Parallel Scenarios: A New Paradigm and Evolution Path for Scenario-Based Applications of Artificial Intelligence

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ABSTRACT Scenario engineering has emerged as a promising approach for deploying artificial intelligence in manufacturing, transportation, healthcare, and other real-world domains. However, its current development still faces several structural limitations, including an overemphasis on models rather than scenarios, on access rather than restructuring, and on capability rather than governance. To address these challenges, this paper proposes a new paradigm of parallel scenarios grounded in the framework of parallel intelligence, namely Artificial Societies, Computational Experiments, and Parallel Execution (ACP). In this paradigm, a parallel scenario is defined as an intelligent application system composed of real scenarios, experimental scenarios, and ideal scenarios. The real scenario represents the physical operational environment, the experimental scenario provides a controllable space for simulation, deduction, and optimization, and the ideal scenario serves as the value-oriented target for system evolution. Through the ACP operating mechanism, these three types of scenarios are dynamically connected through continuous interaction, parallel operation, and iterative tuning, thereby forming a closed-loop mechanism for scenario evolution and intelligent decision-making. On this basis, the paper further develops an operational paradigm driven by parallel scenarios, including scenario sensing, plan simulation, implementation, and feedback iteration, and clarifies the functional role of AI agents in cross-scenario coordination. In addition, model context protocol, the agent-to-agent collaboration protocol, and the ACP communication protocol are introduced to support autonomous collaboration among agents across the three scenario types. This study provides both a theoretical foundation and a practical framework for advancing scenario engineering from isolated technical deployment toward systematic value creation and intelligent governance.

INDEX TERMS ACP method, AI agents, autonomous intelligence, parallel scenarios, scenario engineering

I. INTRODUCTION

SCENARIO engineering has emerged as an important pathway for advancing artificial intelligence from model-centered research to practical deployment in complex industrial environments. Rather than treating a scenario as a passive container for algorithms, scenario engineering regards it as an active unit for system design, calibration, validation, and continuous optimization. This perspective is rooted in earlier studies on industrial structure and material engineering [1], and has been increasingly reinforced by recent research on cyber-physical-social intelligence. In particular, recent studies have reported representative progress in areas such as education, healthcare, supply chain resilience, smart manufacturing, financial services, and critical infrastructure [2]–[7]. At the same time, research on parallel control, cyber-physical-social systems, multi-agent systems, agent-oriented software engineering, intelligent agents, digital twins, and smart manufacturing has provided a broader theoretical and technical foundation for scenario-based intelligent systems [8]–[15].

Despite this progress, current scenario engineering still exhibits several important limitations. Many existing approaches remain centered on specific tasks, models, or application interfaces, and thus lack a unified mechanism for linking real-world operation, low-risk simulation, long-term objectives, and continuous feedback. As a result, it is still difficult to form a closed-loop process that supports scenario evolution, decision optimization, and sustained value creation under dynamic, uncertain, and strongly coupled conditions [3]–[5]. Similar challenges have also been observed in related studies on parallel control, agent-oriented systems, and digital twin-enabled smart manufacturing [8], [11], [14]. These limitations suggest that scenario engineering must move beyond isolated deployment toward a more systematic paradigm that can coordinate perception, experimentation, execution, and iterative refinement across heterogeneous environments [10], [12], [15].

To address these challenges, this paper proposes the paradigm of parallel scenarios. Different from conventional scenario engineering based on a single real environment, the proposed paradigm extends the scenario concept to the coordinated interaction among three scenario types, namely real scenarios, experimental scenarios, and ideal scenarios. Real scenarios provide the physical basis for operation and feedback, experimental scenarios provide a controllable space for simulation, evaluation, and optimization, and ideal scenarios represent the target state that guides system evolution. Their interaction is enabled through the ACP method, grounded in the ACP framework of parallel intelligence, i.e., Artificial Societies, Computational Experiments, and Parallel Execution. In this way, parallel scenarios establish a dynamic closed-loop mechanism that connects real-world conditions, experimental deduction, and goal-oriented evolution. This idea is consistent with recent studies on parallel financial systems and true autonomous organizations [6], [16], and also follows the broader development of cyber-physical-social systems, parallel control, and digital twin-based cyber-physical integration [8], [9], [12].

