A Study of on-line monitoring of electric energy balance of agricultural power grid under internet of things

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ABSTRACT

For the seven hydropower stations with different installed capacities and substations with different construction scales built in different periods under the power system of Yunnan Agricultural Reclamation Power Co., Ltd, the technical standards of different equipment are not fully compatible with the centralized control system, forming several information silos, which has failed to achieve the power generation and supply balance monitoring of the power system of Yunnan Agricultural Reclamation Power Co., Ltd. This article uses cloud computing and 4G communication technology, combined with deep learning algorithms, to construct an online monitoring system for electric energy balance that is suitable for the production and operation of the current power system. Practice has shown that this system can improve the overall monitoring level of the power system, effectively reduce power dispatch and technical management costs, and provide reference for the construction of a new regional power grid in the next stage.

Keywords: Internet of Things, electric energy balance, power system monitoring, load forecasting

1. INTRODUCTION

PIoT（Power Internet of Things） is an effective way to realize the extensive participation and sharing, comprehensive and sustainable upgrading of the power industry, and is a feasible solution to promote the orderly evolution of smart grid to transparent power grid and zero-marginal cost power grid in Ref [1]. PIoT represents the power industry's development towards the Energy Internet. It faces a new era of digital transformation, especially in monitoring and management. Existing data transmission schemes are inadequate, necessitating the introduction of advanced ones as digital pioneers to lead and improve PIoT construction (Ref [2])..

There are incompatibilities in the planning, construction, operation, installed capacity, technical standards, and other aspects of multiple power generation stations, transformation stations and other power facilities under Yunnan Agricultural Reclamation Power Co., Ltd, during different periods. Due to isolated operation of power stations, data cannot be effectively transmitted in real-time to decision-makers, leading to limitations in adjusting generator output, load distribution, switch capacitors, reactors, and ultimately failing to achieve electric energy balance control. When the power supply is insufficient, it needs to be disconnected from the superior power grid. However, due to the imbalance of electric energy in local areas and the lack of information on load reversal to the decision-making level, load reversal cannot be controlled.

With the development of cloud computing technology and the popularization of new generation communication networks and other IoT technologies in China, in recent years, Sun, Y.Y. et al in Ref [3] and Chen, H.Y. et al in Ref [4] have provided new technological routes and solutions to solve the above problems. This article adopts Internet of Things technologies such as cloud computing and wireless communication technology, and proposes an online monitoring system for the implementation of power supply balance in power grids without changing the original equipment or adding personnel and equipment. Through practice, it achieves real-time query of current and historical power generation and sales/purchase data of each power station on the mobile and PC ends, and provides big data analysis results for decision makers.

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2. THE DESIGN SCHEME OF SYSTEM

2.1 The architecture diagram of system

This paper proposes an online monitoring system for the electric energy balance of agricultural power grids under the Internet of Things (IoT). It builds upon previous works by Wang et al. (Ref [5]), Hu et al. (Ref [6]), Tang et al. (Ref [7]), and Zhou et al. (Ref [8]). The system architecture, as depicted in Figure 1, integrates components from these works, including Wang's implemented system, Hu's event detection scheduling for wireless sensor networks, Tang's short-term optimal scheduling model for hydro-power station groups, and Zhou's peer-to-peer energy trading strategy for prosumers using model predictive control.
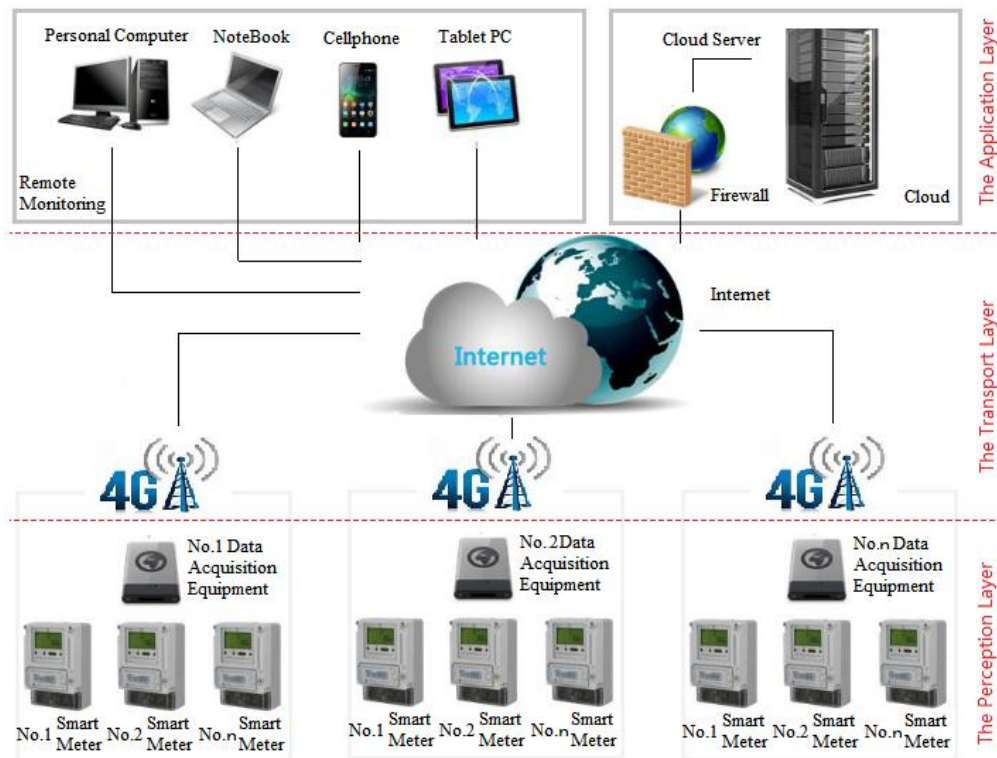

