DOI 10.52209/2706-977X_2026_2_25 IRSTI 55.01.77 UDC 658.984

A Methodology for Optimizing Material Flows in Mechanical Engineering Enterprises Based on Big Data Technologies

Zhetessova G.S.[1], Zharkevich O.M.[1], Kozhanov M.G.[1], Khrustaleva I.N.[2], Buzauova T.M.[1*]
[1]Abylkas Saginov Karaganda Technical University, Karaganda, Kazakhstan
[2]Peter the Great St. Petersburg Polytechnic University, St. Petersburg, Russia
*corresponding author

Abstract. This paper presents the development of a digital model of the production process at a mechanical engineering enterprise, aimed at improving management efficiency using Big Data technologies and multi-criteria optimization methods. The structure of a machine shop was formalized, identifying the main functional elements of the production system, including production areas, buffers, product flow routes, and intra-shop logistics. Parametric models of production units were developed, enabling the assessment of throughput, equipment utilization, work-in-progress volumes, and operating costs.The study analyzed the influence of machining process parameters on surface quality indicators. Predictive dependences of machining quality on cutting speed, feed rate, vibration level, spindle power, and tool wear were constructed. Three-dimensional models of surface roughness variations and heat maps of equipment utilization were developed, enabling the identification of bottlenecks in the production process. An intelligent methodology for optimizing a production system is proposed, based on machine learning, multi-criteria analysis, and digital modeling. The obtained results confirm the possibility of applying the developed approach to creating digital twins of production processes and improving the management efficiency of mechanical engineering enterprises.

Keywords: Big Data, digital model, digital twin, mechanical engineering enterprise, multi-criteria optimization, production process, parameterization, machine learning, work in progress, workload heat map.

Introduction

In today's evolving mechanical engineering industry, improving the efficiency of production processes is becoming a priority for industrial enterprises. Increased competition, rising demands on product quality, reduced manufacturing lead times, and the need to quickly respond to changes in the production program require the implementation of intelligent production system management methods [1]. This problem is particularly pressing for multi-product and single-item production [2], where process routes are characterized by high variability, uneven equipment loading [3], and significant volumes of work in progress. Under these conditions, optimization of material flows is particularly important, ensuring the consistency of process operations, rational resource allocation, and the stable functioning of the production system.

Material flows in mechanical engineering represent the combined movements of blanks [4], semi-finished products, tools [5], fixtures, and auxiliary resources between different production areas [6]. The efficient organization of these flows directly impacts the duration of the production cycle, equipment loading, operating costs, and the quality of the manufactured products [7]. Insufficient synchronization of process operations leads to downtime, the accumulation of work in progress, the formation of bottlenecks, and a decrease in overall enterprise productivity. Therefore, optimizing the structure and parameters of material flows is a key area for improving production processes at mechanical engineering enterprises.

The current development of digital technologies, industrial automation systems, and the Industry 4.0 concept are creating the preconditions for the transition to intelligent production process management based on big data analysis [8]. The use of Big Data technologies enables the collection, processing, and analysis of information on equipment status, process mode parameters, production area loads, product quality, and material flow in real time. The use of data mining and machine learning methods enables the identification of hidden patterns, forecasting the state of a production system, and the development of adaptive solutions for production flow management [9].

Scientific research devoted to the optimization of production processes [10] examines various approaches to improving the performance of mechanical engineering enterprises, including mathematical modeling, [11] digital design, multi-criteria optimization, and the construction of digital twins of production systems [12]. Particular attention is paid to synchronizing process operations [13], reducing the volume of work in progress, balancing equipment loads, and ensuring the stability of the production process [14] in the face of changing production factors. However, existing approaches are often focused on solving individual local problems and do not provide for the comprehensive integration of process parameters, production logistics, and analytical data processing tools into a single intelligent material flow management system.

In this regard, a pressing scientific challenge is the development of a methodology for optimizing material flows at mechanical engineering enterprises based on Big Data technologies. This methodology provides a comprehensive analysis of the production system, formalization of its structural elements, and the application of intelligent data processing methods to improve the efficiency of production process management. The development of such a methodology requires the creation of parametric models of production areas, the development of mechanisms for analyzing equipment loading, assessing the throughput of process routes, and identifying factors that influence the quality of processing and the productivity of the production system [15].

1. Research methology

The research methodology is based on systems analysis, mathematical modeling, data mining, and multi-criteria optimization of production processes. Parametric models were developed to calculate throughput, cycle time, and work-in-progress volume. The study focused on the production route for a flange-type part. Machine learning methods were used to analyze the processing quality and operational efficiency of the production system, and the results were visualized using 3D models and equipment utilization heat maps.

