

Non-governmental Organization
International Center of Scientific Research



PROCEEDINGS OF THE
IX INTERNATIONAL SCIENTIFIC
AND THEORETICAL CONFERENCE

CURRENT ISSUES OF
SCIENCE, PROSPECTS
AND CHALLENGES

12.09.2025

SYDNEY
AUSTRALIA

SCIENTIA
COLLECTION OF SCIENTIFIC PAPERS

with the proceedings of the

IX International Scientific and Theoretical Conference


**Current issues of science,
prospects and challenges**

12.09.2025

Sydney, Australia

Sydney, 2025

UDC 082:001
C 95

 <https://doi.org/10.36074/scientia-12.09.2025>




Chairman of the Organizing Committee: Goldenblat M.

Responsible for the layout: Bilous T.

Responsible designer: Bondarenko I.

C 95 **Current issues of science, prospects and challenges:** collection of scientific papers «SCIENTIA» with Proceedings of the IX International Scientific and Theoretical Conference, September 12, 2025. Sydney, Australia: International Center of Scientific Research.

ISBN 979-8-88955-780-7 (series)  Bowker

DOI 10.36074/scientia-12.09.2025

Papers of participants of the IX International Multidisciplinary Scientific and Theoretical Conference «Current issues of science, prospects and challenges», held on September 12, 2025 in Sydney are presented in the collection of scientific papers.

The conference is included in the Academic Research Index ReserchBib International catalog of scientific conferences and registered for holding on the territory of Ukraine in UKRISTEI (Certificate № 475 dated June 10th, 2025).



Conference proceedings are publicly available under terms of the Creative Commons Attribution-ShareAlike 4.0 International License (CC BY-SA 4.0) at the www.previous.scientia.report.

UDC 082:001

© Participants of the conference, 2025

© Collection of scientific papers «SCIENTIA», 2025

ISBN 979-8-88955-780-7

© NGO International Center of Scientific Research, 2025


SECTION 5.

AUTOMATION AND APPLIANCES MAKING

SCIENTIFIC RESEARCH GROUP:

Igor Nevliudov 

Doctor of Engineering Science, Professor
Head of Department of Computer-Integrated Technologies, Automation and Robotics
Kharkiv National University of Radio Electronics, Ukraine

Murad Anver oglu Omarov 

Doctor of Engineering Science, Professor,
Vice-Rector on International Cooperation
Kharkiv National University of Radio Electronics, Ukraine

Vladyslav Yevsieiev 

Doctor of Engineering Science, Professor,
Professor of Department of Computer-Integrated Technologies, Automation and Robotics
Kharkiv National University of Radio Electronics, Ukraine

Elgun Jabrayilzade 

Ph.D. student Department of Computer-Integrated Technologies, Automation and Robotics
Kharkiv National University of Radio Electronics, Ukraine

METHODS FOR OPTIMIZING THE BUILDING OF COLLABORATIVE ROBOT ROUTES IN A DYNAMIC ENVIRONMENT

Modern collaborative robots (cobots), which work alongside humans in a shared workspace, must plan trajectories that simultaneously meet the requirements of safety, smooth motion, timely responsiveness to dynamic obstacles (people, other robots, moving objects), energy efficiency, and task accuracy [1,2]. The dynamic environment imposes additional constraints on the planner: incomplete information about future obstacle trajectories, uncertainty in sensor measurements, rigid kinematic/dynamic constraints of the robot, and the need for fast real-time response [3-5]. Because of this, trajectory optimization in a collaborative context usually requires a combination of: predictive models of human/obstacle behavior, rapid local corrections, and global optimality criteria — which is why the comparison of methods should focus not only on “trajectory quality” but also on computational costs, safety guarantees, and integration with human behavior prediction [6-9].

Below is an analysis of existing optimization methods that can be used to build a route for a collaborative robot in a dynamic environment:

- sampling-based planners (sampling-based: RRT, RRT*, PRM, and their modifications). Advantages: work well in high-dimensional configuration spaces, quickly find feasible paths in irregular geometry; there are asymptotic guarantees of optimality in the RRT* and PRM* versions. Disadvantages for dynamic environments: basic versions do not take into account the time component (i.e., moving obstacles) without extensions; if smoothness/dynamics are required, further trajectory optimization is often necessary; sensitive to the frequency of obstacle map updates. Practical considerations: used as a fast global search (to find a homotopy or rough trajectory), followed by local optimization;

- trajectory optimization methods (CHOMP, TrajOpt, STOMP, etc.). Advantages: directly minimize quality functionals (energy, smoothness, distance to obstacles), easily introduce kinematic/dynamic constraints, produce smooth trajectories, convenient for high-dimensional manipulators. Disadvantages: require good initialization (to avoid local minima), can be computationally expensive, basic variants are non-dynamic (but there are extensions for dynamic obstacles). Practical notes: often combined with sampling - sampling gives the initial path, the optimizer smooths and adjusts to the constraints;

- Model Predictive Control (MPC / NMPC). Advantages: naturally takes into account time constraints, robot dynamics, and predicted obstacle movements in the form of a prediction window; allows you to set constraints and objective functions in “online” mode, well suited for real time with fast optimizers. Disadvantages: requires an accurate model (or its adaptive update), computational costs can be high for complex nonlinear models or long prediction horizons; sensitivity to errors in predicting human movement. Practical considerations: MPC is particularly useful as a local controller/planner working on a pre-found global trajectory or as a standalone online planner with powerful hardware and optimizers such as PANOC/HPIPM;

