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Large Model-Enabled Intelligent Operations and Maintenance in Enterprises: Implementation Challenges and Strategic Solutions

Mengran Zho

School of Electrical and Information Engineering, Anhui University of Science and Technology, Huainan, China

Abstract: ***With the deepening and expansion of digital transformation, traditional IT operation and maintenance models face severe challenges. Large model technology, learning, recognition, and generation capabilities, provides new solutions for enterprise intelligent operation and maintenance. However, the implementation of large models in the operation and maintenance field presents core challenges such as talent scarcity, data quality and governance issues, complexity in business scenario decomposition, and cost-benefit balance. This paper systematically analyzes these difficulties and proposes targeted solutions. Through high-value scenario pilots, progressive promotion, and continuous iterative optimization, enterprises can gradually achieve intelligent transformation of operation and maintenance, ultimately improving IT operation and maintenance efficiency and system stability.***

Keywords: Enterprise Intelligence; Data Replication; Intelligent Operations and Maintenance.

1. INTRODUCTION

In the wave of digital transformation, enterprises have increasingly high requirements for IT operation and maintenance. Traditional operation and maintenance models rely on manual monitoring and rule scripts, and their limitations have gradually become prominent. Problems such as low operation and maintenance efficiency, analysis lag caused by data explosion, passive fault response, and difficulty in knowledge management have severely restricted enterprise development [1-2]. The rise of large model technology provides a new solution path for intelligent operation and maintenance. Its powerful natural language processing, data analysis, and prediction capabilities help enterprises achieve active fault prevention, automated task execution, and systematic knowledge precipitation [3-4]. However, the implementation of large models in the operation and maintenance field still faces many challenges.

This paper systematically sorts out the practical path of large model-enabled intelligent operation and maintenance from four dimensions: implementation difficulties, team capability requirements, core problem solving, and tool integration strategies, aiming to provide enterprises with a reference implementation plan.

2. CORE CHALLENGES IN ENTERPRISE IMPLEMENTATION OF LARGE MODEL INTELLIGENT OPERATIONS AND MAINTENANCE

The core challenges in enterprise implementation of large model intelligent operation and maintenance are distributed in three aspects: talent, technology, and cost. Among them, technical difficulties stem from two directions: training data and business scenario decomposition.

2.1 Scarcity of New-Type Operation and Maintenance Talents

Traditional operation and maintenance teams have weak AI knowledge reserves. Traditional operation and maintenance personnel are mostly experts in Linux operating systems, networks, or hardware, with limited understanding of artificial intelligence, machine learning, and the capability boundaries and application methods of large models, lacking the foundation to promote intelligent implementation.

Divergences in technical fields lead to a scarcity of compound talents. As emerging technical fields, large models and machine learning have a significant gap between their knowledge systems and the practical needs of traditional operations and maintenance (O&M). The core skills in the O&M field focus on operating systems like Linux, network protocols, and automation tools, whose knowledge system has almost no overlap with the knowledge and capabilities required for mastering AI technology and large model training, such as data science and deep learning. This division results in distinctly different educational backgrounds and career development paths for the two types of talents, making it difficult for enterprises to fill talent gaps through conventional recruitment or internal training.

2.2 Challenges in O&M Data Quality and Governance

Data is a core element of large model training, and its scale and quality directly determine the upper limit of model performance. Only when data covers sufficiently extensive O&M scenarios can the model establish accurate representation capabilities and avoid systematic biases in specific tasks [5]. The quality of data annotation is equally critical; noisy data can cause the model to learn incorrect correlations, and improving model reliability must rely on strictly verified data. The performance improvement of large models largely depends on the expansion of data scale and the advancement of data cleaning technologies. Currently, O&M data intended for model training mainly faces two issues: data quality and insufficient data samples.

2.2.1 Data Silos and Diverse Formats

Historical O&M data is scattered across various locations such as logs, monitoring and alarm platforms, and O&M records of different operating systems and software applications, resulting in data silos. Furthermore, their recording formats, styles, storage methods, and retention periods are inconsistent, with much noise and varying standards in data sources. These phenomena affect data usability and the efficiency of model training [6].

