. The data acquisition device converts real-time power parameters into digital signals, which are then transmitted to the backend system through a high-speed network.

Table 1. Performance of synchronous phasor measurement equipment

Measuring equipment model	Measurement accuracy	Response time (ms)	Data update frequency (Hz)
PMU-001	0.1%	30	50
PMU-002	0.05%	35	60
PMU-003	0.08%	40	55
PMU-004	0.12%	25	50

The software platform for this experiment consists of a data analysis system, a fault diagnosis module, and visualization tools. Specifically, the artificial intelligence models and the experimental evaluations were implemented using Python 3.9 within the TensorFlow framework. The synchronous phasor data processing, mathematical signal transformations, and system visualizations were executed using MATLAB R2023a. The data analysis system uses processing algorithms to monitor and analyze the distribution network in real-time. The fault diagnosis module uses machine learning to quickly detect and locate faults by comparing real-time data with historical data. The integration of these software and hardware components ensures efficient and accurate results. Table 1 summarizes the performance characteristics of synchronous phasor measurement equipment.

As shown in the table, PMU-002 performs excellently in measurement accuracy and data update frequency, with an accuracy of up to 0.05% and an update frequency of 60Hz. This makes it ideal for real-time monitoring tasks that demand high-precision and high-frequency data acquisition. While PMU-003 offers high measurement accuracy, its response time is slower and its update frequency is lower, making it better suited for applications where high real-time performance is not critical. The performance of PMU-001 and PMU-004 is moderate, but PMU-004 performs more outstandingly in response time, so it is more suitable for rapid response requirements in fault detection.

In order to analyze the error comparison of different synchronous phasor measurement devices under varying accuracies and assess their impact on distribution network fault monitoring, this paper compares the synchronous phasor measurement errors across devices with different measurement accuracies. The results of this comparison are presented in Figure 3.

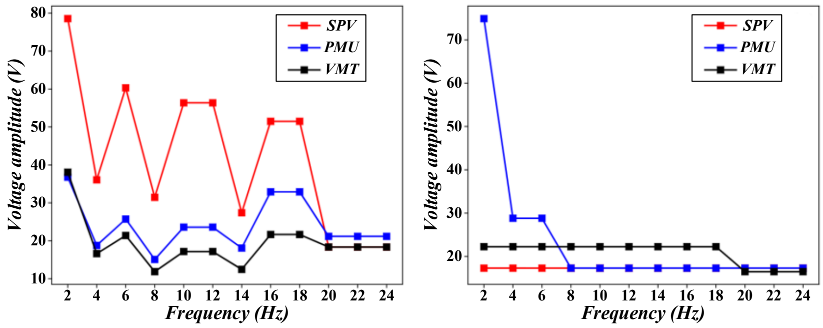

Figure 3: Comparison of synchronous phasor measurement errors under different measurement accuracies

As shown in the figure, where SPV represents synchronous phasor, PMU stands for phasor measurement unit, and VMT refers to measurement error, the data reveals that the measurement error of SPV is relatively large at low frequencies. Additionally, the error exhibits significant fluctuations as the frequency changes. This highlights the sensitivity of synchronous phasor measurements to frequency variations, particularly at lower frequencies, which could impact the accuracy of fault monitoring in the distribution network. PMU and VMT are relatively stable in measurement accuracy, especially VMT has a small error and a stable response to different frequencies. SPV has a large error when the frequency changes greatly, while PMU and VMT provide more accurate measurement results, especially at high frequencies. PMU and VMT can maintain a lower error rate.

To show the frequency of faults in different periods of the distribution network, analyze the load characteristics of the distribution network in each period and the possible high-incidence period of faults, this paper analyzes the relationship between the fault incidence rate of the distribution network and the period, and the results are shown in Figure 4.

