

OR-LLM-Agent: Automating Modeling and Solving of Operations Research Optimization Problem with Reasoning Large Language Model

Bowen Zhang^{*1} Pengcheng Luo^{*23}

Abstract

Operations Research (OR) has been widely applied in various fields such as resource allocation, production planning, and supply chain management. However, addressing real-world OR problems requires OR experts to perform mathematical modeling and programmers to develop solution algorithms. This traditional method, heavily reliant on experts, is costly and has long development cycles, severely limiting the widespread adoption of OR techniques. Few have considered using Artificial Intelligence (AI) to replace professionals to achieve fully automated solutions for OR problems. We propose OR-LLM-Agent, the first AI agent that enables end-to-end automation for solving real-world OR problems. OR-LLM-Agent leverages the Chain-of-Thought (CoT) reasoning capabilities of Large Language Models (LLMs) to translate natural language problem descriptions into formal mathematical models and automatically generate Gurobi solver code. In OR-LLM-Agent, OR-CodeAgent is designed to automate code execution and repair within a sandbox environment, facilitating the derivation of the final solution. Due to the lack of dedicated benchmark datasets for evaluating the automated solving of OR problems, we construct a benchmark dataset comprising 83 real-world OR problems described in natural language. We conduct comparative experiments with state-of-the-art (SOTA) reasoning LLMs, including GPT-o3-mini, DeepSeek-R1, and Gemini 2.0 Flash Thinking. The OR-LLM-Agent achieved the highest pass rate of 100% and the highest solution accuracy of 85%, demonstrating the feasibility of automated OR problem-solving. Data and code have been publicly available at

https://github.com/bwz96sco/or_llm_agent.

1. Introduction

Operations Research (OR) plays a vital role in addressing complex decision-making challenges encountered by businesses and industries (Saban & Weintraub, 2021; DeCroix et al., 2021). By formulating mathematical models and employing optimization algorithms, OR enhances efficiency and maximizes economic benefits across various domains, including resource allocation, production planning, and supply chain management. However, translating real-world problems into solvable mathematical models remains a significant challenge, as OR problems are often described in natural language. Bridging this gap requires domain expertise to systematically extract key elements, define decision variables, formulate constraints, and establish objective functions, ensuring mathematical rigor and solvability.

Traditionally, companies addressing complex optimization problems have relied on OR and mathematical experts to formulate problem-specific models. While expert-driven modeling ensures theoretical rigor and tailored solutions, it is often costly and time-intensive, limiting the broader adoption of OR techniques in business applications. Moreover, even with a well-defined mathematical model, implementation remains a challenge. Effective utilization of OR solvers such as Gurobi and CPLEX requires proficiency in programming, debugging, and solver-specific syntax, posing additional technical barriers that further restrict the accessibility and practical deployment of OR methods.

The rapid advancement of Artificial Intelligence (AI), particularly the emergence of Large Language Models (LLMs), has introduced new opportunities to address these challenges. LLMs have demonstrated remarkable capabilities in natural language understanding (Liu et al., 2024; Yang et al., 2024) and, through training on vast textual corpora, have acquired extensive domain knowledge spanning mathematics, programming, and beyond. These models not only comprehend human instructions but also execute complex tasks such as mathematical problem-solving (Abdin et al., 2024) and code generation (AnySphere, 2025). Furthermore, the development of reasoning LLMs (OpenAI, 2024b) has

^{*}Equal contribution ¹Nanyang Technological University, Singapore. ²Ningbo Artificial Intelligence Institute, Shanghai Jiao Tong University, Ningbo, PR, China. ³Department of Automation, Shanghai Jiao Tong University, Shanghai, PR China. Correspondence to: Pengcheng Luo <luopeng69131@sjtu.edu.cn>.

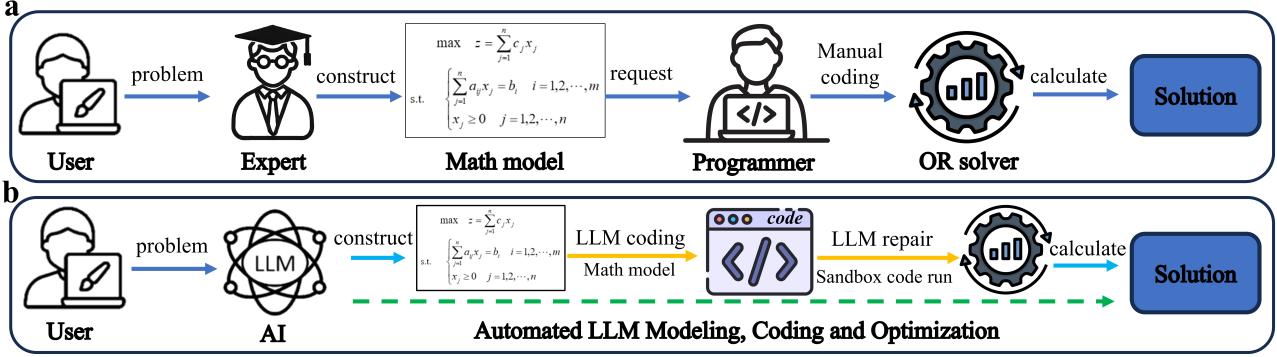


Figure 1. OR Expert Solution (a) vs. AI Automated Solution (b).

significantly enhanced their ability to perform systematic and structured reasoning, enabling more rigorous problem-solving in programming and mathematical domains. This reasoning capability allows LLMs to emulate human-like deliberation, facilitating more complete and effective solutions to complex scientific problems.

