CISFA: A Decision-Support Agent Framework and its Allied Implementation with Generated AI in Oil and Gas Industry

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Abstract. With a rapid development of artificial intelligence generative content (AIGC), a set of human-machine interactive models have been changed. However, with limited understanding of the purposes of industry, even though fined-tuned by the professional data. The manuscript proposes a multi-role, self-closed-loop intelligent agent collaborative system framework (CISFA) that can compensate for the shortcomings of LLM in professional semantic understanding, multi-round self-interaction, and judgment and decision-making application scenes based on feedback and self-supervision between multiple role agents in multi-round Q&A based decision-making scenarios. Meanwhile, feasibility of applying medium-sized LLMs to aforementioned industry scenarios to achieve performance similar to that of very large-scale base models have also been considered. Through joint application with AIGC large models in three standard industry scenarios: drilling well control, device asset operation and maintenance management, as well as refining device operation guidance searching, it is proven that CISFA agent framework is effective in reducing the engineering application threshold of large models, simplify the prompt process and interpretation of industry mechanisms, and reducing application costs since medium-sized LLM been proven to show similar performance as very-large LLM by the allied application with CISFA.

Keywords: AIGC, Multiple-agent, Allied implementation, Oil & gas industry, Tasks division, Self-supervision.

1 Introduction

The value chain of oil and gas industry mainly consists of five parts: oil and gas exploration, exploitation, storage and transportation, refining and marketing. With rapid development of technologies such as hydrogen energy and multi-energy complementation, as well as the carbon restriction policy, higher requirements are put forward for cost reduction and efficiency improvement of the oil and gas industry [1]. At the same time, combined with uncertainties in internal and external political and economic environments, industry reshuffling upstream and downstream of the industry chain, and energy consumption market reconstruction, the development of oil and gas storage, production and supply, as well as the integration of oil, gas, hydrogen, electricity and non-energy development, have become important measures to ensure national energy security and the main development trend [2]. This trend has put

PMIS 2024, March 15-17, Changsha, People's Republic of China

DOI 10.4108/eai.15-3-2024.2346419

forward better requirements for the stability and precision of traditional oil and gas production and supply. In terms of exploration and development safety collaboration, refined flexible production and intelligent real-time optimization, precise innovative marketing, and intelligent auxiliary decision-making throughout the entire chain, more refined management, safer production, and more accurate decision-making are needed to promote the implementation of new business models such as targeted production and multi-energy collaborative complementation. The application of digital technology will help improve the intelligent level of data services involved in knowledge data distribution, scheme generation, process planning arrangement, predictive analysis and decision-making in the above scenarios, significantly improving the user experience [1-3].

Utilizing large-scale pre-training models, generative artificial intelligence (AIGC) technology has progressed significantly, evolving AI from specific point-based applications to general AI (AGI) capable of multi-scene generalization. This advancement has also shifted human-computer interaction from traditional keyboard-mouse interfaces to natural language-based modes, broadening participation in model training, tuning, and application among non-professionals. This transition has further facilitated the adoption of AI by ordinary end users. Additionally, the integration of large-scale pre-training models with content generation technology has significantly improved the performance of AI-driven data services across various scenarios, including search, customer service, machine translation, code generation, semantic understanding, and process automation [4]. Following the introduction of ChatGPT [5], the landscape of large generative AI models (LLM) has experienced rapid growth, with model updates occurring on a monthly basis. Over 100 enterprises and academic institutions, including GPT-4 [6], Wenxin-Yiyuan, Tongyi Qianzhi, Xinghuo, and others, have released their respective LLMs [7]. Concurrently, the emergence of innovative model training techniques such as thinking chain (COT) [8], prompt engineering, LoRa [9], LangChain [10], and other fine-tuning frameworks, coupled with the transformation in human-computer interaction brought by LLMs, has simplified the training and fine-tuning processes of LLMs. This, in turn, has empowered a broader range of low-level developers with the ability to debug and apply LLMs, further accelerating the iteration speed of the AIGC large model industry.

