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AI and Robotics for Flexible Manufacturing in Composite Industry

WHITE PAPER

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Glossary:

- Advanced Manufacturing Readiness Facility (AMRF)
- Advanced Manufacturing Series (AMS)
- Augmented Reality (AR)
- Australian Centre for Robotics (ACFR)
- Australian Composites Manufacturing Cooperative Research Centre (ACM CRC)
- Australia and New Zealand (ANZ)
- Artificial Intelligence (AI)
- Compound Annual Growth Rate (CAGR)
- Digital Twin Cyber-Physical Production System (DT-CPPS)
- Human-Robot Interaction (HRI)
- Infrared (IR)
- Internet of Things (IoT)
- Learning from Demonstration (LfM)
- Linear Programming (LP),
- Minimum Order Quantity (MOQ)
- Mixed Integer Linear Programming (MILP)
- Mixed Integer Nonlinear Programming (MINLP)
- National Institute of Standards and Technology (NIST)
- National Reconstruction Fund (NRF)
- Original Equipment Manufacturer (OEM)
- Quality Assurance (QA)
- Radio Frequency Identification (RFID)
- Simulation to Pick Localize and placE (SimPLE)
- Simultaneous Localisation And Mapping (SLAM)
- Steel Beam Assembler (SBA)
- Universal Manipulation Interface (UMI)

This White Paper was initiated by ACM CRC to gather industry intelligence on skills gaps and training needs in the Australian composites manufacturing sector, including practitioners, suppliers, R&D agencies and educational institutions.

EXECUTIVE SUMMARY

The Australian Centre for Robotics (ACFR) at the University of Sydney has composed this white paper investigating how Artificial Intelligence (AI) and Robotics can enhance Australian composite manufacturing, with a focus on a bespoke, agile and responsive production style that this white paper refers to as flexible manufacturing.

This white paper is the product of many surveys and facility inspections conducted by the ACFR of Australian Composite Manufacturing Cooperative Research Centre (ACM CRC) industry partners, with contributions and expertise from every partner involved.

In total, 12 manufacturing facilities were visited, reflecting the entire spectrum of size and complexity, from startups to large scale operations.

Standardised survey questions and in-person observations of process bottlenecks were used to benchmark against the current leading scientific understanding of robotics and automation to determine if an autonomous solution is technically feasible, and if not, what are the scientific barriers preventing one.

Through this investigation, the most consistent and important observation to emerge is that composite manufacturing in Australia is characterised by a bespoke style of production, often with smaller volumes but higher complexity and customisation. Therefore, it is the authors belief that conventional automation systems employed by large-scale composite manufacturers in Europe, Asia and America are not suitable for the Australian sector, as they are not designed for our dynamic production style.

ACFR investigators perceive this agile and responsive style of **flexible manufacturing** as a national strength, and proposes **AI and robotic** solutions to enhance the efficiency and flexibility of existing composite manufacturing techniques.

These proposals are rooted in the real-world discoveries made during surveys, visits and case studies of partner companies, as well as the state-of-the-art developments in the most recent robotic research.

In this white paper, the ACFR has identified and outlined four main domains and many small research directions where cutting-edge robotic techniques can contribute to improving **flexible manufacturing** in the Australian composite industry.

These range from providing a better macroscopic overview of the production line to enabling intelligent and autonomous automation of each manufacturing step. The proposed solutions can benefit both individual partners as well as the overall industry in a precompetitive manner.

It is the opinion of this study that building upon the highly skilled and agile nature of our region's manufacturers, combined with recent scientific innovations that enable more dynamic robotics and intelligent systems, and due to a clear gap in commercially available systems servicing our sector, there is a unique opportunity to simultaneously rebuild Australia's manufacturing sector using these novel systems and create an entire new class of robotic systems and industries here in the process.

INTRODUCTION

In recent years, there has been renewed focus on rebuilding Australia's manufacturing output. This can be seen through a variety of both state and federal initiatives, such as the recently completed $260M Advanced Manufacturing Readiness Facility (AMRF) in NSW, and the National Reconstruction Fund (NRF) and Future Made in Australia federal initiatives.

It is universally acknowledged that robotics and automation technologies will be central to achieving this goal as these technologies are listed as critical enabling technologies in several of these government strategies and policies. The 2024 National Defence Strategy and 2024 Integrated Investment Program, the National Reconstruction Fund, the National Science Priorities and National Robotics Strategy, are just some of the core government policy documents that outline robotics and automation as key enabling technologies.

However, to successfully target research and development investment of these technologies for Australian industries, we first need to contextualise these opportunities against our international peers, and the types of robotics and automation these regions adopt to support their respective manufacturing sectors.

Understanding what Australian industry does differently will allow us to design investment strategies for robotics innovation that will maximise productivity growth and return on investment for the taxpayer. To the best of our knowledge, such analysis does not exist, and this report is the first step in a longer-term effort to change that.

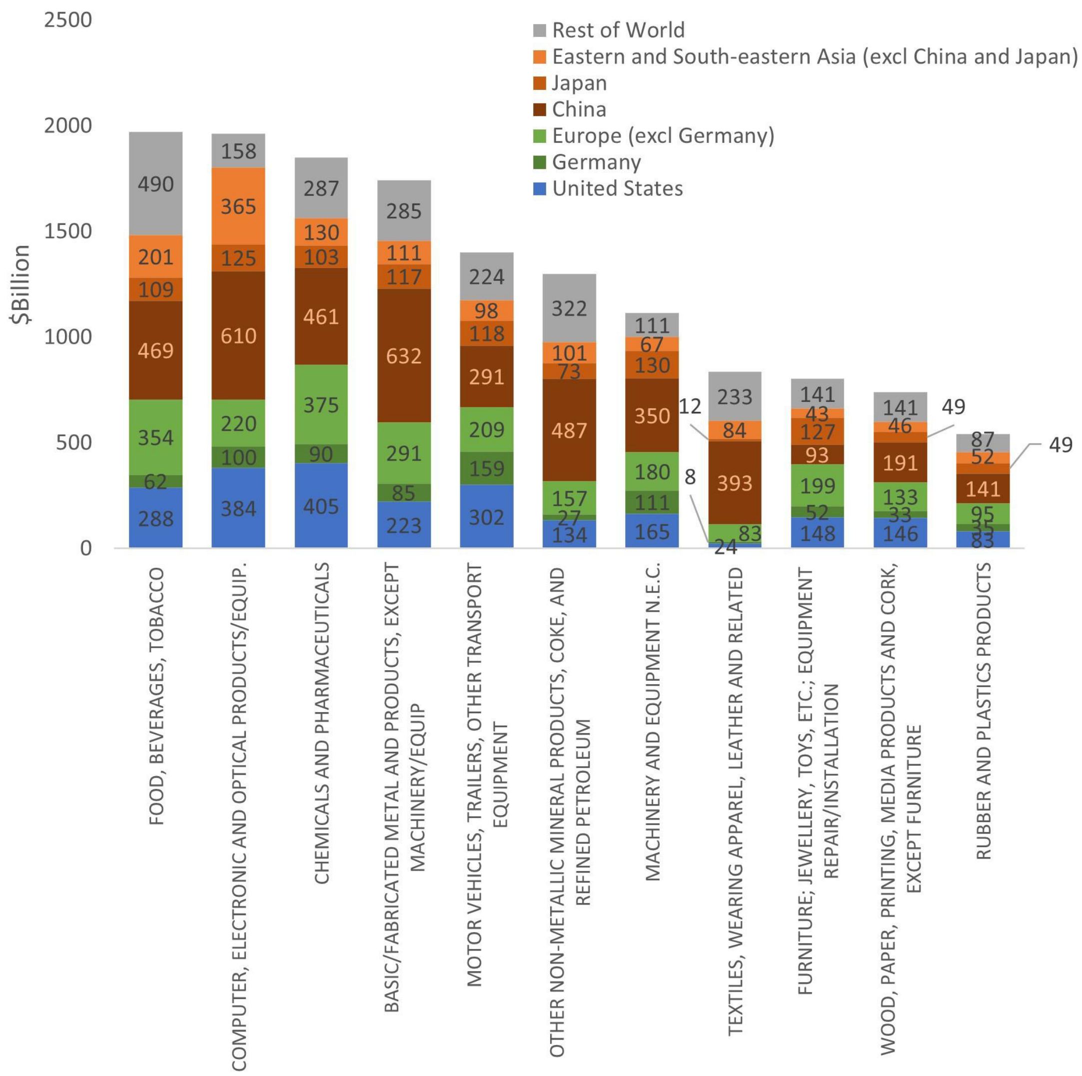

Figure 11 Global Manufacturing Value Added by Industry, by Country/Region (2020) as reported by NIST AMS 600-16 [1].

Chinese Context

In 2024, China's manufacturing value-added reached USD $4.67 trillion [2], which was 29 percent of the global total, and more than the next four largest manufacturing economies combined (the United States, Japan, Germany, and India). China's manufacturing output has evolved considerably over the past two decades from low value add to increasingly higher value products such as electrical goods which now represent the single largest manufacturing sector within China [3]. Despite this transition, Chinese manufacturing continues to be predominantly large batch production and high minimum order quantity (MOQ). Over 80% of Chinese manufacturing falls into this category.

As with most markets, composites parts are increasingly integrating as Original Equipment Manufacturers (OEMs) to these sectors [4]. In 2023 the Chinese composite market was valued at $15.3 billion with projections to grow to $21 billion by 2030 with a compound annual growth rate (CAGR) of 5% from 2024 to 2030 [5]. Unsurprisingly, growth in composites market is being largely driven by mass production manufacturers, namely the automative and transport industry but also aerospace, defence, marine, renewable energy and electronics.

It is important to note that these industries are typified by the production of repeat parts and therefore, automation and robotics technology deployed in these operations are deployed to perform repeat tasks in a controlled environment. The intelligence and versatility of the robot is less important than its ability to reliably perform a single task repeatedly.

European Context

In 2022, manufacturing contributed €9.8 trillion to the European economy, approximately one-quarter of the European economy [6]. If we look closer at the sectoral break down of European manufacturing, we see that well over 60% of operators are focused on large batch, high throughput or assembly line styles of production including; machinery and equipment, food, motor vehicles and trucking, chemical products, to name a few.

This is supported by data indicating 66.0% of value-added manufacturing being generated by large enterprises (more than 250 employees). These firms are responsible for 48.3% of manufacturing employment in Europe, jumping to 70% when including medium enterprises (50-250 employees). Much like in China, these industries are typified by high levels of automation performing repeat tasks in controlled environments.

Furthermore, the European composite manufacturing sector which was valued at USD $19.35 billion in 2022 and is expected to grow at a CAGR of 6.3% through to 2030, is also largely aligned supplying composite parts to these major manufacturers in wind energy, automotive, transportation, aerospace, and defence [7].

This indicates that composite manufacturing is largely focused on producing repeat parts to supply these industries. Robotic systems used in this sector will largely be articulating systems performing repeat tasks. While there is sparse information on the breakdown of robotic system by industry, robotics installations in the automotive industry appear to have the strongest utilisation. Germany being the largest user of industrial robotics for this reason [8].

United States context

The United States is the second largest manufacturing nation after China. In 2024, manufacturing value-added output was estimated to be USD $2.925 trillion, roughly 10% of US GDP [9]. If we break this down by subsectors, it is clear US manufacturing is being driven by large scale production within a few major categories like chemical production, electronics, automative and transport, machinery, food and beverage, material products, to name a few.

This is reflected in the employment data. Despite 93% of US manufacturing firms considered to be small (less than 100 employees), 59.0% of all employees in the sector work for large firms with 500 or more employees, just 1.6% of US manufacturers [9]. As with both Europe and China, these are all sectors where robotics and automation technologies have been well established for several decades.

As it relates to the US composite sector, we also see the same trend, that these sectors are driving demand for composites. In 2023 the U.S. composites market was estimated to be USD 15.58 billion with a CAGR of 5.3% from 2024 to 2030. This growth is largely being driven by the automotive and transportation industry's need for lightweight components [10].

