SOLVING COMPLEX RESOURCE MANAGEMENT PROBLEMS: FROM CLASSICAL OPTIMIZATION AND GAME THEORY TO MULTI-AGENT TECHNOLOGIES FOR REACHING CONSENSUS

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Abstract. Challenges and complex problems arising in the resource management of modern enterprises are considered. The existing resource planning models, methods, and tools for enterprises are reviewed, and new requirements for adaptive multicriteria resource planning in real time are presented. The concept of autonomous artificial intelligence (AI) systems for adaptive resource planning based on multi-agent technologies is discussed. The evolution of the approach to solving complex resource management problems is described: from traditional optimization of a single objective function, ignoring the individual interests of participants, to game theory with their competition and cooperation. The approach to finding and maintaining a competitive equilibrium (consensus) between participants is further developed via conflict identification and negotiations for conflict resolution with mutual trade-offs. A basic model of a multi-agent demand-supply network with a virtual market and a compensation method for reaching consensus for adaptive resource planning are presented. The functionality and architecture of intelligent adaptive resource planning systems are considered. The implementation results of AI solutions for industrial applications are provided, and the possibility of improving the effectiveness of resource usage by enterprises is shown. Finally, the lessons learned from the experience in R&D work and the prospects of this approach are discussed.

Keywords: resource management, complexity, artificial intelligence, demand-supply networks, autonomous systems, adaptability, multi-agent technologies, self-organization, real-time economics.

INTRODUCTION

The growing complexity of elaborating and realizing optimal decisions in the modern economy is largely explained by the sharp increase in the complexity of demand-supply dynamics, when various perturbing events become a norm rather than an exception [1], and the related need for quick adaptation of enterprises to the changing conditions of economic activity.

At the same time, the growing complexity in enterprise management is, more and more, due to the increasing number and diversity of the objectives and characteristic properties of participants in coordinated decision-making processes with their individual preferences and constraints, e.g., in complex international or national supply chains. Unforeseen events include large-scale ones (the appearance of new major customers, partners, or competitors, the development of new products and technologies, or changes in product supply chains) and day-to-day events (such as equipment failures and delays in operations).

The usual response of company's top managers to poorly predictable business events is to attract additional resources, e.g., hiring new managers and increasing the stock of goods in warehouses and the size of warehouses. Within the traditional decision-making system, the response time to emerging events increases, including the collective elaboration, coordination, adoption, and implementation of decisions. As a consequence, the quality of customer service decreases, downtimes in the use of resources grow, orders are lost, or costs rise; finally, there is a general reduction in the effectiveness and competitiveness of the business [2].

One reason for this situation is the application of traditional models, methods, and tools for resource planning and optimization with centralized multi-level hierarchical enterprise management and packet data processing. This approach complicates the proper consideration of the individual characteristics, preferences, and constraints of the participants in enterprise management processes, important for the activities carried out; as a result, they are often ignored.

The solution of this problem requires the development of a new paradigm of creating maximally autonomous intelligent resource management systems that make decisions on the current management of enterprise resources instead of a human. This paradigm is oriented towards the emerging real-time network economy with a high level of management autonomy, which, in turn, requires the high adaptability of resource management in case of various unforeseen events [3].

Nowadays, it is becoming possible to solve this problem using artificial intelligence (AI) systems, which operate continuously and can autonomously (independently) make decisions for real-time resource allocation, planning, optimization, monitoring, and control of results, as well as adaptively rearrange the plans based on events.

However, current research projects in the field of AI systems are still mainly focused only on autonomous robots and unmanned aerial and ground vehicles [4]. The ongoing projects in other areas of AI technologies include big and small data analysis, pattern recognition and machine vision, machine learning, etc. Strangely enough, AI technologies for resource management have not yet been included in this list, although using AI for autonomous adaptive management to improve the efficiency of enterprises with increasing order volumes and diversity of attracted resources is a very topical and significant problem.

This paper presents theoretical foundations and practical results of solving complex adaptive resource management problems using AI systems based on the multi-agent technology. Compared to the traditional approaches, this technology allows creating self-organizing schedules of orders and resources with higher openness and flexibility to changes.

