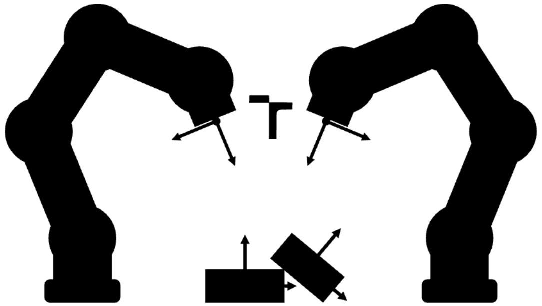


Design of Advanced Methods in the Field of Industrial Robotics fitting into the Concept of Industry 4.0

Doctoral Thesis

Brno University of Technology, Faculty of Mechanical Engineering, Institute of Automation and Computer Science

Author: Ing. Roman Parák

Supervisor: prof. Ing. Radomil Matoušek, Ph.D.

Co - Supervisor: Ing. et Ing. Stanislav Lang, Ph.D.

Brno, Czech Republic, 2024

Research Objectives

Design of a versatile robotic workstation in accordance with the Industry 4.0 concept.

- Vertical system integration for seamless interoperability.
- Human-machine interface (HMI) and a simulation tool using Unity3D.

Development of advanced methods in the field of industrial robotics.

- Comprehensive approach to kinematic solutions and motion planning across a variety of robotic manipulators, including under-articulated, articulated, and over-articulated structures.
- Collision avoidance mechanism to prevent collisions with external objects or self-collision, all while ensuring computational efficiency.

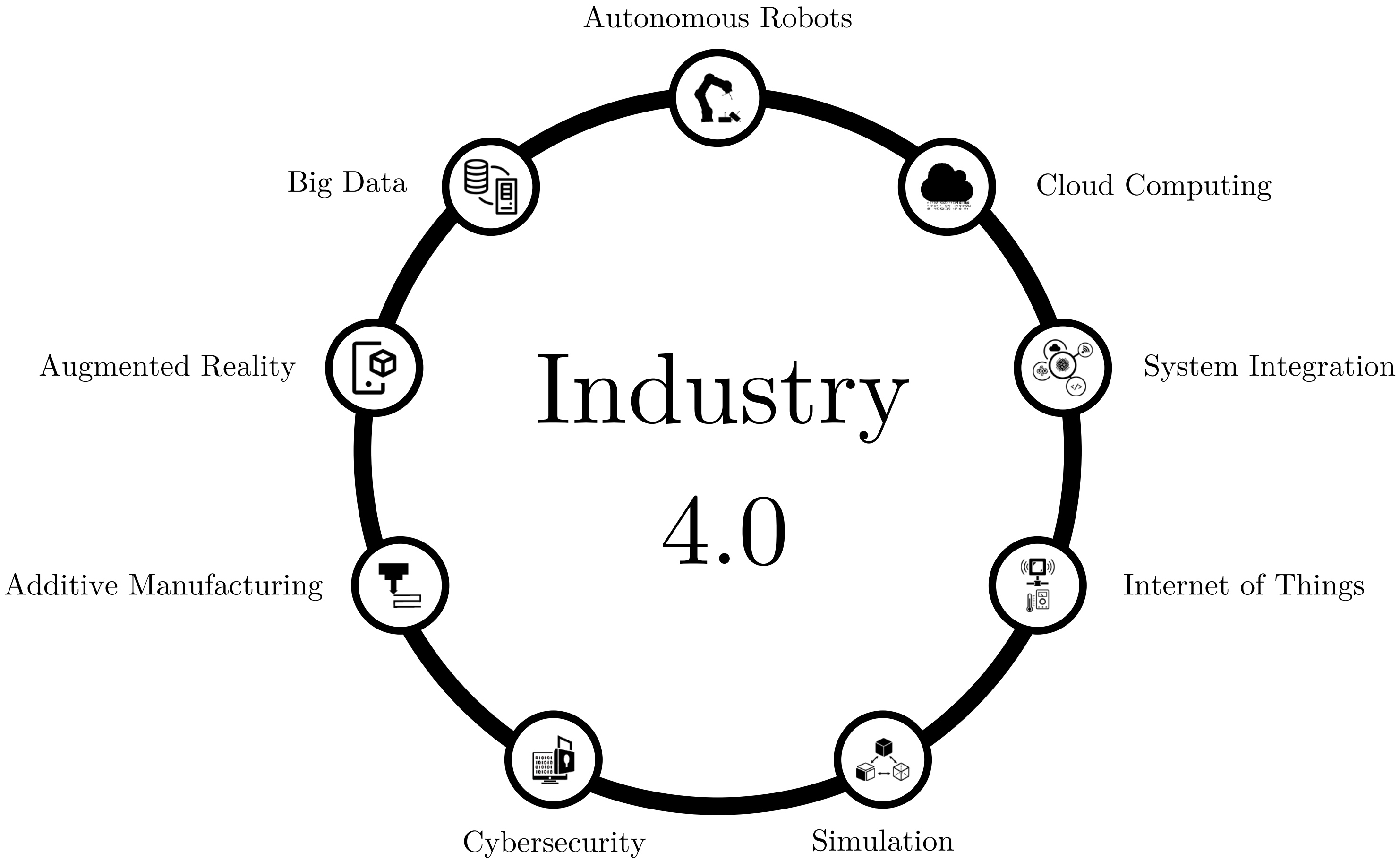
A critical research objective is to consider the impact of versatility, education, and future expansion.

Theoretical Part

Current State in the Field of Industry 4.0

Kinematics

Motion Planning

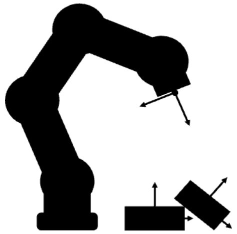


Theoretical Part

Current State in the Field of Industry 4.0

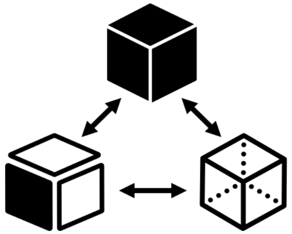
Kinematics

Motion Planning



Autonomous Robots

System Integration



Simulation

Theoretical Part

Current State in the Field of Industry 4.0

Kinematics

Motion Planning

The Future of the Industry?

~~Industry 5.0~~

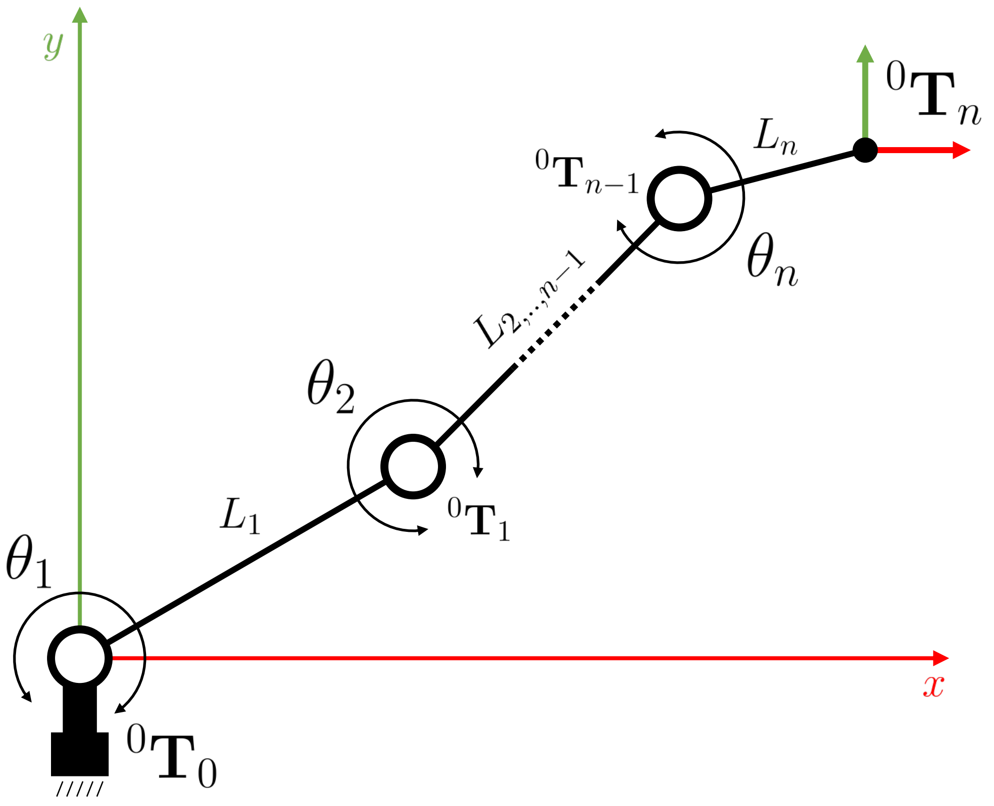
- Artificial Intelligence
  - Autonomous Robots
  - Simulation
  - ...
- Versatility
- Modularity
- Adaptability

Theoretical Part

Current State in the Field of Industry 4.0

Kinematics

Motion Planning



Forward Kinematics

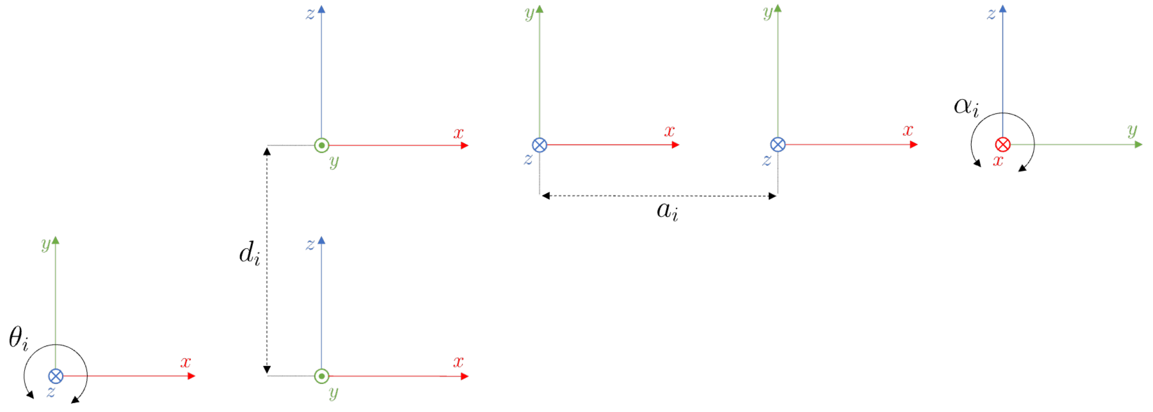
$$f(\theta_{1,\dots,n}) = {}^{0}\mathbf{T}_n$$

Inverse Kinematics

$$\theta_{1,\dots,n} = f^{-1}({}^{0}\mathbf{T}_n)$$

Theoretical Part

Denavit-Hartenberg Convention



Standard Convention

$$
{}^{i-1}\mathbf{T}_i = \mathbf{Rot}_{x,\alpha_i}\mathbf{Trans}_{x,a_i}\mathbf{Rot}_{z,\theta_i}\mathbf{Trans}_{z,d_i}
= \begin{bmatrix} c_{\theta_i} & -s_{\theta_i}c_{\alpha_i} & s_{\theta_i}s_{\alpha_i} & a_i c_{\theta_i} \\ s_{\theta_i} & c_{\theta_i}c_{\alpha_i} & -c_{\theta_i}s_{\alpha_i} & a_i s_{\theta_i} \\ 0 & s_{\alpha_i} & c_{\alpha_i} & d_i \\ 0 & 0 & 0 & 1 \end{bmatrix},
$$

