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The Task of Allocating Operations to Work Centers: Modern Approaches to Cost Minimization and Efficiency Improvement under Resource Constraints

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Abstract

Allocation of operations to work centers is a key management task in modern production systems. Its relevance stems from the need to optimize the use of limited resources to achieve high efficiency and productivity. However, the problem is complicated by the combinatorial complexity associated with the discrete nature of operations and the need to consider multiple factors, including resource constraints, time constraints, and process requirements. This requires specialized approaches to find efficient solutions. This paper is devoted to analyzing such approaches. The paper considers actual problems of optimization of operations distribution to work centers in modern production systems. Particular attention is paid to the problems of minimizing variable costs associated with the changeover of equipment and increasing the overall efficiency of production processes. The paper considers the limitations of classical optimization methods such as linear programming, a review of modern approaches, including combinatorial algorithms, methods of the theory of schedules. Special attention is paid to heuristic algorithms, such as genetic algorithms, simulated annealing, and ant algorithms, which allow us to find acceptable solutions in a short time. The paper also discusses the key factors affecting the scheduling, such as resource constraints, time constraints, and technological requirements. Considering the conditions of the production problem posed in the paper problem and based on analyzing the advantages and disadvantages of existing methods of its solution, as an alternative it is proposed and substantiated the use of multi-agent approach with the application of heuristic algorithms for the distribution of work operations at production enterprises.

Keywords: NP-complete problems, schedule theory, agent, system, multi-agent approach, efficiency, business process, heuristic algorithms

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Задача Распределения Операций по Рабочим Центрам: Современные Подходы к Минимизации Затрат и Повышению Эффективности в Условиях Ограниченных Ресурсов

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Аннотация

Распределение операций по рабочим центрам представляет собой ключевую задачу управления в современных производственных системах. Ее актуальность обусловлена необходимостью оптимального использования ограниченных ресурсов для достижения высокой эффективности и производительности. Однако решение задачи осложняется комбинаторной сложностью, связанной с дискретным характером операций и необходимостью учета множества факторов, включая ограниченность ресурсов, временные рамки и технологические требования. Это требует применения специализированных подходов для нахождения эффективных решений. Анализу таких подходов посвящена настоящая статья. Особое внимание уделяется задачам минимизации переменных затрат, связанных с переналадкой оборудования, и повышению общей эффективности производственных процессов. В статье рассматриваются ограничения классических методов оптимизации, таких как линейное программирование, осуществляется обзор современных подходов, включая комбинаторные алгоритмы, методы теории расписаний. Особое внимание уделено эвристическим алгоритмам, таким как генетические алгоритмы, метод имитации отжига и муравьиные алгоритмы, которые позволяют находить приемлемые решения за короткое время. В работе также обсуждаются ключевые факторы, влияющие на формирование расписаний, такие как ограниченность ресурсов, временные рамки и технологические требования. С учетом условий поставленной в статье производственной задачи, а также на основе анализа преимуществ и недостатков существующих методов ее решения, в качестве альтернативы предложено и обосновано использование мультиагентного подхода с применением эвристических алгоритмов для распределения рабочих операций на производственных предприятиях.

Ключевые слова: NP-полные задачи, теория расписаний, агент, система, мультиагентный подход, эффективность, бизнес-процесс, эвристические алгоритмы

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1. Introduction

The problem of allocating operations to work centers is one of the central management challenges in modern manufacturing processes. This is due to the need to optimally distribute operations over a limited number of resources while striving to maximize efficiency and productivity. Schedule theory, which occupies an important role in solving these problems, aims to develop methods and algorithms for generating schedules that maximize the satisfaction of the requirements (Lazarev, A. A., Gafarov, E. R., 2011). However, the task is complicated by the significant combinatorial complexities that arise when considering discrete operations and the need to consider multiple factors such as resource constraints, time constraints and technological requirements.

In conditions of limited resources, the task of minimizing variable costs arising during equipment changeover is particularly relevant. This requires the introduction of advanced planning approaches that go beyond classical linear programming methods (Skobelev, P. O. et. al., 2010). In complex production systems, traditional optimization methods are often ineffective due to their inability to consider the full complexity of the operational context.

Modern research offers various approaches to solving these problems, the features of which are discussed in this article.

2. Literature review

The problem of allocating operations to work centers and optimizing production processes is actively studied in the framework of schedule theory, combinatorial optimization and multi-agent systems. Such works of domestic authors in the field of scheduling theory as the studies of Lazarev and Gafarov (2011) have laid the foundation for the analysis of NP-complete problems related to resource allocation and cost minimization. These works emphasize the complexity of scheduling problems, especially under resource constraints and tight time constraints.

In the context of heuristic algorithms, works on genetic algorithms (Goldberg, 1989) and the simulated annealing method (Kirkpatrick et al., 1983) have made significant contributions. Greedy algorithms and local search methods are also widely used to minimize overscheduling and optimize resource utilization. Pinedo (2012) in "Scheduling: Theory, Algorithms, and Systems" details various scheduling approaches, including heuristics for resource-constrained tasks.

