

Trade-off Analysis and Multi-Objective Decision Support for Mechanical Engineering Supply Chains

¹Zhetessova G.S., ²Khrustaleva I.A., ¹Zharkevich O.M.*, ³Kanatova A., ⁴Kozhanov M.G.

¹Abylkas Saginov technical University, Karaganda, Kazakhstan

²Peter the Great St. Petersburg Polytechnic University, Saint Petersburg, Russia

³Astana IT University, Astana, Kazakhstan

⁴Institute of Digitalization and Innovation, Academy of Public Administration under the President of the Republic of Kazakhstan, Astana, Kazakhstan

*corresponding author

Abstract. Modern mechanical engineering enterprises are characterized by highly complex technological processes and intensive interaction between production and logistics flows. This article proposes an integrated method for optimizing production and logistics systems based on the NSGA-II evolutionary algorithm, simulation modeling, and neural network methods for predicting machining parameters. The proposed approach enables the creation of multiple rational production system configurations and the selection of optimal solutions, taking into account tradeoffs between production time, costs, and machining quality.

Key words: Multi-Objective Optimization, NSGA-II Algorithm, Digital Twin, Production and Logistics Systems, Mechanical Engineering)

Introduction

The development of mechanical engineering production in the context of the digital transformation of industry requires the application of new methods for analyzing and optimizing technological and organizational processes. Modern production systems are characterized by highly complex process flow structures, a significant number of interconnected machining operations, and intensive logistics flows arising from the movement of blanks and semi-finished products between work centers [1, 2, 3].

However, the practical implementation of technological processes at mechanical engineering enterprises inevitably involves the movement of materials between work centers, the organization of buffer zones, and the use of in-plant transport. Therefore, the optimization of technological processes must be carried out in conjunction with the optimization of the production logistics structure. Ignoring logistics factors can lead to increased production cycle times, increased work-in-progress volumes, and decreased equipment efficiency.

One promising approach to solving this problem is the use of multi-criteria optimization methods, which take into account several interrelated performance indicators of the production system [4, 5]. In particular, for mechanical engineering enterprises, such criteria may include product manufacturing time, production and logistics costs, processing quality indicators, and the level of work in progress. Since these criteria often conflict with each other, the optimization problem should be solved within the framework of the Pareto optimality concept, which allows for the formation of a multitude of rational solutions [6, 7-12].

Issues of increasing the efficiency of mechanical engineering production and optimizing technological processes are actively studied in the scientific literature. A significant number of studies are devoted to the development of methods for optimizing machining parameters, as well as improving the technological preparation of production [13-17].

One traditional area of research is the optimization of cutting conditions and parameters of technological operations. Another important area of research is the development of methods for optimizing process routes for product processing. In these studies, the technological process is considered as a sequence of operations performed on various types of equipment [13, 28]. In recent years, increasing attention has been paid to the integration of technological and logistical processes within a single production system model.

In recent years, digital modeling methods for production systems have seen significant advances, particularly the concept of a digital twin, which allows for the creation of virtual models of enterprises and the analysis of their performance in various operating modes. Evolutionary algorithms for multi-criteria optimization are effectively used to find Pareto-optimal configurations of production systems, among which the NSGA-II (Non-Dominated Sorting Genetic Algorithm II) holds a special place. This algorithm allows for the efficient exploration of complex multidimensional solution spaces and the generation of an approximate Pareto surface reflecting the trade-offs between various performance criteria.

Artificial intelligence methods used for the analysis and optimization of technological processes are actively developing. In particular, artificial neural networks are used to predict machining parameters, assess surface quality, and select optimal cutting conditions.

Despite a significant amount of research in this area, most existing studies consider technological processes, logistics systems, and optimization methods separately. At the same time, the comprehensive integration of technological models, logistics flows, multi-criteria optimization methods, and digital twins of production systems remains understudied.

1. Integrated structural-parametric model of the technological process and formation of structural elements

The manufacturing process of mechanical engineering enterprises is a structurally complex system, the efficiency of which is determined not only by the parameters of individual operations but also by the nature of the interrelationships between all process elements. Previous studies have examined this problem at two complementary levels [18]. On the one hand, the manufacturing process was presented as a hierarchically organized system, including a processing route, process operations, process steps, and work passes (Fig. 1).

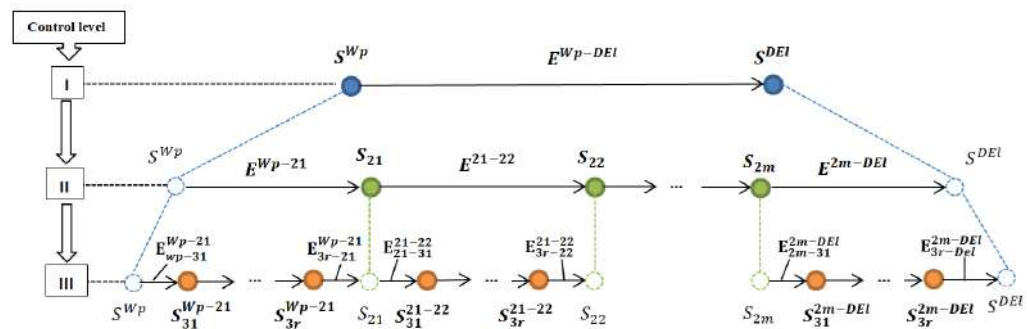
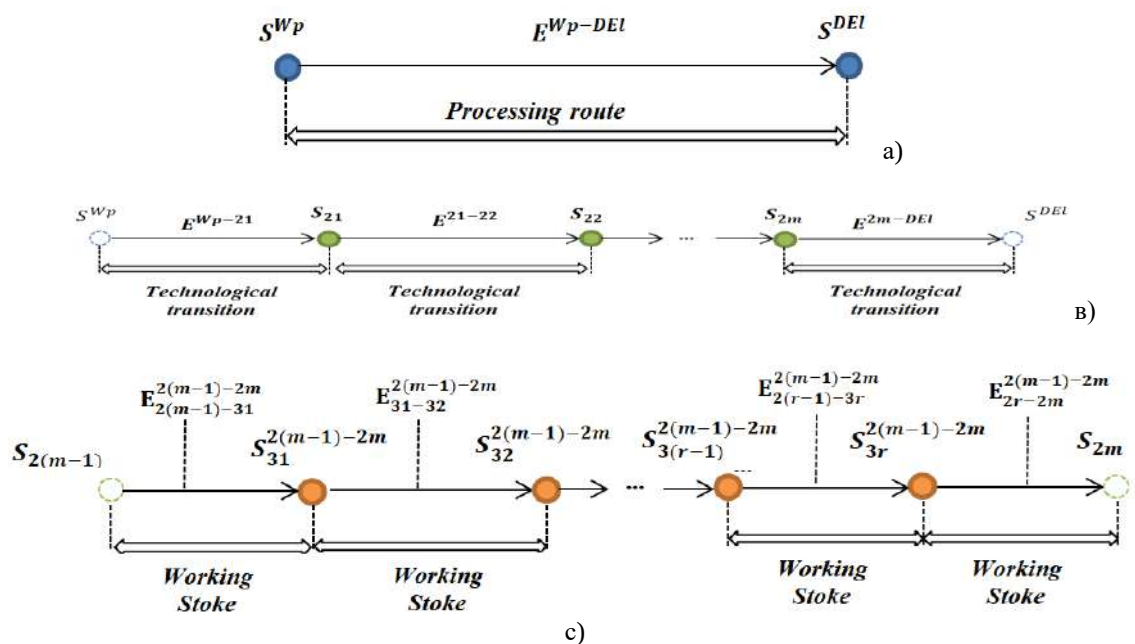