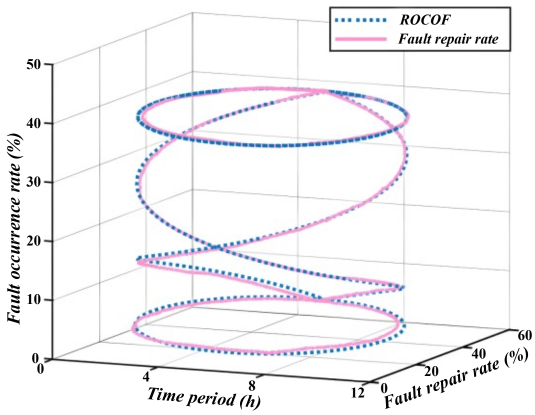

Figure 4: Relationship between fault incidence rate and time period of distribution network

It can be seen from the figure that with the change of period, the failure incidence rate and repair rate show periodic fluctuations. In the first half, the failure rate is high, close to 40%, and the failure repair rate is low, only about 10%-20%. When the period is about 6 to 12 hours, the failure rate gradually decreases to about 10%, and the repair rate increases significantly, reaching about 50%. This change shows that in some specific periods, the failure frequency of the system is high, while the failure repair efficiency is low.

In order to compare the recovery time and frequency of different types of faults to evaluate the fault handling efficiency and system repair capability, this paper compares the recovery time and frequency of different types of faults, and the results are shown in Figure 5.

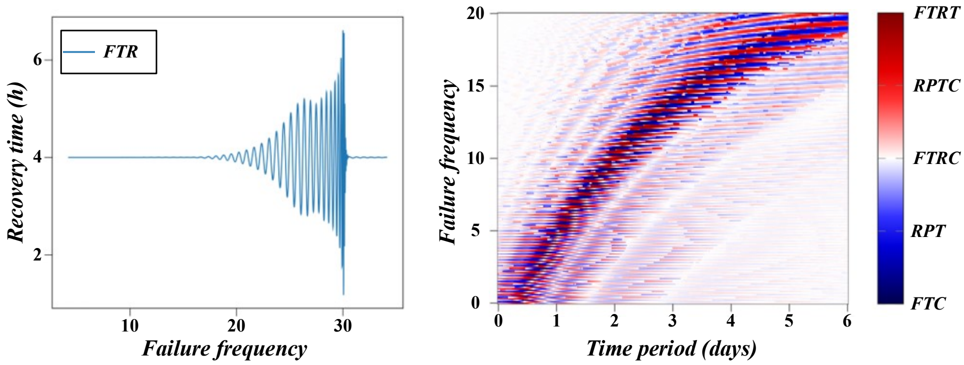

Figure 5: Comparison of recovery time and number of failures for different fault types

FTR represents the fault recovery time, FTC represents the number of faults, and RPT represents the recovery time and fault type. This figure shows the recovery time compared to the number of failures for different failure types. The left panel shows the FTR as a function of fault frequency. It can be seen that with the increase of fault frequency, the recovery time presents a trend of oscillation fluctuation, and the maximum recovery time reaches about 6 h, while when the fault frequency is low, the recovery time is shorter, about 4 h. The increase of fault frequency leads to the instability of recovery time, which reflects that high-frequency faults will affect the efficiency of system recovery. The figure on the right shows the change of fault frequency of different fault types in different periods through a heat diagram. The color shade in the heat map indicates the fault frequency under different fault types, and the redder the color, the higher the frequency. The data show that when the period is about 1 to 3 days, the fault frequency of FTRT and RPTC types is higher, indicating that the frequency of these types of faults is more concentrated. In the cycle of more than 5 days, the failure frequency is relatively low, and the system recovery is relatively stable. There is a certain relationship between the recovery time and the frequency of different types of faults. High-frequency faults in a short time will lead to a longer recovery time, but in a longer time period, the fault recovery is more stable.

