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Construction of Digital Transformation Management System for Power Grid Enterprises Based on Artificial Intelligence Algorithm

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The application of digitalization has transformed the lives of individuals as well as the operational aspects of public and private sectors. In particular, it has led to the construction of digital management systems for many enterprise-management models. At present, the application of digitization in enterprise management is increasing, and advanced methods and technologies are being used to gather and display information. This paper aims to achieve the digital transformation of the power grid enterprise management system in the artificial intelligence environment. It draws on the principles and laws of artificial intelligence to construct and optimize the management system of the digital model, and achieve the digital transformation of enterprises as a development strategy. In a survey of employees, which sought their opinions on the management system after the transformation, 63.62% of respondents believed that the current new management system was very effective, 23.73% thought it was average, and the remaining 12.65% thought it was not very effective. Therefore, it is very important to build a digital management system for the future development of power grid enterprises.

Keywords: enterprise management system, digital transformation, artificial intelligence algorithm, data acquisition algorithms

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1. INTRODUCTION

Power supply companies are essential to China's economy. The security of the power system determines the country's overall economic and social development as well as the daily work and life of the people. Hence, the power system plays a vital role in ensuring China's security, social stability, and people's well-being. At present, the security of China's power grid work environment is constantly changing, new problems and challenges are emerging, power grid enterprises are facing many types of risks, and security management is grim. First, the demand for power grid is increasing, the discrepancy between power grid supply and demand is prominent, new energy is connected on a large scale, and the grid security risks caused by the systematic and structural discrepancies in the power grid have existed for a long time. Second, new businesses and new formats continue to emerge, a large amount of new equipment is being deployed, the operation and maintenance of new and old power grid equipment is more difficult. Moreover, natural disasters are occurring frequently, and safety hazards associated with equipment safety continue

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to increase. Third, the high-risk operation links of power grid infrastructure projects are relatively concentrated, employees have insufficient safety awareness, and the risk of personal injury is increasing. At present, international cooperation in regard to electric power is strengthening, and the pace of internationalization of power grid enterprises is accelerating.

Massive data and lack of knowledge is a common problem for most enterprises at present, and China's power grid enterprises are no exception. After more than ten years of informatization construction and smart grid business development, power companies have accumulated a large amount of production, operation and business data. Currently however, electric power companies in most provinces and cities use only grid data storage, query, statistics and other functions related to the most basic online transaction processes of traditional relational databases. Some companies have built data warehouse systems for reporting and simple business operations. However, their systems do not have the capacity to mine big data for valuable information which could assist management to make more appropriate and effective decisions. In recent years, with the rapid growth of data volume and the current wave of Internet + and artificial intelligence development, power companies have also generated strong demand for analysis technology and artificial intelligence technology management [1]. In the current era of rapid technological development, artificial intelligence will have a huge impact on China's social economy, technology and other aspects. The power grid is the country's basic energy source, and the power grid information system, being the basic information support system of the national grid energy, must respond to this change [2]. Therefore, in this paper, in order to deeply understand the technology of artificial intelligence connotation, it starts with artificial intelligence technology and supports the company's business decision-making. Currently, China's power grid system is undergoing reform, and the development of power grid systems, the research and design of artificial intelligence algorithms that support the storage, management, analysis and application of artificial intelligence in power grids, is expected to provide exploratory insights for the management and decision-making levels of power grid enterprises that will enable them to cope with the challenges posed by the era of artificial intelligence.

The digitalization of enterprise management is a hot issue at present, and has attracted a great deal of research. In their study, Koscheyev et al. (2019) analyzed the theoretical methods applied for the digital transformation of companies, and investigated the specific characteristics and problems of certain transformations related to the organization of power grids [3]. Koch et al. (2019) investigated the role of digital transformation in Scandinavian electricity utility projects [4]. Neizvestny (2021) stated that artificial intelligence is related to the process of making important, large-scale management decisions in the network management of the digital society. The impact of artificial intelligence decision-making in the digital society on the digital transformation of enterprises has not been fully studied [5]. Allen (2021) proposed that in order to maintain business growth, contractors, suppliers and logistics providers need to undergo transformation, which involves digitizing their supply chains through interconnected networks and automated processes [6]. Liu and Jing's (2021) research explored the operations of an emergency management system, emergency management legal system, digital emergency management technology, emergency management concept and emergency culture creation in various countries in the world, which provides effective support for the construction of emergency management mechanism and related management decisions in China [7]. However, their research is only at the theoretical stage due to the lack of survey data, and their findings have not been applied in real-world contexts.

The use of artificial intelligence algorithms to build an enterprise digital management system is a very novel concept, and many studies are currently studying this approach. In this regard, Shamsutdinova (2020) proposed a cognitive model of learning path based on the digital footprint, and analyzed its test results [8]. Denisova et al. (2020) presented the results of research on various countries' experiences with various tools applied to support *e*-government and digital governance systems [9]. Skrynnyk (2021) aimed to identify data access restrictions for the digital systems used for organizational development and to investigate user attitudes towards personal data marches through artificial intelligence [10]. Manjaly et al. (2021) examined the risks, rewards, use cases and approaches to AI adoption by power companies. They also investigated the return on investments, and the main purpose of some of the tools used by financial institutions and central banks [11]. Vatlina (2021) carried out a study to identify the specificity of introducing digital tools using different types of competencies in public administration [12]. However, this research focuses on the basic traditional management system, and does not provide a comprehensive understanding of the enterprise management model. Very few studies have explored the concepts and principles of artificial intelligence algorithms and enterprise digital management, and it is impossible to truly integrate the two.