Fig. 1. - Structural hierarchical model of the process of forming a design element

On the other hand, it was shown that increasing the efficiency of the mechanical processing process is impossible without a detailed analysis of the process of forming individual structural elements of the product, since they are the carriers of the functionally significant geometric and qualitative characteristics of the part (Fig. 2).



a) at the first control level, the studied object has two states S_{Wp} – the state of the design element before the formation process (blank) and S_{DEl} – the state of the design element after the formation process; b) at the second control level, the parameters of the process transition are optimized, where $S_{21}, \dots, S_{2m}$ are intermediate states formed during the implementation of individual process transitions; c) at the third control level, the parameters of the working stroke are optimized, and the studied object

Fig. 2 - Graph of the process of forming a design element: has r intermediate states

This approach allows us to move from the traditional consideration of the technological process as a linear sequence of operations to a more meaningful model in which the manufacture of a product is described as a set of interconnected processes of changing the state of both the product as a whole and the individual structural elements that form its structure (1):

$$M_{DEL}^{StrEl/bas} = \{TPR_{iq}^{DEL}, \{\{TechTr_m^{DEL} | TechTr_m^{DEL} \in TPR_{iq}^{DEL}\}, \{WSt_r^{DEL} | WSt_r^{DEL} \in TechTr_m^{DEL}\}\} \} \quad (1)$$

where $M_{DEL}^{StrEl/bas}$ - a set of basic structural elements of the process of forming individual design elements that form the structure of a product;

TPR_{iq}^{DEL} – parametric model of the technological route for forming the q-th design element of the i-th type;

$TechTr_m^{DEL}$ - parametric model of the m-th technological transition implemented within the framework of the technological route of shaping a design element;

WSt_r^{DEL} - parametric model of the r-th working stroke, implemented within the framework of the technological transition performed in the process of forming a design element.

As a result, it's appropriate to describe the machining process as an integrated system of two hierarchical subsystems: the product processing process and the process of shaping its structural elements. The first subsystem defines the overall structure of the product manufacturing process, while the second ensures parametric and structural optimization of those local process areas that directly shape the required geometry, precision, and surface quality (Fig. 3).