Australian context and this white paper

While data and analysis on the three primary manufacturing regions is imperfect and measured differently between sources, a picture does emerge that is useful for Australian manufacturers and policy makers.

Notably, these markets are dominated by a smaller number of major, high throughput producers responsible for between 60-80% of the region's manufacturing value added, and 50-70% of manufacturing jobs. In the absence of a more comprehensive comparative analysis, assumptions can be drawn that these sectors are highly automated to perform high volume repeat tasks, and consequently, as the largest employers in their respective regions, their workforce is predominantly trained in this high throughput repetitive style of manufacturing.

It also paints a picture of the "type" of robotics and automation deployed in these regions, that being articulating arms, closed system processing of materials and chemicals, automating production and processing lines. While innovation in these systems is always occurring, we have been using versions of this technology for several decades now.

All of this is very important context as it relates to the Australian manufacturing sector where figures present an almost completely opposite picture. In Australia, manufacturing accounts for $105B value added, considerably less than these international markets as a proportion of the national productivity at just 5.5% [11].

A sectoral breakdown shows that many industries comparable to other markets (eg, chemical production, electronics, automative, transport, and machinery) have been in sharp decline for decades [11]. This is reflected in the employment distribution where 91.9% of manufacturing jobs are at firms with 19 or less employees, 7.5% at firms with 20-199 employees, and just 0.6.% at firms with over 200 [11].

The number of employees at firms comparable to large US industries (greater than 500) is likely incredibly small. This comparison is stark, as 59% of US manufacturers are employed by these large firms, and therefore the skills and experience of Australian manufacturers are likely very different as a result [11].

Consistent with international markets however, is the growth of the Australian composite manufacturing sector which has demonstrated consisting strong CAGR of 9.70%, almost double the rate of our international peers [12]. Composite manufacturing in Australia is one of only a handful of manufacturing sectors that are growing against the general downward trend experienced in other segments with a market size estimated to be USD $2.4B in 2024 and projected to double to ~$5.6B USD over the next decade [12].

While composite manufacturing in the aforementioned international markets is dominated by large, vertically integrated OEMs, the Australian composite manufacturing sector is comprised largely of SMEs, typically born out of domestic material engineering research and innovation [13]. This is a valuable insight, as the operational requirement of Australian composite SMEs will strongly align with the broader Australian manufacturing community.

It is reasonable to assume given the dominance of small manufacturers in Australia that robotics and automation are less common in workflows. Investment cost is likely one factor, but perhaps more accurately it is the limitations of commercially available industrial robotics that focus on high throughput, repetitive tasks, not an agile and constantly changing operation.

For a small firm to remain commercially viable it must either have a large and reliable customer, or a variety of smaller ones. Given the absence of large firms in Australia, the latter is most likely the scenario, and by extension, the workforce in these smaller firms must be highly skilled and dynamic to meet the needs of their heterogenous customer base.

Throughout this study we visited a variety of composite manufacturing facilities. This is exactly what we observed.

Through our collaborations with the ACM CRC, ACM CRC members and industrial partners, we have identified specific pain points in current composite manufacturing workflows where targeted research in robotics and automation can drive high-impact improvements.

The ACM CRC represents a broad distribution of composite manufacturers and manufacturing techniques (for more information on ACM CRC industry partners please refer to the ACM CRC website). For this white paper we visited 12 manufacturing facilities observing processes and technologies, combined with surveys of key staff. Importantly, two industry peak bodies were either involved or engaged in this process enabling the study team to validate findings of the sample group with the broader experience of the sector.

Most composite manufacturers in Australia and New Zealand (ANZ) are characterised by unique and bespoke jobs where product designs and production lines change on a regularly basis [14, 15], e.g. monthly and even weekly, based on the requirements of the clients.

This is largely due to a confluence of macro-economic forces local industries have no control over, such as the market size of a smaller population, proximity to global markets, a higher paid and skilled workforce, to name a few. Consequently, ANZ manufacturers need to be **agile and responsive** to a diverse range of customer needs, making conventional repetitive automation solutions for large-scale production lines less relevant to their workflows.

The absence of large-scale production line manufacturers is often framed in the media as a negative, evidence of Australia's declining manufacturing capability. This is a gross mischaracterisation, and in fact being agile and bespoke in manufacturing and production typical of our region requires, and has produced, a highly competent and highly skilled workforce capable of meeting constantly changing production demands. We refer to production techniques with such characteristics as **flexible manufacturing**.

It is the opinion of this white paper that being agile and flexible is a unique strength; and rather than focussing on why there are so few large-scale production line operators in ANZ, we should instead be leaning into our flexibility and agility as our advantage and characteristic, and ensure we are the world leaders at **flexible manufacturing**. In order to achieve this, there is a clear need for manufacturing technology, systems and processes that can easily and efficiently adapt to changes in jobs and conditions.

With **flexible manufacturing**, we aim to reduce as much unnecessary cost of labour, time, energy and money as possible in design, fabrication, inspection as well as decision making in the overall production line, which is a desired outcome expressed by ANZ manufacturers whom we have visited in our surveys. Furthermore, it is clear from our engagement with local manufacturers that this is a clear gap in the technology offering, as technology developers focus predominantly on larger scale operations. This affords an opportunity to not only bolster and grow our **flexible manufacturing** sector, but in doing so develop a new class of technology producers in the process.

This white paper will focus on the **Robotics** and **Artificial Intelligence** (AI) technologies with the potential to enhance **flexible manufacturing** and introduce intelligence into production processes. We will discuss both existing technologies as well as the scientific barriers that must be addressed to overcome limitations in the current state of the art. Further to this, we will also outline a series of research projects targeting low hang fruit through to high value multi-stakeholder initiatives required to develop **flexible manufacturing** technologies and project the benefit of such investments to the sector as a collective.

In this white paper, we categorise opportunities of **flexible manufacturing** into four general domains, namely:

- *Process Digital Twin and Optimisation*,
- *Robotics and Automation*,
- *Design Optimisation and Automation*, and
- *Quality Assurance (QA) and Inspection*.

We will discuss challenges that the current composite industry in ANZ faces and how **AI and robotic** technologies can help address them.

For each domain we propose tangible solutions, and discuss and rate the proposed solutions from the angles of theoretical research and industrial deployment in the context of the **four specified measures**.

The corresponding values will be presented in a table format (see next page for the measures and format), accompanied by specific comments for clarity.

RESEARCH RECOMMENDATIONS
FOUR SPECIFIED MEASURES:

1	**Theoretical understanding difficulty** reflects the conceptual and mathematical complexity of the underlying theory. This will be rated on a scale from 1 to 5:	**LOW (1-2):**	Well-established and accessible foundations.
		MEDIUM (3):	Requires specialist knowledge with moderate complexity.
		HIGH (4-5):	Involves novel or ambiguous theory and advanced models (e.g., nonlinear PDEs, probabilistic reasoning).
2	**Experimental difficulty and cost** identify practical challenges and financial burden associated with building prototypes, acquiring hardware, collecting data, etc. This will be rated on a scale from 1 to 5:	**LOW (1-2):**	Simulations or standard lab setups,
		MEDIUM (3):	Custom experimental setups or moderately priced hardware,
		HIGH (4-5):	Expensive equipment and/or data collection, custom fabrication, safety constraints.
3	**Deployment difficulty in real world scenario** evaluates how challenging it is to adapt, integrate and use the systems outside controlled lab environments:	**LOW (1-2):**	Easily deployable with existing infrastructure,
		MEDIUM (3):	Require moderate adaptation, engineering effort, and dedicated infrastructure,
		HIGH (4-5):	Demands significant customization, complex engineering integration, and the development of specialized infrastructure.
4	**Value of a successful system** refers to the impact/return if the system performs reliably in practice:	**LOW (1-2):**	Marginal gains or targeted to a niche application,
		MEDIUM (3):	Delivers significant benefits within a specific domain,
		HIGH (4-5):	Transformative impact, strong commercial potential, or substantial contributions to operational safety.

1. PROCESS DIGITAL TWIN AND OPTIMISATION

Based on discussions with industry representatives, this section explores approaches to enhance manufacturing processes and optimize factory floor logistics. It emphasizes the use of Digital Twin technologies for monitoring and modelling production lines, enabling and automating intelligent decision-making. Optimising the logistical aspects of the manufacturing production is the most common desire voiced by the industry partners that we have discussed with.

The optimisation of production lines will allow our industry partners to more efficiently utilise labour and high value hardware, to increase productivity while decreasing costs, and to more intelligently incorporate and leverage emerging **robotic and automation technologies** (such as those discussed in Section 2, 3 and 4).

Automating these optimisation processes also ensures operations can be highly responsive to sudden changes or unexpected work stoppages, drastically reducing the labour and productivity costs of downtime, and Digital Twin is instrumental in providing real-time insights, predictive analytics, and scenario testing to proactively mitigate disruptions and enhance overall efficiency.

During our engagement with partners for this white paper, it soon became apparent the considerable human resources employed specifically to minimise this problem. Many facilities have employees dedicated to monitoring the factory floor and machine utilisation rates, as well as experienced engineers designing manufacturing and fabrication workflows and adapting them upon any interruptions such as machine break-down or material delivery delay.

There are a lot of time and labour resources spent solely on these logistics, and we believe this is a domain where robotic technologies can greatly assist the human labours and improve the intelligence in the production process.

It is the opinion of the authors that this is perhaps the biggest opportunity for **flexible manufacturers** in our region, and for several reasons.

Firstly, current commercially available systems are not designed to address this problem for manufacturers that need a high degree of flexibility, as is typical of our region.

Second, process modelling and optimisation as well as Digital Twin technologies are relatively well understood problems in the robotics research community (e.g. robot path planning, perception and 3D scene reconstruction, etc.), indicating that projects in this space are highly likely to produce immediate positive outcomes for partners.

Third, our observations indicate this problem is not only resource intensive for partners, but is a ubiquitous issue in the sector, meaning that this is a shared issue that partners can collaborate on solving where the return on investment will benefit all considerably.

Fourth, better optimisation systems of this nature and **Digital Twins** of the factory floors can form the foundation for the development of **bespoke robotic systems and innovations** (Section 2) customised to the needs of individual partners. Meaning, it would be expected that all future robotics systems deployed to support enhanced productivity in an operation would "plug-in" to this foundational system to ensure continued operational efficiency improvements.

1.1 Manufacturing process modelling and optimisation

Many manufacturers in ANZ have already been employing management software to digitise and manage their production line, e.g. STRUMIS and Tekla for steel (metal composite) fabrication. However, during our survey visits, they have also voiced limitations in such software not providing the exact functionalities they desire, for example, being unable to adjust the production plan when unforeseen incidents occur.

In the field of robotics, **Digital Twins** are emerging as a powerful tool to model the factory floor with the intention of optimising the production process. Virtually representing the factory floor [16] and monitoring the physical production line using **Internet of Things** (IoT) techniques [17] enables real-time analysis of the manufacturing process and improves decision-making in the production planning and optimisation [18, 19].

To systematically find the optimal strategy for a workflow, the robotics community employs techniques such as Linear Programming (LP), Mixed Integer Linear Programming (MILP) and Mixed Integer Nonlinear Programming (MINLP) across a wide range of different industries [20, 21, 22, 23].

By modelling each manufacturing step, their requirements and objectives using linear relationships, the overall production line can be optimised mathematically. This problem has been studied by roboticists over many decades [24, 25].

We therefore propose working with partners to create **Digital Twins** of their factory floors. These **Digital Twins** will capture the physical and logistical relationships of each manufacturing step, allowing us to model production lines and optimise them using LP/MINLP techniques.

These models will then enable the autonomous optimisation of manufacturing processes and workflows. Instead of replacing human involvement completely, we intend for such an algorithm to be a tool used by engineers to speed up the process of optimising the workflow and responding to incidents, to alleviate the burden on the few experienced human experts in each company responsible for such optimisation.

Figure 2 An AI-powered Digital Twin example for a factory floor and the planning of movements on it (video demo) [26].