2.2.2 Insufficient O&M Data Samples

Currently, most O&M operations are still command-based and scripted, and historical fault solutions and log data lack systematic summarization. This leads to insufficient data samples available for modeling, resulting in a lack of high-quality corpus for large model training, which makes it difficult to support effective large model training

2.3 Complexity of Business Scenario Decomposition and Implementation

The O&M environment is complex and changeable, and the problem localization process is also complex and variable, even requiring cross-device troubleshooting. Different fault-causing factors lead to different repair solutions. How to decompose O&M scenarios into subtasks understandable by large models requires technical personnel to have a deep understanding of both business scenarios and large model functions. Different O&M tasks have significant differences in their requirements for model capabilities, and how to select and deploy models to ensure a balance between resource utilization and effectiveness is a challenge.

Meanwhile, enterprises’ IT systems have issues such as coexistence of self-developed and purchased systems, inconsistent IaaS standards, etc., which increase the difficulty of data docking and integration, forming multiple obstacles from data sources to models.

2.4 Dilemma of Balancing Costs and Benefits

Most enterprises have strict data security requirements and prohibit data from being transmitted outside the corporate network, making it difficult to apply public cloud large models. Private deployment, on the other hand, faces pressure from computing power and costs, such as hardware investments like GPUs required for large model training, and expenses for data cleaning and governance, which are difficult for small and medium-sized enterprises to bear [7]. In addition, regarding the datasets needed for model training, relying solely on the operation and maintenance data of small and medium-sized enterprises themselves is insufficient to support model training; they may also need to purchase data from third-party data platforms or buy pre-trained models.

However, the benefits and effects of intelligent operation and maintenance are difficult to measure intuitively. The outputs of operation and maintenance optimization, such as improved system stability and reduced MTTR, need to be indirectly reflected through downstream business indicators and are interfered by multiple variables, making attribution analysis difficult. Furthermore, investments in improving operation and maintenance quality and efficiency are similar to quality costs, a type of "prevention cost," with invisible benefits that need to be measured over long-term returns, featuring significant invisible value and lag effects. Their returns are often difficult to directly quantify through traditional financial indicators. Therefore, enterprises lack motivation to invest in them [8].

3. KEY ISSUES AND SOLUTIONS FOR LARGE MODEL INTELLIGENT OPERATION AND MAINTENANCE

3.1 Data Collection and Cleaning

Comprehensive, accurate, diverse, balanced, and clean data can significantly enhance the analysis and reasoning capabilities of large models.

First, for data collection, professional monitoring systems and burying point technology should be used to achieve comprehensive collection of multi-dimensional indicators. Attention should be paid to unified data formats, and metadata standards need to be established, such as adopting standard protocols like OpenTelemetry to achieve data compatibility and unified input between different systems; or converting logs, indicators, and alarm data into standard Schema (e.g., JSON) to facilitate model training. Subsequently, data cleaning and data governance should be carried out, combining NLP technology to remove redundant and invalid information, such as filtering control characters and reducing the proportion of low-value logs.

3.2 Designing an Effective Execution Mechanism for Automated Operation and Maintenance Tasks

Establish a sound Agent mechanism. Decompose complex tasks and build corresponding Agents, then construct executable function calls to connect large models with automated scripts through Agent function calls. Based on historical logs and preset intentions, achieve automatic triggering and rapid response in specific scenarios. When pre-set scenarios or intentions are identified in the logs, the corresponding repair Agent function can be triggered to complete the task, realizing a closed-loop full link from monitoring analysis to task execution.

At the same time, good human-machine collaboration should be ensured. The large model should submit each repair measure to manual review and decision-making before implementation. For execution results, automated real-time monitoring mechanisms and manual monitoring mechanisms should be introduced to evaluate and feedback task effectiveness, optimizing strategies and call links.

3.3 Enhancing Model Interpretability to Alleviate "Black Box" Anxiety

By optimizing prompt design, the process is made transparent. Prompts can guide the model to output thinking paths, citation sources, and list multiple solutions for manual comparison and reference. To balance performance and interpretability, simple-structured models and deep learning black-box models can be combined to form hybrid interpretable models. In this way, while maintaining high model performance, model interpretability is achieved, explaining the model’s internal decision-making process and prediction results [9]. In addition, decision-making mechanisms should be embedded by writing operation and maintenance red lines and decision approval logic into model prompts to reduce the risk of misjudgment caused by model "hallucinations". Finally, multiple solutions can be generated for manual decision-making.

