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Report on Applied Research Directions and Future Opportunities for Swarm Systems in Defence

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Executive Summary

The Australian Government's 2020 Force Structure Plan outlined a total package of capability investment of approximately $200 billion over the next decade (2020). This expenditure will equip Defence to meet challenges in the future with new investments in strike platforms, littoral assets, helicopters, information effects, logistics resilience, and emerging robotics and autonomous systems. The 2018 Army Robotics and Autonomous Systems (RAS) Strategy (Australian Army, 2018) identified swarming technologies as a force multiplier for Defence, generating mass that would enable fewer humans to achieve greater output capacity than they can today. These technologies offer novel opportunities for Defence to develop cross-domain effects, delivering persistent and scalable capabilities not previously possible.

This paper outlines the current state of swarm and counter-swarm research and technologies through a high-level review of academic, industry, and coalition partner efforts. The analysis is a systematic survey of academic literature in **Part One** and a survey of the publicly available swarm and related programs in **Part Two**. The purpose is to inform the current capability state, illuminate current efforts and challenges, and identify possible options to prioritise the generation of future swarm and counter-swarm capabilities for Defence. The advancement of technology in Australia's near region is seeing the development of disruptive engagements at an accelerated rate, with asymmetric capabilities fielded across multiple domains.[1]

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1 The Australian Defence Force *Concept for Multi-Domain Strike* defines the five domains as land, air, maritime, space, and cyber.

First, we discuss *swarming*, *swarm intelligence*, and *swarm system*. We present the term *swarming* as a tactic in that swarming may be a plan utilised by a force to achieve its desired end state. The Australian Defence Glossary (ADG) states that swarming is '[t]he large mass of autonomous systems interoperating collectively to act and respond in a coordinated effort to provide an overwhelming effect'. The ADG definition of swarming implies that the tactic may only be implemented by large masses of agents[2] (akin to a plague) to provide an overwhelming effect. However, not all systems that use the tactic of swarming may constitute a plague. For example, a flock of sheep may employ the tactic of swarming in support of a survival strategy.

Considering swarming as a tactic applied by a system, the property of a system to realise the swarming tactic is *swarm intelligence*. Swarm intelligence is the collective behaviour exhibited by agents to self-organise (Bayındır, 2016), such that rules specifying the interactions between the agents are executed based on purely local information, without reference to the global pattern, and is an emergent property of the system rather than a property imposed by an external ordering influence (Bonabeau, Theraulaz, & Dorigo, 1999).

Given the tactic of swarming and the property of swarm intelligence, the definition of a swarm system offered by Abbass and Hunjet (2020) is appropriate: *a team with actions of individuals aligned spatially and temporally using a synchronisation strategy*. Similarly, Farina, Chisci, and Fedi (2017) define a swarm system employing the tactic of swarming as *emergent behaviour arising from simple rules that are followed by individuals that does not involve any central coordination*. A deduction of the tactic of swarming, realised using the property of swarm intelligence and employed by a swarm system capability, is that swarms do not require complex engineering of autonomy inside each agent. Instead, autonomy is distributed across the swarm mass, which simplifies the single-agent design and reduces costs, enabling an effect to be generated.

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2 An agent is a computer system capable of autonomous action—of deciding for itself what behaviours are needed to satisfy its design objects, and capable of interacting with other agents. The ADG definition of an agent only considers a computer system, whereas Sahin (2005) defines an autonomous robot as a physical embodiment in the world, situated, can physically interact with the world and be autonomous. Both an agent and an autonomous robot, by the presented definition, can interact with other agents. We define agent in this work as *an autonomous component of a team or system, capable of interacting with other agents or systems. An agent may have a physical form or be a computer system capable of autonomous control of physical actuators*.

We define the tactic of swarming as *the synchronised actions of a team of autonomous agents to provide a coordinated effect*.[3] We define the property of swarm intelligence as *the ability of a team of autonomous agents to collectively self-organise*. We define swarm system capability as *a team of robust, flexible, and scalable agents who act collectively to achieve an effect*. The ADG defines *countermeasure as the reactive methods used to prevent an exploit from successfully occurring once a threat has been detected*. Through this lens, and given that a swarm system will display robustness, flexibility, and scalability (emergence), we define the term counter-swarm as *the offensive and defensive measures employed to deny a capability from achieving a swarming effect*.

Various militaries are exploring swarm-related capabilities across several lines of effort, spanning from concepts to research and physical trials. Current naval efforts focus on autonomous underwater vehicles (AUVs) research for subsurface swarm surveying and directed energy weapons for future surface-platform swarm defence. Land efforts focus on the guidance and control of multiple uninhabited ground vehicles (UGVs), while research efforts in the air domain heavily favour teamed autonomous collaborative platforms with small-scale physical tests. Swarm demonstrations have successfully integrated and operationally tested heterogeneous swarms, ranging in numbers from 20 to 250, in military settings.

