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MODELING DETERMINANTS OF PRODUCTION MANAGEMENT USING DISTRIBUTED INTELLIGENCE

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Abstract:
This article presents a decision-making model to support production management, developed with the application of distributed intelligence (DI). A systematic literature review (SLR) identified a significant gap in the integration of distributed decision-making methods with existing production systems. The proposed model incorporates dynamic selection of resources – workstations and employees – for production tasks, taking into account their competencies, availability, and technological constraints. The optimization process is performed using a particle swarm optimization (PSO) algorithm, implemented in the MATLAB environment. The model was validated through a case study conducted in a metalworking company. Empirical findings confirm the hypothesis that introducing elements of distributed intelligence into the production decision-making process enhances the quality of outcomes. Furthermore, the reorganization of the organizational structure was shown to reduce the time required to access information, enabling flexible adaptation of the production workflow to the company's evolving operational conditions. This research contributes to the development of decision support systems and outlines future directions for predictive and autonomous production planning.

Key words: production management, distributed intelligence, particle swarm optimization, decision support systems

INTRODUCTION

Production management constitutes the cornerstone of efficient operations in modern enterprises, influencing not only their effectiveness but also their competitiveness and adaptability in the global marketplace [1, 2]. In an environment characterized by increasing volatility, shorter product life cycles, and growing customer expectations for product personalization, critical decisions regarding the "*what*", "*where*", "*when*", and "*how*" of production must be made [3, 4]. Research indicates that traditional hierarchical management models have become inadequate in today's business context due to their limited flexibility, delayed information flow, and centralized structure. These shortcomings present significant obstacles to achieving the desired operational performance.

Previous efforts to improve production management have predominantly focused on implementing integrated MRP II, ERP, and CIM information systems [5, 6]. These systems have facilitated the digitization of numerous aspects of production and enhanced planning processes however, they continue to assume a centralized decision-making process based on static data and a sequential management structure. Contemporary challenges demand the adoption of novel management paradigms, such as real-time operations, system reconfiguration in response to dynamic environments, and decision-making autonomy [7, 8].

In response to these challenges, the concept of *intelligent manufacturing* (IM) has been developed, representing one of the key pillars of Industry 4.0 [9]. The IM concept is predicated on the interaction of IT, physical, and decision-making systems, and their ability to operate autonomously and proactively. The literature emphasizes that the essence of IM encompasses not only automation, but also the capacity to self-learn, collaborate, and adapt to evolving production conditions [10, 11].

One of emerging approaches supporting the concept of intelligent manufacturing is *distributed intelligence*, defined as decentralized decision-making by autonomous entities (agents), such as workstations, machines, or employees. As demonstrated in studies, distributed decision-making structures enhance system resilience to disruptions, improve response times, and enable more flexible modeling of production paths [12, 13, 14]. Despite growing interest, however, the application of distributed intelligence in the domain of production management remains limited. The difficulties arise from the challenge of integrating decentralized decision-making structures with hierarchical management models, which leads to delays in the flow of information and prevents a complete representation of the actual state of the enterprise. In practice, problems occur in decision-making communication between departments, as well as in the absence of mechanisms ensuring the continuous reflection of the dynamics of production processes. These constraints constituted the starting point for formulating the research problems presented in the subsequent sections of this study.

Distributed intelligence was applied primarily as an organizational concept aimed at structuring the decision-making process within the enterprise. This perspective emphasizes the decentralization of responsibility and the utilization of knowledge available at the level of individual resources.

The objective of the present article is develop and empirically verify a decision-making model based on distributed intelligence and to provide a comprehensive overview of the current state of the art in this field. The model enables the dynamic allocation of production activities to available workstations and employees under real-world conditions. It incorporates a multifaceted consideration of operator skill level, resource availability, and technological constraints, with optimization performed using the particle swarm optimization (PSO) algorithm.

LITERATURE REVIEW

A preliminary analysis of the existing literature indicates a growing number of publications on distributed intelligence and decision-making systems, with these concepts increasingly being integrated across various fields. However, in the context of production management, their application remains limited, as revealed by a thorough review and analysis of the literature. The objective of this review is to identify relevant research domains and to determine the primary research directions and challenges associated with the implementation of distributed intelligence in production management.