Table 2. Distribution of fault types in distribution network

Type of failure	Number of failures (times)	Failure rate (%)	Average recovery time (minutes)
Short circuit fault	120	40	15
Open circuit fault	80	26.7	25
Equipment failure	60	20	30
System load abnormality	40	13.3	20

The distribution of fault types in the distribution network is shown in Table 2. As can be seen from the table, short-circuit fault is the most common type of fault, accounting for 40% of the total number of faults, and the recovery time is relatively short, averaging 15 minutes. This indicates that short-circuit faults are generally the most common and easiest to handle type of fault. Open circuit failures and equipment failures are rare, but the recovery time is relatively long, especially for equipment failures, which require more time to repair and recover. System load abnormalities. Although the failure rate is low, the recovery time is 20 minutes, indicating that this type of failure may require some system adjustment or load management.

In order to explore the relationship between load fluctuation and voltage stability of the distribution network, this paper analyzes the correlation between load fluctuation and voltage stability of the distribution network, and the results are shown in Figure 6.

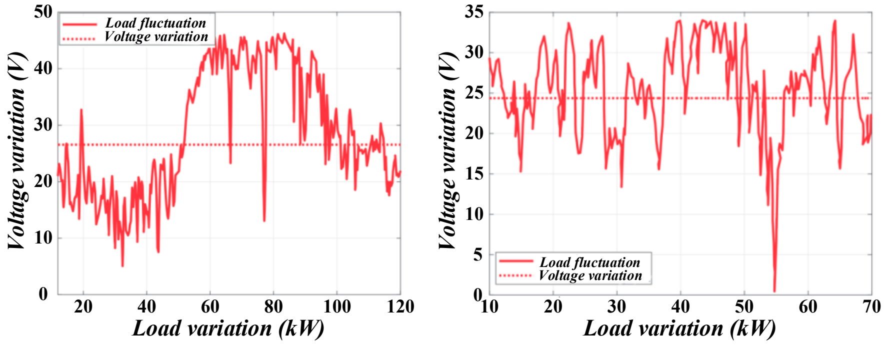

Figure 6: Correlation analysis between load fluctuation and voltage stability of distribution network

It can be seen from the figure that with the increase of load, the amplitude of voltage fluctuation also increases, especially in the range with large load fluctuation, where the voltage fluctuation is violent, and the maximum voltage change is close to 40V. At this time, there is a strong correlation between voltage fluctuation and load fluctuation, and voltage change and load change are almost synchronized. The figure on the right shows that when the load fluctuation range is small, the voltage fluctuation amplitude is small, the voltage change is relatively stable, and the highest voltage change is about 25V.

In the interval with small load, the voltage change is relatively stable, and the fluctuation amplitude is small, which indicates that the fluctuation of load has little influence on voltage stability.

To compare the performance of different fault diagnosis system models in terms of accuracy and false alarm rate, to evaluate the effectiveness and reliability of various models in practical applications, this paper compares the accuracy of fault diagnosis system models with false alarm rate, and the results are shown in Figure 7.

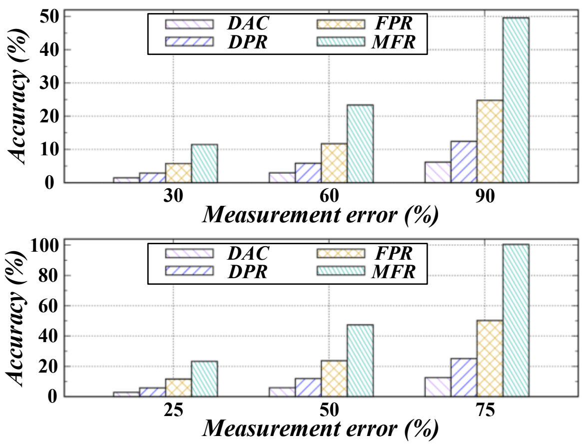

Figure 7: Comparison of model accuracy and false alarm rate of fault diagnosis system