In Section 1, the reasons for the growing complexity and dynamics of modern production resource management are investigated. In Section 2, we briefly analyze the limitations of the existing methods and tools for resource planning and optimization, including classical and heuristic optimization methods and methods based on game theory. Section 3 considers the concept of an autonomous AI system for adaptive resource management based on the notion of a multi-agent demand-supply network and a virtual market of program agents for orders, operations, resources, and products. As is shown, the solution of the complex resource management problem can be built by identifying and resolving conflicts through auction-like multi-iteration negotiations using the satisfaction, bonus, and penalty functions of agents and the compensation method in case of mutual trade-offs. Section 4 presents the functionality and architecture of autonomous AI solutions for adaptive resource management. The implementation results of AI solutions for industrial applications are described in Section 5, particularly the possibility of improving the effectiveness of resource usage by enterprises. In Section 6, we discuss the lessons learned from the experience in R&D work on these solutions and their business benefits. The main outcomes of the survey, as well as possible directions of future R&D work in the field of such resource management systems, are outlined in the Conclusions.

1. THE COMPLEXITY OF MODERN RESOURCE MANAGEMENT

Examples of modern resource management problems in enterprises are diverse and may include managing a fleet of trucks, machine shop floors, supply chains, train movements, constellations of satellites and drones, and other applications.

Several examples of such problems have already been considered previously by one of the authors; see [5]. The experience accumulated over the past time allows identifying their main features and formulating, more precisely, the requirements for the approaches applied.

The following key complexity factors are typical of these problems: the large number of daily orders, multi-criteria resource management (maximizing service quality, minimizing financial costs and delivery time, and maximizing profits), an individual approach to orders and resources and their multiple features (shared orders, reusable resources, renewable resources, etc.), the interdependencies between the jobs to be done, the specifics of the resources applied, common or shared costs, flexible or fixed prices, etc.

A main factor in the complexity of resource management is that, in practice, people face many conflicting requirements dictated by many participants in the processes of doing business, from the strategic targets of an entire enterprise to the tactical targets of its departments, as well as the operational targets of executors "on the ground": truck drivers, workers, logisticians, dispatchers, economists, and other employees. According to the common opinion of experienced dispatchers, a good schedule is a well-balanced schedule that considers the preferences and constraints of all participants in each particular situation. Thus, an AI system must generate schedules that, in each situation and at each particular time instant, reflect the balance of many conflicting interests, preferences, and constraints, which is extremely difficult and time-consuming within traditional approaches to resource planning.

Moreover, such schedules are often inhomogeneous, i.e., different fragments of the schedule differ depending on the criteria relevant at a particular time instant, which may change with the arrival of new orders and the occurrence of other events during the computation process. We emphasize that the achieved balance of interests always depends on the development of the situation but refers to a particular time instant. Therefore, at a next time instant, a coordinated "optimal" schedule may lose optimality and even become unrealizable in principle.

This "sliding optimization," actually with harmonizing the interests of all participants in each situation and in real time, requires interactive communication with decision-makers, who can add new events and, moreover, modify their preferences and constraints, approve or reject decisions, and make counter-offers.

In this regard, adaptability should be treated as one of the most important functions of such solutions. It can be defined as the ability of an AI system to rearrange the schedule partially, resolving internal conflicts by negotiations without stopping the system, and maneuver resources flexibly to achieve its goals under uncertainty due to the permanent occurrence of events changing the situation at a priori unpredictable time instants.

2. RESOURCE MANAGEMENT: A REVIEW OF THE EXISTING METHODS AND TOOLS

Traditional packet methods and tools for resource planning and optimization based on linear, dynamic, or constraint programming are well known [6, 7].

However, most of these methods and tools are designed for a problem statement where all orders and resources are known in advance and do not change in real time. Therefore, in the field of enterprise resource planning (ERP), classical package planners offered by SAP, Oracle, Manugistic, i2, ILOG, J-Log, and other companies still dominate the market; in practice, however, these packages tend to implement mainly accounting functions due to the increasing problem dimension, and the built-in modules for resource allocation, planning, optimization, and communication with business participants are of limited application.

To decrease the complexity of combinatorial search, methods with heuristic and metaheuristic rules are practiced to make acceptable decisions in a more reasonable time by reducing the solution search domain [8, 9]:

– greedy local search algorithms based on heuristic rules of a subject matter;

– AI methods based on neural networks and fuzzy logic;

– metaheuristics: genetic algorithms and tabu search;

– simulation, including simulated annealing, etc.;

– stochastic methods such as the Monte Carlo method;

– ant colony and particle swarm optimization algorithms;

– combinations of parallel heuristic optimization algorithms, etc.