3 This remains a partially incomplete definition. Traditional swarming is defined by decentralised coordination efforts; however, some modern swarming systems also incorporate elements of centralised coordination. This is reflective of the rapidly evolving state of swarm system characteristics and may require further investigation in future. As such, it is important to recognise and differentiate the delivery of a swarming effect from swarming behaviour. To deliver a swarming effect, the system requires its agents to possess not only swarming behaviour but also a shared goal and a synchronisation mechanism.

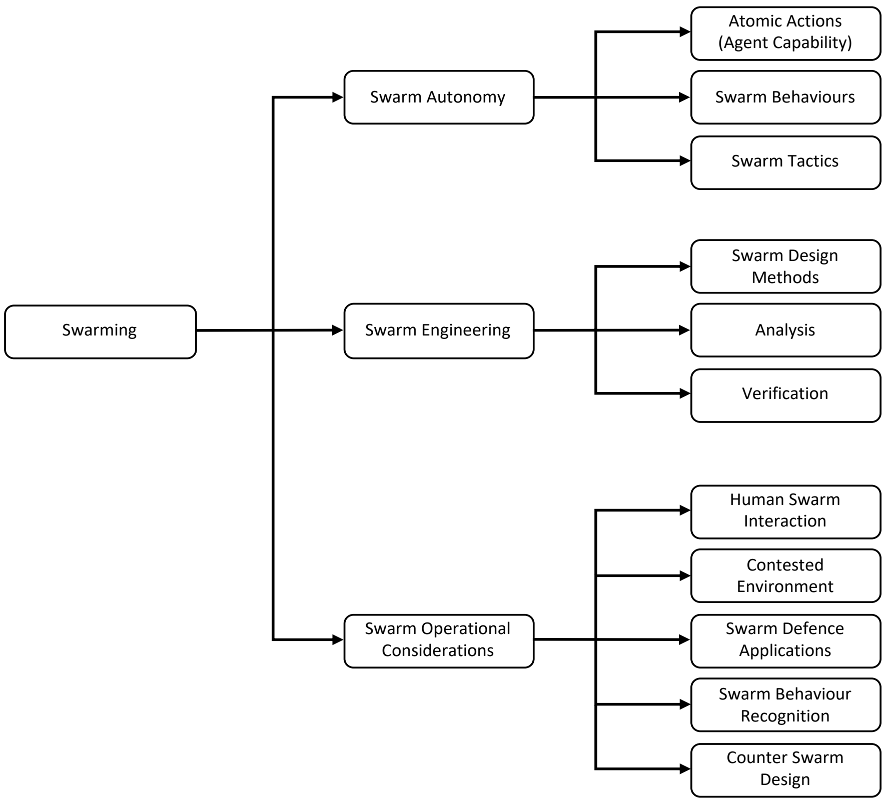
Contemporary Research State and Coalition Partner Swarm Capability Efforts

Swarm robotics is a relatively recent field of study, with Bonabeau et al. (1999) presenting the seminal work. Swarming in a robotic context can be traced to G Beni (1988) and Fukuda and Nakagawa (1988). This was closely followed by the introduction of the concept of swarm intelligence by Gerardo Beni and Wang (1993). Early work primarily explored biological swarming systems in ants, birds, and fish. This work focused on creating artificial swarm behaviours such as flocking, foraging, sorting and cooperation, and realising these behaviours within robotic systems (Cheraghi, Shahzad, & Graffi, 2022). These systems were primarily homogenous, with simple agents that operated without high levels of individual cognitive autonomy (G Beni, 1988).

Dorigo, Theraulaz, and Trianni (2021) noted that swarm research significantly accelerated post 2000, with swarm robotics being formalised by Sahin (2005). This acceleration was paralleled by increased interest within the international defence community. Potential implications of swarm control and swarm intelligence in the defence context were first examined around this time (Clough, 2002; Fleischer, 2003; Gaudiano, Shargel, Bonabeau, & Clough, 2003), with specific investigations ranging from swarm use in navigation and mapping (Gage, 2000) to perimeter formation (Bruemmer, Dudenhoeffer, McKay, & Anderson, 2002) and general uninhabited aerial vehicle (UAV) swarm command and control (C2) methods (Milam, 2004).

Since the foundational work of the mid-2000s, defence requirements have necessitated the investigation of more complex agents to expand the potential operational applicability of swarm systems. As highlighted by the Defense Advanced Research Projects Agency (DARPA) OFFensive Swarm-Enabled Tactics (OFFSET) program, swarming research is now trending towards heterogeneous and flexible swarms of competent (complex) agents that are designed for use within an operational context and that can be intuitively controlled by operators (T. H. Chung, 2021). For the defence context, swarm capability literature can be broadly separated into three primary research fields: swarm autonomy, swarm engineering and swarm operational considerations, with further sub-fields presented in **Figure 1**.