Multi-agent systems (MAS) represent a state-of-the-art approach to solving operations allocation problems. Wooldridge (2009) in his paper "An Introduction to Multiagent Systems" emphasizes that MAS allow efficient task allocation among autonomous agents, which provides flexibility and adaptability in dynamically changing environments. Research by Skobelev (2010) demonstrates that multi-agent systems using heuristics can minimize equipment downtime and optimize production processes.

Yu, W., Chen, G., Cao, M., & Kurths, J. (2010) and Wang, Ji (2012) discuss methods for decision matching in multi-agent systems, which is particularly important for operation allocation problems. Kim, Matson (2016) propose approaches to task allocation in heterogeneous systems, which is relevant for manufacturing environments with heterogeneous resources. Additional research in the area of multi-agent systems includes Jennings, N. R., Sycara, K., & Wooldridge,

M. (1998), which addresses the principles of agent coordination in complex environments, and Leitao (2009), which focuses on the application of MAS in industrial systems.

In the area of heuristic algorithms, it is also worth noting the work of Glover and Laguna (1997), on metaheuristics such as Tabu Search, which are effectively applied to scheduling problems. Dorigo, M., Birattari, M., & Stutzle, T (2006) in their studies of ant algorithms have shown their applicability to routing and resource allocation problems. In addition, Potvin (2010) proposed hybrid heuristics methods that combine the advantages of different approaches to improve the efficiency of solutions.

GRASP (Greedy Randomized Adaptive Search Procedure) algorithms deserve special attention and have been extensively applied to operations planning problems. GRASP combines greedy strategies and randomized choices to find high-quality solutions in a reasonable amount of time. Feo and Resende (1995) proposed a basic approach to GRASP, which has been successfully applied to combinatorial optimization problems, including operation allocation problems. Resende and Ribeiro (2016) extended this approach by proposing adaptive versions of GRASP that account for dynamic changes in the production environment. A study by Festa and Resende (2009) examined applications of GRASPs to scheduling tasks in resource-constrained environments, making them particularly useful for operations allocation tasks across work centers.

Additional studies include Brucker (2007), who proposed methods for solving complex scheduling problems using combinatorial algorithms, and Lawler (1993), which addressed theoretical aspects of scheduling problems with constraints. Garey and Johnson (1979) in their classic paper "Computers and Intractability" emphasize fundamental constraints in solving NP-complete problems, which is relevant for operation allocation problems. Smith (2008) proposed adaptive scheduling methods that can accommodate real-time changes in the production environment. Van Laarhoven et al (1992) developed approaches to schedule optimization using stochastic methods.

Prospects for further research are related to the development of hybrid approaches combining machine learning techniques, multi-agent systems and heuristic algorithms. This will make it possible to create more adaptive and intelligent scheduling systems that can work effectively under uncertainty and dynamically changing environment. According to this the problem statement is formulated.

3. Materials and methods

3.1. Problem statement

Operations planning (set of operations *O*) can be formalized as a problem of distributing a set of tasks (operations) over available resources (set of resources *M*) in order to optimize given performance criteria, such as minimization or maximization of certain indicators.

Let a set of resources $M = \{m_1, m_2, \ldots, m_k\}$, each of which has a certain capacity *m* and has its own schedule consisting of *r* time intervals of fixed length. The interval length can be expressed in minutes, hours, days or other time units. To simplify the model, the resources are assumed to function without interruption, but the scheduling time horizon is limited by the number of *r* intervals. These resources need to allocate a set of orders represented as operations $O = \{o_1, o_2, \ldots, o_n\}$. Each operation has a duration equal to the length of one-time interval on any resource, and can be performed on any resource from the set *M*. This means that resources are universal and can perform operations of any type. Each operation also has a fixed realization cost. If operations o_i and o_j belong to the same order, then operation o_i must be executed strictly before operation o_j. This means that there is a rigid sequence of operations within one order, and parallel execution of operations is not allowed. The goal (one of the optimization criteria) may be to minimize the number of changeover operations that occur when switching from operation o_i of type A to operation o_j of type B on one resource. In this case, the cost of changeover between operations of different types is fixed and unchanged. Another criterion may be the maximum distance of the order realization time from the delivery time defined by the operator or the system. In any case, there can be many criteria, it is accepted that the method of their convolution is defined, and the choice of optimal allocation is possible.

In this problem formulation, the number of possible variants of operations distribution by resources for further selection of the optimal solution (e.g., minimizing the number of changeovers) is determined by combinatorial search of all admissible distributions considering constraints on the strict sequence of operations of one order and impossibility of their parallel execution. Formally, this number can be expressed as a function of the number of operations *n*, the number of resources *k* and the number of time intervals *r* as follows:

$$C(n, r) \cdot m^r$$

Where:

$C(n, r) = \frac{n!}{r!(n-r)!}$ – number of ways to choose *r* strictly increasing intervals from *n* available intervals;

n – the total number of time slots on each resource;

r – the number of operations to be performed;

m – the number of available resources.