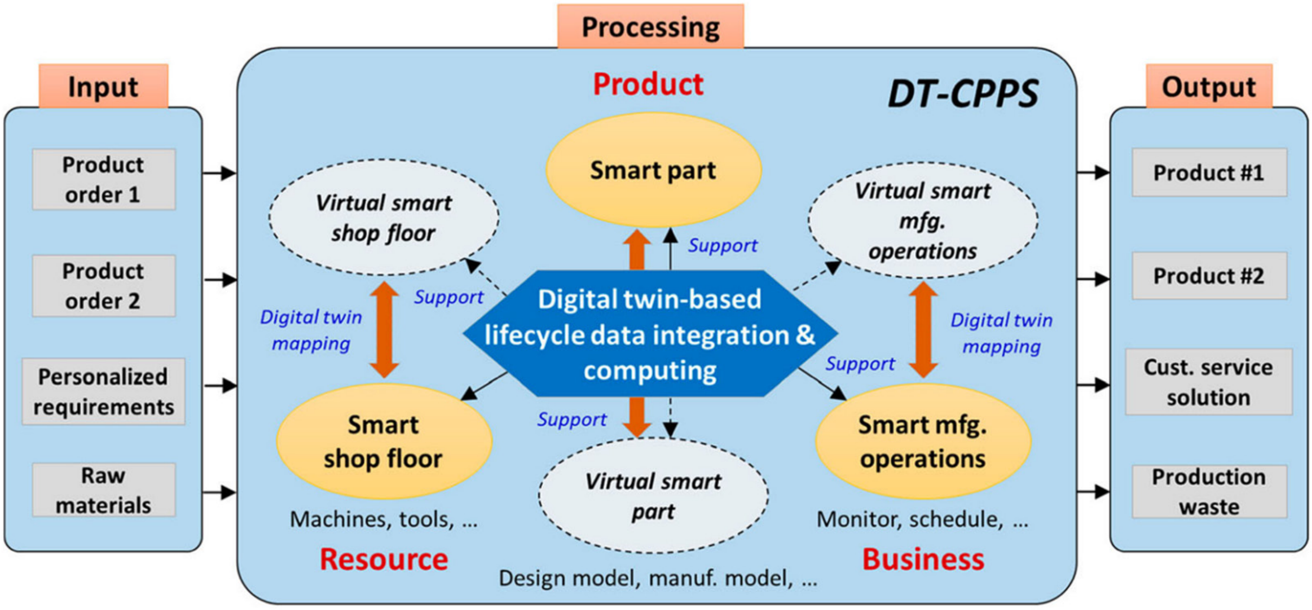

Figure 3 An example of a Digital Twin Cyber-Physical Production System (DT-CPPS) and how it models a smart factory floor created by Ding et. al. [19].

1.1 RESEARCH RECOMMENDATIONS

A research project on methodologies for developing a Digital Twin for a factory floor or production line, coupled with logistics optimization using LP, MILP, and MINLP, can focus on algorithmic design and adaptability. This study would explore how mathematical models can be refined and updated to accommodate varying constraints and dynamic behaviours along the production line, leveraging an industry-provided mock factory floor model as a reference framework.

MEASURE	RATING OUT OF 5	COMMENTS
1 Theoretical understanding difficulty	3	An established field of research, however will require adaptation to context.
2 Experimental difficulty and cost	3	Low-cost simulation-focused experiments in the development stage.
3 Deployment difficulty in real world scenario	4	Deployment in real-world scenarios will require significant input from partners and adaptation.
4 Value of a successful system	5	Common desire shared by many partners, and will immediately provide the benefit of reducing cost.

RESEARCH SOLUTIONS

Such a project can take three years for a PhD student, or two years for a Postdoctoral researcher. To tailor such a system for any particular partner, the project will additionally involve a technical engineer to gather the specific needs for the partner, and to bridge between the theoretical research and the software deployment.

1.2 Productivity management of machineries and operators

In order to achieve the most realistic model of the production line, it is essential to carefully monitor the utilisation of each machinery on the factory floor so as to accurately model them in the **Digital Twin**. Additionally, **human action and activity recognition** is a well-established topic in robotics and AI and integrating these techniques can enhance the **Digital Twin** of the factory floor by accurately modelling human factors for productivity management while also improving workplace safety and preventing hazardous situations.

Partners we have visited in our survey have all expressed interest in monitoring the utilisation rate/efficiency of their machineries, especially their newly invested automation robots, as well as in understanding human operator productivity.

Many of our visited partners rely on operators logging onto and off each machine, such as via scanning custom QR codes, to digitally record the utilisation of each machine. To better monitor machine utilisation, some partners are leveraging IoT devices, such as FourJaw's energy monitoring suite (video introduction to FourJaw) [27], to track and log the productivity of machines.

Visual sensors, e.g. security cameras which most companies have already installed, can be leveraged to recognise and analyse human activities on the factory floor [28, 29]. We further purpose installing privacy preserving cameras [30] on the factory floor instead to improve the security of personal and corporate information.

Finding correlations between operators and machine utilisation can help create a more accurate **Digital Twin** of the production line that incorporates human-based productivities [16]. Such a project will incorporate **AI-based activity recognition** algorithms [28, 29] and studies on modelling human activities in a **Digital Twin** as optimisation problems [16].

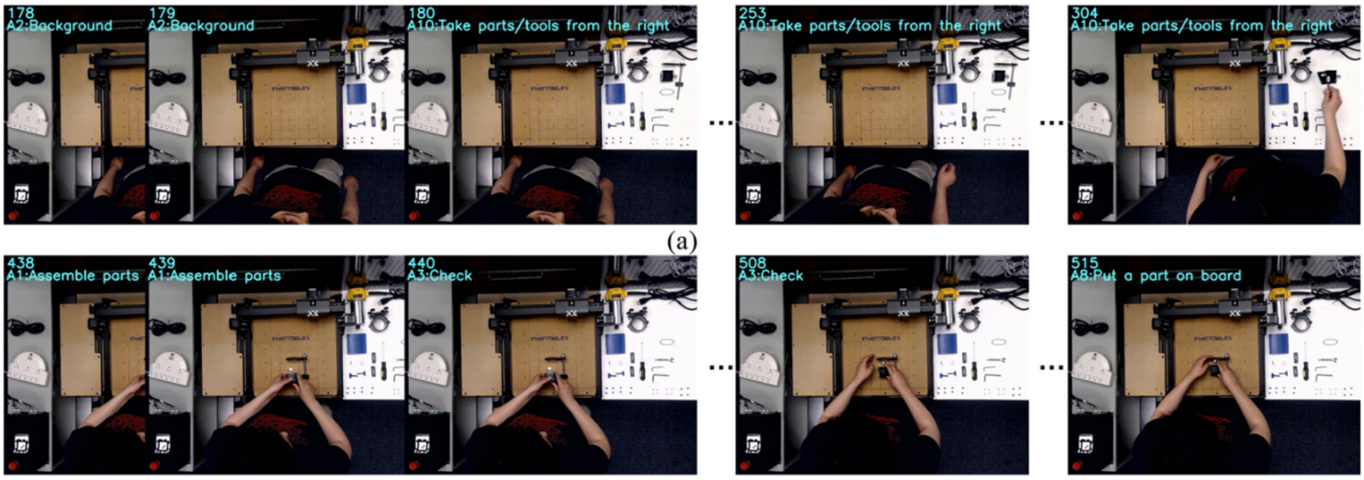

Figure 4 Fine-grained activity recognition on assembly by Chen et. al [31].

1.2 RESEARCH RECOMMENDATIONS

A research project on methodologies for developing a Digital Twin for a factory floor or production line, coupled with logistics optimization using LP, MILP, and MINLP, can focus on algorithmic design and adaptability. This study would explore how mathematical models can be refined and updated to accommodate varying constraints and dynamic behaviours along the production line, leveraging an industry-provided mock factory floor model as a reference framework.

	MEASURE	RATING OUT OF 5	COMMENTS
1	Theoretical understanding difficulty	3	Based on established and highly practical technologies, but unique contexts will require tailoring. However, privacy preserving AI/vision technology is a field still being explored.
2	Experimental difficulty and cost	3	Experimental verification will require accessing factory floors for real-world assessment.
3	Deployment difficulty in real world scenario	4	Similar technologies exist - the challenge lies in customisation as well as ensuring the solution does not invade operator privacy.
4	Value of a successful system	5	It will provide detailed information on how the production lines run, pinpoint the limitations in existing processes and save significant hours from supervision roles.

RESEARCH SOLUTIONS

We estimate this to take two years for a PhD student, or a year for a postdoctoral researcher. The practical deployment of existing solutions on factory floor and will take one additional year for a PhD student and an engineer, mainly to tailor the system for any partner.

1.3 Material tracking on factory floor

Tracking materials on the factory floor is one key aspect of **smart and flexible manufacturing**, assisting the optimisation of the production process and providing better guidance for accurate manufacturing [32].

Optimising and minimising movement of heavy materials within the workshop will also reduce the cost and improve safety. Each company has their own methods, ranging from barcodes on the job to IDs written on chalk. Radio Frequency Identification (RFID) is another established technique employed by smart factory in **Industry 4.0** [33].

Accurately tracking materials will significantly improve how closely the **Digital Twin** reflects the actual factory floor, especially in certain industries such as steel fabrication where a lot of resources, i.e. man hour and energy, are invested in handling heavy materials.

On the other hand, a **Digital Twin** of the factory floor can also advise the safest and most efficient scheduling and/or path of material transportation, as well as monitoring the consumption of raw materials to advise purchases in advance.

However, a labelling method that can withstand most or all manufacturing process while being economical remains a challenge, as advised by many partners that we have surveyed. There is therefore a direction for further investigation on what is the best method/sensor/software combination for labelling and tracking materials on the factory floor.

1.3 RESEARCH RECOMMENDATIONS

This project also contributes to the overarching factory floor Digital Twin and optimisation project as outlined in Section 1.1. The theoretical study on tracking and modelling material transportation on the factory floor is estimated to take one year in a PhD student project, or half a year for a postdoctoral researcher, which will also include the exploration on how the Digital Twin can feedback into tracking and monitoring materials.

	MEASURE	RATING OUT OF 5	COMMENTS
1	Theoretical understanding difficulty	2	The research is less theoretical and more practical.
2	Experimental difficulty and cost	3	Experiments focus more on making sure it works on the factory floor, so the cost can increase.
3	Deployment difficulty in real world scenario	4	Key aspect of this project is deployment, and it is essential that the tailored solution can endure the manufacturing processes.
4	Value of a successful system	4	Streamline and automate material tracking on factory floor, which facilitates further automation.

RESEARCH SOLUTIONS

The investigation of the most appropriate labelling technique involves designing a tailored system for each individual partner on a case-by-case basis. We recommend partners to consult experts on robotic solutions, and we estimate the deployment to take half of year for an engineer.

1.4 Pricing estimation and advising

Every partner that we have visited so far has mentioned that there is a significant amount of historical data on job pricing and productivity collected throughout the years. We believe that such data can be leveraged to estimate and advise cost and pricing for future projects [34, 35], which is a useful guide for job quoting and contract drafting.

A **Digital Twin** of the factory floor will be able to provide a reliable estimation for the required time and resource cost, based on the historical data, the accurately modelled manufacturing processes and the production scheduling.

This will be a data-driven AI-based algorithm that can both be company-specific as well as a cross-industry tool, depending on whether the modelling of the manufacturing processes is based on any company specific data.

1.4 RESEARCH RECOMMENDATIONS

This project can be another component of the Digital Twin project, focusing on the realistic applications of the Digital Twin and how it can further benefit our partners beyond production optimisation. The theoretical exploration of this project will take up a year in a PhD student project given the readiness of said data.

MEASURE	RATING OUT OF 5	COMMENTS
1 Theoretical understanding difficulty	2	The theoretical foundation is established, but how these methods apply to composite industry and where existing methods fail is unknown.
2 Experimental difficulty and cost	2	Experiments are purely in simulation, but the complication lies in real-world verification.
3 Deployment difficulty in real world scenario	3	The difficulty of deployment is in accessing the large amount of historical data and adapting it to different contexts.
4 Value of a successful system	3	This has been raised by a few partners as a great source of advice for job quoting.