However, although the AIGC large model has shown significantly better performance than traditional methods in general scenarios, in scenarios such as industrial manufacturing, energy production, and asset management, the user demand side prefers to combine phenomena to obtain corresponding inference decision conclusions [11]. Unlike general tasks such as content retrieval, content generation, and inference, which have relatively low fault tolerance, pan industrial scenarios have characteristics such as low fault tolerance, specificity, and strong expert experience dependence. They require high requirements for the logic, accuracy, guidance, interpretability, and decision value of large model retrieval conclusions and inferred content [11]. Due to the fact that pre-trained large models are mostly trained through massive general data, and their knowledge and data in some oil and gas specialties are not deep enough, their reasoning, judgment, interpretation, plan decomposition, and auxiliary decision-making abilities in the vertical field of oil and gas are also lacking. In such scenarios, it is currently difficult to meet the response and inference needs of users by directly applying general large models or fine-tuning large models with professional data.

The complex interactive reasoning task oriented towards vertical domains remains a bottleneck for the application of LLM in vertical domains. The professional semantic understanding, problem decomposition, root cause inference, information retrieval, conclusion generation, summary analysis, etc. involved in this process are essentially similar to an observable Markov decision process [12]. Due to the relative independence of each decision process in LLM, users find it difficult to stimulate the emergence ability of LLM through relatively simple human-machine interaction and achieve complex interactive reasoning tasks. Based on the combination of multi-agent systems and LLM [13], through the connection between agents and LLM, multi-agent frameworks such as SAYCAN, REFLEXION, SWIFT-SAGE [13-16] aimed at LLM are utilized. The multi-agent collaboration framework is used as a supplement to the decision-making thinking chain of large models, and LLM has shown better performance in games, script writing, planning intelligence, content summary generation, and other aspects. However, the aforementioned types of intelligent agent systems are more targeted towards open-loop scenarios with relatively low fault tolerance (reproducible), and the design of open-loop intelligent agent systems is more conducive to stimulating the open emergence of LLM; But in vertical fields such as industry, on the one hand, more open-loop systems stimulate emergence while significantly increasing the uncertainty of recovery; On the other hand, for industrial and other intelligent agent systems, the design of self supervision mechanisms has not been considered to achieve continuous self optimization between intelligent agents and large models, thereby further reducing the difficulty of continuous post operation and maintenance required for LLM, and limiting its application in vertical fields.

This manuscript proposes a multi role, self closed loop intelligent agent collaborative system framework - self closed loop intelligent agent collaborative system framework (CISFA), which integrates Dual process theory [17], draws on the idea of self supervised learning, establishes cooperation and self closed loop mechanisms with pre trained large models through agents of different roles, and based on feedback and self supervision between multiple agents of different roles, To compensate for the shortcomings of large models in professional semantic understanding, multi round self interaction, and decision-making in question and answer decision-making scenarios, while exploring the application of medium scale LLM for vertical scenarios, achieving feasibility similar to the performance of ultra large base models, continuously optimizing through the self cooperation mechanism between intelligent agents, and continuously generating and optimizing prompt language for large models, Enable intelligent agents to better generate professional knowledge retrieval, judgment, and decision-making solutions for the oil and gas industry. Through the analysis of well control accidents, generation of equipment asset fault location and disposal suggestions, understanding of refining equipment operation tasks and generation of operating procedures, as well as comparative research on models with a scale of hundreds of billions and tens of billions, it has been proven that this framework helps to achieve the effectiveness of industrial intelligent application self closing loop with lower application and computational costs in the industrial field.

2 CISFA framework

Based on the prompt engineering [8], LLM is assigned the roles of planner (Agent A), executor (Agent B), and supervisor (Agent C) to fulfill different responsibilities in multi-agent systems. Drawing on the Dual process theory [17], the cognitive thinking and behavior of intelligent agents are divided into rational processes (slow, conscious cognitive processes) and intuitive processes (fast, subconscious cognitive processes). Agent-A and Agent-B respectively perform decision-making and plan resolution (rational processes), as well as plan execution and result feedback (intuitive processes). At the same time, in order to supplement the problem of information flow feedback being unable to self check and self converge between the rational and intuitive thinking processes [14], this article attempts to add the role of an Agent-C in the system. Agent-C evaluates the execution results of Agent-B in real time and forms feedback to achieve continuous optimization of the plan formulated by Agent-A. Through a self supervision mechanism, it achieves a convergence closed-loop for specific scenarios.