1.1 Mechanical processing section

Here, a single production cell is a group of identical workstations (for example, a turning or drilling section), and the optimization parameters are the number of workstations, average workload, order distribution, and reserves.

The parameterized model will look like this:

$$THU = (M_U \cdot 60 / CT_U^{avg}) \cdot \eta \quad (1)$$

where THU - throughput capacity of the node, pcs/h,

M_U - number of workstations/machines in the unit,

CT_U^{avg} - average cycle time per element (min),

η - technical readiness coefficient (uptime).

1.2 General warehouse

WIP Pool, where the single production cell is a centralized warehouse/buffer for shift batches, and the optimization parameters are turnover, average time, and availability index.

The parameterized model will look like this:

$$DB = f(KB, THin, THout) \quad (2)$$

1.3 Workshop

Shop-Floor Level, where a single production cell is the collection of all routes, nodes, and buffers, and the optimization parameters are global WIP, turnover, balancing, and energy profile.

The parameterized model will look like this:

$$CTtotal = \sum(u=1,N)CTu + \sum(b=1,M)D_B + \sum(tr)Ttrans \quad (3)$$

$$Ctotal = \sum(u)(Cenergy + Cwage + Ctool + Cmaint) \quad (4)$$

Cost model:

$$OPEXu = Cenergy \cdot t + Ctool^{use} + Clabor + Crepair. \quad (5)$$

Table 1 presents the main variables and parameters of the workshop.

Table 1. Main variables and parameters of the workshop

Designation	Description
(CT_i)	Average cycle time in section (i), min
(TH_i)	Section capacity (i), part/hour
(\rho_i)	Equipment loading at site (i), share
(WIP_i)	Work in progress at site (i), parts
(Q_i)	Yield in section (i), %
(OPEX_i)	Operating costs at site (i), USD/day
(E_i)	Energy consumption, kW·h
(K_{ij})	Buffer size between sections, parts

Therefore, the structural elements of the workshop can be represented in the form of the following dependencies:

- production areas (units): $Ui \in \{ U\text{turning}, U\text{milling}, U\text{grinding}, U\text{control}\}$;
- buffers/warehouses between sections: Bi,j;
- product movement routes: $R=\{U1 \to U2 \to \ldots \to Un\}$;
- logistics/transport: intra-shop movements Tij.

The workshop can be represented as a directed graph:

$$G=(V,E),\ V=\{U1,U2,...,Un\},\ E=\{(Ui,Uj)\} \quad (6)$$

Each edge (Ui,) contains:
- buffer Kij;
- travel time $Ttransij$.

The visual model of the workshop structure is presented by the code:

```
[Warehouse]
  ↓
[Lathe unit] --⟶ [Milling unit] --⟶ [Grinding unit] --⟶ [Control]
  ↓           ↓            ↓
 K12        K23          K34            ...
```

Each node contains:
- machines Mi,
- processing parameters v, s, ap,
- technical constraints,
- queue and buffer.

Using a flange-type part as an example, a calculation for the structural elements of the workshop was obtained (Table 2).

Table 2. Calculation of structural elements of the workshop

Plot	CT_i (min)	M_i (machine tools)	η (accessibility)
Lathe	6.5	3	0.95
Milling	5.0	2	0.90
Drilling	4.5	2	0.92
Control	2.0	1	0.88

The throughput of the TH is the bottleneck of the milling machine, which limits productivity (Table 3).

Table 3. Section capacity

Plot	TH_i (part/hour)
Lathe	≈ 26.31
Milling	≈ 21.6
Drilling	≈ 24.53
Control	≈ 26.4

Work in progress is distributed efficiently, without overload (Table 4).

Table 4. Average number of unfinished parts

Plot	WIP_i (unit)
Lathe	≈ 2.85
Milling	≈ 1.80
Drilling	≈ 1.84
Control	≈ 0.88

The developed shop-floor parametric model enables multi-criteria optimization of the production process, as well as a comprehensive assessment of equipment utilization, manufacturing costs, overall operational efficiency, and product quality indicators. This model creates the prerequisites for the creation of digital twins of production routes and supports the implementation of adaptive methods for planning and optimizing material flows in real time.

The resulting parametric model of the production site defines the computational and structural basis for implementing multi-criteria optimization. However, the effectiveness of its practical application directly depends on the correct selection and formalization of evaluation criteria. In the context of multi-parameter technological processes, a key aspect is the transition from describing the structure and parameters of the production system to quantitatively assessing its performance. The use of formalized criteria allows for linking the parameters of process modes and organizational characteristics of the production process with optimization targets, ensuring the comparability of alternative management decisions.