The figure above shows that DAC stands for fault diagnosis accuracy, FPR stands for false alarm rate, DPR stands for diagnostic performance, and MFR stands for the comparison of model accuracy and false alarm rate. When the measurement error is 90%, the accuracy of the DAC model decreases to about 10%, while the DPR model is relatively high and remains around 30%. The accuracy of the FPR model is low at 90% measurement error, only about 5%, while the MFR model is even worse, with almost zero accuracy. As the measurement error decreases, the accuracy of all models improves, especially the DPR and DAC models, which reach 40%-50% accuracy at 30% measurement error. In the figure below, the accuracy of all models is generally high at 25% and 50% measurement errors, with the DPR model approaching 100% accuracy. The accuracy of the DAC model decreases slightly at 50% error, but it still maintains a high accuracy. However, the performance of FPR and MFR models is poor, and their accuracy is still not ideal, even at low error, and the accuracy of the FPR model is only about 30% at 50% error.

To analyze the relationship between the response time of synchronous phasor measurement equipment and the data update frequency, and evaluate the impact of equipment response speed on real-time monitoring, especially when a distribution network fault occurs, this paper analyzes the relationship between the response time of synchronous phasor measurement equipment and the data update frequency. The results are shown in Figure 8.

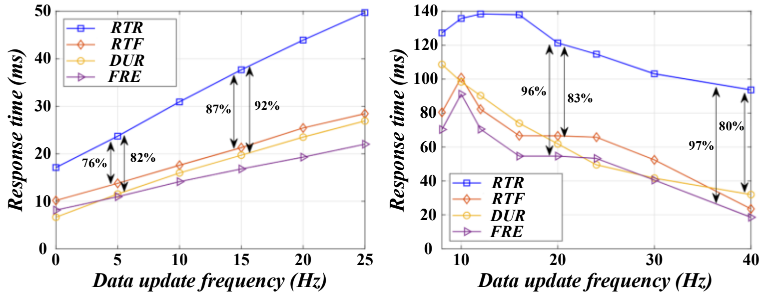

Figure 8: Relationship between Response Time and Data Update Frequency of Synchrophasor Measurement Equipment

As can be seen from the chart, RTR represents response time and frequency, RTF represents response time and frequency change, DUR represents delay and update frequency, and FRE represents update frequency and response time. In the left panel, the response time gradually increases as from 0 to 25 Hz. Specifically, the response time of the RTR model increased from about 10 ms to close to 50 ms, an increase of about 76%; The response time of the RTF model also increased from about 8ms to about 35ms, an increase of 82%;

The response times of the DUR and FRE models changed less, with increases of 87% and 92%, respectively. The figure on the right shows a higher update frequency, and the response time trend is different at this time, the response time gradually decreases. RTR model decreased significantly, from 120 ms to about 50 ms, with a reduction of 96%; The response time of the RTF model decreased from about 100ms to about 70ms, a reduction of 83%; The response time was reduced by 80% and 97% for the DUR and FRE models, respectively.

Table 3. Accuracy evaluation of fault diagnosis model

Model Type	Accuracy (%)	False alarm rate (%)	Underreporting rate (%)	Average response time (s)
Rule-based model	90	5	10	1.2
Machine learning-based models	95	2	5	0.8
Deep learning-based models	98	1	3	0.6
Hybrid model	97	1.5	4	1.0

The accuracy evaluation of the fault diagnosis model is shown in Table 3. As can be seen from the table, the fault diagnosis model based on deep learning performs best in terms of accuracy and false alarm rate, with an accuracy rate of 98% and a false alarm rate of only 1%. Although deep learning models are slightly slower than other models in response time, their high accuracy makes them well worth adopting in practical applications. The model based on machine learning also performs well, with an accuracy rate of 95% and the shortest response time, making it suitable for scenarios with high real-time requirements. The rule-based model has low accuracy, but it can still function effectively in some simple fault cases.

In order to compare the performance of different fault detection models in terms of false negative rate and response time, and analyze their impact on distribution network fault detection efficiency, this paper compares the false negative rate and response time of distribution network fault detection models, and the results are shown in Figure 9.

