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# AUTOMATIC CONTROL OF LOW VOLTAGE LOAD IN POWER SYSTEMS BASED ON DEEP LEARNING

YAOHUI SUN*, HONGYU ZHANG†, HAOLIN LI‡, SHU WANG§ AND CHUNHAI LI¶

**Abstract.** Due to the interference of false data, there is a large error in the mining results of low voltage loads in the power system. In response to this problem, the author proposes a design of an intelligent mining system for low voltage loads in the power system based on deep learning. Using ARM+DSP dual CPU structure, initializing the adapter agent, and using dual arm spiral antennas, designing a low-voltage load monitor to detect partial discharge signals in the 500-1500 MHz frequency band and suppress noise interference; By transmitting monitoring information to the intelligent switch through CAN bus or 485 bus, remote monitoring can be achieved; Based on the contact points and current characteristics of the circuit breaker, a current transformer has been designed to reduce the range of induced voltage variation; Construct a continuous set of functions MMD in the space, adjust the original network structure, establish a deep learning mining model, initial network parameters, eliminate false data in the network, optimize the network using target domain data, and combine mining engines to achieve intelligent data mining. According to the experimental results, the maximum difference between the load of phase A of the data processing system based on numerical simulation and the actual data is 1000 kVA at a time of 6 seconds; When the load of phase B is 4 seconds, the maximum difference between it and the actual data is 2000 kVA; When the load of phase C is 8 seconds, the maximum difference between it and the actual data is 2000 kVA. It has been proven that the mining error of the system is 0, and it has a precise mining effect.

**Key words:** Deep learning, Power system, Low voltage load, Intelligent mining

**1. Introduction.** The construction of the power system is an important guarantee for the well-being of the people, social stability, and national prosperity, and is an important lifeline industry. Promote green development, promote harmonious coexistence between humans and nature, accelerate the green transformation of development methods, coordinate the high-quality development of the economy and the improvement of ecological environment level, reduce energy consumption and carbon dioxide emissions per unit of GDP by 13.5% and 18% respectively [19]. This is a new requirement proposed by Premier Li Keqiang on behalf of the State Council to the energy and power industry at the Fourth Session of the 13th National People's Congress. The production and consumption of electricity are completed simultaneously, and large-scale and long-term energy storage technology is not yet mature. In power load forecasting, there is a common phenomenon of imbalance and disharmony between multiple prediction results. Without accurate and reliable load forecasting, it will result in large-scale energy waste, environmental pollution, and economic losses. In a broad sense, power load forecasting refers to the prediction of electricity consumption based on multiple influencing factors in the next hour to several years. Short term load forecasting is of great significance in ensuring the planning, reliability, and economic operation of power systems. The author mainly discusses the application of deep learning in short-term power load forecasting [16].

One of the traditional load forecasting methods is time series based forecasting methods, such as regression analysis, exponential smoothing, multiple linear regression, Autoregressive Integrated Moving Average Model (ARMA), and its improved algorithm ARIMAX. The basic idea is to predict future load values from the past and present load values of random time series. Its advantage lies in considering the temporal relationship of the data, while its disadvantage lies in the fact that the required time series is stationary and has limited predictive ability for nonlinear relational data, and has strict requirements for the stationarity of temporal data [12]. Due to the advancement of computer technology, the field of machine learning is undergoing another wave. Machine

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learning algorithms are widely used in various fields such as image recognition, object detection, natural language processing, and have also achieved good results in power load forecasting. Various advanced machine learning technologies such as reinforcement learning and transfer learning have been used in load forecasting. The limitation of machine learning lies in the insufficient learning ability of high-dimensional data. Deep learning can simplify the original data of scum, extract effective information, and form features. Artificial Neural Network (ANN) is one of the fundamental algorithms of machine learning, which is a standard neural network composed of input layer, output layer, and hidden layer. Another machine learning algorithm for load forecasting is Support Vector Machine (SVM), which has good performance in small-scale data processing but poor performance in handling massive data. Deep Learning (DL) is a branch of machine learning, whose architecture is based on neural networks and more complex models. It has more hidden layers and loop structures, which endows it with stronger learning ability, adaptive ability, fault tolerance, autonomous reasoning ability, and generalization ability.