Modified Convention

$$
{}^{i-1}\mathbf{T}_i = \mathbf{Rot}_{x,\alpha_{i-1}}\mathbf{Trans}_{x,a_{i-1}}\mathbf{Rot}_{z,\theta_i}\mathbf{Trans}_{z,d_i}
= \begin{bmatrix} c_{\theta_i} & -s_{\theta_i} & 0 & a_{i-1} \\ s_{\theta_i}c_{\alpha_{i-1}} & c_{\theta_i}c_{\alpha_{i-1}} & -s_{\alpha_{i-1}} & -d_i s_{\alpha_{i-1}} \\ s_{\theta_i}s_{\alpha_{i-1}} & c_{\theta_i}s_{\alpha_{i-1}} & c_{\alpha_{i-1}} & d_i c_{\alpha_{i-1}} \\ 0 & 0 & 0 & 1 \end{bmatrix}.
$$

Theoretical Part

Current State in the Field of Industry 4.0

Kinematics

Motion Planning

Inverse Kinematics

Numerical Solutions

Jacobian Matrix

$$J(\theta) = \begin{bmatrix} \mathbf{J}_P \\ \mathbf{J}_O \end{bmatrix} = \begin{bmatrix} \mathbf{J}_{P_1} & \dots & \mathbf{J}_{P_n} \\ \vdots & \ddots & \vdots \\ \mathbf{J}_{O_1} & \dots & \mathbf{J}_{O_n} \end{bmatrix} = \begin{bmatrix} \frac{\partial p_e^x}{\partial \theta_1} & \dots & \frac{\partial p_e^x}{\partial \theta_n} \\ \vdots & \ddots & \vdots \\ \frac{\partial \omega_e^z}{\partial \theta_1} & \dots & \frac{\partial \omega_e^z}{\partial \theta_n} \end{bmatrix}$$

Jacobian Transpose Method

$$\dot{\theta} = \alpha J(\theta)^T \mathbf{v}_e$$

Newton-Raphson Method

$$\dot{\theta} = (\mathbf{H})^{-1} J(\theta)^T \mathbf{W}_e \mathbf{v}_e$$

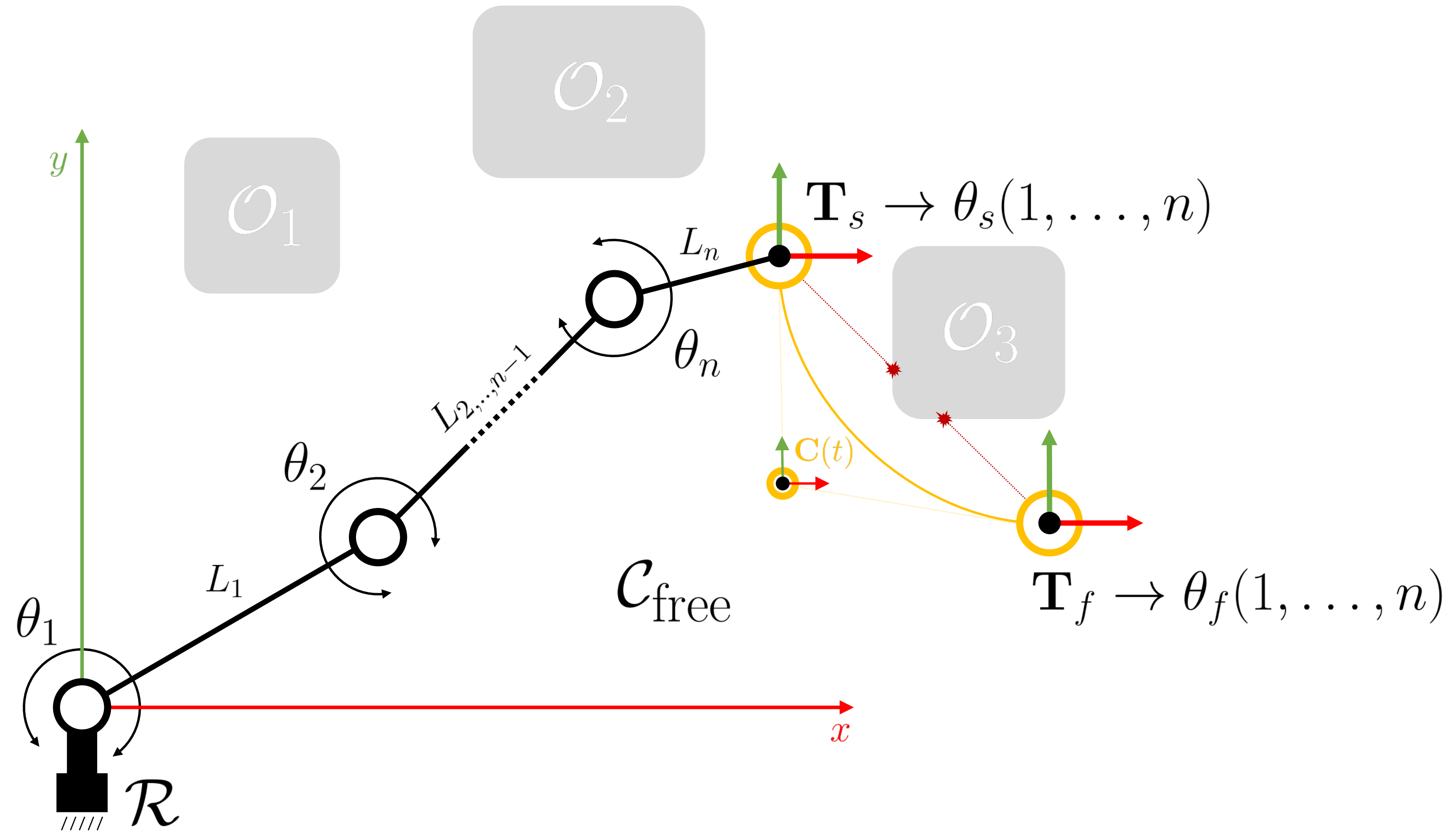
Gauss-Newton Method

$$\dot{\theta} = (\mathbf{H})^{-1} J(\theta)^T \mathbf{W}_e \mathbf{v}_e$$

Levenberg-Marquardt Method

$$\dot{\theta} = (\mathbf{A})^{-1} J(\theta)^T \mathbf{W}_e \mathbf{v}_e$$

Theoretical Part



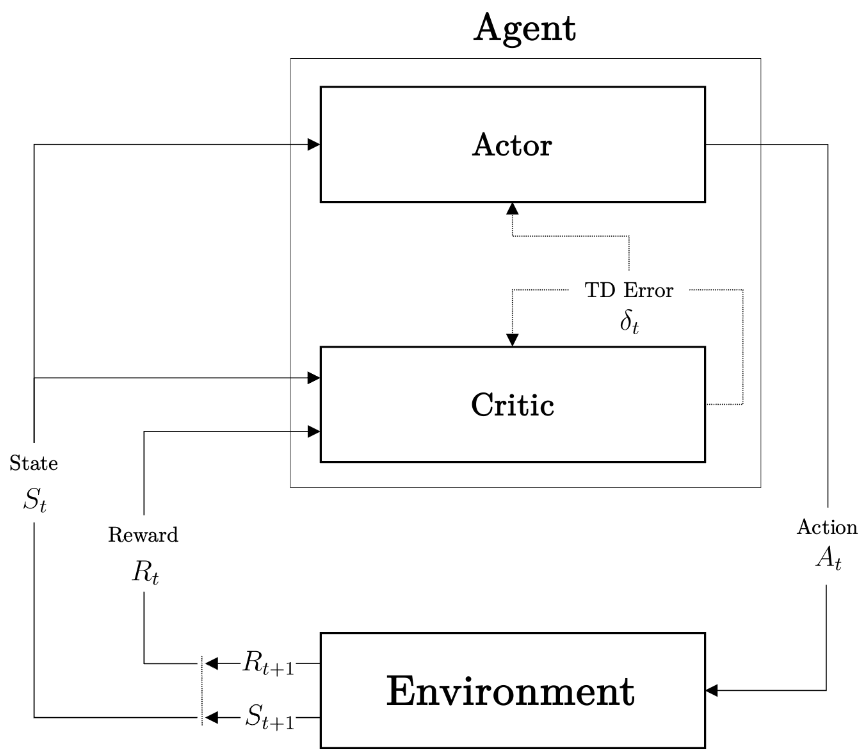
Theoretical Part

Current State in the Field of Industry 4.0

Kinematics

Motion Planning

Deep Reinforcement Learning



Theoretical Part

Current State in the Field of Industry 4.0

Kinematics

Motion Planning

Deep Deterministic Policy Gradient (DDPG)

$$L(\theta, D) = \mathbb{E}_D[(Q_\theta(s,a) - (R_t + \gamma(1-d)\max_{a'} Q_{\theta_{\text{targ}}}(s', \mu_{\text{targ}}(s')))^2]$$

Twin Delayed Deep Deterministic Policy Gradient (TD3)

$$L(\theta_i, D) = \mathbb{E}_D[(Q_{\theta_i}(s,a) - (R_t + \gamma(1-d)\min_{i \in 0,1} Q_{\theta_{i,\text{targ}}}(s', \mu_{\text{targ}}(s')))^2]$$