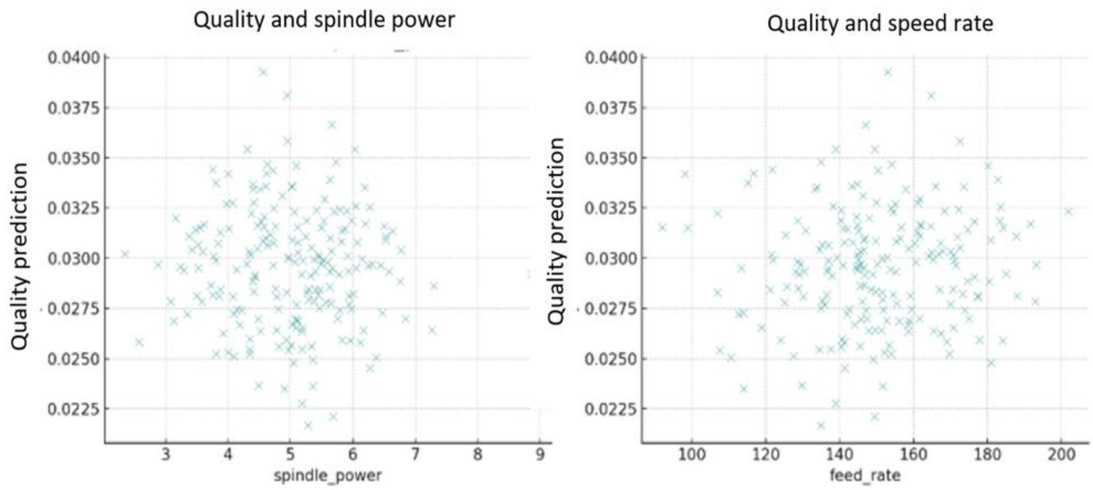
Based on the developed system of criteria, analytical and predictive analysis becomes possible, including the construction of dependencies between output quality indicators and key production process parameters. This approach creates the preconditions for the application of forecasting and optimization algorithms, which is implemented in the further presentation.

Prediction code:

```
import matplotlib.pyplot as plt
import seaborn as sns

# Add model predictions to a DataFrame
X_test_copy = X_test.copy()
X_test_copy['quality_predicted'] = model.predict(X_test)

# Plot graphs of quality dependence on each parameter
fig, axes = plt.subplots(2, 3, figsize=(18, 10))
axes = axes.flatten()

for idx, column in enumerate(X.columns):
    sns.scatterplot(
        ax=axes[idx],
        x=X_test_copy[column],
        y=X_test_copy['quality_predicted'],
        alpha=0.6,
        color="teal"    )
    axes[idx].set_title('quality vs {column}')
    axes[idx].set_ylabel('quality forecast)
    axes[idx].set_xlabel(column)

# Delete the empty last cell
fig.delaxes(axes[-1])
plt.tight_layout()
plt.show()
```

2.Results and discussion

The results of the study of the influence of the main technological parameters on the quality indicators of surface treatment are presented in Figure 1.