RESEARCH SOLUTIONS

The deployment of such a system in industry will involve working tightly with the industry or the partner to identify where existing forecast techniques fail, processing the historical data, and exploring and applying existing AI techniques.

2. ROBOTICS AND AUTOMATION

Another key aspect in production line optimisation is to automate each manufacturing step. Leveraging state-of-the-art robotic technologies, a highly automated production can achieve significant improvement in reliability, repeatability and consistency, as well as reduction in material waste, manufacturing lead time and cycle time, and cost in general [36].

We have observed this phenomenon in many conventional mass-production industries, e.g. automobile, where the rigidity in their production processes simplifies the mechanisation and automation of the assembly lines. The composite manufacturing industry has similarly started to leverage such solutions as automated tape laying, fibre placement and filament winding [36, 37].

Among the partners whom we have visited during this survey, we have noticed the trend of investing and incorporating robotics into their production lines so as to mechanise and automate certain manufacturing processes. However, these systems are not yet fully capable of delivering what the real-world industry desires, especially in the context of **flexible manufacturing**, which results in such investments being less than economical.

For example, conventional automation techniques that focus on repetition are not as feasible when the job specification changes regularly. Many partners have noticed that manually reprogramming the automation for a new design takes a comparable amount of time to the original non-automated process. We instead focus on improving the **autonomy of the production line**, in addition to simple automation.

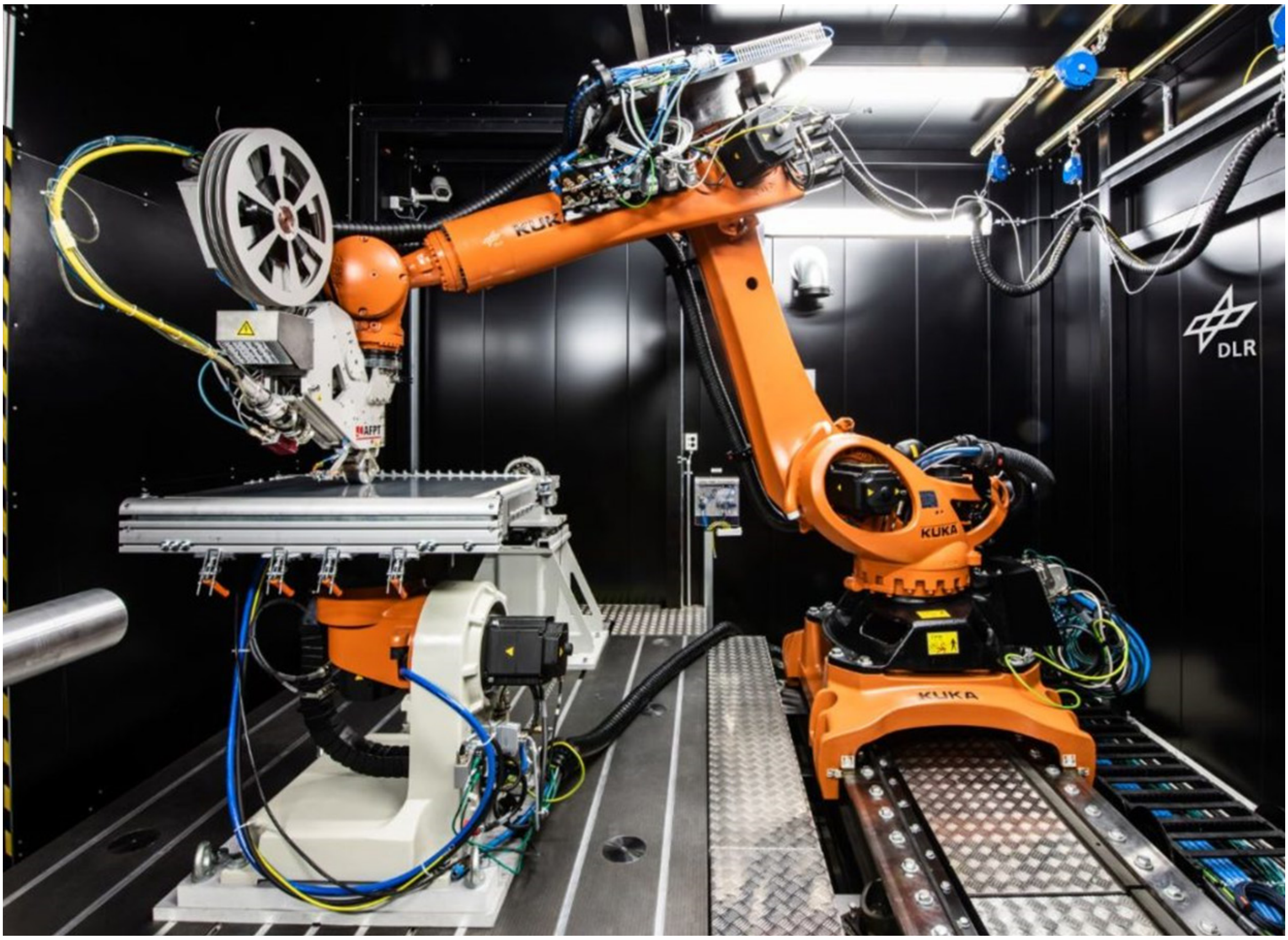

Figure 5 The Thermoplastic Automated Tape Placement design by German Aerospace Centre (DLR) [38] - *video demonstration*.

2.1 Perception-in-the-loop manufacturing

Conventional automation systems in the manufacturing industry are designed for assembly lines and usually expect standardised and repetitive interfaces with the materials they are to operate on, with minimal awareness of the environment and little flexibility for on-the-fly adjustments. If the material is not placed in the exact position the robot expects, the automated execution is prone to fail or produce subpar products.

Additionally, many of these automated systems require human operators to teach them the new execution command for a new job [36], which takes a significant amount of time comparable to manual execution and therefore diminishes the benefit of automated execution when the production batch is small-scale and bespoke, as pointed out by many partners we have visited.

The key to enable autonomous decision-making towards **flexible manufacturing** tasks, i.e. with fast-changing product design and dynamic factory environment, is the **perception and understanding** of the environment [14]; hence we propose **perception-in-the-loop** systems as the foundation for intelligent automation in **flexible manufacturing**.

Sensors commonly used in the field of robotic perception range from conventional RGB cameras [39] to Infrared (IR) depth cameras [40] and laser scanners [41, 42], each providing a unique modality of data that can be used to both localise the robots and map the environment and the materials.

Simultaneous Localisation And Mapping (SLAM) methods can provide the robotic systems with accurate representation of the environment and where it is with respect to it [43, 44], and algorithms such as 3D registration can align and compare a reconstruction of the product with its CAD model [45, 46], giving the robotic system a real-time understanding of its job and the ability to make on-the-fly decisions on how to proceed.

A few industrial robot manufacturers have recently presented similar products with built-in perception systems, such as Zeman's Steel Beam Assembler (SBA) [47] (Zeman SBA demonstration).

Furthermore, the emerging field of **Learning from Demonstration** (LfM) has shown promising results on human experts teaching complex tasks to robotic manipulators through simple demonstration [48, 49, 50] (Universal Manipulation Interface (UMI) demonstration).

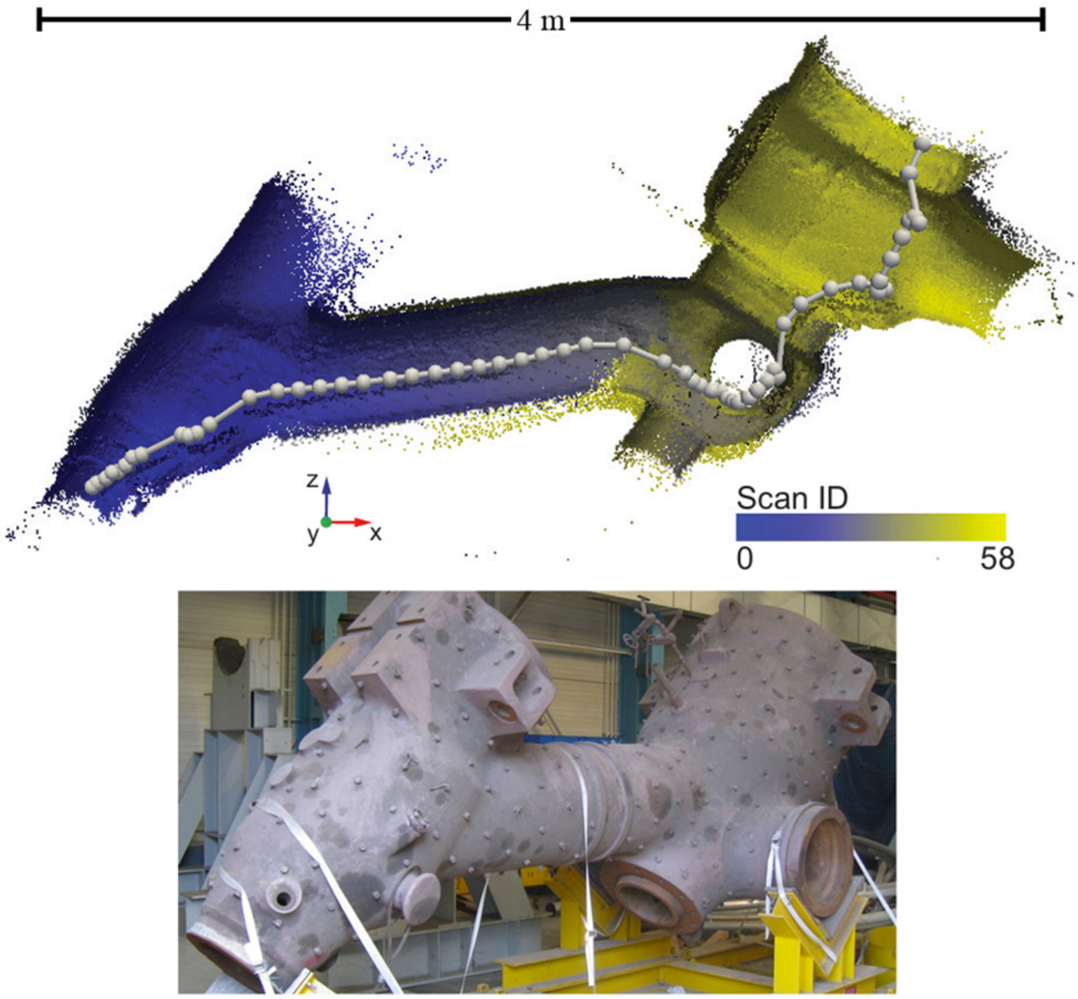

Figure 6 An example of an accurate dense point cloud (top) collected by chest-inspection robots compared with the actual steam chest (bottom), presented by Pomerleau et. al. [45].

Perception systems are used to capture the human operators' behaviours and AI technologies translate that into robotic executions. Such technology can further improve the flexibility of robotic systems when handling frequently changing tasks.

Similarly, perception and AI techniques have enabled robotic fabric manipulation in recent years [49] (video of fabric manipulation through LfM), which used to be a key challenge that limits the application of robotic and automation in composite manufacturing.

Exploring these cutting-edge research field and bringing them into real-world application will significantly benefit the composite industry in Australia.

2.1 RESEARCH RECOMMENDATIONS

A research project on a perception-in-the-loop robotic prototype should take a PhD student a year of their candidature or a postdoctoral researcher up to one year depending on the specific application. To investigate the exact limitation of existing industrial solutions and to deploy such a system in a factory or tailor the prototype for the specific needs of any partner will require in addition another half of year and an engineer working alongside the research.

MEASURE	RATING OUT OF 5	COMMENTS
1 Theoretical understanding difficulty	4	LfM is an emerging research area and will require thorough investigation.
2 Experimental difficulty and cost	3	Robotic hardware experiment is essential for this project, but commercially available and conventional hardware will suffice.
3 Deployment difficulty in real world scenario	4	The robotic solutions have to be reliable, robust and safe to be deployed on the factory floor.
4 Value of a successful system	5	It plays a core role in enabling automated production lines.

