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OPC UA Application Study in Oil and Gas Pipeline Network Monitoring Data Forwarding

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Abstract

INTRODUCTION With the continuous development of oil and gas pipeline network monitoring and control technology, the need for data transmission and communication is becoming more and more prominent. In this context, OPC UA has attracted wide attention. This study aims to explore the application of OPC UA in data forwarding for oil and gas pipeline network monitoring in order to improve the efficiency, reliability and security of data transmission.
PURPOSE: The purpose of this study is to evaluate the applicability of OPC UA in oil and gas pipeline network monitoring and to verify its performance in data forwarding through empirical studies. By gaining an in-depth understanding of the characteristics of OPC UA, it aims to provide a more advanced and efficient monitoring data transfer solution for the oil and gas industry.
METHOD: The study adopts a combination of field monitoring and laboratory simulation. First, the essential characteristics and requirements of monitoring data in oil and gas pipeline networks were collected. Subsequently, a monitoring system with OPC UA as the communication protocol was established and field tested. In the laboratory environment, data transmission scenarios under different working conditions were simulated, and the performance of OPC UA under different conditions was analyzed.
RESULT: The field monitoring results show that the data transmission efficiency is significantly improved by using OPC UA as the communication protocol for data forwarding in oil and gas pipeline network monitoring. Meanwhile, the system performs well in different environments with high reliability and security. The laboratory simulation results further verify the stability and adaptability of OPC UA under complex working conditions.
CONCLUSION: OPC UA is an effective communication protocol that can meet the data transmission requirements for oil and gas pipeline network monitoring. Its efficient, reliable, and secure characteristics make it an ideal choice for improving the communication performance of monitoring systems in the oil and gas industry. The empirical results of this study provide reliable technical support for the oil and gas industry in the field of data transmission and a vital reference for the optimization and upgrading of monitoring systems in the future.

Keywords: OPC UA; oil and gas pipeline network; monitoring data; data forwarding

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1. Introduction

Underground oil and gas pipelines play an indispensable role in the construction of the national economy as the essential equipment for the transportation of oil and gas fields(Shah et al., 2022). These pipelines are responsible for transporting oil and gas from the source to where it is needed; however, pipeline safety is of great concern due to the flammable and explosive nature of oil and gas. The potentially hazardous nature of the transportation process, coupled with the relative complexity of the underground environment, increases the risk of pipeline damage(Kotelnikov et al., 2021). Such damage can lead to significant natural resource losses, environmental pollution, and even severe personal injury, posing a potential threat to society and the ecosystem. Currently, research on the management of underground oil and gas pipelines focuses mainly on the establishment of safety assessment and monitoring systems for underground oil and gas pipelines of the accident alarm type(LIJunling, 2022). However, these systems only have the function of passively minimizing accidental damages of buried pipelines and have limited ability to conduct comprehensive investigations of the potential information in oil and gas pipeline data(Yuan et al., 2023). Therefore, there is an urgent need for an in-depth study on how to apply data analysis and processing techniques to create an intelligent online monitoring and assessment system capable of providing early warning of risks at critical nodes in underground oil and gas networks and responding more proactively to potential safety hazards.

Despite the relative safety, practicality and economic importance of underground oil and gas pipelines in transporting oil and gas fields, millions of kilometres of pipelines are currently used extensively worldwide to transport large quantities of fuel, oil and gas. Although the transportation of dangerous goods is relatively safe, a number of serious pipeline accidents still occur, particularly with underground pipelines(Panfilov et al., 2021). Underground pipelines have become ideal for the growing number of underground oil and gas networks being built in large cities due to their convenience and space-saving advantages(Agomuoh et al., 2021). However, the raw materials transported through underground oil and gas pipelines are classified as Class A hazardous substances, consisting mainly of various hydrocarbons, which increases the risk of fires, explosions and other accidents associated with oil and gas transportation. In addition, oil and gas pipelines are buried deep underground, making it difficult to monitor and control them through traditional manual control lines(Seghier et al., 2022). Due to the complexity of the underground environment, pipelines are not only subject to long-term external factors such as environmental contamination, material corrosion, and structural vibration. Still, they are also susceptible to impacts and damage from the pipelines themselves. Therefore, the key to addressing these issues is to fully understand and proactively manage underground oil and gas pipeline systems to ensure their safety and reliability during transportation. Although the likelihood of oil and gas safety measures is relatively low, there can be severe consequences. An accident or series of accidents can cause serious damage, pollution or even severe destruction of natural resources(Myssar et al., 2021). For example, in July 2014, a natural gas explosion in an underground pipeline in southern Taiwan caused the most significant oil disaster in Taiwan's history, damaging about 6 kilometres of roadway and causing significant losses.

The operation and reliability of underground oil and gas pipelines are critical to their safe and efficient operation(Lembo, 2022). A deep understanding of the system supports managers in developing more rational maintenance and preventive measures and in responding to potential fire and explosion risks in a more timely manner. Despite the widespread use of underground pipeline monitoring technology and even the requirement for effective monitoring systems in some countries, there still needs to be a lag in some areas(Chuanbao et al., 2021). In particular, when fires and explosions occur without prior warning, the damage caused by the accident will be reactive if not dealt with in a timely manner.

With the development of information technology and big data, big data technology is gradually applied to different industries. In the monitoring and prevention of underground pipeline networks, the combination of underground pipeline monitoring technology and big data requires proper analysis of all unclean data(Cao, 2021). However, the diversity of underground pipeline data in many forms, including digital, audio, and video, as well as fragmentation from semi-structured or unstructured data, complicates the organization and analysis and requires appropriate methods to extract potential data from a large number of underground pipelines(Moradi et al., 2023). From a Big Data perspective alone, it may provide little application value. In the age of big data, many oil and gas companies may need to take full advantage of the vast amount of tracking data available, and they need to be able to utilize fragmented data effectively (Hirst, 2021). However, factor correlation analysis of monitoring data may replace sensitivity probabilistic assessments, leading to more reliable assessments of risk in underground oil and gas pipelines; if these irregular and variable data can be handled efficiently, the potential value between the data can be extracted, and the data can be allowed to be applied appropriately(Benson et al., 2021). To ensure effective monitoring of mining data, risk assessment of underground oil and gas pipelines, and to address delays in current pipeline monitoring methods, the implementation of data analysis and processing methods requires in-depth research(Peng et al., 2023). Therefore, the establishment of an intelligent early warning and safety system is essential for underground oil and gas pipelines to ensure a timely response to potential risks and to safeguard the safe operation of pipelines.