**2. References.** The Unified Power Flow Controller (UPFC) has gradually been put into current engineering applications due to its ability to quickly and independently control the active and reactive power of transmission lines, and adjust the distribution of system power flow. However, while UPFC brings many technological advantages, it also significantly increases the complexity of the power grid structure and operation mode, posing great challenges to the safe and stable operation of the power system. Therefore, studying the safety correction control of power systems containing UPFC is of great significance for ensuring the safe operation of the power grid.

At present, the conventional calculation methods for power system security correction are mainly divided into two categories, namely sensitivity based methods and optimization planning based methods. The sensitivity method generally ignores the influence of reactive power, so there is a lack of consideration for the reactive power control capability of UPFC in systems containing UPFC. In contrast, optimization planning methods can be better applied to scenarios with UPFC [4]. In summary, when considering the minimum number of adjustment components and the minimum adjustment amount as the optimization objectives for system safety correction, current research usually adopts the establishment of mixed integer nonlinear programming (MINLP) models, but these models are computationally complex and often accompanied by solveless situations. Therefore, how to improve traditional physical model based security correction methods and maximize the computational efficiency and convergence of security correction is the main problem currently facing research in this field [3].

In recent years, artificial intelligence has developed rapidly, and machine learning methods represented by deep learning have been widely favored in the field of power systems due to their ability to process large-scale data and high computational accuracy.

Song, Z. Z. J proposed a new adaptive learning deep belief network (ALDBN) with a series of growth and pruning algorithms to dynamically adjust its structure when extracting features using ALDBN. Specifically, a neuron growth algorithm considering individual and macro influences was designed to detect unstable hidden neurons, and a new hidden neuron was added around each unstable neuron to compensate for the shortcomings of local structure in feature extraction [14]. Huang, Q applies pumped storage hydropower (PSH), which can quickly track load changes, operate flexibly and reliably, balance system power, and minimize bus voltage deviation. In addition, in order to obtain the optimal control strategy for PSH, a deep reinforcement learning algorithm, namely a deep deterministic strategy gradient, is used to train the agent to solve the continuous transformation problem of the pumped storage hydroelectric wind solar (PSHWS) system [7]. Wen, T considered a multi-agent system based load frequency control method for multi-area power systems under false data injection attacks. This study can provide a better solution for load frequency control in multi region power systems under false data injection attacks. Firstly, an event triggering mechanism was introduced to determine which data should be transmitted in the controller to save limited network bandwidth. In addition, a network attack model was established using Bernoulli random variables. Then, the conditions for the system to maintain asymptotic stability under attack are given. Finally, the effectiveness of the theory proposed in this paper was verified through simulation [18].

In response to the problems existing in the traditional system mentioned above, the author proposes a design method for an intelligent mining system for low-voltage loads in power systems based on deep learning. This method can analyze the complex features hidden in low-voltage loads of high-voltage switchgear in detail,

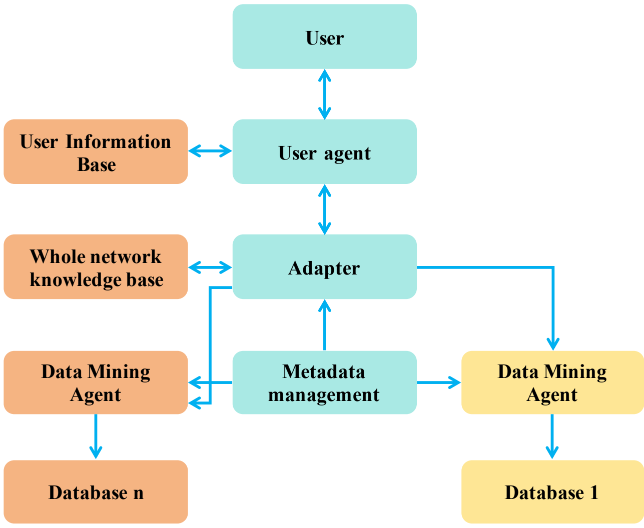


Fig. 2.1: System hardware structure

and accurately mine low-voltage loads in power systems under complex monitoring task conditions.