RESEARCH SOLUTIONS

Developing a LfM system for industry-specific applications will be at least a two-year project for a PhD student or a one-year project for a postdoctoral researcher, and an additional year for deployment in the factory with an engineer for tech support. This amount of time is estimated for a robotic fabric manipulation project.

2.2 Mobile robotics on factory floor

Traditional automation setups transport materials along the assembly lines and have stationary robots work on them. Manufacturers that handle large and/or heavy materials therefore often have to rely on huge machineries to manipulate their materials, a typical example of which is the steel fabrication industry.

The transportation and handling of these large materials is dangerous and resource-consuming (time, labour and energy), and in certain cases prone to error. In addition, conventional assembly line robots usually have hardware limitations on the dimension and weight of the materials they can handle. A few partners have mentioned such constraint being a bottleneck for robotic production line.

We therefore propose employing mobile robots to minimise the need to move heavy/large materials on the factory floor. Instead, robots such as omnidirectional platforms can carry robotic arms and tools the material to automate assembly, fabrication and manufacturing tasks [51, 52, 53], with state-of-the-art perception algorithms enabling accurate and safe execution.

Such a system can mitigate the need to use heavy machineries and significantly reduce the movement of large and dangerous materials, which would in turn improve the safety of the factory floor and reduce the cost in investment and energy.

Figure 7 Toyota CDI120 Automated Horizontal Carrier [54] for warehouse and factory floor (*video demonstration*).

2.2 RESEARCH RECOMMENDATIONS

A research project exploring feasible solutions for deploying mobile robotics on the factory floor would investigate the use of multiple robots to perform complex tasks, optimize planning and utilization, and develop perception systems tailored to the factory environment.

	MEASURE	RATING OUT OF 5	COMMENTS
1	**Theoretical understanding difficulty**	3	Mobile robotics is an emerging field and have been studied over the years, but still need more research for executing complex tasks cooperatively on factory floors.
2	**Experimental difficulty and cost**	3	The involvement of robotic hardware raises the experiment costs, but conventional platforms are sufficient.
3	**Deployment difficulty in real world scenario**	5	Deploying mobile robots on the factory floor presents challenges in the safety and robustness of these robotic systems, especially with humans around.
4	**Value of a successful system**	5	It will significantly reduce the investment in large-scale machineries.

RESEARCH SOLUTIONS

Designing such a system is expected to take approximately two years for a PhD student or one year for a postdoctoral researcher, with a primary focus on ensuring safety in human-rich environments. Further research—around one additional year for a PhD student or six months for a postdoctoral researcher—would be required to enable these robots to execute manufacturing tasks effectively. Deployment would necessitate the involvement of an additional engineer for at least one year.

2.3 Force sensing and control, and handling deformable material

Our partners in carbon fibre manufacturing industry have pointed out that the mechanical properties of this type of composite materials, such as their brittleness and deflection capacity, are a challenge for automating the post-production machining processes such as drilling and trimming [55, 56]. The fabric form of these materials during the layup stage also makes them hard to handle with robotic manipulators [57, 49].

Mass composite manufacturing can be economically automated with 3D printed tools (moulds) and automated lamination process, addressing these material handling challenges. However, in small-scale productions of highly customised jobs, the flexibility in manufacturing processes require more intricate and adaptable handling of the materials.

For human operators, feeling the surface of materials and the pressure on the hands is what allows us to handle intricate materials. Similarly, the ability to measure force exerted by and applied to the robotic manipulator plays a key role in handling delicate materials.

Better informed control decisions can be made for the robot to more accurately execute its task. In recent years, **soft robotics** and **touch/tactile sensors** are two relevant emerging researching field in robotics, both greatly contributes to handling brittle or fabric-like materials [58, 59].

However, **tactile sensors** are prone to damage when used repeatedly, such as in an industrial context. Alternatively, **torque and inertia sensors** embedded in the joints of robotic arm are commonly used to estimate the force on arm [60, 61].

With assistance from **perception-in-the-loop** systems [62] (video demonstration of ARM-SLAM) and well-informed and well-designed control systems [63], these robot systems can also be deployed to conduct highly intricate manipulation tasks such as handling composite fabrics and brittle products as well as polishing and cleaning the detailed surfaces of tools [64]. It also enhances the safety of the robots in human-present environments, e.g. factory floor.

The combination of perception and force sensing capability can also be leveraged to handle materials with deflection capacity that poses challenges to traditional industrial automation as well as conventional robotic solutions.

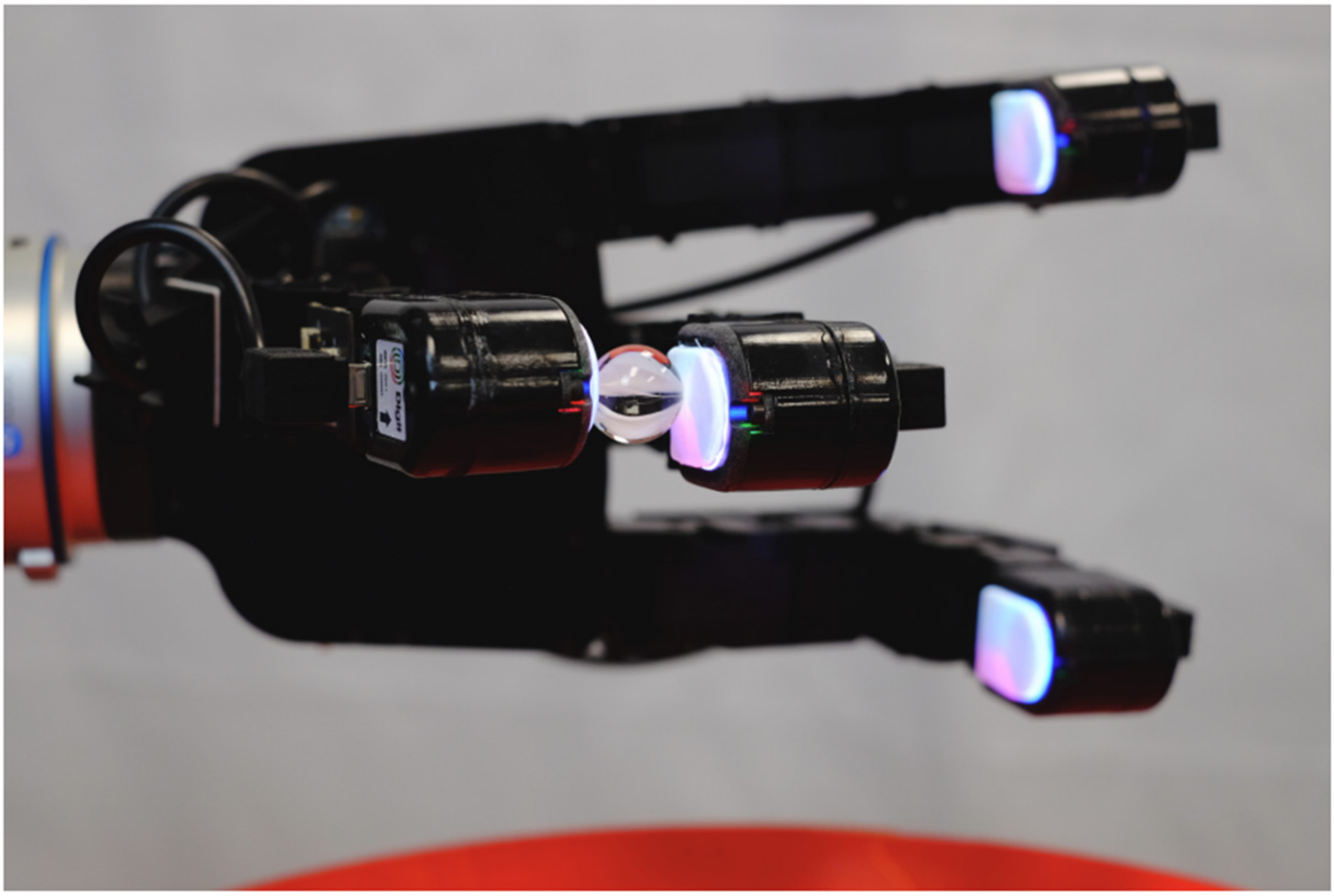

Figure 9 DIGIT, tactile sensor for in-hand manipulation by Lambeta et. al. [58]

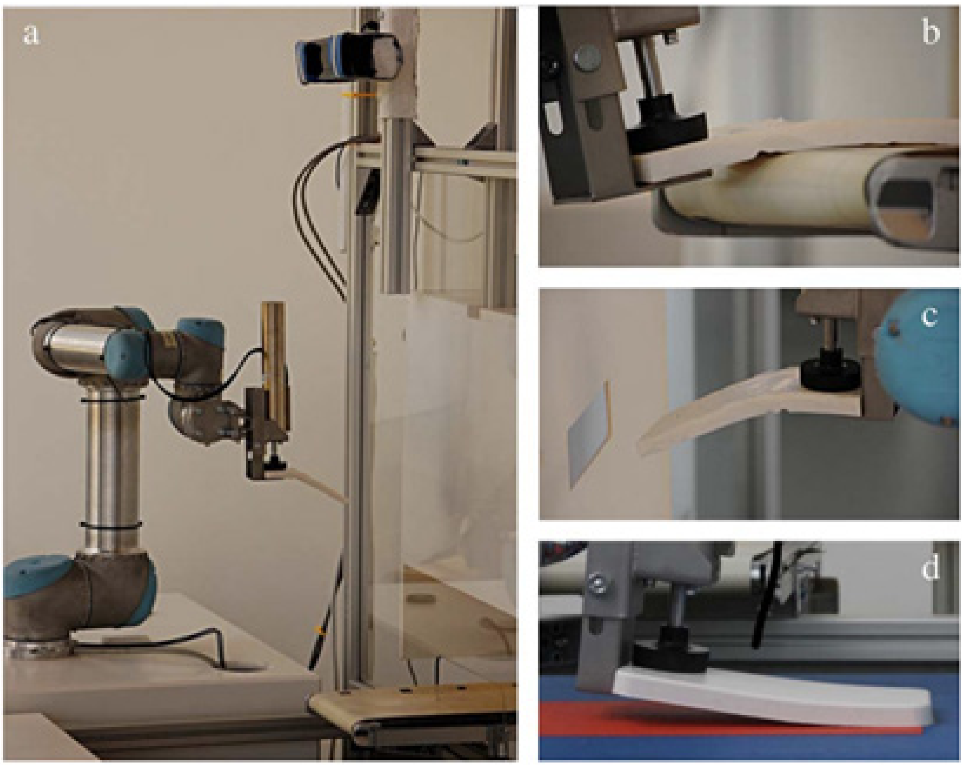

Figure 8 An adaptable robot system manipulating flexible objects by Bodenhangen et. al. [57].

2.3 RESEARCH RECOMMENDATIONS & SOLUTIONS

Tactile, haptic, and force sensing technologies have been studied for decades, but they still require further research to optimize their integration into real-world applications. A project on tactile, haptic or force sensing integration in a robotic manipulation of sensitive materials will require a PhD student three years, or a postdoctoral researcher one year.

To design a control system that leverages force sensing will be a one-year project for a PhD student, or half a year for a postdoctoral researcher. Its deployment will need an additional engineer working alongside the researcher for half a year.

MEASURE	RATING OUT OF 5	COMMENTS
1 Theoretical understanding difficulty	4	Force-based control is an established field, but haptic/tactile sensing or a robust force sensor is an open research topic.
2 Experimental difficulty and cost	4	Designing such a system will require customised robotic hardware and sensor design.
3 Deployment difficulty in real world scenario	3	eploying the sensor is straightforward, but to leverage the sensor will require heavy customisation of the existing robotic software.
4 Value of a successful system	4	The biggest value of such a project lies in the safety of robotic systems on the factory floor, especially working with humans.