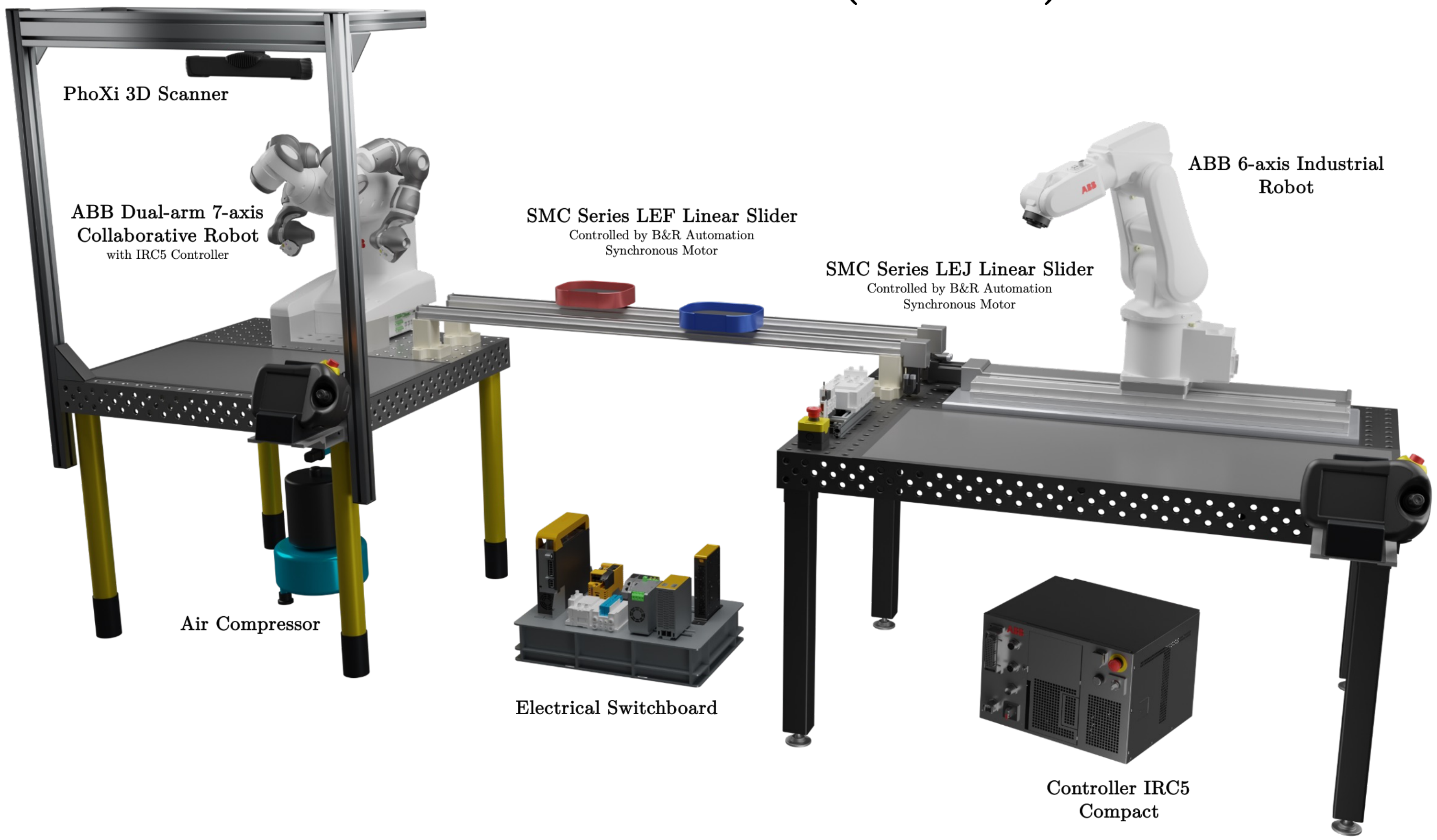
Soft Actor-Critic (SAC)

$$L(\theta_i, D) = \mathbb{E}_D[(Q_{\theta_i}(s,a) - y(r,s',d))^2]$$

$$y(r,s',d) = R_t + \gamma(1-d)(\min_{i \in 0,1} Q_{\theta_{i,\text{targ}}}(s', a') - \alpha \log \pi(a' \mid s'))$$

Practical Part

Versatile Intelligent Robotic Workstation (VInRoS)



Practical Part

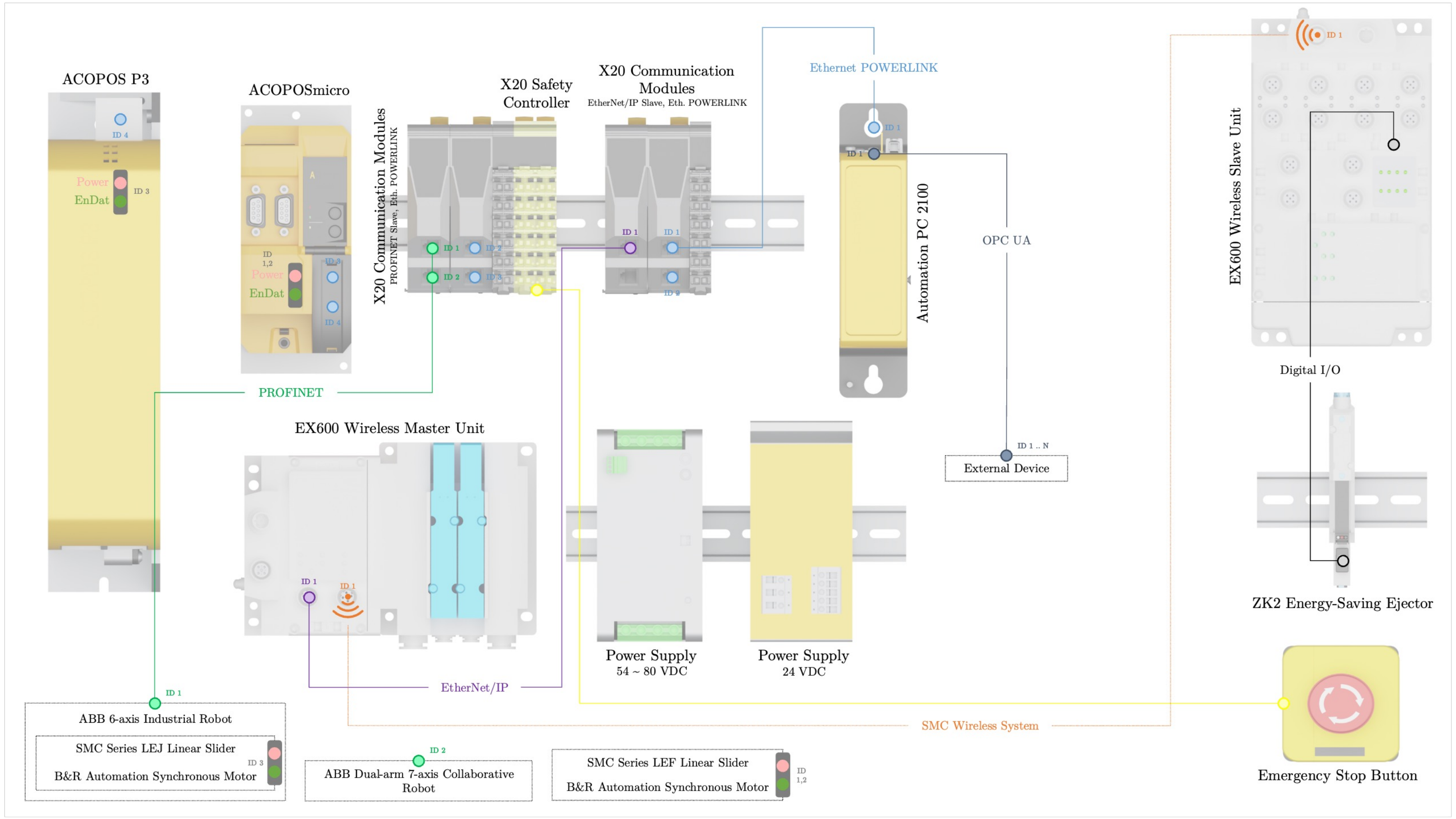
Construction Design of a Robotic Workstation

Human-Machine Interface

Comprehensive Approach to Kinematics Solutions

Physics-Based Simulators for Industrial Robotics

Deep Reinforcement Learning-Based Motion Planning



Practical Part

Practical Part

A **web-based** Human-Machine Interface (HMI) that manages data using the **OPC UA** (Open Platform Communications Unified Architecture).

Efficient **control**, **error handling**, and **monitoring** of the entire system.

Practical Part

Construction Design of a Robotic Workstation

Human-Machine Interface

Comprehensive Approach to Kinematics Solutions

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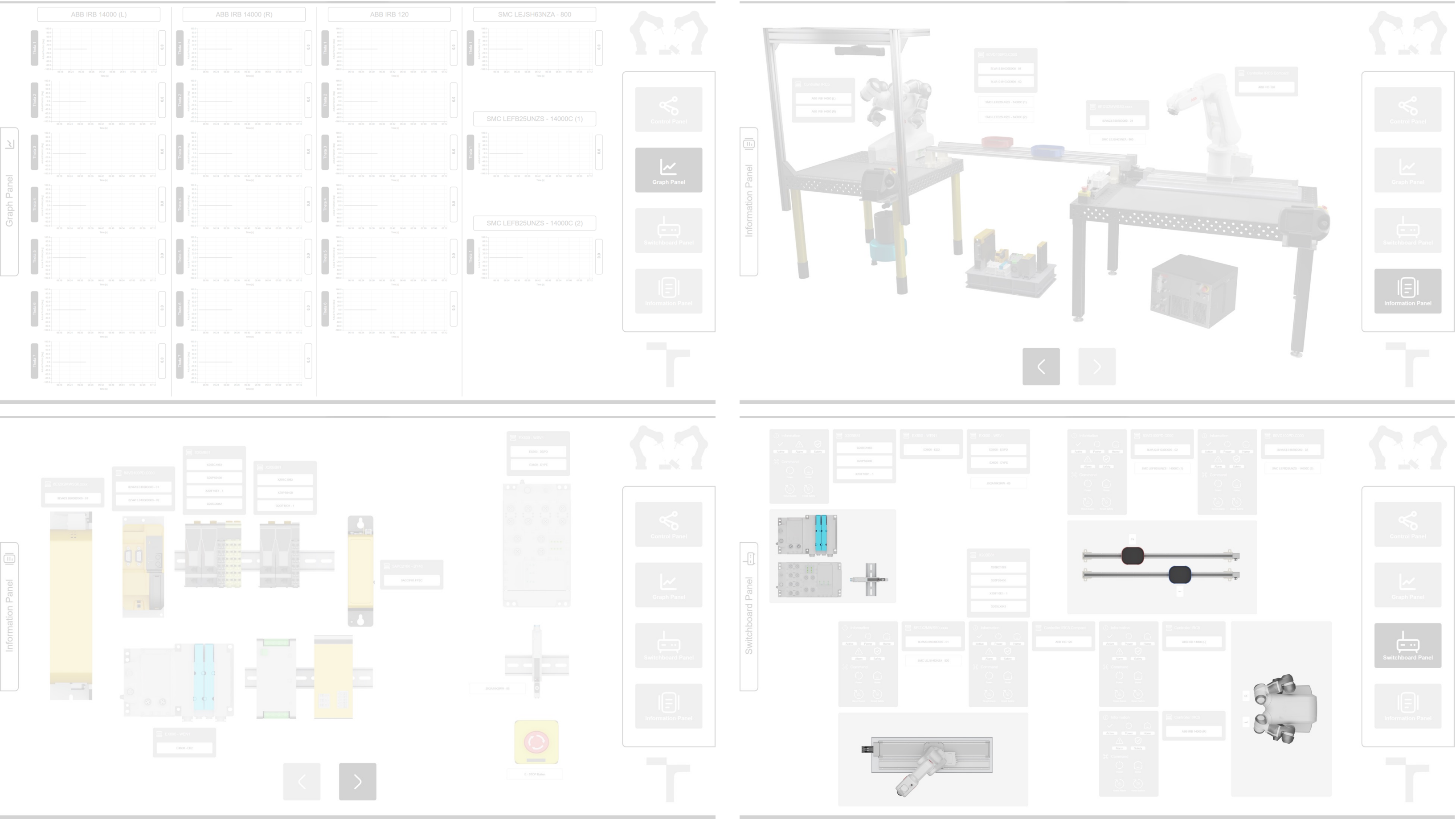
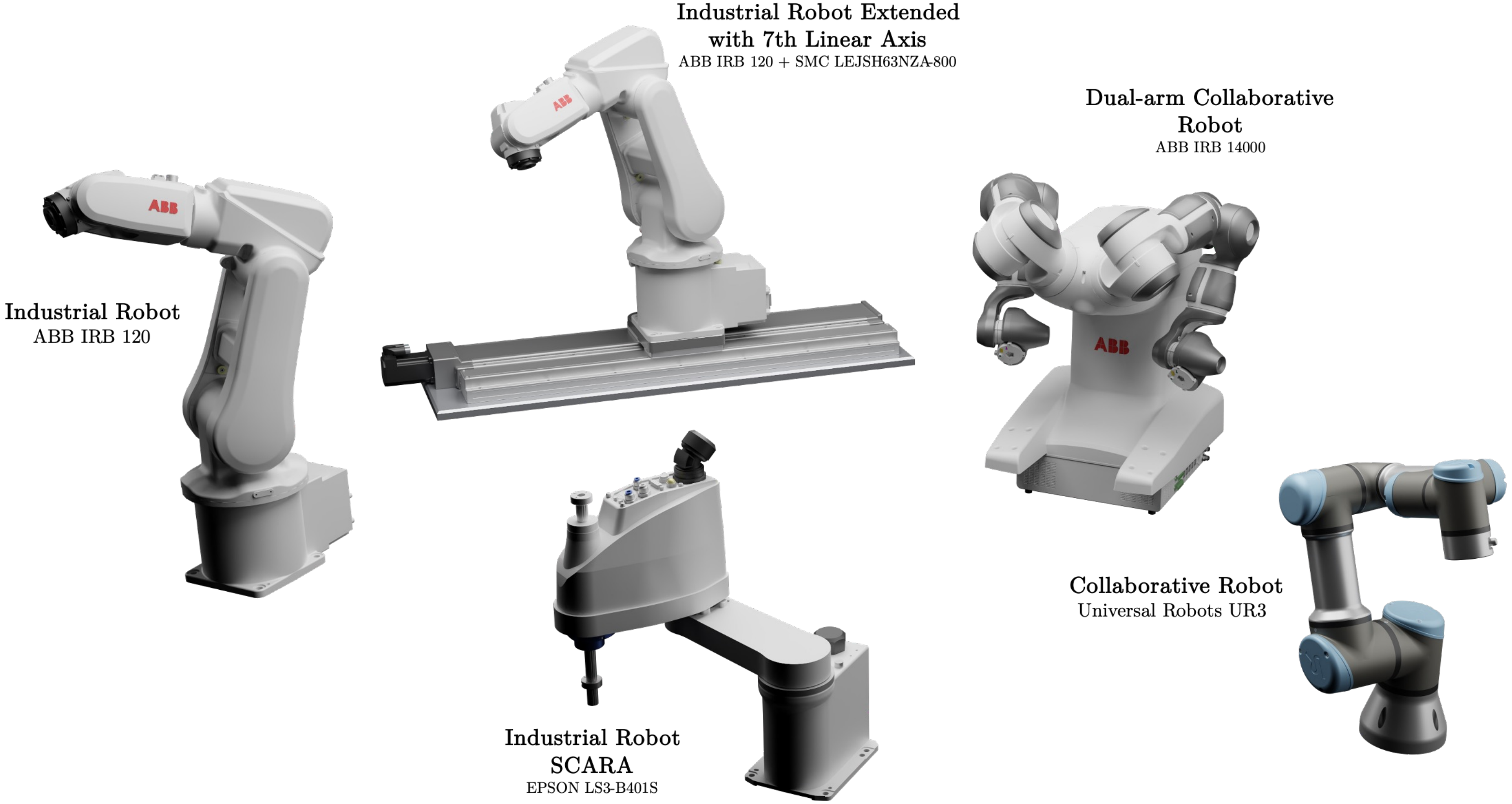
Deep Reinforcement Learning-Based Motion Planning