3.2. Task complexity

The problem belongs to the NP-complete class [9], which makes it impossible to use linear optimization methods, such as simplex method or full brute force. The simplex method is effective for linear, continuous problems where the variables can take any value within the constraints. This problem involves many integer variables and discrete constraints, which prevent the application of classical methods. Also, the possible number of distributions obtained by increasing the number of resources, time intervals of resources or operations may be such values that a complete enumeration could take years, which does not allow solving the problem in a short time, although it allows finding an optimal solution.

Let us consider how the number of possible options for allocating operations to resources increases as the number of available time slots increases for a fixed number of resources and operations:

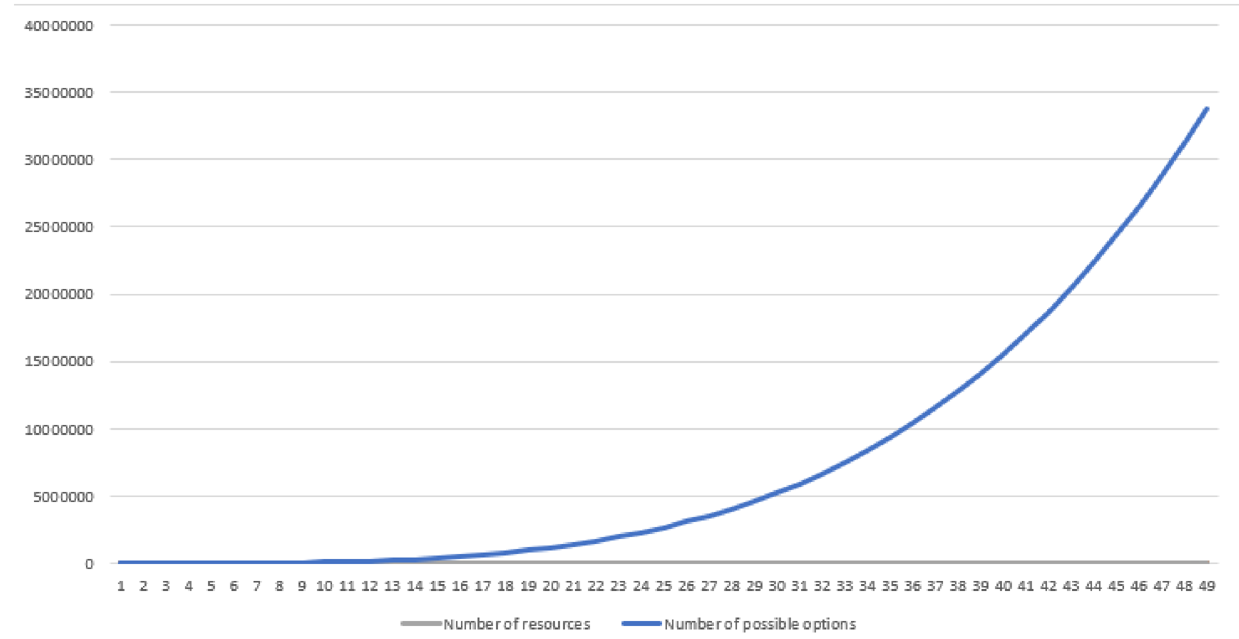

Figure 1. Effect of increasing resource time intervals on the number of possible allocation options

Also, consider how the number of possible choices for allocating operations to resources increases as the number of available time slots and resources increases for a fixed number of operations.

