September 5, 2025;
Boston, USA

SECTION 9.
AUTOMATION AND APPLIANCES MAKING

DOI 10.36074/logos-05.09.2025.019

STUDY OF INTELLIGENT METHODS OF TRAJECTORY CONSTRUCTION FOR MOBILE ROBOTS IN A DYNAMIC ENVIRONMENT

Igor Nevliudov[1], Murad Anver oglu Omarov[2], Vladyslav Yevsieiev[3], Elgun Jabrayilzade[4]

1. Doctor of Engineering Science, Professor
Head of Department of Computer-Integrated Technologies, Automation and Robotics
Kharkiv National University of Radio Electronics, UKRAINE
ORCID ID: 0000-0002-9837-2309

2. Doctor of Engineering Science, Professor,
Vice-Rector on International Cooperation
Kharkiv National University of Radio Electronics, UKRAINE
ORCID ID: 0000-0003-4842-4972

3. Doctor of Engineering Science, Professor,
Professor of Department of Computer-Integrated Technologies, Automation and Robotics
Kharkiv National University of Radio Electronics, UKRAINE
ORCID ID: 0000-0002-2590-7085

4. Ph.D. student Department of Computer-Integrated Technologies, Automation and Robotics
Kharkiv National University of Radio Electronics, UKRAINE
ORCID ID: 0000-0003-2932-4976

Modern mobile robots are actively being introduced in industry, logistics, the service sector, and autonomous transport, which requires them to be able to effectively navigate dynamic and unpredictable environments [1,2]. Building safe and optimal trajectories in real time is becoming a key challenge, as traditional planning methods do not provide sufficient flexibility and speed [3]. Intelligent approaches based on optimization, machine learning, and adaptive control open up new opportunities for accounting for uncertainties, predicting object motion, and improving the efficiency of navigation systems [4]. Research into such methods is relevant for the creation of robotic systems capable of safe and autonomous interaction with humans and the environment in the Industry 5.0 concept [5-7].

Modern intelligent methods for constructing trajectories for mobile robots in dynamic environments are focused on ensuring safety and real-time operation, combining classical algorithms and the latest approaches. Global planning is traditionally based on graph methods such as A-star (A*), Dynamic A-star (D*) and their modifications, which form the basic route, while local corrections and frequent replanning ensure adaptability in changing conditions. Sampling algorithms, such as Rapidly-exploring Random Tree Star (RRT*) and Probabilistic Roadmap Method (PRM), allow working in complex state spaces but require integration with optimization methods and motion predictors to account for temporal dynamics. Optimization-based approaches such as Model Predictive Control (MPC), Timed Elastic Band, and Model Predictive Path Integral (MPPI) are gaining popularity. These approaches view the problem as minimizing cost while taking into account constraints and obstacle trajectory predictions and using fast solvers to operate in real time. In multi-agent scenarios, decentralized collision avoidance schemes based on Velocity Obstacles remain effective, providing fast response without global coordination. Significant progress has been made in the use of learning methods, including simulation and reinforcement learning, which are integrated with classical approaches and MPC to create hybrid systems with safe control. An important element is the prediction of other participants' movements using graph models and transformers, which improves the smoothness and reliability of planning. In cases of uncertainty, stochastic and chance-bounded MPCs are used, as well as event-triggered strategies that balance safety and computational efficiency. For swarms and cooperative systems, models that combine task distribution with local avoidance and provide scalability are promising. Modern hybrid solutions combine global planning based on graph or sampling methods with local optimizers, trajectory prediction, and machine learning elements, enabling effective operation in complex Industry 5.0 scenarios. A comparison of the advantages and disadvantages of trajectory planning methods is presented in Table 1.

Table 1

Comparison of the advantages and disadvantages of trajectory construction methods

Method	Advantages	Disadvantages
1	2	3
A*, D* (graph algorithms)	Guarantee optimality (A*) or near-optimality (D*), suitable for global planning, work well in static and known maps	Slow with large maps, require frequent route adjustments in dynamic conditions, do not take into account the kinematics of the robot.