2. Background of the study

In the current era of big data, people are faced with a vast amount of information, a high-speed emergence rate, and increasing data complexity. In particular, the data obtained through real-time monitoring of underground oil and gas pipelines urgently needs to be processed by real-time data analysis algorithms instead of using traditional batch analysis methods(Luo et al., 2022). The processing of high-speed monitoring data requires data mining algorithms capable of evaluating monitoring data generated by pipeline networks in real-time and continuously to avoid the challenge of processing large amounts of monitoring data simultaneously. To address this challenge, unique computational mechanisms that can represent the subsurface data of the entire oil and gas network through a relatively small amount of real-time data are required(Xue et al., 2021). In this context, monitoring subsurface oil and gas pipeline data with the help of Hewhart's control chart theory is a feasible approach to detect the process of hazardous dynamic transformation of subsurface oil and gas pipelines. This method helps to detect anomalies in a timely manner in the case of continuous generation of monitoring data and provides support for early problem-solving. Due to the possibility of false data in underground pipeline networks, it is necessary to think carefully about the method of false data calibration in underground pipeline networks(D. Wang et al., 2021). Minor problems usually trigger significant accidents, and once a minor problem evolves into a danger, the monitoring data may change abnormally. The monitoring data of underground pipelines are continuously generated while presenting a certain degree of cyclical or episodic changes. Therefore, in-depth monitoring of data indicators to analyze the dynamic changes in threat development and to obtain early warning and recovery effects can help to solve the problems of underground oil and gas pipelines in advance. In researching how to more accurately identify false information in underground oil and gas pipelines, artificial neural network technology is widely used in pipeline accident analysis and research. Specifically, the BP network is chosen as the main algorithm to analyze the abnormal data.BP neural network has strong learning ability, which can extract reasonable data monitoring principles from complex falsified data generated by underground oil and gas pipelines and continuously study and modify the decision rules based on new data. Even if the local neurons in the BP neural network are damaged, the learning results will not be significantly affected. From the perspective of stability, the BP neural network is highly fault-tolerant and can support continuous real-time processing of false data generated from underground oil and gas pipelines(Bang et al., 2021). The combined application of this series of methods and technologies is expected to effectively ensure the safety and reliability of underground oil and gas pipeline operations. Through real-time data analysis, anomaly detection, and false data identification, the challenges brought by the era of big data can be better dealt with, and the safe operation of underground oil and gas pipelines can be guaranteed.

This research combines theory and practice and combines control theory and machine learning to solve the core problem of underground oil and gas pipeline extraction that generates large amounts of data. Developing learning algorithms for oil and gas network data, fully utilizing potential data, and accurately assessing network anomalies can effectively reduce financial and human losses for companies(Yajian. Wang et al., 2022). This research has important theoretical and practical implications for detecting potential hazards in underground oil and gas pipelines and preventing and eliminating these hazards at an early stage. Given the complexity, importance and high risk of underground oil and gas pipelines, potential risks are identified and eliminated in real-time, and false monitoring data are linearly processed. Created scientific and practical monitoring mechanisms that combine control algorithms with machine learning to enrich the field of pipeline and network monitoring. Developed artificial neural network algorithms to deal with false data in underground oil and gas pipelines. From the perspective of error assessment and early warning, an improved and integrated method for processing underground data in oil and gas networks using artificial neural networks is proposed to reduce the discrepancies in the education data and to address the overweight and threshold variations. By selecting false valuable information, critical information can be identified accurately and reasonably, achieving the goal of identifying potential threats before a hazardous event occurs and developing tools to manage rapid response(Chen et al., 2021). The test approach is both practical and pragmatic. Early intervention can provide a basis for controlled decision-making and improve the speed, efficiency and accuracy of analytical decisions. Examples and applications in industrial and related industries are presented, as well as new ideas for research monitoring and data processing in other industries.

3. Research methodology

3.1 Methodological discussion of oil and gas pipeline network monitoring data

The underground network of oil and gas pipelines is often covered with charging equipment that reacts with the soil and corrodes the pipes. External pressures can also affect pipelines. Complex environmental corrosion can seriously interfere with the control of underground pipelines. Highly acidic and alkaline carbon steel pipelines corrode uniformly. Based on measurements, the service life of the pipeline can be reasonably calculated. Unlike common corrosion caused by strong acids and bases, localized corrosion of pipelines is closely related to their peak depth.

When conducting pipeline monitoring, a number of critical factors must be considered comprehensively, including but not limited to a wide range of elements such as pipeline material, inner diameter, outer diameter and temperature range. For a long time, the international community has been working tirelessly, focusing on in-depth research and continuous improvement of technologies for monitoring oil and gas leaks. However, due to the unique complexities of underground oil and gas pipelines, a universal methodology has yet to emerge for comprehensive monitoring. Considering the intricate nature of these pipelines, a large amount of real-time information must be generated at different levels to understand and grasp the safety status of pipelines more fully. As big data technologies continue to advance and data processing efficiency increases, monitoring data can be utilized more effectively to gain a deeper understanding of the relevant information, leading to more comprehensive monitoring and assessment of the state of oil and gas networks. In the era of big data, researchers have emphasized the importance of creating big data in pipeline operations by digging deeper and assessing the correlations between the underlying data. This not only helps to identify potential problems in a timely manner but also provides more comprehensive information support to ensure the safe operation of oil and gas networks. Therefore, large-scale information networks play a crucial role in the safe operation of oil and gas pipelines, providing more efficient and accurate monitoring and management tools. OPC UA node diagram, as shown in Figure 1.

