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PREDICATE-BASED MODELLING OF TECHNOLOGICAL PREPARATION PROCESSES AND LOGISTICS OPTIMIZATION

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Abstract

In the context of the digitalization of mechanical engineering production, ensuring consistency between technological preparation of production (TPP) and operational logistics has become a critical task. This paper presents an intelligent Digital Twin architecture that addresses the semantic gap between process planning and shop-floor scheduling. The methodology employs a predicate logic apparatus to formalize technological constraints and constructive-technological elements at the level of mathematical operation description. This mathematical model serves as a "technological filter," limiting the search space for the NSGA-II multi-criteria optimization algorithm and preventing the generation of technologically infeasible production routes. The proposed approach ensures the physical feasibility of production plans while simultaneously optimizing production cycles. This research demonstrates that the synthesis of fundamental predicate-based modelling with modern optimization methods is a necessary condition for creating autonomous manufacturing systems within the Industry 5.0 paradigm.

Keywords: predicate modelling; production optimization; manufacturing logistics; digital twin; CAPP.

1. Introduction

The digitalization of manufacturing has become one of the key drivers for improving industrial competitiveness within the Industry 5.0 paradigm, which is based on the integration of digital technologies, artificial intelligence, and intelligent decision-support systems [1], [2]. Modern manufacturing systems are characterized by increasingly complex technological routes, numerous interconnected machining operations, and intensive material flows associated with the movement of workpieces and semi-finished products between workstations and production resources [3], [4]. Under these conditions, decisions made during process planning determine the structure of technological routes, equipment utilization, production lead time, work-in-progress inventory, and overall manufacturing cost.

In recent years, significant advances have been achieved in the development of Digital Twins, big data analytics, Knowledge Graphs, and knowledge-based process planning systems, providing new opportunities for production monitoring, integration of technological information, and intelligent decision support [5], [6], [7], [8], [9], [10], [11]. Nevertheless, the practical implementation of manufacturing processes still requires effective coordination between

technological routes, available production resources, and intralogistics constraints. As emphasized by Kusiak [12], the efficiency of intelligent manufacturing depends not on the volume of collected data, but on the ability to transform production information into formalized models suitable for automated engineering decision-making.

Multi-objective optimization methods based on Pareto optimality and evolutionary algorithms are widely applied to identify efficient technological routes [13], [14], [15], [16], [17], [18]. However, most existing approaches assume that the set of feasible technological routes has already been generated and satisfies all technological constraints. Consequently, optimization is performed without prior verification of technological feasibility, which may result in manufacturing plans that are optimal with respect to the selected objective functions but cannot be implemented under real production conditions.

The results of our previous research [19] demonstrated that, in high-mix manufacturing environments, the absence of formal verification of technological transitions leads to increased equipment idle time, higher work-in-progress inventory, and lower utilization of production resources. The most common causes include the selection of inappropriate manufacturing resources for specific product features, violations of the required sequence of technological operations, inconsistency between machining conditions and intralogistics constraints, and the lack of a formal mechanism for verifying the feasibility of technological states and transitions.

Therefore, the objective of this paper is to develop a formal method for process planning based on predicate logic, integrating technological constraints with multi-objective optimization of manufacturing and intralogistics processes. Unlike existing approaches, the proposed method verifies the technological feasibility of manufacturing routes before the optimization stage, ensuring that only feasible alternatives are considered during multi-objective optimization. The proposed model can be integrated into a manufacturing Digital Twin as an intelligent decision-support module for generating technologically feasible production plans and improving manufacturing and intralogistics efficiency.

2. Predicate-Based Modelling of Technological Preparation Processes

2.1 Hierarchical Representation of the Technological Process

The manufacturing process in mechanical engineering is a multi-stage engineering task in which the initial product design is progressively transformed into a sequence of manufacturing operations. During process planning, decisions are made regarding machining methods, the composition and sequence of operations, machining steps, manufacturing resources, cutting and auxiliary tools, fixturing schemes, and the allocation of operations to production units.

In conventional process planning, the manufacturing process is primarily represented as a technological route consisting of an ordered sequence of operations and machining steps. As a consequence, conventional route-based representations are insufficient for formal verification of technological feasibility and for generating alternative manufacturing routes prior to optimization [3], [4], [11].

Therefore, the manufacturing process should be considered not as a fixed sequence of operations but as a hierarchically organized system of interconnected objects. The proposed model is based on the structural decomposition of the feature generation process, making it possible to identify alternative manufacturing methods for achieving the required geometry, dimensional accuracy, and surface quality. The model comprises three hierarchical levels describing successive technological states of the workpiece at different stages of the manufacturing process and establishing their relationships with manufacturing resources, including machine tools, cutting tools, setups, and auxiliary equipment. As a result, the manufacturing process is represented as a sequence of technological state transitions from the initial workpiece to the finished product (Fig. 1) [19], [20].