Despite the vast potential of LLMs across various domains, their application in OR remains largely unexplored in both academia and industry. Few studies have explored using LLMs to replace human OR experts in transforming natural language descriptions of real-world OR problems into mathematical models, effectively bridging the gap between language and mathematical formulation. Moreover, even with a well-defined mathematical model, translating it into executable code for automated solving remains a challenge. Existing automated code generation approaches, such as code agents, predominantly rely on non-reasoning LLMs, which struggle with long-text comprehension and complex instructions. These limitations necessitate intricate workflows to enhance code generation success rates, leading to overly complex software that hinders adaptability and secondary development. Consequently, such agents are ill-suited for automated programming, solving, and debugging of mathematical models, and their direct application to OR remains limited. Furthermore, there is a lack of dedicated datasets to systematically evaluate LLMs in automated OR modeling and solving.

This paper addresses the challenging problem of automating the solution process for real-world OR problems. By leveraging natural language descriptions of these problems and harnessing the reasoning capabilities of LLMs, the approach enables end-to-end automation from problem description to optimal solution. We propose the AI agent OR-LLM-Agent, which translates OR problems described in natural language into mathematical models, automatically programs these models into executable code for OR solvers, automatically executes the code, and ultimately obtains the optimal solution. A comparison of the AI method OR-LLM-Agent with

the traditional human expert method is shown in Figure 1. The main contributions of this paper are as follows.

- To the best of our knowledge, we are the first to propose OR-LLM-Agent, an AI agent framework that fully automates the process of solving real-world OR problems using reasoning LLMs. OR-LLM-Agent seamlessly transforms natural language problem descriptions into mathematical models, generates and executes solver code, and directly obtains the final solution.
- We designed OR-CodeAgent, which enables automated code execution and repair within a sandbox environment. OR-CodeAgent utilizes self-repair for iterative code refinement and self-verification for mathematical model correction when no feasible solution exists, enhancing robustness and reliability.
- We construct a dataset containing natural language descriptions of 83 real-world OR problems to evaluate the performance of the OR-LLM-Agent. In the experiments, we compare OR-LLM-Agent with state-of-the-art (SOTA) LLMs such as GPT-o3-mini, DeepSeek-R1, and Gemini 2.0 Flash Thinking. Experimental results demonstrate that OR-LLM-Agent achieved the highest pass rate and solution accuracy for 100% and 85%.

2. Related Work

2.1. Large Language Model

The representative technology of LLMs is the Generative Pre-trained Transformer (GPT) model. Based on the Transformer (Vaswani et al., 2017) architecture, the GPT model utilizes large-scale unsupervised pre-training followed by fine-tuning strategies to achieve deep modeling of natural language (Radford et al., 2018; 2019; Brown et al., 2020). The model leverages self-attention mechanisms (Vaswani et al., 2017) to capture long-range dependencies, enabling the generation of high-quality and coherent text. It has

demonstrated outstanding performance in various Natural Language Processing (NLP) tasks, such as text generation, translation, and question answering. Recently, with the continuous expansion of model parameter sizes and the emergence of Reinforcement Learning from Human Feedback (RLHF) (Ouyang et al., 2022), GPT models such as ChatGPT (Brown et al., 2020) and GPT-4 (Achiam et al., 2023) have exhibited remarkable advantages in understanding complex contexts and generating logically coherent content, making them a core technology in modern NLP. In 2024, OpenAI released GPT-4o, which made breakthroughs in multimodal capabilities, reasoning abilities, and inference speed. However, GPT-4o (OpenAI, 2024a) still suffers from the issue of “hallucinations”, meaning that it occasionally produces incorrect responses, especially when dealing with complex mathematical, programming, and reasoning problems.

2.2. Chain-of-Thought and Reasoning LLM

Chain-of-thought (CoT) prompting is a technique designed to elicit intermediate reasoning steps from LLMs prior to generating a final answer. By explicitly guiding the model to produce a sequence of logical inferences, CoT prompting emulates the step-by-step reasoning process typically employed by humans when solving complex problems. This approach has been shown to significantly enhance model performance on tasks involving mathematical reasoning, logical deduction, and other forms of multi-step problem-solving. Moreover, CoT improves the interpretability of model outputs by making the reasoning process transparent. As such, it serves as a foundational mechanism for enabling advanced reasoning capabilities in LLMs.