However, these methods also use packet processing and do not provide the real-time adaptation of schedules as events occur.

Direct analysis of the above solutions reveals the following problems:

– There are no models, methods, and tools for adaptive resource management.

– Under changes in problem specifications, it is necessary to revise the methods applied and attract experts to reprogram the system.

– Available systems support centralized management based on top-down commands, without considering the opinions and interests, preferences, and constraints of executors.

– Due to the hierarchical rigidity of the systems, it is impossible to respond to events promptly and flexibly, and the schedules are realigned only partially.

– The systems are internally passive and operate in the packet mode only at the user's request.

– The systems are focused on data rather than corporate subject-matter knowledge necessary for automated decision-making.

– Business processes are excessively standardized and hence ignore the individual preferences and constraints of decision-makers.

The high complexity and dynamics of the problems under consideration make traditional centralized hierarchically organized sequential methods and algorithms of combinatorial search or heuristics inefficient when solving the problem of adaptive resource management (in terms of acceptable quality and time required). This factor restrains the implementation of the AI enterprise management systems in practice.

3. NEW MODELS AND METHODS FOR REACHING CONSENSUS IN ADAPTIVE RESOURCE MANAGEMENT

Multi-agent technologies are a key trend in AI; for example, see the monographs [10, 11] and the papers [12, 13].

Recently, multi-agent technologies have been associated with AI agents and *Large Language Models* (LLM), but the basic property of multi-agent technologies is still the ability to create self-organizing systems where each element makes its own decisions. As a result, such systems are more open to change, flexible, and effective in various complex problems.

In this regard, multi-agent technologies are a possible method for solving optimization problems [14]. In the last decade, new models and methods for the distributed solution of resource planning and optimization problems have been developed on the basis of multi-agent technologies. The description of such models and references to the relevant literature can be found in the reviews [15–20].

Note that the transition to multi-agent technology for adaptive locally optimal scheduling reflects a significant change in the problem paradigm compared to the approach with standard packet optimization technologies, where the solution is constructed by a centralized sequential deterministic algorithm. In contrast, a schedule within the multi-agent approach is a distributed and dynamic object in which the scheduling problem is solved in a non-deterministic way with parallel and asynchronous computation processes evolving over a common data structure, mirroring the state of enterprise resources at any given time instant. In this case, each event initiates a transition process from one non-equilibrium state to another, which is realized by the partial adaptive rearrangement of the schedule of orders and resources; in other words, the revision of previously made decisions and the redistribution of previously distributed orders by resources are allowed.

Thus, the problem is to rearrange promptly the schedule in a finite time, which defines the characteristics of the target space of system states achievable within a given period from a given initial state by the method under consideration.

The idea of using models and methods based on agents' self-organization in resource management looks very attractive for software developers. Many useful properties of such algorithms are well studied: they are intuitive, able to cover the individual criteria, preferences, and constraints of all participants, reliably correct, naturally parallelizable, deployable in distributed systems, (in many cases) stable to changes in the problem specification, etc. Of particular interest is the systematic comparison of the results of multi-agent and packet optimization approaches, presented, e.g., in [21, 22]. It is necessary for "marking" the effectiveness of multi-agent algorithms depending on the characteristic modes of the problem.

In general, the architecture of multi-agent distributed optimization models is divided into two large classes: models with autonomous agents and models with additional participation of intermediary agents (mediators). A key element of multi-agent technology is a negotiation protocol that ensures that the process of reaching an agreement between program agents of demand (e.g., necessary actions) and supply (resources) is initiated and evolves. In models with autonomous agents, the latter act independently; in models with mediators, the limited control intervention of agents is possible.

Most of the works use different versions of the *Contract Net Protocol* [23, 24], which regulates the process of submitting and analyzing requests. The discussion of such protocols and their comparative analysis were presented in [25].

The supply-demand balance protocol is implemented using a market pricing mechanism that implies the existence of internal virtual money. Thus, multi-agent models realize the concept of a virtual market (VM), where agents iteratively negotiate, concluding and revising contracts among themselves as well as exchanging jobs and money. Each agent begins the solution search with some initial set of jobs, possibly empty, and then enters into a process of negotiating new solutions. An important part of the solution search is the joint consideration of planning and scheduling. This issue was studied in the survey [16] and the publications cited therein. As a result, an optimal schedule is searched within the process of dynamic self-organization in a network of agents; for models with autonomous agents, the ultimate goal of this process, from a general theoretical point of view, is to reach the state of competitive equilibrium (consensus) in which none of the agents will further improve the result for the entire system. As noted above, the key factor of quality is the finite time to obtain the solution and, as a consequence, the possible difference between the solution obtained in this time and the optimal one.

