Department of Engineering Science, Faculty of Engineering and Science,
Chatham Maritime, Kent, ME4 4TB

PROJECT SPECIFICATION REPORT 2024/2025

ABSTRACTING CONTROL OF INDUSTRIAL ROBOTS USING MACHINE LEARNING HEURISTICS

George Mathieson [001156616]
BEng (Hons) Computer Engineering (EXT)

Supervisor: **Dr Wim Melis**

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Abstract

Existing industrial robotics systems are designed with an unintuitive and rigid approach to both the setup and optimisation of operation. As a direct consequence of this, programming and reprogramming even the most basic of tasks requires much experience and a specialised skillset; this leads to significant resource inefficiencies – whether by the compromised utilisation of time, personnel, equipment, capital, materials, or energy – when, in this world of ever-advancing machine learning technologies, this simply doesn't have to be the case.

By integrating recent innovations in reinforcement machine learning and digital simulation with a FANUC LR Mate 200iC, the hope here is to bring us closer to a more planet and human-friendly future by demonstrating joint position optimisation for more effectively performing industrial tasks from high-level commands. This report dives into the analyses undertaken on existing research in preparation for the project, defines the sheer scale and importance of pushing for such progress in this industry, and sets expectations of what can be achieved.

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1.1 Background of Project

Since the mid-20th century, developments in industrial robotics have aimed to lessen the burden on humans by automating tasks deemed unsafe, unpleasant, and/or undesirable (Wallén, 2008) – often outperforming us in metrics of speed, consistency, and accuracy, among many more. As the technology improves and the relevant markets grow (see Figure 2), we observe positive trends in the reduction of cost (Figure 1), increase of supply, and availability of talent relating to the development and utilisation of these systems; any movement in what is such a fundamental part of our society has a ripple effect on the global economy and, in this case, enables advancements in manufacturing whilst simultaneously shifting job standards ever-higher (simulated in Figure 4).

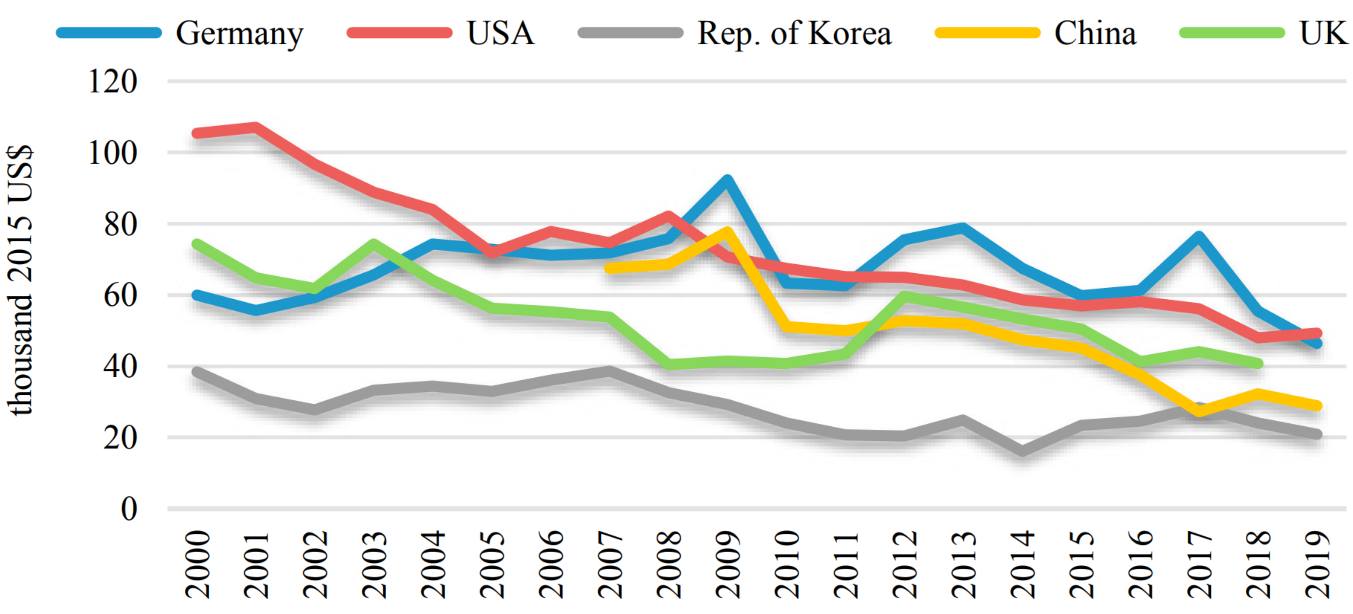

Figure 1: Plot of industrial robotics systems' cost by country, over time (Gryczka, 2023).