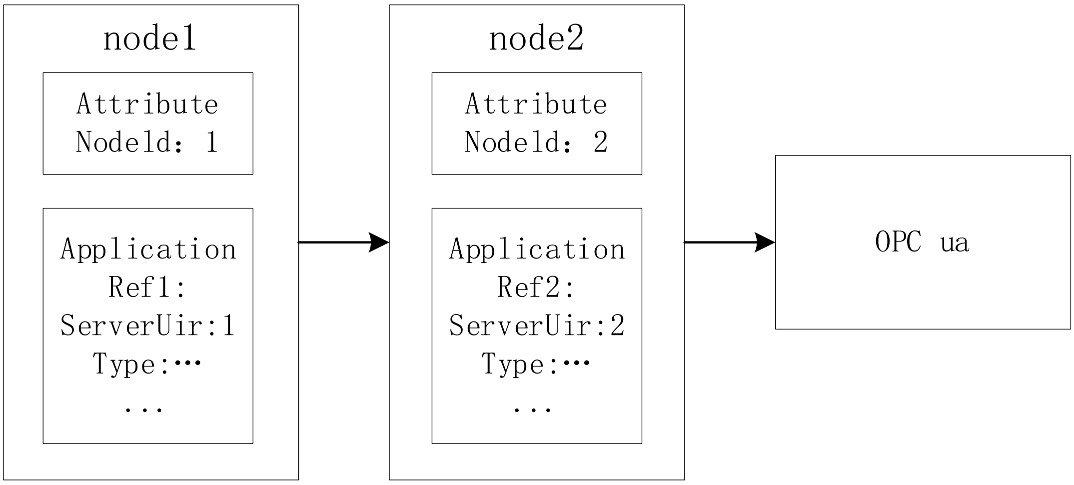

Figure 1 OPC UA node diagram

This software approach can effectively monitor the big data generated by underground oil and gas pipelines. This software approach uses a computerized system to collect real-time information about pipeline pressures, temperatures, and velocities. Using a generalized model, the state of the network can be calculated and managed. Signal-based monitoring methods detect pipeline errors based directly on the error data generated when a pipeline fails. One of the most common methods for vacuum waves is to determine the location of pipeline leaks based on the current pressure of a localized pipe. Some researchers have made more stringent requirements for extensive data monitoring based on pipeline signals. Pipeline condition parameters are evaluated and compared to actual monitored values to determine the occurrence of risk using real-time models, real-time modelling, and pipeline modelling. This testing method requires a large amount of relevant simulation data to obtain good assessment results. Algorithms such as machine learning and statistics are used for AI monitoring to determine the potential value of data collection and foresight.

3.2 OPC UA-Related Discussions

In order to standardize the flow of data from the processing level to the management level, the OPC Foundation has created various user interfaces and software specifications called OPC specifications. Depending on industry requirements, there are three specifications: the OPC DA, OPC A&E, and OPC HDA. The OPC DA is a data interface function that includes read, write, and sort nodes. The OPC A&E interface allows for the receipt of events and alarms. The OPC HDA provides access to stored data. The OPC uses the client/server (C/S) model for data exchange. If a client needs to manage server data, save the data on the server and send it to the client. This connection allows the client and server to manipulate the server data without separate communication.

The traditional OPC interface is based on Microsoft COM and DCOM technology. It was successful when Windows became popular for a while. However, it had two significant drawbacks: the OPC technology was based on the Windows platform, and DCOM could not be used for Internet communications. OPC UA endeavours to replace Microsoft-based communication standards without compromising functionality and performance. In addition, OPC UA is vendor-independent and can be customized by any developer. It is not limited to operating systems and programming languages. OPC UA uses a service-oriented architecture (SOA), which classifies and connects a variety of services through defined interfaces and protocols, increasing the scalability and availability of the system. The OPC UA Logic Diagram is shown in Figure 2.

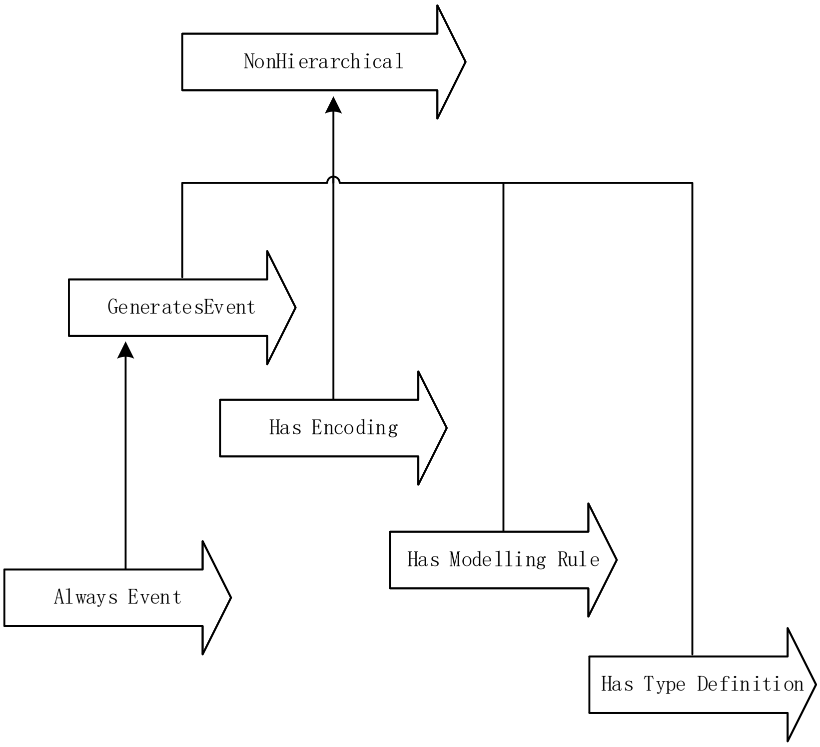

Figure 2 OPC UA Logic Diagram

OPC UA is a service-driven, architecture-independent platform initially designed for the exchange of data between various devices and machines in an industrial environment. These specifications form the common foundation of OPC UA, and understanding the modelling and use of information is critical to the system.

When a client needs to access server data, the communication between the client and the server follows the primary communication mechanism of the C/S architecture, handling the entire signal request, call request, or response service stack in the server interface, connecting and initiating the data transfer. Functionally, the OPC UA client is integrated into the application as a communication bridge and handles requests and responses between the client and the server through user interface calls. The OPC UA communication stack supports communication. This is the data processing performed by the communication blocks that collaborate with the server to share server data resources and memory file system communication stacks. Understand how the client application performs four main events: message requests, message responses, order requests, and notifications. An OPC UA server can be multiple devices in the field or even an OPC UA cloud device. The OPC UA client interface and the OPC UA communication stack form the OPC UA client.