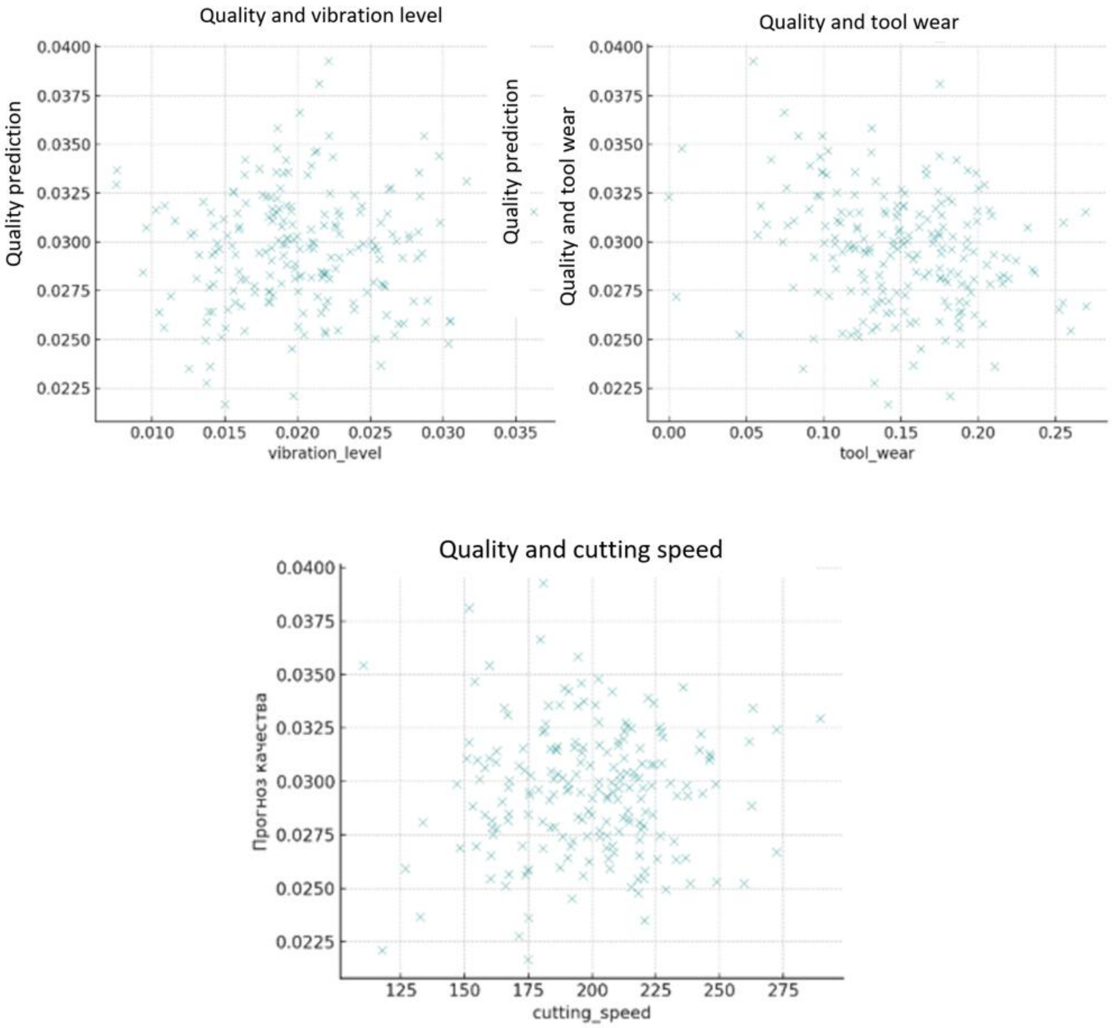


Fig. 1. - Quality dependencies on the mechanical processing modes of the technological process

Based on the analysis of the presented graphical dependencies (Figure 1), the following conclusions can be drawn regarding the influence of the main process parameters on surface finish quality:

- spindle power has a noticeable, but not dominant, effect on the quality of the formed surface. In the range up to approximately 6.5 kW, changing this parameter does not lead to a significant deterioration in roughness. However, when this threshold is exceeded, a tendency toward an increase in surface defects is observed, which is likely due to increased dynamic loads and heat generation in the cutting zone;

- feed rate is a significant factor determining machining quality. An increase in feed rate is accompanied by an increase in the roughness parameter Ra, indicating a deterioration in surface quality. For high quality machining requirements, it is advisable to limit the feed rate to no more than 160 mm/min, since further increases in this parameter lead to a sharp decrease in quality.

- cutting speed exhibits a pronounced nonlinear relationship with quality indicators. An analysis of the graphs reveals an optimal cutting speed range of 180–220 m/min, which achieves the most favorable combination of cutting conditions and surface quality. Deviations from this range are accompanied by deterioration in machining results.

- vibration level is the most sensitive and critical parameter in terms of machining quality. Even a slight increase in vibration amplitude, for example, from 0.02 to 0.03, leads to a sharp increase in surface roughness and the appearance of defects. This indicates the dominant role of the dynamic stability of the process system in determining surface quality.

- cutting tool wear has a consistent and virtually linear effect on machining quality. As wear increases, surface roughness consistently increases. At wear values exceeding 0.2 mm, the likelihood of producing a surface with unsatisfactory quality becomes extremely high, indicating the need for timely tool replacement or repair. A three-dimensional dependence (Figure 2) of the machining quality indicator, expressed through the surface roughness parameter *Ra*, on the main machining parameters - cutting speed and feed rate is constructed. The visualization is presented as a spatial surface, allowing for a clear depiction of the combined influence of these factors on surface quality.

In this model, the X-axis corresponds to the cutting speed expressed in m/min, the Y-axis to the feed rate in mm/min, and the Z-axis to the surface roughness value *Ra*. This 3D dependence allows for the identification of areas of optimal cutting mode combinations that achieve minimal roughness values, as well as areas of parameters that lead to deterioration in machining quality.

