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Analysis of Situational Awareness in Substation Equipment Health Management

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Abstract

Situation awareness has been widely applied in disaster warning, equipment detection, monitoring and other scenarios. Its data fusion and analysis methods have developed in a diversified way. For the health management of substation equipment, there is still room for improvement in order to effectively integrate information from multiple sites, analyze the operating status of multiple devices, detect and locate faults, and predict the overall situation. This paper discusses the concept of situation awareness, analyzes its role in the automation and intelligence process of substations, and summarizes the commonly used algorithms for data processing, situation evaluation, and prediction in recent years.

Keywords

Situation Awareness; Equipment Health Management; Substation; Data Fusion Algorithm.

1. Introduction

As a node of power supply, the stable operation of substations is a crucial link to guarantee the daily life and industrial production electricity. On the other hand, ensuring the effective operation of power equipment is the core mission of power enterprises. The traditional operation and maintenance method in China's industry relies on regular inspection and power outage maintenance to identify faults and maintain equipment. This involves a lot of human resources and material and time resources. On the one hand, there are problems of excessive maintenance and prolonged power outages, and on the other hand, there is a risk of failure to repair in time. In recent years, as the power system has expanded and the power grid structure has become increasingly complex, the increasing number of substation sites and the need to cope with a variable open application environment have posed challenges to equipment management and maintenance in the power industry. Scholars both at home and abroad have been vigorously constructing intelligent power equipment situation awareness systems to achieve proactive health management through the analysis of equipment behavior states. This can achieve rapid and precise fault location and also evaluate and predict the power system situation. To connect various sites and utilize the data collected by secondary equipment, it is necessary to perform noise reduction and standardization on multi-source heterogeneous data for easy processing. Then, data fusion technology is adopted to interpret the observed environmental information, and based on this, evaluate and predict the operation status of power equipment. Scholars at home and abroad have done a lot of work in this field and made significant progress in various directions. However, how to improve the algorithm's performance, save expenses, and make the situation awareness system flexible to respond to new situations and threats in the open world has always been the technical focus of research on the application of situation awareness in civil fields.

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1.1 Overview of Situational Awareness

Different scholars have different definitions of situational awareness. Generally, situational awareness refers to the observation of situational elements within a certain time and space, and then using data fusion methods to analyze and understand the acquired information to obtain knowledge of the interested domain, and then use this knowledge to predict and infer the future status of these situational elements. In this definition, the concept of situational awareness is divided into three levels: perception level, understanding level, and prediction level. The perception level refers to the perception of environmental elements, the understanding level refers to the understanding of the current situation, and the prediction level refers to the inference of the future situation. Some scholars have summarized the operation of the situational awareness system into four stages: extraction of situational awareness elements, situational evaluation (information fusion and situational analysis), prediction of situational changes, and visualization of situational analysis, distinguishing between human decision-makers and electronic information systems and emphasizing the system's tool attributes.

The perception stage has an impact on subsequent processing depending on the observer relied upon. When humans act as observers, the input is natural language text information, which often poses challenges to preprocessing and algorithm design, while sensors can always convert other signals into electrical signal form for input to the system. When sensors act as observers, they record physical phenomena such as sound, light, electricity, temperature, or vibration truthfully. Compared with humans, sensors do not deliberately report false or withhold information, nor do they make subjective judgments. The cost of most sensors is less than human resources. When supported by a certain level of industrial technology, the probability of sensor failure is small, and even if a failure occurs, it is usually easy to troubleshoot. Sensors are usually placed in specific locations for specific purposes, even if they are placed on moving platforms such as drones or cars, there are means to quickly locate and track them. In the situational awareness system, sensors are reliable observers and important members of the perception layer.

Processing heterogeneous data from multiple sensors to obtain effective knowledge is a key content of the situational awareness system. Data processing includes preprocessing, analysis, and integration. In the preprocessing stage, noise filtering is first performed on the signal to obtain data containing more valid information and less redundant and interference information, and then all data are structured and standardized to reduce the burden of subsequent operations and avoid numerical overflow and other problems. Since data is collected from different sensors, different methods are mostly used for analysis, feature extraction, classification recognition, and selective retention or removal of detailed information. Finally, data is integrated according to a certain specific standard to obtain a consistent interpretation or description of the measured object.