The OPC UA model is shown below:

$$X = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{1}$$

where X is the mean value obtained for the i-vector, and the number of i-vectors is n.

$$S = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - X)^2} \tag{2}$$

where S is the standard deviation of the statistical values calculated using the least squares method.

$$UCL = x + 3S \tag{3}$$

The UCL is an indirect calculation of the overall value of the cubic variance through the excess of the unknown x.

$$CL = x \tag{4}$$

CL is redefined as a free variable for model re-testing.

$$net_j = \sum_i W_{ij} y_j + b_j (j = 1,...m) \tag{5}$$

Net_j is a summation of the number of nodes.

4. Results and discussion

4.1 Problems and solutions of oil and gas pipeline monitoring data

By categorizing and summarizing the above methods of data monitoring in underground oil and gas networks, the critical role of data in monitoring oil and gas networks can be confirmed. Many researchers have also made significant contributions to the management of subsurface data in oil and gas networks. However, building on these discussions, ongoing research on the management of underground oil and gas networks raises two additional issues without considering the rapid elimination of security threats and the facilitation of port construction in risk management. Many of the commonly used methods of data monitoring are based in large part on the experience of experts on specific issues related to oil and gas networks. It may be easier to exploit potential oil and gas pipelines fully by scrutinizing the large amount of irregular data on underground oil and gas pipelines. Not only must deficiencies in widely used data monitoring methods based primarily on traditional expert experience be corrected, but joint management paradigms such as preventive care and incident alerts must also be improved. Therefore, there is a need to develop a methodology to examine possible pipeline network models and to facilitate the development of risk ports. Thus, real-time studies of intelligent monitoring of underground oil and gas pipelines take complete account of the specific forms of port migration objectives for ongoing big data production and risk management.

The subsurface environment of oil and gas networks is multidimensional and contains multidimensional knowledge attributes such as pressure, flow rate and temperature. Traditional data monitoring methods are mainly based on the experience and knowledge of some pipeline experts. As a result, some pipeline system experts may need help finding the best decision rules to address the changes in the complex environment. Instead of processing extensive tracking data simultaneously, data mining algorithms can track and process small data in real time, creating a unique subsurface data processing mechanism for oil and gas networks.

Incorrect dynamic data in underground oil and gas pipelines must be carefully scrutinized to facilitate risk management platforms. However, serious accidents are evolving from small problems, from initially minor anomalies to unavoidable extreme hazards, all of which have an inevitable progression. When maintaining oil and gas networks, data from monitoring indicators used to monitor and manage the development of hazards often need to be more accurate. This analysis of data processing rules enables early identification of potential threats to oil and gas pipelines through data analysis, early warning, and reduction of economic and human losses. In order to detect this incorrect information, the Hughart control card can filter the monitoring indicators for the purpose of quickly understanding the dynamics of an incident. Restrictions on the management of monitoring data can be used to determine whether the data generated by the system fluctuates regularly, whether there are incorrect characters in the system, and whether the monitored objects are under control. A comparison of OPC UA and OPC UI logic is shown in Figure 3.

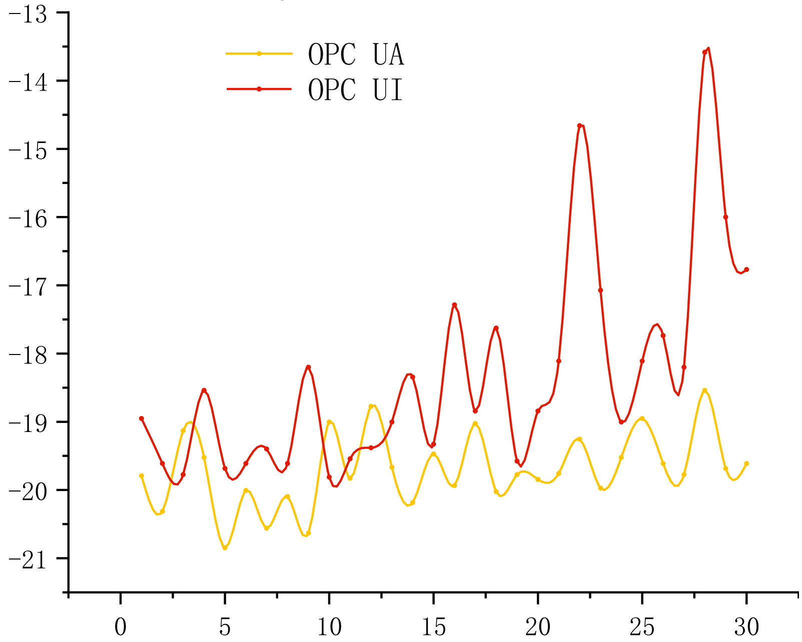

Figure 3 Comparison of OPC UA and OPC UI logic

Hewhart control panels have been an essential scientific management tool from the beginning, especially in quality management, and have been widely used in many fields. In this paper, Hewhart control charts are utilized to monitor faults in underground oil and gas pipelines. National researchers have suggested the application of the Sheehart control theory to the monitoring of error states, and experimental studies have shown that Sheehart control cards can be used for the storage and transportation of oil and gas with good results. Therefore, Sheehart control charts can be used to monitor data from underground oil and gas pipelines.

In the era of big data, underground oil and gas pipeline monitoring data are characterized by large data volumes, fast speeds, and complex data. However, monitoring data for underground pipelines and oil networks are generated in real-time, so the algorithm focuses on fast data processing and requires real-time data processing rather than batch analysis. Due to the large volume of data, the data retrieval algorithm does not need to process extensive tracking data at one time, but it needs to be able to process small-scale data online during the tracking process. Erroneous monitoring data is entered for decision-makers, data is preprocessed using EF-PNN, decision-makers are categorized, and risk assessment is performed using a BP network. The mathematical model has been validated for oil and gas pipeline system calculations in a chemical company's oil and gas field pipeline system.

