Towards Autonomous AI Systems for Resource Management: Applications in Industry and Lessons Learned

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Abstract
Complexity of modern resource management is analyzed and related with a number of decision makers, high variety of individual criteria, preferences and constraints, interdependency of all operations, etc. The overview of existing methods and tools of Enterprise Resource Planning is given and key requirements for resource management are specified. The concept of autonomous Artificial Intelligence (AI) systems for adaptive resource management based on multi-agent technology is discussed. Multi-agent model of virtual market and method for solving conflicts and finding consensus for adaptive resource management are presented. Functionality and architecture of autonomous AI systems for adaptive resource management and the approach for measuring adaptive intelligence and autonomy level in these systems are considered. Results of delivery of autonomous AI solutions for managing trucks and factories, mobile teams, supply chains, aerospace and railways are presented. Considerable increase of enterprise resources efficiency is shown. Lessons learned from industry applications are formulated and future developments of AI for solving extremely complex problems of adaptive resource management are outlined.

Key words: complexity, artificial intelligence, autonomous systems, adaptability, resource management, multi-agent technology, demand-resource networks, self-organization, competitive equilibriums, real-time economy.

1 Introduction

The growing complexity of the modern economy is already widely recognized and associated with the increased uncertainty and dynamics of demand and supply, where disruptive events become rather norm than exception [1].

However, until now typical reactions to unpredictable events in business have been widely the following: bringing oversized resources, increasing costly safety stocks or injecting slack-time. The result of such reactions is decreased service quality, reduced utilization of resources, lost orders or increased costs pushed onto the customer and, finally, drastic decrease in business efficiency and competitiveness [2].

This challenge demands new type of industrial solutions for resource management that need to support a high level of adaptability and responsiveness [3].

Nowadays it becomes possible to address the challenge with the use of autonomous Artificial Intelligence (AI) systems working continuously and able to make decisions on their own - providing resource allocation, scheduling, optimization, co-ordination and control of results in real time. AI technologies are becoming the hot topic in science and technology but many R&D projects on autonomous systems are still mainly focused on robots and unmanned vehicles [4]. Some other areas of AI technologies include big data analytics, pattern recognition and machine vision, language processing, machine learning, etc. However, AI technologies for resource management are usually not included in this list – probably, due to the lack of industrial applications.

In this paper we present practical results of solving complex problems of adaptive resource management in industry with the use of autonomous AI systems based on multi-agent technology. These systems can be categorized, from one hand, as "weak (narrow)" AI systems that augment intelligence of humans in business. But, from the other hand, they exhibit more generic *emergent intelligence* based on self-organization of agents. This new property of developed systems can be considered as the first step to "strong" AI which is regulated by human-like cognitive abilities including the ability to modify its own functioning by learning from experience and reprograming the AI to achieve better results. These systems will be used in future for managing not only humans but also swarms of unmanned vehicles of any kind: taxi, trucks, sea vessels, drones, satellites, etc (https://www.youtube.com/watch?v=r7vKK9XnTCE).

In Section 2-3 of the paper we analyze complexity of modern resource management and show the limitations of existing models, methods and tools for supporting the growing complexity and adaptability of business. In Section 4 we consider the concept of autonomous AI system for adaptive resource management based on the virtual market of agents and the method of solving conflicts by multi-iterative auctions. The functionality and architecture of autonomous AI solutions for adaptive resource management are presented in Section 5. The examples of developed autonomous AI solutions for managing trucks and factories, mobile teams, supply chains, aerospace and railways are presented in Section 6, showcasing increase of enterprise efficiency of up to 15-40%. The ways of measuring adaptability and level of autonomy of AI solutions, business experience and lessons learned are presented in Section 7.

Conclusion summarizes the benefits of developed solutions and outlines the plan of future developments.

2 Complexity of Modern Resource Management

Many modern enterprises are now looking for the better quality and efficiency of their products and services, transforming their businesses into new models: demand-oriented; subject to intense change and volatility; distributed, usually globally; operating in real time; needing agility to re-plan and re-allocate scarce resources; seeking improvement; concerned about costs and enterprise security, etc.