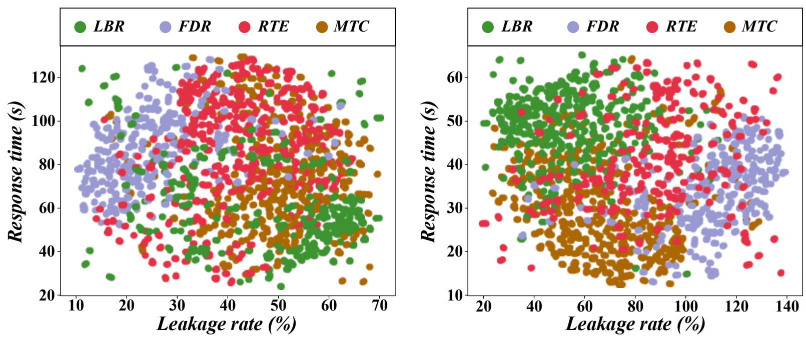

Figure 9: Comparison of false negative rate and response time of distribution network fault detection model

As can be seen from the figure, the response time of most models shows a downward trend as the false negative rate increases. Specifically, the LBR model has a shorter response time under a wide range of false negative rates and exhibits a faster fault response speed. In contrast, the response time of the MTC model is higher, especially when the false negative rate is high, showing a slower fault response. The false negative rates of different models have different effects on the response time, but overall, the response time of FDR and RTE models is moderate. The data suggest that there is a certain trade-off between false negative rate and response time, and a higher false negative rate may lead to shorter response time for some models, but it may also increase the error rate of fault detection, especially for MTC and RTE models.

5. Conclusions

In this study, the real-time monitoring and fault diagnosis of the distribution network are deeply discussed by synchronous phasor measurement technology, and an effective fault diagnosis method is put forward by combining with a computer-intelligent algorithm. The experimental results show that this method can effectively improve the monitoring accuracy and fault recovery speed of the distribution network.

In the experiment, the PMU equipment used, such as PMU-002, has a measurement accuracy of 0.05% and a data update frequency of 60Hz, which can provide high-precision and real-time power grid operation data. PMU equipment not only captures transient changes but also comprehensively monitors of the power grid, thus providing reliable data support for fault diagnosis.

According to the analysis of fault types, short-circuit fault is the most common fault type, accounting for 40% of the total number of faults, and its average recovery time is 15 minutes, which is relatively short. In contrast, the recovery time for open circuit failures and equipment failures was longer, 25 minutes and 30 minutes, respectively. The experiment also shows that the load fluctuation of the distribution network has a significant influence on the voltage stability. When the load fluctuation is large, the voltage fluctuation range can reach 40V, which indicates that the load fluctuation has a great influence on the stability of the power grid.

Experimental data based on deep learning reaches 98%, and the false alarm rate is only 1%. Although its response time is relatively long, the model has high reliability and feasibility in practical applications due to its high accuracy. In addition, although the machine learning-based model is slightly inferior in terms of accuracy, it has a shorter response time when the real-time requirements are high, and is suitable for rapid fault diagnosis scenarios.

The real-time monitoring and fault diagnosis system of the distribution network based on synchronous phasor measurement technology, combined with deep learning and machine learning technology, can significantly improve the accuracy and automation level of fault diagnosis. This system will play an increasingly important role in the intelligent management and fault recovery of the distribution network, providing a strong guarantee for the stability and reliability of the power system. Furthermore, the experimental results presented in this study—such as the distribution of fault types, load-voltage interactions, and comparative model performance—offer valuable references for utility companies and grid operators in designing more resilient and adaptive distribution networks. The proposed framework not only advances academic research in power system monitoring but also demonstrates strong potential for real-world deployment in smart grid environments.

Funding

This work was supported by Southern Power Grid Technology Project (GZKJXM20232530).