Practical Part



Practical Part

Construction Design of a Robotic Workstation

Human-Machine Interface

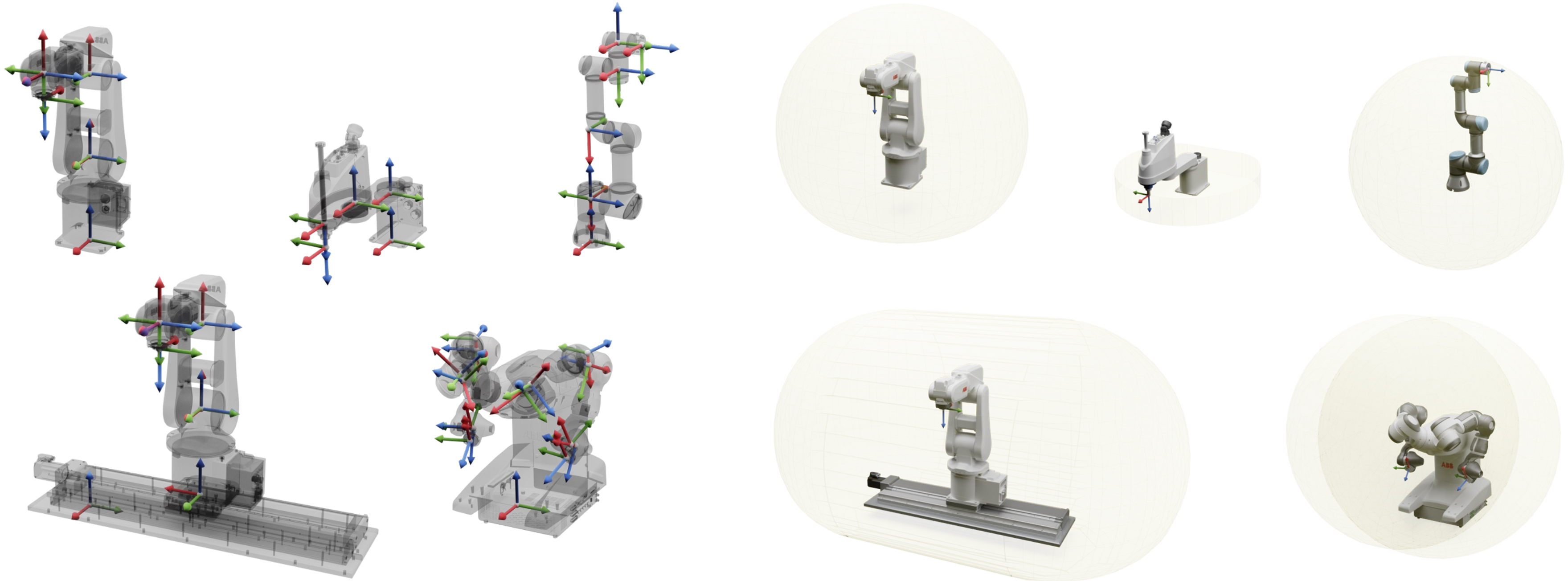
Comprehensive Approach to Kinematics Solutions

Physics-Based Simulators for Industrial Robotics

Deep Reinforcement Learning-Based Motion Planning

Geometric Representation

$$f(\theta_{1,\ldots,n}) = {}^{0}\mathbf{T}_n$$



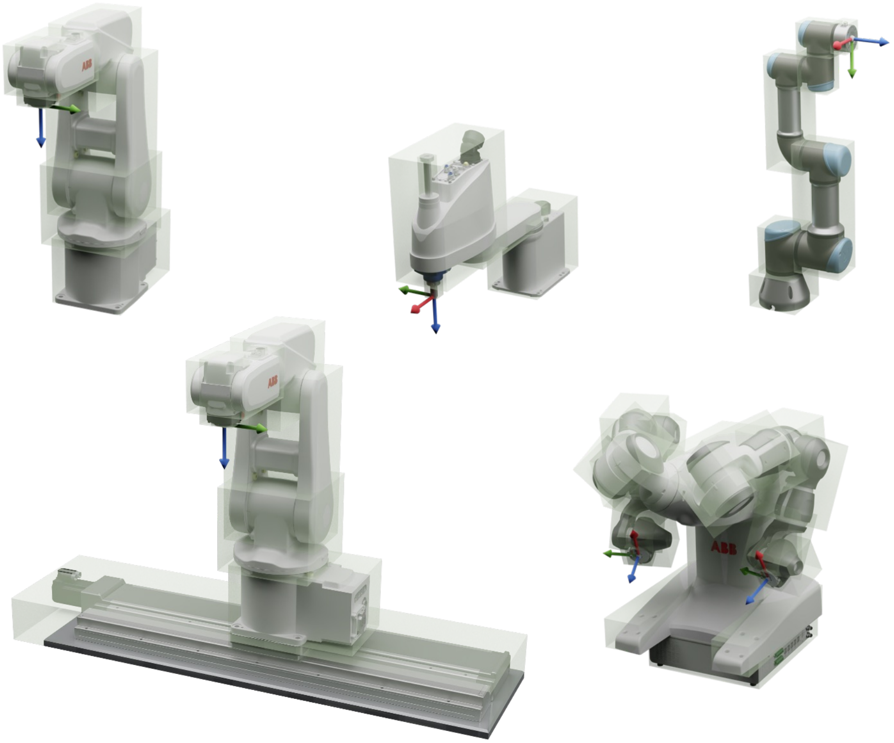
Practical Part

Total result time in seconds obtained by the test, which consists of 100,000 random targets, for Forward Kinematics calculation using the specified method.

Robot Type	Standard Denavit–Hartenberg Parameters	Modified Denavit–Hartenberg Parameters	Simplified Denavit–Hartenberg Parameters
Universal Robots UR3	13.32	13.55	5.66
ABB IRB 120	13.88	14.39	5.69
ABB IRB 120 Ext.	16.34	16.80	5.98
ABB IRB 14000 (L)	17.33	17.78	7.59
ABB IRB 14000 (R)	17.32	17.75	7.57
Epson LS3-B401S	10.17	10.45	3.38

Practical Part

Collision Structure



Approximation of the individual parts of the robotic structure using **bounding boxes**.

The static objects forming the base of the robot were approximated with **Axis-Aligned Bound- ing Boxes (AABBs)**, and dynamic objects such as joints with **Oriented Bounding Boxes (OBBs).**

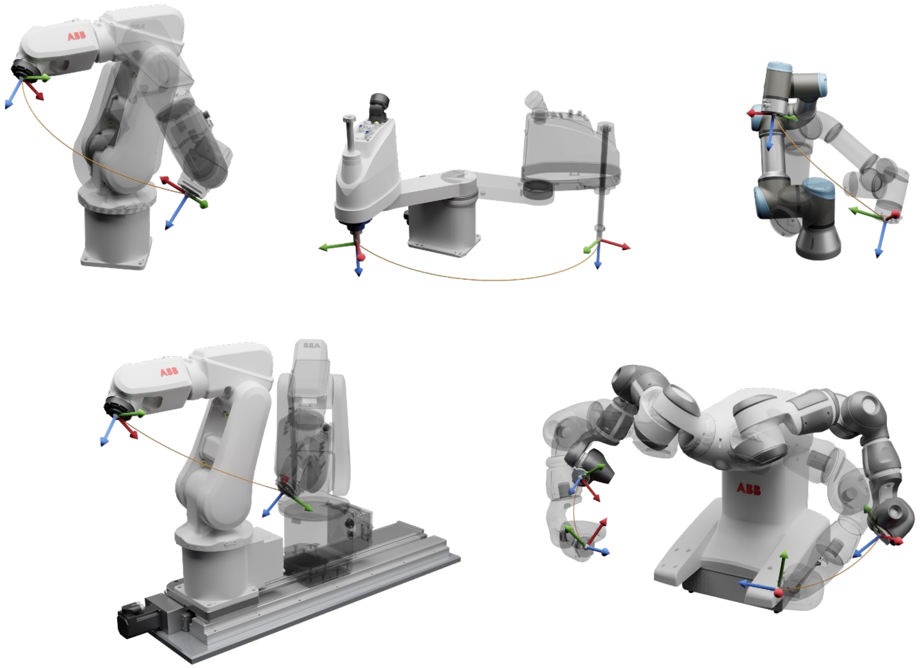
Individual components of the structure were **automatically approximated** and aligned using homogeneous transformation matrices.