The main contributions of this paper are summarized as follows. First, we propose parallel scenarios as a new paradigm for scenario-based artificial intelligence applications based on the ACP framework of parallel intelligence. Second, we clarify the respective roles of real scenarios, experimental scenarios, and ideal scenarios, and explain how these three scenario types interact through Artificial Societies, Computational Experiments, and Parallel Execution. Third, we develop a scenario-driven operational paradigm for enterprises by constructing a closed-loop process consisting of scenario sensing, plan simulation, implementation, and feedback iteration. Fourth, we further examine the role of AI agents in parallel scenarios and discuss how MCP, A2A, and the ACP communication protocol can support the transition from autonomous scenarios to autonomous intelligence.

II. CURRENT APPLICATIONS AND DEVELOPMENT BOTTLENECKS OF SCENARIO ENGINEERING

A. CURRENT APPLICATIONS OF SCENARIO ENGINEERING

Scenario engineering has been increasingly adopted in both the real economy and social governance, and is gradually becoming an important pathway for translating artificial intelligence from technical capability into practical value. In intelligent manufacturing, it has supported safer, more adaptive, and more collaborative human–robot interaction [5], [14], [15]. In healthcare, it has enabled intelligent path planning and delivery optimization in hospital environments [3]. In supply chain management, it has improved replenishment strategies and enhanced system resilience under uncertainty [4]. In financial services and power systems, it has further contributed to the development of resilient and governable cyber-physical-social infrastructures [6], [7]. More broadly, research on digital twins and cyber-physical systems indicates that scenario-based intelligent systems are becoming a key technical route toward smart manufacturing and Industry 4.0 [12]–[15].

The current development of scenario engineering exhibits several common characteristics. First, it is increasingly driven by the demands of real operational environments, rather than by isolated algorithmic performance alone. Second, it relies on structured system modeling to describe actors, tasks, rules, and constraints within specific domains. Third, it is typically oriented toward value creation in concrete operational settings, such as safety improvement, efficiency enhancement, and resilience optimization. These characteristics suggest that scenario-based artificial intelligence is no longer merely a deployment strategy for existing models, but is gradually evolving into a systematic approach for organizing intelligent applications in complex environments [6], [7], [17].

B. DEVELOPMENT BOTTLENECKS

Despite this progress, current scenario engineering still faces several fundamental bottlenecks. First, scenario representation remains largely static. Many existing systems are designed for predefined tasks and fixed operating conditions, and therefore cannot adequately capture the temporal evolution, contextual variation, and adaptive requirements of real scenarios [12]–[15]. Second, scenario optimization remains highly dependent on real-world trial and error. When validation and revision are conducted mainly in physical environments, the costs and risks of testing, adjustment, and failure correction become difficult to control [3], [4], [13]. Third, coordination across different scenario states is still insufficient. A large number of studies focus on a single task, a local process, or a specific optimization objective, while lacking a unified framework that can connect perception, experimentation, execution, and feedback across multiple scenarios [3]–[5]. Although some studies address operational optimization problems such as disassembly planning and process coordination, they still do not establish a coherent multi-scenario interaction mechanism [14], [15], [17]. Fourth, system operation continues to rely heavily on human intervention. As suggested by foundational research on intelligent agents and multi-agent systems, complex and uncertain environments require stronger autonomous coordination, distributed decision-making, and continuous adaptation than current scenario engineering can generally provide [10], [11].

These limitations indicate that current scenario engineering has not yet formed a closed-loop mechanism for virtual-real interaction, dynamic tuning, and continuous evolution.

What is still missing is not merely better optimization within a single scenario, but a new paradigm capable of coordinating real-world operation, controllable experimentation, and goal-oriented evolution in an integrated manner.

III. PARALLEL SCENARIOS: A MULTI-SCENARIO COORDINATION PARADIGM BASED ON THE ACP METHOD

In this paper, four related but distinct terms are used around ACP. The ACP framework refers to the general theoretical foundation of parallel intelligence, namely Artificial Societies, Computational Experiments, and Parallel Execution. Based on this foundation, the ACP method in this study denotes the way in which the ACP framework is applied to organize the real, experimental, and ideal scenarios into a unified parallel scenario system. The ACP operating mechanism further refers to the specific closed-loop process through which these three scenarios are modeled, optimized, executed, and iteratively adjusted. In contrast, the ACP communication protocol is introduced at the agent-coordination level to regulate how heterogeneous agents exchange data, tasks, goals, and feedback across scenarios.

