Int j simul model 24 (2025) 4, 601-610
Original scientific paper

A BEE COLONY OPTIMISATION APPROACH FOR WORKPIECE POSITIONING IN MULTIAXIAL MACHINING

Brezocnik, M.[*] & Brezovnik, S.[**]
[*] University of Maribor, Faculty of Mechanical Engineering, Smetanova 17, Maribor, Slovenia
[**] Gorenje gospodinjski aparati, d.o.o., Partizanska cesta 12, Velenje, Slovenia
E-Mail: miran.brezocnik@um.si, simon.brezovnik@gorenje.com

Abstract
This paper presents a Bee Colony Optimisation (BCO) algorithm for optimizing the setup of multiaxial machining systems. The study focuses on improving manufacturability by determining an optimal workpiece (blank) position that allows complete processing with a single clamping configuration. The developed optimisation framework consists of two main modules: the forecasting module, which integrates the BCO algorithm to generate candidate positioning solutions, and the evaluation module, which models and verifies the manufacturability of each configuration. The modules operate in a feedback loop, enabling adaptive refinement of positioning based on workspace accessibility and collision constraints. The proposed approach was tested on a robotic system applying a protective coating to a large boat mould. Results confirmed that the BCO-based method successfully identified an optimal single-clamping position within the extended robot workspace, reducing setup complexity and time while maintaining high accuracy and full process accessibility.
(Received in August 2025, accepted in October 2025. This paper was with the authors 1 month for 2 revisions.)

Key Words: Multiaxial Machining, Workpiece Positioning, Robotics, Optimisation, Machine Learning, Bee Colony Optimisation (BCO)

1. INTRODUCTION

Real-time design and planning of product processing significantly reduces total development costs while enhancing manufacturability [1, 2]. Manufacturability, defined as the ease of achieving desired quality and productivity at optimal costs, measures the correlation between product design and fabrication process [3]. In small-series production, product manipulation time (re-clamping/setup) accounts for 25–40 % of total manufacturing costs. Thus, design-stage planning of production scenarios and potential obstacles is essential for cost reduction.

Researchers in the field of manufacturing systems address the challenge of blank positioning within the machine workspace using a variety of analytical and optimization approaches. Spensieri et al. and Olaiz et al. [4, 5] propose methods for determining the optimal workpiece positioning with respect to workspace utilisation and functional accessibility. Caro et al. [6] further extend this by optimising the workpiece orientation and position relative to cutting forces, machining quality including tolerance verification, and overall machining system cost. Tsarouchi et al. [7] compare the use of single versus dual robotic mechanisms, evaluating their impact on manufacturability and workspace-management efficiency. Meanwhile, Bartelt et al. [8] examine multi-robot gripper architectures, highlighting their potential for highly flexible manufacturing operations while also raising concerns regarding the cost-effectiveness of such solutions.

After reviewing available CAM machining process-planning software, we found that several commercial packages already provide basic options for positioning a workpiece within the machining system workspace. However, the user or designer must still manually define the scenario by selecting optimization parameters, and the resulting solution is therefore not guaranteed to be optimal.

https://doi.org/10.2507/IJSIMM24-4-739

Although boundary conditions can be defined numerically in external optimisation tools, we show in this article that optimisation can be performed directly within the CAM environment, providing realistic spatial data that closely reflect actual machining conditions.

In our proposed approach, the CAM environment represents all relationships between the optimized objects directly in full three-dimensional space. During each generation of the optimization cycle, the Bee Colony Optimization algorithm (BCO) predicts new candidate workpiece positions using the knowledge accumulated from previous generations. This is followed by a validation stage, in which each candidate solution is evaluated by measuring real spatial relationships within the CAM model. This enables accurate determination of distances, workspace accessibility, and possible collision volumes. The tight forecast-validation loop gives the proposed optimization procedure significant practical value. We therefore introduce an optimization system for manufacturing machinery and machining systems based on the BCO algorithm. At the same time, we address a key question relevant to five-axis machining systems with serial or hybrid mechanisms: Is it possible to manufacture the desired part on the selected machining system with a single clamping position within the region of optimal mechanism flexibility?