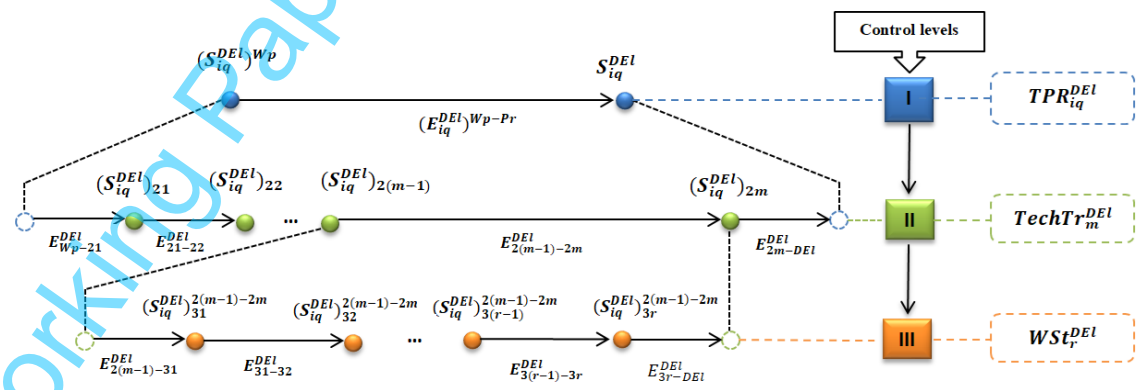

Fig. 1. Hierarchical representation of technological states for a design element

A housing-type part is used as the modeling object in this study. The selected component contains primary and auxiliary planes, holes of various functional purposes (Fig. 2), slots, shoulders, grooves, threaded and fastening features,

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as well as surfaces constrained by positional and geometrical relationships. The geometric complexity and diversity of technological features make the housing-type part a representative benchmark for validating the proposed modeling approach.

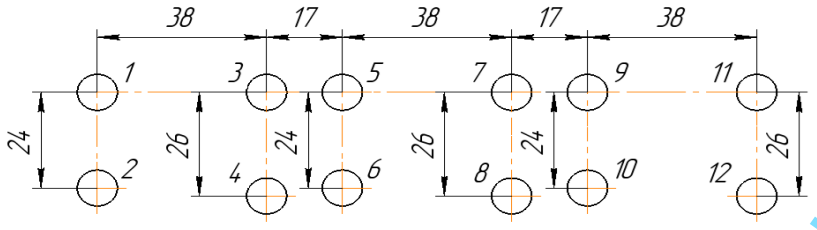

Fig. 2. Geometric parameters of the hole pattern

The machining of these features can be performed using different manufacturing methods, machine tools, and workpiece setup configurations. Consequently, several alternative process plans may be generated for the same part. The proposed technological model is based on the structural decomposition of the housing-type part into manufacturing features representing individual feature-generation tasks.

Such decomposition transforms the product description from a single geometric object into a set of local machining tasks [7], [10], [11]. Each task may have several feasible manufacturing alternatives. For example, a hole can be produced by drilling, enlarging, countersinking, reaming, boring, or a combination of these operations. The selection of a particular machining method depends on the hole dimensions, required dimensional accuracy, surface quality, workpiece material, the availability of a pre-existing hole, and the capabilities of the available manufacturing resources.

At the same time, manufacturing features cannot be considered independently because technological dependencies exist between them. For example, the machining of primary datum surfaces must precede operations in which these surfaces are used as technological references. Therefore, the structural decomposition should represent not only the manufacturing features themselves but also the technological relationships that later form the basis of the predicate model (Fig. 3).