To identify the key factors that significantly increase complexity in resource management, let us consider the real cases solved in the past [5]:

– **Managing Trucks for a National Logistics Company**: 500 trucks on the road, 100 orders daily, horizon up to 10 days, 600 destinations, criteria: profit, service quality, preferred loading/unloading time (fixed and variable), backhauls, consolidation, vehicle capacity, loading sequence (backdoor and curtain sider), constraint stressing, planning in continuous mode, handling driver breaks, cross-docking, trucks utilization, drivers regulations, load compatibility.

– **Supply Chain of a Food Delivery Company**: up to 10 thousand products, 5 hundred nodes in the network, including 5 factories, 300 storages, 1000 shops, 500 delivery channels, 2 thousand orders a day, horizon up to 10 days; criteria: service level, minimum costs and penalties for manufacturing, transport and storages.

– **Field Services of Technicians for a Regional Gas Company**: 50-250 orders a day, 43 teams for region equipped with special equipment; scheduling horizon – 5 days, team working hours - 8-12 hours; time for reaction on event – up to 1 min, criteria: the number of executed orders, minimum of empty miles, balance of resource loading.

– **Delivering Cargo for the International Space Station**: 3500 types of cargos (fuel, air, food, equipment, etc.), about 4-8 spaceships yearly, time of mission, number of astronauts, orbits and ballistics, sun activity, norms of cargo use, period of 6-12 months, criteria: safety and security of cosmonauts, reliability of equipment, timetable for scientific programs, capacity of ships and fuel tanks, number of ports.

– **Workshop of a Jet Engine Manufacturing Factory**: 150 workers and 300 units of equipment, one component requires from 10 to 25 mechanical, thermal and other operations, 100 tasks per day, one plan for a worker for 2-3 days includes 100 operations, horizon up to 6 months. Considering specifics of orders, sequences of operations, skills of workers, availability of equipment, materials, etc. Criteria: delivery in time and in budget, quality of products, no broken parts and products.

– **Project Management at an Airspace Enterprise**: one department – 250 engineers, 5-15 R&D projects annually in one pool of resources, each project has 300 – 500 tasks. Each day, 15-25 new tasks or other events are identified. Horizon of scheduling is mainly 3-6 months; the schedule is about 5000 interconnected tasks. Criteria: priorities of projects, deadlines, project budget, calendar of engineers availability, competencies of engineers, etc.

– **National Railways - Dispatching Center of the Moscow - Saint Petersburg region**: 49 stations, 48 railways segments (2-4 lines), number of blocks – 3500, 800 trains daily, horizon – 24-36 hours, 50 events daily, including maintenance windows, train plan – 40-50 operations. Criteria: minimum average delay, safety intervals, execution of master timetable of trains, time of stops, etc.

– **Moscow Online Store / Delivery of Food**: 18 supermarkets of Auchan, Metro and other chains, 300 orders daily, delivery at the preferred time of the current day (earliest 3 hours after order time). Supporting pick-up – workers who consolidate goods for customers; consolidating goods from supermarkets and delivering to customers; changing routes and schedules adaptively “on-the-fly” because of new incoming orders; considering trucks as “mobile storages” in case they are stopped in a traffic jam.

The summary of key complexity factors typical for the considered resource management cases includes: number of daily orders, resources, products and tasks, multi-objective resource management (maximize service quality, minimize costs and time of delivery, maximize profitability), variety of decision makers, which require solving conflicts and harmonization of interests, individual approach to orders and resources, interdependencies between processes and tasks, specifics of order execution such as a dividable orders or alternative processes and resource usage including shared resources, re-usable or consumed resources, recovery of resources, shared costs, etc.

But one of the most important factors of resource management complexity is that in practice humans develop schedules that are not homogeneous - parts of the schedule can differ by applied criteria, preferences and constraints. It reflects the fact that a "good schedule" is usually a well-balanced one among many actors with conflicting interests. However, the achieved balance of interests always depends on the situation – the "optimal" decision becomes event-driven and can change when a new event arrives.

Real time harmonization of users interests requires on-line communication with decision makers, which can not only enter new events, but change their preferences and constraints at any moment, approve or reject decisions and make counter-proposals.

As a result, we consider adaptability as a one of the most important challenges for such applications across all domains which can be defined as the ability to achieve changeable goals under conditions of frequent occurrence of unpredictable events.