The concept of a virtual market implemented in multi-agent models fits naturally into the general concept of formulating optimization problems in terms of the virtual economy of interacting agents [26–28], particularly within game theory [29–32]

For models with autonomous agents, game theory underlies the general analysis of possible outcomes of interaction among such agents, including the analysis of game-theoretic Nash equilibria in multi-agent systems (MASs) and algorithms for finding them.

For the scheduling problem, Nash equilibria were analyzed, in particular, in [19, 33, 34]. The main result is a formal proof that finding Nash equilibria in such problems is NP-hard. Note that the problems under consideration are not exceptional in this sense: except for a narrow group of special problems, the search for Nash equilibria in pure strategies belongs at least to the complexity class of PPAD ("*Polynomial Parity Arguments on Directed graphs*") [11]. At the qualitative level, this means that the time to construct a solution is exponential in the parameter(s) reflecting the system heterogeneity. Under a limited time for building a modified schedule, it may be impossible to find the corresponding Nash equilibrium.

Clearly, the NP-hardness of game-theoretic equilibria emphasizes the significance of time constraints in scheduling. An important circumstance, potentially decisive for the classification of the corresponding modes, is the existence of a phase transition by the computational cost of solving NP-hard problems, in particular, scheduling problems [35, 36], that separates phases with easy- and hard-to-find solutions.

As for game-theoretic equilibrium search algorithms, the situation becomes even more complicated: no *universal* algorithms of this kind have been developed to date. For example, the existence of configurations in which no solution can be found was demonstrated [39] for one of the most natural and attractive equilibrium search algorithms based on auction theory [11, 37, 38]. As is also known, in some cases, competitive multi-agent models yield no satisfactory solution, reaching a *deadlock* [40]. The deadlock reflects the insufficiency of a certain protocol used in competitive MASs to resolve conflicts. In this regard, MASs with *mediators* [17, 18] are of significant interest. The general multi-agent architecture with mediators was described in [41]: in addition to the basic competitive layer of agents, it includes mediators that can be addressed by competitive agents to resolve conflicts. In contrast to autonomous agents, mediators have access to a significantly larger amount of information, allowing for more precise planning of dynamic rescheduling. According to the comparison of competitive and mediated architectures [42–44], the introduction of mediators can improve the indicators of solution quality. Various multi-agent models with mediators were considered in [40, 44–48].

An essential issue of MAS architecture design is the analysis of hierarchical and holonic architectures, which was discussed in [49–51].

From the theoretical point of view, in addition to the above interaction architectures, cooperative models are of significant interest, in which the interaction protocol of agents is described within cooperative game theory [11, 41, 44]. In particular, this interest is related to that, except for special cases, competitive equilibrium in game theory is inefficient in terms of overall solution quality. In the current context, this problem was reflected in the review [47].

Since 1999, a similar software development approach for implementing multi-agent solutions of optimization problems was elaborated within the projects described in the monograph [5]. In particular, the attractive properties of such algorithms were already manifested in the first multi-agent prototype of the system for a Volkswagen plant to supply and replace wooden parts for the interior design of luxury cars. The problem was that an expensive car ready for delivery often failed quality control due to deviations of the color or pattern of wooden interior parts from the standard. Such a car was driven to the parking lot, and it took a long time to find, deliver, and mount the new part (significant costs). Note that the SAP production system required 12 to 24 hours to resolve the problem; in practice, the plant's department heads simply called each other and settled the issue through negotiations. It was necessary to develop a system that would quickly and adaptively rearrange the schedule using SAP data. The resulting MAS allowed solving the problem within a few seconds (up to a minute).

In the next period, the multi-agent technology was refined according to the concept of holonic systems: the basic agents of products, resources, and orders and the staff agent (or the agent of the entire system) were implemented within the PROSA reference architecture [48]. Further, the technology took the important step of detailing agents to the level of business-process agents and each individual job; also, the classes and roles of agents were introduced that form multi-agent demand-supply networks representing self-organizing schedules with proactivity and mutual compensations in conflict resolution. For the agents of DS networks, an adaptive decision-making method with compensations under the mutual trade-offs of orders and resources in the virtual market based on satisfaction and bonus-penalty functions was proposed to provide elastic decision-making when resolving conflicts and reaching a new consensus among such agents [52–54].