Results of reducing the number of collision pairs through optimization performed on 100,000 random targets.

Robot Type	Number of Base Colliders $\mathcal{O}_{\mathbf{base}}$	Number of Joint Colliders $\mathcal{O}_{\theta}$	Initial Number of Collision Pairs	Optimized Number of Collision Pairs
Universal Robots UR3	1	6	21	8
ABB IRB 120	1	6	21	7
ABB IRB 120 Ext.	2	7	36	14
ABB IRB 14000 (L)	6	7	78	26
ABB IRB 14000 (R)	6	7	78	26
Epson LS3-B401S	1	4	10	2

Practical Part

Numerical Solution of Inverse Kinematics using the Informed Levenberg-Marquardt (LM) Method



Levenberg-Marquardt Method

$$\dot{\theta} = (J(\theta)^T \mathbf{W}_e J(\theta) + \mathbf{W}_n)^{-1} J(\theta)^T \mathbf{W}_e \mathbf{v}_e$$

Spatial velocity of the end-effector from the end-effector's current pose to the desired pose.

$$\mathbf{v}_{e,i}(\theta) = \begin{bmatrix} \mathbf{p}_d - \mathbf{p}_i \\ \alpha(\mathbf{R}_d {\mathbf{R}_i}^T) \end{bmatrix}$$

Quadratic error.

$$E = \frac{1}{2} {\mathbf{v}_e}^T \mathbf{W}_e \mathbf{v}_e$$

Practical Part

Results of the kinematic solution obtained through the informed Levenberg-Marquardt method, based on one hundred generated points. The tolerance E was set to 1e-30. The position error is given in metres.

Robot Type	**Mean Position Error** $\bar{e}_p$	**Mean Orientation Error** $\bar{e}_Q$	**Mean Quadratic Error** $\bar{E}$	**Mean Number of Iterations** $\bar{N}$
Universal Robots UR3	4.012e-16	1.060e-14	2.608e-31	7.633
ABB IRB 120	1.227e-16	1.230e-14	4.602e-32	6.861
ABB IRB 120 Ext.	2.460e-16	1.601e-14	1.168e-31	6.514
ABB IRB 14000 (L)	2.466e-16	2.077e-05	1.281e-31	6.683
ABB IRB 14000 (R)	1.879e-16	1.538e-05	8.873e-32	6.792
Epson LS3-B401S	4.386e-16	2.880e-14	1.673e-31	10.702

Practical Part

Construction Design of a Robotic Workstation

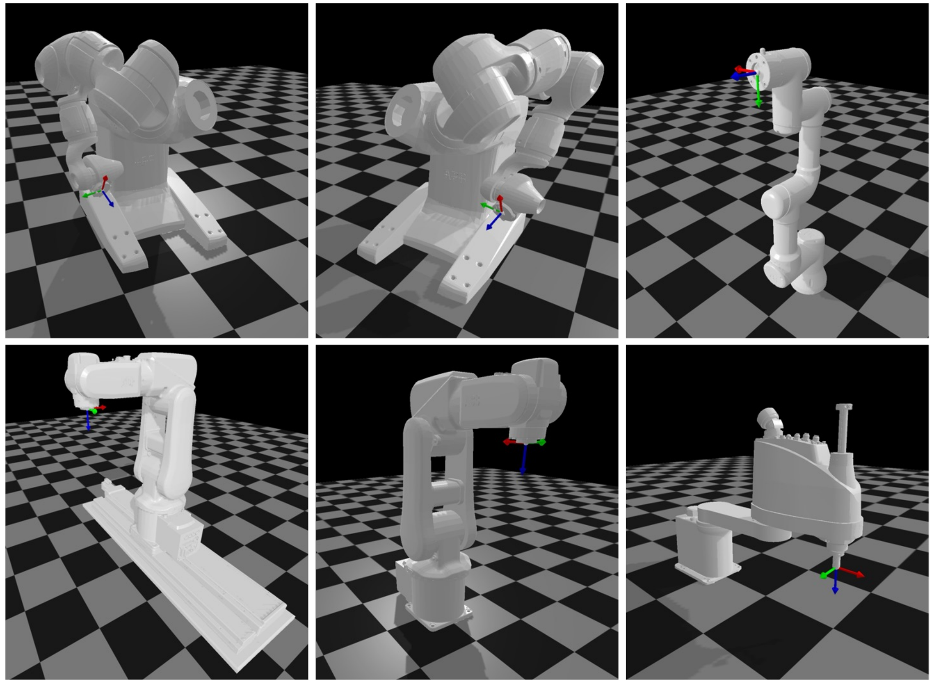
Human-Machine Interface

Comprehensive Approach to Kinematics Solutions

Physics-Based Simulators for Industrial Robotics

Deep Reinforcement Learning-Based Motion Planning

Bullet Real-Time Physics Simulation

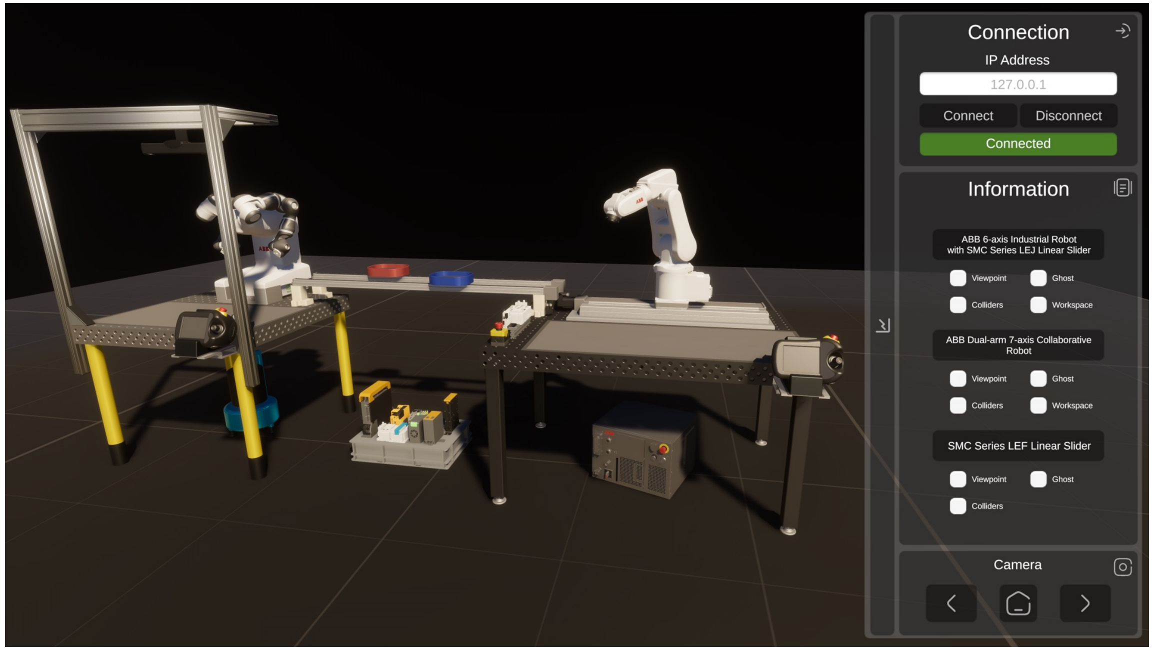


Automatic generation of **Universal Robot Description Format (URDF)** files from Denavit-Hartenberg (DH) parameters.

Validation of **kinematics, collision avoidance mechanism,** and **trajectory generation** across a variety of robotic manipulators.

Practical Part

Unity Real-Time Development Platform



Custom simulation tool based on Unity3D to integrate the entire VInRoS.

The application's data management is entirely based on the **OPC UA** architecture.

Practical Part

Construction Design of a Robotic Workstation

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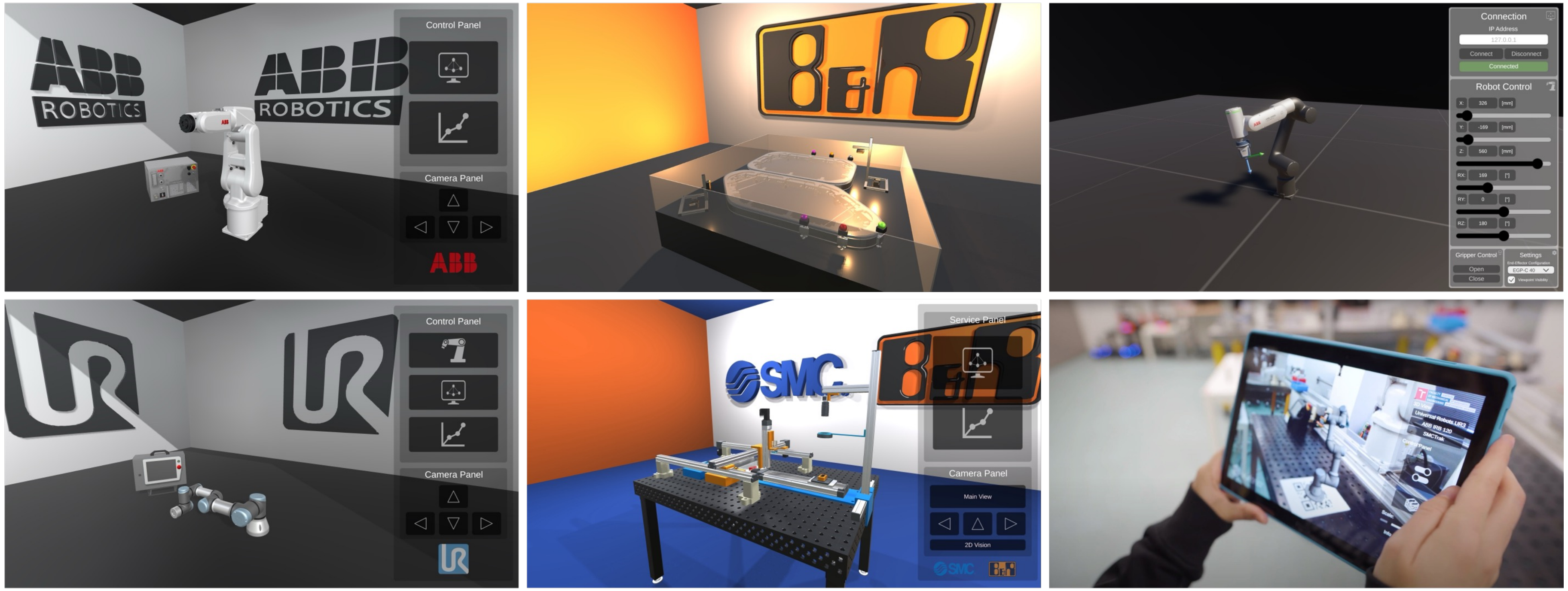
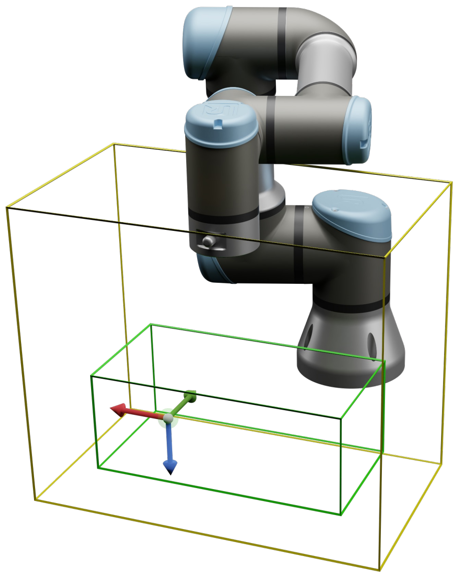
Unity Real-Time Development Platform