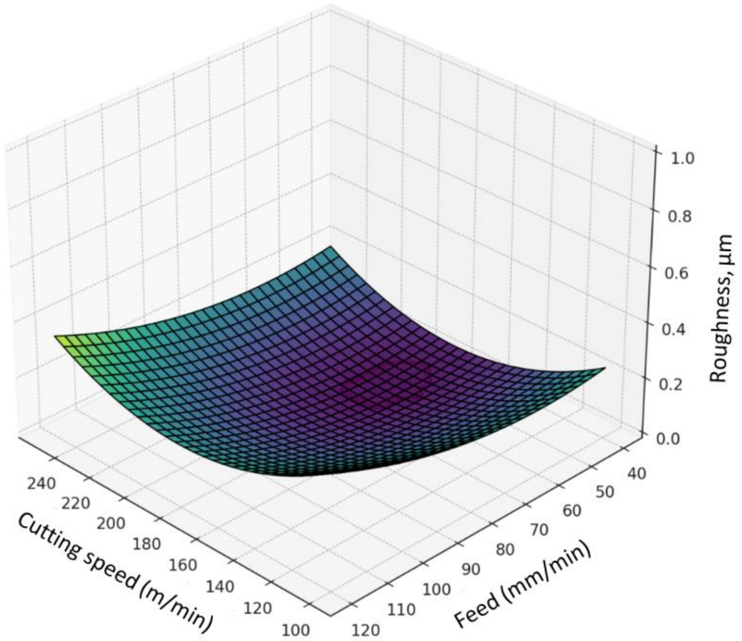


Fig. 2. - Three-dimensional dependence of the processing quality indicator expressed through the surface roughness parameter *Ra*

An analysis of the graphical dependence shows that the greatest risk in terms of machining quality is posed by conditions in which the surface roughness parameter Ra exceeds 0.03, which is outside the permissible limits. Operating the process in these conditions results in a surface with unsatisfactory quality characteristics and requires prompt adjustment of the machining parameters.

To prevent deterioration in surface quality and stabilize the machining process, it is advisable to implement daptive adjustment of the process parameters. Specifically, a 10–20% reduction in feed rate is recommended, which reduces the height of surface irregularities. Additionally, the cutting speed should be adjusted toward the nominal value of approximately 180 m/min, which ensures the most stable cutting process. Monitoring the condition of the cutting tool is also essential, as increased wear is a key factor in increasing roughness and the appearance of surface defects.

As part of the study, the structural elements of the production shop were parameterized for the manufacture of a flange-type part. Parameterization encompasses the key elements of the production system, including process equipment, workstations, workpiece and semi-finished product flows, and the relationships between individual operations along the process flow. Implementing this stage allows us to formalize the shop floor structure and represent it as a set of parameters suitable for subsequent analysis, modeling, and optimization of the production process.

Code for loading machines has been created:

```
    import pandas as pd
    import numpy as np
    import seaborn as sns
    import matplotlib.pyplot as plt
# Example of machine loading data
data = {
  'Machine': [' Machine _1', ' Machine _2', ' Machine _3', ' Machine _4', ' Machine _5'],
  '08:00–10:00': [75, 30, 55, 20, 90],
  '10:00–12:00': [85, 60, 40, 70, 95],
  '12:00–14:00': [65, 80, 90, 30, 60],
  '14:00–16:00': [50, 45, 80, 100, 55],
  '16:00–18:00': [40, 35, 70, 90, 60]}

    df = pd.DataFrame(data)
    df.set_index('Machine', inplace=True)
```

```
# Building a heat map of machine loading
plt.figure(figsize=(10, 6))
sns.heatmap(df, cmap='coolwarm', annot=True, fmt=".0f", linewidths=0.5, cbar_kws={'label': 'Загрузка (%)'})
plt.title('Machine tool loading heat map (flange batch))')
plt.ylabel('Machine')
plt.xlabel('Time interval)
plt.tight_layout()
plt.show()
```

During the study, a heat map of the workload of metal-cutting machines in the production area was constructed (Figure 3), which makes it possible to evaluate the distribution of the production load over time and identify potential bottlenecks in the technological process.