## 3. Methods.

**3.1. System hardware structure design.** The power system adopts advanced ARM+DSP dual CPUs, which receive three-phase current data collected by the power system monitor and send it to the station control service center through the IEC61850 protocol, achieving the remote monitoring function of the power system. The hardware structure of the system is shown in Figure 2.1.

*(1) Adapter.* The adapter is used to process the initialization information of the agent and achieve communication between the agent and the remote data collection system. This system includes the health status, location, and current system resources of each agent [11]. Each agent has an alias in the adapter, so the agent only needs to know its alias when communicating to determine where to run. Another function of this adapter is to decompose mining requests sent by UIA, and then send them separately to the corresponding DMA. After the mining process is completed, the results are directly merged and sent to UIA.

*(2) Low voltage load monitor.* The low-voltage load monitor is mainly used to monitor the insulation characteristics of the box, as shown in Figure 3.1.

From Figure 3.1, it can be seen that the online monitor is composed of a detection circuit, an IED, and an integrated information platform. It transmits partial discharge signals through high-frequency double shielded antennas, obtains as much discharge information as possible through the detection circuit, and can better suppress noise interference. Adopting a dual arm spiral high-frequency double shielded antenna, it can detect partial discharge signals in the 500 1500 MHz frequency band. Realize high-frequency dual shielding results through the IED display screen, and transmit the results to the integrated information platform through optical fiber to complete data monitoring.

*(3) Server.* The controller is designed using a dual CPU structure of ARM9 chip S3C2440A and TMS320F28335, with CAN network interface, RS-485 network interface, and RFID module set on the periphery. The IRIG-B code matching is used to provide accurate and unified time reference [2]. The high-voltage power system fully considers the impact of electromagnetic interference on equipment, and divides and isolates the power supply during the design of the power supply section. The server structure is shown in Figure 3.2.

As shown in Figure 3.2, the monitoring information is transmitted by the server to the intelligent switch through CAN bus or 485 bus. The intelligent identification unit identifies the information of the exchange device through RFID module and communicates with the service center according to the IEC61850 protocol to achieve remote monitoring function.