During preliminary development, we also tested several other population-based optimization approaches. These included particle-swarm variants inspired by birds, fish and termites, as well as differential evolution and genetic algorithms. All methods were evaluated on the real-world task of determining the optimal positioning of a large boat mould within the workspace of a robot equipped with an additional linear axis. After analysing the performance of all tested methods, we found that the BCO approach yielded the best results in terms of generation-to-generation convergence speed. It also produced the best (shortest) final solution. For this reason, the results presented in this article focus on the bee colony-based optimization approach.

2. MATERIALS AND METHODS

2.1 Proposed Bee Colony Optimisation system

The optimisation system we developed is divided into two main modules, Fig. 1. The first module is the forecasting system, which incorporates the BCO algorithm. The second module is the evaluation system, which models and assesses the manufacturing process.

To support process optimisation, these two modules are linked in a feedback loop: the forecasting system proposes a candidate solution, and the evaluation system then assesses that solution and sends the results back to the forecasting module.

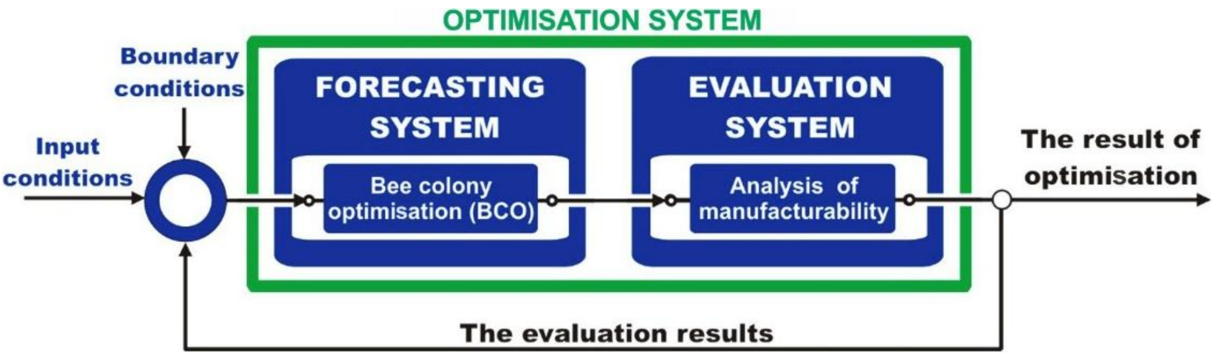


Figure 1: Architecture of the optimisation system.

Because the modules are designed to be both modular and independent, the optimisation system can be adapted and applied to a broad variety of production systems and equipment.

We defined the input conditions and boundary conditions (i.e., parameters) so that the objective function and solution guidelines can be configured during the optimisation process.

The input conditions include two categories: general optimisation parameters (e.g., swarm size, number of iterations, and minimum acceptable error) and process-specific parameters (e.g., convergence thresholds and strategies for increasing or decreasing the swarm size).

The boundary parameters define the evaluation environment: the dimensions of the simulation area, the size and shape of simulation objects, a table of critical conditions (e.g., collisions), and constraints on object movement within space.

2.2 Background of the Bee Colony Optimisation for workpiece positioning in robotic machining

In the developed optimisation system, we employed the BCO approach, which imitates the natural behavioural patterns and communication principles observed in bee colonies.

The BCO algorithm [9, 10] is a population-based metaheuristic, conceptually similar to other swarm-intelligence algorithms such as Ant Colony Optimisation (ACO), Particle Swarm Optimisation (PSO), the Gravitational Search Algorithm (GSA), Grey Wolf Optimizer (GWO) and the Firefly Algorithm (FA), as well as evolutionary approaches including Genetic Algorithms and Genetic Programming. These algorithms have been successfully applied to various problems in manufacturing systems and process optimisation [11-22].