4.2 OPC UA Technology Nodes and Objects

The goal of the OPC UA server build is to emulate a server endpoint for client-server interaction. The OPC UAServer application can play or maintain physical objects from within. The main task of the server is to perform various functions on variable nodes of addresses. When the process is complete, one order administrator sends a notification to the order server, and the other directly asks the customer to return the appropriate response message. Both responses require messages to be sent through the OPC UA server interface and the OPC UA communication stack. All physical data models of the device nodes are stored in message templates. The OPC UA address range model is described as follows. The OPC DATE order. As shown in Figure 4.

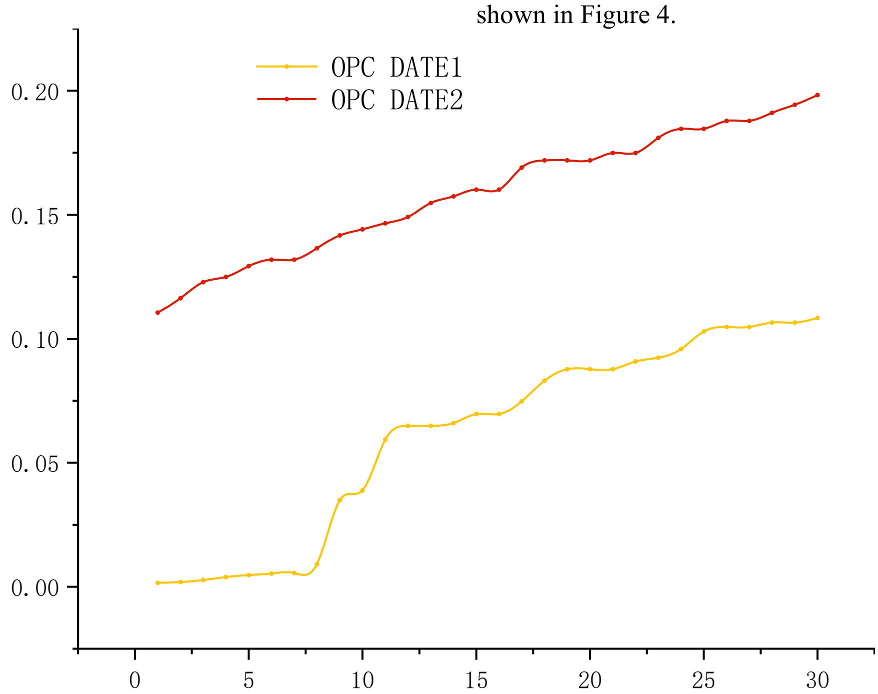

Figure 4 OPC DATE sequence

All OPC UA data and data are located in the address space, providing customers with a unified data interface. In traditional OPC, the address space is defined differently for different services. Still, OPC UA combines the address space, security, and service models to integrate and consolidate all data and provide a unified interface to the outside world, significantly improving performance. Each UA OPC server has a set of tree objects that clients can access. All objects have a controller node where objects, variables and methods are grouped into a hierarchy. An area consisting of multiple OPC UA nodes is an address area. Data Physical Systems (CPS) typically require connections to networks and physical processes, and nodes provide suitable containers in the address space. Each physical device corresponds to an address range node, and multiple system devices can be managed based on a node identifier specified in the address range. This abstraction of accessible but logically interconnected devices is unique to an object. The address space includes not only abstract nodes but also many services used by external subsystems for address space management, including information management, monitoring and control management, and information modelling.

OPC UA provides a standard way to represent these abstract physical objects. When customers need to search for device data, these abstract physical objects are defined by logical relationships between nodes that combine node attributes and links to find critical nodes in a family of nodes. In addition, these objects can be reused, and many similar objects can be simulated using the public data model. Support for OPC UA web services enables OPC UA clients to view and edit objects in address mode on the OPC UA server. The main task of the Service Management Container is to store data in the LAN Management Container and to transfer data from the Management Container to the user. This enables the efficient management of the address space and the realization of services. The address space structure is used to manage the address space. The main task is to create five management containers in one space and to create a complete service interface. The OPC DIG efficiency. It is shown in Figure 5.

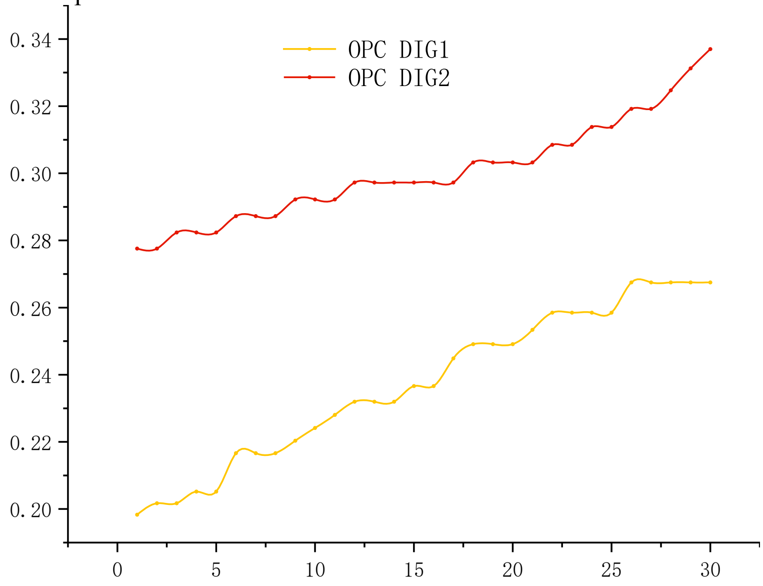

Figure 5 OPC DIG Efficiency

Objects are essential functional units in the address space. As mentioned earlier, OPC UA also has an object-oriented concept in which physical devices are abstracted as objects stored in the address space. A client using the address model can view multiple nodes and their relationship to objects. The object model encompasses the interaction between objects and the relationship between two objects relative to each other. Objects have object nodes and variable nodes. The relationship between them is a component, which is the OPC UA data model. Objects can be connected using a component and then added to the address area of the server. If OPC U contains a method of an object type, add a reference to the method instead of copying it to the object. When using the example object. All objects of the same type have a reference to the same method. An OPC UA object is a data container that is located in the address region. The method referred to. A common type of method is an object located at the top of the server. Each of these objects is referred to as a node, and there are many nodes in the address area, such as object nodes, variable nodes, etc. Monitoring data Comparison is shown in Figure 6.