Figure 1: Contemporary areas of swarm research



Within the context of a swarm capability, one dimension of swarm autonomy encompasses the collection of theoretical distributed swarm properties and tactics realised within a swarming system. This is the 'toolbox' of potential behaviours and tactics that a swarm can implement to achieve mission outcomes. The swarm engineering process, being a collection of systematic methods to design, analyse and verify behaviour within a swarm system, can then be used to convert swarm autonomy methods and capability intent into a swarm capability (Brambilla, Ferrante, Birattari, & Dorigo, 2013). Here, swarm engineering aims to achieve 'the design of predictable, controllable swarms with well-defined global goals and provable minimal conditions' (Kazadi, 2000) and is an inherently iterative process.

Further swarm system demonstrations have occurred across many defence applications, with substantial bodies of research undertaken for physical UAV swarms that highlight the technological feasibility (T. H. Chung, 2021; Escamilla, 2020; Williams, 2018). Other swarm demonstrations have facilitated agile network connectivity in contested environments (P. Smith, Hunjet, Aleti, & Barca, 2017) and explored intelligence, surveillance and reconnaissance (ISR) opportunities in the maritime domain for sea state estimation (Nathan K Long, Sgarioto, Garratt, Sammut, & Abbass, 2019), target identification (Gulosh, 2018), and chemical, biological, radiological and nuclear (CBRN) environment mapping (Kopeikin et al., 2020). In non-physical settings, Holloway (2009) demonstrated a swarm-based solution to detect and respond to threats in several cyber network scenarios, including detecting, engaging, assessing and responding to target intrusions and anomalies.

Experimental campaigns have continued to grow in complexity and scale, such as demonstrating a 50-UAV swarm in the United States Naval Postgraduate School (NPS) Advanced Robotic Systems Engineering Laboratory (ARSENL) program flight trial (T. H. Chung et al., 2016; Escamilla, 2020). These campaigns have highlighted the necessity for an experimental swarming capability to identify and address critical limitations in specific individual platform technologies. The operationalisation and scaling of such technologies are imperative to realise practical physical swarming systems within a defence context, particularly for the concepts of interacting and teaming with a swarm.

Sovereign Summary of Options to Address and Accelerate Defence's Swarm Capability

We have developed a range of options to address barriers to adopting swarm capabilities in Defence, such as challenges within industry and academia and other impediments that prevent the accelerated adoption of technology from meeting Defence objectives. The portfolio of options presented here is intended to address the barriers to the achievement of swarm capabilities by Defence. These impediments include challenges in the areas of skilled workforce, investment continuity, sovereign manufacturing capability, resource prioritisation, and high barriers to entry. The options are summarised as follows:

a. Consider **antifragile swarming** (countering counter-swarming) technologies to understand possible mechanisms and technologies that an adversary may apply against a future Defence capability.
b. Conduct **experimentation to develop the processes, procedures, and policies for swarm doctrines** to develop the operational concepts and procedures and the use-case scenario concepts and demand signal for how Defence seeks to employ swarm systems in the future operating environment.
c. **Prioritise swarm mission-based investment** by developing capability and operations-based challenges, framed within desired end-state use-case scenarios as challenges to solve.
d. **Co-invest** in enabling elements such as experimentation platforms, ICT hardware, modelling, and simulation (M&S), experimentation and support infrastructure, and field-testing areas to reduce barriers to entry.
e. **Develop investment targets** for swarm research and concept development to sustain sovereign contemporary research and development efforts.
f. Develop the **Defence applied workforce** to prepare for situations of human teaming with future swarm systems, in the roles of both technical development (science and engineering) and force generation.
g. Support the **Defence academic and industry technical workforce** to address contemporary capacity challenges for sovereign design, manufacturing, integration and maintenance of swarm and related systems.
h. **Build partnerships** with non-traditional Defence industries to develop dual-use technologies.
i. **Enhance international collaboration** with coalition and partner nation efforts.

Based on a review of the current state of swarm and counter-swarm research and technology development, the next part of this paper introduces and defines the key lexicon used to describe swarm system capabilities. The analysis identifies considerations and challenges for Defence to progress sovereign swarm technologies. The paper concludes by identifying future options for Defence to accelerate technology realisation, highlighting priority enabling technology and investment areas.

Part One—Introducing Swarm Systems

This part introduces the critical literature and underpinning definitions of swarm and counter-swarm research and technologies. The review is separated into three major conceptual areas aligned with the swarming capability development taxonomy presented in **Figure 1**. These are Swarm Design, Swarm Production, and Swarm Operationalisation. This analysis also shows the interconnectedness of swarm and counter-swarm capability development.

The term *swarm autonomy* encompasses the collection of theoretical and distributed swarm behaviours and tactics that can be realised within a swarming system within the context of swarm capability development. This is a toolbox of potential behaviours and tactics that a swarm can implement to achieve mission outcomes. Swarm autonomy, combined with overall capability intent, provides the primary input to the swarm engineering process, a collection of systematic methods to design, analyse and verify behaviour within swarm systems.

Within the Defence context, swarm operational considerations include operational factors that influence the organisation's capacity to realise practical swarming systems. These considerations include human-swarm interaction (HSI) mechanisms, operation within contested environments, refinement of specific defence applications, and counter-swarming activities to identify and nullify adversarial swarms. These considerations actively influence swarm and counter-swarm design processes and represent a high-level feedback mechanism.