The premise of making appropriate decisions is a comprehensive understanding of the current situation and an accurate prediction of the trend of the situation. However, the real-world application scenarios are often open, full of ambiguous or even conflicting information. Therefore, it is necessary to construct a high-level information fusion system that can cope with such environments. Such a system can discover the intrinsic correlations between data rather than treating observed events as isolated, and balance the confidence levels of each event rather than being biased or completely negating a certain possibility, so as not to fail when facing conflicting information. The number and complexity of input information required by the system will be controlled within a reasonable range. Within a certain range, with the increase of data volume, more accurate predictions of the situation can be made, and marginal decreasing effects will be demonstrated after exceeding a certain threshold. In order to construct a reasonable and usable situational awareness system, it is necessary to consider the specific application scenarios and the characteristics of the target objects, and comprehensively use various methods and technologies such as sensing, communication, data processing, and decision-making.

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2. Health Management of Substation Equipment

2.1 Power Measurement System of Substation

A single substation can have multiple power measurement systems connected in parallel to the busbar. The data concentration device will collect, convert and send their measurement results to the power dispatch automation system, as shown in Figure 1. The power measurement system consists of main unit, transmission unit, and conversion unit, which can convert the analog current and high voltage of the primary system into digital current and voltage signals for remote transmission [6]. The main unit is composed of transformers, which can convert larger primary analog quantities into smaller secondary analog quantities. The transmission unit not only includes the secondary circuit for transmitting electrical quantities, but also includes a merging unit device for merging and processing electrical quantities into a specified format of digital signals for forwarding. The conversion unit will convert the signals into messages suitable for transmission.

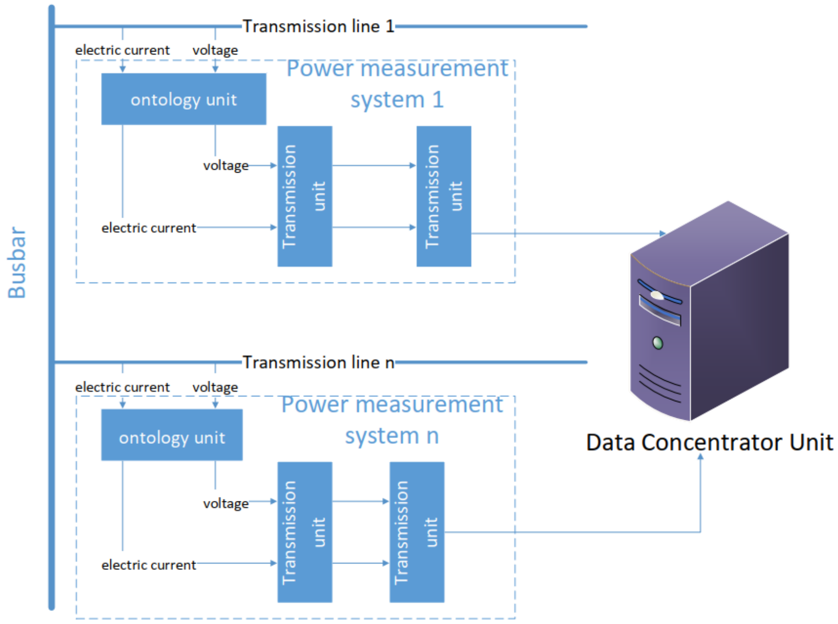

Figure 1. Power measurement system configuration of a single substation.

Multiple substations are connected to each other through transmission lines and are all connected to the power dispatch automation system through communication lines, as shown in Figure 2.