In the context of solving an optimisation problem using BCO, the biological analogy is mapped as follows: the search performed by a bee colony for the optimal food source corresponds to the search for an optimal blank position within the robot's workspace that ensures maximum mobility and accessibility of the mechanism.

During each iteration, a random exploration of the search space by the bee population contributes to estimating the average quality of the discovered food sources – analogous to the average flexibility or accessibility of the blank positioning within the defined workspace.

The resulting estimate of the average range of motion across all machining points is then incorporated into the subsequent prediction step, determining the new direction for the next exploration (i.e., the next candidate blank position) within the workspace.

In other words, each flight of the bee swarm corresponds to relocating the blank with its machining points to a new position, where a new average value of the mobility range of all processing points is evaluated.

The initial random exploration performed by the bees is defined by Eq. (1):

$$g_{mi} = min_i + (rand(0,1) \cdot (max_i - min_i)) \tag{1}$$

where g_{mi} is the vector of food presence estimate values, which in the context of robotic machining corresponds to the manipulability of the workpiece at locations randomly sampled *rand* (0, 1) within the robotic mechanism's workspace. The vector g_{mi}'s size is determined by the number of bees m in the population, where $m = 1, 2, \ldots, STC$, and STC (swarm total count) denotes the total population size. The values min_i and max_i values represent the minimum and maximum estimates of the current search area (workpiece positioning).

In each iteration, the bees with the highest current food presence estimate values (manipulability) are identified. If the number of bees with better estimates increases between iterations, the direction of the next flight (workpiece translation and rotation) follows the best food gatherers from the previous iteration. The new food searching location (workpiece position) is determined by Eq. (2):

$$w_{mi} = x_{mi} + \sigma_{mi} \cdot (x_{mi} - x_{ki}) \tag{2}$$

Here, w_{mi} represents the new neighbourhood around x_{mi} where the food (or the workpiece) is found in the previous iteration. x_{ki} value is a randomly selected location of previously found food, and the index i is chosen randomly to prevent stagnation in local optima. σ_{mi} is a random value within the reference space (X, Y, Z) in the search area (i.e., of the robotic workspace) [23].

After scout bees return (before updating the new workpiece positioning), the predictive algorithm computes the fitness function by comparing w_{mi} and x_{mi}. This identifies the current best estimate of food presence – that is, the point with the highest manipulability – within the search area (the robotic mechanism's workspace), as defined by Eq. (3):

$$fit_{mi}(x_m) = \begin{cases} \dfrac{1}{1 + b_m(x_m)}, \text{when } b_m(x_m) \geq 0 \\ 1 + abs\big(b_m(x_m)\big), \text{when } b_m(x_m) < 0 \end{cases} \tag{3}$$

where the $b_m(x_m)$ is the optimal solution in the search area x_{mi}. Bees in areas with higher food availability (i.e., greater manipulability) are more likely to attract other bees than those in areas with lower food availability (i.e., lower manipulability). The decision about which bees the worker bees still in the hive will join in a new flight (new workpiece positioning) is determined by probability $p(m)$, given by Eq. (4):

$$p(m) = \frac{fit_{mi}(x_m)}{\sum_{m=1}^{stc} fit_{mi}(x_m)} \tag{4}$$

This ensures that locations with lower food (lower manipulability) are less likely to be selected in subsequent iterations, prioritizing areas with higher food availability (higher manipulability).

3. RESULTS AND DISCUSSION

As an example, we consider the region of the blank that remains manufacturable with only one clamping, or with as few clampings as possible. During manufacturing planning, we use this process to identify solutions that cannot be achieved with classical methods due to the complexity of planning combinations. This approach increases the manufacturability and productivity of the desired product and consequently reduces the overall manufacturing cost.

When designing complex processes, particularly for larger workpieces, it is often impossible to complete the initially planned operations with a single blank clamping due to the mobility limitations of the machining system. Planning the position of the processing zero point is constrained by spatial limitations, as it is nearly impossible to fully define the kinematics and required workspace of the manufacturing system needed for five-axis or multi-axis processing. Therefore, information on manufacturability scenarios and the number of workpiece clampings operations is crucial during the development phase.