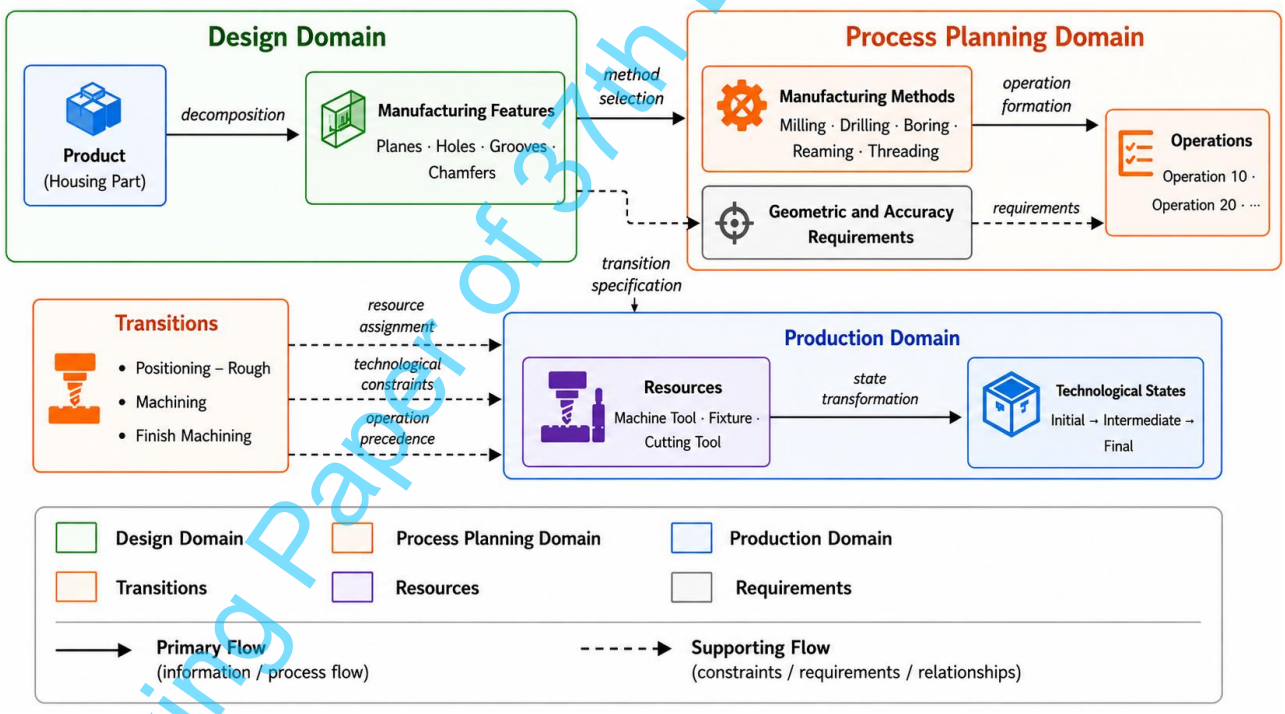

Fig. 3. Hierarchical representation of the technological process and the relationships between design, process planning and production domains

The first level of the hierarchy represents the product as the manufacturing object. The second level consists of manufacturing features that require machining. At the third level, a set of alternative manufacturing solutions is generated for each feature. Consequently, the proposed hierarchical model generates a branching graph of feasible manufacturing routes rather than a single predefined process plan, providing the basis for subsequent predicate filtering and multi-objective optimization (Table 1).

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Hierarchical level	Modelled object	Main technological content
Product level	Housing part	Design requirements and final manufacturing objective
Feature level	Constructive-technological element	Geometry, dimensions, accuracy and surface requirements
Solution level	Alternative technological solution	Possible processing methods and machining strategies
Operation level	Technological operation	Completed part of the process performed at a workplace
Transition level	Technological transition	Elementary technological action changing the workpiece
Resource level	Work centre, tool and fixture	Production resources required for execution
State level	Technological state	Current condition of the workpiece after processing

Table 1. Hierarchical levels of technological process representation

Relationships between the hierarchical levels are directional. Decisions made at higher levels constrain the set of feasible alternatives available at subsequent levels. The hierarchical model decomposes the process planning problem into interconnected levels of detail while preserving the dependencies between them. As a result, alternative manufacturing routes are generated not by arbitrary combinations of operations but by technological relationships between product features, manufacturing methods, and available production resources.

However, the existence of structural relationships alone does not guarantee the feasibility of the generated process plan. Automatic verification of technological feasibility requires a formal description of the properties of manufacturing features and the conditions governing their interactions. To address this issue, the following section introduces a predicate-based representation of technological states and the relationships between them.

2.2 Predicate Description of Technological States

The hierarchical process planning model is based on a formal representation of each technological state, which reflects the set of part characteristics obtained after the execution of a specific technological transition. To ensure that technological states are represented independently of specific manufacturing resources or optimization procedures, a predicate-based representation is proposed. Unlike conventional process planning models, which describe manufacturing processes as predefined sequences of operations, the proposed predicate model focuses on the resulting technological state of the workpiece.

This approach makes it possible to formalize the conditions governing transitions between technological states, verify the feasibility of technological requirements, and employ a unified representation for both the generation of alternative manufacturing routes and their subsequent multi-objective intralogistics optimization.