Swarm Autonomy

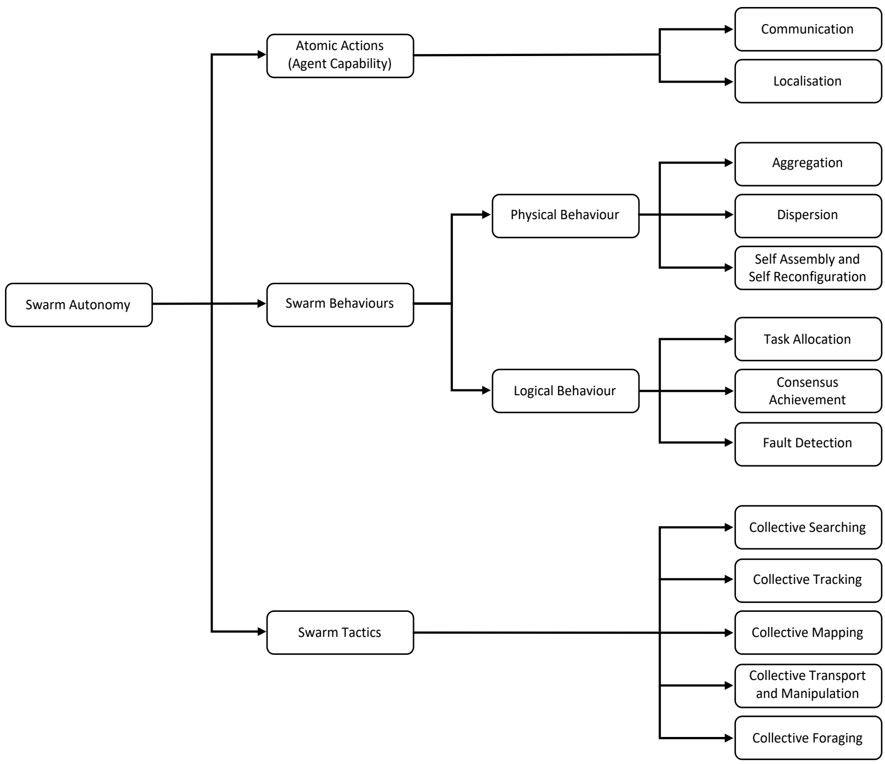
A substantial portion of contemporary swarming research focuses on developing distributed algorithms to achieve common tasks through emergent behaviour, where a swarm collectively exhibits behaviour not otherwise achievable by any specific agent (Bayındır, 2016; Brambilla et al., 2013; Cheraghi et al., 2022; Majid, Arshad, & Mokhtar, 2022; Schranz, Umlauft, Sende, & Elmenreich, 2020). Extending the taxonomy given by Majid et al. (2022), general swarming behaviours can be classified within the hierarchy presented in **Table 1**, with further elaboration in **Figure 2**. At an atomic level, individual agents must possess capabilities to interact with swarm members and the environment, most notably communication and localisation (sensing) methods. Swarm behaviour algorithms can then coordinate agent-to-agent interactions with the necessary atomic actions within the swarm itself. This coordination includes behaviours of a physical (aggregation, dispersion, pattern formation) and logical (task allocation, consensus achievement and fault detection) nature. Once a swarm can coordinate itself, swarm tactics are used to coordinate the swarm within the environment to achieve tasks such as collective targeting[4] search, mapping, and effects delivery. T. H. Chung (2021) shows that these tactics can then be used to meet overall mission requirements.

Table 1: Swarm Autonomy Taxonomy

Class	Level	Example
Actions	Operating as an individual	Communication, localisation
Behaviours (Low Level)	Operating within the swarm	Aggregation, dispersion, self-assembly, pattern formation and flocking
Tactics (High Level)	Operating within the environment	Searching, mapping, foraging, transport

4 A target is an entity or object which may be subject to an effect.

Figure 2: Primary areas within swarm autonomy



Atomic Actions (Agent)

Communication

Effective communication is imperative to all swarming behaviours (Schranz et al., 2020). Hunjet et al. (2018) posit that communication is separated into three general categories: passive action recognition, such as the waggle-dance (Barnali Das, Couceiro, & Vargas, 2016) approach that conveys information through motion; indirect communication methods; and direct communication methods. Early swarm studies relied heavily on using stigmergy, which is a termite-inspired indirect communication method in which communication is achieved through the environment—for example, where ants use pheromones to direct other ants to food (Beckers, Holland, & Deneubourg, 1994; Grassé, 1959; Shen, 2002; White, 2005). However, stigmergic communication can often be slow, inflexible and sensitive to dynamic environments (Trianni, Labella, & Dorigo, 2004). Direct communication can help alleviate these issues and is now employed within swarm systems. Systems using direct communication agents to exchange information through the swarm typically form a Mobile Ad Hoc Network (MANET), representing an arbitrary communication network known for its flexibility (Phillips, 2008; Wen, He, & Zhu, 2018). To date, direct communication has been achieved through various EM emissions, such as radio, infrared and optical, in addition to sound (Bruemmer et al., 2002; Dorigo et al., 2006; Wen et al., 2018). However, using a UAV swarm, Hunjet et al. (2018) demonstrated that indirect stigmergic communication may be more suitable in contested or denied environments where direct communication becomes sensitive to interference, suggesting that multiple communication methods may be necessary in practice. Communication is also directly relevant to cyber systems, achieved by transferring information packets between agents on a network to convey intent.