A. CORE DEFINITION OF PARALLEL SCENARIOS

Parallel scenarios represent an advanced paradigm of scenario engineering grounded in the ACP framework of parallel intelligence [8], [9]. Different from conventional scenario engineering, which typically operates within a single real-world setting, parallel scenarios organize artificial intelligence applications through the coordinated interaction of three tightly coupled scenario types: the real scenario, the experimental scenario, and the ideal scenario. These three scenarios do not constitute a simple juxtaposition of physical space, virtual space, and target vision. Rather, they form an integrated dynamic system in which data, plans, constraints, and value objectives continuously circulate and evolve across scenarios. This paradigm is closely related to earlier studies on parallel control, cyber-physical-social systems (CPSS), and digital twin-enabled cyber-physical integration [8], [9], [12].

The essential difference between parallel scenarios and traditional scenario engineering lies in their multi-scenario coordination logic. Traditional approaches usually focus on optimization and deployment within a single operational environment, whereas parallel scenarios explicitly establish a closed-loop relationship among reality, experimentation, and goals. More specifically, this paradigm exhibits three defining characteristics. First, it is multi-scenario and parallel, in the sense that the real, experimental, and ideal scenarios coexist and interact simultaneously. Second, it is dynamic and evolutionary, because models, plans, and coordination mechanisms are continuously adjusted in response to environmental changes and feedback. Third, it is goal-oriented and value-driven, since the ideal scenario provides the direction of system evolution, the experimental scenario supports low-cost simulation and optimization, and the real scenario provides operational demands, data support, and implementation space. As illustrated in Fig. 1, these three scenarios are linked through the ACP operating mechanism and multiple feedback loops, thereby forming a closed-loop process for scenario modeling, optimization, and deployment.

B. THREE MAIN COMPONENTS OF PARALLEL SCENARIOS

The internal structure of parallel scenarios can be understood through the functional division and coordinated interaction of the three scenario types. Each scenario undertakes a distinct role, yet none of them operates independently. Their value lies precisely in their mutual coupling and iterative coordination.

1) Real Scenario

The real scenario constitutes the practical foundation and point of departure of the entire system. It refers to the actual physical environment, organizational processes, operational rules, and feedback mechanisms involved in enterprise operation or industrial development. It includes real actors, real tasks, real constraints, and real performance outcomes. Its primary role is to provide authentic demands, operational data, and the final implementation space for intelligent planning and system deployment. Existing studies in healthcare, supply chain management, and smart manufacturing have repeatedly shown that intelligent methods can generate practical value only when they are firmly grounded in real operational settings [3]–[5]. Related research on digital twin applications further reinforces the necessity of anchoring intelligent systems in real-world processes and feedback [13], [15].

2) Experimental Scenario

The experimental scenario serves as the core carrier for simulation, deduction, and optimization. It is constructed in virtual space by abstracting and modeling the key elements, process structures, operational rules, and constraints of the real scenario. Its main function is to provide a controllable and low-risk environment in which alternative plans can be tested, compared, and improved before real deployment. In this sense, the experimental scenario is not merely a digital replica of reality, but a computational space for systematic experimentation and policy optimization. This idea is consistent with earlier studies on parallel control and digital twin-based system design, both of which emphasize the importance of simulation-driven decision support and low-cost iterative improvement [8], [12], [13].

3) Ideal Scenario

The ideal scenario represents the target state and long-term evolutionary direction of the system. It is constructed on the basis of enterprise strategy, industrial standards, governance requirements, and future development objectives. Unlike the real scenario, which reflects present conditions, and the experimental scenario, which supports comparative evaluation,