This paper makes a valuable contribution to the field of power grid systems: through technological innovation, constructs a powerful dispatching technical support system that can greatly improve the dispatcher's ability to manage the operation of the power grid. It greatly improves the systems' ability to analyze and resolve grid incidents quickly and accurately, and greatly reduces the incidence of so-called fault phenomena, thereby safeguarding company employees and preventing equipment problems. Through advanced scheduling technology, employees can remotely control on-site work, further reducing labor and transportation costs, and improving production efficiency. The quick recovery can reduce the output loss due to an accident, and bring huge economic benefits.

2. GRID MANAGEMENT SYSTEM ARCHITECTURE BASED ON ARTIFICIAL INTELLIGENCE ALGORITHM

Power grid artificial intelligence permeates all aspects of power grid production and management such as generation, transmission, transformation, distribution, and utilization, and

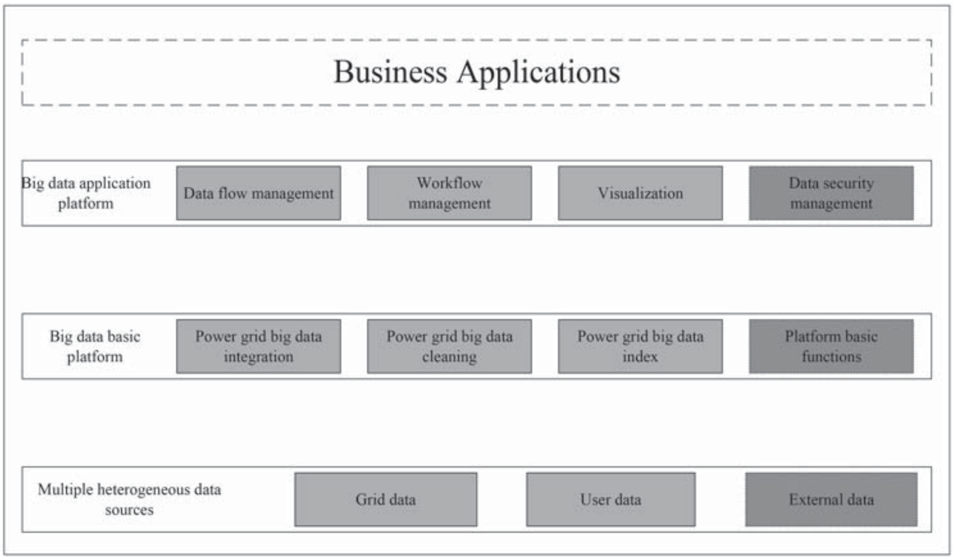

Figure 1 Framework of digital grid management system.

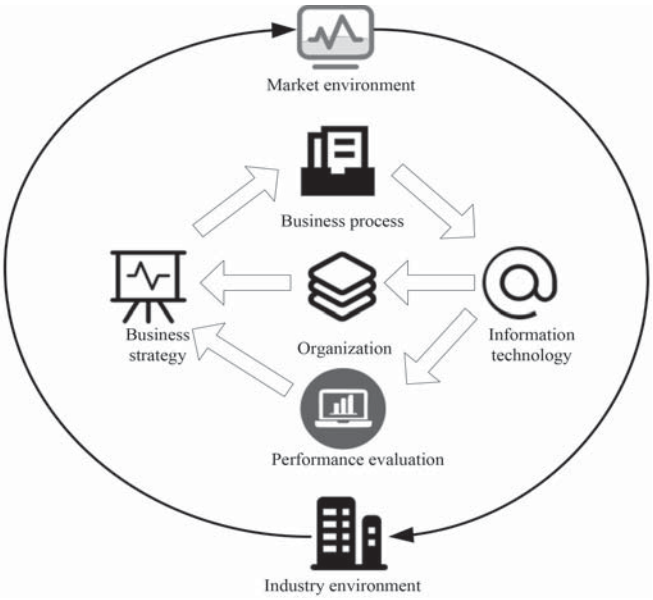

Figure 2 Management factor analysis model.

is dispersed and distributed in companies' respective business systems [13]. These data can be integrated into a unified system through integration technology facilitated by artificial intelligence [14–15]. In order to break through the technical bottleneck of power grid artificial intelligence technology management, and after conducting an in-depth exploration of the application requirements of power grid artificial intelligence, this paper proposes an artificial intelligence system architecture for company A's power grid, as shown in Figure 1.

As can be seen from Figure 1, the architecture has the characteristics of scalability, customizability and diverse processing capabilities, in addition to good adaptability, low cost and strong expansibility. The entire system architecture is divided into three layers: the artificial intelligence basic system layer, the artificial intelligence application system layer and the business application layer. Based on the general functions of artificial intelligence, the artificial intelligence basic system layer achieves the grid artificial intelligence integration, grid artificial intelligence cleaning and grid artificial intelligence indexing with power grid characteristics.

2.1 Basic Design of Power Grid Network Security Management System

(1) Analysis of management elements

The management element analysis model analyzes the relationship between management elements such as enterprise strategy, business process, organizational structure, information technology and performance evaluation [16–17], as shown in Figure 2.

(2) SWOT analysis

SWOT is an enterprise-centric strategy that considers the internal and external environments of a business by examining a company's strengths and weaknesses (internal factors), and

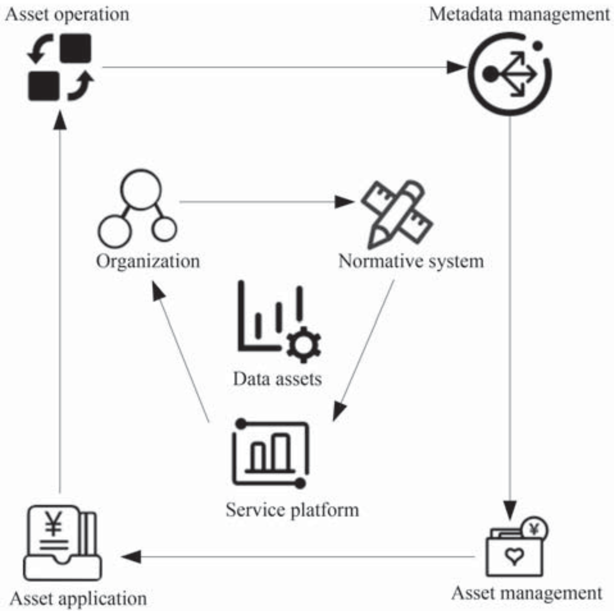

Figure 3 The overall framework of the data asset management system.

the opportunities and threats (external factors). These can be graphically represented as a matrix which can be analyzed and used for decision-making and the formulation of business strategies [18].