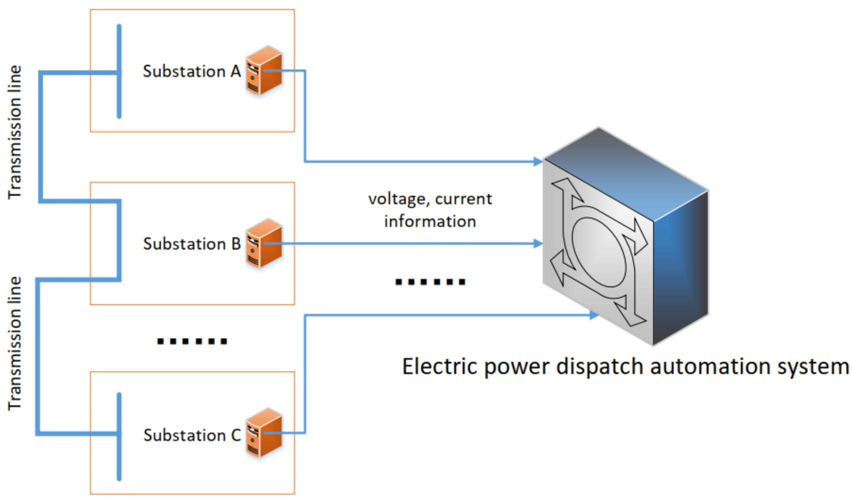

Figure 2. Schematic diagram of signal transmission and conversion.

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2.2 Substation Situation Awareness System

The substation situation awareness system consists of three levels: perception, understanding, and prediction. The perception stage considers both measurement and transmission. In China, substations are equipped with complete secondary equipment that can measure the electrical quantities of transmission lines to monitor the operation of the primary circuit. When a fault occurs in the primary circuit, the secondary circuit can also play a control role, stopping the primary circuit to prevent the fault from expanding. Information transmission within the station relies on Sampled Value (SAV) and Generic Object Oriented Substation Event (GOOSE) messages. GOOSE messages are used for command downstream protection actions for switching operations and to transmit switch status information, while SAV messages mainly transmit data exchange information of current and voltage values. Messages sent to the power dispatch automation system must conform to the IEC 104 standard.

The understanding stage involves data preprocessing and data fusion. Data preprocessing includes noise filtering and data normalization. With the increasing level of intelligence in the power grid, large amounts of data are generated during grid operation and equipment testing. In this trend, data preprocessing is an important guarantee for efficient and reliable data quality management. When selecting noise filtering algorithms, it is necessary to consider that the electrical signals in the substation system are non-stationary and have sudden changes. When selecting data normalization algorithms, the balance between running efficiency and resource consumption should be considered, and overly complex methods should be avoided. Data fusion is the core content of situation awareness. When designing this part, the algorithm's adaptability to open application environments and its ability to make accurate decisions under common conditions should be considered. The calculation results should also be sufficient to serve as a reference for human decision-making.

3. Data Preprocessing and Fusion

3.1 Data Preprocessing

3.1.1 Noise Filtering.

Wavelet transform is based on short-time Fourier transform, introducing scale function and translation factor, and its window function can adaptively change with scale [8]. Compared with Fourier transform, wavelet transform can perform multi-resolution analysis and is more proficient in processing transient signals, making it suitable for denoising signals collected by power measurement systems. Si Yang applied wavelet denoising to harmonic analysis in power systems, determined the wavelet basis, and proposed a threshold modification method to prevent harmonic components from being eliminated as noise [9]. Gu S et al. addressed the problem of fast extraction of electrical equipment state signals in digital substations, optimized ant threshold estimation using wavelet denoising, and obtained the global optimal threshold [10]. Tan Xue et al. improved the threshold function of wavelet so that it is continuous at the temporary threshold, thus solving the drawback of soft and hard thresholds, and proved through simulation that it is superior to traditional threshold functions [11]. The reasonable selection of wavelet basis functions determines the effectiveness of wavelet denoising. However, the wavelet basis is artificially selected.

Empirical mode decomposition (EMD) does not require the presetting of basis functions but rather adaptively decomposes signals according to their own characteristics, thus widely used in the field of non-stationary signal filtering [12]. Huang E believes that any complex signal can be decomposed into the sum of several intrinsic mode functions with a single instantaneous frequency, and proposed the algorithm for decomposition, namely, empirical mode decomposition [13]. A·Komaty et al. proposed a filtering algorithm that reconstructs signals from some sub-signals after EMD decomposition, using the Euclidean distance of probability density functions as the filtering criterion [14]. Y·Kopsinis et al. proposed a filtering and denoising algorithm that performs hard threshold filtering on sub-signals and then reconstructs signals [15]. Huang Huiting proposed an improved soft threshold filtering method and demonstrated through experiments that it has better denoising effect than the aforementioned hard threshold filtering method [16]. Compared with wavelet transform,

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empirical mode decomposition has unique advantages but lacks mathematical theoretical support and has relatively slow calculation speed [17].