To this end, the Systematic Literature Review (SLR) method was employed [15], supplemented by bibliographic network visualization analysis using VOSviewer. The Web of Science (WoS) Core Collection, provided by Clarivate Analytics, was selected as the source for identifying scientific publications due to its interdisciplinary scope.

The scope of analysis was defined on the basis of the following query sequence: "production management" AND "distributed intelligence" AND "decision making." The database was searched across the following fields: title, abstract, and author-defined keywords. Only peer-reviewed studies published in English were considered, with no temporal restrictions applied. The selection process was carried out in two stages: an initial screening of titles and abstracts to exclude publications of limited relevance, followed by a full-text analysis of potentially significant studies. In total, 95 peer-reviewed scientific papers meeting the specified criteria and verified for editorial and review quality were identified in the WoS database. This approach reduced the risk of fragmented results and the duplication of publications across multiple databases, while ensuring consistency in the application of search criteria. It should be noted, however, that the exclusion of other databases, such as Scopus or IEEE, may result in an incomplete review. For this reason, future stages of the research will extend the analysis to additional sources and formalize the process in accordance with PRISMA guidelines.

Figure 1 presents a graph illustrating the number of publications over time. A clear upward trend is visible, particularly after 2018, indicating an intensification of research efforts focused on DI.

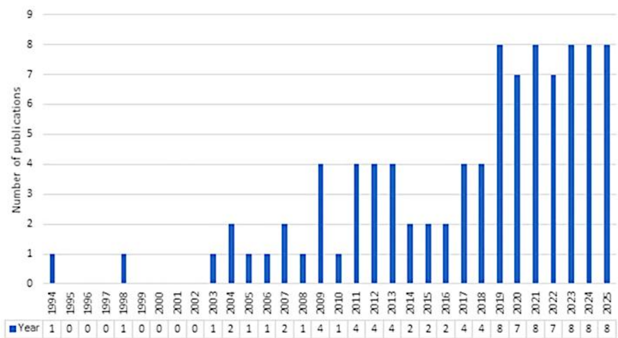

Fig. 1 Number of Publications from year

The majority of articles were assigned to the following WoS categories: Computer Science (33), Computer Science Theory & Methods (16), Engineering (16), Electrical & Electronic Engineering (16), Industrial Engineering (16), Manufacturing Engineering (16), Computer Science Interdisciplinary Applications (15), Computer Science Information Systems (14), Automation & Control Systems (11), and Operations Research & Management Science (11). Additional areas of study include Computer Science Software Engineering, Analytical Chemistry, Multidisciplinary Engineering, Management, Business, and Economics.

Subsequently, an analysis of keywords from all identified publications indexed in the WoS database was conducted. The use of VOSviewer software enabled the generation of a comprehensive map encompassing all keywords (Fig. 2).

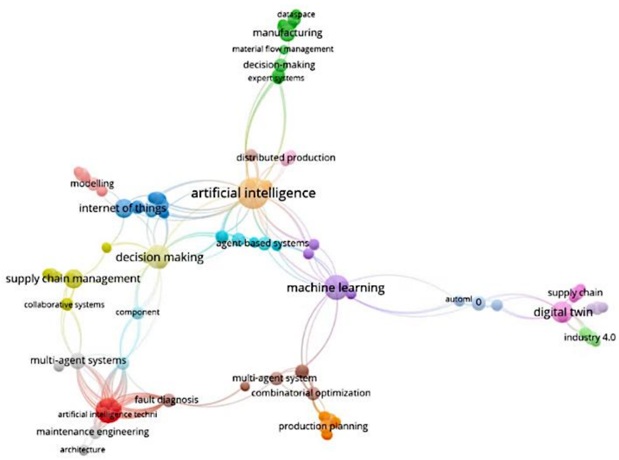

Fig. 2 Map of connections between all keywords

As illustrated in the keyword cooperative map, certain areas are either unrelated or only weakly related to the scope of production management. Therefore, it was decided to limit the number of keyword occurrences by applying a minimum correlation strength of 2. The revised association map is presented in Figure 3.