2.2 Overall Framework of the Data Asset Management System

The overall framework of the data asset management system is shown in Figure 3, with data assets as the management object. Taking the organizational structure, system specification and service system as the core, it carries out all-round management of metadata, asset analysis, asset governance, asset application and asset operation.

It can be seen from Figure 3 that metadata can be regarded as enterprise information data, which can be obtained in two ways, one is collected manually, and the other is extracted directly from the existing information system. In addition to bloodline analysis, impact analysis, and analysis indicators, metadata management also has the following basic functions: modifying metadata, auditing metadata quality, collecting metadata statistics and analyzing metadata usage, and data life cycle management. These functions provide strong support for the operation and maintenance management and effective control of data assets, and facilitates the effective acquisition and use of data assets [19]. In terms of data asset cost assessment, this is intended to accurately assess data asset activities, data asset costs and business value, continuously collect core data assets, and promote effective management and appropriate control of a company's data assets.

2.3 Data Collection Algorithm under Artificial Intelligence Algorithm

In this kind of network, the mobile node replaces the static node; it not only has the function of perception and detection, but is also responsible for data forwarding. The detected scene will no longer have a large number of static sensors, but will be replaced by mobile sensors that "roam" the network [20–21]. Mobile sensors collect environmental data and send the data to other sensors or base stations for data collection [22–23]. At the same time, the sensor can be controlled by the base station to complete the related collaborative environment control tasks. The choice of mobile nodes in the network can also be different; it can be a robot car whose trajectory is controlled by the network system, or it can be an uncooperative mobile individual in the network, such as pedestrians, cars, and migrating animals. Its network architecture is shown in Figure 4.

As shown in Figure 4, a mobile wireless sensor network usually consists of a three-layer network architecture. The bottom layer of the network is comprised of the static sensors widely distributed in the network, which are responsible for generating and collecting sensor data, and uploading the collected data to the mobile nodes. Above the static sensor layer is the mobile node layer, which is often used as a tool to assist communication between static nodes. In this network architecture, the mobile node itself has no sensor function. The mobile node carries the data and is responsible for forwarding the data to other static sensors, or uploading the data to the data-acquisition base station. At the same time, the mobile node can also issue the control commands of the data-acquisition base station to the static sensors. The top layer of the network is the data-acquisition base station. These base stations are usually small in number and have powerful communication functions. They can be connected to each other by the backbone network to share data [24]. The data base station is responsible for the collection, summary and analysis of sensor data, and can issue control commands to the entire network based on the collected data information.

(1) Energy consumption optimization of static sensor data communication

Set the energy consumption of each static sensor in the mobile wireless sensor network to transmit data for T_d

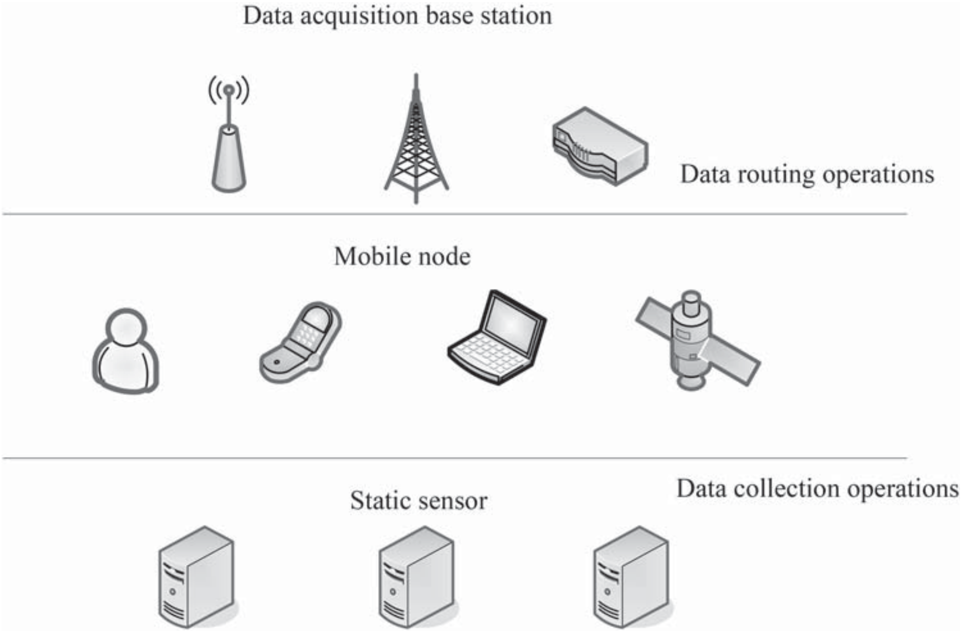

Figure 4 Three-layer architecture of mobile wireless sensor network.