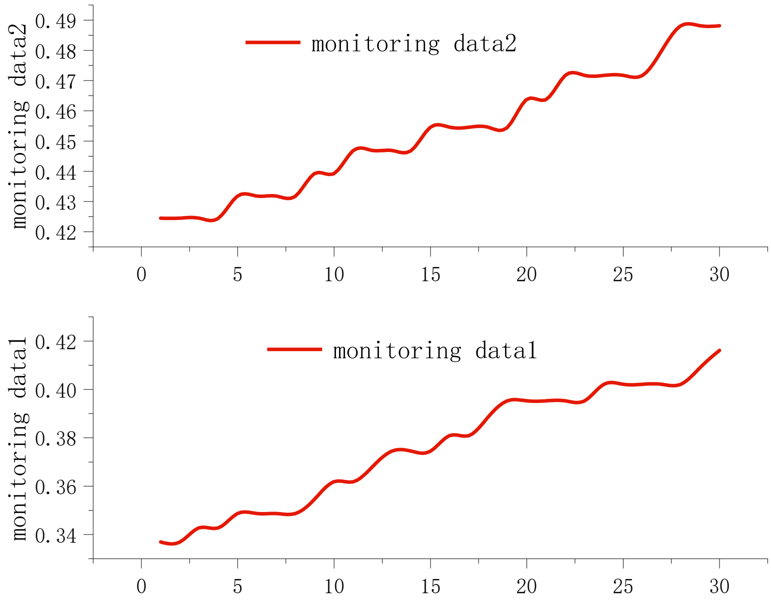

Figure 6 Comparison of Monitoring data

The address model is based on nodes. In the system, the address range can be represented as a whole, consisting of many essential nodes and their derivatives. The metadata model defines only the essential attributes of a node and is an unattainable abstraction of the same node type. However, it is possible to expand and create other nodes by enabling essential nodes. When configuring a node, it is necessary to specify its attributes and links, which are the main components of the node. Node attributes are data elements that describe a node. Each node must contain the main node attribute and other attributes specified by the node type. Clients can access attribute values by reading, writing, polling, and article subscription/tracking. The link describes values that have no real meaning and are not available for communication between nodes. It can only be accessed indirectly through a viewer or client service.

4.3 Oil and gas pipeline network monitoring data network

In the field of underground oil and gas pipelines, the backpropagation neural network (BP network) has demonstrated excellent performance as the main algorithm to combat false data. The network stands out for its strong learning capability and its ability to flexibly adapt to dynamically changing environments. With updated decision rules, BP networks are highly flexible in handling new data. Its excellent fault tolerance and high reliability make it ideal for the real-time processing of continuous data from oil and gas pipelines. In the study, the nature of the BP network is discussed in depth, focusing on the computational principle of the neural network, and the accuracy of the BP network computation is further improved by constantly adjusting the new weights and thresholds through experiments. The combination with the implicit neural network further enhances the performance of the BP network. The working principle and steps of the improved algorithmic model are explained in detail, emphasizing its vital role in performance enhancement. Ultimately, the significant improvement in computational accuracy of the improved algorithmic model over the conventional BP network is verified by using open-source data. However, despite the wide application of BP neural networks in the field of underground oil and gas pipelines, they still need to overcome a series of challenges. Network crowding leads to a reduction in learning errors but an increase in testing errors. At the same time, the slow convergence rate may cause it to fall into local minima, making it challenging to find the optimal global solution. To overcome these problems, experts and researchers have made efforts to improve the performance of BP networks by optimizing parameters and employing sophisticated optimization algorithms. However, these efforts may sometimes need to pay more attention to the potential impact of learning data differences on the learning stability of BP networks. Based on this realization, a new approach is proposed as a strategy for neural networks to handle forged data in real-time. By propagating the training data into the training dataset and forming multiple related BP networks, the efficiency and accuracy of the neural network in processing certain classes of data are improved. Ultimately, the effectiveness of this improved algorithm is verified with open-source data as an example, which provides new ideas and solutions for data processing in the field of underground oil and gas pipelines.

Integration of possible neural networks and BP networks into the augmented model through a learning process: randomization of N-labeled data into learning and test data. As a learning algorithm used for monitoring, the possible neural network learning is independent of the learning material. Meanwhile, the K-Fold cross-checking technique is used to help the potential neural network explore and categorize all the learning data. The K-Fold cross-checking method decomposes all the data into K-parts, and whenever the K-1 series is used for training, the remaining data are used to evaluate the model. In learning material classification, probabilistic neural network-based data is divided into N subsets of learning materials and the N-BP network is used to form different learning materials. After training, the optimal weight and threshold are saved. Monitoring F is compared, as shown in Figure 7.