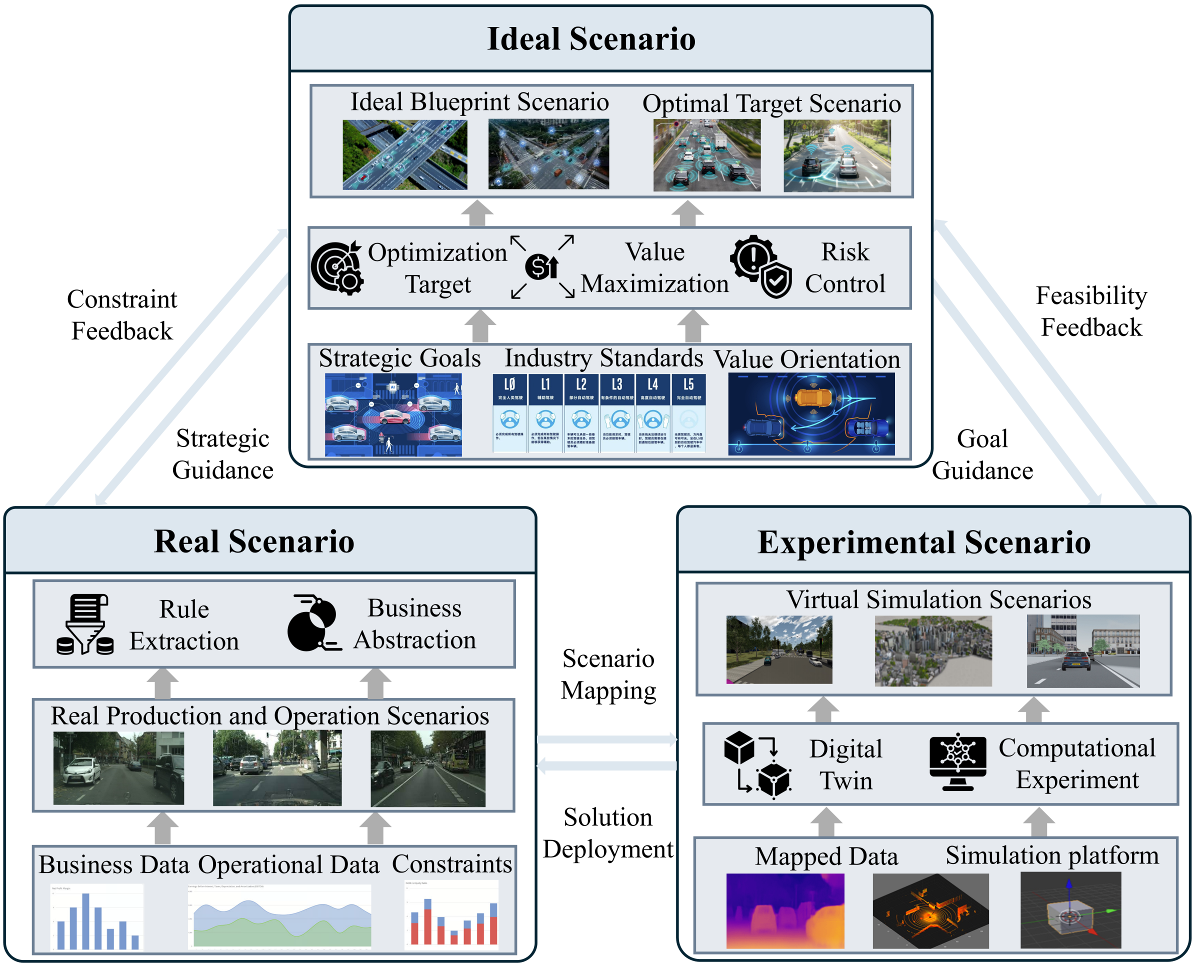

FIGURE 1: The ACP-based tri-scenario framework comprises the Real Scenario, Experimental Scenario, and Ideal Scenario. The Real Scenario provides real-world environments, data, constraints, and deployment conditions. The Experimental Scenario is derived from the Real Scenario through abstraction, rule extraction, and formalization, enabling simulation and optimization. The Ideal Scenario defines target states and long-term directions, and further guides scenario selection and optimization. Through iterative feedback and interaction among the three scenarios, ACP forms a closed-loop framework for scenario evolution.

the ideal scenario provides normative guidance for what the system should evolve toward. Its role is therefore to define target states characterized by higher value, greater efficiency, stronger resilience, and lower risk, and to guide both simulation and real-world execution toward these objectives. Existing studies on CPSS and intelligent enterprises suggest that intelligent systems require explicit system-level objectives and value-oriented coordination, rather than relying solely on local optimization under immediate constraints [9], [12].

C. ACP OPERATING MECHANISM

The ACP operating mechanism provides the operational logic through which the three scenario types are connected into a unified closed-loop system. In this study, this mechanism is realized through Artificial Societies, Computational Experiments, and Parallel Execution. Through these three processes, the real scenario, experimental scenario, and ideal scenario are transformed from isolated representations into an interacting and co-evolving scenario system.

1) Artificial Societies

Artificial Societies constitute the modeling stage of parallel scenarios. At this stage, the key entities, rules, processes, constraints, and data of the real scenario are extracted and formalized to construct the experimental scenario. At the same time, the ideal scenario is established according to strategic goals, governance requirements, and expected future states. This process therefore creates two essential mappings: one from the real scenario to the experimental scenario, and the other from long-term objectives to the ideal scenario. In essence, Artificial Societies provide the structural basis for making both the current operational world and the target evolutionary world computationally representable.