Based on the above mentioned process, the CISFA framework can be expressed as:

$$A(P，E，R)=Iteration\ (either,\ P\ or\ E\ or\ R == 1); \quad (1)$$

$$A(P，E，R) =Convergence(while,\ P\ \&\ E\ \&\ R == 0); \quad (2)$$

Among them, P, E, and R respectively represent Agent A/B/C, that is, achieving mutual self supervision and self closure among the three through mutual prompts between multi role agents.

Figure 1 takes the oil and gas field drilling well control scenario as an example to demonstrate how a multi-agent system can achieve task decomposition, subtask execution, and continuous feedback optimization for well control accident judgment through a self supervised intelligent agent framework with continuous feedback. Users assign three roles to LLM through prompt engineering, and Agent-A analyzes the essence of the task based on task description. The task plan is decomposed through LLM and transmitted to Agent-B one by one. When Agent-B obtains each step of the decomposed task, it executes the corresponding task of the corresponding role through LLM and provides the task execution result. Feedback the task results to Agent-C. Agent-C performs self inspection and evaluation of task execution results through LLM, reviews unreasonable process results, and transmits the results in reverse to Agent-B. Through the interaction between Agent-A/B and relying on LLM, it optimizes the execution process and iteratively formulates strategies for planning. Three intelligent agents complete the construction of a stable system by continuously iterating in a closed loop until no reverse information flow is generated. At this point, it can be considered that the intelligent agent system has the ability to continuously iterate based on self supervised mechanisms, and can perform plan decomposition, judgment, decision execution, and interpretable tasks in vertical scenes.

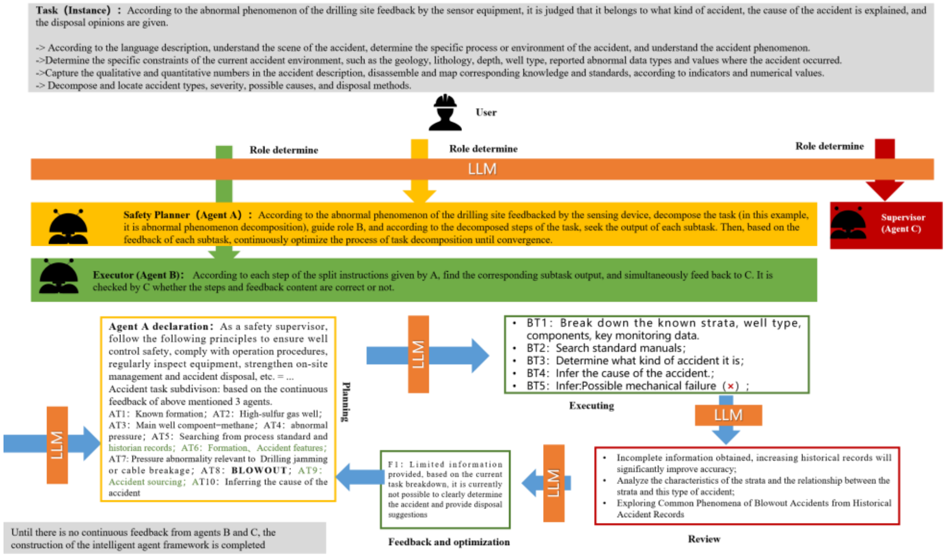

Figure 1. Example workflow of CISFA on scene of drilling accident identification and solution planning.