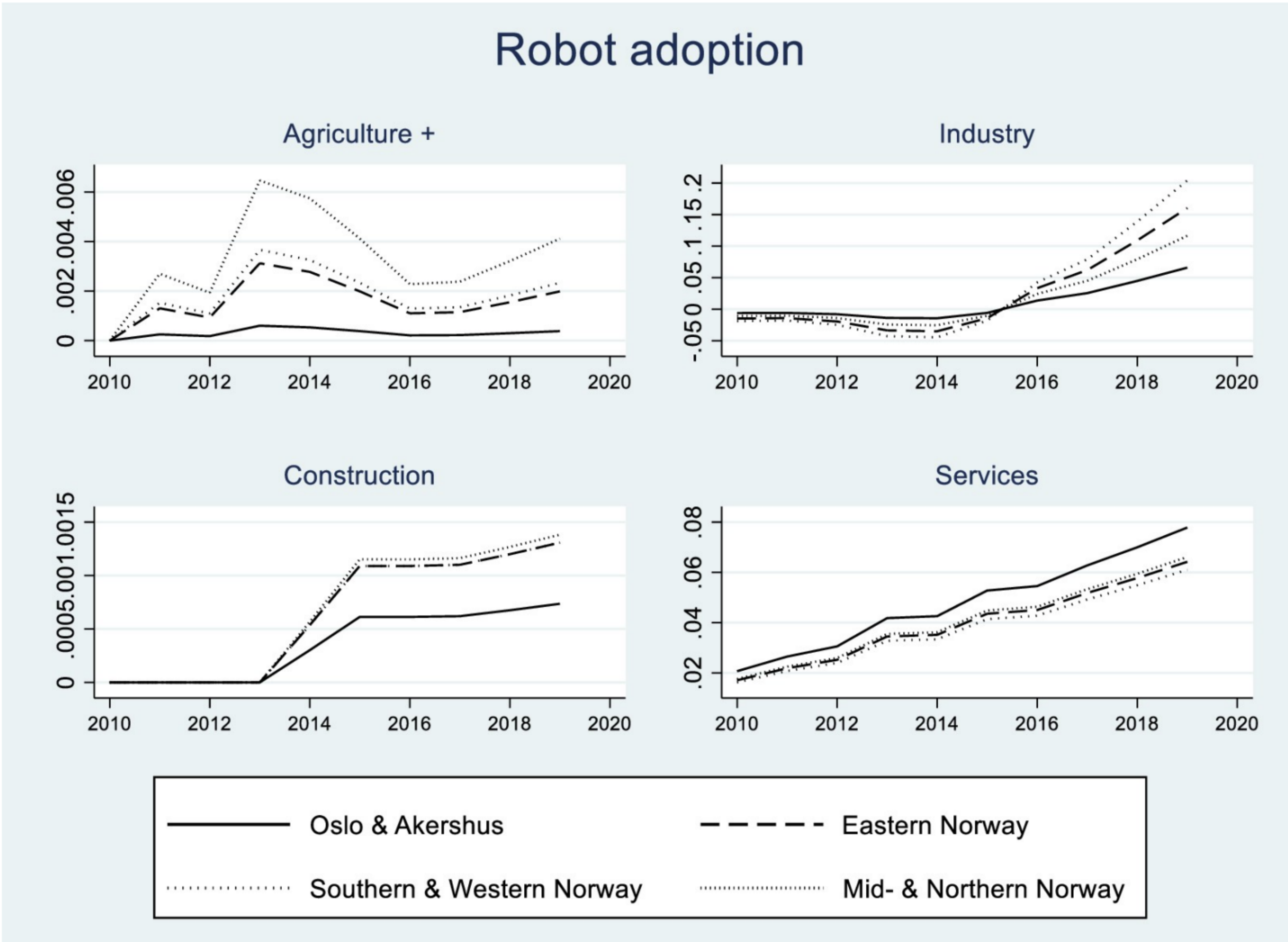

Figure 2: Plot of Norwegian industrial robotics adoption rates by industry (Schwabe and Castellacci, 2020).

These same trends can have a negative impact on many people's lives in the near term, with factory workers being one of the countless examples over the past half-century of professionals (typically with labour-intensive roles) being made redundant in favour of automated alternatives (as shown in Figure 3); there are similar accounts of workforces losing motivation from the mere possibility of such displacement. The narrative of those most affected enforces the importance of maintaining the availability of jobs with lower barriers of entry in order to flatten the distribution of wealth (for a simulation of the existing trend, see Figure 5).

