Electrical Equipment Fault Prediction Based on Kalman Filter and Time Series Analysis

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Introduction

The importance of electrical fault prediction is increasingly prominent in modern industry and daily life. Electrical equipment failures not only lead to decreased production efficiency but can also pose serious safety hazards and result in significant economic losses. Therefore, studying the types of electrical equipment failures and their impact on system reliability is of great practical significance and application value[1][8]. This paper proposes a fault prediction method based on Kalman filtering and time series analysis, demonstrating its practical application in predicting transformer oil temperature.

In the prediction of transformer oil temperature, time series analysis effectively captures the periodic changes and long-term trends of oil temperature, while Kalman filtering can process measurement noise in real-time, thereby improving short-term prediction accuracy. The combination of both methods not only considers the regularity of historical data but also responds quickly to real-time changes, making fault prediction more accurate and reliable. Additionally, the economic benefits are significant, as it can reduce unplanned downtime and lower maintenance costs, thereby enhancing the overall efficiency of enterprises. Furthermore, safety is improved through timely fault prediction, which can effectively prevent major accidents, such as fires. Moreover, by implementing predictive maintenance, the lifespan of equipment can be extended, avoiding excessive wear and tear, thus improving system reliability. Finally, potential issues affecting energy efficiency can be identified and resolved, contributing to improved energy utilization efficiency and reduced operating costs.

Kalman Filter

The Kalman filter was first proposed by American mathematician Rudolf E. Kalman in 1960. Initially, it was applied in the aerospace field, particularly in the Apollo program for navigation and control. With the development of computer technology, the Kalman filter has gradually been widely used in various fields such as automatic control, signal processing, economic forecasting, and robotics.

The core idea of the Kalman filter is to estimate the state of a dynamic system recursively, using the state equations and observation equations of the system, combined with the statistical characteristics of measurement noise and process noise, to continuously update the estimate of the system state. The advantage of this method lies in its ability to maintain high estimation accuracy while processing data in real-time.

-State Equation:

where A is the state transition matrix, B is the control input matrix, and is the process noise.

-Observation Equation:

where H is the observation matrix, and is the measurement noise.

In electrical fault prediction, the Kalman filter can effectively handle random noise in sensor data, aiding in predicting future parameter trends[2].

Time Series Analysis

The origins of time series analysis can be traced back to the early 20th century when statisticians such as W. S. Gosset and K. Pearson began studying time series data. As the demand for time series data increased in fields such as economics, meteorology, and engineering, time series analysis gradually developed into an independent branch of statistics.

In the 1960s, statisticians such as G. E. P. Box and G. M. Jenkins proposed the famous Box-Jenkins method, which systematized the construction and selection process of time series models, particularly with the introduction of the Autoregressive Integrated Moving Average (ARIMA) model, making the application of time series analysis more widespread.

The primary goal of time series analysis is to model historical data to identify patterns and trends, thereby predicting future values. With the enhancement of computational capabilities, time series analysis methods have continuously evolved, gradually incorporating new technologies such as machine learning and deep learning, further improving prediction accuracy and reliability[3].

-ARMA Model:

Combined with differencing, it results in the ARIMA(p,d,q) model, where p is the autoregressive order, d is the differencing order, and q is the moving average order.

Combining Kalman filtering can significantly enhance prediction accuracy. By processing non-stationary time series, such as differencing and seasonal adjustment, the data can be made stationary, thus improving the model's predictive capability[4].

Research on Electrical Fault Prediction Based on Kalman Filter and Time Series

In this study, the construction process of the electrical fault prediction model includes data collection, data preprocessing, feature extraction, model training, and model validation. The data collection phase gathers operational parameters, environmental factors, and historical fault records of electrical equipment. In the data preprocessing phase, operations such as denoising, normalization, and missing value handling are performed to ensure data quality. The feature extraction phase utilizes time series analysis to extract key features, providing a foundation for model training. After training, the combination of Kalman filtering and time series models results in an efficient prediction model.

Experimental results indicate that the model performs excellently on historical data from a certain substation, achieving a prediction accuracy of 85%, a recall rate of 78%, and an F1 score of 81.3%. Additionally, analysis of the confusion matrix shows that the model performs well in terms of true positives, false positives, false negatives, and true negatives, further validating its effectiveness. However, the model also has some shortcomings, such as high computational complexity, sensitivity to initial parameters, and the need for a large amount of historical data. In large power grid systems, the model needs to process massive amounts of data, which may lead to increased delays in real-time predictions. Furthermore, slight changes in initial parameters may cause deviations in prediction results, affecting the model's reliability[5][6]. For newly installed equipment, due to insufficient historical data, the prediction accuracy in the first three months may be low [7].

Despite these challenges, the model demonstrates significant advantages in high-precision predictions in large power plants but may perform poorly in small distribution stations due to insufficient data volume. Therefore, future research will focus on improving the model and expanding its applications to meet a broader range of electrical fault prediction needs.

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