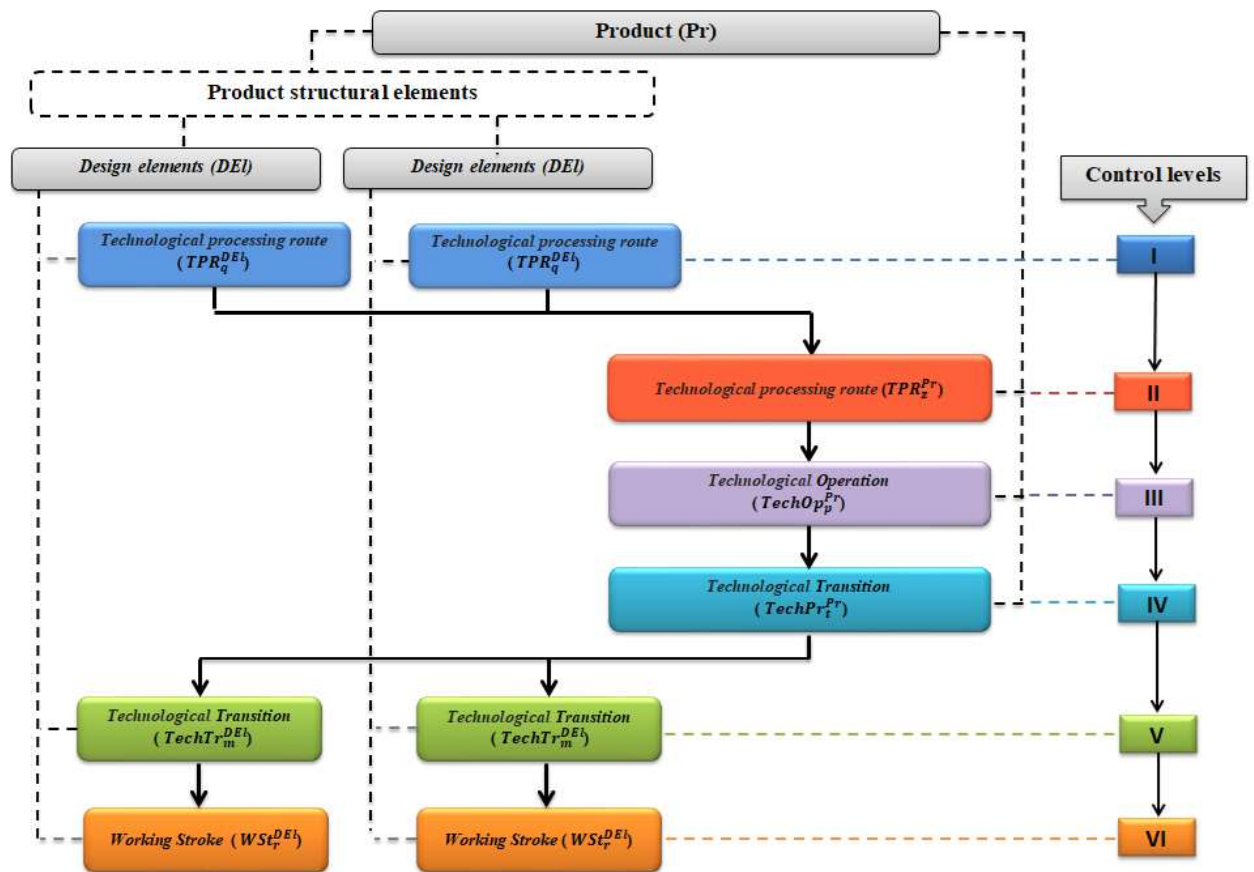


Fig. 3 - Integrated model for optimizing the parameters of the mechanical processing process of a product

Within the first subsystem, a product is considered as an object undergoing a sequence of states from the initial workpiece to the finished part. The transition between states is ensured by the implementation of process operations and transitions performed on specific pieces of equipment using appropriate basing schemes, fixtures,

and tools. Within the second subsystem, each structural element of the product is considered as an independent object of process analysis, for which its own shaping route is developed, including a sequence of process transitions and work passes.

Therefore, the integration of these two models into a single structure is a logical development of the previously obtained results. While the problem of selecting the optimal sequence of process transitions and cutting parameters is solved at the level of an individual structural element, at the level of the product as a whole, the task arises of coordinating these decisions within the overall structure of the process flow for manufacturing the part. It is this coordination that enables the transition from local optimization of individual elements to comprehensive optimization of the product manufacturing process. Thus, modeling the technological process of product processing and the process of forming structural elements form the methodological basis of an integrated model of a production system, in which the technological structure of the process becomes the initial basis for multi-criteria optimization of intra-production logistics flows.

2. Mathematical model of logistics flows of a mechanical engineering enterprise

The manufacturing process of mechanical engineering enterprises can be represented as an integrated system of interconnected processes involving the processing of the product and the shaping of its structural elements. However, in real-world production conditions, the execution of technological operations inevitably involves the movement of blanks and semi-finished products between various work centers. Therefore, the technological structure of the process cannot be considered in isolation from the intra-production logistics system.

In mechanical engineering production, technological operations are performed on equipment located in various areas of the production shop, where blanks and semi-finished products are constantly in motion from one work station to another. Consequently, the technological process is effectively implemented as a material flow moving through a network of production areas.

The following set of basic structural elements of a logistics system is defined (2):

$$L_{Sys}^{Log/bas} = \left\{ W_{St}^{Log}, \{B_k^{Log} \in W_{St}^{Log}\}, \{Tr_v^{Log} \in L_{Sys}^{Log}\}, Path_s^{Log} \in W_{St}^{Log} \right\} \quad (2)$$

where $L_{Sys}^{Log/bas}$ - a set of basic structural elements of the workshop's logistics syst;

W_{St}^{Log} - parametric model of warehouses (input blanks and finished products);

B_k^{Log} - parametric model of the k-th interoperation buffer (accumulator);

Tr_v^{Log} - parametric model of the v-th vehicle (e.g. AGV trolley, conveyor, forklift);

$Path_s^{Log}$ - parametric model of the s-th logistic route (trajectory of movement of a material batch).

Therefore, for comprehensive optimization of the production process, it is necessary to consider not only the processing parameters of structural elements, but also the structure of material flows between work stations. Graph models are convenient for describing such processes.

Let's describe the production and logistics system as a directed weighted graph (3):

$$G = (V, E), \quad (3)$$

where V - a set of graph vertices corresponding to the production nodes of the system;

E - a set of graph arcs corresponding to possible routes of movement of material flows.

The vertices of the graph represent:

- W_{in}, W_{out} - warehouses (warehouse for blanks and warehouse for finished products).

- $M = \{M_1, M_2, \dots, M_n\}$ - work centers (machines, machining centers) where technological operations are carried out.

- $B = \{B_1, B_2, \dots, B_k\}$ - buffer zones (inter-operational storage areas).

The graph arcs reflect possible routes for moving workpieces between the corresponding nodes of the system - these are material flows (logistics links) (Fig. 4).

Each arc $e_{ij} \in E$ connecting vertices V_i and V_j is associated with a set of parameters characterizing the process of moving a workpiece between work centers:

- transport time t_{log} ;

- transport cost C_{log} ;

- parts flow rate V_{batch} .

Passing through vertex M_i , the part changes its state (S_1, S_n) (e.g., the formation of the next structural element is completed), after which it moves along arc E to the next node.