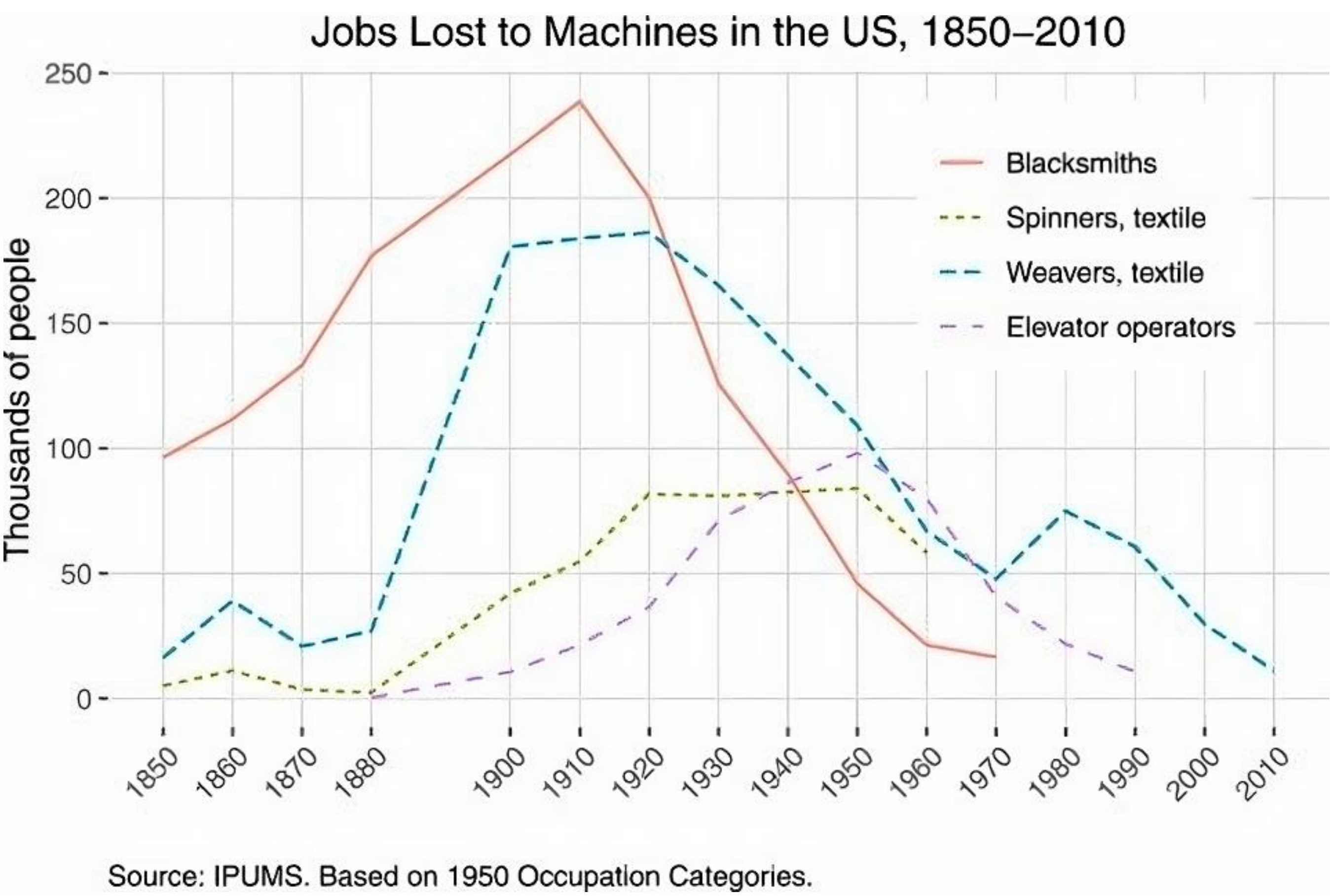

Figure 3: Plot of professions lost in the US to automation over time (Güven, 2024).

Some might argue that this is merely a redistribution of skillsets, where one job area is lost for another of a similar nature to grow and accommodate new demands. As already alluded to, the benefits of automation can, in fact, increase living standards overall through reductions in the cost of consumer goods, local economic growth from increased productivity, and – in the longer term – the availability of higher-paid employment opportunities.

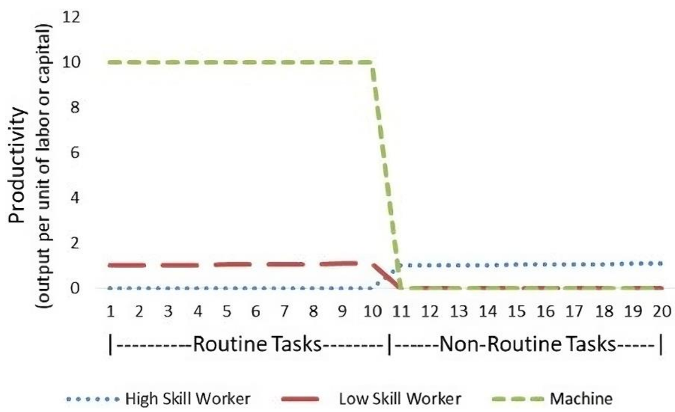

Figure 4: Plot of simulated data for the effect of task automation on labour distribution (Upreti and Sridhar, 2024).

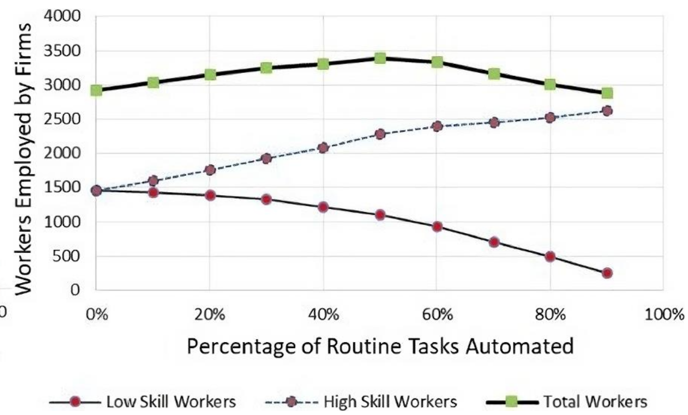

Figure 5: Plot of simulated data for the effect of task automation on job security (Upreti and Sridhar, 2024).