Recent developments have seen deep learning methods used to improve communications accuracy, reduce required bandwidths, and improve network security (Alsamhi, Ma, & Ansari, 2019, 2020). A particular example is the development of information encoding and intelligent routing algorithms to reduce transmission delay and resource requirements (Alsamhi et al., 2020).

Localisation

Agents must localise within the environment (absolute localisation) and swarm (relative localisation) to avoid collisions and coordinate motion. For absolute localisation, the agent's position within the environment is critical for swarm tactics and optimising interaction with the external environment. Standard technologies such as Global Positioning System (GPS), Inertial Measurement Units (IMUs) and speed sensors are widely used to achieve position measurements where possible (Coppola, McGuire, De Wagter, & de Croon, 2020). However, for accurate contextual environment localisation and perception (interpretation of the environment), computer vision and light detection and ranging (LiDAR)[5] technologies are now considered superior (Coppola et al., 2020; Shi, He, Zhang, & Zhang, 2016). Using one or multiple cameras, agents can use Visual Inertial Odometry (VIO) to track their position within an environment. Simultaneous Localisation and Mapping (SLAM) expands on this technique to actively generate an environmental map,

5 LiDAR is a remote sensing capability which uses light as the medium for range measurements.

which can be used for later activities such as path finding (Cadena et al., 2016; Shi et al., 2016). This approach is slightly different from that taken within a cyber network, where absolute localisation is achieved by directly monitoring IP addresses and ports.

For relative localisation, the position of one swarm agent compared to another is critical for swarming behaviours such as pattern formation, flocking and collective transport. Achieving relative localisation is often the limiting factor for the overall achievement of swarming capabilities (Coppola et al., 2020; Dorigo et al., 2021). In addition to computer vision techniques, alternative sensing solutions have been used to achieve accurate localisation results. These include infrared, sonic and radio-based sensing (Brambilla et al., 2013; Coppola et al., 2020; Majid et al., 2022). Communication-based ranging has also been successful, utilising signal strength to position neighbouring agents (Soria, Schiano, & Floreano, 2022).

Swarm Behaviours (Intra-Swarm)

Swarm behaviours coordinate inter-agent motion and allow the swarm to function as a collective. This intra-swarm behaviour can be broadly separated into physical (coordinated physical movement) and logical (coordinated decision-making) behaviours.

Physical Behaviour—Aggregation

The process of swarm system agents gathering within the spatial domain is known as aggregation. This behaviour is often necessary to prepare the swarm for future behaviours and interactions such as self-assembly, self-reconfiguration and task allocation (Majid et al., 2022; Schranz et al., 2020). Aggregation can occur at a specific location within the environment (cued) or independent of the environment (uncued) (Camazine et al., 2001). Research has also been conducted on ‘discrete domain’ aggregation, which provides utility in more abstract domains (such as gathering at network nodes in cyber applications or within discrete physical settings such as different buildings) (Mondal & Chaudhuri, 2020; Sadhu, Sardar, Das, & Mukhopadhyaya, 2019).

Physical Behaviour—Dispersion

Dispersion is simply spreading and maintaining a minimum distance (Navarro & Matía, 2013). This can occur in known or unknown environments and in bounded or unbounded contexts, and is generally limited by overall communication constraints (Majid et al., 2022). Dispersion is a primary behavioural requirement within searching tasks to optimise the overall coverage area. A popular swarm application that heavily relies on dispersion is the sensor network application, with a dispersed array of sensors within an environment (Derakhshan & Yousefi, 2019; Jahagirdar, Bobade, Dhuri, & Mangala, 2020; Reina & Trianni, 2013). Dispersion can also facilitate information transfer. For example, P. Smith et al. (2017) present an exemplar UAV communication network that relies on dispersion to transmit data between two non-swarm devices in a contested environment.