In this context, we propose a solution by extending the workspace of serial mechanisms. If processing the desired workpiece is not possible within the available workspace using a single clamping, the workpiece positioning optimisation includes an additional option: linear motion of the machining system along rails in the X or Y direction of the reference coordinate system. This provides the manufacturing system with extra workspace by allowing linear movement of the entire serial (robotic) mechanism along the rails. Manufacturing the workpiece with a single clamping is crucial, as the manipulation time required for re-clamping during processing significantly increases the total manufacturing cost. Fig. 2 illustrates the extended workspace of the serial mechanism, incorporating linear rail movements along the X direction of the reference coordinate system. The optimal solution provided by the predictive system defines the minimal extended workspace required for the planned processing.

The general criterion for the expansion of the robot workspace is the accessibility of all points that the robotic mechanism must reach to ensure the technologically correct application of the protective coating on the boat's surface. The required distance and application angle are specified by the protective-coating manufacturer. These specifications serve as input conditions for determining the optimal application path and the minimal necessary expansion of the robot workspace to satisfy accessibility and ensure a technologically correct coating application.

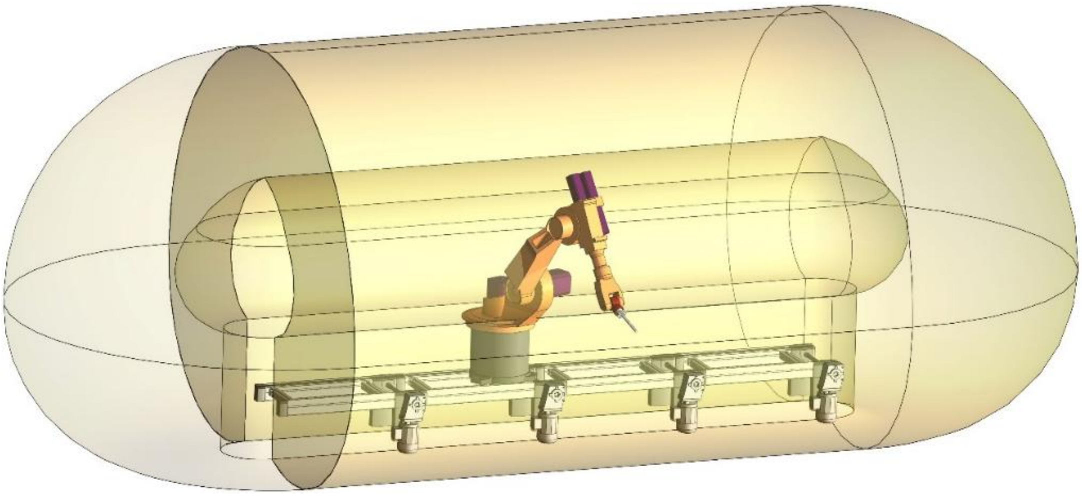


Figure 2: Workspace extension of the robotic mechanism in the X direction.

Extending the workspace offers an additional option for planning processing points within the extended workspace of a serial mechanism using linear movement of the entire mechanism. This extension remains disabled during workpiece positioning optimisation until convergence reaches the minimum error criterion. If the average manipulability value remains below the critical threshold, the workspace is extended via linear movements of the machining system in the X or Y direction. The size of the workspace extension depends on the magnitude of the critical value of the manipulability value when the threshold is reached. The critical estimate of manipulability is indicated by a large negative value. If many processing points are critically evaluated, the size of the linear movement is determined relative to the critical manipulability value. This means that, if one point is evaluated with the critical value of manipulability, the linear movement increases by 1 mm. Since the workspace extension is proposed only in one direction, it is necessary to choose the direction of extension, either the X or the Y direction. The direction is determined based on the set of points that have received the critical evaluation. If the average value of the X coordinate of the critically evaluated processing points is greater than the average value of the Y coordinate, the linear movement is applied in the X direction, and vice versa. As manufacturing workspaces are typically constrained, linear movement sizes in the X or Y direction can be limited by additional optimisation boundary conditions.