In the method developed, the agents of orders and resources, as well as those of jobs and products, first select the best conflict-free alternatives and then resolve conflicts until the system is balanced to a new consensus and none of the new alternatives can improve the overall goal function of the system (e.g., profit).

This process reflects the existing practices of experienced managers and dispatchers who generate complex schedules by resolving conflicts and balancing the conflicting interests of all parties to the decision-making process.

The formal problem statement and the description of the method were given in [55].

Recently, the interest in AI systems for enterprise management has increased significantly due to the massive adoption of electronic maps, ERP systems, and the Internet of Things, cell phones, and other devices that translate business into a digital model reflecting the state of resources in real time [56–59]. Here, AI capabilities are mainly associated with prediction, planning, and knowledge extraction during learning, in combination with classical resource planning and optimization and various heuristics. The problem of building a dynamic self-organizing schedule with a prompt, flexible, and efficient rearrangement based on real-time events has not been formulated so far.

4. THE FUNCTIONALITY AND ARCHITECTURE OF THE SOLUTION

The functionality of AI systems for adaptive resource management aims to support the full cycle of autonomous resource management, including:

- collecting new events via sensors, external systems, and mobile devices;
- distributing orders among resources by identifying the most appropriate ones;
- planning orders and resources, i.e., calculating the best possible sequence and determining the start and end time of a job (operation) to fulfill orders;
- optimizing orders and resources (if time is available), i.e., continuously improving the goal functions of all agents involved in resource management;
- predicting new events (new orders or failures) that will be handled as virtual events for the preliminary dynamic reservation of critical resources;
- implementing online communication with users: approving system recommendations, changing preferences or making counter-offers, correcting facts, etc.;
- monitoring and controlling plan fulfillment, i.e., comparing planned and factual results, identifying gaps, and initiating a re-planning event for top management;
- adaptive re-planning in case of a growing gap between the plan and reality (e.g., if the user ignores recommendations and exceeds the time limits);
- experience-based learning, i.e., clustering of events, comparing the planned and factual job completion times (e.g., for analyzing employee productivity);
- real-time "what-if" simulation (multiple simulation lines can be run in parallel with the main plan trajectory to explore the future in real-time);
- evolutionary restructuring of the business network, i.e., generating suggestions to improve the quality and efficiency of operations (selecting a better storage space, etc.).

The approach developed can be generalized to the concept of Smart Solution as an autonomous system for real-time intelligent resource management with the following types of users (Fig. 1) [60, 61]:

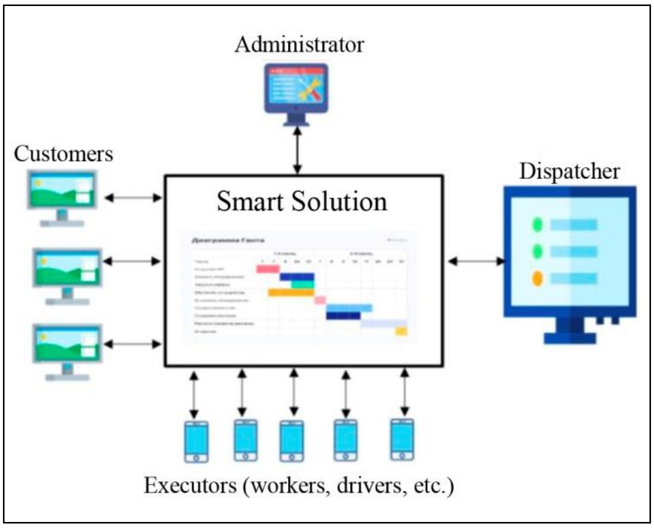

Fig. 1. The concept of an autonomous intelligent resource management system.

– customers, who specify necessary orders, coordinate incoming offers, and further observe the step-by-step fulfillment of their orders;

– dispatchers, who specify planning criteria and approve system-built plans, correct results, and settle the remaining issues;

– executors, who receive shift targets and mark up their fulfillment (when necessary) and introduce unforeseen events causing the adaptive change of plans.

– administrators, who generate logins and passwords for user authorization, manage system databases, etc.