2) Computational Experiments

Computational Experiments constitute the optimization stage of parallel scenarios. At this stage, the experimental scenario is used to evaluate multiple plans, policies, or configurations under different conditions and assumptions. Guided by the value direction provided by the ideal scenario, the system compares candidate schemes, analyzes expected performance and risks, and selects more suitable plans for real deployment. The key significance of this stage lies in shifting optimization from costly real-world trial and error to controllable computational experimentation. This mechanism extends the plan-testing and optimization logic reflected in studies on supply chain control, hospital routing, and disassembly optimization [3], [4], [17].

In addition, if computational experiments indicate that certain target states are infeasible, excessively costly, or inconsistent with real constraints, the ideal scenario may be adjusted before deployment in the real scenario.

3) Parallel Execution

Parallel Execution constitutes the deployment and feedback stage of parallel scenarios. At this stage, the optimized plan generated through computational experiments is implemented in the real scenario. The resulting operational feedback, including performance outcomes, deviations, constraints, and emerging risks, is then transmitted back to both the experimental scenario and the ideal scenario. Based on this feedback, the experimental scenario is recalibrated to better reflect changing real-world conditions, while the ideal scenario may also be refined to accommodate updated strategic goals or governance requirements. Through this process, the system forms a continuous loop of execution, feedback, correction, and re-optimization. The importance of such resilient and adaptive execution across real infrastructures has also been highlighted in recent studies on financial systems and power systems [6], [7].

The ACP operating mechanism enables parallel scenarios to move beyond static scenario representation toward dynamic interaction and deep coordination among real conditions, simulation space, and long-term goals. It is through this tri-scenario coupling and iterative operation that parallel scenarios become not only a framework for scenario modeling, but also a new paradigm for intelligent system evolution and scenario-driven value creation.

IV. SCENARIO-DRIVEN: A NEW PARADIGM FOR ENTERPRISE OPERATION

A. CORE LOGIC OF SCENARIO-DRIVEN OPERATION

Supported by parallel scenarios, scenario-driven operation redefines enterprise management from a mode centered on fixed processes or isolated technologies to a mode centered on operational scenarios. In traditional enterprise systems, decisions are often made either by following predefined workflows or by introducing new technologies into existing processes. By contrast, scenario-driven operation begins with the actual operating context of the enterprise, including task conditions, resource constraints, risk exposure, customer demand, and strategic objectives, and organizes decision-making, process adjustment, and resource allocation around these scenario elements. Under this logic, enterprise operation is no longer a one-way execution process, but a closed-loop mechanism in which sensing, simulation, implementation, and feedback are continuously connected.

1) Scenario Sensing

Scenario sensing is the starting point of scenario-driven operation. At this stage, the enterprise continuously collects and integrates data from production systems, supply networks, market dynamics, customer demand, equipment status, and external operating environments. The purpose is not merely to accumulate data, but to identify the current operational state, emerging constraints, possible disruptions, and changing demands in a timely manner. In other words, scenario sensing provides the factual basis for determining what problem the enterprise is facing, what kind of adjustment may be needed, and which risks should be addressed first. In manufacturing and healthcare, this capability is closely related to safe collaboration, dynamic task allocation, and efficient service execution [3], [5], [15].

2) Plan Simulation

Once key scenario information has been identified, the corresponding data and constraints are transmitted to the experimental scenario for plan simulation. At this stage, the enterprise does not directly implement a response in the real system. Instead, it first evaluates multiple candidate plans in a controllable environment. Guided by the target state defined by the ideal scenario, the system compares alternative schemes in terms of expected efficiency, cost, robustness, and risk, and then selects a more suitable plan for deployment. The practical significance of this stage lies in reducing dependence on direct trial and error in real operations. Before changing a production schedule, adjusting inventory policies, or reallocating service resources, the enterprise can first estimate possible outcomes and identify potential side effects through simulation. Similar optimization logic has been reflected in studies on supply chain replenishment, hospital delivery, and disassembly balancing [3], [4], [17].

3) Implementation

After simulation and evaluation, the selected plan is implemented in the real scenario. This stage transforms computational decisions into actual operational actions, such as adjusting production schedules, reallocating manpower and equipment, modifying replenishment strategies, or updating service processes. The key point is that implementation is not based on experience alone, but on plans that have already been tested and optimized under experimental conditions. As a result, resource adjustment and process execution become more targeted and more consistent with current scenario requirements. In smart manufacturing, this may involve adapting robot behavior according to human state and task context

[5], [14]. In supply chain systems, it may involve dynamically modifying replenishment and coordination strategies under uncertainty [4].