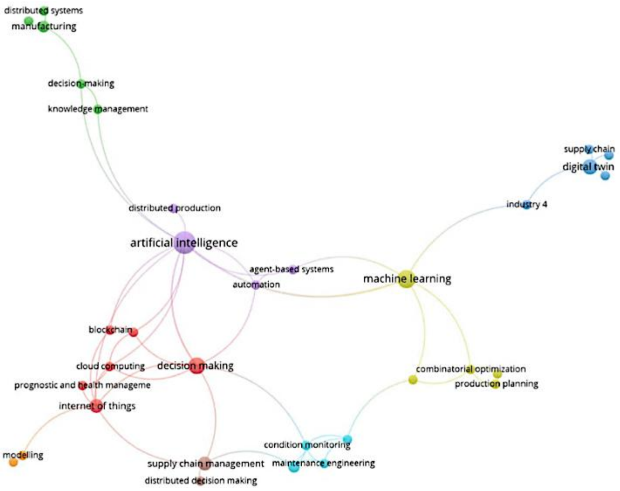

Fig. 3 Keyword map for a minimum keyword occurrence strength of 2

The revised map of connections facilitates the identification of the most and least frequent co-occurrences of keywords in the analyzed literature. The strongest connections are observed between the terms "*artificial intelligence*", "*machine learning*", and "*decision making*", which aligns with the adopted search criteria. In contrast, the weakest correlations are found in the domains of modeling, manufacturing, distributed decision-making, production planning, and digital twins. This finding indicates the presence of research gaps in the areas of decision-making, as well as in modeling and production planning that incorporate distributed activities.

In order to identify research areas, an in-depth analysis of selected studies was carried out (Table 1).

Table 1
Literature review by research area

Research area	Publications
Production management	[2, 3, 4, 6, 7, 8, 9, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26]
Artificial intelligence and machine learning	[28, 29, 30, 31, 32, 34, 35, 36, 37, 38, 39, 40, 41, 42, 43]
The Internet of Things and Industry 4.0	[3, 4, 8, 9, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53]
Decision support systems (DSS)	[20, 26, 27, 54, 55, 56, 57, 58, 59, 60, 61, 62, 63, 64, 65]
Measurement systems in production	[10, 12, 14, 31, 61, 66, 67, 68, 69]
Blockchain and distributed technologies	[45, 48, 49, 70]
Multi-agent systems and distributed structures	[59, 71, 72, 73, 74, 75, 76, 77, 78, 79, 80]

These are the basis for trends, research gaps and recommendations regarding the research results (Table 2).

A thorough analysis of the reviewed articles clearly indicates that the application of distributed intelligence in production management is a rapidly developing yet still insufficiently explored area of research. The identified trends, including the integration of artificial intelligence-based solutions in the context of decentralized decision-making, define new directions for the design of flexible and adaptive production environments.

Table 2
Main trends in articles, research gaps, and recommendations for future research directions

Research area	Main trends in articles	Research gaps	Opportunities for development/future research
Production management	Production process optimization, scheduling, digital transformation	A small number of studies on integration with AI elements in discrete manufacturing areas	Implementation of AI for production simulation, real-time data analysis
Artificial intelligence and machine learning	Use of machine learning models (e.g., SVM, CNN, LSTM), predictive analytics	No applications of data standardization, challenges in correctly interpreting models	Explainable AI (XAI), hybrid applications: machine learning (ML) models with decision support systems (DSS)
The Internet of Things and Industry 4.0	Integration of sensors with the cloud, failure prediction	Insufficient interoperability of systems, data security	Development of universal protocols, cybersecurity for IoT devices
Decision support systems (DSS)	Multi-criteria models, production scenario simulations	No integration with IoT and AI models	Adaptive DSS with online learning, integration with AI (PSO)
Measurement systems in production	Sensor calibration, vision systems, industrial metrology	No applications in a dynamic manufacturing environment	Development of smart sensors, real-time calibration
Blockchain and distributed technologies	Transparency, security, data tracking	No applications of interoperability, scalability issues, and processing time	Integration with IoT/MAS, real-time applications
Multi-agent systems and distributed structures	Agent autonomy, decentralized control, system adaptability	Limited actual implementations, lack of standardization of agent interactions	Hybrid MAS + blockchain systems, intelligent control in CPS

The issue of modeling production management determinants using distributed intelligence discussed in the article is directly related to current research trends. At the same time, it responds to identified research gaps in the integration of decision support systems and AI technology elements.