3 Experimental results

3.1 Experimental setup and evaluation

To verify the effectiveness of the joint application of this intelligent agent framework and LLM in the vertical field, the author selected three industrial application scenarios: drilling well control accident analysis and countermeasure generation (Scenario 1), device asset fault reporting and countermeasure generation (Scenario 2), and refining equipment operation task understanding and operation procedure decomposition (Scenario 3), and tested the performance of LLM under two interaction/pre training methods: external knowledge base and incremental pre training. Selecting the aforementioned three scenarios aims to utilize scenarios with strong content specialization, a large number of tasks decomposed and interpreted to generate programs, cumbersome steps, and poor fault tolerance, in order to more accurately test the performance of the intelligent agent system designed in this article. To verify the effectiveness of the self closing loop mechanism in the intelligent agent system when combined with LLM of different parameter scales in vertical industrial scenarios, and whether the proposed intelligent agent architecture can to some extent enable pre trained models of small and medium-sized scales to achieve near or exceeding the effect of ultra large scale LLM in fields such as energy industry with strong professionalism, high personalization, and small data scale, To preliminarily demonstrate the feasibility of low-cost and flexible deployment of LLM in the industrial sector. In this paper, two hundred billion level commercial models, Tongyi Qianwen and Wenxin, and two open source models, Baichuan -13B and ChatGLM-6B, are selected to compare the effects of direct application, joint application with the self closed loop agent framework, and joint application with the long short memory agent framework (SWIFT-SAGE). To verify whether the intelligent agent system design mentioned in this article can achieve better performance of LLM in event decision-making and strategy push scenarios in the energy industry vertical field with strong professional attributes with lower debugging thresholds and computational costs, this article only discusses two methods: external knowledge base and incremental pre training. Due to the high level of automation in current process industrial systems, in order to reduce interference with steady-state systems, it is necessary to consider minimizing the impact of human feedback on the intelligent agent in the loop [18]. This article only discusses the effects of zero shot and one shot prompts.

Based on the above experimental strategies, the selected data are: (1) Drilling well control: drilling operation engineer exam questions, industry and external common and special accident disposal guidelines, accident prevention and disposal manuals, with a total word count of over 2 million standard words; (2) Operating standards and guidelines for refining companies in various regions, exceeding 400000 words; (3) Equipment Asset Management: The equipment asset operation and maintenance management manuals, training materials on common faults and maintenance strategies, equipment asset operation and maintenance exam materials, and other public and private literature of refining companies in various regions, totaling over 400000 words. The Baichuan and Chatglm models selected in this article were trained on 2 and 3 NVDIA-V100 cards for 5 days, with epochs of 72 and 300, respectively. The lowest achieved losses were $7.24e^{-4}$ and $8.68e^{-4}$, respectively.

Due to the strong professionalism of drilling well control, oil and gas production equipment asset management, and device operation guidance, and the low fault tolerance of abnormal result determination, solution decomposition, and countermeasure formulation in practical applications, conventional AI model evaluation indicators have shortcomings that are inexplicable and difficult to measure model performance in this application. Furthermore, it is also difficult to evaluate the experience of large models. Therefore, in the evaluation stage, the author selected 30 engineers or operators with no less than 1 year of frontline practical experience as evaluation volunteers for the three professional directions of refining, well control, and equipment asset management. Due to the fact that the evaluation content belongs to the category of industrial production, the impact of gender differences among volunteers on the evaluation results is not considered. The age distribution of the volunteer population is between 21 and 50 years old, with an average age of A_ Age=39.6 years old, SD=5.7. To further ensure the professionalism of the evaluation scope, terminology standards, etc., the model evaluation corpus in this evaluation experiment was designed by intermediate or above process managers from the three majors mentioned above. Each scenario had 500 test questions, and each test question corresponded to 3 professional prompt sentences, numbered separately, to form an evaluation question bank.

During the test, each volunteer uses a random number generator to select 100 non repeating question numbers from the question bank, and selects 100 test questions according to the question numbers for evaluation. Allowing participants to autonomously modify input questions based on their own habits without changing the general meaning of the evaluation questions, in order to create certain disturbances to the LLM and test the robustness of the intelligent agent system described in this study. Meanwhile, as volunteers do not have a clear understanding of all the test questions in the question bank, standard answers for the 100 selected evaluation questions are also provided for reference. Due to the low fault tolerance rate in industrial scenarios and the large amount of output content, the evaluation results are simplified into correct and incorrect, which are directly judged by the evaluation volunteers.

For each scenario, the scoring results of 30 volunteers are based on

$$Mark=round\ (mean\ (sum\ (A, Scene))), \tag{3}$$

where variable A represents the rating of each evaluation volunteer and variable Scene represents three experimental testing scenarios.