4) Feedback Iteration

Feedback iteration closes the operational loop and enables continuous improvement. After a plan has been executed in the real scenario, the enterprise collects operational outcomes such as efficiency changes, cost variations, service quality, execution deviations, and newly emerging risks. These feedback data are then transmitted back to the experimental and ideal scenarios. On the one hand, the experimental scenario is recalibrated to better reflect actual operating conditions; on the other hand, the ideal scenario can also be refined when strategic objectives, governance priorities, or market expectations change. Through this process, enterprise operation becomes an iterative mechanism of execution, evaluation, correction, and re-optimization, rather than a one-time decision process. Such closed-loop improvement is particularly important for resilient financial systems and critical infrastructures, where continuous adaptation is essential [6], [7].

B. PRACTICAL VALUE OF SCENARIO-DRIVEN OPERATION

The practical value of scenario-driven operation lies in its ability to improve enterprise decision quality, operational responsiveness, strategic consistency, and organizational coordination in a unified manner.

First, it reduces decision risk and operating cost. Because candidate plans can be tested in the experimental scenario before real deployment, enterprises can identify infeasible or high-risk options in advance and avoid costly trial and error in real operations. This advantage is especially important in scenarios where mistakes are expensive or difficult to reverse, such as supply chain adjustment, healthcare delivery, and financial operations [3], [4], [6].

Second, it improves operational responsiveness and adaptability. Since real-time sensing is directly connected with simulation and feedback, enterprises can respond more quickly to demand fluctuations, environmental disturbances, and resource constraints. This helps shorten the cycle from problem identification to response implementation, and enables the enterprise to maintain more stable performance under uncertainty. Recent studies in manufacturing and healthcare have already shown the practical importance of such adaptability [3], [5], [15]. Related work on digital twins and smart manufacturing further supports this point [13]–[15].

Third, it helps align short-term operations with long-term development objectives. In many enterprises, short-term efficiency optimization and long-term strategic goals are often disconnected. Scenario-driven operation mitigates this problem by introducing the ideal scenario as a persistent source of direction. As a result, local operational decisions can be evaluated not only by immediate performance, but also by their consistency with broader goals such as resilience, sustainability, governance, and future competitiveness. This is consistent with governance-oriented thinking in true autonomous organizations and parallel financial systems [6], [16].

Fourth, it strengthens cross-functional coordination within the enterprise. Because scenario-driven operation requires data, processes, and decisions to be linked across sensing, simulation, execution, and evaluation, it naturally promotes tighter coordination among departments such as production, supply, service, planning, and management. In this sense, its value is not limited to better operational decisions at isolated points, but extends to a more integrated and intelligent mode of enterprise organization and execution.

V. AUTONOMOUS SCENARIOS: FROM MULTI-PROTOCOL COORDINATION TO AUTONOMOUS INTELLIGENCE

Parallel scenarios provide the structural basis for scenario-driven operation, but their long-term value lies in the further evolution toward autonomous scenarios and autonomous intelligence. This evolution reflects a shift from static deployment and human-guided adjustment to closed-loop autonomous coordination and self-evolving intelligent systems. As shown in Fig. 2, the proposed framework supports a progressive evolution from Scenario Engineering to Parallel Scenarios, then to Autonomous Scenarios, and ultimately to Autonomous Intelligence through multi-scenario expansion, agent-based coordination, and continuous self-evolution.

A. AI AGENTS AND MULTI-PROTOCOL COORDINATION

The next stage of parallel scenarios is the transition from scenario-driven operation to autonomous scenarios. In autonomous scenarios, the real, experimental, and ideal scenarios no longer depend mainly on human intervention. Instead, they are supported by AI agents that can sense, decide, communicate, and execute tasks autonomously. Foundational studies on intelligent agents, agent research, and agent-oriented software engineering, together with recent survey work on large language model-based autonomous agents, provide important support for this direction [10], [11], [18].

Different groups of AI agents can be deployed in different scenario types. Agents in the real scenario collect and return data. Agents in the experimental scenario conduct simulations and optimize plans. Agents in the ideal scenario maintain and refine target states. Recent studies on digital twins, cyber-physical integration, and human-machine interaction in smart manufacturing have also shown the value of stronger coordination among physical systems, cyber models, and intelligent decision units [13]–[15].