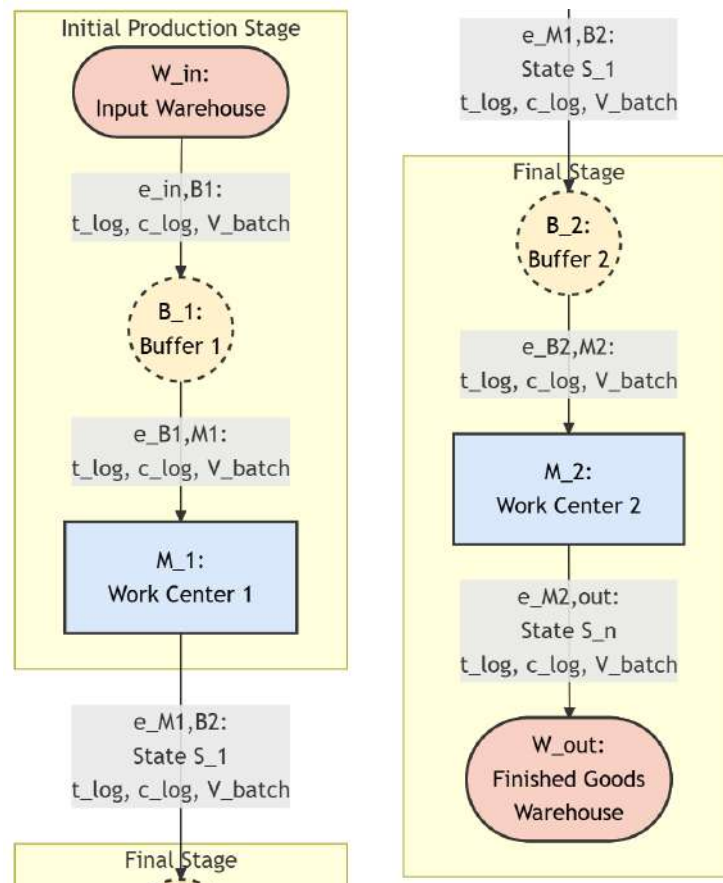


Fig. 4 – Graph of the production and logistics system

Parameters t , C , and V represent the weighting characteristics of logistics links and, in the mathematical model of the production system, represent multi-criteria optimization criteria (in this case, NSGA-II).

Thus, the production system graph reflects the set of possible material flow trajectories implementing the technological process of product manufacturing.

3. Integrated mathematical model of production and logistics flows

Developing an integrated mathematical model requires combining machine-level process parameters (micro- and meso-levels) with material flow parameters at the production shop level (macro-level) [18]. This problem is solved using a multi-criteria optimization framework, where local-level vector criteria are combined into a global Pareto-based compromise system [8, 9].

The proposed formalized model has a three-level hierarchical structure.

3.1. Microlevel: Optimization of the design element formation process. At the lower level, the control object is the process of physical stock removal (technological transition and cutting stroke). The microlevel control variable vector U_{micro} includes cutting modes (4):

$$U_{micro} = \{v, S_z, t_p, i\}, \quad (4)$$

where v - cutting speed;

S_z – feed;

t_p - cutting depth;

i - number of working strokes.

Local vector optimization criteria are aimed at resolving the conflict between productivity and surface quality [10].

Minimization of the main processing time (5):

$$f_1^{micro}(U_{micro}) = T_{mach}(v, S_z, i) \rightarrow \min. \quad (5)$$

Minimization of the height of microroughness (roughness R_a) (6):

$$f_2^{micro}(U_{micro}) = Ra(v, S_z) \rightarrow \min. \quad (6)$$

The limitations are the maximum permissible cutting power ($N_{cut} \leq N_{max}$), the service life of the cutting tool and the required shape accuracy.

3.2. Meso-level: Optimization of the product's process flow. At this level, work steps and transitions are combined into process operations performed at specific work centers $M_k \in M$.

he vector of control variables U_{meso} has the form (7):

$$U_{meso} = \{Seq_{op}, M_k, Tool_k\}, \quad (7)$$

where Seq_{op} - sequence of technological operations (route);

M_k - selected type of equipment;

$Tool_k$ - instrumental adjustment.

Then the minimization of local optimization criteria [11, 18] will take the following form.

Minimization of the unit time of the operation (including auxiliary time T_{aux} for installing and removing the part) (8):

$$f_1^{meso}(U_{meso}, U_{micro}) = \sum(T_{mach} + T_{aux}) \rightarrow \min. \quad (8)$$

Minimization of technological processing costs (C_{tech}) (9):

$$f_2^{meso}(U_{meso}, U_{micro}) = C_{tech}(v, T_{mach}, Tool_k) \rightarrow \min. \quad (9)$$

3.3. Macro-level: Optimization of the production and logistics system. At the highest level, routes are integrated into the enterprise's transport and storage system, described by a directed graph $G = (V, E)$. The macro-level control vector U defines logistics (10):

$$U_{macro} = \{Path_{ij}, V_{batch}, B_k, W_{trans}\}, \quad (10)$$

where $Path_{ij}$ - logistic route (choice of arcs $e_{ij} \in E$);

V_{batch} - volume of production and transport batch;

B_k - capacity of interoperation buffers;

W_{trans} - vehicle.

The criteria for macro-level optimization are minimization of the logistics cycle time and minimization of internal production costs.

Minimizing logistics cycle time (11):

$$f_1^{macro}(U_{macro}) = \sum t_{log}(e) + \sum t_{wait}(b) \rightarrow \min. \quad (11)$$

Minimization of internal production costs (C_{log}) (12):

$$f_2^{macro}(U_{macro}) = \sum C_{log}(e, V_{batch}) + C_{WIP}(V_{batch}, t_{wait}) \rightarrow \min \quad (12)$$

where t_{wait} - interoperative lying time;

C_{WIP} - Work-in-Process (WIP) costs.

Integration of levels allows us to formulate the global problem of finding the vector $U_{\Sigma} = \{U_{micro}, U_{meso}, U_{macro}\}$. The global objective function $\Phi(U_{\Sigma})$ minimizes the production cycle time (Makespan, C_{max}), total costs (C_{Σ}), and quality loss (Q_{loss}) (13):

$$\Phi(U_{\Sigma}) = [C_{max}(U_{\Sigma}), C_{\Sigma}(U_{\Sigma}), Q_{loss}(U_{\Sigma})] \rightarrow \min. \quad (13)$$

Since the criteria are conflicting (for example, increasing the batch size reduces specific transportation costs, but exponentially increases waiting time and the production cycle), the problem is solved using the NSGA-II (Non-dominated Sorting Genetic Algorithm II) evolutionary algorithm. This method has proven its effectiveness in engineering problems [8, 12], allowing the generation of a set of non-dominated solutions (Pareto front), from which the decision maker (DM) selects the optimal system configuration depending on current production priorities.