2.4 Multi-robot collaboration material

As the complexity of manufacturing process rises, there is often the need for multiple actions to be executed at the same time. For instance, in the context of welding in steel fabrication, two pieces of steel will be held against each other while being welded together.

To automate processes of such nature, existing industrial robotic solutions such as Zeman's SBA [47] employ multiple robot arms, each handling one simple task and collaborating each other. To facilitate the collaboration among multiple robots, the first cornerstone is to accurately understand the position and joint configuration of each robot with respect to each other, and perception-based **multi-agent localisation** and SLAM [65, 66] (video demonstration for CCM-SLAM) is a well-studied area in robotics. State-of-the-art robotics systems such as Simulation to Pick Localize and placE (SimPLE) [67] further demonstrate that combining multiple sensor modality, e.g. visual and tactile (Section 2.3) can greatly improve the intelligence of multiple manipulators collaborating with each other on industrial tasks (video demonstration of SimPLE).

In addition, existing industrial solutions often incorporate large structures to accommodate for the various dimensions from job to job and/or to facilitate material handling, which in turn require large footprints on the factory floor.

We propose breaking these large monolithic robots into smaller individual robots, potentially mobile ones too as discussed in Section 2.2. We expect such a strategy to significantly reduce the hardware investment involved in these robotic solutions, and instead leverage state-of-the-art **multi-agent localisation** algorithms [65, 68] to ensure the accurate interactions among robot arms.

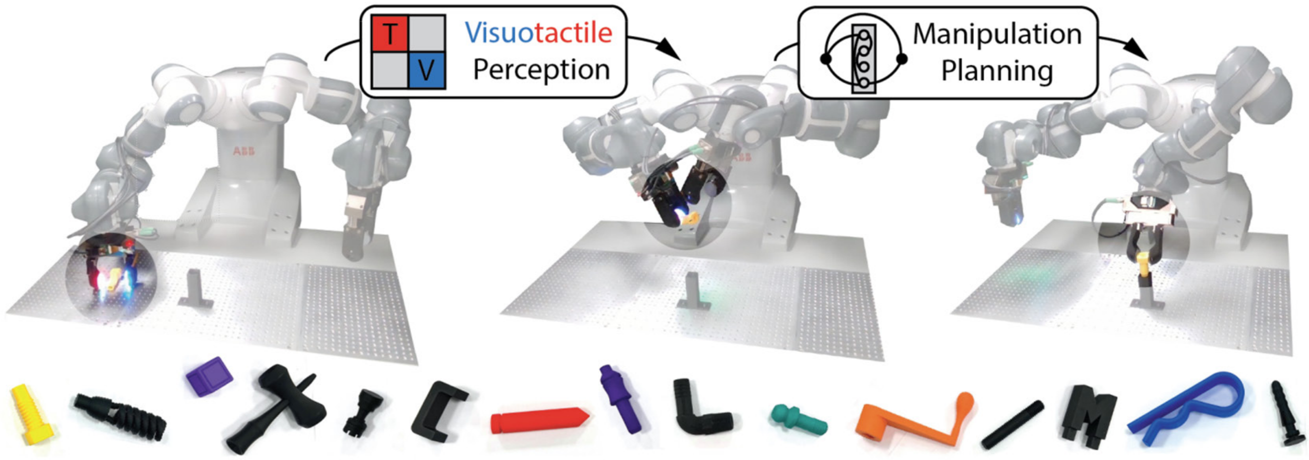

Figure 10 SimPLE, a state-of-the-art picking and placing multi-manipulator system that leverages visuotactile perception [67]

2.4 RESEARCH RECOMMENDATIONS & SOLUTIONS

Collaboration among multiple stationary robots is a well-studied area and will take a PhD student one and half years, and a postdoctoral researcher one year. Its deployment will require an engineer working with the researcher for half a year.

Designing a swarm of mobile robots on the factory floor that collaborate with each other to execute complex manufacturing tasks will be a three-year project for a PhD student and at least a two-year project for a postdoctoral researcher. The deployment of such a system on the factory floor will need a lot of verification in safety. The required length of time will be dependent on many real-world aspects such as the factory floor plan.

	MEASURE	RATING OUT OF 5	COMMENTS
1	Theoretical understanding difficulty	4	The challenge lies in the mobile collaborative robots as it is a complex system with many moving parts.
2	Experimental difficulty and cost	5	Experiments will require multiple complex robotic hardware systems.
3	Deployment difficulty in real world scenario	5	The safety concern of such a system working with humans on the factory floor is the biggest challenge.
4	Value of a successful system	5	This technology can lead to a fully automated factory floor with minimal human involvement.

2.5 Human-robot interaction (HRI)

For mobile robots to be conducting manufacturing on the factory floor, there is a growing need in safety for robots and humans to work in the same environment. The emerging field of **cobots**, i.e. collaborative robots, has encouraged the development of many new designs that are safer to work alongside human operators, such as Universal Robotics' robot arms [69].

One of the key features for **Human-Robot Interaction** (HRI) safety is compliant control—robot arms can be safely pushed around by human due to their light weight and compliant joint [70]. In addition, **force and torque sensing** capability (Section 2.3) can better inform these **cobots** the amount of force required as well as detect potential collisions, further improving HRI safety [70] (HRI video demonstration).

Last but not least, mitigating the need of heavy machineries and replacing them with smaller robots, as discussed in Section 2.2, also considerably improves the safety of human operators on a highly automated factory floor, because heavy machineries operate with significantly more power and are therefore far less compliant compared to light-weight robots.

In addition to hardware innovation, it is beneficial to have an intelligent navigation system that is aware of the random movement of humans and able to quickly respond to them [70].

Dynamic object motion tracking and estimation based on perception is an emerging field in robotics [71, 72], and we are seeing promising results that can be leveraged to improve the safety of robots interacting with humans.

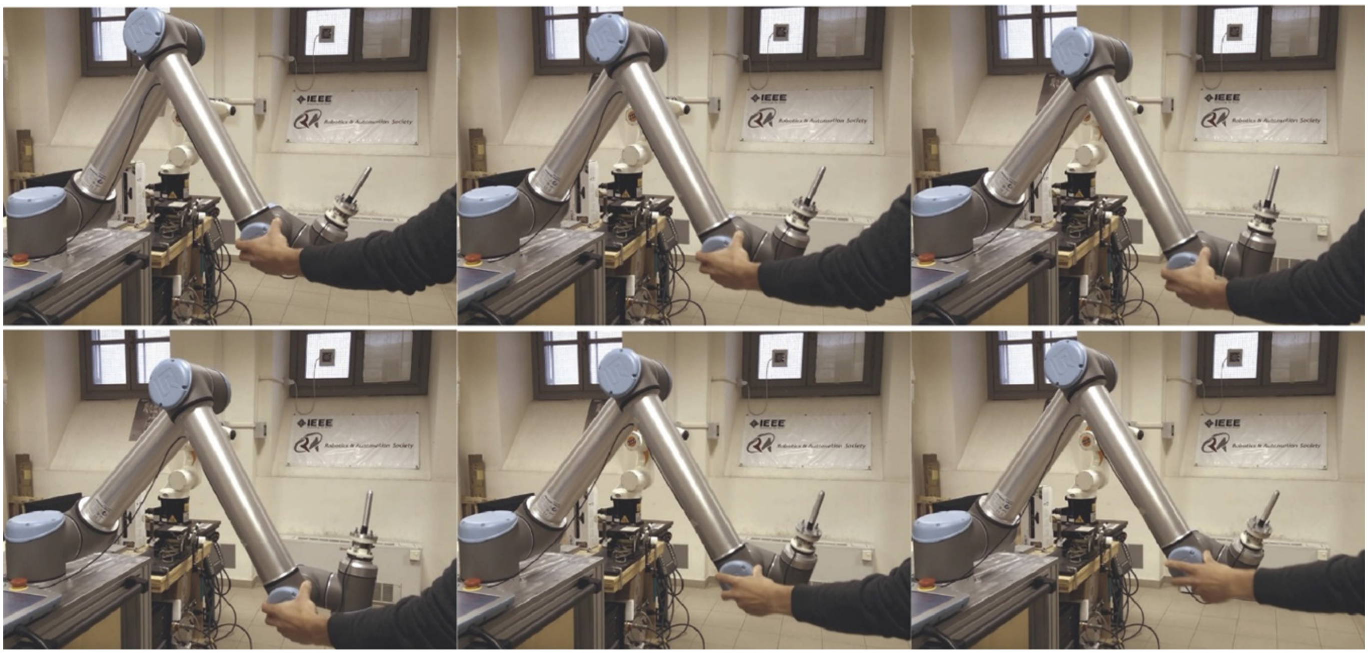

Figure 11 An example of a collaborative human-robot task with a UR10 robot by Gaz et. al [64].

2.5 RESEARCH RECOMMENDATIONS & SOLUTIONS

The core technical exploration and development on HRI should take a PhD student two years or a postdoctoral researcher one year. Tailoring such a system for a particular task or a partner will require another year of an engineer working with the researcher to ensure safety, and a variety of robotic platforms might be involved depending on the desired task.

	MEASURE	RATING OUT OF 5	COMMENTS
1	Theoretical understanding difficulty	3	Further research is still required to improve the existing solutions, but there is on-going research in many required aspects of such a system.
2	Experimental difficulty and cost	3	There might be a need for different robot platforms to assess different aspects of HRI.
3	Deployment difficulty in real world scenario	5	The main challenge is the safety concerns when robots and humans interacts with each other.
4	Value of a successful system	4	The key value of this system is the improved safety of robotic systems in general on the factory floor.

2.6 Specialised sensor selection

There is a wide collection of sensor types available for robotics research as well as industrial purposes, each providing a unique modality applicable for specific needs.

For example, highly reflective surfaces (high specularity), e.g. metals, pose challenges to conventional perception sensors like camera and LiDAR, and there are scanners tailored for such materials [73].

We recommend partners to consult robotic experts when choosing sensors for automation systems on the factory floor. Experts can help assess the specific needs of the application, taking into account the environmental conditions, surface properties of materials, and performance requirements.

A comprehensive understanding of the sensor's capabilities, limitations, and integration requirements is essential to ensure that the chosen sensors align with the goals of the automation system.

3.1 Automated design assist

To fully realise an end-to-end automated manufacturing process, we also need to automate the design stage. Many partners we have surveyed so far identifies the manual design process being time consuming and a bottleneck in the production, especially when the job changes regularly and requires flexible designing and detailing process [14].

For example, in the steel fabrication industry, drawings need to be populated with details such as bolts, nuts and welds. In composite manufacturing, the design process involves translating structural and performance requirements into selecting the appropriate fibre or fabric materials, defining the optimal layup configurations and designing the end product [36]. All these processes have well-defined standards in each corresponding industry.

We therefore propose leveraging AI-based methods to learn how to design the production process as well as each manufacturing step [74, 75, 76], with the intention of assisting human designers to improve the efficiency and reduce involved manhour.

This technology will have far-reaching impacts beyond the composite industry, and contribute manufacturing in general. For instance, t here has been a few emerging directions on AI-based methods for improving prefabricated house designs [77, 78, 79]

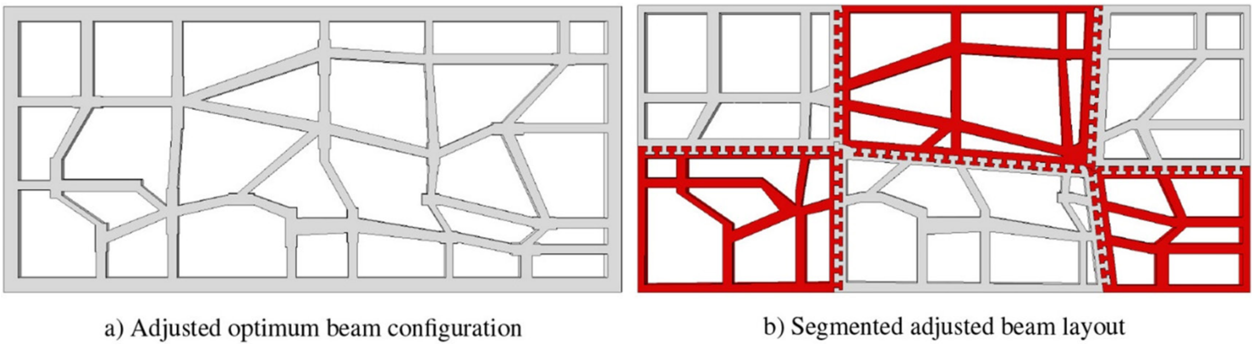

Figure 12 AI-assisted segmentation design for prefabricated wall-floor building by Baghdadi et. al [77].