Table continuation 1

1	2	3
PRM, RRT* (sampling)	Effective in high-dimensional spaces, work well in complex geometries.	High sensitivity to dynamic disturbances, no guarantee of optimal performance without additional procedures, high computational load.
TEB (Timed Elastic Band	Easily integrated into local planning, takes into account time factors and robot kinematics, quick for online adjustment.	Limited in complex scenes with lots of moving objects, requires accurate local maps.
DWA (Dynamic Window Approach)	Very fast in real time, easy to implement, takes into account the dynamics of the work.	Local method - may get stuck in local minima, does not guarantee global optimality.
MPC (Model Predictive Control)	Takes into account dynamics and limitations, capable of predicting future states, integrates obstacle movement forecasts.	High computational complexity, fast optimization solvers required, sensitive to model accuracy.
MPPI (Model Predictive Path Integral)	Works well for nonlinear systems, noise resistant, suitable for multi-agent systems.	Computational overhead, complex implementation for limited resources.
IL (Imitation Learning)	Quick learning from demonstrations, acquires “human” logic of movement.	Limited generalization - may not work well in new scenarios.
DRL (Deep Reinforcement Learning)	Learns complex policies, suitable for dynamic and uncertain environments.	Requires large amounts of data, complex sim-to-real transfer, no security guarantees without additional modules.
CBF (Control Barrier Function)	Provides formal security guarantees, integrates with other methods.	It is not an independent planning method, but only an add-on for restrictions.

An analysis of current methods shows that the choice of approach for designing routes for collaborative robots in dynamic environments depends on the requirements for accuracy, speed, and the level of interaction between agents. Classic A* and D* algorithms remain relevant for global planning due to their predictability and stability, but their effectiveness decreases in scenarios with rapid changes, requiring frequent replanning or integration with local methods. Sampling algorithms PRM and RRT* work well in complex geometries but have limited performance in multi-agent systems, requiring combination with optimization approaches. Optimization-based methods, such as MPC, MPPI, and TEB, are more suitable for collaborative scenarios because they take into account robot dynamics, time constraints, and allow for the integration of other participants' motion predictions. In multi-robot systems, decentralized approaches such as ORCA and VO play an important role, ensuring fast collision avoidance without global coordination, although they do not guarantee optimal trajectories. The use of learning methods, especially DRL in combination with MPC or CBF, increases adaptability and allows for complex dynamics to be taken into account, but requires significant computational resources and proven safety mechanisms. Hybrid architectures that combine global planning with local optimization, trajectory prediction, and learning are currently considered the most promising for designing collaborative robot routes in the context of Industry 5.0.

Conclusions. The study showed that no single method is universal for building trajectories in a dynamic environment, and the best results are achieved using hybrid approaches that combine global planning, local optimization, and object motion prediction. The integration of optimization methods such as MPC or TEB with learning algorithms and safety mechanisms ensures adaptability, fast response, and increased safety for collaborative robots in Industry 5.0.

REFERENCES:

[1] Langås, E. F., Zafar, M. H., & Sanfilippo, F. (2025). Exploring the synergy of human-robot teaming, digital twins, and machine learning in industry 5.0: A step towards sustainable manufacturing. Journal of Intelligent Manufacturing, 1-24.

[2] Alonso, R., Sánchez, T. F., Alfaro, D. A., Cruz, Y. J., Villalonga, A., & Castaño, F. (2025). Automation and robotics pilot lines in the context of industry 5.0. Applied Sciences, 15(5), 2510. https://doi.org/10.3390/app15052510

[3] Amer Abu-Jassar, Hassan Al-Sukhni, Yasser Al-Sharo, Svitlana Maksymova, Vladyslav Yevsieiev, Vyacheslav Lyashenko, "Building a Route for a Mobile Robot Based on the BRRT and A*(H-BRRT) Algorithms for the Effective Development of Technological Innovations," International Journal of Engineering Trends and Technology, vol. 72, no. 11, pp. 294-306, 2024. Crossref, https://doi.org/10.14445/22315381/IJETT-V72I11P129

[4] Yevsieiev, V. Comparative Analysis of the Characteristics of Mobile Robots and Collaboration Robots Within INDUSTRY 5.0. / V. Yevsieiev, D. Gurin // Sectoral research XXI : characteristics and features : collection of scientific papers "SCIENTIA" with proceedings of the VI International Scientific and Theoretical Conference, September 8, 2023. - Chicago : European Scientific Platform, 2023. - P. 92-94.

[5] Nevliudov, I., Yevsieiev, V., Baker, J. H., Ahmad, M. A., & Lyashenko, V. (2020). Development of a cyber design modeling declarative Language for cyber physical production systems. J. Math. Comput. Sci., 11(1), 520-542.

[6] 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.

[7] 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.