The main types of Smart Solution users and their capabilities may vary depending on the application, but the above basic functionality remains the same for different modifications.

The Smart Solution architecture has the following main components (Fig. 2):

– web systems of users, which are intended to support the business processes of user work;

– an ontology-driven knowledge base, which contains formalized knowledge (classes of concepts and relations) to support real-time decision-making;

– an onto-MAS, which is an ontologically customizable MAS for real-time resource management

– integration, which consists of integration modules with traditional accounting systems (1C, etc.).

The decisions made (in the form of current plans, instructions, or commands) are transmitted to the cell

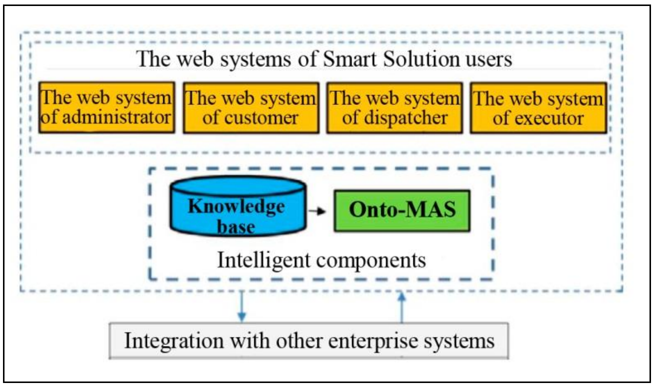

Fig. 2. The main components of the autonomous intelligent system for real-time resource management.

phones of executors or enterprise equipment, with requesting acceptance or confirmation; they can be adaptively revised at any time instant via system-generated or user-entered events if the situation changes.

5. THE RESULTS OF INDUSTRIAL IMPLEMENTATIONS

Based on the above approach, 15 industrial prototypes and full-scale MASs for adaptive resource management were developed between 2000 and 2008, including tanker management, corporate taxi, freight transportation with consolidation, and quite a few different prototypes and small applications (adaptation of a meal plan or workout plan, ordering of household goods, etc.).

During the development and implementation of the systems under consideration, a methodology was elaborated to assess improvements in the effectiveness of resource usage. This methodology evaluates two types of costs:

• direct costs (the reduced time of transporting goods or executing production orders, the decreased use of materials, machinery and machine tools, the reduced wages paid to workers, etc.) and

• overhead costs (the reduced staff of the enterprise (low-level managers, logisticians, dispatchers, economists, etc.).

The economic effect calculated also includes the decreased complexity and labor intensity of management operations, the reduced time of processing unforeseen events, the reduced costs of personnel training, etc.

The problem statement and implementation results were described in detail in [5]. Here, we summarize the main business benefits:

– the increased number of completed orders with the same or reduced resources;

– the reduced order completion time;

– the reduced annual downtime per resource;

– the increased effectiveness of resource usage;

– the formal and systematic knowledge of the subject matter used in decision-making;

– the reduced amount of penalties and fines for delayed order fulfillment;

– the reduced complexity and labor intensity of work for dispatchers, managers, logisticians, and economists;

– the reduced costs of management personnel training.

With these advantages, investment in the systems under consideration is returned on average in three months to one year.

Some of the solutions were used as simulation and decision support tools; however, most have been fully implemented and are still in operation.

At the next stage (2009–2024), the approach was significantly improved and extended from manufacturing and transportation enterprises to new areas of management, particularly the management of passenger and freight railway trains, satellite constellations, beverage supply chains, coal railway car distribution, and other types of resources.

We highlight the additional business benefits identified at this stage (for details, see [62–64]:

– the reduced costs of order execution;

– the reduced number of managers;

– the increased speed and flexibility of decision-making;

– the possibility of business development simulation simultaneously with operational management.

At the first stage of implementation, many additions are made to the knowledge base, which are revealed only when the resource planning results of the system are compared with the work of practitioners. When the quality of decisions made by the system exceeds 50% compared to humans (i.e., the AI system makes more correct decisions than experienced users), we can talk about the beginning of the transition to autonomous AI for “unmanned” enterprise management.

The main result of this period was a more seamless integration of adaptive resource planning and optimization capabilities with monitoring and control of order execution, enabling the creation of “digital twins” of enterprise departments operating in parallel and asynchronously with enterprises and synchronized with them by real-time events.