The optimisation system process with the extended workspace was tested by positioning points for the robotic application of a protective coating to the bottom of the boat mould. The length of the boat mould (3,478.11 mm) exceeds the size of the robotic mechanism's workspace, which has a diameter of 4,560 mm, because the protective coating must be applied to the boat mould at a specified distance (120 mm) with a perpendicular orientation of the tool. However, the size of the robot's workspace does not meet these specified requirements. Therefore, we included the possibility of extending the workspace with a linear drive, as shown in Fig. 3. The objective of the proposed optimisation system is to determine the optimal position of the boat mould within the smallest expanded workspace of the robotic mechanism required for applying the protective coating to the bottom surface of the mould. The application of the protective coating to the sides of the boat mould is not discussed in this paper. In the boundary conditions of the optimisation system, we defined the permitted movements of the mould along the translational axes X, Y, and Z, and the rotational movements around the X and Y axes relative to the reference coordinate system.

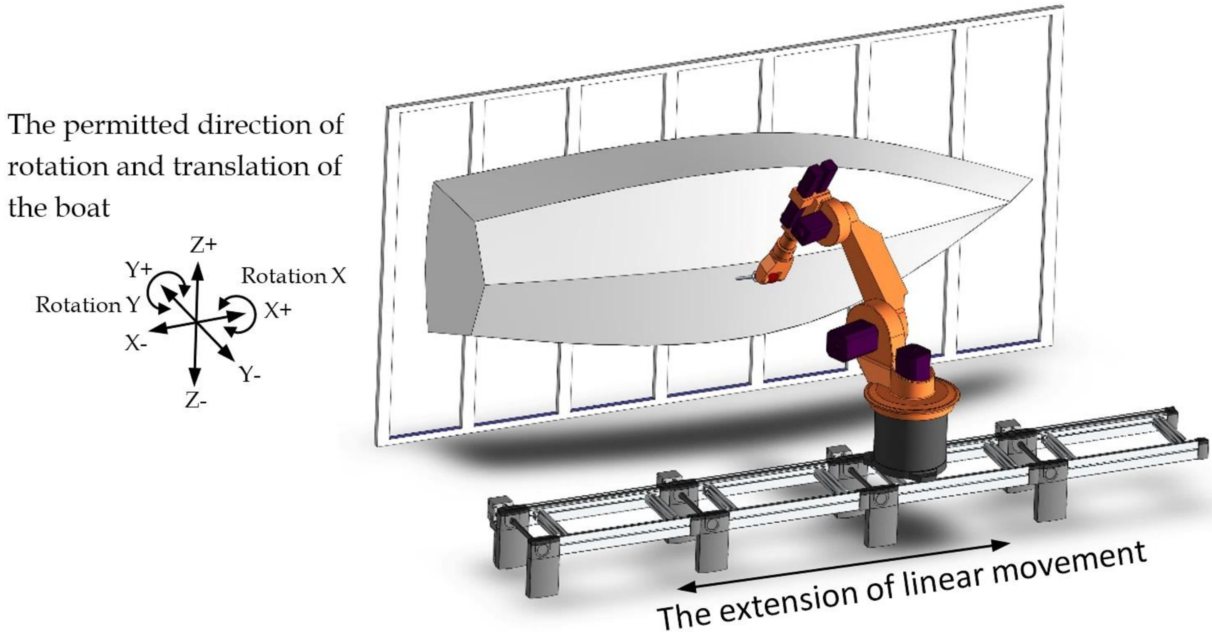


Figure 3: Robotic application of protective coating to boat moulds.

For the workspace-extension optimisation, we used the BCO algorithm to guide the search process. The population-based method identifies workspace regions with optimal manipulability for each protective-coating application point. Here, the basic BCO algorithm is modified by sequentially adding additional search areas whenever the convergence error reaches the minimum criterion (5 %). The optimisation convergence error represents the rate of convergence of the BCO algorithm through iterations. The smaller the rate of convergence, the lower the error percentage, and vice versa.