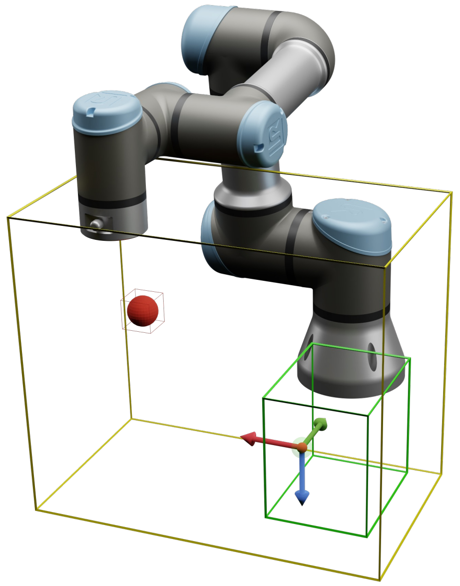
Practical Part

Comparison of Actor-Critic Methods for Reaching Tasks in Pre-Defined Spaces

$\mathcal{E}_1$



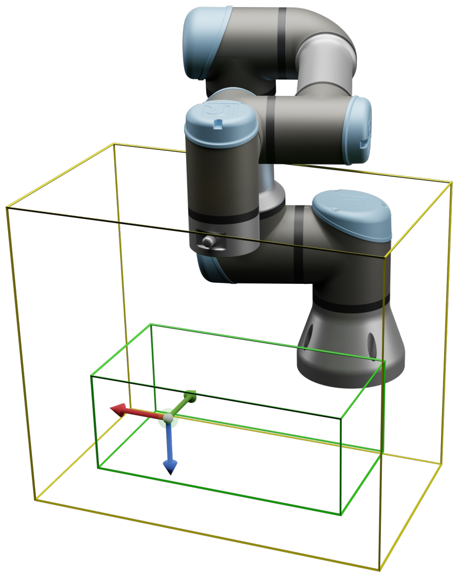
$\mathcal{E}_2$



Practical Part

Configuration Space without any External Collision

$\mathcal{E}_1$



The action space consists of the **end-effector movement** command in **three-dimensional Euclidean space.**

Reward Function

$$R_i = -(\|\mathbf{p}_d - \mathbf{p}_i\|)$$

Practical Part

Construction Design of a Robotic Workstation

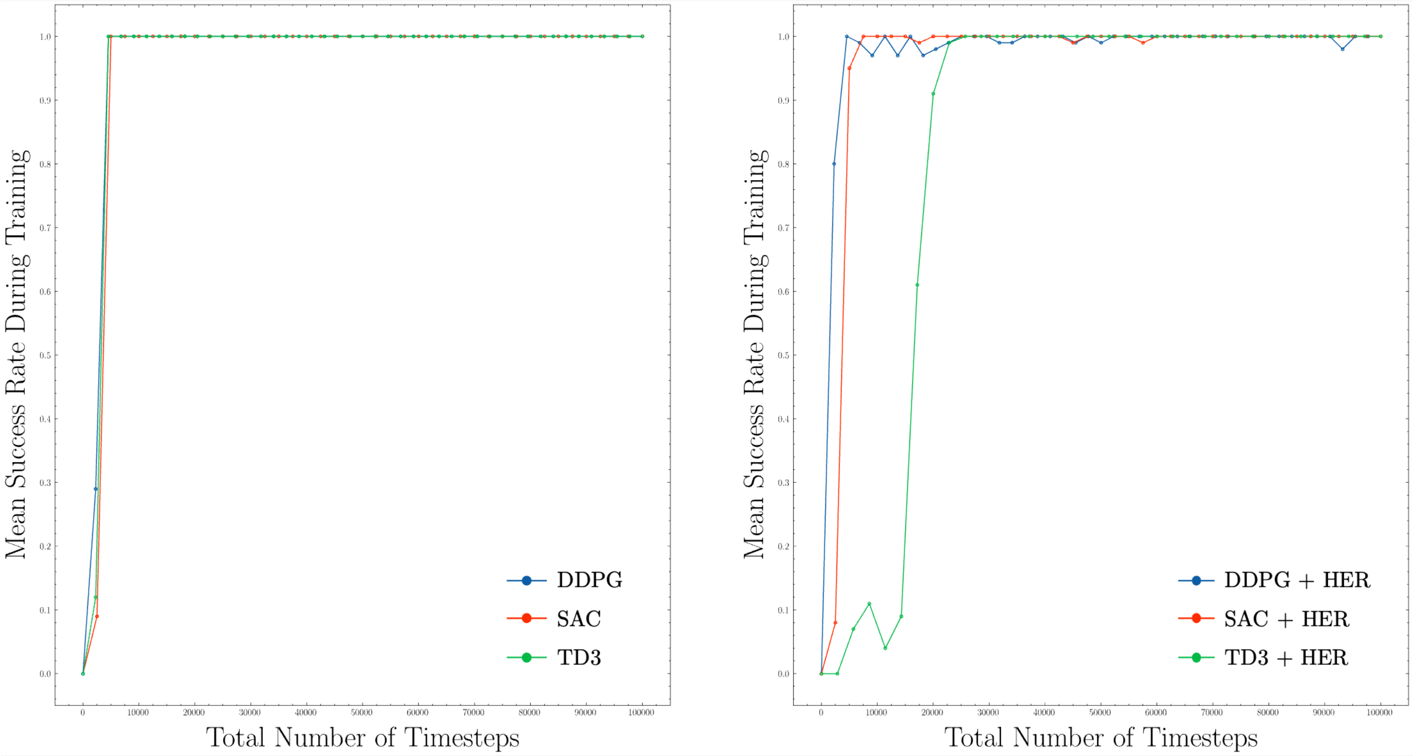
Human-Machine Interface

Comprehensive Approach to Kinematics Solutions

Physics-Based Simulators for Industrial Robotics

Deep Reinforcement Learning-Based Motion Planning

Configuration Space without any External Collision



Practical Part

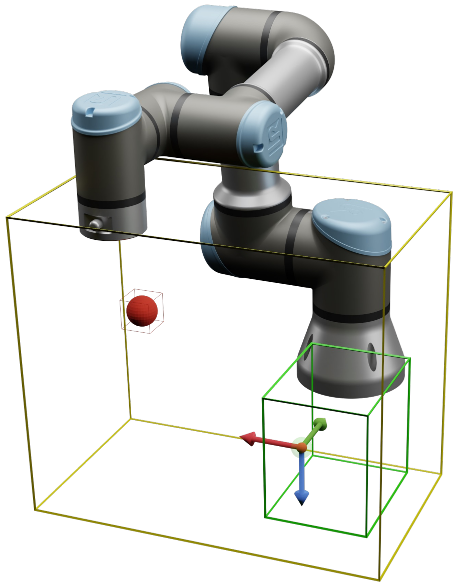
Results comparing various DRL algorithms. The minimum success rate required to meet the specified criteria was set at 0.98.

Algorithm	Success Rate	Percentage of Successful Targets	Mean Reward per Episode	Mean Episode Length
DDPG	$0.98 - 1.0$	95.86%	-0.388	5.299
DDPG + HER	$0.98 - 1.0$	89.83%	-0.387	5.431
SAC	$0.98 - 1.0$	96.52%	-0.408	5.682
SAC + HER	$0.98 - 1.0$	94.85%	-0.407	5.701
TD3	$0.98 - 1.0$	96.61%	-0.386	5.298
TD3 + HER	$0.98 - 1.0$	78.73%	-0.395	5.720

Practical Part

Configuration Space with the Presence of a Statically Positioned External Collision Object

$\mathcal{E}_2$



The action space consists of the **end-effector movement** command in **three-dimensional Euclidean space.**

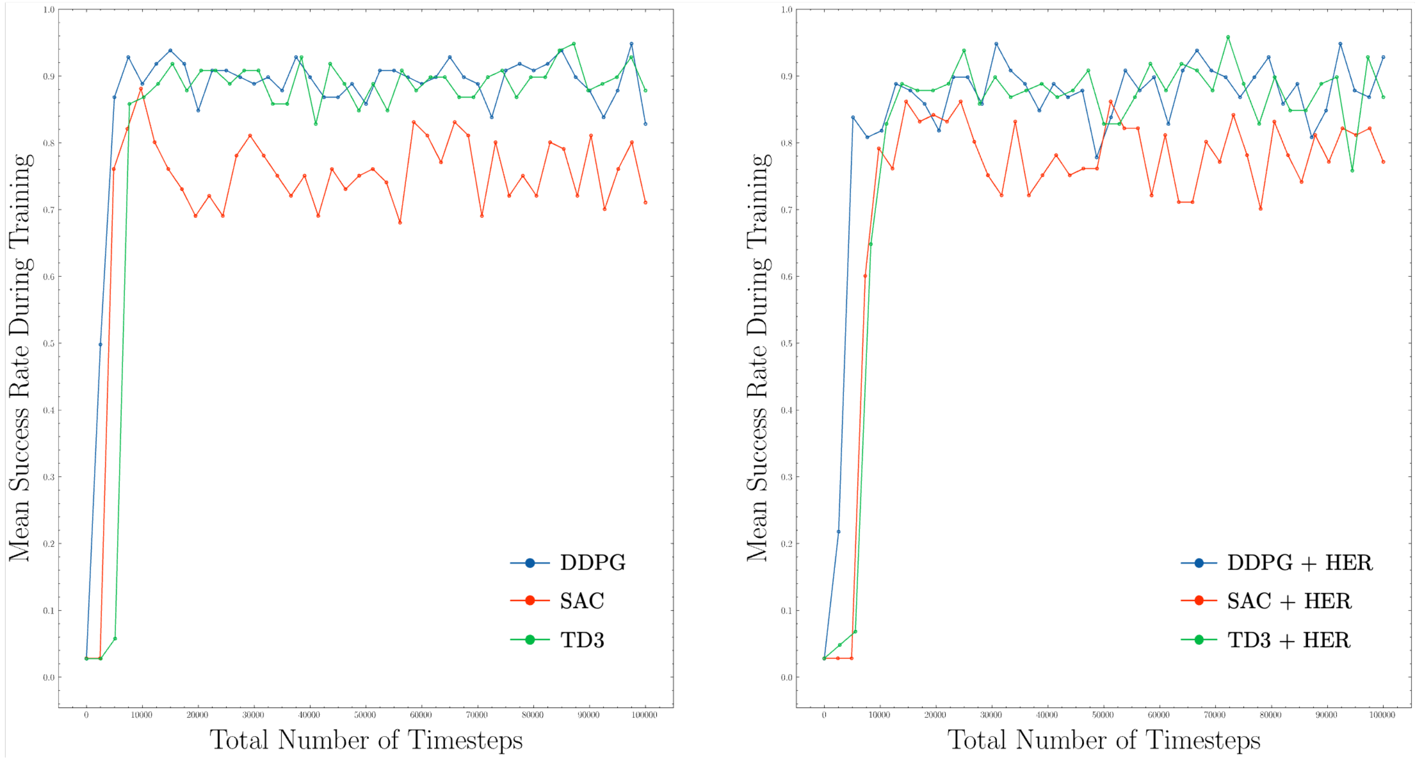
Reward Function

$$R_i = -(\|\mathbf{p}_d - \mathbf{p}_i\| + \frac{\gamma_{\mathcal{O}}}{1 + \|\mathbf{p}_{\mathcal{O}} - \mathbf{p}_i\|})$$

Penalty term with respect to the collision object.