While final management decisions are still being offered to users for their agreement and approval, the growing trend of gradual transition to autonomous systems designed for the above unmanned management is already visible.

On average, the theoretically proven and confirmed effect from implementing the systems under consideration may reach 15–40% [62], allowing enterprises to execute more orders with the same amount of production resources (i.e., significantly increasing their efficiency).

6. LESSONS LEARNED AND KEY BENEFITS

The above analysis has revealed several problems arising in the practical implementation of AI enterprise management systems:

• The development of such AI systems needs the participation of highly qualified experts and programmers, takes a lot of time, requires extensive testing, etc.

• The development of self-organizing solutions for business users is a challenging task:

– It is often difficult to assess the “distance” between the result obtained by the system and the “optimal” solution.

– The results depend on the history of the events.

– Small changes lead to an unexpectedly large response (the “butterfly effect”).

– The response of the system may slow down in case of transition between equilibrium states.

– If the system is restarted, the planning result may differ.

– Interaction with users becomes more complex and dynamic in the real-time mode.

– The solution is sometimes difficult to explain to the user (the loss of causality), etc.

• Enterprise resource management is business-critical, so this area is still very conservative in adopting new AI solutions.

• Much of the corporate knowledge for decision-making is usually not realized and hidden in the heads of experts; identifying and formalizing this knowledge requires direct communication with dispatchers, engineers, workers, drivers, etc.

• Much of the effort is related to the development of network user interfaces, which must be customizable and inexpensive.

• For a wider range of small- and medium-sized enterprises, further evolution seems to run toward the development of digital SaaS (*Software as a* Service) platforms for an ecosystem of services and additional solutions that can be integrated with existing systems.

In practice, these difficulties are manageable but require special tools for the initial analysis of customer data and integration with (often) out-of-date systems containing possibly irrelevant and incorrect data.

The above difficulties are compensated for by the advantages of Smart Solution, as they:

– improve the effectiveness of resource usage by passing to real-time decision-making;

– solve complex planning problems by replacing combinatorial search with conflict analysis and reaching consensus;

– provide adaptive re-planning with prompt response to events;

– offer a personalized approach to every order, job, product, and resource;

– support active two-way interaction with users for coordinated teamwork;

– reduce the role of the human factor in decision-making;

– reduce development costs by reusing the code in new applications;

– simulate the “if-then” scenario and make predictions to improve decisions;

– create a new digital platform to support business growth without proportionate growth in management staff.

The R&D results can be applied in a wide range of resource management problems within the Industry 5.0 and Society 5.0 concepts, which are oriented to knowledge digitalization and transition to autonomous collective intelligence systems [65].

CONCLUSIONS

A new class of autonomous intelligent systems for unmanned enterprise resource management opens up new opportunities for raising the efficiency of business management, improving customer satisfaction, making businesses more flexible, lowering order execution costs, and reducing lead times and risks.

Time constraints on the elaboration of optimal decisions require the theoretical understanding and revision of existing approaches. In fact, the matter concerns the development of a new methodology of “guided self-organization” and “smart optimization” for elaborating quasi-optimal solutions of exponentially difficult problems with constraints under which the system independently assesses the results and decides on the completion of calculations or the branches of optimization to be further investigated.

The industrial applications developed prove that the multi-agent technology is able to solve a wide range of resource management problems under high uncertainty, complexity, and dynamics. Adaptive resource management helps to increase business efficiency, reduce response time, and improve the quality of service for new orders, as well as raise the effectiveness of resource usage.

As expected, the next step is to create a digital network-centric platform and an ecosystem of digital twins of enterprises to solve complex multi-level resource management problems of large industrial enterprises, transportation and service companies, etc.

As it seems, future work will combine adaptive planning with experience-based learning using neural networks and user interaction based on LLM to build an enterprise knowledge base and to organize a natural language dialog with users, also capable of explaining and harmonizing decisions.

Acknowledgments. *The work of P.O. Skobelev was supported by the Ministry of Science and Higher Education of the Russian Federation.*

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This paper was recommended for publication by A.A. Lazarev, a member of the Editorial Board.

Received January 27, 2025,
and revised April 24, 2025.
Accepted April 29, 2025.

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Cite this paper
Leonidov, A.V. and Skobelev, P.O., Solving Complex Resource Management Problems: From Classical Optimization and Game Theory to Multi-Agent Technologies for Reaching Consensus. *Control Sciences* **2,** 11–21 (2025).

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