time as E. It can be known from the network model that each sensor node always chooses the communication mode with lower energy consumption between the independent communication mode and the cooperative communication mode [25], which is:

$$E = \min\{E_{IC}, E_{cc}\} \tag{1}$$

where E_{IC} and E_{CC} are the energy consumed by the static sensor to send T_d-hour data respectively. The solution flow for the optimization problem is:

$$P = P\left\{\bigcap_{i=1}^{NL} A_i\right\} > C \tag{2}$$

That is, the energy consumption of each static sensor is minimized under the constraints of the network on the data collection efficiency. In the independent communication mode, the energy consumption of the sensor is only the energy consumption of data transmission, namely:

$$E_{IC} = T_d P_t^{IC} \tag{3}$$

where P_t^{IC} is the power consumption required by the sensor in order to send data to the mobile node with distance r in the independent communication mode, and the power consumption includes two parts. One is the power consumption P_{PA} of all power amplifiers during data transmission, and the other is the power consumption P_C of other circuit units during data transmission, then:

$$P_{out} = \frac{P_r^{IC}}{G_t G_r}\left(\frac{4\pi}{\lambda}\right)^2 r^k \tag{4}$$

where P_r^{IC} is the effective received power of the mobile node receiving end. It can be considered that when the signal power of the receiving end is greater than P_r^{IC}, the data can be effectively received and successfully decoded with a very low error rate, therefore:

$$P_{PA} = \frac{\xi}{\eta} P_{out} \tag{5}$$

where ξ is the peak-to-average ratio of the transmitted signal, and η is the drain efficiency of the RF power amplifier, at this time:

$$\xi = 3\frac{\sqrt{M}-1}{\sqrt{M}+1} \tag{6}$$

The formula for calculating the loss of other circuit units is:

$$P_C = P_{DAC} + P_{mix} + P_{filt} \tag{7}$$

In summary, the sensor communication power consumption in independent mode is:

$$P_t^{IC} = \frac{\xi}{\eta}\frac{P_r^{IC}}{G_t G_r}\left(\frac{4\pi}{\lambda}\right)^2 r^k + P_c \tag{8}$$

At this time, the energy consumption of the sensor sending data for T_d time is:

$$E_{IC} = T_d\left\{\frac{\xi}{\eta}\frac{P_r^{IC}}{G_t G_r} r^k + P_c\right\} \tag{9}$$

Using this adaptive optimization cooperative communication algorithm, in the cooperative communication mode, the energy consumed by each static sensor when sending T_d-duration data is:

$$E_{CC} = LT_d P_t^{CC} + (2L+1)T_m P_{lc} + LT_d P_{lc} \tag{10}$$

The first item in the above formula represents the energy consumption of the static node sending data to the mobile node. Here, it is assumed that the static sensor combines only the sensors in the cluster to form a shared information

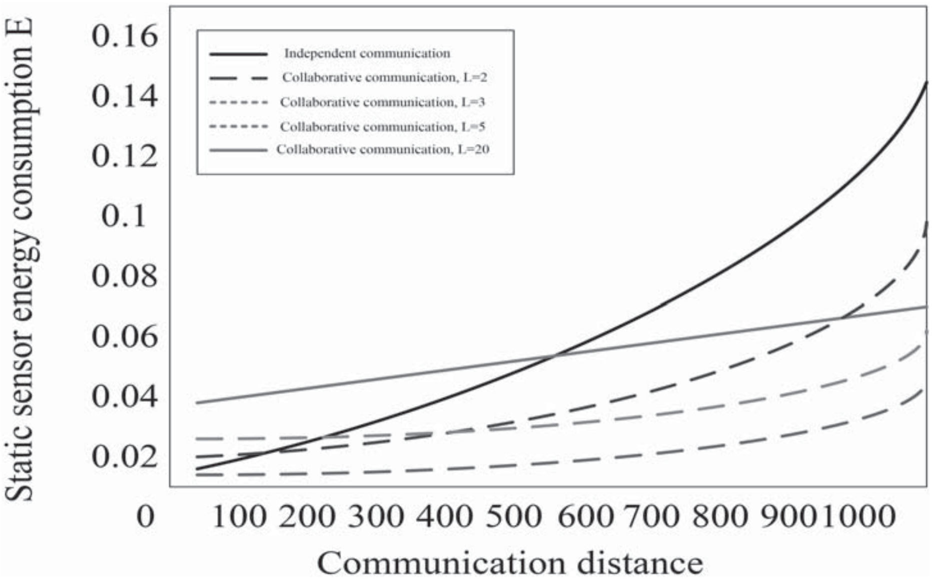

Figure 5 Energy consumption ratio between independent communication distance and cooperative communication distance.

transmission, without data fusion and aggregation. Therefore, the data transmission duration T_d is the sum of the data durations of each sensor [26]. The second term is the energy consumption of synchronous communication among nodes in the cluster. The third item is the energy consumption of information sharing among nodes in the cluster. Both P_t^{CC} and P_{lc} can be obtained by a calculation method similar to that of P_t^{IC}, which is calculated as follows:

$$P_t^{CC} = \frac{\xi}{\eta}\frac{P_r^{CC}}{G_t G_r}\left(\frac{4\pi}{\lambda}\right)^2 r^k + P_c \tag{11}$$

$$Plc = \frac{\xi}{\eta}\frac{P_r^{lc}}{GtGr}\left(\frac{4\pi}{\lambda}\right)^2 d_0^k + P_c \tag{12}$$

In summary, the energy consumption expression of static sensors in cooperative communication mode is shown in formula (13):

$$E_{CC} = \left\{\frac{\xi}{\eta}\frac{P_r^{IC}}{G_t G_r}\left(\frac{4\pi}{\lambda}\right)^2 r^k + P_c\right\} + (2L+1)T_m P_{lc} + LT_d P_{lc} \tag{13}$$

The relationship between the energy consumption of the sensor node and the distance between the sensor and the mobile node in the independent communication mode and the cooperative communication mode is shown in Figure 5.