3.4 Construction of Operation and Maintenance Team Capability System

To truly unleash the value of large models, the team needs to build a multi-dimensional capability system. In addition to being familiar with various knowledge and technologies in the operation and maintenance field, they should also be proficient in data science knowledge and large model technologies, and possess toolchain and business scenario implementation capabilities.

3.4.1 Familiarity with data science and data management systems

The operation and maintenance team needs to establish a sound data science knowledge system, be able to identify valuable operation and maintenance data, and have the ability to collect, clean, and annotate logs to ensure high-quality training data to support the input and training of large models.

3.4.2 Ability to integrate operation and maintenance domain knowledge with large models

The operation and maintenance team needs to be able to decompose and transform operation and maintenance scenarios such as fault diagnosis and performance optimization into tasks understandable by the model, abstract them into callable functions, and verify the accuracy and rationality of their outputs.
In addition, the operation and maintenance team should have programming skills and basic认知 of large models, be familiar with the open-source/commercial rules of mainstream large models, master technologies such as fine-tuning and Prompt engineering, and be able to quickly verify through APIs or local deployment (e.g., vLLM).

3.4.3 Mastery of common technologies and engineering capabilities

First, in terms of operation and maintenance tools, they should be proficient in using monitoring and log analysis tools such as Prometheus, ELK, and Zabbix; in terms of AI toolchains, they should master fine-tuning frameworks such as DeepSpeed and Hugging Face, as well as deployment and troubleshooting skills such as Docker and CUDA. On the basis of mastering tools, it is also necessary to deeply analyze business requirements, select suitable large models according to requirements and the characteristics of large models, and have local deployment and optimization capabilities; moreover, optimize model outputs through experiments and continuously improve based on real operation and maintenance feedback.

3.4.4 Focus on team capability development

Attention should be paid to the development of the team's overall capabilities. In addition to clear division of labor and ensuring the technical expertise of various personnel, attention should also be paid to the completeness of team members' knowledge systems to reduce communication costs and improve team collaboration capabilities. The team's overall AI technical capabilities can be enhanced through systematic training, organizing technical sharing, and increasing practical opportunities beyond business expertise.

4. IMPLEMENTATION PATH

Considering the balance between cost input and revenue, the following implementation path may be considered:

Firstly, enterprises need to clarify their goals and scenarios, and prioritize high-value, low-risk areas (such as log analysis) as pilot projects to verify technical feasibility and control initial risks. Secondly, a phased promotion strategy should be adopted, starting with basic data governance, gradually transitioning to model validation, and ultimately achieving full-process automation, avoiding blind pursuit of one-step completion that leads to resource waste. In terms of talent, it is necessary to build a compound team that understands both traditional operations and AI technology through a combination of external cooperation and internal training to fill the gap in cross-disciplinary talent. Finally, establish a continuous iteration mechanism to continuously optimize models and processes based on actual business feedback, such as using Retrieval-Augmented Generation (RAG) technology to dynamically update the knowledge base, ensuring that the system adapts to changes in operational needs over the long term. This gradual path can help enterprises balance technology investment and practical results, and steadily achieve the intelligent transformation of operations

At the same time, since investing in enhancing operational capabilities using large models is a preventive cost, it is difficult to directly measure the benefits, affecting sustained investment. Consider referring to the benefit measurement methods of quality management work. For example: establishing a baseline for preventive investment to ensure sustainable construction investment; using a risk heat map to display problems that have been avoided or quickly resolved to demonstrate construction outcomes; and incorporating the impact of improved operational stability on capital costs into calculations through long-term tracking and data statistics

5. CONCLUSION

Intelligent operation and maintenance with large models is an important means to enhance enterprises' IT capabilities, but its implementation also faces difficulties in technology integration, training data collection, talent reserve development, cost and revenue planning, etc. Enterprises should improve their capabilities in data management, data governance, technology reserve, technical team building, and cost control. Considering implementation feasibility and enhancing management and investor confidence, in terms of implementation path, enterprises should rationally evaluate their own conditions and achieve the transformation and upgrading from traditional operation and maintenance to intelligent operation and maintenance in a "small steps, quick runs" manner

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