- reactive and behavioral methods (potential fields, dynamic window, velocity obstacles, ORCA). Advantages: fast response, ease of implementation, natural integration into resource-constrained systems; useful for avoiding immediate collisions. Disadvantages: no guarantee of global optimality, susceptibility to local minima, difficult to guarantee smoothness and comfort of movement when operating in a human environment. Practical notes: effective as a “quick layer” of collision avoidance in the planning hierarchy (the reactive layer increases safety between global plan updates). (see reviews on avoidance);

- learning approaches: reinforcement learning (RL), imitation learning, hybrid learning+planner. Advantages: capable of learning complex behavior policies in unpredictable conditions, adapting to people's styles in collaboration, can reduce computation during execution (policy inference is faster than optimization “on the fly”). Disadvantages: require large amounts of data/simulations, fewer formal safety guarantees; difficult to certify in industry. Practical considerations: often used in hybrid architectures - trained policy provides initialization/quick response; optimization methods provide guarantees and accuracy.

- hybrid/multi-level approaches. The most practically viable solutions combine global sampling or a trained global planner + local MPC/optimization + a reactive layer for instant collision avoidance. This division allows the strengths of each approach to be leveraged: global optimality/topology awareness, local dynamic coordination, and guaranteed safety in the face of unforeseen events. Recent studies show that parallel optimization of multiple homotopies or generation of sets of evacuation trajectories significantly increases resilience to unforeseen events.

Conclusions. Research into methods for optimizing the construction of collaborative robot routes in a dynamic environment has shown that there is no universal approach, and that the effectiveness of solutions depends on a combination of global and local strategies. The analysis demonstrated that sampling-based algorithms, such as RRT* or PRM*, are well suited for quickly finding feasible trajectories in complex spaces but require additional smoothing and optimization. Optimization-based methods, such as CHOMP and TrajOpt, ensure smoothness and take kinematic constraints into account, but have high computational complexity and sensitivity to initialization. Model predictive control (MPC) has proven to be an effective approach for dynamic scenarios, as it takes into account the time component and allows for the integration of human movement predictions, but requires high computational resources and an accurate system model. Learning methods and hybrid architectures combine the strengths of classical algorithms with adaptability, which is especially important for working in conditions of uncertainty. The results of the study confirm that the optimal solution involves a multi-level planning structure, where a global planner, local optimizer, and reactive layer work together to ensure safety, smooth traffic flow, and real-time compliance. Thus, to achieve high efficiency and reliability in collaborative systems, it is advisable to combine several optimization methods, taking into account the specifics of the environment and the limitations of the hardware platform.

References:

1. Fu, S., Yang, D., Mei, Z., & Zheng, W. (2025). Progress in Construction Robot Path-Planning Algorithms. *Applied Sciences*, 15(3), 1165. <https://doi.org/10.3390/app15031165>

2. Keshvarparast, A., Battini, D., Battaia, O., & Pirayesh, A. (2024). Collaborative robots in manufacturing and assembly systems: literature review and future research agenda. *Journal of Intelligent Manufacturing*, 35(5), 2065-2118.
3. Guo, T., Huang, L., & Han, H. (2025). An effective path planning method based on VDWF-MOIA for multi-robot patrolling in expo parks. *Electronics*, 14(6), 1222. <https://doi.org/10.3390/electronics14061222>
4. Nevliudov, I., Yevsieiev, V., Maksymova, S., Gopejenko, V., & Kosenko, V. (2025). Development of mathematical support for adaptive control for the intelligent gripper of the collaborative robot manipulator. *Advanced Information Systems*, 9(3), 57-65. <https://doi.org/10.20998/2522-9052.2025.3.07>
5. Maksymova, S., Yevsieiev, V., Chala, O., & Ababneh, J. (2025). DECISION-MAKING MODEL FOR CONTROLLING A COLLABORATIVE ROBOT-MANIPULATOR BASED ON THE SENSOR FUSION METHOD AND THE RULES OF RULE-BASED SYSTEMS. *Multidisciplinary Journal of Science and Technology*, 5(6), 526-538.
6. Невлюдов, І. Ш., Євсєєв, В. В., & Гурін, Д. В. (2025). Model development of dynamic representation a model description parameters for the environment of a collaborative robot manipulator within the industry 5.0 framework. *Системи управління, навігації та зв'язку. Збірник наукових праць*, 1(79), 42-48.
7. Nevliudov, I., Yevsieiev, V., Maksymova, S., Demska, N., Kolesnyk, K., & Miliutina, O. (2022, September). Object Recognition for a Humanoid Robot Based on a Microcontroller. In *2022 IEEE XVIII International Conference on the Perspective Technologies and Methods in MEMS Design (MEMSTECH)* (pp. 61-64). IEEE. <https://doi.org/10.1109/MEMSTECH55132.2022.10002906>
8. Automated Monitoring and Visualization System in Production / V. Lyashenko, Abu-Jassar Amer Tahseen, V. Yevsieiev, S. Maksymova // *Int. Res. J. Multidiscip. Technovation*, 5(6), 09-18.
9. Attar, H., Abu-Jassar, A. T., Yevsieiev, V., Lyashenko, V., Nevliudov, I., & Luhach, A. K. (2022). Zoomorphic mobile robot development for vertical movement based on the geometrical family caterpillar. *Computational intelligence and neuroscience*, 2022(1), 3046116.