By introducing a more intuitive interface between humans and machines, labourers with little to no relevant prior experience or knowledge would be able to add significant value to heavily automated manufacturing lines by simply allowing for a shorter turnaround time between requirements changing and the successful reprogramming of these systems. Tasks such as these – which are currently undertaken by individuals with skillsets that can be better utilised further up the process chain - can then be offered with lower entry requirements.

1.2 Aims and Objectives of the Project

1.2.1 Project Aims

The ambition of this project is to produce an intuitive interface for programming the behaviours of industrial robots using machine learning for joint optimisations.

1.2.2 Project Objectives

Table 1 (Project Objectives)

Category	Task	Importance	Description
Robot Control	Manual Control	Low	Actuate the robot using the proprietary controller
	Realtime Commands	High	Send commands to the robot for real-time execution
Machine Learning	Digital Twin	High	Develop a digital copy of the robot
	RL Algorithm	High	Implement a suitable control algorithm
	Simulated Training	High	Train model in a virtual gym
User Experience	VR Support	Low	Implement VR headset support for virtual gym
	Motion Controller Support	Low	Implement controller support for position inputs

1.3 Definition of relevant terms

Table 2 (Key Terms)

Term	**Definition**
Machine Learning (ML)	A statistical computing paradigm under the umbrella term of AI (Artificial Intelligence) for producing generalised outputs based on learnings from trends found in training data.
End Effector	A device typically found at the end of a robot's 'arm' that interacts with the world directly.
Work Envelope	The shape and size of the volume able to be occupied by the end effector.
Operating Envelope	A constrained portion of the work envelope (typically for safety).
Inverse Kinematics	A mathematical approach for determining individual joint placement to achieve a desired end effector position.
Joint Interpolation	A control technique for characterising joint movement curve profiles.
FANUC LR Mate 200iC	A high-precision, table-top size 6-axis robot by FANUC.

1.4 Scope of the Project

Despite the promise of revolutionising global manufacturing, this project will merely aim to prove a fraction of the innovations required; as with any prototype system such as this, it is not intended to be inherently scalable but, instead, act as a proof of concept for the viability of more intuitive interfaces between humans and industrial machinery.

Figure 6: Photograph of a FANUC LR Mate 200iC system (Anon, n.d.).

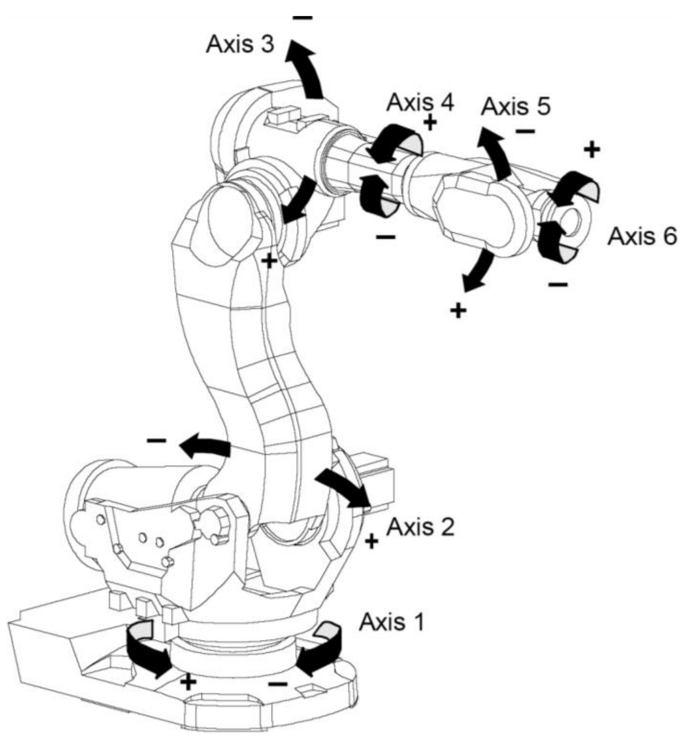

Figure 7: Diagrammatic wireframe of a 6-axis industrial robot arm (Wernholt, 2004).

The robot to be used (FANUC LR Mate 200iC) (as shown in Figures 6-7) is significantly smaller than the systems used in many factories today and, although achieving comparable speed and accuracy, falls far short of the load-bearing capabilities of the larger systems (5kg as opposed to multiple tonnes). Similarly, the work envelope is much more limited compared to standard industrial robots as it directly corresponds to the size of the device; otherwise, interfacing, maintaining, and operating requirements are much the same.