3.1 RESEARCH RECOMMENDATIONS & SOLUTIONS

Researching the theoretical core of an AI-enabled design automation algorithm will take a PhD student one and half years, or a postdoctoral researcher one year. To tailor it for a particular task will require partner involvement, especially in the form of accessing and learning from historical data, which is estimated to require an additional half a year.

MEASURE	RATING OUT OF 5	COMMENTS
1 Theoretical understanding difficulty	4	There exist theories for such problems, but further research is required to bring them to the real world.
2 Experimental difficulty and cost	1	Experiments will focus on simulation with minimal hardware involvement.
3 Deployment difficulty in real world scenario	2	There is little risk in deployment, but it will require partner involvement (accessing real-world data) and feedback.
4 Value of a successful system	5	Common desire shared by many partners, and will immediately provide the benefit of reducing cost in terms of man hour.

3.2 Transportation and batch manufacturing

Within a similar domain as design automation, we further propose using AI-based methods to assist the design of material and product transportation and batch manufacturing. Different industries practise batching at different stages of the production and for different purposes. For example, carbon fibre composite manufacturing industry pre-cuts and groups materials into kits (known as **kitting**) before layup, and arranges pieces within a sheet to minimise waste before automated cutting (known as **nesting**).

In large-scale steel fabrication, the overall design is divided into lots (**lotting**) because there are many steel beams, sections or structural elements that need to be fabricated, transported and assembled on site in a particular order and manner.

Across all these practices, the same theme remains—organising materials and products based on the manufacturing process and the design will improve the efficiency of material handling and production.

Software such as Tekla, JETCAM and Autodesk all have **lotting** or **nesting** tools for automating such processes for their corresponding industry [80, 81, 82] (video demonstration of Autodesk Investor nesting tool). However, several partners have expressed interest in a more intelligent system based on their day-to-day experience with the software.

We therefore propose investigating the limitations of the existing tools and learning the specific needs of the partners, and tailoring an optimisation tool for material batching, handling and transportation towards each partner.

3.2 RESEARCH RECOMMENDATIONS & SOLUTIONS

Because there are existing solutions commercially available for lotting/batching/kitting tasks, and there is an established theoretical foundation, the key research focus lies in first understanding what partners still need in addition to off-the-shelf technologies, and second deploying the theory to solve real-world problems. This will take one and half years for a PhD student or one year for a postdoctoral researcher. Customisation for particular partners might require additional time depending on the task.

	MEASURE	RATING OUT OF 5	COMMENTS
1	Theoretical understanding difficulty	2	There are commercially available solutions – the research will focus on what partners need and is still missing from existing solutions.
2	Experimental difficulty and cost	1	The experiments will be purely digital and in simulation.
3	Deployment difficulty in real world scenario	2	This system will assist human designers like existing solutions, so limited difficulty in deployment.
4	Value of a successful system	3	Such a system can improve upon the existing solutions and reduce human involvement in the design process.

4. QUALITY ASSURANCE (QA) AND INSPECTION

The final piece of the puzzle in a fully automated manufacturing pipeline is the QA and inspection step.

Many partners that we have surveyed have identified QA as another common bottleneck in production time and man hour, as the tolerance is often on the scale of millimetre if not smaller.

In this section, we will discuss a few aspects in automating the QA and inspection process, not with the intention of completely removing the human operators from the loop, but to assist and improve the manual inspection process.

4.1 Automated QA based on CAD model

Due to the availability of CAD models for the products, the QA and inspection process can be translated into a dense reconstruction, registration and change/discrepancy detection problem in robotics.

There exist several handheld solutions for manual scanning and reconstruction [83, 84, 85], and combined with a robot arm, active mapping techniques can automate such a process [86, 62]—a problem that has been studied by the robotics community for a couple of decades [87, 88].

Registering the reconstruction with the CAD model is similarly a well-studied area in robotics, based on which we can highlight the discrepancies between the two for QA and inspection purposes. One key challenge in this case is the tolerance requirement that is beyond the accuracy of usual sensors used in the robotic research domain.

We therefore propose leveraging highly accurate industry-grade sensors [89, 73, 90] and building active mapping and reconstruction systems around these sensors to automate the QA process. Further studies will be needed to tailor the registration and discrepancy detection algorithm for industry partners.

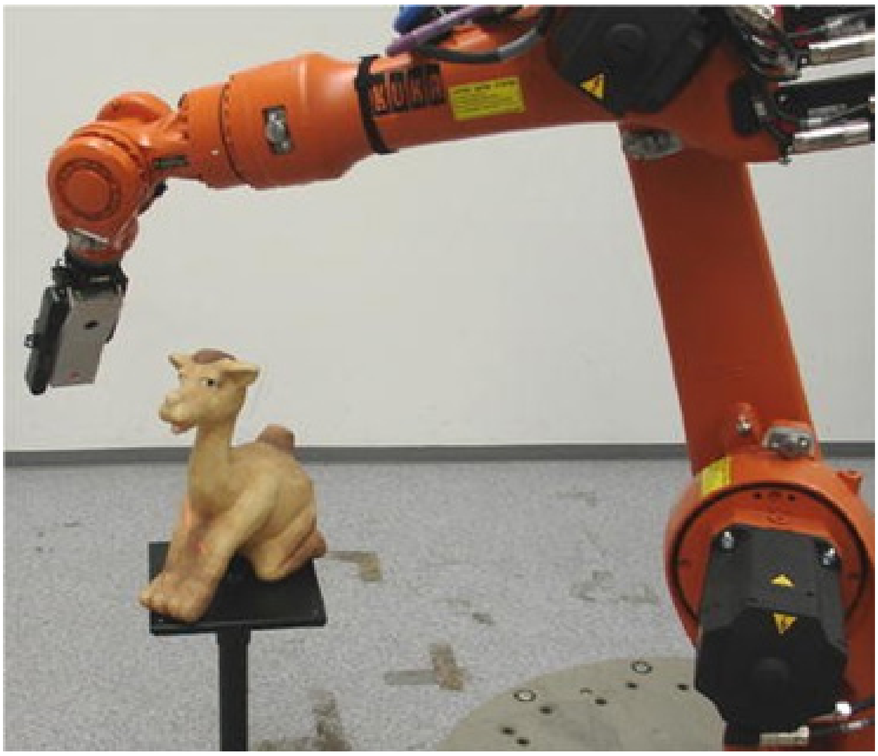

Figure 13 Active mapping system setup using a Kuka robotic arm and a depth camera by Kriegel et. al. [86]

4.1 RESEARCH RECOMMENDATIONS & SOLUTIONS

The project on automated QA using CAD model is expected to be an one-year project for a PhD student, or a half-year project for a postdoctoral researcher. The challenge of deployment mostly involves understanding the particular characteristics of the jobs, e.g. dimensions and materials.

	MEASURE	RATING OUT OF 5	COMMENTS
1	Theoretical understanding difficulty	3	3D reconstruction and alignment is an established field, but specific industry and material can pose unique challenges.
2	Experimental difficulty and cost	2	Most experiment can be conducted in simulation or with minimal physical examples.
3	Deployment difficulty in real world scenario	4	Communicating with partners and tailoring the system for the specific product might raise challenges.
4	Value of a successful system	4	This project can significantly improve the efficiency of QA compared to the manual QA process.

4.2 Non-destructive defect detection

In composite manufacturing, the defects in the product such as delamination, void formation and wrinkles can be hard to detect as they are not always visible on the product surface, and sometimes still hard to visually detect even when they are on the surface. Some defects conventionally require destroying the product to identify, which will naturally cost the manufacturer more.

We therefore propose leveraging other sensor modalities within robotic perception systems to detect defects in these products without destroying the products. Depth sensors and laser scanners can be used to detect wrinkles and boundary edges [91], and ultrasonic to detect defects below the surface to avoid any destructive processes [92, 93].

The key component of such a system lies in choosing the correct sensor as well as interpreting the sensor readings, the latter of which we believe can be handled by a tailored AI-based image processing tool [94, 95].

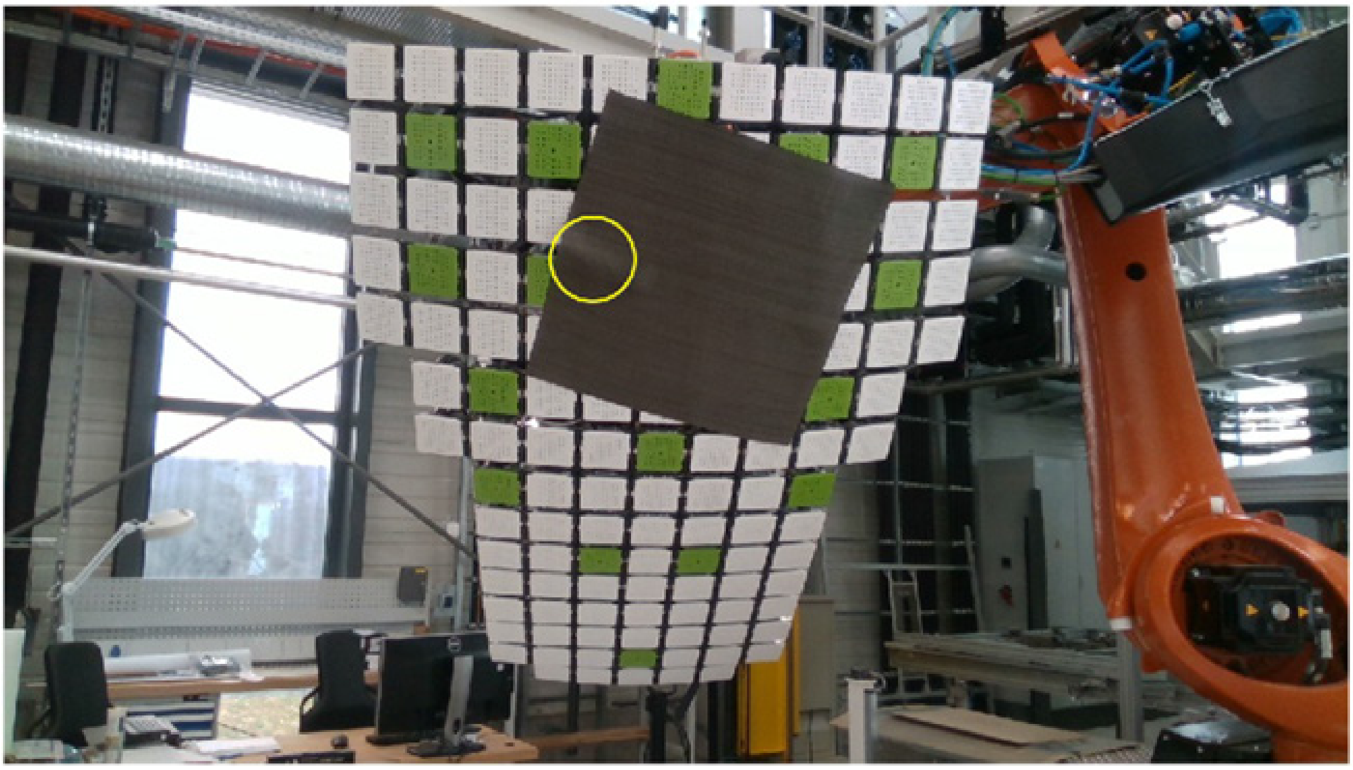

Figure 14 An example of visual wrinkle detection in fiber products by Gutpa et. al [91].