CoT prompting was first introduced by Wei et al. (Wei et al., 2022), who proposed a novel approach to enhance reasoning capabilities in LLMs through the inclusion of explicit step-by-step instructions in prompts, such as ‘Let’s think step by step.’ Their study demonstrated that this strategy significantly improves model performance on tasks involving mathematical reasoning, symbolic manipulation, and common-sense inference. This seminal work was the first to systematically show that guiding LLMs to generate intermediate reasoning steps can effectively mitigate their limitations in handling complex, multi-step problems. Furthermore, their experiments revealed the benefits of CoT prompting scale with model size, underscoring its strong synergy with large-scale pre-trained language models such as GPT-3 (Brown et al., 2020).

To enhance the structured and automated capabilities of CoT, Wang et al. (Wang et al., 2022) proposed the self-consistency strategy, a significant advancement in CoT. Self-Consistency improves the model’s robustness and accuracy in complex reasoning tasks by generating multiple reasoning paths and

selecting the most consistent answer. This method excels particularly in solving mathematical problems, addressing the issue where a single reasoning chain might fail globally due to erroneous steps. The introduction of self-consistency marks the evolution of CoT from single-path reasoning to multi-path consistency verification, offering new perspectives on the credibility of the reasoning process.

CoT works showcases an evolutionary trajectory from simple linear reasoning to complex structured reasoning (Kojima et al., 2022; Yao et al., 2023). These studies have enhanced LLMs’ capabilities in reasoning tasks. However, since these CoT techniques guide the model’s reasoning through prompt engineering, they do not constitute a true development of intrinsic reasoning ability in the LLM.

Reasoning LLMs are large language models specifically designed to exhibit advanced reasoning capabilities, including logical inference, step-by-step deduction, and complex problem-solving. These models demonstrate superior performance across a range of tasks, such as mathematical reasoning (e.g., MATH-500 (Hendrycks et al., 2021), AIME 2024), code generation and algorithmic problem solving (e.g., Codeforces, LiveCodeBench (Jain et al., 2024)), scientific reasoning (e.g., GPQA Diamond (Rein et al., 2024)), and commonsense reasoning (e.g., MMLU (Hendrycks et al., 2020)). In contrast to general-purpose LLMs, reasoning models are optimized to emulate human cognitive processes through structured deduction and incremental analysis. This design enables internal reasoning and self-verification prior to response generation, thereby reducing hallucinations and enhancing solution accuracy. Representative state-of-the-art reasoning LLMs include GPT-o3-mini, Gemini 2.0 Flash Thinking, DeepSeek-R1 (Guo et al., 2025), and Claude 3.7.

Reasoning LLMs acquire CoT reasoning capabilities through Reinforcement Learning (RL). The training process involves guiding the model to discover and refine effective reasoning strategies via reward signals (Guo et al., 2025). By setting rewards, such as those based on accuracy and output format. RL algorithms iteratively optimize the LLM model’s performance. Over time, the model implicitly learns to adopt step-by-step reasoning strategies, such as CoT, integrating them into its problem-solving approach. Importantly, the emergence of CoT reasoning is not explicitly hard-coded but arises naturally as an effective strategy through the RL optimization process.

2.3. Code Agent

Code Agent is an intelligent agent powered by Large Language Models (LLMs), capable of automatically generating, executing, and debugging code. By integrating natural language understanding with code generation, the Code Agent translates user instructions into executable programs. It further monitors code execution in real time and employs

self-repair and debugging mechanisms to iteratively correct errors, forming a closed-loop feedback system. This capability positions Code Agents as highly promising tools for automated programming, software testing, and operational optimization, significantly reducing the need for manual intervention while enhancing the efficiency and accuracy of software development and problem-solving.

Chen et al.([Chen et al., 2021](#)) introduced Codex, a code generation model developed by OpenAI based on the GPT architecture. Codex demonstrated the capability to generate code in multiple programming languages from natural language prompts. Its performance on the HumanEval dataset showed substantial improvements over traditional methods, particularly in solving programming problems with a single-generation approach. Subsequently, Li et al.([Li et al., 2022](#)) proposed AlphaCode, a system that achieves near-human performance in programming competitions by leveraging large-scale sampling and filtering strategies. A key innovation of AlphaCode is its validation mechanism, which generates a diverse set of candidate solutions and selects correct outputs through test case-based filtering, thereby addressing the limitations of single-path code generation.

Wu et al. introduced AutoGen ([Wu et al., 2023](#)), a multi-agent collaboration framework. Within AutoGen, the code agent collaborates with other agents, such as testing and debugging agents, to iteratively refine code through natural language dialogue. The closed-loop design enables agents to automatically adapt strategies—such as rewriting code or adjusting parameters—upon error detection, substantially improving success rates in code generation tasks. Zheng et al. ([Zheng et al., 2024](#)) proposed Open-CodeInterpreter, which integrates code generation, execution, and iterative optimization. Trained on the Code-Feedback dataset, it achieves accuracies of 83.2% on HumanEval and 76.4% on the Mostly Basic Python Programming (MBPP) dataset ([Austin et al., 2021](#)), closely approaching GPT-4's 84.2% and 76.2%, respectively. With synthesized human feedback, its performance further improves to 91.6% and 84.6%. This technology bridges the performance gap between open-source models and GPT-4's Code Interpreter, proving particularly adept for dynamic code refinement scenarios.

