Measuring Adaptability of "Swarm Intelligence" for Resource Scheduling and Optimization in Real Time

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Abstract: In this paper modern methods of scheduling and resource optimization based on the holonic approach and principles of "Swarm Intelligence" are considered. The developed classes of holonic agents and method of adaptive real time scheduling where every agent is connected with individual satisfaction function by the set of criteria and bonus/penalty function are discussed. In this method the plan is considered as a un-stable equilibrium (consensus) of agents interests in dynamically self-organized network of demands and supply agents. The self-organization of plan demonstrates a "swarm intelligence" by spontaneous autocatalitical reactions and other not-linear behaviours. It is shown that multi-agent technology provides a generic framework for developing and researching various concepts of "Swarm Intelligence" for real time adaptive event-driving scheduling and optimization. The main result of research is the developed approach to evaluate the adaptability of "Swarm Intelligence" by measuring improve of value and transition time from one to another unstable state in case of disruptive events processing. Measuring adaptability helps to manage self-organized systems and provide better quality and efficiency of real time scheduling and optimization. This approach is under implementation in multi-agent platform for adaptive resource scheduling and optimization. The results of first experiments are presented and future steps of research are discussed.

1 INTRODUCTION

Growing complexity and dynamics of modern global market demands new paradigms in resource management (Rzevski, 2014; Park, 2014).

New revolutionary approach to increase efficiency of business is associated today with real time economy which requires adaptive reaction to events, ongoing decision making on resource scheduling and optimization and communication results with decision makers. The objective of online communication with users is finding balance of interests and coordination of solutions in real time. New generation of new smart decision support systems for real time resource management will replace traditional rigid waterfall business processes to flexible self-organized networks, batch processing systems – to real time systems, rule engines – to visualization of data and results – to real time forecasting, simulation and learning.

Multi-agent technology is considered a new design methodology and framework to support distributed problem solving methods in real time scheduling and optimization of resources (Mohammadi, 2005).

First part of this paper will address the problem of measuring quality and efficiency of real time adaptive scheduling and optimization methods based on ideas of self-organization of plans and multi-agent technology which become completely different from classical combinatorial methods. In the second and the third parts of this paper we will review briefly modern methods of scheduling and resource optimization (including swarm optimization) (Joseph, 2001, etc) and present developed method of adaptive scheduling and optimization in real time. The developed classes of

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agents have individual satisfaction function formed by the set of criteria and bonus/penalty function. It will be shown that in the developed method the schedule is considered as an un-stable equilibrium (consensus) of agents interests in dynamically self-organized network of demands and supply agents which demonstrates a “swarm (emergent) intelligence” phenomena represented by spontaneous autocatalitical reactions and other not-linear behaviours.

In the fourth and fifth parts of paper multi-agent platform for adaptive resource scheduling and optimization will be presented and it will be shown that multi-agent technology provides a generic framework to research and develop various concepts of “Swarm Intelligence” for real time adaptive event-driving scheduling and optimization.

In the sixth part the developed approach to evaluate the adaptability of “Swarm Intelligence” by measuring the value and transition time from one to another unstable state in case of disruptive events processing will be presented. It will be shown that measuring adaptability helps to manage self-organization processes in systems and provide better quality and efficiency of real time scheduling and optimization.

In conclusions the results of first experiments and future steps of research will be discussed.

2 REAL-TIME RESOURCE MANAGEMENT AND BRIEF OVERVIEW OF SCHEDULING AND OPTIMIZATION METHODS

The main feature of real time scheduling and optimization methods - to produce a result in the specified moment of time or time interval, reacting to unpredictable external and internal, constructive or destructive events (new order coming, order is cancelled, resource unavailable, etc).

The quality and efficiency of decision making in resource scheduling and optimization process can be influenced by the number of factors: the intensity of events flow, the number and current state of resources, individual specifics of orders and resources, time interval between the events and processing time for events, productivity of resources and many others. As a result new orders can be processes quickly in open time slots or may generate conflicts which need to solved by shifts, reallocation or swaps of previously allocated, scheduled and optimized orders or some not so important orders may be dropped-out from schedule and will wait new opportunities to be processed or re-negotiation with clients. Resources allocation, scheduling and optimization should work in such a way that arrived tasks deadlines are ensured. This requirement can be achieved through adaptive, dynamic reschedule only part of plan that is affected by the new event.