Figure 1. The system architecture.

2.2 The perception layer

The perception layer is the information source of the Internet of Things and the fundamental part of the entire system; The perception layer is mainly composed of an electric meter array, which collects important basic data such as current, voltage, environmental temperature, humidity, etc., preprocesses and stores the data.

2.3 The transport layer

The transport layer is the medium for transmitting information on the Internet of Things, mainly composed of communication networks. The communication layer in this article adopts the currently mature 4G IoT module. It features compact and exquisite design, complete functions, and two main working modes: always online or ultra-low power consumption. Users can choose according to their own needs. Real time data collection can be carried out through various methods such as SMS, phone, internet, WeChat, cloud platform, etc.

2.4 The application layer

The application layer serves as the control center of the Internet of Things architecture, directly targeting relevant users. The application layer is mainly composed of databases, servers, cloud platforms, terminal configuration units, etc. Its main task is to intelligently analyze and process the data collected from the transmission layer, and notify relevant personnel to handle it in a timely manner.

3. AN ONLINE MONITORING OF ELECTRIC ENERGY BALANCE BASED ON LOAD FORECASTING MODEL OF RECURRENT NEURAL NETWORK

3.1 The software system

The data collection module is developed using C language and utilizes existing technology to denoise the data. The prediction model is developed using ATS configuration software, and the collected data is manually filtered and processed as the data for training the early warning model.

After powering on, the system initializes and automatically collects data through a data collector, with an interval of 10 seconds; Do not issue any instructions to the original device, it only records the data transmitted to the original data collection terminal and passes it through the 4G/5G network to the cloud server. After activating the prediction function, the prediction model will predict the values within the next half hour based on the collected data.

3.2 The hardware system

This system adopts the DSSD71 electronic three-phase multifunctional energy meter developed by Jiangsu Linyang Energy Co., Ltd. The energy meter incorporates state-of-the-art technologies such as microelectronics, computer technology, electrical measurement, high-precision chips, data communication, and advanced manufacturing techniques. It stands out for its precise measurements, reliability, compactness, lightweight design, energy efficiency, user-friendly operation, expandable management functions, and versatile usage. When the electricity meter is working, the voltage and current of three-phase A, B, and C are respectively sampled by the sampling circuit and sent to the metering chip for processing. The CPU sends the processed data to the display section, communication section, and other data output units as needed.

The ZLAN8308N meter produced by Shanghai ZLAN Information Technology Co., Ltd integrates the CAT14GDTU communication module of P2P technology, and uses the notebook computer with the monitoring software ZLVircom installed to monitor data in real time. A At the beginning of communication, the P2P software ZLVircom on the user's computer first communicates with the ZLVircom P2P server; When using, simply enter the serial number of 8303 to be monitored in the ZLCircom software to establish a P2P connection. P2P mode allows users to get rid of the more cumbersome settings of "port mapping" and "dynamic Domain Name System", and truly realize monitoring anytime and anywhere. At the same time, ZLAN8308 has a specially designed watchdog circuit that can ensure the stable operation of the 4G module for a long time and ensure the stability of the system's data collection.