Moreover, the applications of Code Agents are increasingly extending into specialized domains. For instance, Agent-Coder ([Huang et al., 2023](#)) and MicroAgent ([BuilderIO, 2024](#)) focus on automated testing and performance optimization within software development. These methods not only generate code based on user requirements but also automatically produce unit test cases and optimize code efficiency, making them well-suited for industrial-scale software engineering applications. However, as these code agents were not specifically designed for solving OR problems coding

and are predominantly built upon non-reasoning LLMs, there remains room for improvement in programming capability and portability.

2.4. OR Solvers

OR solvers are advanced software tools designed to solve mathematical optimization problems with high efficiency and accuracy. They are capable of addressing a wide range of complex problem types, including linear programming, integer programming, nonlinear programming, quadratic programming, and mixed-integer programming. These solvers employ a diverse set of algorithms, such as Branch and Bound, Cutting Plane, Interior Point Method, Exterior Penalty Function Method, and Sequential Quadratic Programming, along with supporting techniques like linear relaxation, heuristic search, and metaheuristic strategies. By integrating numerical computation with intelligent search mechanisms, OR solvers are able to efficiently identify optimal or near-optimal solutions within large and complex solution spaces.

Several leading commercial solvers have long held a dominant position in this domain:

- Gurobi ([Gurobi Optimization, LLC, 2023](#)): Renowned for its exceptional solving speed and stability, Gurobi excels in handling large-scale linear programming and mixed-integer programming problems, making it a preferred choice in both industry and academia.
- CPLEX ([Manual, 1987](#)): Developed by IBM, CPLEX boasts a long history and comprehensive functionality, delivering robust performance across various optimization tasks. It enjoys a broad user base and offers extensive modeling interfaces.
- Solving Constraint Integer Programs (SCIP) ([Achterberg, 2009](#)): A powerful non-commercial solver distinguished by its high scalability and flexibility, SCIP allows users to customize algorithms and plugins, rendering it particularly valuable for academic research and algorithm development.
- COIN-OR Branch and Cut (CBC) ([COIN-OR Foundation, 2023](#)): An open-source mixed-integer programming solver under the COIN-OR project, CBC may not match the performance of commercial counterparts but is an ideal option for research and education due to its cost-free accessibility.
- GNU Linear Programming Kit (GLPK) ([Makhorin, 2023](#)): Another widely used open-source solver, GLPK supports both linear and integer programming and is well-suited for educational purposes and basic applications.

These solvers play a critical role in numerous real-world applications, including logistics scheduling, production planning, supply chain management, financial investment, energy optimization, transportation, and smart manufacturing (Wang & Jacquillat, 2020; Cohen et al., 2022). With advancements in computational power and breakthroughs in algorithmic theory, modern OR solvers are increasingly capable of addressing larger-scale and more complex problems. They provide enterprises with powerful and reliable tools for decision-making support and resource optimization, enhancing efficiency and effectiveness across diverse domains.

3. OR-LLM-Agent

We propose OR-LLM-Agent, a reasoning LLM-based framework for fully automated OR optimization. OR-LLM-Agent converts a natural language problem description into a mathematical model, generates and executes the solution code, and thus facilitates an end-to-end automation pipeline from OR problem description to the solution. OR-LLM-Agent comprises modules for user problem description input, LLM mathematical modeling, LLM code generation, and OR-CodeAgent. The LLM mathematical modeling module constructs linear programming models for the OR problem. The LLM code generation module produces OR solver code based on the mathematical model. OR-CodeAgent ensures automated code execution and repair to obtain the final solution. The framework of OR-LLM-Agent is shown in Figure 2.

3.1. Reasoning LLM

Reasoning LLMs, trained to acquire Chain-of-Thought (CoT) capabilities, can perform deep reasoning and generate extended, coherent responses (Guo et al., 2025). This allows them to produce answers that approximate expert-level responses to scientific queries, surpassing the superficial outputs typically produced by non-reasoning LLMs. Consequently, notable improvements have been achieved in tasks such as mathematical reasoning, code generation, and bug fixing. In OR-LLM-Agent, reasoning LLMs function as central components for mathematical modeling, code generation, self-repair, and self-verification.

Before answering a question, a reasoning LLM engages in a thinking process. The reasoning process generated by the model is explicitly marked using `<think>` and `</think>` tags, which helps the LLM learn to generate structured reasoning steps. Through this thinking process, the LLM can systematically consider the questions posed by users and continuously verify the correctness of ideas through reflection (Guo et al., 2025). This enhances the LLM's ability to provide accurate responses while minimizing the impact of hallucinations.