Physical Behaviour—Self-Assembly and Self-Reconfiguration

Self-assembly is the physical connection between many agents to form a more prominent unified agent. In contrast, self-reconfiguration is the modification of the collective agent to adapt to a new task or environment (Majid et al., 2022). The utility of self-reconfiguration behaviour is exemplified by the Swarmbot project, a swarm of small UGVs (Dorigo, 2005; Dorigo et al., 2005; Dorigo et al., 2006). Individual swarmbot agents, known as s-bots, could physically couple and cross terrain gaps significantly larger than those that could be crossed by an individual agent (Dorigo et al., 2006). A similar self-assembly mechanism was demonstrated by PuzzleBots (Yi, Temel, & Sycara, 2021). An extension to the concept of self-assembly and reconfiguration is morphogenetic robotics (Jin & Meng, 2011). Morphogenetic robotic systems are designed to be physically constructed from smaller agents to function like the congregation of individual cells to form a multi-cellular organism, where each 'cell agent' may possess heterogeneous abilities, specific actuation or sensing capabilities (Brambilla et al., 2013; Jin & Meng, 2011). Cross-ball (Y. Meng, Zhang, Sampath, Jin, & Sendhoff, 2011) and cross-cube (Yan Meng, Zhang, & Jin, 2011) are early examples of morphogenic robotics in which a single agent was intelligently constructed from several small 'spheres' and 'cubes' respectively to create dynamically shaped robots that interacted with the environment.

Physical Behaviour—Pattern Formation and Flocking

Coordinated motion throughout space requires pattern formation and flocking. Pattern formation is forming and maintaining a pattern within space without physical contact (Majid et al., 2022). Key examples are the chain formation (Nouyan & Dorigo, 2006) and the leader-follower functionality (Liang, Dong, & Zhao, 2020). Flocking, designed to achieve coordinated swarm motion, also aims to maintain physical agent displacement. However, as it is not limited to specific physical patterns, it does so in a more flexible manner (El-Fiqi et al., 2020). Reynolds (1987) was the first scientist to posit artificial flocking using 'boid' agents, named after the biological inspiration of bird flocks. Since then, there has been significant research into flocking across the domains, including autonomous underwater (Hadi, Khosravi, & Sarhadi, 2021), aerial (Do et al., 2021) and ground vehicles (Soni & Hu, 2018). A significant recent development is the move towards a more general 'shoid' (sheep) flocking model that allows for flock control through an external agent known as a shepherd (Hepworth, Yaxley, Baxter, Joiner, & Abbass, 2020; Strömbom et al., 2014). Other advancements include using machine learning to improve UAV flocking (Azoulay, Haddad, & Reches, 2021) and extending the flocking approach to heterogeneous swarms with internal 'leaders' that can disproportionately influence the swarm motion control (Hepworth et al., 2020).

Logical Behaviour—Task Allocation

Logical swarm behaviour is the concept that describes the collective decisions made within a swarm. Task allocation is the process of regulating group size and allocating tasks to sub-groups and agents (Hoff, Wood, & Nagpal, 2013; Majid et al., 2022). It is a foundation of collective mapping tactics (Almadhoun, Taha, Seneviratne, & Zweiri, 2019). Task allocation is generally a dynamic process that aims to optimise swarm performance over some metric, such as total distance travelled by a swarm or (less commonly) minimising work imbalance between agents (Elango, Kanagaraj, & Ponnambalam, 2013). Heterogenous swarms necessitate greater algorithm complexity due to the existence of additional agent constraints (such as agent capability) (Rizk, Awad, & Tunstel, 2019). Examples of task allocation include the work of Campbell (2019), who developed an auction-based algorithm to allocate tasks to a heterogenous ariel swarm for a military search problem; and Day (2012), who used multi-agent negotiation to defend against an adversarial UAV swarm.

Logical Behaviour—Consensus Achievement

Due to the lack of a centralised control source, a swarm system must converge to agree on a common choice through a process of distributed consensus achievement (Schranz et al., 2020). The available choices can be either continuous, such as a direction to move in; or discrete, such as a location to aggregate or a specific path to take through an environment (Valentini, 2017; Valentini, Ferrante, & Dorigo, 2017). In general, options are evaluated using a mathematical cost function; however, this is often only possible if local information is available to individual agents. Hence, the consensus achievement problem is often approached using stochastic processes.[6]

Logical Behaviour—Fault Detection

Fault detection (FD) is a behaviour that helps to ensure swarm robustness. It aims to identify any deficiencies in individual agents and any deviation from desired swarm behaviour (Schranz et al., 2020). Faults can be topological, such as inconsistent networks or lost communication links; or component-based, such as a malfunctioning sensor or actuator (Qin, He, & Zhou, 2014). While most non-swarm robots rely on endogenous fault detection (detecting and diagnosing their own faults), swarming systems have generally used exogenous methods whereby swarm system agents monitor each other (Graham Miller & Gandhi, 2021). In general, FD can be centralised, where a single agent collects and monitors all information; hierarchal, where separate 'layers' monitor subordinate layers; or decentralised (Qin et al., 2014). Decentralised methods have improved scalability and robustness and are the primary source of current research (Khalastchi & Kalech, 2019; Qin et al., 2014). An example of decentralised FD is presented by Christensen, O'Grady, and Dorigo (2009), which is an early firefly fault detection example where agents use synchronised light pulses to ensure all other agents are functioning correctly. Over the last decade, proposed FD methods have increased in complexity, using behaviour feature vectors and immune-system, data-modelling, and blockchain-based methods. However, to date, the efficacy of such approaches has only been demonstrated in simulation settings (Graham Miller & Gandhi, 2021; Khalastchi & Kalech, 2019).