3 Overview of Methods and Tools for Resource Management

A number of traditional methods and tools of resource planning and optimization based on linear, dynamic or constraint programming is well known [6-7].

However, most of these methods and tools are developed for batch process where all orders and resources are given in advance and are not changed in real time.

As a result, in the domain of Enterprise Resource Planning (ERP) classical batch schedulers offered by SAP, Oracle, Manugistic, i2, ILOG, J-Log and other companies still dominate on the market and mainly focused on accounting - resource allocation, planning, optimization and communication have limited use.

To reduce the complexity of combinatorial search and address some of the issues, new methods consider heuristics and meta-heuristics, allowing acceptable decisions in more reasonable time by reducing search options [8-9]:

- Greedy local search algorithms based on heuristic rules of the domain;
- Artificial intelligence methods, use of neural networks and fuzzy logic;
- Metaheuristics: genetic algorithms, tabu search;
- Simulations including simulated annealing, etc.;
- Stochastic methods such as the Monte Carlo method;
- Ant Colony and Particle Swarm Optimization;
- Combination of parallel heuristic algorithms of optimization, etc.

However, these methods still use batch processing and struggle to take into consideration individual criteria, preferences and constraints, as well as provide real-time adaptation of schedules based on events processing.

Analysis of the above solutions makes it possible to identify the following issues:

- Lack of models, methods and tools for adaptive resource management;
- Solutions require programmers when problem specifications are changed;
- **S**ystems support centralized management based on top-down commands;
- Hierarchical rigidness of systems does not allow for reaction to events;
- Internal passivity and functioning in the batch mode on users' request only;
- Focus on data and not on corporate knowledge;
- Standardization ignores individual preferences of decision makers.

The discussed complexity and high dynamics of business leads to the fact that traditional, centralized, hierarchically organized, sequential methods and algorithms of combinatorial search or heuristics cannot effectively solve the problem of adaptive resource management with the acceptable quality and within the required time.

The search for options for decision making remains very time-consuming, and results are often just not feasible or not comparable to human decisions.

4 New Models and Methods for Adaptive Resource Management: from Optimization – to Consensus

In the last decade, new models and methods of distributed problem solving for resource planning and optimization were developed based on multi-agent technology.

One of most promising approaches is Virtual Market (VM) [10-11], which got a theoretical basis and has become popular staring from 2010.

The idea of VM is based on ongoing demand and supply matching supported by contract-net protocols: in such multi-agent solutions each agent starts out with some initial set of tasks and then enters into a negotiation process. The negotiation consists of agents repeatedly contracting out assignments among themselves, exchanging tasks as well as money. For the matching assignment, it was proven that global optimum admits an auction-like procedure with tight guarantees.

An idea of using VM models and methods based on self-organization of agents for solving any kind of complex problem looks very attractive for software engineers. Solution of a complex problem is forming here as a competitive equilibrium or consensus of agents, which cannot be improved during computation. Many useful properties of such algorithms are already identified: they are intuitive, can serve individual criteria, preferences and constraints of all participants, provably correct, naturally parallelizable, appropriate for deployment in distributed systems settings and tend to be robust to perturbations of the problem specification.

In our multi-agent developments, we have been using the similar software engineering approach starting from 1999 - having discovered the main positive features of such algorithms in the first multi-agent prototype for Volkswagen factory.

In the next period, the developed multi-agent technology was advanced, following the concept of holonic systems that introduced Agents of Products, Resources, Orders and Staff (PROSA) [12]. In our technology, we made the next step in granularity of agents and introduced Business Process and Task Agents, which form Demand-Resource Networks (DRN), representing self-organized schedules with pro-activity. For agents of DRN we provide new VM method of adaptive decision making based on functions of satisfaction and bonuses-penalties – to provide elasticity by compensations for agents in the processes of solving conflicts and forming consensus [13-15].

During the process of self-organization, DRN agents are at first choosing the best free options, and then resolving conflicts until the system is balanced and none of the options can improve the overall performance of the system.

This process reflects the native way experienced managers and dispatchers usually form complex schedules, solving conflicts and finding a balance of conflicting interests among all parties involved in decision making.

The formalized problem statement and description of method is given in [16].