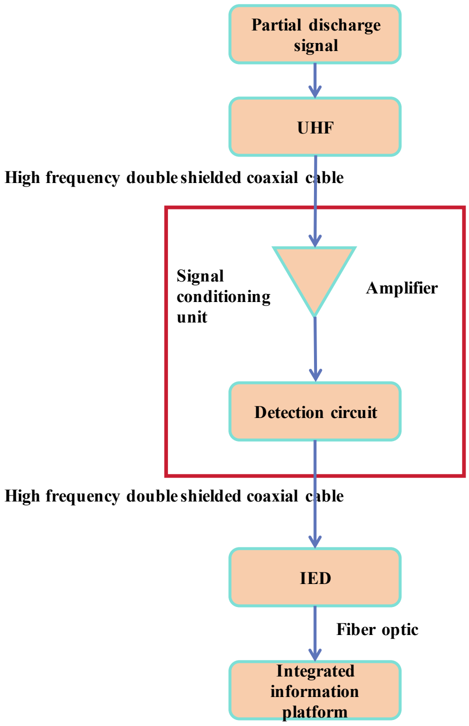


Fig. 3.1: Load data monitor

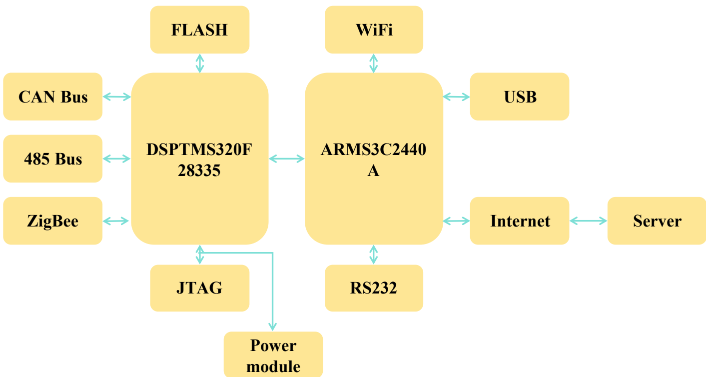


Fig. 3.2: Server structure

*(4) Power supply voltage.* Using a switching power supply module, the input AC 220 V is converted to DC 5 V, which is then converted to 3.3 V by the linear regulator chip MIC29502BU. Finally, by adjusting the chip LM1117, the 3.3 V voltage is converted to 1.5 V as the power supply. Due to the limitations of high-voltage conditions in the power system, the power supply of the monitoring device must be configured internally, using fixed energy sources such as batteries, which cannot guarantee the long-term operation of the system [5]. Therefore, a special current transformer has been designed, using permalloy as the iron core to ensure that the iron core generates high magnetic current when the excitation magnetic core is saturated at low current, thereby reducing the range of induced voltage variation, when the temperature of the busbar rises, based on the contact points and current characteristics of the circuit breaker, the principle of electromagnetic

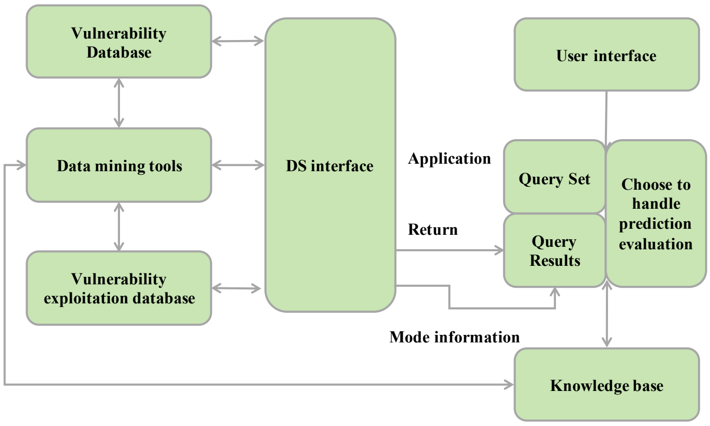


Fig. 3.3: Mining engine system structure

induction monitoring is used to directly obtain the low-voltage power supply of the equipment from the circuit breaker contact plate or busbar.

*(5) Mining Engine.* Unlike general database queries, mining engines use data mining techniques to process databases, generating specific query sets from a specific set of objects, and automatically accessing the database based on the query sets, thereby mining hidden rules in the database. The mining engine focuses on the low-voltage load library and load information library of high-voltage switchgear, achieving data mining of low-voltage loads of high-voltage switchgear. Figure 3.3 shows the system structure of the mining engine.

The mining engine takes object, domain knowledge, and pattern information as inputs, and the system generates some random query data. These query data are used as input to the database model, and the system predicts and evaluates the returned results [6].

**3.2. System software design.** Due to the differences in current distribution across different voltage and active power datasets, which affect the accuracy of mining results, it can be replaced with the weights of the fully connected layer, and the layer connection weights can also be adjusted to retain or abandon the weight feature selection of some source networks, learn new network weights to achieve the goal of retaining both source domain information and absorbing target domain information, and improve the learning ability of the network [8]. The parameters of the non adjustable layer are directly transferred and fixed from the source domain network, while the fully connected layer is retrained using target domain data, replaced and added, eliminating fixed parameters in the network to reduce learning rate, and optimizing the network using target domain data. Based on the hardware structure design of the power system, the intelligent mining process based on the above analysis is shown in Figure 3.4.

In Figure 3.4, first preprocess the source and target domain data; Then, the original deep neural network model or the trained network structure and parameters are trained using source domain data to establish a source domain classification and prediction model [15]; Finally, by analyzing the maximum mean difference between the source domain and target domain data through MMD, the distribution distance is determined, and pre training and preprocessing are carried out to complete the construction of the data mining model. Assuming that $F$ is a continuous set of functions in the sample space, MMD can be expressed as:

$$\mathrm{MMD}[F, p, q] = \sup_{f \in F} \left( E_p[f(x)] - E_q[f(y)] \right) \tag{3.1}$$

Assuming $x$ and $y$ are datasets from distributions $p$ and $q$, and the size distributions of the dataset are $m$ and $n$, the MMD empirical values are estimated as follows:

$$\mathrm{MMD}[F, x, y] = {}^{\sup}_{f \in F} \left( \frac{1}{m} \sum_{i=1}^{m} f\left(x_i\right) - \frac{1}{n} \sum_{i=1}^{n} f\left(y_i\right) \right) \tag{3.2}$$