Eq. (5) represents the search for a new random area of solutions:

$$g_{mi} = min_i + \left(prn_i \cdot rand(0,1)\right) + \left(rand(0,1) \cdot (max_i - min_i)\right) \quad (5)$$

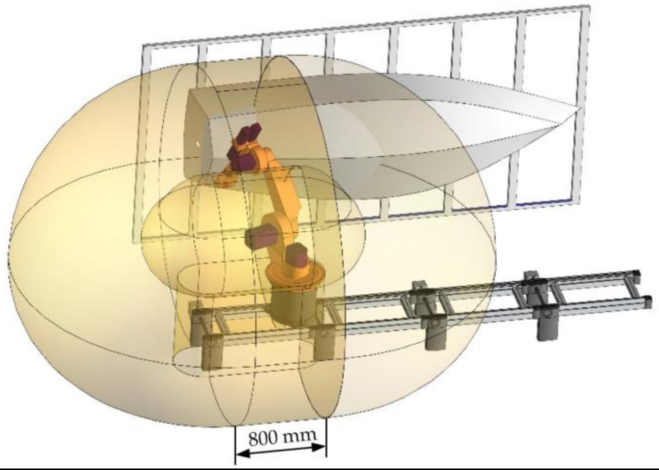
where g_{mi} is the food presence estimate vector at locations randomly sampled using *rand* (0, 1) within the robotic mechanism workspace. min_i and max_i define the minimum and maximum estimated values for the current location screening of the iteration. The additional term prn_i *rand* (0, 1) represents the random contribution resulting from the newly added workspace extension. The optimal solution is obtained using Eq. (6) once the minimum optimisation error criterion (5 %) is reached:

$$res(m) = \frac{fit_{mi}(x_m)}{\sum_{m=1}^{stc} fit_{mi}(x_m)} \quad (6)$$

Fig. 4 shows an intermediate positioning with an extended working space of 800 mm. The extension of the working space is not sufficient to cover all application points required for the automated application of the protective coating, so the solution is evaluated against a critical value. *PVGI*, *MinVGI*, and *MaxVGI* represent the average, minimum, and maximum manipulability values, respectively.

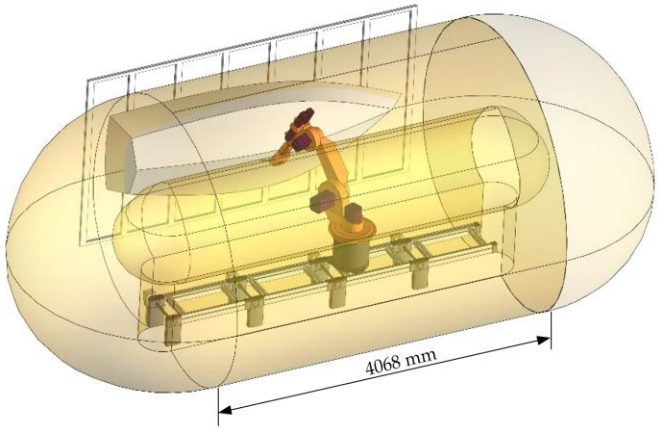
Fig. 5 shows the final optimal solution for positioning the boat mould within the area of optimum mobility of the robotic mechanism for each application point. The extension of the workspace in the X direction was 4,068 mm.

For easier and more comprehensive visualization, the results of the swarm intelligence optimisation were presented graphically using the bicubic colour interpolation algorithm [24].



OPTIMISATION RESULTS	
Optimization type	BCO
Iteration	86,627
Size swarm	250
PVGI	-999,726·10^4
MinVGI	168,745
MaxVGI	469,721
The length of the extension of the workspace	800 mm

Figure 4: Intermediate optimisation result of workspace extension using the BCO algorithm.



OPTIMISATION RESULTS	
Optimisation type	BCO
Iteration	243,954
Size swarm	250
PVGI	497,792
MinVGI	410,681
MaxVGI	508,853
The length of the extension of the workspace	4,068 mm

Figure 5: The final solution for optimal mould positioning and expansion of the robotic mechanism's workspace.