One of the main problem of classical methods and algorithms (Pinedo, 2008, Leung, 2004, Binitha, 2012) is that complexity of scheduling with new criteria grows exponentially. This makes their applications very limited in practice. Many heuristic methods allow to obtain not entirely optimal solution but close to optimal within a reasonable time. Despite the use of the statistic methods in optimization tasks, most of these systems are centralized and deterministic. Nevertheless, hybrid heuristic algorithms are developed that integrate traditional dispatching rules with genetic, neural, swarm and other approaches (Laha, 2008, Burke, 2013). Obvious disadvantages of the centralized methods of scheduling and optimization resource management lead to development other approaches, in particular distributed problem solving methods.

Bio-inspired evolutionary (genetic and swarm) algorithms are applied both in centralized and decentralized systems. They have proved to be more useful, reliable and generic scheduling and optimization tool for business. Their application in the scheduling systems will probably grow and progress quickly. However, there are also many issues that lead to the fast growing complexity of computations, large number of non-productive iterations and no guarantees for good optimum search.

As a result the well-known software systems for enterprise resource scheduling and optimization such as SAP, BAAN, i2, Manugistics, Galaxy and others, do not allow to rebuild the schedules in real-time because they usually work in a batch mode and not able to support adaptive changes of the schedule with new events in real-time.

One of new approaches is based on bio-inspired distributed problem solving of resource scheduling problems based on multi-agent technologies with economic reasoning (Leitao, 2011). This approach can combine benefits of bio-inspired, DCOP and virtual market methods based on multi-agent technology and is designed to support self-organization of schedules to provide flexibility in event processing without full stop and re-start of solution. Firstly, virtual market interpretation of the MAS on the basis of holonic architecture (Skobelev, 2014, Brussel, 1998) with decomposition into order, resource, product and staff agents (that architecture was further expanded by their demand and resources agents) gives a close to a natural way to build an object model of schedule and provide self-organization of parts into resulting schedule. Secondly, there can be performed an ontological specification of the agents properties to set for the specified problem domain knowledge which can drive decision making. Thirdly, there is an opportunity to set simple ant-like logic of agents actions choice based on its satisfaction and virtual profit in the resources trade system.

Due to the distributed decision-making principle and self-organization process such systems for resource management could be more stable to disruptive events, data incompleteness and corruption because final global solution of problem emerges from interaction of agents and finding consensus representing the balance of interests. This method is initially designed to work in real time and support interactive rework of schedules with intervention from users at any time.

3 TRADITIONAL SWARM OPTIMIZATION

Traditional Particle Swarm Optimization (PSO) method belongs to Artificial Intelligence (AI) and can be applied for the approximate solution search of extremely complex or unsolvable problems for numerical maximum or minimum search (Vittikh, 2003). PSO is usually represented by heuristic methods built in a similar way to the social behaviour and communications in such complex nature organisms as bird flocks, shoal of fish, ant and bees colonies. PSO like all the heuristic algorithms implies adjustable parameters, for example, link coefficient in a certain system topology, speed-position dependency ratio. The selection technique of these parameters is called meta-optimization because for PSO parameters adjustment another optimization algorithm is used (Kennedy, 1995).

PSO algorithm convergence analysis is made in (Magnus, 2010). Despite the fact that PSO is a powerful stochastic evolutionary algorithm, its disadvantage is that it can lead to a local optimum. In order to increase algorithm productivity, different methods are suggested: initial swarm parameters improvement, and others (Dong, 2013).

In the multi-agent optimization method with adaptive parameters (Imrana, 2013), it is suggested to adjust the range of speed changes to avoid too fast speed increase, which will allow to reduce search time of the optimal decision.

Also PSO algorithm modification that uses two swarms “driving” and “driven” – Two-swarm Cooperative Particle Swarm Optimization (TCPSO) (Oliinyk, 2011) will allow to increases swarm intelligence adaptability.

Application of evolutionary algorithms and in particular swarm optimization algorithms in multi-agent systems allows to solve problems of high complexity that cannot be solved by other ways, due to the combinatory rising computations complexity (Sun, 2014, Kureichik, 2011).

At the same time, the suggested approach can be improved by introducing agents negotiations allowing to make trade-offs in the conflicts situations.

4 DISTRIBUTED PROBLEM SOLVING IN REAL TIME MULTI-AGENT SCHEDULING AND OPTIMIZATION

To solve the problem of multi criteria scheduling and optimization it is suggested to use Demand-Resource Network concept (DRN) based on holonic approach and compensation method for real-time resource management on a virtual market (Vittikh, 2003). Accordingly with this distributed approach initial complex problem is decomposed into more simple and specific problems - to schedule and optimize orders, resources and products with the use of demand and supply agents. All agents are working continuously trying to maximize their objective functions and use money to solve conflicts by negotiations and finding trade-offs (until local optimum is reached or time is expired) with compensations in case that some of them change position losing money.