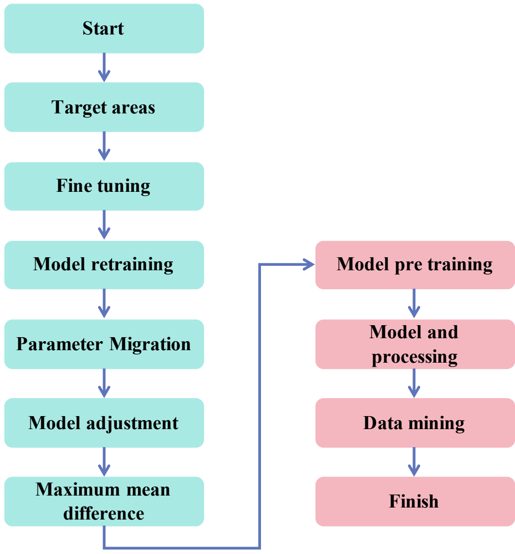


Fig. 3.4: Intelligent mining process for load data of high voltage power system

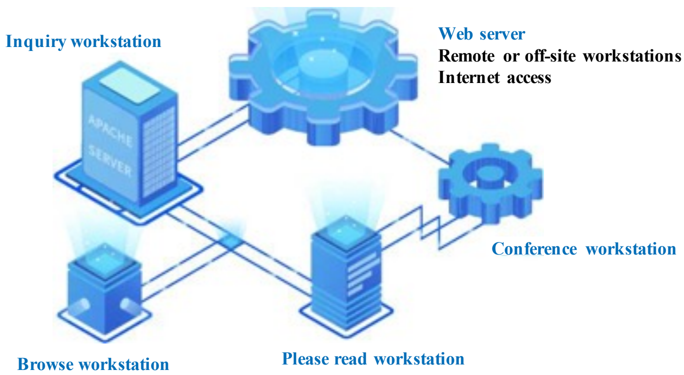


Fig. 4.1: Overall topological sructure of the monitoring center

From equation (3.2), it can be seen that MMD depends on a given set of functions for a specific dataset. Under the same distribution of $p$ and $q$, based on the properties of MMD, MMD is $O$, then it is required that $F$ be sufficiently widespread. In order to improve the convergence speed of MMD empirical estimation, it is necessary to adjust the original network structure based on MMD to obtain a new target domain network structure, while selectively mining the parameters trained from the original network structure.

**4. Experimental Results and Analysis.** In order to verify the rationality of the design of an intelligent mining system for low voltage loads in power systems based on deep learning, experimental verification analysis was conducted.

**4.1. Experimental environment settings .** Applying the system to an airport substation in a certain city, taking the temperature of the three-phase temperature rise monitoring point in the power system as an example, the overall topology of the monitoring center is shown in Figure 4.1 for operation data monitoring from September 20, 2019 to September 24, 2019 [20].

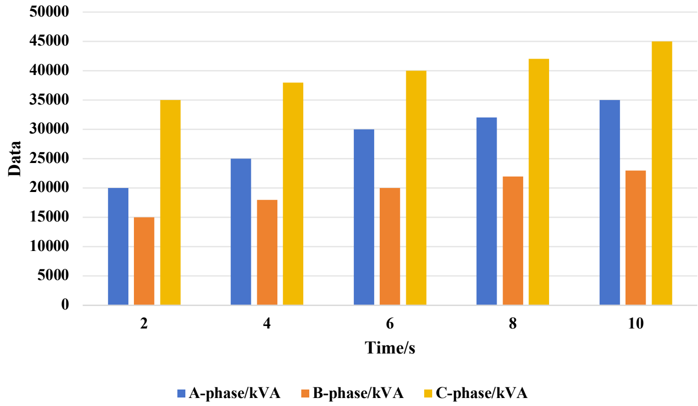


Fig. 4.2: Three phase load monitoring data

**4.2. Experimental data analysis.** Under the normal operation of various sensors in the power system, real-time three-phase load monitoring data can be effectively obtained, as shown in Figure 4.2.