Each technological state, representing the set of workpiece characteristics established after a particular technological transition and determining the feasibility of subsequent processing, is described by a finite set of predicates. These predicates formally represent product features, achieved dimensional accuracy, surface quality parameters, manufacturing resources, and the fulfilment of the technological constraints required for further processing [21], [22].

Accordingly, a technological state is defined as a finite set of logical predicates (1):

$$S_k = \{P_1, P_2, \dots, P_n\}, \tag{1}$$

where S_k – technological state after the execution of the k-th technological transition;
P_n – predicate describing one property of the technological state.

The complete set of predicates characterizes the current state of the workpiece after the execution of a technological transition and provides the information required for generating the subsequent technological state. According to their functional purpose, the predicates are classified into several groups describing geometric features, dimensional accuracy, surface quality, manufacturing resources, and technological constraints.

Each technological transition modifies the workpiece state by introducing new predicates, removing predicates that are no longer valid, or changing their logical values. Thus, the evolution of the workpiece throughout the manufacturing process is represented as a sequence of technological states (2):

$$S_0 \rightarrow S_1 \rightarrow S_2 \rightarrow \cdots \rightarrow S_m, \tag{2}$$

where S_0 – initial state of the workpiece;
S_m – final state corresponding to the finished part.

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Accordingly, a technological state is represented by the following predicate model (3):

$$P_i(a_1, a_2, \dots, a_m) = \begin{cases} 1, & if\ the\ specified\ condition\ is\ satisfied \\ 0, & otherwise \end{cases}, \quad (3)$$

where $a_1, a_2, \dots, a_m$ – predicate arguments describing the manufacturing feature, processing parameters, manufacturing resources, or technological constraints.

This representation provides a unified mechanism for describing the manufacturing process regardless of the number of operations, the structure of the technological route, or the composition of the manufacturing resources involved. Instead of representing technological transitions as sequences of textual process descriptions, the proposed approach models each technological state as a structured set of predicate groups (Fig. 4).

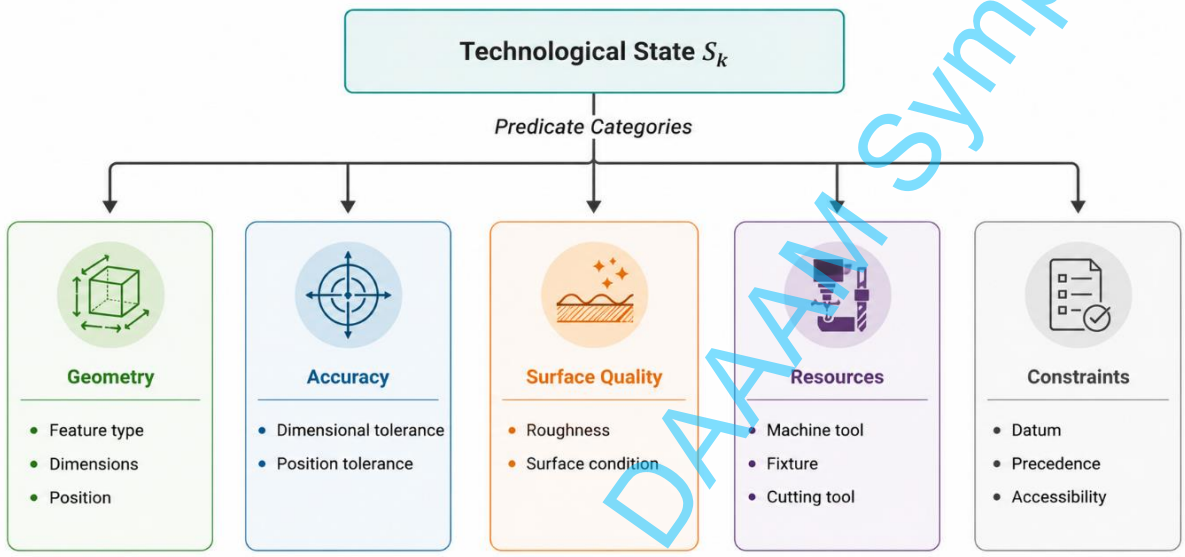

Fig. 4. Predicate representation of a technological state

The proposed predicate representation of the manufacturing process is independent of both the product type and the structure of the process plan, making it applicable to the development of alternative manufacturing routes for a wide range of mechanical products. The composition of the predicate set depends on the type of workpiece and the technological objectives of the manufacturing process. For housing-type parts, the predicate model is primarily composed of geometry, accuracy, surface quality, resource, and constraint predicates.