Extended functionality such as the use of the end effector as a tool is not a priority of this project as it adds significant complexity without acting as anything more than a distraction from the core objective; the alternative here would be to demonstrate appropriate end effector positioning with the complete absence of hard-coded joint behaviours. A system developed under fewer constraints, using the methods and learnings from this project would, however, scale relatively easily and likely have a net positive impact on the industry.

1.5 Literature Review

This section briefly addresses published research and reviews, all of which act as either relevant context to the project or as applicable technological approaches.

1.5.1 Background on Industrial Automation

Between General Motor's nearly two-tonne system (the first-ever proclaimed industrial robot) from 1961 and examples such as KUKA's 16kg system from 2006 (equipped with a sophisticated arrangement of sensors), there have been an immense number of advancements made in the capabilities and scale of industrial robots (IFR, 2012).

Data between 2006 and 2021 from China has shown a relationship of 1.8% increases in industrial robot applications with 1% increases in population aging (Zhao et al., 2024). Similarly, between 1978 and 1991, Japan saw a 3.67% increase in the installations of automation systems correlating with a 1% increase in reported unskilled labour shortages – the opposite effect was observed with shortages of skilled workers (Deng et al., 2023).

During this rapid deployment of automation, Toyota chose to shift in favour of manual labour due to related difficulties with employee retention, motivation, and hiring power (Coffey and Thornley, 2006). In the West, Germany experienced a significant decrease in the number of automation-related patents (a potentially insightful data point relating to the amount of investment in the industry) during an influx of low-skilled immigrant workers (Danzer, Feuerbaum and Gaessler, 2024).

Despite safety concerns, trends in China show that a single standard deviation increase in robot exposure relates to a reduction of 0.1 accidents and 0.0133 fatalities per 1000 population from sample averages of 0.122 and 0.0351 respectively (Luo et al., 2025); this is all in addition to a reduced environmental footprint (Dai et al., 2024). Similarly, the US found a reduction of 1.2 cases per 100 full-time manufacturing workers – saving around $1.67 billion per year in costs – although, unfortunately, they also noted the synonymous decrease in worker wellbeing (Gihleb et al., 2022; Fornino and Manera, 2022).

The 2019 World Robotics Report found that global industrial robot installations crossed 400,000 units annually for the first time in 2018, demonstrating strong growth of the industry with a nearly four-fold increase in about a decade (IFR, 2019); these trends are enhanced by support for the data-driven process optimisations of industry 4.0 (Soori et al., 2024).

1.5.2 Design and Operation of Industrial Robotics Systems

Automation promises enhanced productivity, safety, environmental footprint (Bonello, Refalo and Francalanza, 2024), and longevity which have all encouraged innovation in the physical architecture of facilities (Santana et al., 2017; Strasser et al., 2010) and have introduced novel approaches to process organisation (Bdiwi, Pfeifer and Sterzing, 2017).

Advanced temperature and vibrational analyses now enable the discovery of problems before they arise, which is key to effective facility management and preventing downtime (van Roosmale et al., 2024). Centralised, Configurable Process Control – a methodology for more appropriately handling robotics tasks – has also helped with 12.29% increases in processing rates, 6.31% decreases in errors, and 11.1% decreases in process latency (El-Meligy et al., 2023).

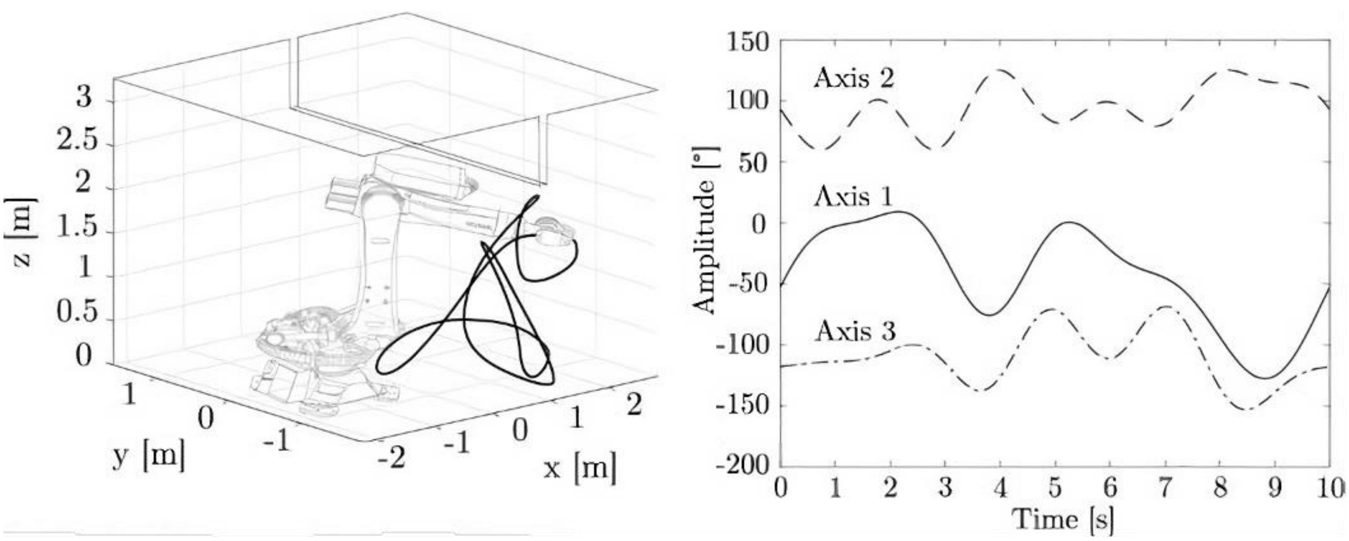

Figure 8: Diagrammatic representation of individual joint actuation in multi-axis industrial robotics (Huynh et al., 2020).