**4.3. Experimental results and analysis.** Compare and analyze the mining results of three-phase low-voltage loads in power systems using machine learning based data processing systems, numerical simulation based data processing systems, and deep learning based data mining systems, as shown in Figure 4.3a-c [13].

From Figure 4.3, it can be seen that the maximum difference between the load of phase A using machine learning based data processing system and the actual data is 5000 kVA at a time of 6 seconds; When the load of phase B is 10 seconds, the maximum difference between it and the actual data is 3000 kVA; The maximum difference between the load of phase C and the actual data is 3000 kVA at a time of 10 seconds [10, 1, 17, 9]. The load of phase A of the data processing system based on numerical simulation, at a time of 6 seconds, differs from the actual data by a maximum of 1000 kVA; When the load of phase B is 4 seconds, the maximum difference between it and the actual data is 2000 kVA; When the load of phase C is 8 seconds, the maximum difference between it and the actual data is 2000 kVA.

**5. Conclusion.** Verified the feasibility of applying deep learning to power system security correction. By using DNN to train and learn massive historical data, a node adjustment state recognition model with high accuracy was obtained. Greatly reducing the optimization space for node adjustment calculation, it is expected to provide good safety protection in the event of limit exceeding faults in large systems. The author has designed an intelligent mining system for low voltage loads in power systems based on deep learning. The intelligent power system not only has the functions of traditional power systems, but also has intelligent monitoring and fault diagnosis functions. It can complete corresponding operations when analyzing and processing the status of the power system locally, accurately mining low voltage loads, and laying the foundation for achieving intelligent control of power systems, however, its anti-interference function still needs to be strengthened, so future research should focus on this and strive to provide reference for relevant research in this field.

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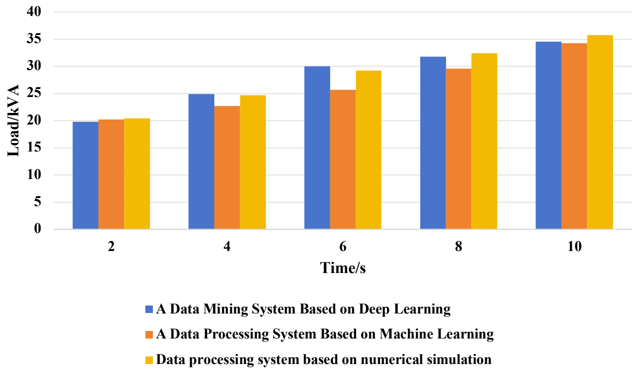
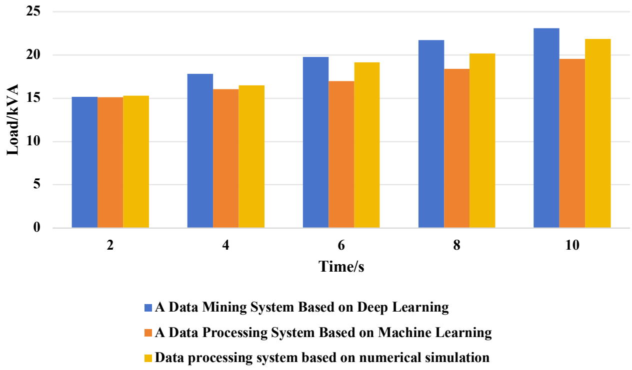
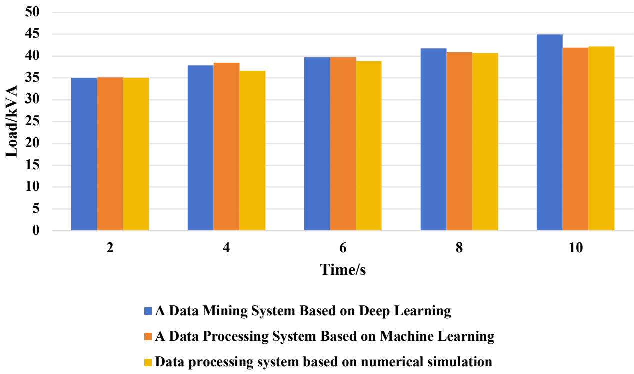



(a) A-Phase




(b) B-Phase




(c) C-Phase

Fig. 4.3: Comparison of data mining results for different systems

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