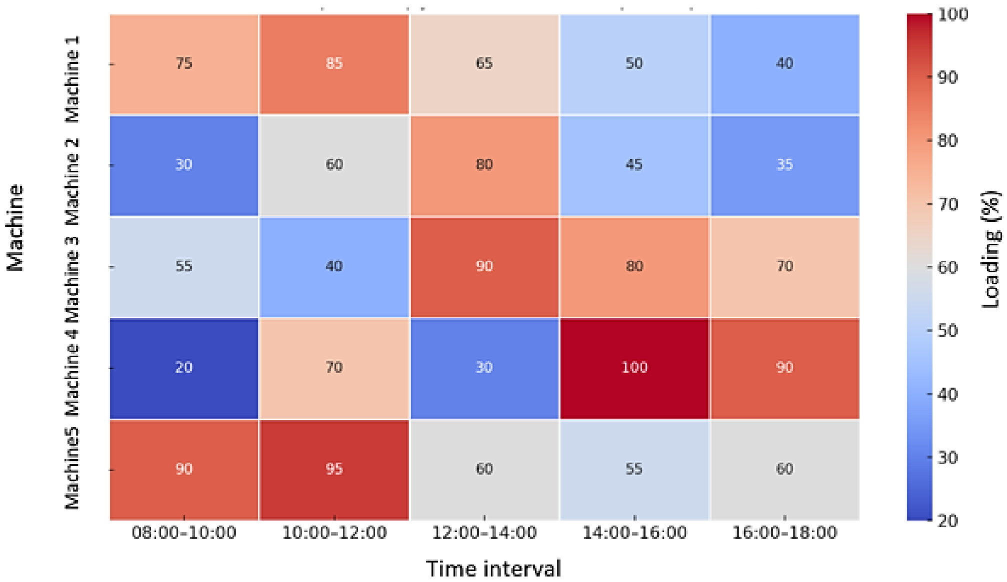


Fig. 3. - Machine tool loading heat map

Heat map analysis revealed that machine 5 is characterized by its highest utilization rate between 8:00 AM and 12:00 PM, indicating a high concentration of operations and a potential bottleneck in the production flow structure. Machine 4 exhibits full utilization (100%) between 2:00 PM and 4:00 PM, potentially leading to equipment overload, increased waiting times for operations, and increased work-in-progress (WIP). Meanwhile, machines 2 and 3 are characterized by a more uniform utilization distribution throughout the shift, allowing them to be considered as reserve resources for the redistribution of individual process steps to stabilize the production flow.

Additionally, the study constructed a Pareto frontier for five alternative machining modes based on a combination of three criteria: machining time, surface quality, and manufacturing operating costs. The analysis was conducted taking into account the requirements of minimizing machining time, reducing surface roughness values, and reducing operating costs. The results of the multicriteria analysis show that mode X4 is the most balanced option, providing minimal surface roughness and operating costs with an acceptable processing time. Therefore, it can be recommended as the preferred mode. Mode X2 demonstrates advantages in terms of cost and surface quality, but is characterized by a slightly increased processing time, making it suitable for use in situations where flexible equipment load redistribution is required. Mode X3 is inferior to the alternatives in all analyzed parameters, characterized by higher roughness and operating costs, and therefore should be excluded from further consideration. Modes X1 and X5 occupy an intermediate position and can be considered as compromise solutions, acceptable for auxiliary or secondary operations.

The study generated a dynamic heat map of the production area's operational efficiency based on a set of key indicators characterizing the time, production, and economic aspects of the process (Figure 4). The following integral indicators were used: average production cycle time for processing one part (Cycle Time, CT), throughput of the section (Throughput, TH), average volume of work-in-progress (Work-In-Progress, WIP) and operating costs for manufacturing a unit of output (Cost, C) (Table 5).

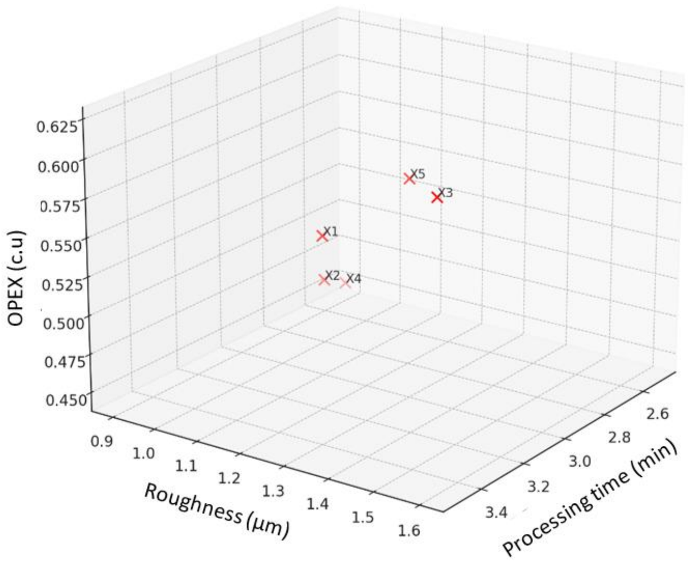


Fig. 4. - Efficiency of the production plot

Table 5. Integral process indicators

Indicator	Designation	Description
CT	Cycle Time (min/unit)	Average processing time per part
TH	Throughput (unit/min)	Production throughput
WIP	Work-In-Progress	Average number of unfinished parts
C	Стоимость (c.u./unit)	Operating costs per unit

Heat map analysis (Figure 5) revealed that Batch A, with the shortest average processing time per part, demonstrated the best results in terms of CT (average processing time per part). Batch B, however, had the longest production cycle, indicating possible equipment overload or a bottleneck in the process flow.