RESEARCH METHODOLOGY

The objective of the research was to develop and empirically verify a decision-making model supporting production management in an enterprise, incorporating contemporary assumptions of distributed intelligence within the frameworks of Industry 4.0 and 5.0. The research sought to streamline the process of assigning production activities to available resources and employees, while minimizing lead times and production costs. The research process was divided into several main stages.

The identification of the decision-making problem

The methodology was developed by initially identifying the limitations of the traditional hierarchical production management model still employed in a significant number of companies. This model, characterized by its unidirectional flow of information, failed to accurately reflect the actual state of the company. As a result, it led to delays in decision-making and incomplete utilization of production potential.

In response to these shortcomings, a management structure model based on distributed intelligence was proposed, enabling dynamic information exchange between all areas of the company. The identification of the research problems was based on the results of the systematic literature review and the analysis of decision-making processes in the examined enterprise. Particular attention was given to the observed difficulties in the functioning of the hierarchical management model, which revealed areas requiring improvement and constituted the basis for formulating the subsequent research assumptions. The primary research problems addressed were as follows:

- delayed information flow between departments,
- lack of real-time representation of the company's status,
- rigidity and ambiguity in decision-making communication.

The development of a decision-making model

The proposed model defines a set of determinants relevant to the decision-making process. A set of production activities, resources (i.e., workstations), and employees with defined skill levels was established. The following notation was adopted for the formal description of the model:

- $W = \{w_1, w_2, \ldots, w_N\}$ – set of activities to be performed,
- $P = \{p_1, p_2, \ldots, p_M\}$ – set of employees,
- $U = \{u_1, u_2, \ldots, u_M\}$ – set of employee skills,
- $UP = \{0, 1, 2, 3, 4, 5\}$ – skill scale, where 0 indicates no skills and 5 denotes the highest level of competence,
- L – set of technological constraints between activities,
- $A = [W, L]$ – system representing the relationships between activities.

The model operates under the assumption that each employee can perform only one activity at a time, provided they possess the required competencies for the given task. To formalize the problem, decision variables were introduced as follows:

$x_{ij} = 1$, if activity w_i is assigned to employee p_j,

$x_{ij} = 0$, otherwise.

The objective function is defined as the minimization of the total execution cost:

$$C = \Sigma_i \Sigma_j c_{ij} \times x_{ij},$$

where:

c_{ij} denotes the cost of performing activity w_i by employee p_j.

The cost c_{ij} consists of determinants such as execution time, employee wage rate, or material consumption.

The proposed model is subject to the following constraints:

1. Each activity is assigned to exactly one employee: $\Sigma_j x_{ij} = 1, \forall w_i \in W$.
2. An employee may perform only one activity at a given time.
3. An assignment is possible only if the employee's skill level $u_j \in U$ is not lower than the required value from UP for the given activity.
4. Technological constraints specified in set L must be preserved, ensuring that interdependent activities are executed in the appropriate sequence.

The model thus defined constitutes the basis for applying the PSO algorithm.

The implementation of the model

The PSO (Particle Swarm Optimization) algorithm, belonging to the class of population-based metaheuristics, was employed for optimization. This method facilitates an iterative search for optimal assignments of activities to resources, based on the mechanism of information exchange between particles and the evaluation of their previous solutions.

The model was implemented in the MATLAB environment. The optimization algorithm operated through repeated generation and evaluation of possible assignments of activities to resources, taking into account the specified number of iterations and the number of solutions in each run. For each solution, an objective function was calculated, defined as the total cost of the project. Upon completion of the iterative process, the optimal solution satisfying the predefined criteria was identified.