It can be seen from Figure 5 that when the distance between the sensor and the mobile node is relatively small (less than 200 in the figure), the energy consumption of the independent communication mode is less. This is because, when the distance is small, the energy consumption when sending data using cooperative communication and independent communication is not much different, while cooperative communication also needs to consider the energy consumption of local shared data and synchronization. At this time, if cooperative communication is used, the energy required for the local sharing of information and synchronization is much greater than the energy consumed when using cooperative communication to send data [27]. When the communication distance is short, it is more energy-efficient to use a cluster with fewer nodes for cooperative communication.. If there are too many nodes in the cluster, the shared data and synchronization within the nodes will consume a lot of energy, reducing the energy efficiency of the sensor. When the communication distance increases, a large number of nodes can cooperate to reduce energy consumption. Therefore, in the design of the static sensor data acquisition algorithm, the number of sensor cluster nodes is a key factor determining energy efficiency. In the selection of sensor communication modes, there is a critical distance r_0.

When the communication distance between the sensor and the mobile node is $r < r_0$, the use of independent communication can reduce the amount of energy consumption. However, when $r \geq r_0$, energy consumption can be reduced by using cooperative communication. Therefore, the energy consumption expression of the static sensor is obtained with:

$$E_{IC} = T_d\left\{\frac{\xi}{\eta}\frac{P_r^{IC}}{G_t G_r}\left(\frac{4\pi}{\lambda}\right)^2 r^k + P_c\right\},\ r < r_0 \tag{14}$$

$$ECC = LTd\left\{\frac{\xi}{\eta}\frac{P_r^{IC}}{G_r G_t}\left(\frac{4\pi}{\lambda}\right)^2 r^k + P_C\right\} + (2L+1)T_m P_{lc} + LT_d P_{lc} + LT_d P_{lc},\ r \geq r_0 \tag{15}$$

The energy consumption of the static sensor is proportional to the communication distance between the sensor and the mobile node. Therefore, in order to minimize the energy consumption of the sensor, it is only necessary to minimize the communication distance *r* under the condition that the data collection efficiency constraints are met.

$$P = P\left\{\bigcap_{i=1}^{NL} Ai\right\} > C\ subject\ to \tag{16}$$

(2) Optimal communication distance under random walk model

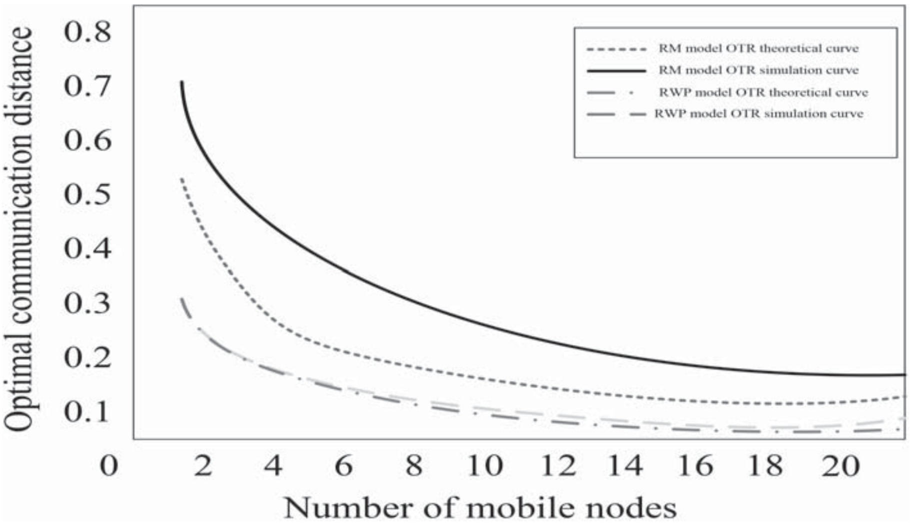

Figure 6 RM model and RWP model OTR expression validation.

Suppose N clusters of sensor nodes are evenly distributed on the unit disk ($R = 1$) , and each cluster contains L nodes. At a certain moment, the probability of a mobile node falling within the sensor communication area is:

$$p = \frac{\theta \pi r^2 / 2\pi}{\pi R^2} \tag{17}$$

Therefore, within a given time limit, the probability of a sensor cluster being visited is given by formula (18):

$$P(N = 1) = 1 - (1 - \frac{\theta}{2\pi})^{MT_{MAX}} \tag{18}$$

The optimal communication distance is the shortest communication distance satisfying $P(N = 1) > C$. Then:

$$P(N = 1) = 1 - \left(1 - \frac{\theta r^2}{2\pi}\right)^{MT_{MAX}} \tag{19}$$

Then

$$r > \sqrt{\frac{2x}{\theta}\left(1 - MT_{MAX}\sqrt{\ }\right)} \tag{20}$$

Therefore, when $N = 1$, the optimal communication distance under the random walk model is:

$$OTR = \sqrt{\frac{2\pi}{\theta}\left(1 - MT_{MAX}\sqrt{1 - C}\right)} \tag{21}$$

(3) Simulation and verification of the optimal communication distance calculation formula

A large number of simulation experiments are used to verify the accuracy of the above formula in calculating the optimal communication distance. Figure 6 shows the optimal communication distance obtained by the simulation experiment and the optimal communication distance curve obtained by the formula.

It can be seen from Figure 6 that each simulation curve was obtained by 108 simulation experiments. In the experiment, all communication distances in [0,1] are traversed, and 103 simulation experiments are carried out under the given communication distance. In each experiment, the mobile node moves on the unit disk with the RM model or RMP model and collects data [28]. According to the definition of optimal communication distance, the shortest communication distance in which all static sensor data are collected is the optimal communication distance in the experiments that satisfy more than $C = 80\%$ of the 108 simulation experiments. The relationship between the optimal communication distance and the number of mobile nodes under the RM model and the RWP model is shown in Figure 7.