Predicate	Description
FeatureType (F_1, Plane)	Feature F_1 is a planar surface
FeatureType (F_2, Hole)	Feature F_2 is a hole
Diameter (F_2, 40)	Hole diameter is 40 mm
Flatness (F_1, 0.05)	Flatness tolerance
PositionTolerance (F_2, F_1, 0.02)	Position tolerance
SurfaceRoughness (F_1, Ra1.6)	Surface roughness
MachineAvailable (MC_{01})	Machine is available
ToolCompatible (T_{05}, F_2)	Tool is compatible with feature F_2
ProcessingSequence (F_1,F_2)	F_1 must be machined before F_2

Table 2. Representative examples of predicates used for the formal description of technological states of a housing-type part

As shown in Table 2, each technological characteristic is represented by a separate predicate describing a specific property of either the workpiece or the manufacturing process. Collectively, these predicates provide a complete logical representation of the technological state. During process planning, predicate values are updated after each technological transition, enabling automatic verification of technological feasibility, resource compatibility, and compliance with manufacturing constraints before subsequent manufacturing routes are generated.

Since each technological transition is associated with a corresponding set of predicates, the feasibility of subsequent transitions can be verified by evaluating their technological compatibility. This principle forms the basis of the predicate-based technological filter described in the following subsection.

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2.3 Predicate-Based Technological Filter

Although multiple alternative manufacturing methods may exist, not every technological transition can be executed from the current technological state of the workpiece. The applicability of a transition is determined by geometric, accuracy, resource, and technological constraints. To eliminate infeasible manufacturing alternatives before route generation, the proposed model employs a predicate-based technological filter that evaluates the predicate set describing the current technological state and determines whether a candidate technological transition is applicable (4):

$$Tr_i: S_k \rightarrow S_{k+1}, \tag{4}$$

where Tr_i – a technological transition.

Each technological transition is characterized by a set of preconditions that must be satisfied by the current technological state and by a corresponding set of predicates defining the resulting state. If all preconditions are satisfied, the transition is considered applicable and a new technological state is generated. Otherwise, the transition is rejected and excluded from further route generation (5):

$$Applicable(Tr_i, S_k) = \begin{cases} 1, if\ all\ required\ predicates\ are\ satisfied \\ 0, otherwise \end{cases}. \tag{5}$$

A new technological state is generated by updating the set of predicates to reflect the results of the executed technological transition (6):

$$S_{k+1} = Tr_i(S_k). \tag{6}$$

Following the execution of a technological transition, some predicates remain unchanged, others are modified, and new predicates are introduced to represent the updated technological state of the workpiece.

The predicate-based technological filter produces the set of feasible technological transitions, R_f, that satisfy all technological constraints. This set is subsequently used to generate alternative manufacturing routes (7):

$$Tr_i \in R_f, \quad if \quad Applicable\ (Tr_i, S_k) = 1. \tag{7}$$

Figure 5 illustrates the workflow of the proposed predicate-based technological filter.

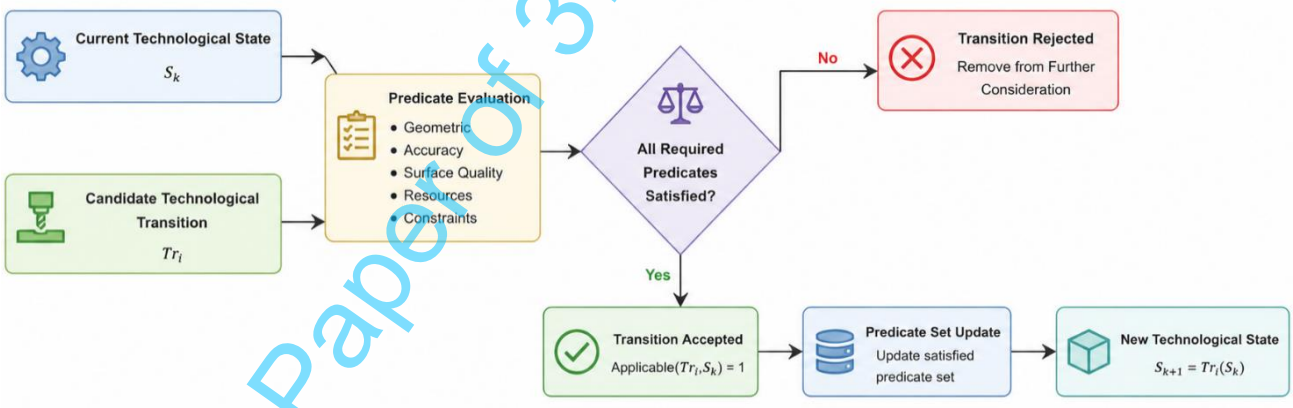

Fig. 5. Operation of the predicate-based technological filter

The predicate-based technological filter receives the current technological state, S_k, together with a candidate technological transition, Tr_i, as input. It then evaluates the geometry, accuracy, resource, and technological constraint predicates. If all required conditions are satisfied, the transition is included in the set of feasible transitions, and a new technological state, S_{k+1}, is generated. Otherwise, the transition is rejected and excluded from further route generation.