The algorithm was structured as follows:

Step 0. Load production project data (L, W, P, U, UP).

Step 1. Initialize algorithm parameters by specifying the number of iterations I and the number of sets in each iteration J.

Step 2. Set $i = 1$ and $j = 1$.

Step 3. For a given swarm value, find the path from the starting point to the end point.

Set $j = j + 1$.

Step 4. If $j \leq J$, return to Step 3; otherwise, proceed.

Step 5. Calculate the value of the project's objective function determined by the set from iteration *i*.
Step 6. Identify the best path in terms of the assumed criterion from iteration *i*.
Step 7. Set $i = i + 1$.
Step 8. If $i \leq I$, return to Step 3; otherwise, proceed.
Step 9. Display the best solution obtained in the final iteration.
Each particle in the PSO algorithm represents a potential assignment of activities W to resources, expressed in the form of a vector in which successive elements correspond to individual tasks, and the value of each element denotes the assigned employee. The solution space encompasses all admissible combinations of assignments. Table 3 presents the parameters of the PSO algorithm.

Table 3
Parameters of the PSO algorithm

Parameter	Value	Note
Number of particles	30	standard in similar scheduling PSO
Max iterations	50	fixed stopping rule
Inertia weight (w)	0.7	balances exploration/exploitation
Cognitive coefficient (c1)	1.5	individual learning
Social coefficient (c2)	1.5	swarm learning

Constraint handling (employee competencies, precedence and simultaneity relations) was implemented through a penalty mechanism in the objective function. In the event of a constraint violation, a penalty (e.g., 10^6) was added to the value of the objective function, which resulted in the elimination of infeasible solutions during subsequent iterations. This ensured that the search process concentrated on solutions consistent with the assumptions of the model.
The overall procedure of the algorithm can be described as follows: after initializing the swarm, particles (randomly generated using the function randi ([1 P], num_particles, W)) update their velocities (initially set to zero) and positions in accordance with the standard PSO equations. At each step, the objective function values are evaluated with the penalties included, and the best individual and global solutions are updated until the stopping criterion is satisfied (execution of max_iter iterations).
A segment of MATLAB code implementing the described algorithm is presented in Figure 4.

```
% --- Problem parameters ---
W = 16;        % number of production tasks
P = 59;        % number of employees
                ...
% --- PSO parameters ---
num_particles = 30;    % number of particles in the swarm
max_iter = 50;         % maximum number of iterations
w_inertia = 0.7;       % inertia weight
c1 = 1.5;              % cognitive coefficient
c2 = 1.5;              % social coefficient
% --- Initialize swarm ---
positions = randi([1 P], num_particles, W); % random initial assignments
velocities = zeros(num_particles, W);       % initial velocities
                ...
% --- Main PSO loop ---
for iter = 1:max_iter
    for i = 1:num_particles
        % Evaluate objective function for particle i
        cost = objective(positions(i,:), costs, skill_required, skills, resources);
                ...
% --- Results ---
fprintf('\nBest task assignment to employees:\n');
disp(gbest_position);
fprintf('Minimal production cost: %.2f\n', gbest_value);
```

Fig. 4 Segment of code in MATLAB

The developed model was subsequently verified to assess the validity of the underlying assumptions and to evaluate the effectiveness of the algorithm in assigning activities to resources while optimizing the costs and lead time of production project execution.

EMPIRICAL RESEARCH

To verify the effectiveness of the proposed decision-making model based on elements of distributed intelligence, empirical research was carried out in a manufacturing company specializing in metalworking. The company is characterized by unit production and a hierarchical structure of production resource management, a simplified diagram of which is shown in Figure 5.