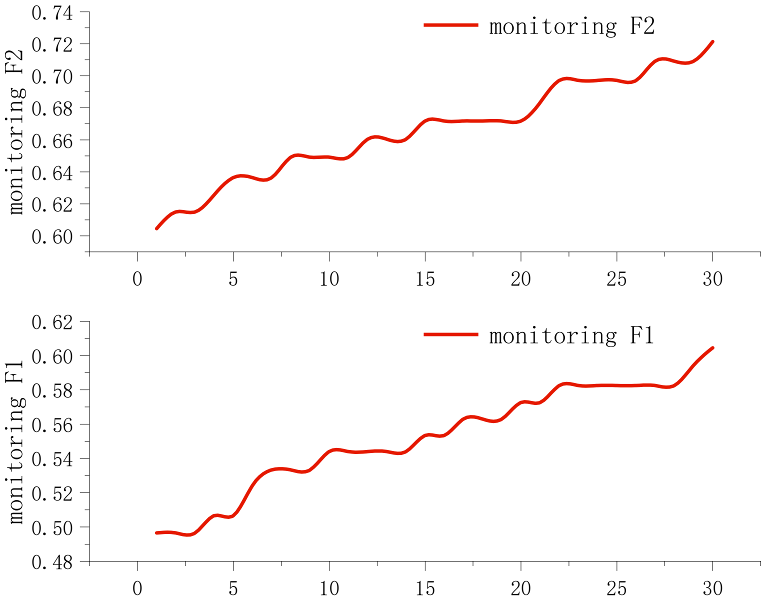

Figure 7 Monitoring F Comparison

According to the decision-making principle of probabilistic neural networks, the network improves computational accuracy by dividing the "training subset" and the "test subset" into the same class, assuming that they are similar. On this basis, the BP network is carefully designed to specialize in specific samples to ensure more accurate results. In order to delve deeper into this theory, the researchers introduced the connection between probabilistic neural networks and BP networks to form the probabilistic structure of BP networks. The proposed structure aims to separate the decision data more efficiently and provides a new direction for the improvement of the model. In a validated process, the improved PNN-BP network demonstrated feasibility and high accuracy in model classification. The validation process involves classifying and identifying the target records using classical UCI records.UCI data proves to be a powerful tool for validating the model, as there is no need to go through cumbersome data preprocessing and feature development, thus increasing the efficiency of the validation process. Specifically, of the processed CMC records, each example contained nine functions, while the training package samples were categorized into three categories, containing a total of 1473 samples. For comparison purposes, the research literature chose to test the dataset using classical BP neural networks and augmented models, and a control group was created. In this study, approximately 70% of the data was randomly selected as the learning space.

In comparison, the remaining 30% was retained as the testing space to ensure the comprehensiveness and reliability of the validation. Taken together, this study provides an insightful theoretical foundation for the new field of combining probabilistic neural networks with BP networks. It demonstrates the superiority of improved PNN-BP networks in practical applications.

In the phase of controlled learning, the researchers succeeded in improving the accuracy of network computation, which was achieved by combining probabilistic neural networks with the network. However, facing challenges in unsupervised learning and regression, the neural network faced some difficulties in separating from the learning data markers. In order to predict specific monitoring metrics for safety monitoring of underground oil and gas pipelines, the researcher emphasized the careful selection of training data entries and applied algorithms to decompose training and experimental data. Finding statistical models is necessary in the process of learning monitoring, unsupervised learning and feedback. By training the weights and thresholds of each background propagation (BP) network, the researcher succeeded in improving the prediction accuracy. This was achieved by differentiating between different datasets so that each BP network only handles outstanding data. In order to better handle large amounts of data, the researchers chose a clustering algorithm to group the learning and testing data and form and test BP networks based on the clustering results. The core of the grouping problem is to divide the data with similar sample attributes into multiple "classes" or "clusters" to improve data processing efficiency and clustering accuracy. This problem is effectively addressed by using the K-Means algorithm to differentiate and process unsupervised and irreversible learning data. The K-Means algorithm is a commonly used clustering method that has the advantage of being able to determine the number of clusters. The algorithm collects data through an iterative solution, randomly selects K objects as initial clustering centres and divides all data based on distance. Each clustering centre and its assigned objects represent a category.

After defining the different categories, the researcher recalculated the existing objects in each category to form new cluster centres. This process was repeated until the specified termination conditions were met. For example, no objects (or at least very few) were assigned to different clusters, the cluster centres did not change again (or at least hardly changed), and there were almost no negligible local errors. This flexibility and effectiveness of the K-Means algorithm makes it ideal for dealing with large-scale datasets and improving the clustering accuracy. Monitoring D Comparison, shown in Figure 8.

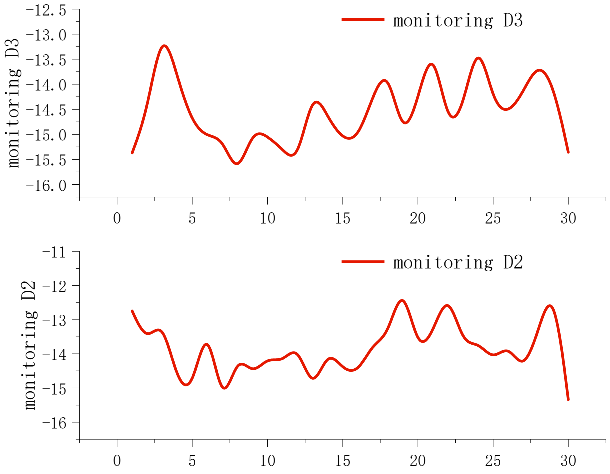

Figure 8 Monitoring D Comparison

CCPP material from the UCI machine learning database was also selected for the experiments. Each sample contains four functions, and the data contains 9568 samples. The five pillars are AT (temperature), V (pressure), AP (humidity), RH (pressure), and PE (output power), with the corresponding PE being the selective output. The neural network of BP is designed to simulate a regression model using learning and learning data. Once the regression model is modelled, the efficiency of the model is evaluated by calculating a set of tests. The BP network and a modified BP KMeans network are used to test the data and create a control team.70% of the data is randomly selected as a learning model. The remaining 30% is used as a test model mainly to study the effect of the new model on the classification of the model.

5. Conclusion

The in-depth discussion and empirical analysis of this research have led to conclusions about the application of OPC UA in data forwarding for oil and gas pipeline network monitoring. This conclusion aims to summarize the main findings of the study and provide insights into future applications and research directions. First, this study clarifies the superiority of OPC UA as a communication protocol in the field of oil and gas pipeline network monitoring. In terms of data transmission efficiency, the adoption of OPC UA significantly improves the performance of the monitoring system, making data transmission faster and more efficient. This is critical to the need for real-time monitoring and rapid response to pipeline network conditions, especially in the complex and changing oil and gas operating environment. Second, OPC UA was observed to perform well under different environmental conditions with high reliability and security. This feature makes the protocol suitable for a variety of complex working conditions and harsh environments, providing a more stable and reliable data transmission solution for the oil and gas industry. In the current era of emphasizing data security, OPC UA's encryption and authentication mechanism also provides a strong guarantee for the pipeline network monitoring system. In addition, the stability and adaptability of OPC UA under complex working conditions are verified through laboratory simulation. This provides strong support for engineering practice in the oil and gas industry and a reliable scientific basis for enterprises to choose OPC UA for practical applications.