References

[1] Abdulkadirov, R., Lyakhov, P., & Baboshina, V. "Physics-informed neural network model using natural gradient descent with Dirichlet distribution," Engineering Analysis with Boundary Elements, vol. 178, pp. 106282, 2025.
[2] Alasali, F., Salem, M., Mustafa, H. Y., Loukil, H., El-Naily, N., Saidi, A. S., & Holderbaum, W. "A clustering-based multi-setting overcurrent protection approach with optimisation and experimental validation for distribution networks," International Journal of Electrical Power & Energy Systems, vol. 170, pp. 110841, 2025.
[3] Almutairy, F., Scekic, L., Matar, M., Elmoudi, R., & Wshah, S. "Detection and mitigation of GPS Spoofing Attacks on Phasor Measurement Units using deep learning," International Journal of Electrical Power & Energy Systems, vol. 151, pp. 109160, 2023.
[4] Badrsimaei, H., Hooshmand, R.-A., & Nobakhtian, S. "Observable placement of phasor measurement

units for defense against data integrity attacks in real time power markets," Reliability Engineering & System Safety, vol. 230, pp. 108957, 2023.

[5] Dong, D., Zhu, N., Wang, J., & Li, Y. "Lattice-based sensor data acquisition strategy to solve sensor position drift in human gait phase recognition system with a single inertia measurement unit," Engineering Applications of Artificial Intelligence, vol. 147, pp. 110286, 2025.

[6] Maji, S., Kayal, P., & Ray, S. "A co-optimized approach for state estimation based micro phasor measurement unit allocation in power distribution infrastructure," e-Prime - Advances in Electrical Engineering, Electronics and Energy, vol. 5, pp. 100224, 2023.

[7] Mei, L., Hong, X., Liu, H., Yang, X., Peng, W., & Kong, Z. "High-resolution measurements of the full-angle aerosol scattering phase function in open path," Optics & Laser Technology, vol. 191, pp. 113386, 2025.

[8] Morato, A., Frigo, G., & Tramarin, F. "Fault simulation in Phasor Measurement Units: A study on system reaction time in a 5G network environment," Measurement: Sensors, vol. 38, pp. 101445, 2025.

[9] Nagarjuna, K., Bhalja, B. R., Agarwal, P., Samantaray, S. R., & Malik, O. P. "Complex plane based adaptive method for protection of series compensated transmission line using phasor measurement unit data," Electric Power Systems Research, vol. 234, pp. 110539, 2024.

[10] Pattanaik, V., Malika, B. K., Panda, S., Rout, P. K., Sahu, B. K., Samanta, I. S., Bajaj, M., Blazek, V., & Prokop, L. "A critical review on phasor measurement units installation planning and application in smart grid environment," Results in Engineering, vol. 24, pp. 103559, 2024.

[11] Venkatachalam, Y., Subbaiyan, T., & Golla, M. "Optimal placement of phasor measurement unit for implementation of WAMS in a grid system," Swarm and Evolutionary Computation, vol. 97, pp. 102041, 2025.

[12] Zhang, T., Liu, J., Wang, H., Li, Y., Wang, N., & Kang, C. "Fault diagnosis and protection strategy based on spatio-temporal multi-agent reinforcement learning for active distribution system using phasor measurement units," Measurement, vol. 220, pp. 113291, 2023.

[13] Zhang, Z., Karkri, M., Huang, Y., Wang, Y., Tankari, M. A., & Ibos, L. "Experimental study on optical properties of paraffin-based phase change material glazing units and their performance optimization based on NSGA-II," Journal of Building Engineering, vol. 108, pp. 112882, 2025.

[14] Ayazi, A. M., Shakarami, M. R., Doostizadeh, M., Namdari, F., & Nikzad, M. R. "Short-term optimal operation of phase shifting soft open point with high accuracy loss model in unbalanced distribution networks," Computers and Electrical Engineering, vol. 123, pp. 110284, 2025.

[15] Chen, Y., Wan, C., & Cheng, P. "Event-triggered stochastic model predictive control based on distributionally robust optimization approach for network control systems under DoS attacks," Signal Processing, vol. 238, pp. 110182, 2026.