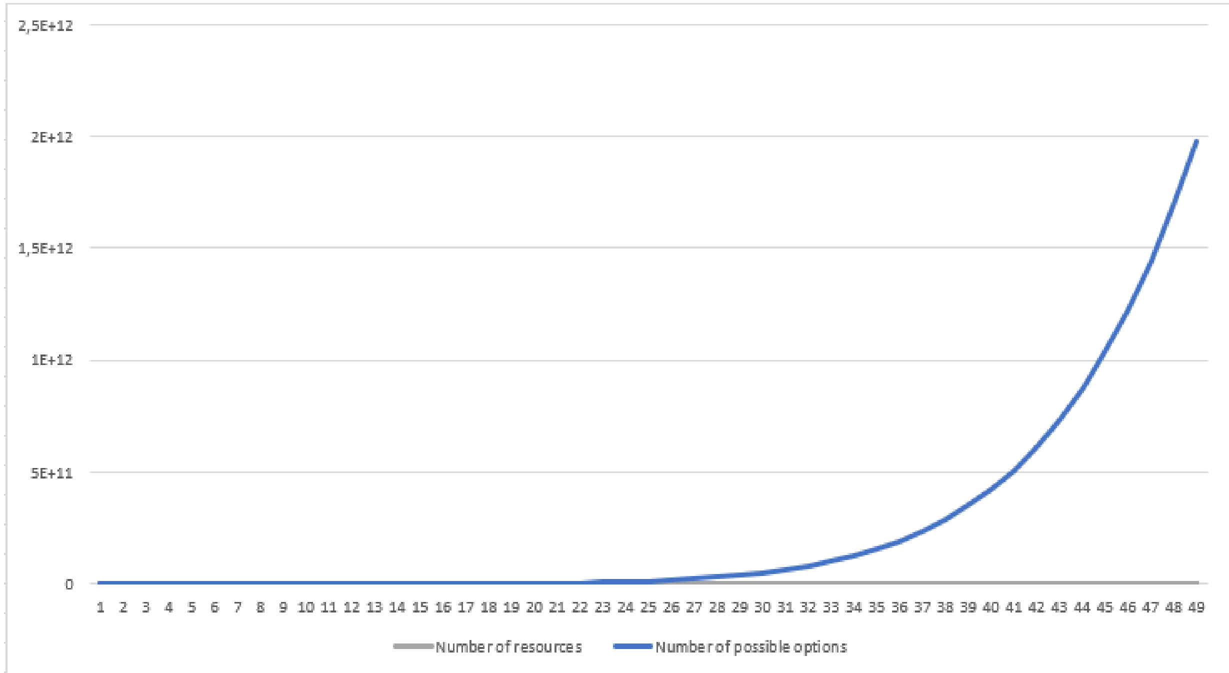

Figure 2. Effect of increasing the time intervals of resources and the number of resources on the number of possible allocation options

The following conclusions can be drawn regarding the growth rate of the number of variants of operations distribution by machines:

– As the number of time intervals n increases, the number of variants grows polynomially.

– As the number of resources m increases, the number of options grows exponentially

– The combined increase in n and m leads to a polynomial-exponential increase in the number of variants.

Thus, it is not possible to use a complete search for solving this type of problem, which makes it necessary to search for more efficient ways of solving this problem.

Further authors will analyze the existing approaches to the solution of the task based on application of methods of analysis and synthesis. The sources of data on existing approaches are scientific sources, a complete list of which is presented in the reference section of the paper.

4. Results

4.1. Methods of solving the problem

Existing methods of solving the problem of distribution of operations by machines, considering the assumptions in terms of optimization criteria, can be presented in the form of Table 1.

Table 1. Comparison of methods for solving the problem of operations distribution by machines

Method	Accuracy	Speed	Difficulty of implementation	Applicability for large tasks
The method of branch and bound	High	Medium	High	Restricted
Dynamic programming	High	Low	High	Restricted
Integer linear programming	High	Low	High	Restricted
Greedy algorithms	Low	High	Low	High
Genetic algorithms	Medium	Medium	Medium	High
Simulated annealing method	Medium	Medium	Medium	High
Ant algorithms	Medium	Medium	Medium	High
Reinforcement learning	Medium	Low	High	High
Neural networks	Medium	Low	High	High

Let us characterize each of the methods by grouping them by type.

Table 2. Description of some methods for solving the problem of operations distribution by machines

Method	Idea	Applicability	Advantages	Disadvantages
Precise methods				
Dynamic programming	partitioning the problem into subproblems whose solution is stored and	suitable for tasks with a small number of operations and machines where	guarantees an optimal solution	requires significant computational resources and memory for high dimensional tasks

Method	Idea	Applicability	Advantages	Disadvantages
	used to construct the optimal solution	the state can be described using a limited number of parameters		
Integer linear programming	formulating the problem as a system of linear equations and inequalities with integer variables	suitable for problems that can be accurately described by linear constraints	the use of powerful solvers (e.g. CPLEX, Gurobi) allows us to find optimal solutions	the computational complexity grows exponentially with increasing dimensionality of the problem
Heuristic methods				
Greedy algorithms	at each step, a locally optimal solution is selected (e.g., assigning an operation to the machine with minimum current changeover cost)	suitable for problems where locally optimal solutions lead to globally optimal solutions	ease of implementation and high speed	does not guarantee an optimal solution
Genetic algorithms	a simulation of the evolutionary process where a "population" of solutions evolves through selection, interbreeding and mutation	suitable for tasks with a large search space	can find good solutions in a reasonable amount of time	it is not guaranteed to find an optimal solution, and requires tuning of parameters (population size, mutation probability, etc.)
Simulated annealing method	gradual "cooling" of the system, allowing it to move out of local optima	suitable for problems with many local optima	can find the global optimum when properly tuned	requires setting of parameters (initial temperature, cooling speed)
Ant algorithms	mimic the behavior of ants that find the shortest route to food	suitable for routing and scheduling tasks	effective for tasks with a large search space	does not guarantee finding an optimal solution and requires adjustment of parameters (number of ants, pheromone evaporation rate)
Methods based on machine learning				
Reinforcement learning	the agent is trained to make decisions that maximize the reward (e.g. minimizing the cost of changeover)	suitable for tasks where the environment and reward can be modelled	can adapt to changing conditions	requires significant computational resources for training

Method	Idea	Applicability	Advantages	Disadvantages
Neural networks	using neural networks to predict the optimal allocation of operations	suitable for data-intensive tasks	can find complex dependencies in data	requires a large amount of data for training

In accordance with the above table, compiled based on known ideas about the strengths and weaknesses of these methods, as well as their applicability to the distribution problem, the following conclusions can be drawn:

– For problems of small and medium dimensionality it is presumably worth using the method of branch and bound or integer linear programming.