2.4 Formation of Feasible Technological Routes

The application of the predicate-based technological filter produces a set of feasible technological transitions that satisfy all specified constraints. Based on this set, alternative manufacturing routes are generated as ordered sequences of technological states connected by feasible technological transitions (8):

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$$Route = \left\{S_0 \xrightarrow{Tr_i} S_1 \xrightarrow{Tr_2} \dots \xrightarrow{Tr_n} S_m\right\}. \quad (8)$$

Each route begins with the initial technological state of the workpiece and terminates at the technological state corresponding to the finished part. After each technological transition, a new technological state is generated and becomes the basis for selecting the next feasible transition. Consequently, route generation is represented as a sequential transformation of technological states governed by predicate-based feasibility verification (Fig. 6).

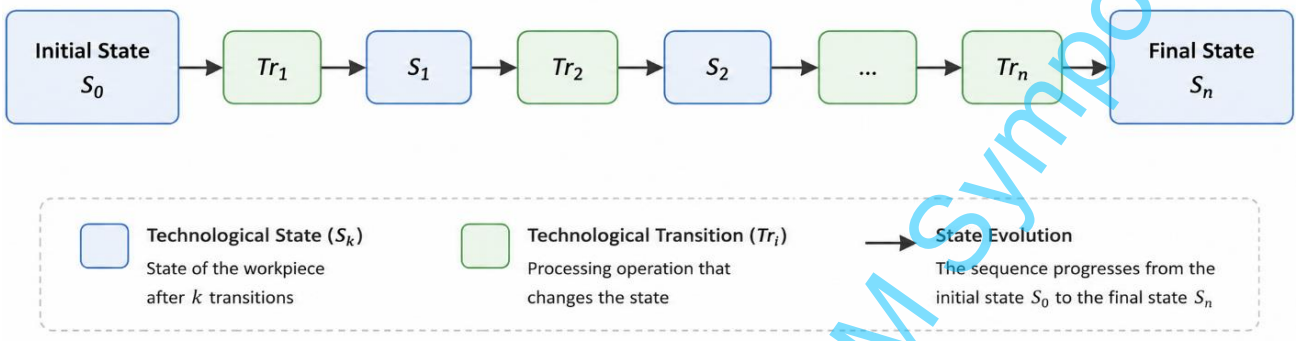

Fig. 6. Formation of a feasible technological route

The proposed predicate-based representation and technological filter ensure that only technologically feasible transitions are incorporated into the generated manufacturing routes. Consequently, every generated route satisfies the specified geometric, accuracy, surface quality, resource, and technological constraints. The resulting set of feasible manufacturing routes constitutes the search space for the multi-objective logistics optimization presented in the following section.

3. Multi-Objective Logistics Optimization of Feasible Technological Routes

Once the set of feasible manufacturing routes has been generated, the next task is to identify the most efficient alternative. All routes generated using the proposed predicate model satisfy the required technological constraints and ensure that the desired final technological state of the workpiece is achieved. However, these routes may differ considerably in terms of processing time, manufacturing resource utilization, transportation requirements, and overall production cost. Consequently, the technological structure of the manufacturing process serves as the basis for the subsequent multi-objective optimization of intralogistics flows.

The proposed multi-objective logistics optimization is based on a hierarchical representation of the manufacturing system in which each feasible manufacturing route is evaluated at three interconnected levels [23], [24].

At the micro level, the evaluation focuses on individual technological transitions, including machining parameters, manufacturing accuracy, and surface quality. The meso level considers the sequence of manufacturing operations, the selection of machine tools and tooling, and the formation of the manufacturing route. At the macro level, the associated intralogistics processes are evaluated, including transportation between workstations, the utilization of buffer areas, and manufacturing resource loading [24], [25].

Accordingly, each feasible manufacturing route generated by the predicate model is regarded as an integrated set of technological and logistics processes. This hierarchical representation enables a comprehensive evaluation of alternative manufacturing routes while simultaneously considering decision criteria at different levels of the manufacturing system.