3.1.2 Normalization

With the increasing application of artificial intelligence algorithms in the field of equipment operational status evaluation, data normalization technology is becoming more and more widely used in power grid data management [18] [19]. Gu Qinghua et al. used linear normalization functions to quickly normalize data collected by multiple sensors when constructing a mine safety and health management situational awareness system [20]. Lin Shunfu et al. used clustering to screen data, using Euclidean distance as an evaluation indicator, and considered data far from the cluster center as outliers and discarded them [21]. Gao Jinlan et al. standardized the feature indicator matrix by using the differential standardization process in the pre-processing stage when designing an algorithm to identify bad data in the power system [22].

3.2 Data Fusion Techniques

3.2.1 Bayesian Networks

Bayesian networks simulate the human reasoning process through a directed acyclic graph, and have good interpretability. As a probabilistic mathematical network model, it can perform inference on uncertainty-related knowledge. When evaluating the reliability of distribution systems, Hou Limin et al. established a multi-state Bayesian network based on the minimum state cutset of components, and used probability indicators to identify the weak points of the system. Zhou Fengli et al. introduced feature extraction and learning strategies into the Bayesian network algorithm, constructed a closed-loop system, and improved the fault classification capability of intelligent substations. Dai Zhihui et al. used dynamic Bayesian networks to analyze the reliability diagram of substation monitoring functions, and demonstrated through examples that it can well describe the dynamic characteristics of the system. Lu Rui et al. of the Wuhan Electrification Bureau of China Railway designed an engineering quality and safety control system based on Bayesian networks for the "Four Electrifications" project of railways, and discussed in detail the ideas of using Bayesian networks for risk management. Bayesian networks have a wide range of applications in the field of engineering, but the modeling process is complex. Whether it is determining the network's topology or constructing conditional probability tables, prior knowledge provided by professionals is required.

3.2.2 D-S Evidence Theory

D-S Evidence Theory uses belief intervals to directly express "unknown" and "uncertain" information, and is a commonly used data fusion algorithm [28]. However, this algorithm cannot effectively handle evidence conflicts [29], and its computational complexity grows exponentially. Many scholars have conducted extensive research to make this algorithm capable of dealing with conflicting evidence. Yager believes that the Dempster combination rule itself has problems, so he adopts a new synthesis formula that converts some of the conflicting evidence into overall uncertainty [30]. However, this method does not satisfy the associative law, and for highly conflicting or completely conflicting evidence, conflicting evidence is still assigned to the empty set, which does not fully utilize the information of conflicting evidence [31]. Haenni has proved that the Dempster combination rule satisfies both the commutative and associative laws, and believes that this rule has both solid mathematical foundations and the potential to handle a large amount of evidence [32]. Some scholars therefore believe that the Dempster combination rule itself is not the problem, but rather the model has issues. Murphy proposed that preprocessing conflicting evidence can both speed up algorithm convergence and handle evidence conflicts [33]. Following this idea, domestic scholars have improved Murphy's algorithm and achieved good results [34][35].

3.2.3 Rough Set

Rough set is an algorithm proposed by Pawlak to find internal correlations in large, highly redundant, and incomplete fuzzy information [36]. This algorithm has zero tolerance for uncertainty, making it lack fault tolerance. Moreover, while rough set theory can handle nonlinear and strongly coupled

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problems, it is relatively less effective in dealing with simple information. Wang and Ziarko proposed a probabilistic rough set model that improved the qualitative partitioning of the classical model to quantitative partitioning [37]. Yao proposed a decision rough set model, which can derive various probability models, thus providing a solid theoretical foundation for rough set theory [38]. Improved rough set models have high fault tolerance and are widely used in fields such as data mining and the Internet of Things [39].