It can be seen from Figure 7 that in both models, the OTR decreases with the increase of the number of mobile nodes. This is because when the number of mobile nodes increases, more areas can be traversed at the same time. Therefore, there is a greater probability of collecting sensor cluster data, and the communication distance of the corresponding sensor cluster can be reduced accordingly.

(4) Relationship between optimal communication distance and data collection time limit

The relationship between the optimal communication distance and the data collection time limit under the RM model and the RWP model is shown in Figure 8.

The different curves represent the effect of setting different numbers of mobile nodes on the simulation results. It can be seen from Figure 8 that, similar to the relationship between OTR and the number of mobile nodes, OTR decreases as the time limit increases. This is because when the given time limit is more sufficient, the mobile node can traverse more areas, so there is a greater probability of collecting sensor data, thereby reducing the OTR.

3. EVALUATION OF POWER GRID ENTERPRISE MANAGEMENT SYSTEM

3.1 Performance Evaluation of Power Grid Enterprise Information Projects

Compared with traditional projects such as engineering infrastructure projects, informatization projects have their

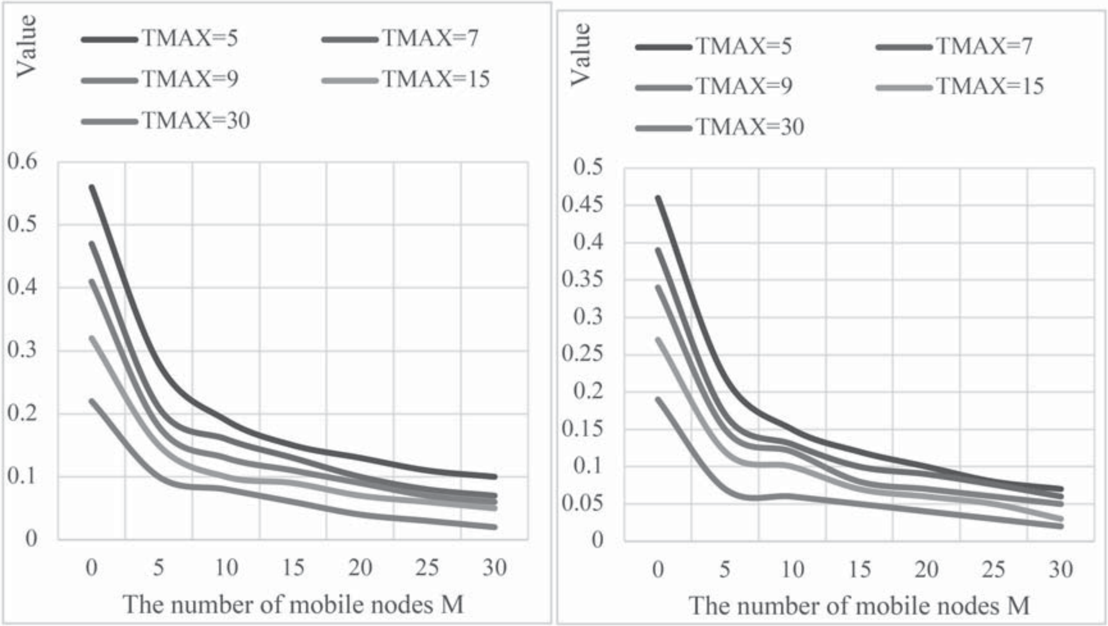

Figure 7 Relationship between optimal communication distance and number of mobile nodes.

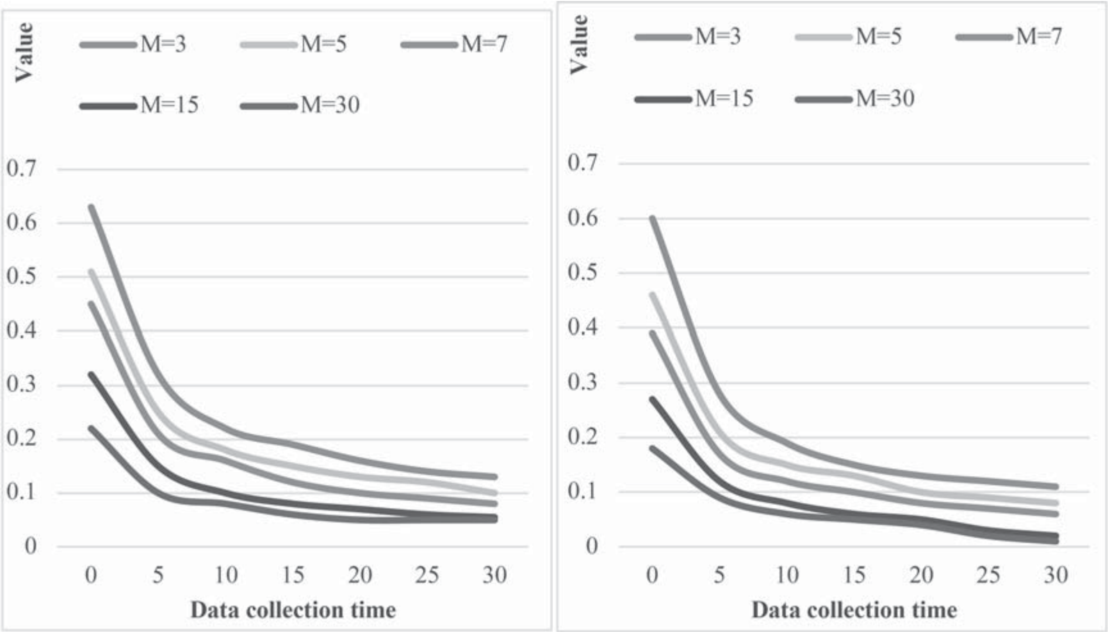

Figure 8 Relationship between optimal communication distance and data collection time limit under the two models.

own characteristics, and there are differences in project objectives, scope, technology, human resources, etc. The main differences are shown in Table 1.