For each feasible manufacturing route, an objective vector is constructed to characterize its overall performance. The resulting multi-objective optimization problem can be formulated as follows (9):

$$F(Route) = [T(Route), C(Route), L(Route), R(Route)] \rightarrow min, \quad (9)$$

where T(Route) — total processing time of the manufacturing route;
C(Route) — total production cost;
L(Route) — intralogistics cost associated with transportation between workstations;
R(Route) — manufacturing resource utilization index accounting for machine workload and setup operations.

The resulting objective vector enables each feasible manufacturing route to be evaluated from multiple perspectives. Since improving one objective generally leads to the deterioration of others, the route selection problem belongs to the class of multi-objective optimization problems [23], [26]. For example, reducing the total processing time may require

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additional machine resources or more frequent setup operations, thereby increasing production costs. Therefore, the optimization of manufacturing routes must account for the interactions and trade-offs among all objective functions.

In the proposed approach, the optimal manufacturing route is selected according to the Pareto optimality concept [23]. As a result, a set of Pareto-optimal solutions is generated, from which the decision-maker selects the alternative that best satisfies the current production requirements.

Because the optimization objectives are inherently conflicting—for example, increasing the batch size reduces unit transportation costs while simultaneously increasing waiting time and overall production lead time—the optimization problem is solved using the NSGA-II (Non-dominated Sorting Genetic Algorithm II). The algorithm identifies a Pareto front of non-dominated solutions. The effectiveness of Pareto-based optimization for constrained engineering problems has been demonstrated in recent studies [21], [22]. The decision-maker subsequently selects the preferred manufacturing route from the generated Pareto front (Fig. 7).

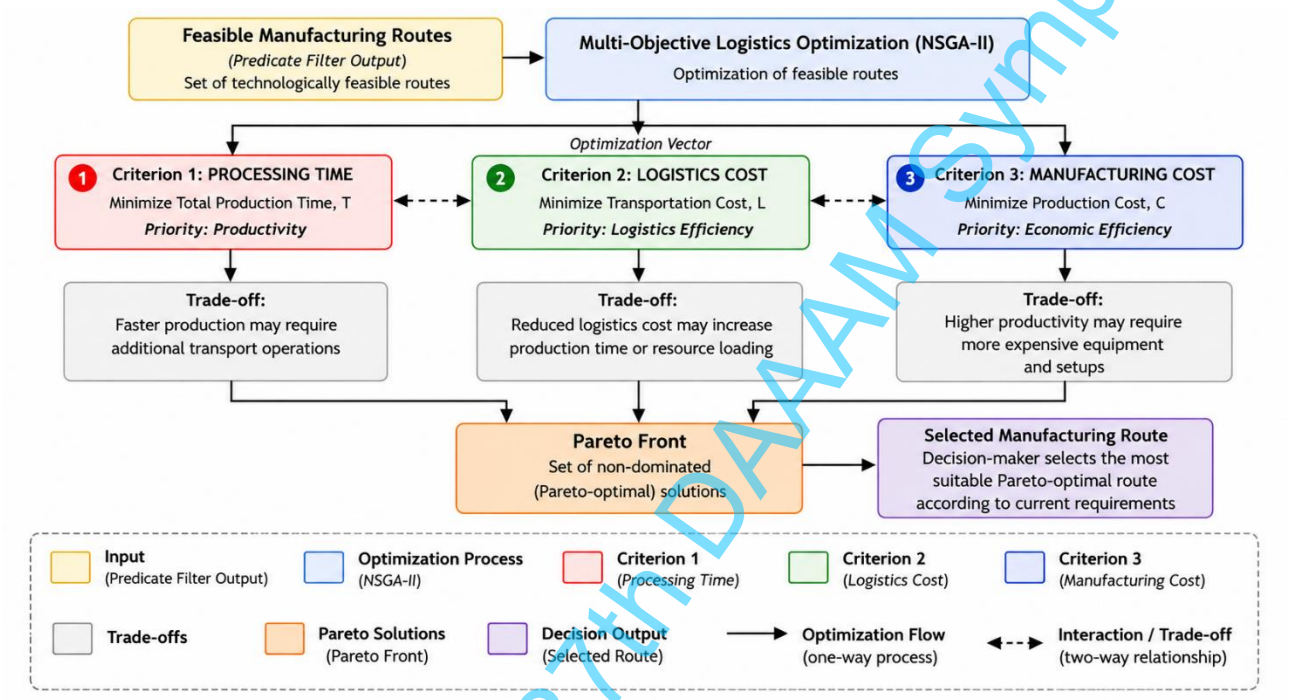

Fig. 7. Trade-offs between optimization criteria in the proposed multi-objective route selection

Each feasible manufacturing route is encoded as an individual solution and evaluated according to the objective functions T(Route), C(Route), L(Route), and R(Route). After applying the non-dominated sorting procedure, the Pareto-optimal set of manufacturing routes is obtained (10):

$$ParetoSet = \{Route_i \mid \nexists\, Route_j : Route_j \prec Route_i\}, \tag{10}$$

where ParetoSet – the set of technologically feasible manufacturing routes generated by the predicate-based technological filter.