– For problems of high dimensionality, it is presumably worth using heuristic methods (greedy algorithms, genetic algorithms, simulated annealing method, etc.).

In a real production environment, finding an optimal solution for scheduling machine operations is often redundant. Instead, the challenge becomes finding an acceptable or good solution that can be implemented in a reasonable time frame given the limited computational resources. In addition, the production environment is often subject to unforeseen changes such as equipment breakdowns, delivery delays, or re-prioritization of orders. In such situations, it is critical not to recalculate the entire schedule all over again, but to perform localized rescheduling that minimizes disruption and preserves the overall efficiency of the production process. Recalculating the entire schedule from scratch every time input changes is computationally expensive and can lead to significant production delays as the constructed plan no longer matches reality. Local rescheduling allows:

1. Minimize reaction time: changes to the schedule are only made to the part directly affected by the change (e.g. machine breakdown).

2. Reduce computational costs: instead of a complete enumeration or complex optimization algorithms, local adjustments are used, which require fewer resources.

3. Preserve stability: localized changes have less impact on already scheduled operations, reducing the risk of cascading delays.

4.2. Multi-agent systems as a solution

Multi-Agent Systems (MAS) represent a promising approach for solving the problem of planning and local re-planning (dispatching) (Goldberg, D.E., Holland, J.H., 1988). In such systems, each agent is an autonomous entity that:

1. Possesses local information. Agents can make decisions based on data that is only available in their local area (e.g. the status of a particular machine or operation queue).

2. Interacts with other agents. Agents coordinate their actions through communication, which allows reaching globally harmonized solutions (Kim, Y. and Matson, E. T., 2016).

3. Adapts to change. Agents can dynamically realign their strategies in response to changes in the production environment.

Advantages of multi-agent systems:

1. Decentralized control: each agent makes decisions on its local information, which promotes decision autonomy and allows the system to scale in terms of both number of tasks and resources (Tsetlin, M. L., 1969).

2. Flexibility and adaptability: division of tasks, organization of interactions and adjustment of plans are optimized independently through negotiation mechanisms and agent interactions.

3. Time Quanta and Parallelism: system flexibility is provided by time quanta of control, allowing the system to adapt to changes in the environment in real time.

4. Interaction optimization: the ability to evaluate different modes of interaction and assignment of time slots makes the system suitable for complex environments and management tasks.

4.3. The role of heuristic algorithms in multi-agent systems

To make decisions, agents can use previously described heuristic algorithms that strike a balance between decision quality and computational complexity (Yu, W., Chen, G. et.al., 2010). Heuristics such as greedy algorithms, simulated annealing method or genetic algorithms allow:

1. Finding acceptable solutions quickly. Heuristics focus on finding good solutions in a short time, which is critical in real-world production environments.

2. Minimize the cost of changeovers. Local heuristics can consider the specifics of a particular machine or operation, which improves planning efficiency.

3. Adapt to change. Heuristics can be easily reconfigured to accommodate new constraints or changes in the production environment (Skobelev, P. O. et. al., 2010).

Let us consider the problem in terms of a multi-agent system, distinguishing two types of agents: order agents and resource agents. Order agents seek to schedule controlled operations by maximizing or minimizing some criterion (set of criteria). Resource agents provide their capacity to implement operations (time slots), while seeking to minimize or maximize their own criteria (e.g. changeover).

Let us consider possible heuristic algorithms that could be used to solve the problem of dynamic allocation of operations to machines in a multi-agent setting. Resource agents are responsible for managing machine schedules and minimizing downtime and changeovers. For this purpose, they can use the following heuristics (Gendreau, M., Potvin, J.-Y., 2018):

Table 3. Types of heuristics applicable for resource agents

Heuristic	Idea	Example	Advantages	Disadvantages
"Least cost of changeover"	selecting an operation that requires minimal changeover cost compared to the current operation on the machine	if the last operation on the machine was of type A, operation type B is selected if the transition cost is minimized	minimizes changeover costs	does not consider global constraints
"Least completion time"	selecting the operation that can be completed the earliest	a machine selects the operation with the shortest execution	reduces the overall lead time of orders	may increase the number of changeovers

		time among the available ones		
"Load-balancing"	distribution of operations between machines to minimize load differences	a machine selects an operation that will not significantly increase its utilization compared to other machines	improves resource utilization	requires coordination between machine agents