5 Functionality and Architecture of Solutions

Functionality of developed autonomous AI solutions for adaptive resource management is aimed to support the full cycle of resource management:

– collecting new events via sensors, external systems and mobile devices;

– allocation of orders to resources by matching of the suitable resource;

– scheduling of orders/resources – computing the best possible sequence and detecting time of task beginning and finishing (operations) for orders execution;

– optimization of orders / resources (if time is available) – the ongoing process of improving KPIs of all agents involved in resource management;

– forecasting new events (new orders or failures) which will be processed as virtual events for dynamic pre-reservation of critical resources;

– on-line communication with users: approval of system recommendations, changing preferences or giving counter-proposals, fixing facts, etc;

– monitoring and control of plan execution – comparing planned and actual results and detecting gaps and triggering re-scheduling event to top-management;

– re-scheduling in case of a growing gap between the plan and reality – for example, if a user is ignoring recommendations and out of given time;

– learning from experience – clustering of events, compare planned and actual time of tasks execution, for example, to analyze productivity of workers;

– real-time “what-if” simulations – in parallel with the main trajectory of plan execution, a few lines of simulations can be running in real time to investigate future;

– evolutional re-design of business network – generating proposals on “how-to” improve quality and efficiency of operations (better place for storage, etc).

The autonomous AI solution for adaptive resource management is designed as a cyber-physical system [17] integrating physical and cyber components (Fig.1):

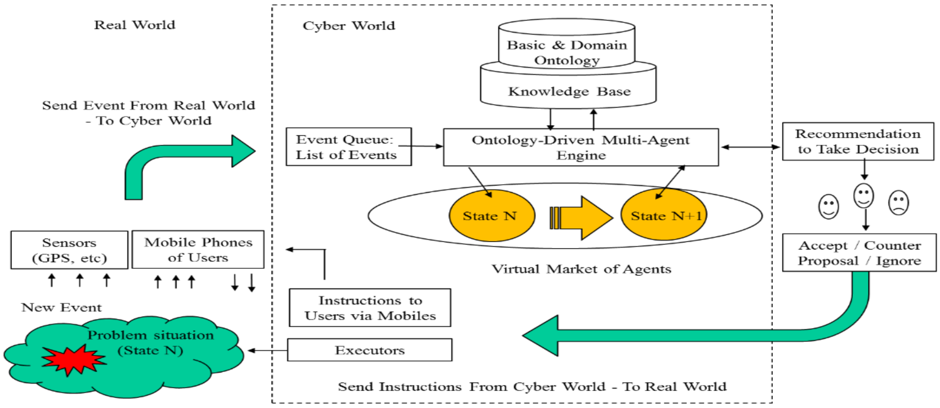

Figure 1. Cyber-Physical Architecture of Adaptive Resource Management System

– basic and domain ontology of resource management – to acquire, keep and modify knowledge of problem domain for resource management;

– knowledge base of enterprise – designed as a semantic wikipedia of an enterprise, based on domain ontology which includes information about instances for specific enterprise (so called onto-model of enterprise);

– event queue – works as a buffer and accumulates events which are coming from the real world, regulates policies for event processing and keeps information on the results of events processing;

– ontology-driven multi-agent engine – the generic scheduler customizable by knowledge base of enterprises;

– virtual market (world) of agents – consists of instances of agent classes to be executed, considered as state machines;

– virtual market states (scenes) – represent the previous state (situation) and the proposed changes in schedule at the specific moment;

– sensors, executors, mobile devices and other application components – make it possible to collect events and implement decisions in the real world.

Ontology is aimed for collecting business requirements, customizing the solution for new domain and enterprise specifics and re-programming the solution “on the fly”.

Virtual world is considered here as a “co-pilot” model of real world (for example, fleet of trucks is moving on the real roads and in parallel in virtual world on server) which is continuously updated by events and is used for generating decisions and recommendations for users.

The decisions made are forwarded to mobile phones of users or equipment in real world as instructions, but can be re-negotiated when required.

6 Industrial Applications

In the period 2000-2008 we have developed about 15 industrial prototypes and full-scale multi-agent systems for adaptive resource management. Most advanced systems, which can be characterized as an autonomous AI solutions, are presented in Table 1.