There appears to be a significant bottleneck in the way that industrial robotics systems are programmed, there are countless examples of joint configurations (Figure 8 depicts a breakdown of such) that cause a 6-axis robot arm to be limited to only 5 degrees of freedom (Bouzgou and Ahmed-Foitih, 2015). One paper found that standard Programmable Logic Controllers are too restrictive to optimise for energy efficiency, proposing an alternative method to address this (Fuhrländer-Völker, Lindner and Weigold, 2021).

For path optimisation in robotics, it is clear that the exact selection of performance metrics directly influences the final solution. Optimising for runtime and path length saw 94% and 50% reductions respectively (Liang, Luo and Qin, 2024), optimising for smoothness of motion over speed and complexity improves reliability by minimising vibrations (Ekrem and Aksoy, 2023), optimising for speed within the hardware's capabilities can increase operational efficiency (Woliński and Wojtyra, 2024), optimising for success rates in relation to speed saw an increase of >35% and a decrease of 0.4 seconds respectively (Yang et al., 2024), and optimising for accuracy led to a 25% improvement in that metric (Woodside et al., 2024).

1.5.3 Machine Learning in Robotics

There are many computing paradigms for solving multi-axis robot control, but machine learning trivialises the balance of adaptability and accuracy; the most suitable algorithm being application-dependent. For example, Gaussian Mixture Model/Regression architectures compromise precision for a lower parameter count, models based on Dynamic Movement Primitives allow for that precision and adaptability but require more parameter tuning, whereas Reinforcement Learning models offer the most adaptability and can work with smaller datasets but are more computationally intensive in the training phase (W. Li et al., 2024).

A deep reinforcement learning approach found a 93% success rate in avoiding dynamic obstacles while completing tasks – ideal for human-machine collaboration (Xia et al., 2024). Equation Embedded Neural Networks adapt to changing conditions and have achieved 97.1% accuracy in torque trajectory fitting despite being less computationally intensive than more conventional options (Deng et al., 2024). Alternatively, Iterative Learning Control algorithms can also increase accuracy by reducing positioning errors up to 85%, although still fall short of less-sophisticated techniques in simpler applications (Marchal et al., 2014).

Safe and efficient model training can be achieved in a virtual training environment, thus reducing costs and allowing for shorter deployment times (Chinthamu et al., 2024). Simulated learning might not consistently perform well in the real world due to conditions that were unaccounted for, but one paper successfully trained a Deep Belief Network on robot movements and associated energy consumption to optimise for the latter, naturally accounting for hardware degradation (Yin, Ji and Wang, 2019).

Combining different approaches can further improve performance, as proven by one paper which added Redistributed Collocation Points – a dynamic sampling technique – to a Physics-Informed Neural Network, improving accuracy by 25-28% without increasing computational cost (Hou et al., 2024). Another paper merged workspace segmentation with bootstrap sampling to reduce errors by 90% compared to a single neural network and by 17-20% compared to each individually (Cagigas-Muñiz, 2023); one used Deep Reinforcement Learning, Model Predictive Control, and Graph Neural Networks to increase accuracy scores by 1.78-8.61%, recall rates (valid path identification) by 4.42-6.45%, and F1 scores (harmonic mean of precision and recall) by 1.13-4.51% (Z. Li et al., 2024).

1.6 Research Methodology

1.6.1 Problem Definition

Existing programming techniques and interfaces for industrial robots appear to be unintuitive, requiring a high level of pre-existing knowledge and experience to operate. As automation continues to displace unskilled workers, there are no viable options for these individuals to retrain and add further value to the industry.

1.6.2 Proposed Solution and Justifications

Through the abstraction of complex robot movements to high-level commands based purely on one or two inputs (end effector position and tool action), displaced labourers would be able to program industrial machinery such as 6-axis robots to perform tasks even with dynamic requirements. This will be achieved through the use of a reinforcement machine learning model trained in a simulated environment that will infer the necessary positions of joints.

1.6.3 Research method for investigation

The first stage will be to ensure that the robot is sufficiently operational and able to be communicated with in real-time. After this point, work will begin on creating a digital twin of the device, encompassing the mechanical design at a high level, joint speed and angle constraints, a limited operating envelope (illustrated in Figure 9), and base anchoring. Using the digital twin, the reinforcement learning algorithm can be developed, trained, and implemented in a virtual environment using a platform such as PyBullet. The model can then be tested in the real world using the FANUC device at various levels of safety and functionality with the option for operation using a motion controller at a later date.