Reasoning LLMs (Guo et al., 2025) employ answer accuracy as the reward signal during RL training. If the model produces an incorrect final answer, it receives no reward, regardless of the reasoning process. Consequently, reasoning LLMs trained under this paradigm are explicitly optimized to improve both reasoning validity and solution accuracy in complex problem-solving tasks.

When performing deep thinking and generating long responses, reasoning LLMs rely on internal CoT mechanisms and predefined multi-role prompt structures to guide the model in generating high-quality, professional, and rigorous answers. LLMs commonly use the following three role prompts in practical applications (OpenAI, 2024a).

- System prompt: The system prompt is used to set the global context and behavioral guidelines for the entire conversation or task. It provides basic instructions at the start of the conversation, such as task objectives, role definitions, and response styles, ensuring that the model maintains consistent professionalism and logic throughout the subsequent generation process. For example, the system prompt can specify that the model should play the role of an OR expert and emphasize that responses need to be based on rigorous mathematical reasoning or code implementation.
- User prompt: The user prompt directly conveys actual questions or task requirements and serves as the input basis for the model's response generation. User prompts typically include specific problem descriptions, relevant data, or contextual information, prompting the model to focus on the core issues when answering. The accuracy and detail of user prompts directly affect the quality of the model's reasoning process and the accuracy of the final output.
- Assistant prompt: The assistant prompt is generated by the LLMs to display its reasoning process and the final answer. To improve the transparency and interpretability of the response, the assistant prompt can include intermediate reasoning steps, which are explicitly marked with `<think>` and `</think>` tags. This helps verify the correctness of the generated answer and provides a basis for subsequent self-repair and self-verification mechanisms.

3.2. Automated LLM Mathematical Modeling and Code Generation

The OR-LLM-Agent employs a mathematical modeling prompt to guide a reasoning LLM in formulating a mathematical model from a natural language description of an OR problem. Subsequently, it utilizes a code generation prompt, along with the previously mathematical model as

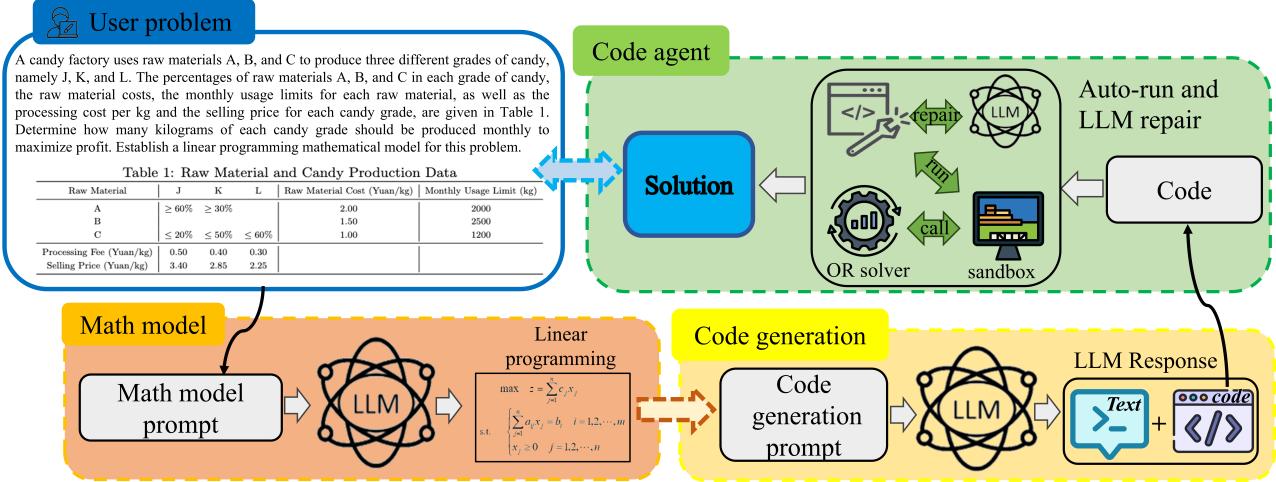


Figure 2. Framework of OR-LLM-Agent.

the context, to direct the LLM in generating executable code for solving the problem. Figure 3 presents the math model prompt and code generation prompt.

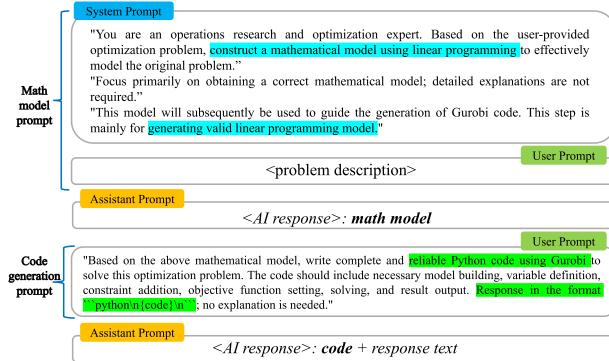


Figure 3. Math Model Prompt and Code Generation Prompt.