3.3 An load forecasting model based on recurrent neural network

Cyclic neural network is an artificial neural network that can model information with time series. It is currently commonly used in sequence prediction tasks that need to consider historical information. Sun et al. (Ref [9]) proposed a bi-directional long-short-term memory network for transient stability assessment in power systems to enhance the accuracy of future data prediction., Ren, J.J. et al proposed an ultra-short-term power load forecasting based on CNN-BiLSTM-Attention in Ref [10], This paper adopts a gated recurrent network structure model. RNN network structure diagram is shown in Figure 2. GRU unit structure diagram is shown in Figure3.
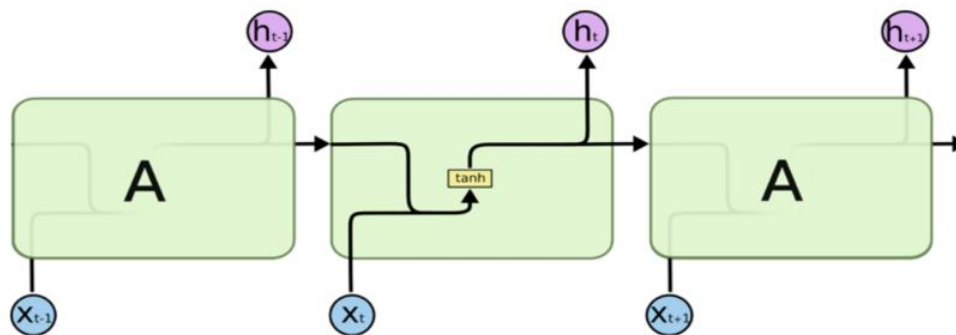

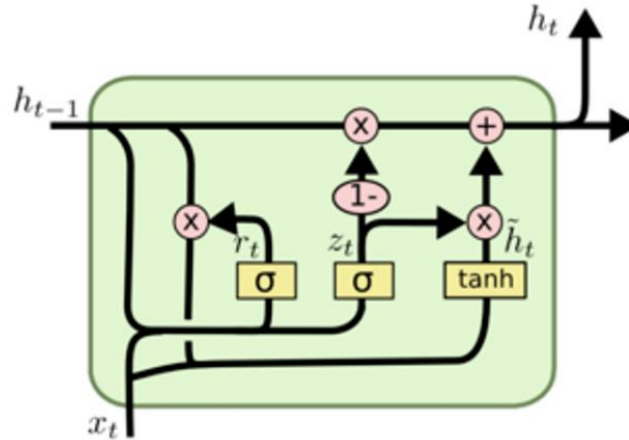Figure 2. RNN network structure diagram.

Figure 3. RNN network structure diagram.

$$z_t = \delta(W_Z \cdot [h_{t-1}, x_t]) \tag{1}$$

$$r_t = \delta(W_r \cdot [h_{t-1}, x_t]) \tag{2}$$

$$\tilde{h}_t = \tanh(W \cdot [r_t * h_{t-1}, x_t]) \tag{3}$$

$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t \tag{4}$$

$$y_t = W * h_t + b \tag{5}$$

Including: x_t is the current input, h_t is the current output.

Input the data into the network in chronological order. After encoding all the data, a hidden state will be given as the final output. This hidden state is used as the input at the time of decoding to predict the value at the next time. The network at the decoding end is consistent with the coding, and GRU network is adopted.

In this system, the positive active power, positive active base, positive reactive power, positive reactive base, negative active power, negative active base, negative reactive power, negative reactive power, negative reactive base, multiplier, power factor and other parameters of each sampling period will be taken as inputs and predicted.

3.4 The experimental conditions

The experimental data comes from 27 substations under the jurisdiction of Yunnan Agricultural Reclamation Power Co., Ltd. This article randomly selected 90000 consecutive data within half an hour from historical data as our dataset, of which 80000 were used as training data, 6000 were used as validation sets, and 4000 were used as testing sets. The sample experimental data of 110kV Line Baqi Kaifaqu are shown in Table 1.

Table 1. The sample experimental data.

Time	Positive active power (kW)	Positive active power base	Positive reactive power (kW)	Positive reactive power base	Reverse active power (kW)	Reverse active power base	Reverse reactive power (kW)	Reverse reactive power base	Power factor
0:00	6600	153.34	0	90.91	0	35.88	0	33.12	1
1:00	0	153.34	0	90.91	0	35.88	0	33.12	1
2:00	0	153.34	13200	90.93	0	35.88	0	33.12	1
3:00	0	153.34	13200	90.95	0	35.88	0	33.12	1
4:00	0	153.34	13200	90.97	0	35.88	0	33.12	1
5:00	0	153.34	13200	90.99	0	35.88	0	33.12	1

6:00	0	153.34	13200	91.01	0	35.88	0	33.12	1
7:00	0	153.34	6600	91.02	0	35.88	6600	33.13	0.99
8:00	0	153.34		91.02	0	35.88	0	33.13	0.58
9:00	153.35	91.02	0	35.88	0	33.13	33.13		0.98
10:00	153.36	91.02	6600	35.89	0	33.13	33.13		0.99
11:00	153.39	91.02	0	35.89	0	33.13	33.13		0.99
12:00	153.41	91.02	0	35.89	0	33.13	33.13		1

The number of hidden layer of encoder is 4, Learning Rate is 0.1, Dropout is 0.3, Optimizer is Adam, Epoch is 2.