Objectives, preferences and constraints of agents are defined by individual satisfaction functions and bonus/penalty functions. As the result of agents decision making a local balance is reached and situation when no agent can change position is recognize as a consensus which stops computations. As a result, the solutions (the schedule of resource usage) comes not from one algorithm but evolves (emerges) dynamically in process of agents interactions and negotiations. Solution search and adjustment process stop when the consensus is found or when the time limit is exceeded for finding a solution, and if not the whole - but partial problem solution will arrive that will be interactively finalized by the user.

The continuous matching between the competing and cooperating demand and supply agents on the virtual market allows to form a solution to any complex problem as a dynamic network of agents, which is changing flexibly in case of events (Skobelev, 2010, Skobelev, 2014). The satisfaction function for every agent is introduced as a deviation of the current value of this function from the given ideal value as a linear combination of weighted criteria for the current step of finding scheduling solution for this agent. The activity of agents depends on bonus/penalty function and current budget allocated on specific accounts for virtual money transfers.

Every demand j has several individual criteria x_i and suggested ideal values x_{ij}^{id}. For every agent of demand j normalized bonus/penalty function is calculated by the component i ("virtual value"), given for example as a piecewise linear function $f_{ij}^{task}(x_i\text{-}x_{ij}^{id})$. In the most of cases, this function has bell form with maximum in the point of suggested ideal value. As a summary value of the result for each demand, the sum of virtual values for each criteria i with the given weight coefficients α_{ij}^{task} is estimated. By the proper selection of signs and form of the function, the goal of each agent can be reformulated as maximizing of virtual value y_j^{task} of demand j (upper index *task* means that the values belong to the demand agents):

$$y_j^{task} = \sum_i \alpha_{ij}^{task} \cdot f_{ij}^{task}(x_i - x_{ij}^{id}),$$

where ∀j weight coefficients are normalized:

$$\sum_i \alpha_{ij}^{task} = 1.$$

Similarly the problem of finding the states x_{ij}* of agents of demands j that maximize the total value of all orders can be formulated:

$$y^{task} = \sum_j \beta_j^{task} y_j^{task} =$$

$$\sum_j \beta_j^{task} \sum_i \alpha_{ij}^{task} f_{ij}^{task}\left(x_i - x_{ij}^{id}\right) \tag{1}$$

$$y^{task^*} = \max_{x_i}(y^{task})$$

where β_j^{task} is demand weight that allows to set and dynamically change the priorities showing importance of criteria. Similarly the value function can be given for the resources. Thus the scheduling and optimization problem is formulated as solving (1).

Multi-agent platform for real-time adaptive resource scheduling systems based on evolutionary approach of swarm optimization techniques is proposed in (Skobelev, 2010).

Developed method and tools for real time scheduling and optimization are in operations for a number of applications including aerospace, railways, production, transportations and supply chains and others (Skobelev, 2014).

5 ADAPTABILITY AS THE INTELLIGENCE MEASURE OF SWARM OF AGENTS

L. Zadeh had introduced one of the first definitions of self-adapting system (Zadeh, 1963) as an automatically changed structure or algorithm. In the suggested approach new orders and other events arrive in multi-agent system from the environment while system is operating. The coming events trigger re-scheduling and re-optimization orders to resources and this asynchronic processes of decision making changes links in network of agents. As a result system re-organizes itself its own structure, and it is process of self-organization.

How to measure impact of self-organization in case of disruptive event? Let's assume that when a new order arrives it is not allocated by the system. At first step system's satisfaction is recalculated and reduces dramatically, because it takes some time for the arrived agent to find the best position and soon the total satisfaction starts to grow by the rescheduling and step-by step improvement of agents satisfaction. Therefore, in order to evaluate multi-agent system dynamics, it is suggested to re-calculate continuously the main DRN agents' satisfaction depending on time.

Let's introduce the coefficient of adaptability γ that represents local balance of agents interests recovery (Fig. 1):

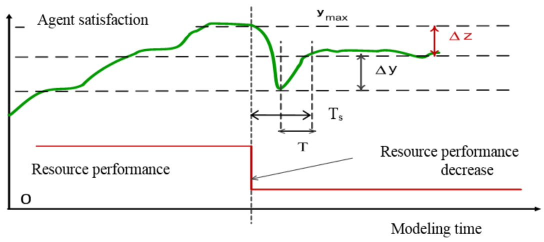

Figure 1: System adaptability by the resources unavailability event.

$$\gamma = \frac{(y_2 - y_1)}{y_{max}} \cdot \frac{T}{T_s}, \tag{2}$$

where y_1 and y_2- mean agents' satisfaction before and after incoming event. After the moment of the maximum fall of the average satisfaction of multi-agent system to the y_1 level, when the T time passes system reaches a new quasi-equilibrium state y_2. $\Delta z = y_{max}$-y_2 – inevitably lost satisfaction (y_1 – minimum value of the satisfaction after the impact, y_2 – average system agents satisfaction after event processing, T – time of the balance recovery of the average satisfaction y_2, T_s – time interval from the start of the event until the transition process ends).