6 Published methods include techniques which are often decentralised and partially observable, such as particular instantiations of Markov decision process (Valentini, 2017).

Swarm Tactics (Extra-Swarm)

Swarm tactics are used to achieve swarm interaction with an environment. They are often performed during the conduct of multiple swarm behaviours and are often considered the primary 'effect delivery method' of a swarm system capability (T. H. Chung, 2021). Achieving robust and intelligent swarming is of utmost importance within an operational setting. The taxonomy presents five critical tactics: collective searching, tracking, mapping, foraging, and transport. We discuss each set of tactics in more detail below. Recent work by Hepworth, Baxter, and Abbass (2022) highlights that a unified conceptual space is required for meaningful teaming between biological and artificial agents. The ontology represents a shared conceptual space enabling the development of interdependent understanding between agents of non-homogeneous physical and cognitive abilities. Based on the concept of shepherding, the ontology presents a spectrum of collective and individual actions and tactics, demonstrated by expanding the aperture of species and their experiences. The expansion of tactics goes beyond classic task orientation to consider the composite sequences and higher order conceptual space (Hepworth et al., 2022).

Collective Searching

Collective searching uses a cooperative swarm to explore a given environment to identify and converge on the location of a target or source. A target can be considered a discrete object(s) classified by label, such as a 'car'; or an attribute, such as being the colour 'blue' or possessing a 'round' shape. A source can be viewed as a target that emits its cues, i.e. sound, light, radio transmitted (Majid et al., 2022).

A range of problems can arise in collective searching. Key variables include the number of targets (i.e. one versus many of either known or unknown quantity), the mobility of targets and searchers, the complexity of the environment and the presence of detectable target cues (Senanayake et al., 2016). Many searching algorithms exist within the relevant literature, including random, heuristic and systematic search methods (Majid et al., 2022; Senanayake et al., 2016), with Ismail and Hamami (2021) identifying particle swarm optimisation (PSO) as the most well-used algorithm basis. In an experimental comparison using 14 e-puck robots (Mondada et al., 2009), a search algorithm using subswarms to increase search space and reduce communication requirements was found to have the highest overall performance in exploration coverage and efficiency (Couceiro, Vargas, Rocha, & Ferreira, 2014).[7] An alternative search method, the Probability of Occupancy Map (POM) target estimation approach, was posited by Risti and Skvortsov (2020). They successfully demonstrated a simulated underwater target search task with no emitted information.

Collective Tracking

Collective tracking often follows a target and source detection updates and maintains location information of a given target that is generally moving (Majid et al., 2022). Collective tracking can include surveillance, observation, and evasion-pursuit tasks where the swarm must follow the target while avoiding obstacles, maintaining pattern formation and ensuring correct separation distance for accurate detection characteristics (Robin & Lacroix, 2016). Tracking can be separated into two major tasks: tracker to target allocation, which ensures collective coverage of targets; and sensor data fusion, which increases the overall tracking accuracy (Soylu, 2012). Tracker to target allocation is significant, with multiple independently moving targets present, including instances where targets outnumber trackers. Some approaches to collective tracking aim to cluster targets to reduce the computational burden (Armaghani, Gondal, Kamruzzaman, & Green, 2012). Other solutions distribute the swarm over the targets to ensure complete target tracking (Senanayake et al., 2016). This is exemplified by Parker (2002), the first to formalise and address the challenges posed by multiple targets using the concept of Cooperative Multi-robot Observation for Multiple Moving Targets (CMOMMT). Specifically, Parker (2002) developed a distributed algorithm for 2D multi-target tracking, known as A-CMOMMT, by maximising the collective observation time across all targets. A-CMOMMT was found to be effective, even when targets outnumbered trackers. Once trackers are distributed, sensor fusion methods such as the Distributed Kalman Filter (Wang & Gu, 2012) provide the means to merge swarm information to increase tracking accuracy. Soylu (2012) presents an entire pipeline incorporating tracker distribution and sensor fusion solutions in a swarm versus swarm tracking scenario.

7 The algorithm implemented was robotic Darwinian PSO (DPSO), inspired by Darwin's natural selection principles.

Collective Mapping

Collective mapping uses a swarm system to generate a globally consistent model of the surrounding environment using distributed sensing information (Majid et al., 2022; Vorobyev, Vardy, & Banzhaf, 2012). The representation of the model can be 2D or 3D and is often used to facilitate subsequent path planning and environmental interaction activities (Majid et al., 2022). The generated model can be constructed from different levels of information and can be considered sparse, semi-dense or dense (Wang & Gu, 2012). Sparse methods generally only provide relative positional information generated through the extraction and comparison of points and lines between images from different swarm members (Forster, Lynen, Kneip, & Scaramuzza, 2013). Dense methods typically aim to produce detailed point clouds using sensors such as depth measuring cameras and LiDAR (3D laser scanner), and SLAM methods. Each agent captures a point cloud, with all clouds merged (typically offline) using expectation maximisation (Wang & Gu, 2012).