[16] Çıkan, N. N. "Pareto Multi-Objective Reconfiguration of IEEE 123-Bus Unbalanced Power Distribution Networks Using Metaheuristic Algorithms: A Comprehensive Analysis of Power Quality Improvement," CMES - Computer Modeling in Engineering and Sciences, vol. 143, no. 3, pp. 3279–3327, 2025.

[17] Cossio-Montefinale, L., Quiñinao, C., & Verschae, R. "Orchard sweet cherry color distribution estimation from wireless sensor networks and video-based fruit detection," Computers and Electronics in Agriculture, vol. 235, pp. 110334, 2025.

[18] Fan, J., Wang, Z., Qin, F., Wu, H., Sun, D., & Wu, J. "A distribution feature extracting network with dual correlation for long sequence time-series forecasting," Neurocomputing, vol. 649, pp. 130806, 2025.

[19] Fu, L., Xu, Y., & Gao, S. "A multi-agent deep distribution approximation strategy optimization algorithm with multi-threaded parallel computing mechanism suitable for large-scale and complex urban road networks," Engineering Applications of Artificial Intelligence, vol. 155, pp. 110999, 2025.

[20] Guo, Z., Ji, X., You, W., Guo, H., Zhang, Y., Zhao, Y., Xu, M., & Bai, Y. "Workload distribution with rateless encoding: A low-latency computation offloading method within edge networks," Computer Networks, vol. 269, pp. 111381, 2025.

[21] Hong, H., & Kim, H. "VFT: A versatile fine-tuning scheme based on feature distribution-aware knowledge distillation for lightweight convolutional neural networks," Engineering Applications of Artificial Intelligence, vol. 159, pp. 111597, 2025.

[22] Kala, H., Rawat, M. S., & Uniyal, A. "Optimal allocation and technoeconomic analysis of solid state transformer in distribution network," Computers and Electrical Engineering, vol. 125, pp. 110417, 2025.

[23] Kumar, P., & Kar, B. "ZBR: Zone-based routing in quantum networks with efficient entanglement distribution," Journal of Network and Computer Applications, vol. 238, pp. 104156, 2025.

[24] Liu, S., Lv, J., Lv, P., & Cheng, Y. "Deep learning-based electricity theft detection for active

distribution networks with high photovoltaic penetration," Computers and Electrical Engineering, vol. 126, pp. 110551, 2025.

[25] Liu, S., Tang, Y., Yang, Y., & Xia, Y. "Analysis of the Standard for the Calculation of the Cost Consulting Fee of the Whole Process of Distribution Network Engineering," Procedia Computer Science, vol. 262, pp. 695–704, 2025.

[26] Liu, Z., Chanentia, F. N., Supvithayanond, P., & Fung, C. C. A. "Release probability distribution modulates attractor state stability and mobility in continuous-attractor neural networks," Neurocomputing, vol. 645, pp. 130450, 2025.

[27] Luo, F., Ren, Y., Yu, Y., Li, Y., Liu, Q., & Zhang, X. "A centralized discovery-based method for integrating Data Distribution Service and Time-Sensitive Networking for In-Vehicle Networks," Ad Hoc Networks, vol. 178, pp. 103950, 2025.

[28] Luo, Y., Liu, C., & Sun, K. "Analytical segmental holomorphic embedding power flow method for integrated transmission and distribution networks," International Journal of Electrical Power & Energy Systems, vol. 170, pp. 110809, 2025.

[29] Shao, S., Luo, S., Zhao, Z., Gong, K., & Pan, L. "Robust detection of unknown adversarial examples in network traffic via enhanced latent spatial distribution analysis with diffusion model," Applied Soft Computing, vol. 181, pp. 113390, 2025.

[30] Sohn, J., Sitaropoulos, K., Salamone, S., & Sela, L. "Multifractal analysis of acoustic signals for leak detection in urban water distribution networks," Advanced Engineering Informatics, vol. 67, pp. 103558, 202