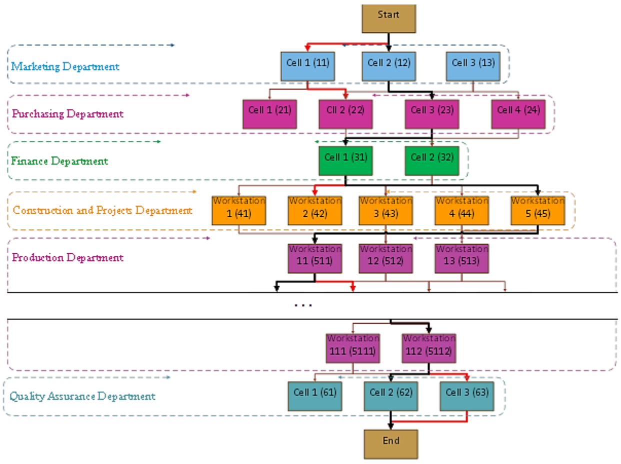

Fig. 5 Simplified layout diagram with a fragment of the production line/process map

The model was tested under real-world conditions. A comparative study was conducted for two scenarios: the first based on the traditional hierarchical decision-making model, and the second employing the proposed distributed structure.
The production order consisted of 16 activities (operations) that needed to be assigned to available resources (workstations) and employees, taking into account their competencies and skills. The study identified 56 workstations and 59 employees, whose competence levels were evaluated on a scale from 0 to 5 (Likert scale: where 0 indicates no skills and 5 denotes the highest level of competence). It was assumed that each employee could perform only one activity at a time, provided they possessed the required skill level for the given task.
As shown in Table 3, the analyzed data set includes selected information related to production activities across the company's various departments, including the required skill levels and the corresponding implementation costs.
The task was carried out using an algorithmic framework based on a swarm structure, which enabled the generation of potential assignments of activities to resources and employees over successive iterations. The objective function was to minimize the total production cost while meeting the time constraints imposed by the customer. In each of the *I* iterations, the algorithm generated multiple

solutions and then selected the optimal production path that satisfied the specified criteria (cost, resource availability, employee skills, and competencies). Upon completion of all iterations, the optimal assignment of positions was determined and presented.

Table 3
Description of production activities, costs, and skills of activity performers

	Cost (PLN/hour)	Required U	Required K	Employee group	Employee	U	K	Availability
Marketing Department	45	3	2	P1	P11	3	2	free
					P12	3	2	occupied
					P13	3	2	free
Purchasing Department	50	3	1	P2	P21	3	1	free
					P22	2	2	occupied
					P23	1	1	occupied
					P24	4	2	free
…								
Quality Assurance Department	60	3	2	P6	P61	4	3	occupied
					P62	3	2	free
					P63	2	2	free

where:
required U and K – required level of skills and competencies necessary to perform the activity,
P1, P2, … – group of employees assigned to perform a specific activity,
P11, P12, … – identifier of an employee belonging to a given group,
U, K – level of individual skills and competencies of an employee.

It was demonstrated that, as a result of implementing the algorithm (*I = 10* iterations), an optimal production path was obtained that accounted for both lead time and cost minimization. The assignment of workstations to individual departments is shown in Table 4 (column "Start"), while the subsequent columns (5, 10, …, 60) present the proposed production scenarios, taking into account the impact of time delays.
The resulting assignment of workstations did not require any corrections, and subsequent runs of the algorithm with a short time delay (5 minutes) did not alter the generated decision path. Only with a substantial time lag (60 minutes) were changes observed, resulting from real-time modifications in resource availability, thereby confirming the dynamic nature of the model. The data obtained from measuring the time required to gather information about the state of the enterprise before and after the introduction of the distributed model demonstrate a reduction from 25 hours and 20 minutes (hierarchical model) to 5 hours and 40 minutes (distributed model).

Table 4
Results of testing the algorithm in the form of assigning workstations for a production task with a time delay