In summary, OPC UA shows significant advantages as a communication protocol for data forwarding for oil and gas pipeline network monitoring. However, it is also recognized that there are some limitations in the study, such as performance variations in specific environments and differences between laboratory simulation and field monitoring. Therefore, future research could further explore application scenarios under a broader range of conditions and provide insights into performance under different scenarios. Overall, this study provides strong theoretical and empirical support for data transmission performance improvement in oil and gas pipeline network monitoring systems. In the evolving field of industrial automation and data communication, the application of OPC UA will bring more innovations and benefits to the oil and gas industry and drive the whole industry in a more innovative and efficient direction.

References

[1] Agomuoh, A. E., Ossia, C. V., & Chukwuma, F. O. (2021). Asset Integrity Management in Mitigating Oil and Gas Pipeline Vandalism in the Niger Delta Region—Deep Burial Solution. World Engineering and Technology, *003*, 009.

[2] Bang, S., Lee, H. W., & Lee, B. W. (2021). Real-time monitoring of the Vacuum Degree Based on the Partial Discharge and an Insulation Supplement Design for a Distribution Class Vacuum Interrupter. *Energies*, *14*, 772. https://doi.org/10.3390/en14237891

[3] Benson, N. C., Asuquo, A. I., Inyang, E. O., & Adesola, F. A. (2021). Effect Of Green Accounting On Financial Performance Of Oil And Gas Companies In Nigeria. *Journal of University of Shanghai for Science and Technology*, *23*, 56–88. https://doi.org/10.51201/JUSST/21/11974

[4] Cao, C. (2021). *Numerical study of underground CO2 storage and the utilization in depleted gas reservoirs*. *45*, 79–93.

[5] Chen, Q., Wu, C., Zuo, L., Mehrtash, M., & Cao, Y. (2021). Multi-objective transient peak shaving optimization of a gas pipeline system under demand uncertainty. *Computers & Chemical Engineering*, *147*(1), 107260.

[6] Chuanbao, W., Jin, H. E., Liang, L. I., & Yue, Z. (2021). Application of BIM Technology in the Construction Management of Oil and Gas Field Stations. *Oil-Gas Field Surface Engineering*, *68*, 747–793.

[7] Hirst, N. (2021). The Future of Oil Majors in the Energy Transition Big oil and gas companies face the prospect of losing a large part of their market as the world transitions away from fossil fuels. Can they carve out a positive role for themselves? *Petroleum Economist*, *10 Suppl.*, 88.

[8] Kotelnikov, N., Urazova, N., & Oparina, T. (2021). Evaluation of the effectiveness of innovative solutions in the construction of oil and gas wells. *IOP Conference Series: Earth and Environmental Science*, *751*, 74783. https://doi.org/10.1088/1755-1315/751/1/012076

[9] Lembo, M. F. (2022). Artificiality and Naturalness: Semi-underground Houses and Their Role in the Construction of a Sustainable Urban Landscape. *Civil Engineering & Construction 16*(7), 331–343.

[10] LIJunling. (2022). Discussion on the Influence of Long-distance Oil and Gas Pipeline Construction on Environment and Protective Measures. Engineering technology, *34*, 1–11.

[11] Luo, P., Harrist, J. D., & Mesdour, R. (2022). Development of Optical Gas Sensor for Well Site Geochemical Analysis and Time-lapse Monitoring. *The Saudi Aramco Journal of Technology*, *Spring*, 56–88.

[12] Moradi, A., Kavgic, M., Costanzo, V., & Evola, G. (2023). Impact of typical and actual weather years on the energy simulation of buildings with different construction features and under different climates. *Energy*, *270*, 126875-. https://doi.org/10.1016/j.energy.2023.126875

[13] Myssar, Al Battbootti, Marin, I., Goga, N., & Popa, R. (2021). Oil and Gas Pipeline Monitoring during COVID-19 Pandemic via Unmanned Aerial Vehicle. *arXiv E-Prints*, *346*, 45–77.

[14] Panfilov, I. A., Antamoshkin, O. A., Bukhtoyarov, V. V., & Vaitekunene, E. L. (2021). Equipment for connecting pipeline elements in oil and gas equipment using induction brazing. *Journal of Physics: Conference Series*, *45*, 242–267. https://doi.org/10.1088/1742-6596/2094/4/042009

[15] Peng, W., Ma, L., Wang, P., Cao, X., Xu, K., & Miao, Y. (2023). Experimental and CFD investigation of flow behavior and sand erosion pattern in a horizontal pipe bend under annular flow. Pipe Technology, *4*, 11–25.

[16] Seghier, M. E. A. B., Hche, D., & Zheludkevich, M. (2022). Prediction of the internal corrosion rate for oil and gas pipeline: Implementation of ensemble learning techniques. *Journal of Natural Gas Science and Engineering*, *99*, 104425-. https://doi.org/10.1016/j.jngse.2022.104425

[17] Shah, R., Kraidi, L., Matipa, W., & Borthwick, F. (2022). Investigation of the Risk Factors Causing Safety and Delay Issues in Oil and Gas Pipeline Construction Projects. *Springer, Cham*, *121*, 34–52.

[18] Wang, D., Tan, Q., Yang, J., & Zhang, Z. (2021). Research on Emergency Treatment Measures for Oil and Gas Pipeline Passing Though Mining Subsidence Area. *IOP Conference Series: Earth and Environmental Science*, *657*(1), 012106 (6pp). https://doi.org/10.1088/1755-1315/657/1/012106

[19] Wang, Yajian., Li, Pengpeng., & Li, Jianfeng. (2022). The monitoring approaches and non-destructive testing technologies for sewer pipelines. *Water Science and Technology : A Journal of the International Association on Water Pollution Research*, *85*(10), 3107–3121. https://doi.org/10.2166/wst.2022.120

[20] Xue, Y. G., Ning, Z. X., Qiu, D. H., Mao-Xin, S. U., Zhi-Qiang, L. I., Kong, F. M., Guang-Kun, L. I., & Wang, P. (2021). A study of water curtain parameters of underground oil storage caverns using time series monitoring and numerical simulation. *Physics and Technology*, *22*(3), 17.

[21] Yuan, J., Mao, W., Hu, C., Zheng, J., Zheng, D., & Yang, Y. (2023). Leak detection and localization techniques in oil and gas pipeline: A bibliometric and systematic review. *Engineering Failure Analysis*, *146*, 107060-. https://doi.org/10.1016/j.engfailanal.2023.107060