Restricting the optimization procedure to technologically feasible manufacturing routes significantly reduces the search space. Routes violating geometric, accuracy, resource, or precedence constraints are excluded during the predicate-filtering stage and are therefore never considered by the optimization algorithm. Consequently, the multi-objective optimization is performed exclusively within the feasible solution space defined by the predicate model.

To illustrate the proposed optimization procedure, a case study was carried out using the feasible manufacturing routes generated by the predicate-based model presented in Section 2. Each route satisfied all technological constraints and represented a complete manufacturing sequence for the selected housing-type part. The generated routes differed in processing time, production cost, manufacturing resource utilization, and intralogistics characteristics, providing a representative solution space for multi-objective optimization.

The NSGA-II algorithm was applied to evaluate the feasible routes according to the objective functions defined above. Each manufacturing route was treated as an individual solution, while the objective values were calculated from the corresponding manufacturing operations, transportation activities, and manufacturing resource utilization. The optimization produced a Pareto front of non-dominated solutions representing different trade-offs among productivity, manufacturing cost, and intralogistics efficiency (Fig. 8).

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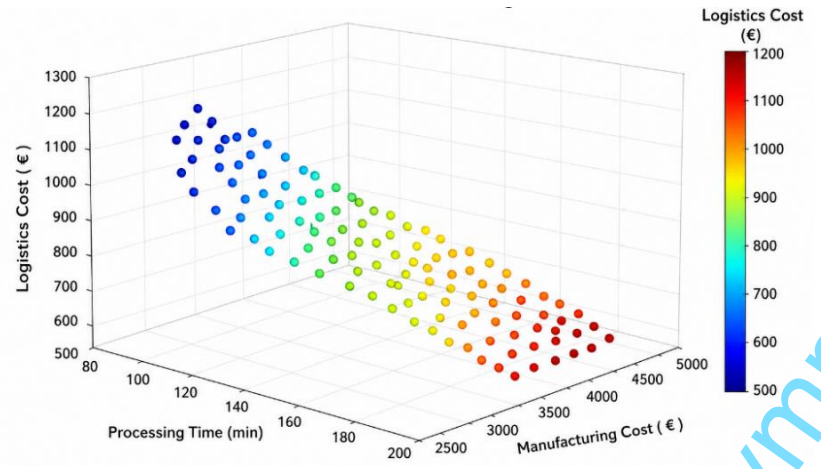

Fig. 8. Three-dimensional Pareto front for the feasible technological routes generated by the predicate-based model

The obtained Pareto front confirms the effectiveness of the proposed integrated optimization framework. Its principal advantage lies in the fact that every Pareto-optimal solution is technologically feasible. Since the optimization procedure evaluates only the manufacturing routes generated by the predicate-based technological filter, all candidate solutions inherently satisfy the geometric, accuracy, resource, and technological constraints defined during process planning. Consequently, the optimization is performed exclusively within the feasible solution space, reducing the computational search effort while improving the practical applicability of the obtained solutions.

4. Conclusions

A predicate-based process planning model has been proposed for generating technologically feasible manufacturing routes and performing their subsequent multi-objective intralogistics optimization. The proposed approach is based on a hierarchical representation of process planning objects connected through a system of predicates describing product geometry, accuracy and surface quality requirements, manufacturing resources, and technological constraints. Predicate-based filtering eliminates infeasible technological transitions and ensures that only technologically feasible manufacturing routes are generated.

The resulting manufacturing routes are evaluated using multiple objective functions, including processing time, production cost, intralogistics cost, and manufacturing resource utilization. The NSGA-II algorithm is employed to identify Pareto-optimal solutions, providing a set of compromise manufacturing routes for subsequent decision-making.

The proposed framework integrates predicate-based process planning and multi-objective logistics optimization into a unified decision-support methodology. Unlike conventional approaches, the optimization stage is performed only after the technological feasibility of manufacturing routes has been verified, thereby reducing the search space and eliminating infeasible solutions from consideration. Future research will focus on extending the predicate model and applying the proposed framework to adaptive process planning and logistics optimization in digital manufacturing environments.

5. Acknowledgments

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