Order agents are responsible for finding the right machine for the operation and minimizing waiting times. To do this, they can use the following heuristics:

Table 4. Types of heuristics applicable for order agents

Heuristic	Idea	Example	Advantages	Disadvantages
"Least loaded machine"	selecting the machine with the lowest current load	an operation is assigned to the machine that will complete it the earliest	reduces waiting time for operations	may increase the number of changeovers
"Minimum changeover cost"	selecting a machine on which the operation will require minimal changeover cost	a type *A* operation is assigned to a machine where the last operation was also type *A*	minimizes changeover costs	can lead to uneven loading of machines
"Prioritize the nearest available machine"	choosing the machine that will be released the earliest	an operation is assigned to the machine that will complete the current operation the fastest	reduces waiting time	does not consider the cost of changeover
"Prioritize by transaction type"	selecting a machine that specializes in a certain type of operation	a type *B* operation is assigned to the machine that most often performs type *B* operations	reduces the number of changeovers	can lead to overloading of specialized machines

By interacting, the agents can find acceptable solutions in a short time, while the method itself provides convergence, provided they are willing to spend more time on search. Also, the multi-agent approach avoids the need for a complete schedule recalculation in case of equipment emergencies or re-prioritization of orders, which provides system flexibility.

5. Conclusion

In this paper, the resource allocation problem, which plays a key role in optimizing manufacturing processes, has been considered. The problem is the need for efficient allocation of operations to machines, considering factors such as minimizing changeover costs, reducing machine downtime and providing flexibility in a dynamically changing manufacturing environment. Traditional methods such as branch-and-bound and brute-force search, while providing optimal solutions, are often not applicable in practice due to their high computational complexity and inability to adapt quickly to changes.

As an alternative, a multi-agent approach is proposed, which combines flexibility, scalability and adaptability. A multi-agent system (MAS) allows decision-making to be distributed among autonomous agents, each responsible for managing a specific resource (machine) or order (operation). This approach allows for localized rescheduling in the event of unforeseen changes, such as equipment breakdowns or re-prioritization of orders, without the need for a complete schedule recalculation. This is particularly important in a real production environment where speed of response and minimizing disruption are critical factors.

To improve the efficiency of decision making, agents can use heuristic algorithms that allow them to find acceptable solutions in a short time, which makes them applicable in conditions of limited computational resources and tight time limits. At the same time, combining different heuristics and their adaptation to specific production conditions allows us to achieve a balance between the quality of solutions and the speed of finding them.

Further studies of the multi-agent approach in real production conditions are relevant, as well as comparison of its effectiveness with traditional methods, such as the method of branch and bound and complete search, etc. The multi-agent approach with heuristic algorithms is a promising direction for solving machine operation planning problems. Multi-agent approach using heuristic algorithms is a promising direction for solving machine scheduling problems, providing high flexibility, adaptability and efficiency in real production conditions.

References

Brucker, P., 2007. Scheduling Algorithms. Springer Berlin, Heidelberg. https://doi.org/10.1007/978-3-540-69516-5

Dorigo, M., Birattari, M., and Stutzle, T., 2006. Ant Colony Optimization. IEEE Computational Intelligence Magazine, 1(4), pp. 28-39.

Feo, T. A., and Resende, M. G. C., 1995. Greedy Randomized Adaptive Search Procedures. Journal of Global Optimization, 6, pp. 109-133. https://doi.org/10.1007/BF01096763

Festa, P., Resende, M. G. C., 2009. An Annotated Bibliography of GRASP – Part I: Algorithms and Applications. Journal of Global Optimization, 43(2-3), pp. 209-235. DOI:10.1111/j.1475-3995.2009.00663.x

Garey, M. R., and Johnson, D. S., 1983. Computers and Intractability: A Guide to the Theory of NP-Completeness. Journal of Symbolic Logic. 48 (2), pp. 498-500.

Gendreau, M., Potvin, J.-Y., 2018. Handbook of Metaheuristics. Springer Cham. https://doi.org/10.1007/978-3-319-91086-4

Glover, F., and Laguna, M., 1997. Tabu Search. Springer New York, NY. https://doi.org/10.1007/978-1-4615-6089-0

Goldberg, D.E., Holland, J.H., 1988. Genetic Algorithms and Machine Learning. Machine Learning 3, 95–99. https://doi.org/10.1023/A:1022602019183

Gorodetsky, B. I., Skobelev, P. O., 2017. Multi-agent Technologies for Industrial Applications: Reality and Perspective, Proc. technologies for industrial applications: reality and perspective, Proc. SPIIRAN, 2017, issue 55, 11-45. DOI: 10.15622/sp.55.1

Jennings, N. R., Sycara, K., and Wooldridge, M., 1998. A Roadmap of Agent Research and Development. Autonomous Agents and Multi-Agent Systems, 1(1), pp. 7-38. https://doi.org/10.1023/A:1010090405266

Kim, Y. and Matson, E. T., 2016. A realistic decision making for task allocation in heterogeneous multi-agent systems. Procedia Computer Science, vol. 94, pp. 386-391. doi: 10.1016/j.procs.2016.08.059

Lawler, E. L., Lenstra, J. K., Rinnooy Kan, A. H. G., and Shmoys, D. B., 1993. Sequencing and Scheduling: Algorithms and Complexity. Handbooks in Operations Research and Management Science. Graves, S.C., Rinnooy Kan, A.H.G., and Zipkin, P.H. (Eds.), Vol. 4., Logistics of Production and Inventory, North-Holland, Amsterdam, the Netherlands, pp. 445-522.