3.2 Results and discussion

The experimental results of the aforementioned design are shown in the table below. From table I, it can be seen that on the basis of the original base model, the Wenxin model has significant advantages in problem localization in the three scenarios of well control, asset fault handling, and device operation task understanding, only through the form of an external knowledge base. However, compared to the other two billion level models, the performance of Tongyi Qianwen does not show significant advantages. Based on this, it can be inferred that for highly specialized industrial fields, the contribution of pre-training data to LLM is greater than the parameter size of the model. By adding prompt statements, overall, there is a certain improvement in the hit rate of problem localization and solution output for most LLMs, but there are also a few LLMs that have decreased. This shows that the quality of professional prompt language design has limited impact on the effective information from the model. This experiment further confirms the role of incremental pre-training. Through incremental pr-training of two medium-sized LLMs, their problem localization and solution output are significantly higher than those of direct application of LLMs. At the same time, it is also higher than directly applying models worth billions. However, after relatively accurately locating the problem, there are generally errors such as imprecise output of strategy schemes, wide or narrow content coverage, which will lead to information overload or limitation for users. This is related to the lack of sufficient multi round interaction prompts and task decomposition assistance ability in LLM, which leads to the inability of LLM to correct the proposed output plan and strategy through the decomposed phenomenon prompts after locating the full solution strategy.

Based on the analysis of the results evaluated by professional personnel in table II, through the joint application of LLM and self supervised intelligent agents, overall, whether it is a direct external knowledge base application or incremental pre training, a self supervised and self feedback loop is formed through a group of three intelligent agents, achieving multiple rounds and continuous human-machine interaction, providing LLM with more accurate input-output information interaction, and making LLM's performance significantly higher than direct application, In terms of the number of correct answers in the output of countermeasures, there is a significant improvement compared to direct application, and the performance on medium scale LLM is similar or partially better than that of a hundred billion level model. This indicates that the self supervised and self feedback intelligent agent proposed in this study has good self-locking ability, can provide more accurate input for LLM, effectively explore the potential of LLM, and provide a potential feasible solution for the economic and effective deployment of LLM applications.

To further compare and evaluate the advantages and disadvantages of different intelligent agent frameworks in vertical industrial applications, table III compares and evaluates the performance of another intelligent agent framework, Swift Sage [14], which has the ability of "long-term planning+short-term thinking" in the energy industry. Due to the fact that the Swift

Sage framework is built around GPT-4 and the main interaction language is English, during the experiment, all the interaction language materials used were translated using professional translation software, and after confirmation by professional personnel that the basic meaning remained unchanged, they were applied. At the same time, the results output from the framework were translated into Chinese and evaluated by the aforementioned volunteers. From the comparison of evaluation results, it can be seen that the combination mechanism of real-time imitation learning and long-term planning adopted by the Swift sage intelligent agent system can also significantly improve the performance of LLM in scheme output, but its performance is relatively inferior to the self supervised agent system described in this article. This is partly due to the fact that this system is trained on English corpus and relies on GPT-4 design, which limits its understanding of Chinese corpus and results in poor performance when applied to Chinese native large-scale LLM; In addition, due to the differences in emergence ability caused by different model parameters, ultra large scale LLMs have better self improvement ability compared to medium scale LLMs. The lack of feedback information flow limits the planning ability of medium scale LLMs.

Table 1. Comparative study of using of LLM in oil & gas industry -- by directly use

Task	LLM	Direct use of LLM							
		External knowledge base (Zero-shot)		External knowledge base (One-shot)		Incremental pre-train (Zero-Shot)		Incremental pre-train(One-Shot)	
		Abnormal identification	Solution output	Abnormal identification	Solution output	Abnormal identification	Solution output	Abnormal identification	Solution output
Analysis of well accidents control	Tongyi	53	38	53	31	/	/	/	/
	Wenxin 4.0	91	47	92	54	/	/	/	/
	Baichuan-13B	77	41	86	47	73	55	73	55
	ChatGLM-6B	67	39	73	41	73	60	73	60
Generation of fault location and disposal suggestions for	Tongyi	58	22	54	24	/	/	/	/
	Wenxin 4.0	72	59	71	50	/	/	/	/
	Baichuan-13B	58	54	59	48	81	66	77	50

device assets	ChatGLM-6B	54	46	53	48	85	63	74	49
Understanding of operational tasks and generation of operating procedures for refining equipment	Tongyi	53	27	30	18	/	/	/	/
	Wenxin 4.0	67	43	67	49	/	/	/	/
	Baichuan-13B	55	41	53	48	76	41	80	56
	ChatGLM-6B	58	29	53	44	70	29	80	52