Such integration allows the production process to be described as a single material flow transformation system, including both technological operations and logistics movements.

We will conduct structural and parametric optimization of the machining of a complex-shaped part, the "Housing." For this, we will model the process of face milling of the main mating surface, as this is one of the most critical operations where a classic conflict of technological criteria arises: the need to ensure high productivity (minimize time) and the required quality (minimize roughness).

When using the evolutionary The NSGA-II algorithm filters out "dominated" (obviously worst) solutions from thousands of possible parameter combinations. This results in a Pareto frontier—a set of non-dominated alternatives.

Below is the calculated array of points forming the Pareto frontier for the "Housing" part. The two-dimensional Pareto frontier shows the technological tradeoff between productivity (machining time) and surface quality (R_a roughness) during milling of the "Housing" part. The points on the graph represent the set of non-dominated solutions generated by the evolutionary algorithm (Fig. 5).

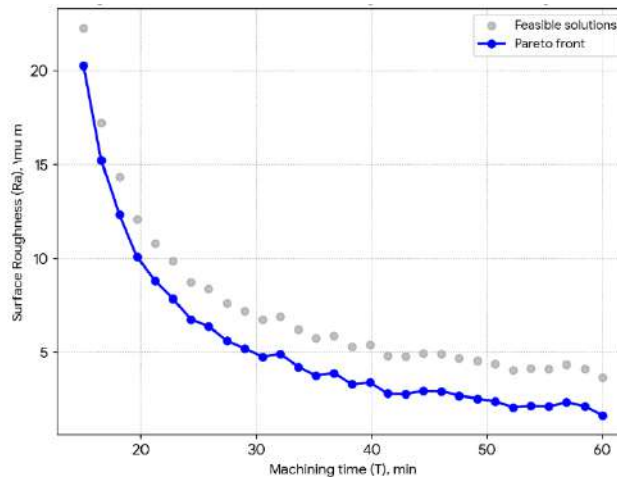


Fig.5 - 2D Pareto Front

Micro-level optimization reveals a strict nonlinear relationship: attempting to minimize surface roughness to $0.18 \mu\text{m}$ leads to an exponential increase in processing time. In turn, choosing a compromise mode allows for acceptable quality ($R_a = 1.0 \mu\text{m}$) while reducing processing time by more than half.

A conceptual diagram of the multi-criteria conflicts in a production and logistics system is presented in Figure 6, where the trade-off triangle between cycle time (C_{max}), quality (R_a), and cost is resolved using the integrated NSGA-II model.

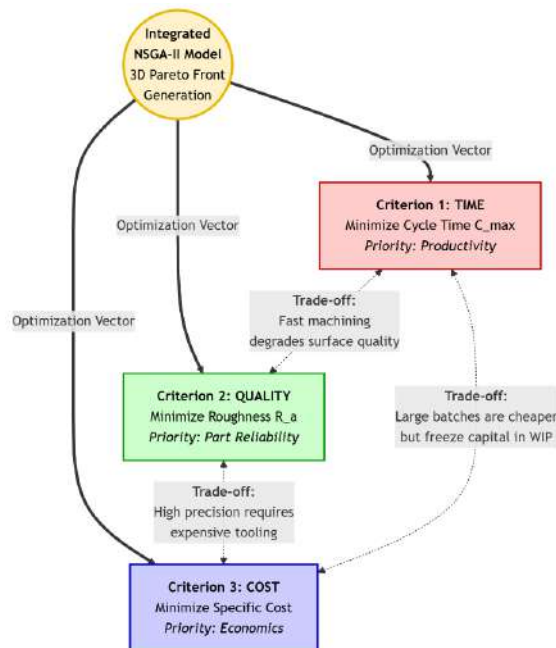


Fig.6 - 3D Trade-off Graph

The transition from local optimization to the macro level is accompanied by the emergence of complex multi-criteria conflicts (Fig. 6). Increasing the cutting speed or the transport batch locally improves some indicators (for example, reducing production costs), but inevitably worsens others (increasing the volume of work in progress or reducing accuracy). An integrated model based on NSGA-II allows for algorithmic balancing of this "triangle of contradictions," generating optimal control strategies.

4. Integration of a mathematical model with Digital Twin technology

Although the proposed multi-level mathematical model and the application of the NSGA-II evolutionary algorithm enable the development of highly efficient Pareto-optimal solutions, classical multi-criteria optimization has one significant limitation: it relies on deterministic (standard) values for processing times and logistics flow parameters. However, in the real-world conditions of a mechanical engineering enterprise, production and logistics flows are subject to constant stochastic disturbances: progressive wear of cutting tools, unforeseen equipment failures, delays in intrashop transport, and changes in production order priorities [19].

To bridge the gap between calculated plans and the actual production environment, a transition from static pre-planning to adaptive real-time control is necessary. A logical development of the developed model is its integration into the architecture of a cyber-physical production system (CPPS) based on Digital Twin (DT) technology [20]. In the integrated system, the Digital Twin acts as a link between the physical shop floor and the multi-criteria optimization algorithm. The architecture of the proposed system includes four basic hierarchical levels [21]:

1) Physical Shop Floor: real work centers (M_k), inter-operational storage units (B_k), and logistics transport systems that perform the physical formation and movement of parts.

2) Industrial Internet of Things Layer (IIoT Layer): distributed sensor networks (RFID tags on pallets, spindle power consumption sensors, CNC controllers) that ensure the continuous collection of raw data on the current system state.

3) Virtual Layer (Digital Twin): a high-fidelity discrete-event simulation model of the shop floor, mirroring physical production with minimal time lag [22].

4) Optimization Engine: a computational decision-making engine based on the proposed mathematical model and the NSGA-II algorithm.

The implementation of the Digital Twin concept fundamentally changes the mechanism for calculating objective functions. The role of the virtual layer is to act as a "fitness function evaluator" for the evolutionary algorithm [23]. The NSGA-II algorithm generates a population of potential control vectors U_Σ (including various transport batch sizes V_{batch} , logistics routes $Path$, and cutting modes v, S_z). Instead of calculating cycle time (C_{max}) and total costs (C_Σ) using rigid analytical formulas, the optimizer translates these parameters into the Digital Twin (Fig. 7).