It can be seen from Table 1 that there are many different ways of expressing enterprise informatization, but the core is the application of advanced information and communication technology and modern enterprise management methods. These methods can standardize enterprise management processes, improve labor productivity, improve service quality and user experience, strengthen management-assisted decision-making, change enterprise operation models, and ultimately maximize profits. The process of enterprise informatization runs through the whole life cycle of a product or service, including: market demand, product planning and design, research and development, manufacturing and service [29].

(1) Evaluation index system

According to the construction experience of informatization projects, the main factors that affect the performance of informatization projects include pre-project planning, project construction process, technical ability level, application effect, safe and reliable operation and economic benefits, etc. The details are shown in Figure 9.

As can be seen from Figure 9, the application effect of the information system is the most intuitive manifestation of the performance level of the total information item, which is reflected in the application and dependence of the enterprise business on the system. The system application and degree

Table 1 Statistics of power grid informatization projects.

elements	traditional project	Informatization project
scope	Single professional, clear demarcation of projects	interdisciplinary, interprofessional
skills requirement	Mature technology, relatively slow development	Technological development
Personnel requirements	Mainly for business personnel, professional background is relatively simple	Mix of business people and ICT staff
effect	A necessary part of the main business, and sometimes the main business itself	Auxiliary main business
Business needs	stable, clear	different levels of awareness
degree of importance	usually more important	Multidisciplinary collaboration with high complexity

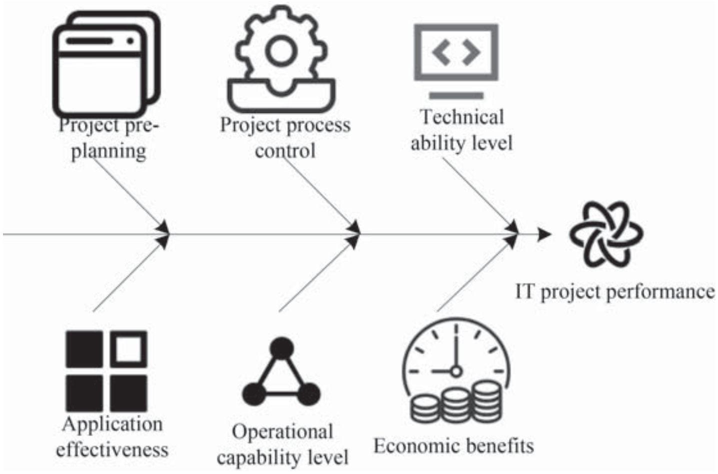

Figure 9 Analysis of key factors in the evaluation of informatization projects.

of dependence are related to the economic benefits of process informatization project construction brought to business by information systems, which are an important component of project performance, and have both direct and indirect benefits. Through the above analysis, this paper comprehensively identifies and classifies the five key factors that affect the performance of power grid enterprise informatization projects: construction ability, technical ability, application ability, operation ability and economic ability.

(2) Building capacity indicators

The construction capability index is used to determine whether the power grid enterprise informatization project achieves the project's objectives in accordance with the planning requirements, whether the project construction process is standardized, and whether the project organization, progress, quality, cost, risk and other process control of the project are effective. The construction capability index includes six secondary indicators: target completion, construction standardization, project organization, process management and control, risk management and control, and outsourcing management and control. A detailed description of the indicators is shown in Table 2.

(3) Technical Capability Index

The technical capability index includes 4 secondary indicators, which are technical maturity, technological innovation, product quality, and team capability. The detailed description of the indicators is shown in Table 3.

(4) Application capability index

The application capability index is used to examine the actual application level of the information system of the power grid enterprise, which is generally reflected in the degree of dependence of the enterprise business on the information system and the degree of support the information system provides to ensure business continuity. The adoption of an information system can improve business standardization and efficiency, and enhance the satisfaction and experience of those who use the system. The application capability index consists of four secondary indicators: degree of business application, level of business support, business effect, and service satisfaction. A detailed description of the index is shown in Table 4.

3.2 Questionnaire Survey on Attitudes of Grid Employees towards the Management System

In order to determine the effectiveness of the digital management system, a questionnaire-based survey was conducted twice: before and after the trial implementation of the system. The surveyed participants were randomly selected by a generator software. Then, two of the younger employees (under 35 years of age), were selected as part of a three-person investigation team to refine the division of responsibilities. According to the division of labor, they went to various

Table 2 Indicator details.

first-level indicator	Secondary indicators	Indicator description
building capacity	goal completion	After the development of the information system is completed, compare it with the pre-project planning
	construction standard	Mainly inspect the compliance of informatization project construction
	project organization	Mainly inspect the project organization structure
	Process control	Investigate the ability to manage and control the whole process of the project
	risk management	Investigate the ability to deal with risks in the whole process of project construction
	Outsourcing control	Evaluation of management and control capabilities for project outsourcing

Table 3 Description of technical capability indicators.

first-level indicator	Secondary indicators	Indicator description
technical skills	technology maturity	Inspect whether the project design and development adopt mature, industry-proven technology
	degree of technological innovation	Technical capabilities, which can ensure that the functions of the information system meet the relevant technical requirements
	product quality	Determine whether the project development process includes a certain degree of innovation
	team ability	Investigate the quality of information system products

Table 4 Description of Application Capability Indicators.