Department	Start	Time delay [min.]				
		5	10	20	30	60
		Workstation				
Marketing	11	11	→ 13	→ 12	none	→ 12
Purchasing	24	24	→ 22	none	→ 23	→ 23
Finance	31	31	none	→ 32	→ 32	→ 32
Construction and Projects	42	42	none	→ 44	→ 44	→ 43
Production	512	512	→ 511	→ 513	→ 513	→ 511
	522	522	→ 523	→ 521	→ 521	→ 524
	532	532	→ 536	→ 532	→ 531	→ 534
	546	546	none	→ 543	→ 542	→ 544
	554	554	→ 551	→ 552	none	→ 553
	561	561	→ 565	→ 564	→ 563	→ 563
	574	574	→ 573	none	→ 572	→ 573
	583	583	none	→ 581	→ 581	→ 581
	592	592	→ 591	→ 593	→ 593	→ 593
	5101	5101	none	none	none	none
	5111	5111	→ 5112	none	→ 5112	→ 5112
Quality Assurance	62	62	→ 61	→ 12	→ 63	→ 62

where:
none (green) – same position as in the previous column,
→ – change of position

This represents a 77% reduction in the time needed to obtain decision-making data, thus enabling a significantly faster response to operational changes. Enhanced efficiency in resource allocation and a better alignment between employee competencies and assigned tasks were also observed (improvement in OEE about 11.35%, in accordance with the classical formula (Availability × Performance × Quality)). The distributed intelligence model facilitated the acquisition of initial data, which became available as early as 30 minutes after the order was initiated.
A thorough analysis of the research findings identified resource availability as the primary factor influencing the selection of production scenarios. Employee competencies and the cost-effectiveness of positions had a smaller, though still significant, impact. The developed decision-making model has proven effective in reflecting the actual state of the company and may serve as a foundation for further work on the automation and optimization of production processes.
The validation results are subject to certain limitations. The study was conducted within a single enterprise, which hinders the full generalization of the outcomes to other industries and organizational models. The applied employee competence scale (0-5), which was employed in the task allocation process, has not been psychometrically verified and therefore requires further evaluation in terms of reliability and validity.
Moreover, the study has a preliminary character and was carried out on the basis of a single case study, which further restricts the generalizability of the findings. At the current stage, no sensitivity analysis or statistical testing

was performed, which constitutes a direction for subsequent empirical investigations.

SUMMARY

The article presents a decision support model in production management based on the concept of distributed intelligence. This solution enables the dynamic allocation of production tasks to available workstations and employees, taking into account technological constraints, skill levels, and the current availability of resources. As part of the research, a particle swarm optimization (PSO) algorithm was developed and implemented in the MATLAB environment, which made it possible to determine optimal execution paths of production processes under the criterion of cost minimization. The model was empirically verified in a company from the metal processing sector, which allowed for an assessment of its practical applicability in real production conditions. The study confirmed that the distributed approach significantly improves data acquisition time, the quality of operational decisions, and the flexibility of task planning.

CONCLUSIONS

The conducted research demonstrated that the application of the distributed decision-making approach can contribute to increasing the flexibility, accuracy, and timeliness of decisions. The time required to obtain information on the enterprise's condition was reduced from more than 25 hours to less than 6 hours (a reduction of approximately 77%), which significantly increased the responsiveness to changes in the production environment. The implementation of the system also enabled the elimination of ambiguities in interdepartmental communication, improved the consistency of the decision-making process, and enhanced the utilization of available resources. An increase in the transparency of management processes and greater flexibility in task allocation were observed, which translated into more effective adaptation of the organization to variable operating conditions. The results indicate that the model can be a useful tool for supporting planning in situations of resource shortages and in a dynamic production environment.

DIRECTIONS FOR FURTHER RESEARCH

Despite its confirmed effectiveness, the developed model has certain limitations resulting from the scope of the study and the assumptions adopted. The verification was carried out in a single enterprise, which limits the possibility of fully generalizing the results to other industries and organizational structures. The model operated as a standalone optimization tool, and employee skill levels were treated as constant values without accounting for their variability over time. The decision-making criteria were limited to costs and resource availability, leaving more complex factors such as energy consumption, reliability, or risk for subsequent stages of research.

Future studies are planned to extend the model with predictive elements, demand forecasting, consideration of employee absences, and factors related to energy efficiency. Another important direction is the integration of the model with real-time data, which will allow for greater automation of decision-making and closer integration with existing management systems in the enterprise. Such developments should make it possible to increase the usefulness of the model in diverse industrial environments.

Taking into account a module enabling comprehensive use of the software, including its advantages and limitations in relation to other optimization methods.

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