Table 1. The first project-based generation of industrial applications

Customer	Project	Results and Value for Customer
Tankers International	Scheduling of seagoing tankers for one of the largest fleets of Very Large Crude Carrier (VLCC) oil tankers consisting of more than 40 ships and representing just below 10 % of the world seagoing tanker capacity.	• Reduction of three days of idle runs, per tanker, annually. • Taking into account the cost of idle runs per tanker and per day, for 40 tankers the savings generated a return on investment (ROI) of less than six months. • Reduced delays of oil deliveries and, consequently, payments of delay penalties. • Domain knowledge on running tankers was for the first time collected and formalized in a computer readable format. • Dispatchers were provided with scheduling options and delivery price during a telephone conversation with a client. • The scheduler typically requires a few seconds to several minutes to complete the analysis.
Addison Lee	Taxi scheduling for 2000 GPS-equipped cabs in London and 13 ths. orders daily	• The total number of processed orders increased by 7% within the first month with the same number of resources. • 98.5% of all orders were allocated automatically without dispatcher’s assistance. • The number of lost orders was reduced to 3.5 (by up to 2 %). • The number of idle runs was reduced by 22.5%. • Each vehicle was able to complete two additional orders per week, which increased the yield of each vehicle by 5 – 7%. • Profitability Increase: +4.8%. • Orders collecting time: 40% faster.

		• Time for Dispatcher Training: reduced by 4 times.
GIST	Consolidation of cargos for trucks with the use of cross-docks and backhauls	• In the past, 2 operators worked for one day to make a schedule for 200 cargos / now it took 8 min. for 200 orders. • Before: planning day 1 for day 3 / After: planning day 1 for day 2 and even day 1 for day 1. • Before: no support backhauls and consolidations in real time / After: scheduling with backhauls and consolidations • Before: no software to schedule 4000 orders with X-Docks and driver shifts (manual procedure only) / After: 4 hours to plan 4000 orders via X-Docks and ability to add new orders dynamically (a few seconds for one order) • Knowledge was hard to share, it was "spread" among experts / Now: capture best practice. • Choosing the best route flexibly with the view of consolidation or other criteria.
Avis (UK)	Rent-a-car scheduling for one of the UK subsidiaries (250 cars / 30 drivers), incl. car washing and fueling, pick-up and delivery, etc	• Solution processes 15-20 reservations per station with about 80-120 events per hour, including new rentals, events from handheld computers of drivers and from web-users. • 90% of all executed decisions have been made 20-30 minutes before fixing of the schedule for execution; • Number of events leading to considerable reorganization of the schedule per day (level of turbulence) ~40%. • Reduce of late deliveries – 10%.
City Sprint	Couriers / Medical Lab Service	• Reduce of order delays, idle runs and fuel consumption; • Possibility to optimize fleet of vehicles.
Channel Four	Banners to Web-sites allocation	• Reduce of complexity of banners re-allocations – 15%. • Efficiency increase for advertising – 5-10%.

Some of designed solutions were used only as a prototypes or decision support tools but some of them got green light for full-scale implementation and work till now.

On the next stage the design of industrial applications was reconsidered and new generation of solutions was developed as products/services in 2010 - 2017 (Table 2).

Table 2. The second product/service-based generation of industrial applications

Product	Customer	Results and Value
Smart Aerospace	Rocket and Space Corporation "Energia"	• System in operation for 8 dispatchers and 120 other users for supplying fuel, water, food, etc. • Speeds-up scheduling for flight programs by 4-5 times. • Simulation of worst-case scenarios for risk estimates. • System is critically important for success of mission.
Smart Trucks	Prologics, Lorry, Monopoly, Trasko, Trans-Terminal, etc.	• Increasing the number of orders – up to 3-5%; • Reduce of late deliveries – up to 5%; • Increase of resource efficiency – 5-10%.
Smart Factory	TyazhMash, Axion-Holding, Airbus, AviaAgregat, Irkut, Kusnetsov	Axion-Holding: • Increase of workshop productivity – 5-10%. • Savings for one workshop for tools production is 7 man-months monthly.
Smart Field Services	Samara Gas Company, Volgograd Water Supply Company, Far East Service Company	Samara Gas Company: • Reduction of reaction time – by up to 5-7 times. • Increase of service efficiency – up to 40% (12 orders a day instead of 7 in the past). • Reduction of mistakes of dispatchers.
Smart Internet Deliveries of Food	Instamart (Moscow)	• Reduction of assembly time of the order by 15%. • Reduction of delays in deliveries to clients by 22%. • Client satisfaction is increased: when one courier has a problem, it can be solved with the help of other couriers.