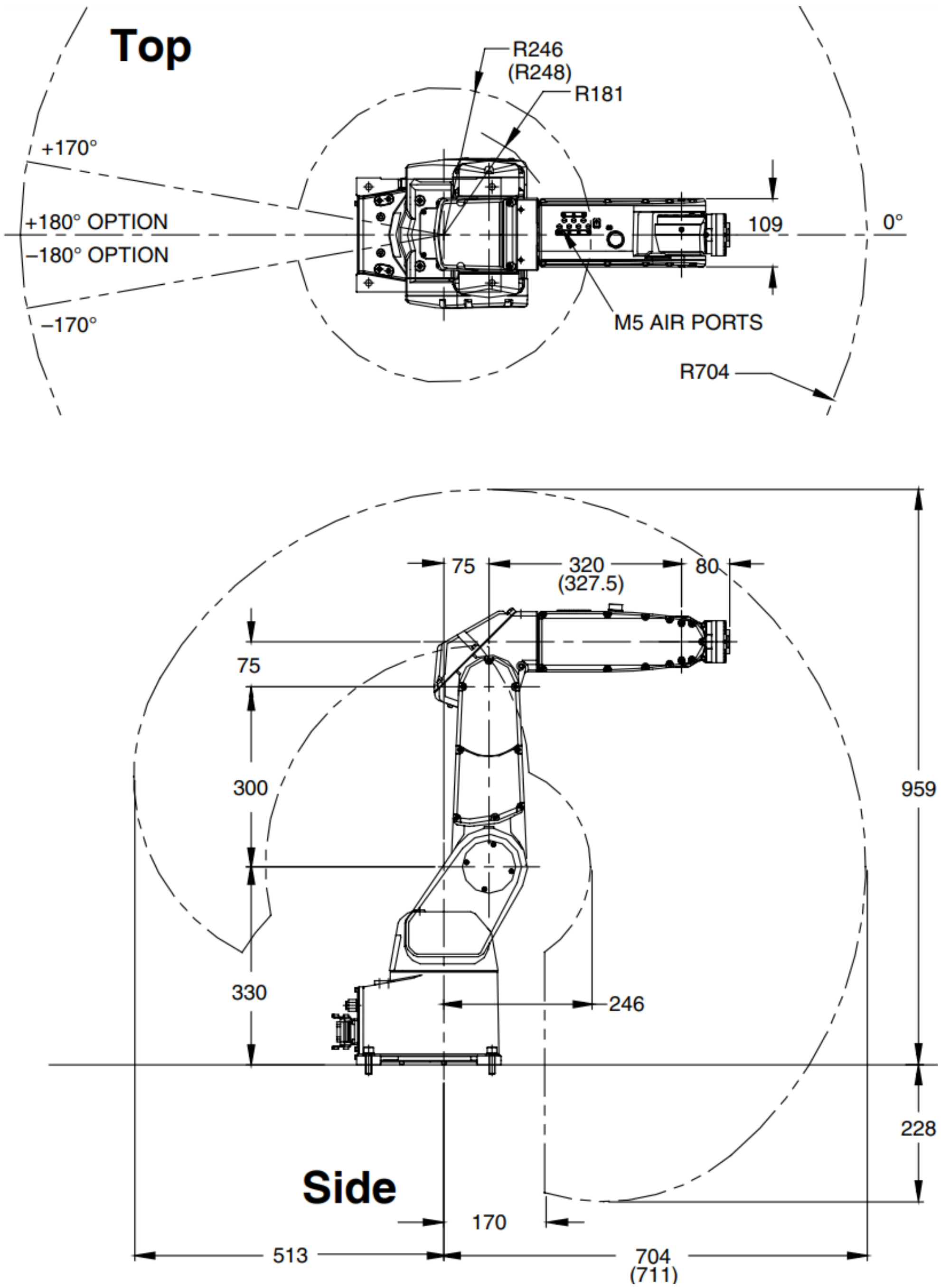

Figure 9: Diagrammatic representation of FANUC LR Mate 200iC's work envelope (FANUC Robotics, 2009).

1.6.4 Research deliverables

Table 3 (Research Deliverables)

Task	**Timeframe**
Project Specification and Literature Review Report	Q4 2024
Operational FANUC LRmate 200iC	Q4 2024
Realtime Communication and Execution of Commands	Q4 2024
Robot Digital Twin	Q4 2024
Virtual ML Training Gym	Q1 2025
Reinforcement Learning Algorithm Implementation	Q1 2025
End-to-End Joint Optimisation Demonstration	Q1 2025
Solution Performance Testing and Analysis	Q1 2025
Progress Logbook (including notes from supervisor meetings)	Q1 2025
Final Report	Q1 2025
Poster Presentation Viva	Q2 2025

1.6.5 Resources needed

Table 4 (Required Resources)

Category	Item
Robot	FANUC LR Mate 200iC
	FANUC controller
	Power supply
	Safe operating environment
Compute	Microsoft Windows computer w/ sufficient local GPU power
	Relevant software
	Cloud GPU service (if required)
Miscellaneous	VR headset (if required)
	VR motion controllers (if required)