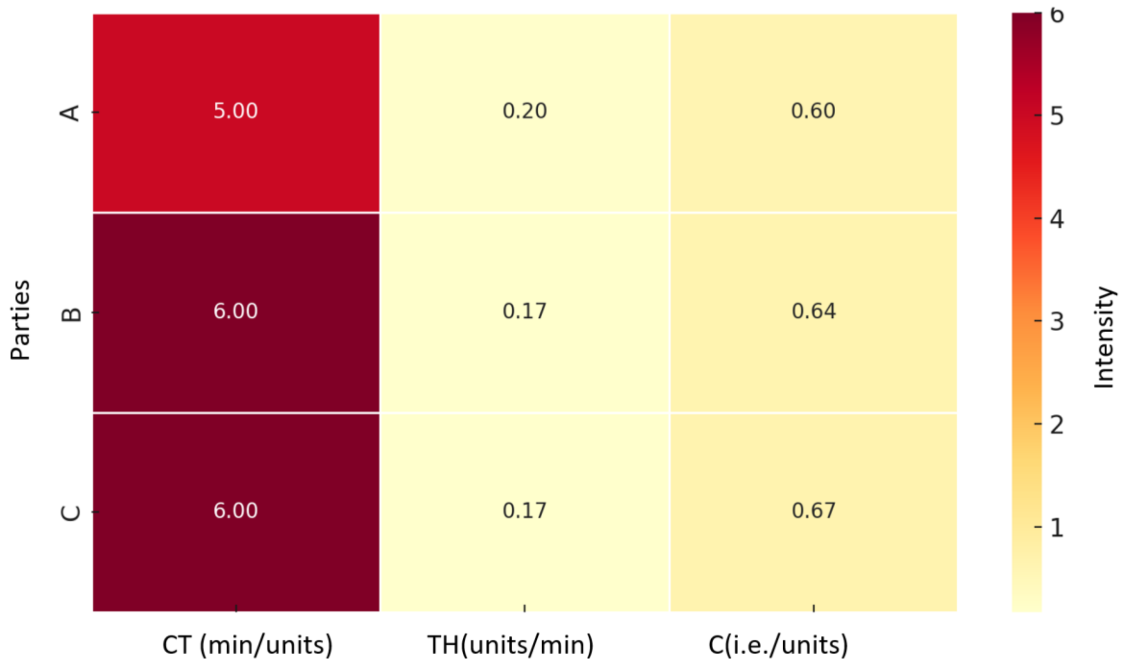


Fig. 5. - Heat map

In terms of TH (throughput), Batch A also leads the way, demonstrating the highest throughput value, indicating a high degree of synchronization of operations and a streamlined production flow. Batch B exhibits minimal values for this indicator, confirming its low efficiency in terms of production speed.

An analysis of unit operating costs (C) shows that Batch A also exhibits minimal costs, suggesting it is the most cost-effective option. Batch C has slightly higher costs, but demonstrates a more balanced balance between processing time and quality indicators, making it an acceptable alternative in the face of changing production priorities.

Based on the results obtained, it can be concluded that this study has developed and validated an intelligent methodology for optimizing the production process based on the principles of multi-criteria analysis. The proposed approach simultaneously accounts for time, production, and economic indicators, utilizes real production data and machine learning methods, and is capable of adapting to changing production system operating conditions and updating as new data accumulates. The developed methodology can be integrated into a digital smart manufacturing platform and used to improve the efficiency of production process management.

Conclusions

A digital model of the production process at a mechanical engineering enterprise was developed, based on the parameterization of production areas and the use of Big Data technologies. The structure of the machine shop was formalized as a directed graph, taking into account production units, buffers, parts flow routes, and transport links. Mathematical models were developed to estimate throughput, production cycle time, volume of work in progress, and operating costs.

It was established that the key factors influencing surface finish quality are vibration level, feed rate, and wear of the cutting tool. Rational ranges of cutting conditions were determined to reduce surface roughness and improve process stability. Heat maps of equipment utilization were developed to identify bottlenecks in the production system and optimize production load distribution.

The use of multicriteria analysis and the Pareto frontier allowed us to determine the most efficient machining modes based on a combination of technological and economic criteria. The proposed methodology can be used to create digital twins of production processes and implement intelligent control systems in mechanical engineering enterprises.

References

[1] Zharkevich O.M., Nikonova T., Gierz Ł., Reshetnikova O., Berg A., Warguła Ł., Berg A., Wieczorek B., Łykowski W., Nurzhanova O. Improving the Design of a Multi-Gear Pump Switchgear Using CFD Analysis //Applied Sciences (Switzerland), 2024, 14(13), 5394

[2] Nikonova T., Zhetessova G., Yurchenko V., Zharkevich O. The development of the computer-aided design system for production processes of component part machining for single-piece production and repair conditions //Journal of Applied Engineering Science, 2019, 17(4). - P. 599–609. doi:10.5937/jaes17-21470.