The math model prompt guides the LLM to formulate a linear programming model from the user's natural language description. At this stage, OR-LLM-Agent focuses on the mathematical structure of the problem and applies relevant principles to construct an accurate formalization. The outcome of this process is typically a well-defined mathematical model representing the problem. Due to the inherent complexity of mathematical expressions, the LLM typically presents the mathematical model using the LaTeX format.

The code generation prompt uses the previously generated mathematical model as the context, instructing the LLM to generate code for solving the corresponding optimization problem. The prompt explicitly specifies the use of Python and the Gurobi solver. The LLM is presumed to have been pre-trained on a substantial amount of Python- and Gurobi-related data, which enhances its ability to generate correct solver code.

Although LLMs can directly generate Gurobi code from a problem description, bypassing the mathematical modeling step, a step-by-step approach has proven to be more effective, particularly for current reasoning LLMs, when solving complex problems. This approach enables the LLM to decompose the problem into manageable sub-tasks, addressing each step sequentially while leveraging context from previous stages. By promoting structured and thorough reasoning, the approach aligns closely with the CoT. Furthermore, complex problems often require longer reasoning chains (Guo et al., 2025); however, LLMs are constrained by limited output windows. If prompted to generate code directly, the reasoning LLM may still internally consider the underlying mathematical model; however, the pressure to conserve output space often leads to abbreviated reasoning, increasing the likelihood of incorrect solutions.

3.3. OR-CodeAgent, Self-Repair and Self-Verification

To facilitate automated code execution, we developed OR-CodeAgent. OR-CodeAgent runs LLM-generated Python code within a sandboxed environment, automatically invoking self-repair and self-verification mechanisms upon detecting runtime exceptions or infeasible solutions. The workflow of OR-CodeAgent is illustrated in Figure 4.

The reasoning LLM will generate Python code that calls the Gurobi solver. The generated code will be executed in a sandbox. If existing errors during execution, the LLM will be invoked to self-repair based on the error messages. The repaired code will be re-executed in the sandbox again until the code runs successfully and obtains the solution. If errors persist after three repair attempts, or if the solver's result indicates no feasible solution, a self-verification mechanism will be triggered to check for errors in the mathematical model. Subsequently, the code will be regenerated and

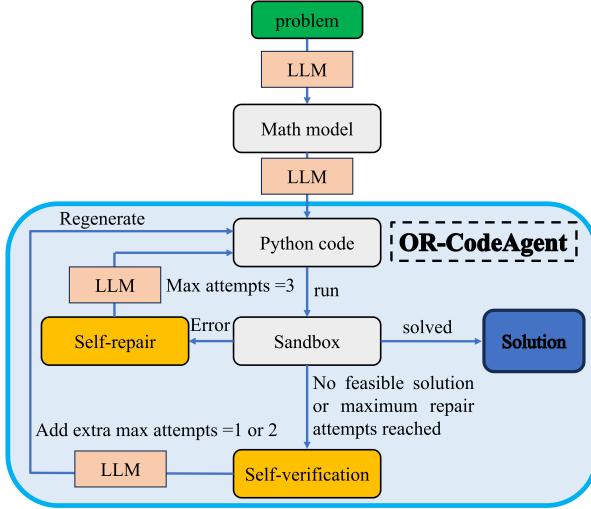


Figure 4. Workflow of OR-CodeAgent.

executed.

The self-repair process is illustrated in Figure 5. In each round of repair, the repair prompt and code from the previous round are saved in the context. However, the self-repair process ultimately does not retain the prompts from intermediate repair attempts; only the prompt that generated the correct code is preserved.

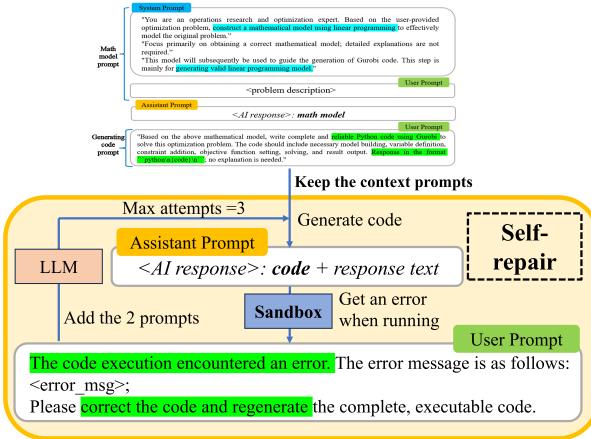


Figure 5. Process of Self-Repair.