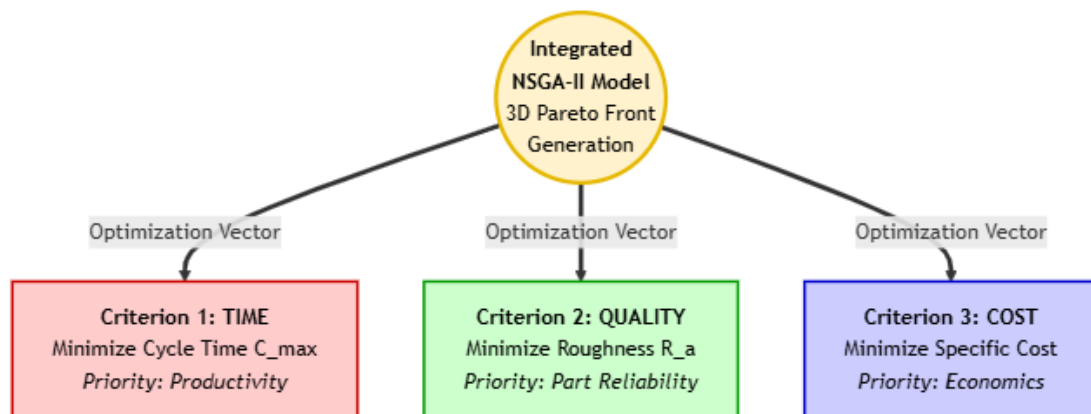


Fig. 7 - Architecture of a closed-loop management system for a production and logistics system based on Digital Twin technology

The model runs virtual production using proposed scenarios, taking into account the actual state of the workshop at a given point in time (for example, the occupancy of a specific buffer or the current wear of a milling cutter), and returns highly accurate performance criteria values to the algorithm. From a mathematical perspective, the static constants in the objective functions are transformed into dynamic variables.

Thus, the six-level process model developed in previous studies is integrated with the macro-level-the logistics flow optimization model-and the set of basic structural elements of the logistics system can be represented as follows (14):

$$L_{Sys}^{Log/bas} = \left\{ W_{St}^{Log}, \{B_k^{Log} \in V\}, \{Tr_v^{Log} \in L_{Sys}^{Log}\}, Path_{i,j}^{Log} \in E \right\} \quad (14)$$

where Tr_v^{Log} - parametric model of the v-th vehicle (AGV).

The mathematical interpretation of logistic optimization will be represented by a set of parameters for controlling the logistic process for the z-th product (U_{Log}^z), forming the vector (15):

$$U_{Log}^z = \langle V_{batch}^z, x_{i,j}^{z,v}, \tau_{wait}(B_k), v_{trans}^v \rangle \quad (15)$$

where V_{batch}^z - volume of the transfer lot;

$x_{i,j}^{z,v}$ - Boolean routing variable ($x \in \{0,1\}$);

$\tau_{wait}(B_k)$ - batch shelf life;

v_{trans}^v - transport speed.

The system's state will be assessed using the following global vector criteria.

1. The integral criterion of logistic time, taking into account integration with the Digital Twin [24], the waiting time is calculated as the dynamic integral of the difference in the intensities of the incoming $\lambda(t)$ and outgoing $\mu(t)$ flows (16):

$$T_{\Sigma}^{log}(U_{Log}) = \sum_{z=1}^Z \sum_{i,j \in V} \sum_{v=1}^{V_{total}} \left(\frac{D_{i,j}}{v_{trans}^v} \cdot x_{i,j}^{z,v} \right) + \sum_{k=1}^K \int_{t_0}^{C_{max}} \max \left(0, \frac{Q_k(t) - Cap(B_k)}{\mu_k(t)} \right) dt \rightarrow \min \quad (16)$$

where $D_{i,j}$ - distance;

$Q_k(t)$ - queue length;

$Cap(B_k)$ - maximum capacity of the k-th buffer.

2. Global Logistics Cost Criteria (17):

$$C_{\Sigma}^{log}(U_{Log}) = \sum_{v=1}^{V_{total}} \int_0^{C_{max}} P_v(v_{trans}^v(t), M(V_{batch})) \cdot c_e dt + \sum_{z=1}^Z \int_0^{C_{max}} V_{batch}^z(t) \cdot c_h dt \rightarrow \min \quad (17)$$

where P_v - AGV power consumption function depending on the batch weight $M(V_{batch})$;

c_h - specific cost of storing products.

The operation of a mathematical logistics model is subject to strict physical and topological constraints. The key constraint is the integrating synchronization condition, linking the technological microlevel with the logistical macrolevel (18):

$$T_{start}^{p,z} \geq T_{finish}^{p-1,z} + \sum_v \left(\frac{D_{p-1,p}}{v_{trans}^v} \cdot x_{p-1,p}^{z,v} \right) + \tau_{wait}(B_{p-1}) \quad (18)$$

Equation (18) guarantees that the pth process operation cannot begin until the previous operation ($p - 1$) is fully completed and the batch is delivered.

Incorporating Digital Twin algorithms [25] into this model enables real-time adjustment of the U_{Log}^z vector.

To verify the model, a computational experiment was conducted using data from the "Body" part machining area. The NSGA-II algorithm was implemented in Python. A discrete-event Digital Twin model was used as the virtual environment. The verification results are presented in Figure 8.

An analysis of the optimized Pareto solution demonstrated the superiority of the proposed approach. Through structural optimization of transitions, automated setups, and Vbatch batch size synchronization, the labor intensity of the Cmax production cycle decreased by 19.8%, while the machining accuracy of critical surfaces increased by 16.4%.