First-level indicator	Secondary indicators	Indicator description
Application Ability	business application rate	Investigate the actual application of the enterprise information system after the construction is completed
	business support	Investigate the continuous support ability of power grid enterprise projects for enterprise business
	business effect	Investigate the application of power grid enterprise information system
	service satisfaction	Investigate the satisfaction of enterprise users with the services provided by the information system

departments to find the corresponding respondents, distributed a total of 330 questionnaires, and informed the participants of the survey deadline. The 330 questionnaires were collected on schedule, the validity of responses was confirmed, and the valid responses were statistically summarized. The statistical results of the two sets of questionnaires, before and after system implementation, are shown in Figure 10.

As can be seen from Figure 10*a*, in the first survey, 108 (32.69%) respondents chose 'very reasonable'; 124 (37.39%) chose 'relatively reasonable'; 72 (21.84%) thought that it was 'unreasonable'; and 26 (8.09%) thought it was 'very unreasonable'. As can be seen from Figure 10*b*, in the second survey, 210 (63.62%) respondents thought it was 'very reasonable'; 58 (23.73%) thought it was 'relatively reasonable'; 35 (10.4%); thought it was 'unreasonable'; 8 (2.25%) chose 'very unreasonable', which is a low proportion compared with the results of the first survey. These statistics indicate that through continuous reform and optimization, the correct performance management concept can be established from top to bottom, and the scientific layout and bold promotion have been able to greatly improve the recognition of the reformed and optimized management system by all leading employees. In particular, the support of grass-roots management personnel and general personnel for the company's implementation of the digital management system has also increased significantly. The satisfaction of all staff in regard to the management system indicators, the application of performance appraisal results, and the information communication during the appraisal process has been greatly improved, which is helpful for more accurate appraisal of each department and employee.

4. CONCLUSIONS

This paper has analyzed the development trend of the power grid against the background of the research on the development of intelligence. Combined with the current

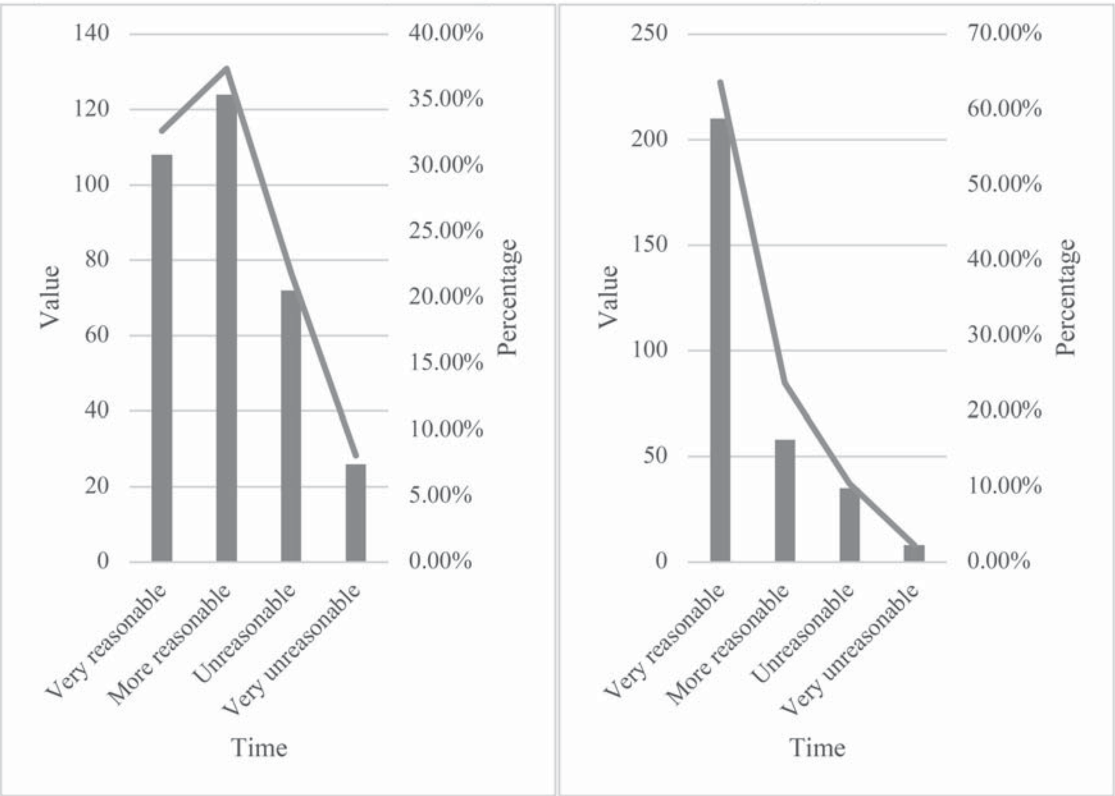

Figure 10 Comparison of the statistical results of the two questionnaires.

status of the management system of power grid enterprises, an artificial intelligence algorithm is proposed for the construction of the power grid dispatch management, network security management and performance management mode. It was demonstrated that the intelligent and efficiency-intensive operation mode that meets the economic, social and environmental requirements is the inevitable development trend of power grid companies' delivery of energy to the consumer. Taking into account the characteristics of the current power grid digitization, this paper designs a power grid artificial intelligence management system framework for company A, to provide solutions for enterprise management decision-making. It focuses on the design of the power grid artificial intelligence basic system, the power grid artificial intelligence application system, and the power grid artificial intelligence technology management framework. Based on these research results, the experimental environment of the power grid artificial intelligence system is built. Specifically, it includes a grid-oriented distributed file system, multi-tenant unified resource management and control, SQL-based artificial intelligence technology management, artificial intelligence columnar database and artificial intelligence visualization, etc.

The effectiveness of the proposed algorithm in practical applications is tested. The grid intelligent system stores data by establishing a columnar database table, and realizes the query of single condition and combination condition to return the result within three seconds. For addresses and user names, the full-text indexing technology is used to achieve fuzzy query returns within five seconds.

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