To support coordination among these agents, three protocols are especially important. MCP provides AI agents with a secure and unified way to access external tools, data sources, sensing devices, and computing resources. A2A supports communication, task coordination, and state synchronization among heterogeneous agents. The ACP communication

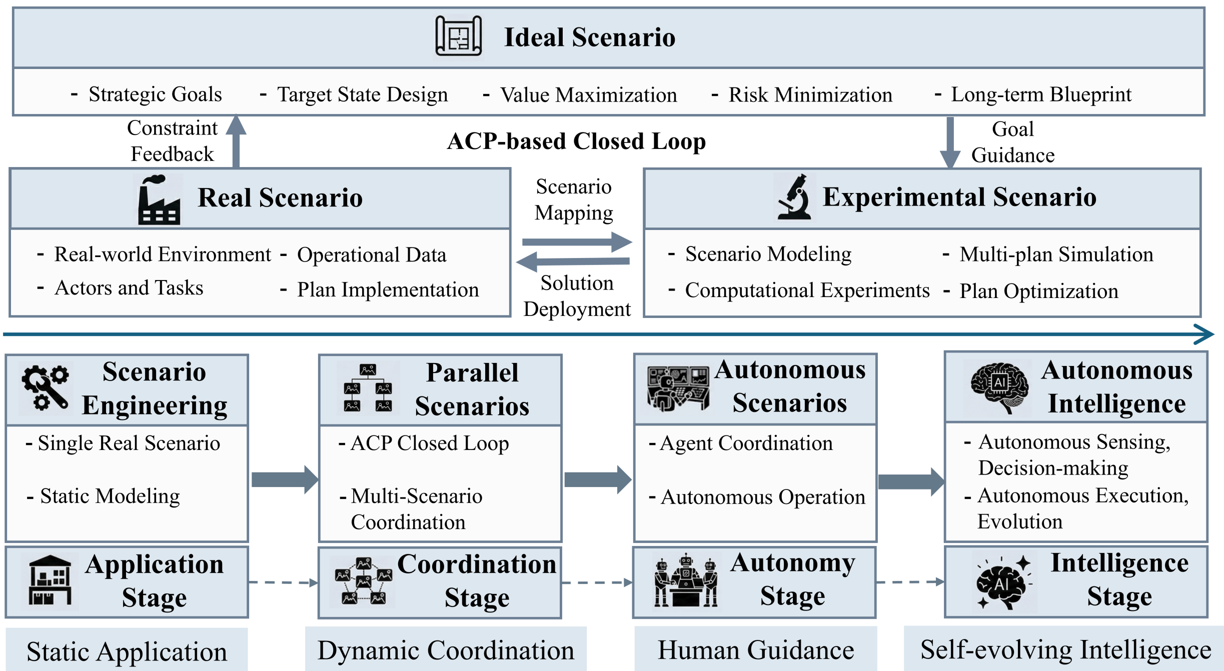

FIGURE 2: Evolution path from scenario engineering to autonomous intelligence. The ACP closed loop, composed of the real, experimental, and ideal scenarios, serves as the core mechanism of the parallel scenarios stage, supporting the progression from static application to dynamic coordination, human-guided autonomy, and ultimately self-evolving intelligence.

protocol provides a common standard for identity management, message exchange, data rules, and security rules, so that agents built on different systems can still cooperate efficiently. In this framework, these protocols provide the communication basis for turning a multi-scenario structure into an autonomous operating system.

B. ACP COMMUNICATION PROTOCOL FOR CROSS-SCENARIO AGENT COORDINATION

The ACP communication protocol is not intended as a replacement for the ACP framework or the ACP operating mechanism. Instead, it functions as a communication-layer specification for autonomous scenario coordination. Its role is to support structured interaction among agents in the real, experimental, and ideal scenarios, including state synchronization, task delegation, simulation-result delivery, execution feedback, and goal adjustment.

More specifically, the protocol may include four basic components. First, identity and role definition, which specifies the scenario affiliation and functional authority of each agent. Second, message structure, which defines standardized fields for state data, constraints, simulation outputs, execution commands, and feedback reports. Third, coordination rules, which regulate when and how messages are exchanged across scenarios. Fourth, security and governance rules, which ensure data consistency, access control, traceability, and safe inter-agent collaboration.

Under this protocol, agents in the real scenario first transmit operational states and constraints to the experimental scenario. Agents in the experimental scenario then conduct computational experiments and return candidate plans. Agents in the ideal scenario evaluate these plans against long-term objectives, value requirements, and governance constraints. After plan selection, execution commands are sent back to the real scenario, and the resulting feedback is transmitted to both the experimental and ideal scenarios for recalibration and goal refinement.