Such an effect of the partial recovery can be observed not only when the resources are disabled but also when the new order is coming, time delays recognized, etc. So the faster the system gets out of the downfall caused by the new event and the higher is the rise – the higher is the level of system's adaptability, which in fact allows interpreting the adaptability as a measure of swarm intelligence in terms of processing of disruptive events.

The limits of adaptability depend on the intensity of events. For example, when a large flow of new orders are introduced that overcome the resources power, satisfaction falls down and will only grow again with time, because the effect of dissatisfaction growth of the arrived new orders will not be covered by the partial growth because of the rescheduling. And that is also an important feature of the considered systems. Task agents' adaptability γ_{task} and the resource agents' adaptability γ_{res} can be considered in the similar way.

6 EXPERIMENTS FOR MEASURING ADAPTABILITY

Let's assume that four orders (tasks) arrive into the multi-agent scheduling system at the initial time, which should be scheduled for an execution on the resource 1. After the balance is reached (there is no more re-scheduling), second resource is disabled in the moment of time 16. The tasks are removed from the schedule from the resource 2 and look for a place on the resource 1. Then task #5 improves its schedule by moving closer to the deadline. System's satisfaction drops to 0.3, but by the moment of time 27 it recovers to the intermediate level (0.62) (Fig. 2).

In general the experiments with designing new generation of designed multi-agent solutions for scheduling and optimization are showing a number of special phenomena:

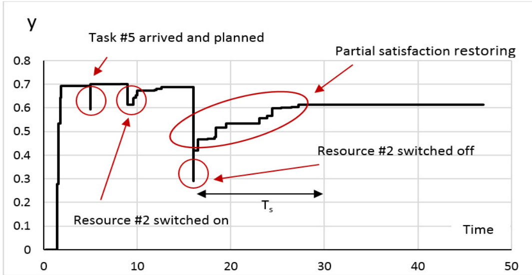

Figure 2: Average agents' satisfaction level on time.

- in real time adaptation of schedules it's very difficult to estimate how far current solution is to "optimal";
- results of real time scheduling depend on history of events (pre-history sensibility);
- non-linearity: small changes at the input sometimes lead to unexpected big changes at the output ("butterfly effect");
- under some conditions "catastrophe" of schedule takes place as an example of spontaneous big structural changes of schedule;
- system reaction can be unexpectedly slowed down in case of transition from one equilibrium to another with long chain of changes;
- not-deterministic: in case of system re-start with the same data the result of scheduling can be different, system is continuously working and it is not easy in practice to stop and re-start systems under the same conditions and time;
- due to evolutional decision making process it is difficult to "roll back" the system decisions (evolution-driven results are not reversible);
- sometimes systems becomes too "nervous" and re-schedule resources if even it is not required urgently and it is possible to wait a little bit before taking any new decisions;
- system decision can be hardly explained to user because it's the result of hundreds and thousands agent interactions and big picture is a result of a number of small decisions in cooperation (loss of causticity of results).

Mentioned above features not only generate new research topics but also form basis to provide quality of schedules which is better than humans can make.

7 CONCLUSIONS

Complex multi-agent systems dynamics defined by the set of different individual criteria and cost functions can be investigated in the developed prototype of multi-agent platform for real time adaptive scheduling and optimization.

Adaptability of such systems can reflect level of “swarm intelligence” of the multi-agent systems for real time scheduling and optimization with self-organized network of demand and resource agents in case of unpredictable events coming in real time. Definition of the level of adaptability as a measure of changes in satisfaction related to the time of finding the new balance of agents interests helps to develop mechanisms to control self-organization processes and increase the level of adaptability dynamically with the view on changes of situation in case of disruptive events.

The future research works will be focused on developing thermodynamic model for the dynamic schedules adaptable in real time which can be characterized by level of order and chaos. Transition between unstable equilibriums can be considered as a catastrophes, bifurcations and other phenomena in complex systems dynamic. Money equivalent interpretation as some sort of energy coming into the open dissipative system and its redistribution between agents could be described in the terms of non-linear thermodynamics for guiding self-organization in the process of evolving solutions. The suggested approach provide new opportunity to investigate complex processes of searching options in multi-agent systems and control their behaviour which is not-deterministic by nature.

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