When reaching the maximum number of repairs or no feasible solutions, a self-verification mechanism is invoked. Self-verification requires the LLM to recheck the generated mathematical model for errors and regenerate the code. Self-verification focuses on checking for errors in the mathematical model, unlike self-repair, although both ultimately result in code regeneration. The self-verification prompt is shown in Figure 6. When resetting the maximum number of self-repair attempts, the no solution scenario and the

scenario of reaching the maximum repair attempts of 3 are reset to 1 and 2, respectively.

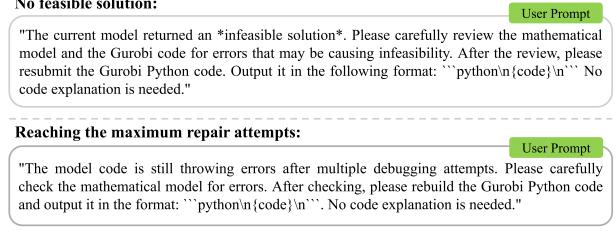


Figure 6. Prompts of Self-Verification.

4. Experiments

4.1. Experimental Setting

This experiment aims to evaluate the performance of the proposed automated OR-solving agent in handling problems described in natural language. We selected 83 real-world OR problems, each presented in natural language and accompanied by essential tabular data. The tabular data is formatted in LaTeX or Markdown to ensure compatibility with the LLM input. All problems are sourced from classic OR textbooks (Hu, 2010; 2012), and their standard solutions have been manually curated and verified. The dataset can serve as the benchmark for evaluating the solution accuracy of AI models. Figure 7 shows the descriptive details of the benchmark dataset.

In the experiment, each AI model takes the natural language description of the OR problem as input and generates executable code to call the OR solver, obtaining the result as the output. To evaluate the performance of AI models, we use the 2 metrics:

- Pass rate: The proportion of cases where the generated solver code executes successfully. This metric reflects the overall reliability and stability of the automated solving process.
- Solution accuracy: The proportion of correct answers, where a solution is considered correct if its deviation from the ground truth is within 0.1. This metric measures the reasoning capability of the model and its effectiveness in solving OR problems.

Gurobi is the default OR solver. OR-LLM-Agent employs GPT-o3-mini as the core LLM. The temperature parameter for all AI models is set to 0.2.

4.2. OR-LLM-Agent vs. State-of-the-art LLMs

We compare OR-LLM-Agent with state-of-the-art (SOTA) reasoning LLMs, including GPT-o3-mini, DeepSeek-R1,

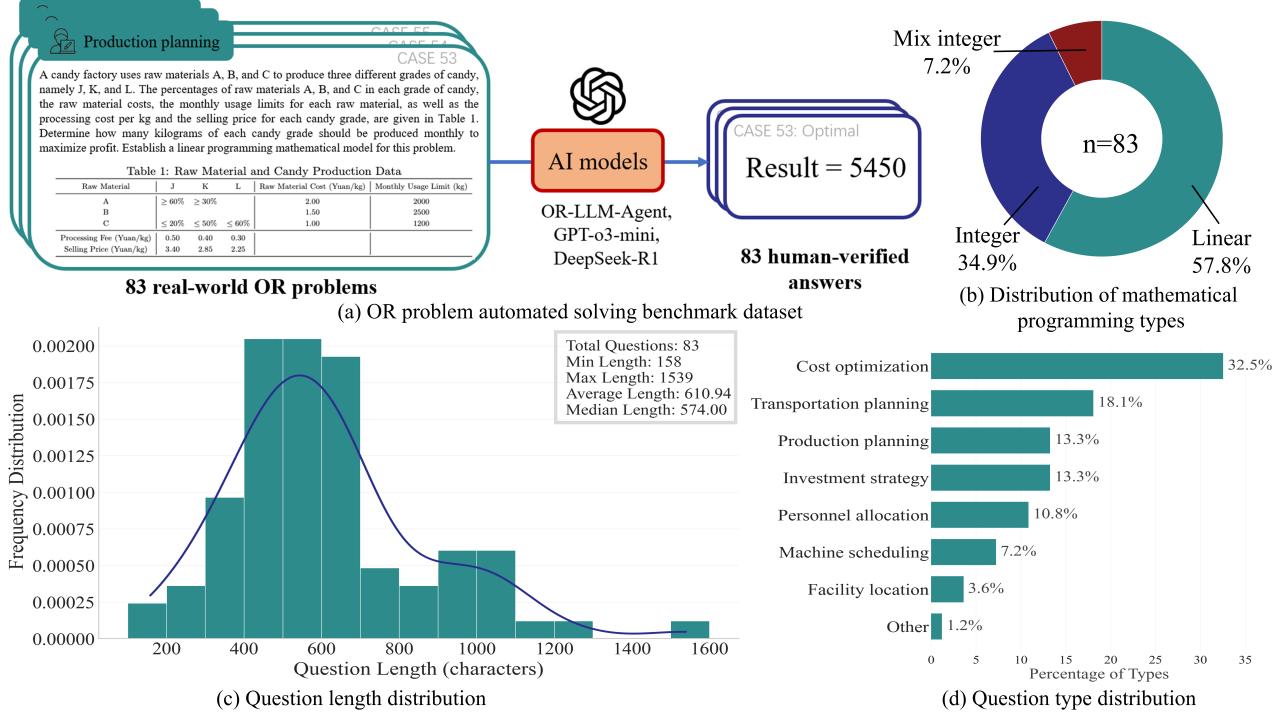


Figure 7. Overview of the Real-world OR Problem Dataset.