Practical Part

Configuration Space with the Presence of a Statically Positioned External Collision Object



Practical Part

Results comparing various DRL algorithms. The minimum success rate required to meet the specified criteria was set at 0.8.

Algorithm	Success Rate	Percentage of Successful Targets	Mean Reward per Episode	Mean Episode Length
DDPG	$0.8 - 0.97$	95.01%	-0.710	5.866
DDPG + HER	$0.8 - 0.96$	86.72%	-0.711	5.944
SAC	$0.8 - 0.85$	5.048%	-0.709	5.684
SAC + HER	$0.8 - 0.88$	19.07%	-0.713	5.844
TD3	$0.8 - 0.96$	89.59%	-0.711	5.901
TD3 + HER	$0.8 - 0.94$	81.99%	-0.718	6.146

Practical Part

Application of Selected Algorithms to a Wide Range of Robotic Structures $\mathcal{E}_1$

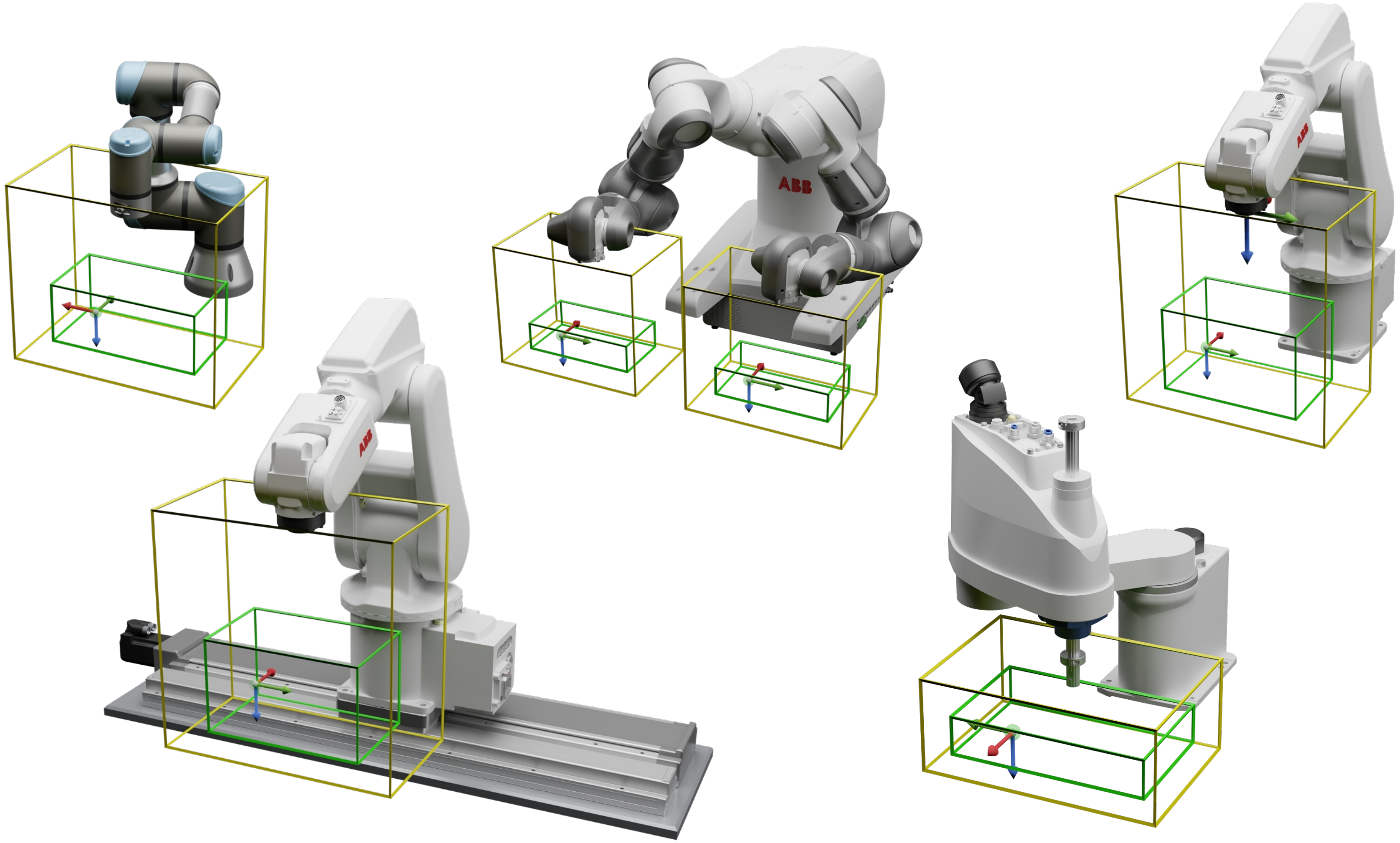
Construction Design of a Robotic Workstation

Human-Machine Interface

Comprehensive Approach to Kinematics Solutions

Physics-Based Simulators for Industrial Robotics

Deep Reinforcement Learning-Based Motion Planning



Practical Part

Comparison of a wide range of robot structures using the TD3 algorithm in the training process. The minimum success rate required to meet the specifications was set at 0.98.

Robot Type	Success Rate	Percentage of Successful Targets	Mean Reward per Episode	Mean Episode Length
Universal Robots UR3	0.98–1.0	96.61%	−0.386	5.298
ABB IRB 120	0.98–1.0	84.32%	−0.602	6.073
ABB IRB 120 Ext.	0.98–1.0	87.65%	−0.637	6.647
ABB IRB 14000 (L)	0.98–1.0	94.51%	−0.256	4.593
ABB IRB 14000 (R)	0.98–1.0	91.69%	−0.256	4.608
Epson LS3-B401S	0.98–1.0	94.39%	−0.064	2.474

Comparison of a wide range of robot structures using the TD3 algorithm for one hundred randomly generated targets. The position error is given in meters.

Robot Type	Success Rate	Mean Reward per Episode	Mean Episode Length	Mean Absolute Position Error
Universal Robots UR3	1.0	−0.365	4.94	0.0024
ABB IRB 120	1.0	−0.501	5.26	0.0055
ABB IRB 120 Ext.	1.0	−0.502	5.16	0.0061
ABB IRB 14,000 (L)	1.0	−0.233	4.21	0.0024
ABB IRB 14,000 (R)	1.0	−0.228	4.13	0.0028
Epson LS3-B401S	1.0	−0.059	2.32	0.0030

Practical Part

Application of Selected Algorithms to a Wide Range of Robotic Structures $\mathcal{E}_2$

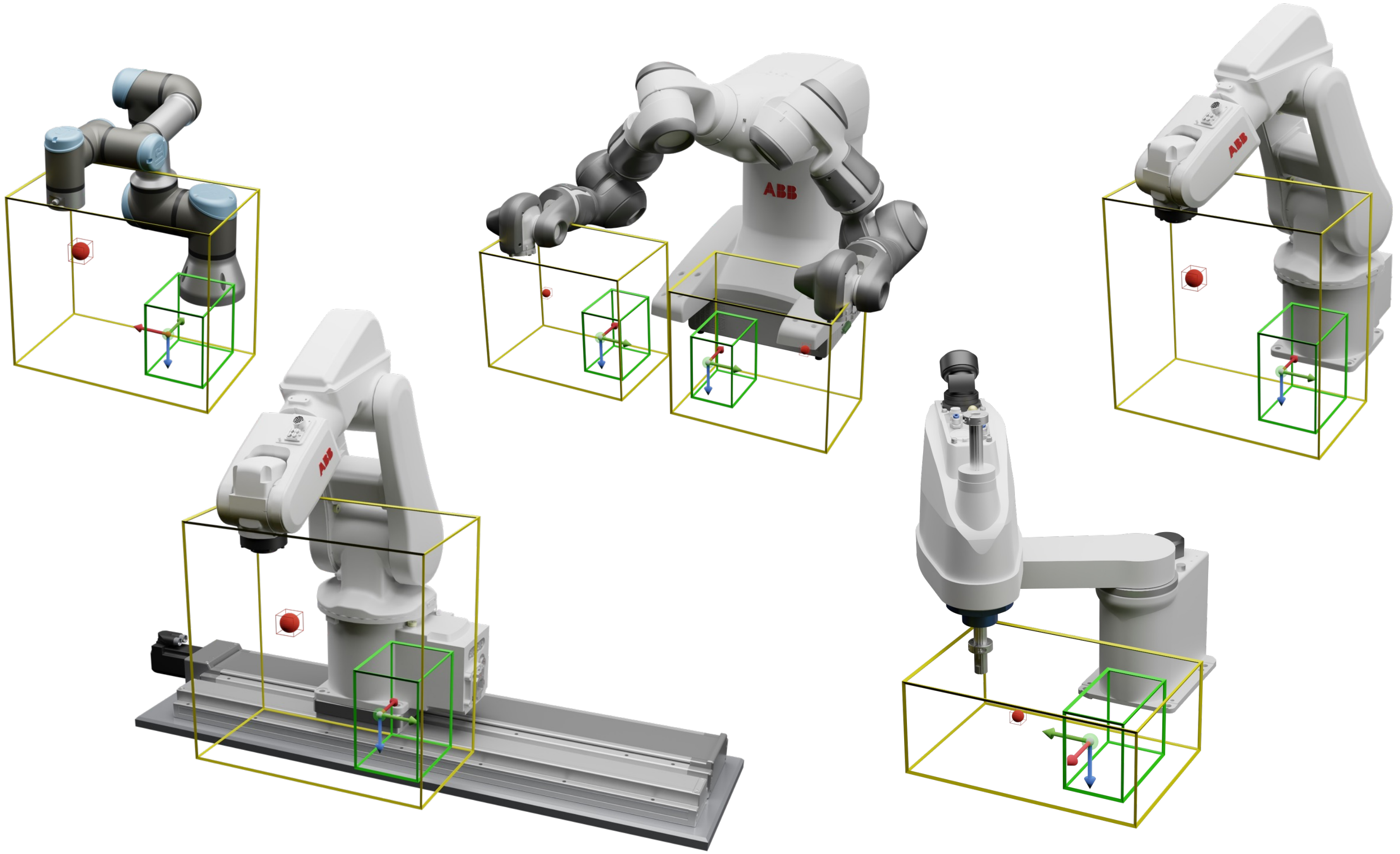
Construction Design of a Robotic Workstation

Human-Machine Interface

Comprehensive Approach to Kinematics Solutions

Physics-Based Simulators for Industrial Robotics

Deep Reinforcement Learning-Based Motion Planning



Practical Part

Comparison of a wide range of robot structures using the DDPG algorithm in the training process. The minimum success rate required to meet the specifications was set at 0.8.