4.2 RESEARCH RECOMMENDATIONS & SOLUTIONS

To develop a reliable AI for recognising defects in composite will require two years from a PhD student, and one year from a postdoctoral researcher, as well as a significant amount of annotated data on physical products provided by partners.

	MEASURE	RATING OUT OF 5	COMMENTS
1	Theoretical understanding difficulty	3	Defects in composite materials are well-understood, and image processing via AI is an established field. Putting them together is novel but not impossible.
2	Experimental difficulty and cost	4	Developing a learning-based algorithm require a significant amount of data (from physical products) and annotation for training and testing.
3	Deployment difficulty in real world scenario	2	The deployment should only require commercially available sensors.
4	Value of a successful system	5	Being able to completely avoid destructive inspection is very beneficial to the composite manufacturing industry.

4.3 AR-assisted inspection

We further propose developing an **Augmented Reality (AR) system** to enhance human inspection processes. Many of our surveyed partners currently use tablets, such as iPads, to visualize QA results after inspections.

By integrating AR with an automated QA and inspection workflow, we can provide real-time visual overlays that **instantly highlight discrepancies**, enabling inspectors to identify and address issues on the fly, improving accuracy and efficiency.

4.3 RESEARCH RECOMMENDATIONS & SOLUTIONS

Building such an AR system is estimated to be a one-year project for a PhD student, or a half-year project for a postdoctoral researcher. To deploy such a system on the factory floor will additionally require an engineer working with the researcher.

MEASURE	RATING OUT OF 5	COMMENTS
1 Theoretical understanding difficulty	2	The theory for this project is similar to the automated QA technology, and focuses mostly on realising the AR system, the theory of which is well-established.
2 Experimental difficulty and cost	2	Experiments is ideally conducted with some minimal physical examples.
3 Deployment difficulty in real world scenario	1	The hardware required for deployment is expected to be mostly commercially available.
4 Value of a successful system	3	This project will improve the efficiency of manual inspection.

4.4 Online quality monitoring and manufacturing adjustments

In addition to QA at the end of the production, a similar technique can be leveraged to analyse the product quality during manufacturing, which can in turn advise how the manufacturing process should adjust on-the-fly to avoid error creeping [96, 97], by feeding the observed error back into the design instead of mechanically following a predetermined manufacturing process.

This is especially applicable in additive manufacturing processes such as layup and fibre placement [95], even just to detect the defect during production to avoid further wastage.

A similar concept can be leveraged during site erection to detect any discrepancy to the design. Such a system will require frequent and regular scans of the construction from multiple viewing angles as well as robust localisation with a global reference frame to accurately map out the overall structure, which is a well-established field in robotics.

4.4 RESEARCH RECOMMENDATIONS & SOLUTIONS

Researching the theoretical core of an AI-enabled design automation algorithm will take a PhD student one and half years, or a postdoctoral researcher one year. To tailor it for a particular task will require partner involvement, especially in the form of accessing and learning from historical data, which is estimated to require an additional half a year.

	MEASURE	RATING OUT OF 5	COMMENTS
1	Theoretical understanding difficulty	2	An established field of research, however will require adaptation to context, such as the dimension of the product.
2	Experimental difficulty and cost	3	Such a project will require example real-world details from the partner, or even conduct field experiments to correctly model the errors.
3	Deployment difficulty in real world scenario	3	Large-scale products can introduce difficulty to deployment.
4	Value of a successful system	4	Detecting error during production instead of at the end of it can have a significant impact on saving cost.

5. KEY RECOMMENDATIONS FOR THE COMPOSITE MANUFACTURING SECTOR

Industry and academic research and development

As we have stated throughout this white paper, the most prominent theme to emerge from this investigation is how highly dynamic and agile Australian and New Zealand manufacturers are, and must be, as they are servicing a highly heterogenous regional market.

It is clear from this investigation that technology vendors are focusing on easier to solve repetitive task automation over the higher skill and performance requirements of manufacturers in our region. We have termed the non-uniform operational nature that is typical of our region, '**Flexible Manufacturing**'.

While this is of course a great frustration to the sector, which we have seen through numerous costly procurements of systems not fit for purpose, there are two noteworthy trends regarding the observed technology gaps and needs.

Firstly, the primary high value capability gaps we observed across partners we do not consider to be scientifically or technically unfeasible. Meaning, the lack of commercially available solutions is due to a lack of investment in the research and development of robotic and autonomous systems for the **flexible manufacturing** market.

Second, the capability gaps we have identified in this white paper are shared by all stakeholders and are largely '**pre-competitive**' core operational capabilities, making them product agnostic. This means stakeholders can safely collaborate on the research and development of these systems without giving up the competitive advantage they have in their respective product classes.

The convergence of these factors presents an exciting opportunity for **flexible manufacturers** in our region to work together on systems that will ensure ANZ becomes globally recognised as leaders in flexible and dynamic manufacturing, but also to collaborate on the development of an entirely new class of technology and industry in our region.

Due to the above mentioned reasons, we see tremendous value in a multi-industry partner collaboration that can share costs and risk of an ambitious larger effort, from research to startup.

For this reason, this white paper strongly recommends a shared cost model where partners invest a portion of their contribution to fund a small team of academic and technical resources that are working on these core scientific issues. Partners will be able to leverage these shared developments, using their remaining investment to tailor them to their unique application needs.

The various projects outlined in the research development document range in size and complexity. Each one represents a small but concrete stepping stone towards a larger more ambitious effort and goal. Due to their commonality between stakeholders they can be funded in a variety of ways:

1. **Directly** - where one partner will directly fund the projects they are most interested in. They will bear the cost alone and retain the IP for themselves. This is a higher risk strategy and constrains innovations to the financial limitations of the partner.
1. **Joint funding** – partners can collaborate and fund projects of most relevance to them. They will share access and ownership of the IP. Investment is derisked proportional to the number of industry partners.
1. **Consortium (authors recommendation)** – a multiparty collaboration and co-investment in a series of projects of most interest to the group. IP is shared amongst stakeholders. Stakeholders take on significantly less risk while benefitting from a substantially larger investment and it potential returns.

Importantly, these projects have the potential to become commercially viable products, either through technology partners, new in-house capabilities, or startups. Throughout this study, we have observed several high value gaps in the market that are reflected here and these projects aim to address.

Project and logistics optimisation systems for **flexible manufacturer**s stands out as a particularly high value startup opportunity as there is no obvious commercially available system, all partners expressed this as a major pain point, a solution capable of supporting **flexible manufacturers** would also be useful in less dynamic operations.

KEY RECOMMENDATION TO INDUSTRY AND ACADEMIA

It is the opinion of the authors that the formation of industry research consortium will deliver by far the greatest return on investment to all stakeholders. Research recommendations outlined in this white paper represent individual development opportunities that collectively form a comprehensive suite of interacting solutions to the most pressing issues we observed. Furthermore, they are primarily operationally precompetitive in nature, allowing partners to safely collaborate and share the gains.

A consortium approach will significantly derisk investment for all stakeholders enabling the pursuit of a wider range of common interest problems from low hanging fruit to high risk, high reward projects. Furthermore, government funded industry support programs typically view consortiums more favourably as a more efficient, lower risk deployment of funding. The pooling of resources will demonstrate a stronger commitment from industry to government and funders while simultaneously attracting a larger quantum of funding to be spread across a greater number of development opportunities.

The ACM CRC is the immediately obvious pathway likely to be supportive of a consortium approach. Cooperative Research Centre Projects (CRC-P), and ARC Linkage Industrial Transformation Research Program (ITRP) are other initiatives where a consortium approach could attract significant funding.

For governments and policymakers

As stated in the introduction, we hope this white paper will be the first step towards greater analysis of robotic penetration in manufacturing firms. As far as we have been able to determine, this paper is the first of its kind, attempting to parse robotic utilisation with the style of manufacturing undertaken within said firms. For Australian operators and policy makers, this is essential information that is simply not available.

There is a suite of policies and grants at state and federal levels incentivising manufacturers to invest in robotic systems. These policies are predicated on the assumption that robotics are the key to the revitalisation of our manufacturing sector, sentiments the authors of this white paper agree with.

However, for these policies to deliver on their ambition we need to understand how our regional firms operate and manufacture to ensure they are procuring technology that is going to boost their productivity.

GDP in markets discussed (China, US, and Europe) which have the highest penetration of robotics, is predominantly being generated by larger firms. They are also the largest manufacturing employers (59% of US manufacturing jobs are in firms with more than 500 people).

While analysis is sparse on what type of firms are procuring robotic systems and at what rate, we do know that robotics and automation in these markets skew heavily towards larger firms.

This is essential context for policy makers as the Australian market is completely different. Manufacturing GDP is predominantly being driven by smaller firms, who are also the largest employers (92%).

There are clearly legitimate reasons why robotic penetration in our region is lower, many we have outlined here, and these should be explored more thoroughly by the Department of Industry to better target support. Well intentioned but poorly crafted policies may come across as tone deaf as low penetration is likely not to do with lack of knowledge or finances, but more to do with the limitations of commercially available systems.

It is the opinion of this study that it is the latter; in which case we need to work with industry to develop new technologies that meet the needs of their operations.

KEY RECOMMENDATION TO GOVERNMENTS AND POLICYMAKERS

While this white paper is relatively small in size and scope, the uniformity of feedback and observations across industry were stark. Our engagement with relevant peak bodies suggests our findings are representative of a broader regional phenomenon.

This is highly relevant to governments and policymakers concerned with strengthening Australia's manufacturing sector, as the finding of this paper appear to run counter to many mainstream preconceptions regarding the nature and makeup of manufacturing in our region; preconceptions that appear to have been influential in the design of major industrial development policies.

The outcome of which are initiatives incentivising procurement of ill suited 'off-the-shelf' systems, in lieu of policies aimed developing novel robotic systems to meet the needs of the predominantly dynamic and flexible style of manufacturing of our region.

As stated above, we were unable to find any substantive analysis on the intersection of robotic penetration and the style of manufacturing, in any market. It is possible this white paper is one of the first of its kind. If the findings of this white paper are accurate, and Australia is indeed dominated by **flexible manufacturing** firms, this needs to be more thoroughly investigated and understood by policymakers.

We strongly recommend governments and policymakers invest in a larger, more comprehensive analysis on the technology needs of Australian manufacturers in the context of firm size and manufacturing 'style'. Such analysis will ensure industry research, innovation and development policies are highly targeted and Australia centric.

FINAL THOUGHTS AND CONCLUSIONS

In summary, it is clear manufacturers in our region must be highly skilled and dynamic largely due to macroeconomic forces in our region.

It is unrealistic to think that these forces will change in the foreseeable future, and therefore we must lean into our collective strength as **flexible manufacturers**.

It is also clear that this style of manufacturing has been largely neglected by technology vendors as there is no scientific or technical reason preventing the development of solutions for this style of manufacturing.

The major pain points we observed exist primarily in the precompetitive operational domain, meaning that stakeholders will be able to safely collaborate on the development of this technology, sharing the risk and the cost, without compromising competitive advantage in their respective domains.

Furthermore, the lack of fit for purpose commercially available systems presents an incredible opportunity for stakeholders to not only establish themselves and this region as the global standard for high value, dynamic manufacturing, but also to drive the development of a completely new class of technology and high value industry in our region.

Consequently, it is the opinion of this white paper that stakeholders in our region including state and federal governments, industry and academia, will gain significantly greater benefit by forming consortiums around common interest problems to research, develop, and commercialise these novel systems.

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Abstract: This white paper by the Australian Centre for Robotics (ACFR) explores how Artificial Intelligence and Robotics can enhance Australia's composite manufacturing sector through flexible manufacturing — a bespoke, agile, and responsive production approach. Based on surveys and visits to 12 partner facilities of the Australian Composite Manufacturing CRC, the study benchmarks industry practices against leading robotics research to identify feasible autonomous solutions and key barriers. Highlighting opportunities beyond conventional large-scale automation, it proposes AI-driven and robotic innovations to improve efficiency and adaptability, supporting both individual partners and the broader industry in strengthening Australia's manufacturing capability.	
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