C. OPERATING MECHANISM OF AUTONOMOUS SCENARIOS

1) Autonomous Sensing and Mapping

Agents in the real scenario collect operational data through connected devices and data systems. These data are then automatically transmitted to agents in the experimental scenario, where the virtual mapping of the real scenario is updated. In smart manufacturing and hospital operations, this kind of autonomous data flow is closely related to safety, timing, and operational efficiency [3], [5], [15].

2) Autonomous Simulation and Optimization

Agents in the ideal scenario update long-term targets according to enterprise strategy and external changes. These targets are then transmitted to agents in the experimental scenario, which conduct simulations, compare plans, and select optimized schemes. This extends the optimization logic reflected in studies on supply chains, financial coordination, and disassembly systems [4], [6], [17].

3) Autonomous Implementation

The selected plan is transmitted to agents in the real scenario. These agents connect with enterprise systems and carry out the required actions, including resource allocation, process adjustment, and task dispatch.

4) Autonomous Feedback and Iteration

After execution, agents in the real scenario collect performance data and compare actual results with target values. The feedback is then automatically transmitted to the experimental and ideal scenarios, where models and goals are updated for the next cycle. In this way, the parallel scenario system forms a full-process closed loop with autonomous sensing, autonomous communication, autonomous decision-making, and autonomous iteration.

D. FROM AUTONOMOUS SCENARIOS TO AUTONOMOUS INTELLIGENCE

Autonomous scenarios represent an advanced stage of parallel scenarios, but they do not constitute the final stage. With continuous learning, improved protocol coordination, and increasing data accumulation, the system can further evolve toward autonomous intelligence.

Autonomous intelligence means that the scenario system itself acquires the ability to define problems, organize resources, generate plans, verify results, and evolve over time. At this stage, intelligence is no longer attached only to separate tools or agents. Instead, it becomes an internal property of the scenario system itself. This direction is supported by earlier studies on CPSS, parallel control, and multi-agent systems [8]–[10]. It is also supported by research on intelligent agents, digital twins, and smart manufacturing [12], [14], [18]. Broader discussions of cyber-physical-social intelligence and resilient infrastructures point in the same direction [2], [6], [7].

The transition from autonomous scenarios to autonomous intelligence is gradual. At the initial stage, the system may only optimize simple local tasks. It can then coordinate more complex scenarios, support cross-domain interaction, and develop stronger self-adaptive and self-evolving capabilities. In this way, artificial intelligence moves from technical deployment to deep integration with enterprise operation, industrial development, and social governance.

VI. CONCLUSION

This paper proposes parallel scenarios as a new paradigm for scenario-based applications of artificial intelligence. Based on the ACP framework of parallel intelligence, the proposed paradigm organizes real scenarios, experimental scenarios, and ideal scenarios into a unified and evolving system, and establishes a closed-loop mechanism of mapping, simulation, implementation, and feedback. Through this tri-scenario coordination structure, parallel scenarios extend conventional scenario engineering from static deployment in a single real-world environment to dynamic interaction across multiple scenario types. In doing so, they provide a systematic approach to overcoming several key bottlenecks of current scenario engineering, including static modeling, high optimization cost, limited cross-scenario coordination, and strong dependence on manual intervention. More broadly, the progression presented in this paper, from scenario engineering to parallel scenarios, from scenario-driven enterprise operation to autonomous scenarios, and from autonomous scenarios to autonomous intelligence, reveals a fundamental transformation in artificial intelligence. Intelligence is no longer viewed simply as adapting to scenarios, but increasingly as emerging from scenarios that can organize, support, and generate it.

Future research should further examine how the parallel scenario framework can be implemented and scaled in more complex and heterogeneous application domains, especially in enterprise operation, industrial systems, and social governance. Several issues deserve particular attention, including the formal modeling of ideal scenarios, the robust coordination of heterogeneous agents, and the design of a secure and efficient ACP communication protocol across real, experimental, and ideal scenarios. Another important direction is to explore the deeper integration of large language models, autonomous agents, and digital twin technologies into the parallel scenario framework, so as to strengthen its capabilities for autonomous sensing, decision-making, self-optimization, and long-term evolution. Through these efforts, parallel scenarios may develop from a conceptual and operational framework into a more general foundation for autonomous intelligence in complex socio-technical systems.

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