[3] Khrustaleva I., Khrustalev M., Brovkina Ya., Khokhlovskiy V., ShkodyrevV. The Model for optimizing cutting parameters for processing products on metal-cutting machines //Cybernetics and Physics, 2024, Vol.13, 2, 111-122.

[4] Vasendina E., Plotnikova I., Levitskaya A., Kvesko S. Detection and defect correction of operating process// IOP Conference Series Materials Science and Engineering, 2016, 110(1), 012070 DOI: 10.1088/1757-899X/110/1/012070

[5] Zhetessova G.S., Zharkevich O.M., Kozhanov M.G., Khrustaleva I.N. Method for Optimizing the Parameters of Mechanical Processing of Holes to Ensure Cutting Tool Stability and Cost-Effective Machining // Material and Mechanical Engineering Technology, №3, 2025. doi.org/10.52209/2706-977X_2025_3_84 mmet.kstu.kz/download/articles/09012026103035_digest.pdf

[6] Zhetessova G., Khrustaleva I., Shkodyrev V., Zharkevich O., Kanatova A., Kozhanov M., Tattimbetova G., Abdugaliyeva G. Model of Optimization of Process Parameters for Machining of Separate Design Elements of the Product // Applied Sciences, 2025, 15(10), 5395 doi.org/10.3390/app15105395 mdpi.com/2076-3417/15/10/5395

[7] Kozinski O., Kotyrba M., Volna, E. Improving the Production Efficiency Based on Algorithmization of the Planning Process //Appl. Syst. Innov., 2023, 6, 77. https://doi.org/ 10.3390/asi6050077

[8] Berg A., Nurzhanova O., Vytautas T., Vitushenko D. Improvement of Base Sets for Complex Configuration Parts when Assessing their Manufacturability within Industry 4.0 //Material and Mechanical Engineering Technology 2024, 2, 25 – 35

[9] Song Z., Luo S. Application of Machine Learning and Data Mining in Manufacturing Industry //International Journal of Computer Science and Information Technology, Volume 2, Number 1, 2024. - P. 426- 435.

[10] Investigation of materials flow during the cold-rolling process by experimental evidence and numerical approaches //Engineering and it solutions, II, 2022. – P. 39 - 51

[11] Optimizing production processes in machine-building enterprises: a case study on microelement rationing and operational excellence // International Journal on Technical and Physical Problems of Engineering, Issue 6, 2 Volume, 17 Number 1, 2025. – P. 261-269

[12] Zhetessova G., Khrustaleva I., Shkodyrev V., Chernykh L., Zharkevich O., Kozhanov M., Buzauova T. Model for Structural and Parametric Optimization of the Mechanical Processing Technology for a Product //Applied Sciences (Switzerland), 2026, 16(8), 3639. doi:10.3390/app16083639

[13] Aizhambaeva S., Zhetessova G., Nikonova T., Vavilova G., Belik M. Modeling arc spraying process for eccentric sleeve of cone crusher gp 500 using computer-aided design // Materials Science Forum, 2019, 970. - P. 343–355. doi: 10.4028/www.scientific.net/MSF.970.343.

[14] Buzauova T., Smagulov A. Selection of Optimal Parameters for a Cutting Tool When it Comes to Machining Shaped Parts Made of Alloy Steel // Material and mechanical engineering technology, Volume 1, 2021. - P.19-44.

[15] Zhetessova G.S., Shkodyrev V.P., Khrustaleva I.N., Zharkevich O.M., Buzauova T.M., Kozhanov M.G., Savelyeva N.A. Development of digital models of the production process based on multi-criteria analysis of BigData management within the framework of technological preparation of production of mechanical engineering enterprises //Monograph. - Karaganda: Glasir, 2026. - 162 p.

Information of the authors

Zhetessova Gulnara Santayevna, d.t.s., professor, Abylkas Saginov Karaganda Technical University
e-mail: zhetesova@mail.ru

Zharkevich Olga Mikhailovna, c.t.s., professor, Abylkas Saginov Karaganda Technical University
e-mail: zharkevich82@mail.ru

Khrustaleva Irina Nikolaevna, c.t.s., docent, Peter the Great St. Petersburg Polytechnic University
e-mail: irina.khrustaleva@mail.ru

Kozhanov Murat Galiaskarovich, m.t.s, Abylkas Saginov Karaganda Technical University
e-mail: spark@mail.ru

Buzauova Toty Meierbekovna, c.t.s., professor, Abylkas Saginov Karaganda Technical University
e-mail: toty_77@mail.ru