1.6.6 Risk Assessment

Table 5 (Risk Assessment)

Risk Type	**Severity**	**Solution(s)**
Damage to operating environment (surrounding the hardware)	High	- Comply with the University of Greenwich's Health and Safety policy with respect to use of the Hawke building's workshop - A conservative operating envelope will be adopted
Damage to operators (harm to human life)	High	- Maintain a safe distance from machinery when operational, behind protective windows - A conservative operating envelope will be adopted - Safety equipment such as E-Stop buttons will be tested prior to use
Misuse of equipment (hardware malfunction)	Low	- Operate within the performance limits of the hardware - Operate as instructed in OEM manuals
Progress (project drift, loss of work, unforeseen delays)	Low	- Back work up online - Allow for reasonable flexibility with the project roadmap and depth

		- Constant, tight control over the schedule - Contact people both inside and outside the institution for advice where necessary - Attend regular meetings with the project supervisor – Dr Wim Melis.

1.7 Conclusions

There are clearly many viable paths to take in pursuing increased efficiency, safety, operability, and functionality of industrial robotics systems; the research and information presented here is expected to go a long way in supporting continual progress of the project, and the results should effectively portray the benefits of using machine learning algorithms for joint interpolation in industrial robotics as opposed to traditional techniques with the likes of Proportional-Integral-Derivative controllers and hard-coded motor position sequences – especially in the context of Industry 4.0.

The next step in this process will be to develop the technologies outlined in this report with extensive testing along the way and a final demonstration to showcase the solution – all of which will be detailed in a follow-up report and poster presentation viva to conclude the project and address any notable findings.

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Appendix: Gantt Chart

Category	Task	Approximate Duration (Weeks)	Approximate Start Date	Approximate End Date	Q4 2024		
					October	November	December
Robot Motion	FANUC Manuals	1	14/10/2024	21/10/2024			
	Basic Movements	2	21/10/2024	07/11/2024			
	Realtime Commands	3	07/11/2024	30/11/2024			
Machine Learning	Digital Twin	2	01/12/2024	07/12/2024			
	Algorithm	5	07/12/2024	14/01/2025			
	Virtual Training	1	14/01/2025	21/01/2025			
User Experience	VR Support	1	21/01/2025	30/01/2025			
	Controller Support	1	01/02/2025	07/02/2025			
Formalities	Supervisor Meetings	25	01/10/2024	30/03/2025			
	Specification Report	4	01/10/2024	21/10/2024			
	Progress Review	1	01/12/2024	07/12/2024			
	Final Report	23	01/11/2024	21/03/2025			
	Presentation Preparation	2	21/03/2025	07/04/2025			
	Presentation Viva	1	01/06/2025	07/06/2025			

Figure 10: Project Gantt Chart (Q4 2024).

Category	Task	Approximate Duration (Weeks)	Approximate Start Date	Approximate End Date	Q1 2025		
					January	February	March
Robot Motion	FANUC Manuals	1	14/10/2024	21/10/2024			
	Basic Movements	2	21/10/2024	07/11/2024			
	Realtime Commands	3	07/11/2024	30/11/2024			
Machine Learning	Digital Twin	2	01/12/2024	07/12/2024			
	Algorithm	5	07/12/2024	14/01/2025			
	Virtual Training	1	14/01/2025	21/01/2025			
User Experience	VR Support	1	21/01/2025	30/01/2025			
	Controller Support	1	01/02/2025	07/02/2025			
Formalities	Supervisor Meetings	25	01/10/2024	30/03/2025			
	Specification Report	4	01/10/2024	21/10/2024			
	Progress Review	1	01/12/2024	07/12/2024			
	Final Report	23	01/11/2024	21/03/2025			
	Presentation Preparation	2	21/03/2025	07/04/2025			
	Presentation Viva	1	01/06/2025	07/06/2025			

Figure 11: Project Gantt Chart (Q1 2025).

Category	Task	Approximate Duration (Weeks)	Approximate Start Date	Approximate End Date	Q2 2025		
					April	May	June
Robot Motion	FANUC Manuals	1	14/10/2024	21/10/2024			
	Basic Movements	2	21/10/2024	07/11/2024			
	Realtime Commands	3	07/11/2024	30/11/2024			
Machine Learning	Digital Twin	2	01/12/2024	07/12/2024			
	Algorithm	5	07/12/2024	14/01/2025			
	Virtual Training	1	14/01/2025	21/01/2025			
User Experience	VR Support	1	21/01/2025	30/01/2025			
	Controller Support	1	01/02/2025	07/02/2025			
Formalities	Supervisor Meetings	25	01/10/2024	30/03/2025			
	Specification Report	4	01/10/2024	21/10/2024			
	Progress Review	1	01/12/2024	07/12/2024			
	Final Report	23	01/11/2024	21/03/2025			
	Presentation Preparation	2	21/03/2025	07/04/2025			
	Presentation Viva	1	01/06/2025	07/06/2025			

Figure 12: Project Gantt Chart (Q2 2025).