Smart Supply Networks	Lego (Chicago outlets), Coca-Cola (Germany), Siberian Coal Mining, "Gaspromneft"	Lego (US): • Increase of profitability – up to 18%. Coca-Cola, Germany: • Increase of orders delivered on time – up to 7%. • Savings on transport – up to 20%.
Smart Projects	Rocket and Space Corporation "Energia", Ministry of Economics of Samara Region	• Full transparency of projects: from annual plans of delivery in contacts – to daily plans of departments and employees. • Reduction of expenses – 5-10% • Increased number of projects implemented within the budget and on time – 15%. • Increase in motivation of employees.
Smart Railways	Russian Railways (regions of Moscow and Saint-Petersburg, and Siberia-Baykal)	• Reduction of railway train delays – up to 15-25%. • Better quality of decisions and easy for dispatchers. • Faster reaction on events – 2-3 times. • Reduction of human factor. • Increase of train speed for Baykal polygon – up to 3-5%.

The idea of re-designing of solutions was to form a platform and a number of ready-to-use components and deliver products as a services with minimum investments.

Support of the main decision-making cycle in Autonomous AI System provides opportunity to measure value and time of each event or decision made by user with full transparency for the enterprise on profits and losses (Fig. 2):

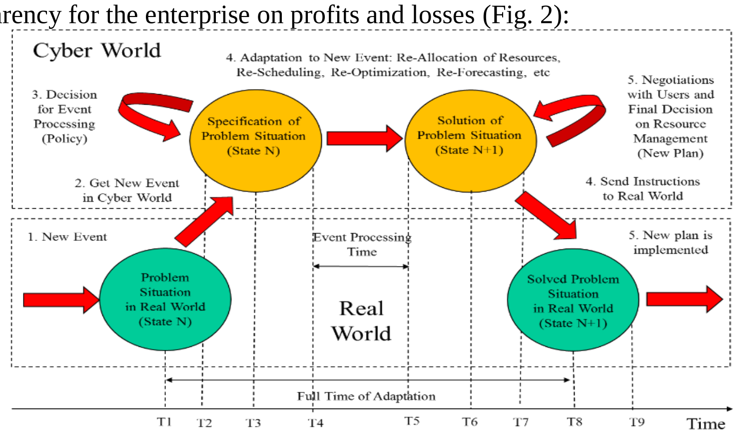

Figure 2. Life-Cycle of Event in Adaptive Resource Management

– Moment T1: new event appears in real world or at third-party systems;

– Moment T2: new event is specified by the user manually or automatically;

– Moment T3: based on the given policy, the new event will be automatically processed or will wait for specific approval from the authorized decision maker;

– Moment T4: the event triggers resource re-allocation, re-scheduling and re-optimization in the system;

– Moment T5: the new decision is formed and presented to users for approval (or counter-proposal and negotiations: user also can ignore proposal, depending on policy for events), but some decisions can go into real life automatically;

– Moment T6: user feedback is taken into consideration and new adaptive re-scheduling starts with new options for decision making or the decision is approved;

– Moment T7: the approved decision will be sent to the real world: to managers, engineers, technicians, workers or drivers for implementation;

– Moment T8: the decision and new revised plan is executed – products are assembled, transported to customer, etc.;

– Moment T9: the communication session with decision makers is completed.

The value of events or decisions related to transition time (time from one equilibrium to another) gives possibility to measure the Level of Adaptability of the solution.

However, it also helps identify the effect of adaptive resource management vs. the batch ERP approach, f.e., for factories where a plan has monthly granularity (Fig. 3).