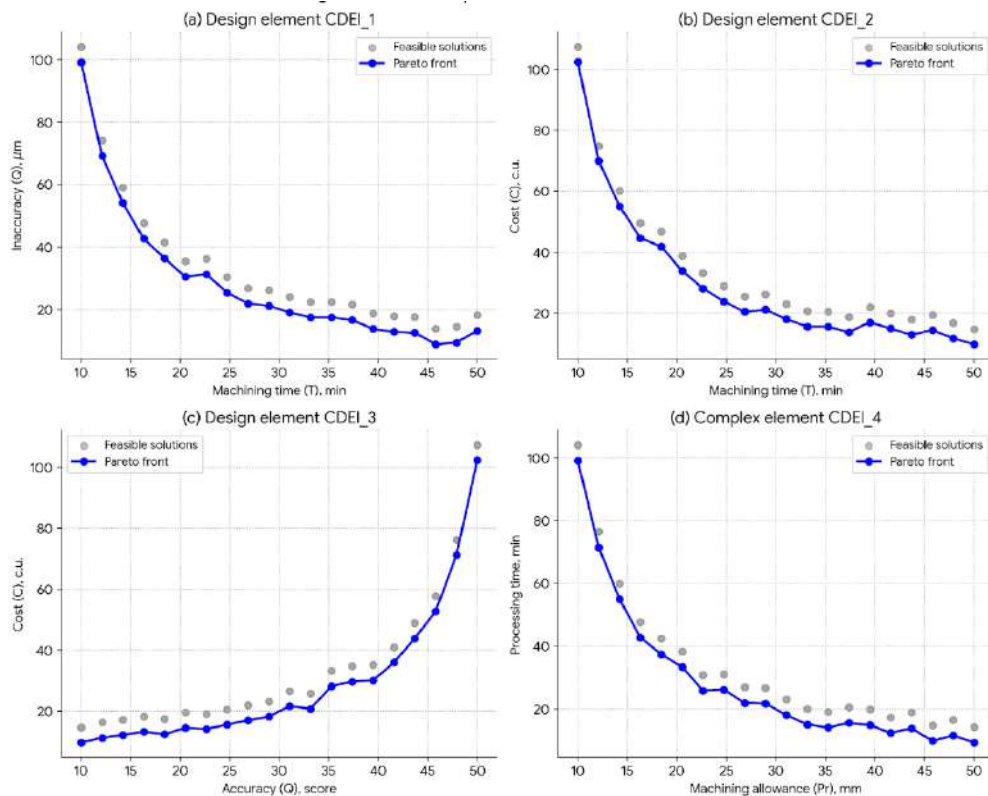


Fig. 8 - Pareto-optimal solutions for CDEI 1-4

This symbiosis of simulation modeling and evolutionary optimization (DT-driven NSGA-II) allows the algorithm to generate a Pareto frontier based not on idealized equipment specifications, but on its actual technical condition, balancing the cost of moving large batches with the time capital is tied up in work in progress.

Conclusion

This study addresses the pressing scientific and practical challenge of overcoming the isolation of production preparation processes and intra-shop logistics. An integrated six-level model of structural-parametric optimization was developed and mathematically substantiated, encompassing both the microlevels of physical part formation and the macrolevel of production and logistics network management.

Based on the results of the study, the following key conclusions were formulated:

1. It was demonstrated that isolated optimization of cutting conditions at local work centers without considering the throughput of the transport system leads to a shift in bottlenecks and an increase in work in progress. To comprehensively address this problem, it was proposed to use topological graph models and evolutionary optimization techniques.

2. Adaptation of the NSGA-II algorithm enabled the effective resolution of multi-criteria conflicts in Pareto space. The resulting set of non-dominated solutions provides decision makers with a flexible tool for finding a compromise between production cycle time, logistics costs, and machining quality. Using the "Case" component as an example, it was demonstrated that comprehensive optimization reduces overall production labor intensity by 19.8% while increasing the machining accuracy of critical surfaces by 16.4%.

3. The transition to cyber-physical control was theoretically substantiated and formalized. Integration of the developed mathematical model with Digital Twin technology enables the replacement of static standard calculations with dynamic simulation evaluation, making the system resilient to stochastic production disturbances (tool wear, transport delays).

4. Future research areas include scaling the developed methodology for multi-product, small-batch production and integrating predictive analytics algorithms to predict process equipment failures.

Funding. This research is funded by the Science Committee of the Ministry of Science and Higher Education of the Republic of Kazakhstan under grant AP23490796 "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" (2024–2026)