Table 2. Comparative study of using of LLM in oil & gas industry -- by allied application with CISFA

Task	LLM	Alled application with CISFA							
		External knowledge base (Zero-shot)		External knowledge base (One-shot)		Incremental pre-train (Zero-Shot)		Incremental pre-train(One-Shot)	
		Abnormal identification	Solution output	Abnormal identification	Solution output	Abnormal identification	Solution output	Abnormal identification	Solution output
Analysis of well accidents control	Tongyi	77	73	73	73	/	/	/	/
	Wenxin 4.0	91	72	86	72	/	/	/	/
	Baichuan-13B	88	80	88	84	92	81	93	84
	ChatGLM-6B	85	72	85	76	87	79	84	79
Generation of fault location and disposal suggestions for device assets	Tongyi	62	54	62	58	/	/	/	/
	Wenxin 4.0	83	77	92	89	/	/	/	/
	Baichuan-13B	83	81	93	84	92	91	90	90
	ChatGLM-6B	79	76	88	84	95	89	93	88
Understanding of	Tongyi	62	54	69	67	/	/	/	/
	Wenxin 4.0	79	72	77	71	/	/	/	/

operational tasks and generation of operating procedures for refining equipment	Baichuan-13B	78	77	79	77	95	80	87	87
	ChatGLM-6B	81	81	81	71	80	79	93	88

Table 3. Comparative study of using of LLM in oil & gas industry -- by allied application with Swift-sage agent

Task	LLM	Swift-sage							
		External knowledge base (Zero-shot)		External knowledge base (One-shot)		Incremental pre-train (Zero-Shot)		Incremental pre-train(One-Shot)	
		Abnormal identification	Solution output	Abnormal identification	Solution output	Abnormal identification	Solution output	Abnormal identification	Solution output
Analysis of well accidents control	Tongyi	63	33	68	31	/	/	/	/
	Wenxin 4.0	86	53	86	56	/	/	/	/
	Baichuan-13B	71	64	74	67	73	70	80	80
	ChatGLM-6B	73	60	80	65	71	65	87	82
Generation of fault location and disposal suggestions for device assets	Tongyi	50	25	54	31	/	/	/	/
	Wenxin 4.0	73	64	79	67	/	/	/	/
	Baichuan-13B	67	58	72	69	89	74	82	77
	ChatGLM-6B	70	70	81	74	85	80	90	82
Understanding of operational tasks	Tongyi	62	54	71	35	/	/	/	/
	Wenxin 4.0	62	55	69	60	/	/	/	/
	Baichuan-13B	57	52	74	71	82	79	86	72

and generation of operating procedures for refining equipment	ChatGLM-6B	69	57	76	56	83	69	89	70

4 Conclusion and future works

The CISFA system proposed in this article achieves continuous self supervision and self closure improvement of the AIGC system through a new multi role self supervised intelligent agent cooperation mechanism and effective interaction between the intelligent agent system and LLM. It has been tested and evaluated on well control, refining equipment asset management, and refining operation procedure generation tasks in the oil and gas industry. Through professional evaluations of each scenario, it has been shown that the system has significantly improved the ability of LLM to locate anomalies, generate solutions, and decompose tasks in the vertical industrial field, enabling LLM to have better business interpretability in the vertical field. At the same time, it has the ability to assist some mainstream medium-sized LLMs in achieving performance that is equivalent to or exceeds a hundred billion level models in specific sub scenarios with relatively small training workload. This provides a relatively cost-effective potential path for the implementation and application of LLM in the industrial field.

Subsequently, with the continuous improvement of LLM technology and performance, by improving the continuous interaction mechanism in the intelligent agent system, on the one hand, it further reduces the number of rounds of continuous feedback, making the debugging process threshold lower; On the other hand, by combining with the multi round dialogue mechanism of existing customer service systems, the feasibility of attempting to break away from the "human in the loop" system cold start mode may be verified, which may enable the intelligent agent system to have self-learning and self-improvement capabilities, further allowing the group intelligence technology based on large models to penetrate into more vertical high-frequency application scenarios and embodied intelligence directions.

Acknowledgment. The work is supported by the National Natural Science Foundation of China (Grant ref: 61401104) & Key R&D plan of PetroChina KY2023YF0007.

Conflict of interest statement: None

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