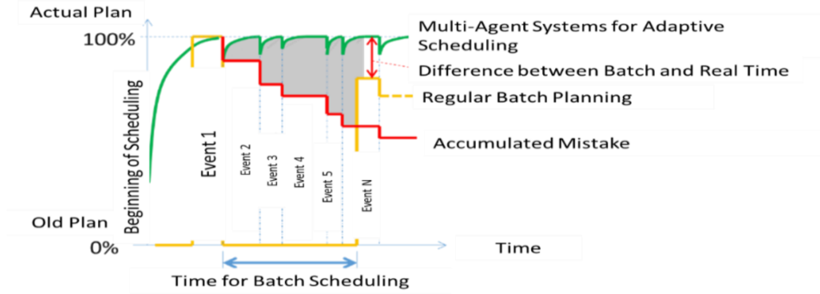

Figure 3. Value of Adaptive Resource Management for Business

Accumulated mistakes of batch planning can generate big losses because of not reacting to a new order, missing deadlines, etc. The estimate of the gap in KPIs between the planned and actual schedules is the key for calculation Return on Investment (ROI).

Another key characteristic of Autonomous Solutions is the number of decisions accepted by users, which can represent the Level of Autonomy.

In our practice, we start with 10-15% of accepted decisions, and then improve it in a step-by-step way up to 50% and more, when the AI system takes more decisions than experienced users.

7 Lessons Learned and Key Benefits

1. Development of the considered systems requires highly qualified domain experts and programmers, is time-consuming, requires a lot of testing, etc.

2. Development of self-organized solutions for business users is challenging: sometimes it is difficult to estimate how far we are from the “optimal” solution; results depend on history of events occurrence (pre-history sensibility); the butterfly effect: small input leads to unexpected big output; system reaction can slow down in case of transition between equilibriums; in case of system re-start, the result of scheduling can be different; it is difficult to “roll back” the system decisions (unreversable); real-time interaction with users becomes sophisticated; system may become too “nervous” during re-scheduling; system decision can be hardly explained to user (loss of causality).

3. Enterprise resource management is critically important for business, and that is why this area is still very conservative in adopting new AI solutions.

4. Big part of enterprise knowledge for decision making is usually hidden and requires direct communication with dispatchers, engineers, workers, drivers, etc. For example, in the “Smart Railways” solution, development started with 2 criteria for decision making (minimum sum of delays and intervals of safety) but after 2 years we

had 84 criteria, including such as limitations for cargo trains to transport friable materials on the oncoming track at the time of a high speed train.

5. Significant part of all efforts is associated with web-based user interfaces, which need to be adjustable and low-cost for developments.

6. Dispatchers are often very resistive to innovations and need to be highly motivated to compete with the solution – for example, by bonuses calculated on results achieved.

7. Way forward is to develop SaaS digital platforms for developing an eco-system of services and Add-On solutions which can be integrated with existing systems.

In practice, all these difficulties are manageable but may require special tools for initial analysis of client data or integration with legacy systems.

The discussed difficulties are compensated by the following benefits:

- Allows enterprises to move to real-time economy visualizing profits and losses;
- Improves efficiency of resources by shift to real time decision making;
- Solves complex scheduling problems replacing combinatorial search by analyzing conflicts and finding trade-offs;
- Provides adaptive re-scheduling with fast reaction to events;
- Provides an individual approach to every order, task, product and resource;
- Supports pro-active interactions with users for coordinated teamwork;
- Reduces the role of human factor during decision making;
- Reduces development costs by reusing the code in new applications;
- Enables modeling of "if-then" scenario and forecast to improve decisions;
- Creates a new digital platform to support the growth of business.

The results of developments can be applied for solving wide range of complex problems of resource management in Industry 4.0 and Society 5.0 focused on developing knowledge, talents and social skills of humans.

8 Conclusion

The new class of autonomous AI solutions for enterprise resource management is opening an opportunity to increase the quality and efficiency of business.

The developed industrial applications prove that multi-agent technology provides powerful solutions for solving complex problems of resource management under conditions of high uncertainty, complexity and dynamics. High adaptability of resource management helps to improve efficiency of business, reduce response time and improving quality of service for new orders, avoid loss of orders in peak time, minimize expenses and penalties, improve utilization of resources, etc.

As the next step, we are designing a swarm of multi-agents schedulers for solving extremely complex problems of resource management for manufacturers, railways, etc. Future works will be focused on powering emergent intelligence of autonomous AI solutions by pattern recognition and learning from experience.

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