Lazarev, A. A., Gafarov, E. R., 2011. Scheduling Theory. Problems and Algorithms [in Russian]. Lomonosov Moscow State University, Moscow

Leitao, P., 2009. Agent-based Distributed Manufacturing Control: A State-of-the-art Survey. Engineering Applications of Artificial Intelligence, 22(7), pp. 979-991. https://doi.org/10.1016/j.engappai.2008.09.005

Paprocka, I., Kempa, W.M., Kalinowski, K., Grabowik, C., Mikhaylov, A., Nedelcu, D. et al., 2014. A production scheduling model with maintenance. Advanced materials research, vol. 1036, Trans Tech Publications Ltd, Silesian University of Technology, Institute of Mathematics, 23 Kaszubska Str, Gliwice, 44-100, Poland (2014), pp. 885-890, 10.4028/www.scientific.net/AMR.1036.885

Resende, M. G. C., Ribeiro, C. C., 2016. Optimization by GRASP: Greedy Randomized Adaptive Search Procedures. Springer New York, NY. https://doi.org/10.1007/978-1-4939-6530-4

Serrano-Ruiz, J.C., Mula, J., Poler, R., 2021. Smart manufacturing scheduling: A literature review. Journal of Manufacturing Systems, 61, pp. 265-287, 10.1016/J.JMSY.2021.09.011

Skobelev, P. O. et. al., 2010. Development of a multi-agent system for production planning, forecasting and modeling [In Russian]. Mechatronics, Automation, Control, 22-30

Smith, S. F., Fox, M. S., and Ow, P. S., 1986. Constructing and Maintaining Detailed Production Plans: Investigations into the Development of Knowledge-Based Factory Scheduling Systems. AI Magazine, 9(4), pp. 45-57. DOI:10.1609/aimag.v7i4.558

Tsetlin, M. L., 1969. Studies in Automata Theory and Simulation of Biological Systems [in Russian]. Nauka, Moscow

Van Laarhoven, P. J. M., Aarts, E. H. L., and Lenstra, J. K., 1992. Job Shop Scheduling by Simulated Annealing. Operations Research, 40(1), pp. 113-125. https://doi.org/10.1287/opre.40.1.113

Varshavskii, V. I., 1973. Collective Behavior of Automata [in Russian], Nauka, Moscow (1973).

Velastegui, R., Poler, R., Díaz-Madroñero, M., 2025. Revolutionising industrial operations: The synergy of multiagent robotic systems and blockchain technology in operations planning and control, Expert Systems with Applications, Vol. 269. https://doi.org/10.1016/j.eswa.2025.126460

Wang, X.-H. and Ji, H.-B., 2012. Leader-follower consensus for a class of non-linear multi-agent systems. International Journal of Control, Automationand Systems, vol. 10, no. 1, pp. 27-35. https://doi.org/10.1007/s12555-012-0104-3

Wooldridge M., 2009. An Introduction to Multiagent Systems. John Wiley & Sons Ltd, ISBN 978-0-470-51946-2

Yu, W., Chen, G., Cao, M. and Kurths, J., 2010. Second-Order Consensus for Multiagent Systems With Directed Topologies and Nonlinear Dynamics. IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics), 40, 3, pp. 881-891. doi: 10.1109/TSMCB.2009.2031624

Список источников

Brucker, P., 2007. Scheduling Algorithms. Springer Berlin, Heidelberg. https://doi.org/10.1007/978-3-540-69516-5

Dorigo, M., Birattari, M., and Stutzle, T., 2006. Ant Colony Optimization. IEEE Computational Intelligence Magazine, 1(4), pp. 28-39.

Feo, T. A., and Resende, M. G. C., 1995. Greedy Randomized Adaptive Search Procedures. Journal of Global Optimization, 6, pp. 109-133. https://doi.org/10.1007/BF01096763

Festa, P., Resende, M. G. C., 2009. An Annotated Bibliography of GRASP – Part I: Algorithms and Applications. Journal of Global Optimization, 43(2-3), pp. 209-235. DOI:10.1111/j.1475-3995.2009.00663.x

Garey, M. R., and Johnson, D. S., 1983. Computers and Intractability: A Guide to the Theory of NP-Completeness. Journal of Symbolic Logic. 48 (2), pp. 498-500.