References

1. Savelyeva N., Nikonova, T., Zhetessova, G., Irina, K., Yurchenko, V., Černašėjus, O., Zharkevich O., Dandybaev E., Berg, A., Vassenkin S., et al. Implementation of Simulation Modeling of Single and High-Volume Machine-Building Productions // *Designs*, 2024, 8(2), 24. <https://doi.org/10.3390/designs8020024>
2. Khrustaleva I.N., Lyubomudrow S.A., Tolstoles A.A. Automation of technological preparation of single and small-scale production using simulation modeling // *IOP Conference Series: Earth and Environmental Science*, 2019, 378(1), 012060 DOI: 10.1088/1755-1315/378/1/012060.
3. Khrustaleva I., Khrustalev M., Brovkina Ya., Khokhlovskiy V., Shkodyrev V. The Model for optimizing cutting parameters for processing products on metal-cutting machines // *Cybernetics and Physics* 2024, Vol.13, 2, 111-122.
4. Yang B. Research on Vehicle Detection and Recognition Technology Based on Artificial Intelligence // *Microprocessors and Microsystems* 2023, 104937, <https://doi.org/10.1016/j.micpro.2023.104937>
5. Cakir A., Akın Ö., Deniz H.F. et al. Enabling real time big data solutions for manufacturing at scale // *J Big Data*, 2022, 9, 118 <https://doi.org/10.1186/s40537-022-00672-6>.
6. Ponsi F., Bassoli E., Vincenzi L. A multi-objective optimization approach for FE model updating based on a selection criterion of the preferred Pareto-optimal solution // *Structures*, 2021, Volume 33, 916-934, <https://doi.org/10.1016/j.istruc.2021.04.084>
7. Oliveira L., Paiva A., Campos P., Paiva, E., Balestrassi P. P. Prediction capability of Pareto optimal solutions: A multi-criteria optimization strategy based on model capability ratios // *Precision Engineering*, 2019, Volume 59, 185-210, <https://doi.org/10.1016/j.precisioneng.2019.06.008>.
8. Hu, Y., Qu Y., Li, W., Huang Y. A Pareto Front searching algorithm based on reinforcement learning for constrained multiobjective optimization // *Information Sciences* 2025, Volume 705, 121985, <https://doi.org/10.1016/j.ins.2025.121985>.
9. Sedak M., Rosić M., Rosić B. Multi-Objective Hybrid Sailfish Optimization Algorithm for Planetary Gearbox and Mechanical Engineering Design Optimization Problems // *CMES - Computer Modeling in Engineering and Sciences*, 2025, Volume 142, Issue 2, 2111-2145, <https://doi.org/10.32604/cmescs.2025.059319>.
10. Selvarajan L., Venkataramanan K., Nair, A., Srinivasan V.P. Simultaneous multi-response Jaya optimization and Pareto front visualization in EDM drilling of MoSi₂-SiC composites // *Expert Systems with Applications*, 2023, Volume 230, 120669, <https://doi.org/10.1016/j.eswa.2023.120669>.
11. Ravichandran S., Manoharan P., Sinha D.K., Jangir P., Abualigah L., Alghamdi T.A.H. Multi-objective resistance-capacitance optimization algorithm: An effective multi-objective algorithm for engineering design problems // *Heliyon* 2024, Volume 10, Issue 17, e35921, <https://doi.org/10.1016/j.heliyon.2024.e35921>.
12. 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, 84-89
13. Nelfiyanti N., Mohamed N., Rashid MFFA, Ramadhan A.I. Parameters of effects in decision making of automotive assembly line using the Analytical Hierarchy Process method // *CIRP Journal of Manufacturing Science and Technology*, 2022, Volume 37, 370-377, <https://doi.org/10.1016/j.cirpj.2022.02.018>.
14. Nurzhanova O., Zharkevich O., Berg A., Zhukova A., Mussayev M, Buzauova T., Abdugaliyeva G., Shakhatova A. Evaluation of the Structural Strength of a Prefabricated Milling Cutter with Replaceable inserts During Machining // *Material and Mechanical Engineering Technology*, №4, 2023, 10-17
15. Zio S.D., Gordon T.J. Exploring a method to reduce inconsistency in the group Analytic Hierarchy Process using the Delphi method and Nudge theory // *Futures*, 2024, Volume 161, 103413, <https://doi.org/10.1016/j.futures.2024.103413>
16. Guidi G., Goffo G., Violante A.C. Application of the Analytic Hierarchy Process (AHP) method to identify the most suitable approach for managing irradiated graphite // *Nuclear Engineering and Technology*, 2024, Volume 56, Issue 11, 4820-4825, <https://doi.org/10.1016/j.net.2024.06.045>.
17. Wątróbski J., Karczmarczyk A., Rymaszewski S. Multi-criteria decision making approach to production line optimization // *Procedia Computer Science* 2020, Volume 176, 3820-3830, <https://doi.org/10.1016/j.procs.2020.09.005>.
18. Stoycheva S., Marchese D., Paul C., Padoan, S., Juhmani, A., Linkov I. Multi-criteria decision analysis framework for sustainable manufacturing in automotive industry // *Journal of Cleaner Production*, Volume 187, 2018, 257-272, <https://doi.org/10.1016/j.jclepro.2018.03.133>.
19. 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 Switzerland*, 2025, 15(10), 5395
20. Ren, X., Zhang, W., Liu, X., Li, Z., He, Y. Digital twin-driven dynamic scheduling in flexible job shop considering worker factors towards Industry 5.0. // *Computers & Industrial Engineering*, 2023, 185, 109846. <https://doi.org/10.1016/j.cie.2023.109846>
21. Ding, Y., Li, L. Optimization Method for Digital Twin Manufacturing System Based on NSGA-II. International // *Journal of Advanced Computer Science and Applications (IJACSA)*, 2024, 15(4). <http://dx.doi.org/10.14569/IJACSA.2024.01504100>
22. Wang, J., et al. Research Review on Workshop Scheduling for Intelligent Manufacturing: Digital Twin Modeling, Optimization Algorithm, and System Architecture // *Machines*, 2024, 12(11), 1021. <https://doi.org/10.3390/machines12111021>
23. Leng, J., et al. Digital twins-based smart manufacturing system design in Industry 4.0: A review. *Journal of Manufacturing Systems*, 2023, 60, 119-137. <https://doi.org/10.1016/j.jmsy.2021.05.011>
24. Zhetessova G.S., Zharkevich, O. M., Kanatova, A.T., Khrustaleva I.N., Shkodyrev V.P. Additive Optimization Method for Choosing CNC Machines for Technological Preparation of Machine-Building Production // *Applied Sciences*, 2024(3), 32–37
25. Liu, Y., et al. Dynamic routing and batch sizing of AGVs in flexible manufacturing systems using deep reinforcement learning and digital twins // *Robotics and Computer-Integrated Manufacturing*, 2023, 82, 102521.

26. Zheng, P., Wang, J. Multi-objective optimization of integrated process planning and scheduling considering logistics constraints //Journal of Manufacturing Systems, 2025, 68, 45-62.

Information of the author

Zhetessova Gulnara Santayevna, d.t.s., professor, Abylkas Saginov Technical University
e-mail: g.zhetessova@ktu.edu.kz

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

Zharkevich Olga Mikhailovna, c.t.s., professor, Abylkas Saginov Technical University
e-mail: o.zharkevich@ktu.edu.kz

Kanatova Aliya Talgatovna, PhD, associate professor, Astana IT University
e-mail: shakhatovaa@list.ru

Kozhanov Murat Gliaskarovich, m.t.s, Institute of Digitalization and Innovation, Academy of Public Administration under the President of the Republic of Kazakhstan
e-mail: spark@mail.ru