In this paper, accuracy rate, recall rate and F value are used as the evaluation indicators of the prediction results. The precision of accuracy measurement results, the breadth of recall measurement results, and the F value is the harmonic average of accuracy (P) and recall (R), considering both accuracy and recall.

This paper uses historical data to study and predict 10 data such as positive active power, positive active base, positive reactive power, positive reactive base, reverse active power, reverse active base, reverse reactive power, reverse reactive base, multiplying factor and power factor. The accuracy, recall and F value results are shown in Table 2.

Table 2. The accuracy, recall and F value results.

Name	P	R	F
Positive active power	0.725	0.786	0.754
Positive active power base	0.72	0.785	0.751
Positive reactive power	0.723	0.788	0.754
Positive reactive power base	0.690	0.752	0.720
Reverse active power	0.683	0.798	0.735
Reverse active power base	0.681	0.750	0.710
Reverse reactive power	0.692	0.72	0.684
Reverse reactive power base	0.682	0.70	0.670
Multiplying power	0.673	0.70	0.670
Power factor	0.712	0.702	0.696

From the experimental results, the model can effectively predict the data within the next half hour, provide reference for the regulation of the power grid load system, and effectively improve early warning ability of system.

3.5 The compilation of ATS configuration software

The system measures and records essential parameters, including instantaneous active power and reactive power of grid-connected points, at a frequency of 500ms. The measurement programs for on-grid active power in grid-connected points are customized based on the design model.

Some programs are as follows:

{double WSP=MDZB_000000000005 SP*GetDir（"MDZB 000000000005"，"P"，1）//No.442 Mandazhou Substation

+DFB_100130001854 SP*GetDir 04（"DFB 100130001854"，"P"，1）//No.201 Dongfeng Substation

+MLB_000000000005 SP*GetDir 04（"MLB 000000000005"，"P"，1）//No.1257 Menglong Substation

+MENGLAB_130100000011 SP*GetDir 04（"MKB 130100000011"，"P"，1）//No.5100 Mengkuan Substation

+XCB 213900000044 SP*GetDir("XCB 213900000044","P",1) //No.354 Xincheng Substation

+MDB 271733000025 SP*GetDir 04("MDB 271733000025,"P",1) //No.2700 Mandiu Substation

+BHB 419500000104 SP*GetDir("BHB 347300000044","P",1)//No.281 Bahe Substation

+MYB 000000000023 SP*GetDir 07("MYB 000000000023","P",1)//No.4721 Mengyuan Substation

+MJBB 3430000000001 SP*GetDir("MJBB 3430000000001","P",1)// No.270 Manjingbao Substation

return WSP}

3.6 The set of interface communication protocol message

Taking an initial message as an example, such as "201000000000002010498Fa21284B29," the message breakdown is as follows: "20" represents the initial message, "000000000020" denotes the meter address, "20" corresponds to the initial frame, "01" indicates the control code, "04" signifies the data length, "98Fa" represents the data identification, "2128" is the measured value, which is decoded as "0006" indicating an instantaneous reactive power of 0.06 kVar. "4B" represents the check code, and "29" represents the end symbol. The setting and analysis processes for key parameters, such as active power, voltage, current, power factor, and others, follow a similar approach.

4. CONCLUSION

Using historical data of Yunnan Agricultural Reclamation Power Co., Ltd as training data, deep learning algorithms are used to effectively predict 10 key parameters in power system of Yunnan Agricultural Reclamation Power Co., Ltd, providing a reference model for timely and effective control of power grid load and supply balance. On this basis, this paper proposes an online monitoring system of electric energy balance and development in Yunnan Agricultural Reclamation Power Co., Ltd. Through practice, it has been proven that it can effectively reduce the cost of power dispatch and management, and improve the detection ability in electric energy balance, providing a model reference for the next stage of new regional power grid construction. Considering that external factors such as elevation, environmental temperature, and humidity of hydro-power plants and substations in power system of Yunnan Agricultural Reclamation Power Co., Ltd are inconsistent, which may affect the measured values of the system to some extent, in the next stage of research, it is planned to further explore the impact of environmental factors on the predicted values.

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