3.2.4 Artificial Neural Networks

Neural networks are a type of artificial intelligence algorithm that mimics the way the human brain processes information. These algorithms have the ability to learn and remember, and after sufficient training, they not only have strong fault tolerance and resistance to noise interference, but also have high accuracy. Multilayer neural networks can solve complex nonlinear problems, and they have a wide range of applications and many practical achievements. Tong Zhongzheng et al. designed a data fusion method that combines neural networks and fuzzy reasoning, which was proven to be able to detect multiple faults in substation equipment simultaneously through experiments [40]. Wang Qi et al. used a convolutional recursive neural network to recognize infrared images that have been segmented into superpixels, and demonstrated through experiments that the system can effectively evaluate the operational situation of substation equipment [41]. Zhu Jiayi et al. designed a short-term electricity load forecasting method based on LSTM neural networks, tested the algorithm using competition data, and proved that its convergence speed and accuracy are superior to traditional algorithms [42]. Wu Yijia et al. constructed a convolutional neural network based on attention mechanism, used the network to extract defect image features of substation equipment, and demonstrated through experiments that this method greatly improves the detection method's anti-interference ability and accuracy [43]. Neural network algorithms require a large number of training samples and occupy a large amount of computing resources, which used to greatly restrict the development of this technology, but these problems have gradually become less prominent. There is currently no suitable mathematical explanation for the neural network model.

3.2.5 Hidden Markov Model (HMM)

Hidden Markov Model (HMM) is a statistical modeling technique for capturing hidden information from observable random variables. It is a specific form of dynamic Bayesian network and can also be seen as a two-dimensional extension of the Markov model [44]. Baum and Petrie proposed a probability model and its statistical inference method, which models the state sequence using a finite state Markov chain and generates an observation sequence from the state sequence [45][46][47]. Ferguson added a variable residence time for each state, making the duration distribution of the state explicit rather than implicit [48]. Rabiner developed the HMM and applied it to speech recognition [49]. Bryan et al. designed an autoregressive HMM and applied it to speech signal recognition, demonstrating that the algorithm can perform well even in the absence of prior knowledge [50]. Danisman argued that the assumption of conditional independence and identical distribution of classical model random variables may not hold in reality and proposed a new model with first-order Markov dependencies between adjacent states [44]. HMM has an unsupervised learning method and is widely used in fields such as speech recognition, text recognition, and weather forecasting, but its computation is slow and real-time performance is poor.

3.2.6 Markov Logic Network (MLN)

Richardson et al. combined first-order logic with Markov models to create a new statistical learning method called Markov Logic Network (MLN) [51]. MLN combines predicate logic and probabilistic graphs, improving the form of probabilistic graphs to compactly represent large Markov networks and facilitate knowledge base integration. The first-order predicate logic is also improved to express uncertain relationships. Snidaro et al. applied MLN to syntax integration and maritime situation assessment, demonstrating MLN's ability to encode uncertain knowledge and compute reasoning based on observed evidence [52][53]. Van Nguyen reviewed the applications of MLN in open-world situation awareness [54]. Yahui Wang et al. proposed a knowledge management framework based on

MLN and studied its application in civilian cockpit design, demonstrating the good combination of MLN with historical cases and knowledge bases [55]. The MLN theory is not yet perfect, and its learning efficiency is lower than previous models, and there are not many practical applications cases.

4. Summary and Outlook

Big data brings about big energy consumption, so the reasonable management of power resources is a necessary prerequisite for technological development. Fault detection and maintenance of substation equipment are important components of this management. Due to the different development status of countries and regions, the choice of fault diagnosis technology for power grid systems is not the same. The mainstream is still to achieve intelligent fault diagnosis through modern signal processing technology and artificial intelligence theory and pursue higher accuracy. China has a large power grid scale, high demand for electricity, and a high level of difficulty in maintaining the system. Therefore, the demand for intelligence is particularly urgent. It is necessary to explore the signal detection characteristics of substation equipment and fault diagnosis methods, to dig out more effective technologies, to find suitable detection methods, and to construct an efficient and practical equipment health management and situational awareness system.

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