Fig. 6 a shows the final optimal positioning solution from the side, while Fig. 6 b, illustrates the suitability test of the optimisation result using a velocity anisotropy graphical projection with colour interpolation. As shown in Fig. 6 b, the optimisation system confirmed the optimal boat mould positioning in both translation and rotation directions, achieving maximum mobility of the robotic mechanism. By extending the workspace in the X direction (4,068 mm), the optimisation system achieved optimal protective coating coverage across the entire area of the boat mould, in accordance with the prescribed orientation and at a sufficient distance. Furthermore, the optimisation system's solution for positioning the boat mould within the area of optimal mobility also ensures optimal guidance of the robotic mechanism in terms of energy efficiency.

The colour palette representing mobility is as follows: (i) red – area with the highest mobility (508,853), (ii) green – area with reduced mobility (254,426), and (iii) blue – area with the lowest mobility (0).

Fig. 7 shows the progress of optimisation convergence over the iterations of the algorithm, depending on the average mobility value (*PVGI*).

If the optimisation result is evaluated as critical despite the workspace extension, further planning involves either adding an additional clamping location or considering the possibility of re-clamping in the same position.

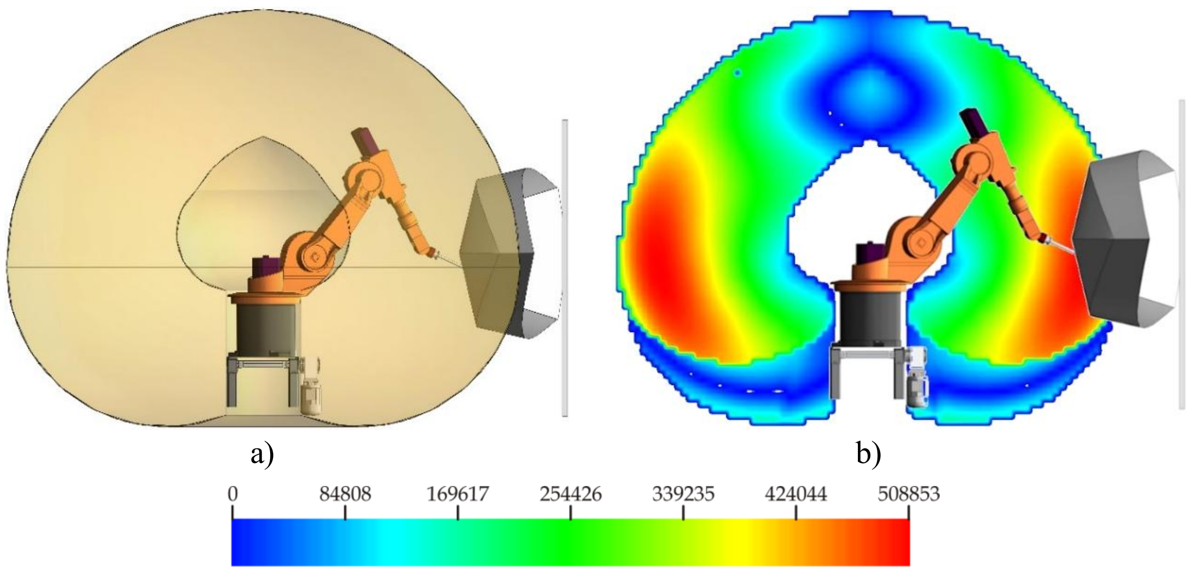


Figure 6: The final solution for optimal mould positioning in the robot mechanism workspace with velocity anisotropy analysis and colour interpolation.