Robot Type	Success Rate	Percentage of Successful Targets	Mean Reward per Episode	Mean Episode Length
Universal Robots UR3	0.8–0.97	95.01%	−0.710	5.866
ABB IRB 120	0.8–0.98	95.26%	−0.874	6.609
ABB IRB 120 Ext.	0.8–0.98	96.83%	−1.031	8.041
ABB IRB 14,000 (L)	0.8–0.97	94.85%	−0.503	5.356
ABB IRB 14,000 (R)	0.8–0.96	92.14%	−0.499	5.227
Epson LS3-B401S	0.8–0.99	98.19%	−0.396	5.040

Comparison of a wide range of robot structures using the DDPG algorithm for one hundred randomly generated targets. The position error is given in meters.

Robot Type	Success Rate	Mean Reward per Episode	Mean Episode Length	Mean Absolute Position Error
Universal Robots UR3	1.0	−0.711	6.04	0.0058
ABB IRB 120	1.0	−0.859	6.45	0.0023
ABB IRB 120 Ext.	1.0	−0.945	6.98	0.0065
ABB IRB 14,000 (L)	1.0	−0.471	5.15	0.0040
ABB IRB 14,000 (R)	1.0	−0.470	5.12	0.0032
Epson LS3-B401S	1.0	−0.374	4.79	0.0027

Conclusion

Conclusion

Outlook for Future Research

Robotic Workstation in Accordance with the Industry 4.0 Concept
Designed the Versatile Intelligent Robotic Workstation (VInRoS), aligned with Industry 4.0 principles. Created vertical system integration for seamless interoperability.

User Interface
Created a web-based Human-Machine Interface (HMI) for the basic control, error handling, and monitoring the entire VInRoS system.

Comprehensive Approach to Kinematics Solutions
Developed the informed Levenberg-Marquardt method to solve kinematics with extensions such as self-collision detection, collision avoidance, and singularity control.

Conclusion

Conclusion

Outlook for Future Research

Physics-Based Simulation Tools
Developed a custom library for PyBullet and a modular simulation tool in Unity3D for comprehensive robotic simulation and data management based entirely on the OPC UA architecture.

Advanced Motion Planning Techniques
Utilized deep reinforcement learning (DRL) to address motion planning challenges, showing high adaptability and efficiency across various environments.

Future Potential and Open-Source Contribution
Emphasized future research and educational impact, with a fully open-source approach for the general public.

Conclusion

Conclusion

Outlook for Future Research

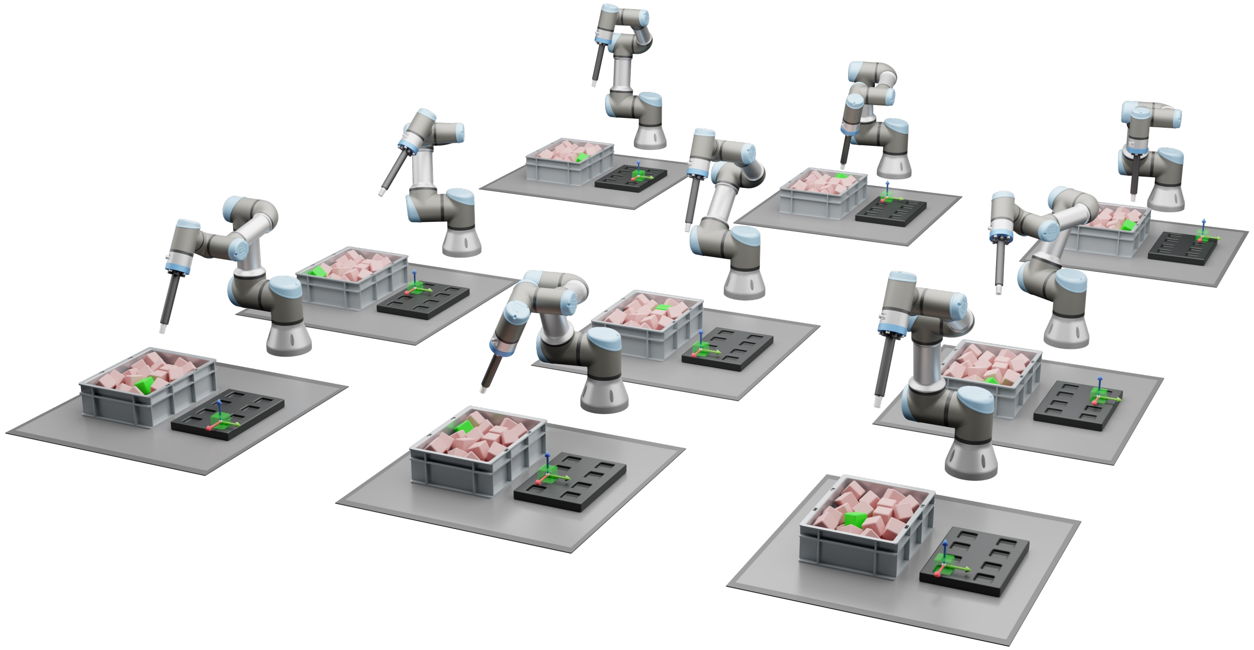
Expand the Capabilities of the Versatile Intelligent Robotic Workstation (VInRoS)
Integrate new hardware and software to increase flexibility.

Use Sophisticated Simulation Tools
Explore advanced simulation tools such as NVIDIA Isaac Sim for simulation of robotic systems.

Leverage Evolutionary Computation Algorithms
Combine with reinforcement learning techniques for more robust solutions.

Advanced Motion Planning Strategies

Develop solutions for complex tasks using multi-agent methods such as Multi-Agent Deep Deterministic Policy Gradient (MADDPG).



Conclusion

Outlook for Future Research

Activities Related to Doctoral Studies

General Activities

Pedagogical Practice

Projects

Conference & Workshop Presentations

Honors & Awards

Traineeship

A six-month Erasmus+ research traineeship in the academic year 2021/22 at the Institute of Robotics, Johannes Kepler University in the field of advanced robotics.

Supervisor: Assoc. Univ.-Prof. DI Dr. Hubert Gattringer

Scientific Publications

Total Publications: 7 scientific papers
Citations: 29 citations by Google Scholar to date
h-Index: 3

R. Parák, J. Kůdela, R. Matoušek, and M. Juříček, "Deep-Reinforcement-Learning-Based Motion Planning for a Wide Range of Robotic Structures," Computation, vol. 12, no. 6, p. 116, 2024.

Cooperation with Industrial Partners

B&R Automation, SMC Industrial Automation, ABB Robotics, Industry Cluster 4.0, Intemac Solutions

Activities Related to Doctoral Studies

Other

Co-organization of conferences such as the International Conference on Soft Computing MENDEL and Principia Cybernetica.

Development of laboratories in the fields of general robotics, augmented reality, machine vision, and programmable logic controllers.

Collaboration on creating a new course for the Master's degree in **'Programming of Robots and Manipulators'** and the Bachelor's degree in **'Industry 4.0'**. Creation of teaching materials for Bachelor's and Master's studies in English and Czech.

Supervisor (13 students) and **co-supervisor (33 students)** for the Bachelor's and Master's study programs in the field of robotics, machine vision, and artificial intelligence techniques. **Reviewer of 26 student** theses.

Activities Related to Doctoral Studies

Academic Year: 2017/18 to 2023/2024

Winter semester
Computer Science (1IN), Control Theory I (VA1), Control Theory I in English (VA1-A), Programmable Controller Systems (VPL & VPL-K), Virtual Reality (V0R)

Summer semester
Automation (6AA), Control Theory II (VA2), Industry 4.0 (0P4), **Programming for Robots and Manipulators (VRM & VRM-K)**, Industry 4.0 in English (VI4-A)

Activities Related to Doctoral Studies

Research in the field of digital twins for the production of electrical switchboards. In cooperation with ABB Group.
Duration: 01.12.2018 — 31.05.2020

Industry 4.0 and Artificial Intelligence methods.
Duration: 01.03.2020 — 28.02.2023

OpenTube: Robotic workplace for analysis test samples of Covid-19. In cooperation with the University Hospital Brno.
Duration: 18.01.2021 — 30.04.2022

ATCZ281 - TESTBED EXCHANGE: Networking of Industry 4.0 testbeds in Czech- Austrian cooperation from the Operational Programme Interreg V-A Austria - Czech Republic.
Duration: 01.10.2021 — 31.12.2022

Activities Related to Doctoral Studies

General Activities

Pedagogical Practice

Projects

Conference & Workshop Presentations

Honors & Awards

R. Parák and B. Lacko, "Introduction to Robotics for Young Scientists," Science enjoys us: Interactive and fun camps for children, Brno, Czech republic, 2018 & 2019.

R. Parák and B. Lacko, "Workshop: Industry 4.0 Cell (I4C)," Trade Media International: Conference on Robotics, Brno, Czech republic, 2020.

R. Parák, "Industry 4.0 Cell (I4C): A Robotic Cell Based on the Industry 4.0 Concept," Trade Media International: Conference on Robotics, Brno, Czech republic, 2021.

R. Parák, "Industry 4.0 Cell (I4C): A Robotic Cell Based on the Industry 4.0 Concept," Industry 4.0 Cluster: Industry 4.0 Conference, Brno, Czech republic, 2021.

R. Parák, R. Matoušek, and B. Lacko, "Industry 4.0 Cell (I4C): A Brief Overview," Networking Czech and Austrian Testbeds for Industry 4.0, Vienna, Austria, 2022.

R. Parák and R. Matoušek, "Industry 4.0 Cell (I4C): A Brief Overview," B&R Headquarters: Networking Czech and Slovak Robotic Laboratories, Eggelsberg, Austria, 2023.

Activities Related to Doctoral Studies

General Activities

Pedagogical Practice

Projects

Conference & Workshop Presentations

Honors & Awards

Silver medal (Team Award), Brno University of Technology, 2020.
Team Award - Robotic workplace for the analysis of test samples within the event Brno University of Technology helps with COVID-19.

Rector's Award for Ph.D. students, Brno University of Technology, 2020.

Rector's Award for Teachers, Brno University of Technology, 2023.
One of the top 10 teachers at the Faculty of Mechanical Engineering, Brno University of Technology, for the Master's program.

Thank You