Gendreau, M., Potvin, J.-Y., 2018. Handbook of Metaheuristics. Springer Cham. https://doi.org/10.1007/978-3-319-91086-4

Glover, F., and Laguna, M., 1997. Tabu Search. Springer New York, NY. https://doi.org/10.1007/978-1-4615-6089-0

Goldberg, D.E., Holland, J.H., 1988. Genetic Algorithms and Machine Learning. Machine Learning 3, 95–99. https://doi.org/10.1023/A:1022602019183

Gorodetsky, B. I., Skobelev, P. O., 2017. Multi-agent Technologies for Industrial Applications: Reality and Perspective, Proc. technologies for industrial applications: reality and perspective, Proc. SPIIRAN, 2017, issue 55, 11-45. DOI: 10.15622/sp.55.1

Jennings, N. R., Sycara, K., and Wooldridge, M., 1998. A Roadmap of Agent Research and Development. Autonomous Agents and Multi-Agent Systems, 1(1), pp. 7-38. https://doi.org/10.1023/A:1010090405266

Kim, Y. and Matson, E. T., 2016. A realistic decision making for task allocation in heterogeneous multi-agent systems. Procedia Computer Science, vol. 94, pp. 386-391. doi: 10.1016/j.procs.2016.08.059

Lawler, E. L., Lenstra, J. K., Rinnooy Kan, A. H. G., and Shmoys, D. B., 1993. Sequencing and Scheduling: Algorithms and Complexity. Handbooks in Operations Research and Management Science. Graves, S.C., Rinnooy Kan, A.H.G., and Zipkin, P.H. (Eds.), Vol. 4., Logistics of Production and Inventory, North-Holland, Amsterdam, the Netherlands, pp. 445-522.

Lazarev, A. A., Gafarov, E. R., 2011. Scheduling Theory. Problems and Algorithms [in Russian]. Lomonosov Moscow State University, Moscow

Leitao, P., 2009. Agent-based Distributed Manufacturing Control: A State-of-the-art Survey. Engineering Applications of Artificial Intelligence, 22(7), pp. 979-991. https://doi.org/10.1016/j.engappai.2008.09.005

Paprocka, I., Kempa, W.M., Kalinowski, K., Grabowik, C., Mikhaylov, A., Nedelcu, D. et al., 2014. A production scheduling model with maintenance. Advanced materials research, vol. 1036, Trans Tech Publications Ltd, Silesian University of Technology, Institute of Mathematics, 23 Kaszubska Str, Gliwice, 44-100, Poland (2014), pp. 885-890, 10.4028/www.scientific.net/AMR.1036.885

Resende, M. G. C., Ribeiro, C. C., 2016. Optimization by GRASP: Greedy Randomized Adaptive Search Procedures. Springer New York, NY. https://doi.org/10.1007/978-1-4939-6530-4

Serrano-Ruiz, J.C., Mula, J., Poler, R., 2021. Smart manufacturing scheduling: A literature review. Journal of Manufacturing Systems, 61, pp. 265-287, 10.1016/J.JMSY.2021.09.011

Skobelev, P. O. et. al., 2010. Development of a multi-agent system for production planning, forecasting and modeling [In Russian]. Mechatronics, Automation, Control, 22-30

Smith, S. F., Fox, M. S., and Ow, P. S., 1986. Constructing and Maintaining Detailed Production Plans: Investigations into the Development of Knowledge-Based Factory Scheduling Systems. AI Magazine, 9(4), pp. 45-57. DOI:10.1609/aimag.v7i4.558

Tsetlin, M. L., 1969. Studies in Automata Theory and Simulation of Biological Systems [in Russian]. Nauka, Moscow

Van Laarhoven, P. J. M., Aarts, E. H. L., and Lenstra, J. K., 1992. Job Shop Scheduling by Simulated Annealing. Operations Research, 40(1), pp. 113-125. https://doi.org/10.1287/opre.40.1.113

Varshavskii, V. I., 1973. Collective Behavior of Automata [in Russian], Nauka, Moscow (1973).

Velastegui, R., Poler, R., Díaz-Madroñero, M., 2025. Revolutionising industrial operations: The synergy of multiagent robotic systems and blockchain technology in operations planning and control, Expert Systems with Applications, Vol. 269. https://doi.org/10.1016/j.eswa.2025.126460

Wang, X.-H. and Ji, H.-B., 2012. Leader-follower consensus for a class of non-linear multi-agent systems. International Journal of Control, Automationand Systems, vol. 10, no. 1, pp. 27-35. https://doi.org/10.1007/s12555-012-0104-3

Wooldridge M., 2009. An Introduction to Multiagent Systems. John Wiley & Sons Ltd, ISBN 978-0-470-51946-2

Yu, W., Chen, G., Cao, M. and Kurths, J., 2010. Second-Order Consensus for Multiagent Systems With Directed Topologies and Nonlinear Dynamics. IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics), 40, 3, pp. 881-891. doi: 10.1109/TSMCB.2009.2031624

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