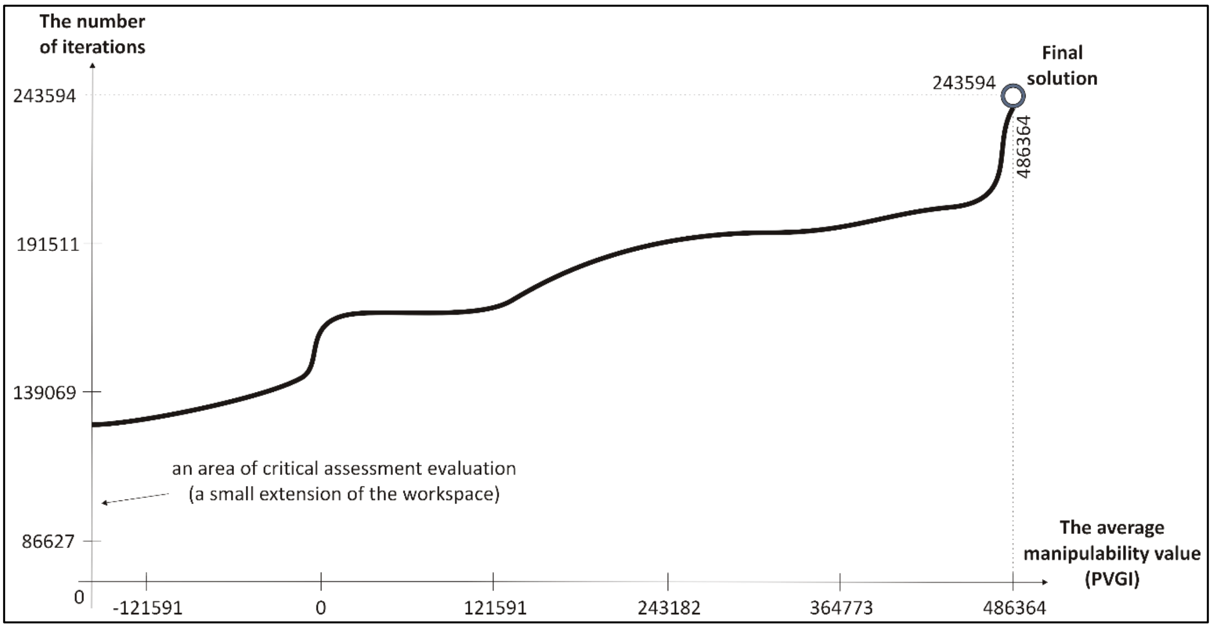


Figure 7: Progress of optimisation convergence over iterations and *PVGI*.

4. CONCLUSION

A key finding of this work is the optimisation system solution, which provides information during the planning phase about the manufacturability of the blank within the area of optimal mobility of the machining system. Information on the blank's manufacturability with the selected machining system clearly indicates whether it can be processed using a single clamping. Knowledge of the product's manufacturability using one or more machining positions is important for evaluating and estimating the total manufacturing cost.

The production workspace and the manufacturing cycle time are two key factors in determining the efficiency of a manufacturing process. A smaller required robot workspace reduces production-area costs, while a shorter operational cycle increases the number of units produced per unit time. The primary aim of this article is to demonstrate the actual optimisation process, which enables planning the minimal required size of the robot workspace and, consequently, achieving an optimal manufacturing-process solution.

In the presented application example, the robot's workspace is extended along the X-axis by approximately 4,068 mm. This extension enables a technologically correct application of the protective coating across the entire mould surface with a single clamping in the shortest possible time. Fig. 6 illustrates another key finding: the boat is positioned within the region of optimal flexibility of the robotic mechanism (red area), which significantly reduces the overall process cycle. Conversely, limited flexibility within the robot's workspace would increase manufacturing time.

The optimisation process assesses the manufacturability of complex products in relation to the mobility of available machining systems. In manufacturing environments with multiple machining systems, a knowledge base can be compiled containing manufacturability-related parameters for each system. As modern manufacturing increasingly relies on small-series production of increasingly complex products, advanced planning is particularly important for minimizing manufacturing time across diverse and complex items.

This case study demonstrates that an optimised manufacturing process is crucial for achieving the desired quality and productivity at minimal cost. Incorporating cost-reduction measures and process optimisation during the planning phase is essential.

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