Table 1. Comparison with SOTA Reasoning LLMs.

	OR-LLM-Agent	GPT-o3-mini	DeepSeek-R1	Claude-3.7	Gemini Thinking
Pass rate	100	100	97.59	92.77	90.36
Accuracy	85.54	77.10	75.90	69.87	56.62

Claude 3.7, and Gemini 2.0 Flash Thinking. Experimental results, shown in Table 4.2, demonstrate that all models achieve pass rates exceeding 90%, confirming the feasibility of using reasoning LLMs to generate executable optimization code. In terms of solution accuracy, OR-LLM-Agent outperforms SOTA reasoning LLMs by at least 8.4%.

Additionally, we compared OR-LLM-Agent with SOTA non-reasoning LLMs, including GPT-4o, DeepSeek-V3, Claude-3.5, and Gemini 2.0 Flash. The results are presented in Table 4.2. OR-LLM-Agent achieves a pass rate at least 7.2% higher and a solution accuracy at least 22.8% higher than non-reasoning LLMs.

The experimental results demonstrate that OR-LLM-Agent exhibits a competitive advantage over SOTA LLMs, validating its effectiveness in automating OR problem-solving.

4.3. Impact of OR-LLM-Agent and Different LLMs on performance

To evaluate the impact of different LLMs on the performance of OR-LLM-Agent, we replaced GPT-o3-mini with

GPT-4o, GPT-4o-mini, and Gemini 2.0 Flash Thinking. The experimental results are summarized in Table 3. When GPT-o3-mini was replaced with the lower-performing GPT-4o and GPT-4o-mini, the solution accuracy dropped by 26.5% and 56.6%, respectively. These results highlight the critical role of high-quality reasoning LLMs in ensuring the effectiveness of OR-LLM-Agent.

Comparing the performance of GPT-o3-mini, GPT-4o, GPT-4o-mini, and Gemini-Thinking with and without OR-LLM-Agent, we observed that using OR-LLM-Agent led to an average improvement of 8.1% in pass rate and 6.6% in solution accuracy. These results demonstrate that OR-LLM-Agent significantly enhances the performance of LLMs in automated OR problem-solving.

5. Conclusion

To the best of our knowledge, OR-LLM-Agent is the first AI agent framework that automates the entire OR workflow, from natural language problem descriptions to mathematical modeling, code generation, and optimal solutions.

Table 2. Comparison with SOTA Non-reasoning LLMs.

	OR-LLM-Agent	GPT-4o	DeepSeek-V3	Claude-3.5	Gemini 2.0 Flash
Pass rate	100	83.13	89.15	92.77	91.56
Accuracy	85.54	50.60	45.78	62.65	55.42

Table 3. Ablation Experiments on Agent Usage and different LLMs.

	o3-mini	GPT-4o	4o-mini	Gemini
Using OR-LLM-Agent				
Pass	100	100	90.36	98.79
ACC	85.54	59.04	28.92	65.06
No OR-LLM-Agent				
Pass	100	100	81.92	91.56
ACC	77.11	50.60	28.91	55.42
Gap (Agent - No Agent)				
Pass	0.00	16.86	8.43	7.23
ACC	8.43	8.43	0.00	9.63

By significantly reducing the reliance on OR experts and programmers, OR-LLM-Agent lowers the barrier to OR technology adoption in enterprises. Leveraging the mathematical and programming capabilities of reasoning LLMs, OR-LLM-Agent automates the entire OR solution process. It constructs a mathematical model from the natural language problem description and generates Python Gurobi solver code based on the model. In OR-LLM-Agent, we have designed OR-CodeAgent to enable automated code execution and bug fixing to obtain the final solution. Compared to other CodeAgents, OR-CodeAgent is specifically tailored for solving OR problems and features a lightweight and streamlined workflow. In the experiments, we construct a dataset of 83 real-world OR problems, which can serve as a benchmark for AI-driven automated OR problem-solving. Experimental results demonstrate that OR-LLM-Agent achieves a 100% pass rate and 85% solution accuracy in automated OR solution tasks. Compared to o3-mini, DeepSeek-R1, and Gemini 2.0 Flash Thinking, OR-LLM-Agent exhibits superior pass rates and solution accuracy, validating its effectiveness in automated OR problem-solving.

In the future, we plan to extend OR-LLM-Agent to domain-specific applications, such as job shop scheduling and cloud computing resource optimization. Additionally, we aim to construct a larger dataset to serve as a benchmark for evaluating automated OR problem-solving.

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