Contemporary methods are moving to map representations that are more information efficient. For example, Yu, Vincent, and Schwager (2021) demonstrated DiNNO. This distributed neural network optimisation framework can achieve online, implicit collective mapping in a 2D environment, negating the requirement of point cloud representations. Mapping is also not limited to spatial data. Kopeikin et al. (2020) and Savidge, Kopeikin, Arnold, and Larkin (2019) physically demonstrated a swarm system of 11 UAVs collectively surveying and mapping radioactivity levels within a CBRN environment. Swarm system agents distributed the overall workload and ensured full environment coverage to generate a combined heat map of radioactivity.

Collective Transport and Manipulation

Swarm behaviours have also been developed to transport and manipulate objects larger than individual agents. Known as collective transport and manipulation, swarm system agents collaborate to move and manipulate objects within the environment. As presented by McCreery and Breed (2014), biological collective transport is conceptualised as occurring in four phases: the decision (deciding on the object), recruitment (recruiting surrounding agents), organisation (moving around the object) and transport (moving the object) phase. Three common approaches are used to transport objects with a swarm system: pushing, pulling, and caging (Torabi, 2015). Caging can be considered a special case of the pushing strategy where agents surround and ‘push’ from all sides (Parker, 2002; Wang & Gu, 2012).

Parker (2002) uses four 's-bots'[8] to transport a heavy circle cooperatively, requiring agents to negotiate overall movement direction. Wang and Gu (2012) use up to eight agent swarms to cage and transport a circular object around obstacles within a lab environment. Classical approaches use probabilistic finite state machines, such as that used by Torabi (2015), pushing a circular mass. By comparison, Groß and Dorigo (2009) created an artificial neural network (through evolutionary methods) to achieve an adaptable collective transport in 16 s-bots to move objects varying in size and geometry.

Collective Foraging

Collective foraging is the search and transport of distributed items within an environment back to a central location, or 'nest'. Due to its composite nature (composed of search, transport, and consensus achievement), it is often used as a benchmark activity to compare other swarm behaviours and tasks (Bayındır, 2016; Majid et al., 2022). Modern foraging algorithms have started to explore more complicated settings, such as searching for heterogeneous objects with different values, known as multi-forging, and considering total energy expenditure when searching (Bayındır, 2016). Pradhan, Boavida, and Fontanelli (2020) identified and compared four different widespread foraging behaviours, including solitary foraging (no interaction), behavioural matching (agents can mimic other successful agents), stigmergic foraging (agents using pheromones to interact) and signalling (explicit communication between agents). In this comparison, Pradhan et al. (2020) showed that explicit communication in signalling foraging was most beneficial in smaller swarms; however, this benefit was lost in larger swarms, where solitary foraging became the highest performing behaviour. Johnson and Brown (2015) presented a 'computation' free foraging approach where control was achieved in simple agents. Talamali et al. (2020) demonstrated stigmergic foraging using over 200 agents; however, larger swarms required strategies to mitigate crowded paths to be fully effective. The NASA Swarmathon (Ackerman et al., 2018; Lu, Fricke, Ericksen, & Moses, 2020) was possibly the most developed physical foraging demonstration to date. Using 100 'Swarmie' UGVs, teams competed to develop algorithms to collect small cubes in a parking lot to replicate the requirements of planetary exploration (Ackerman et al., 2018; Isaacs et al., 2020). Lu et al. (2020) presented further information on foraging theory and demonstrations.

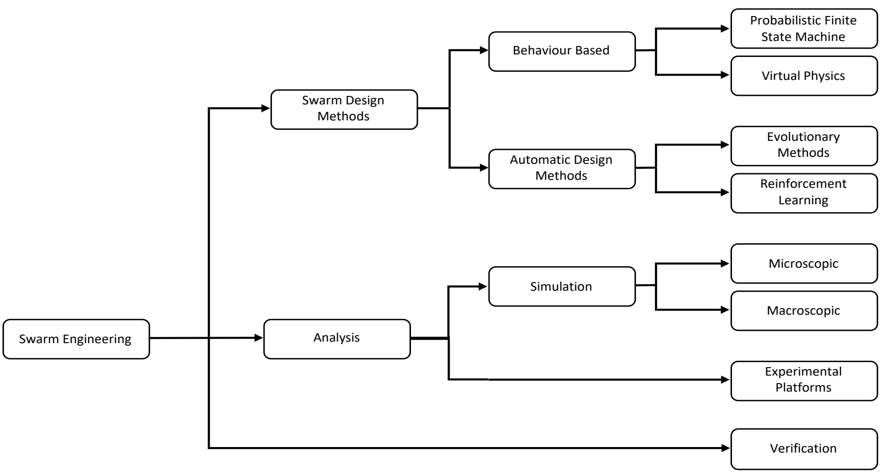
8 For a detailed overview of the s-bot program at the Laboratory of Intelligent Systems (LIS), École polytechnique fédérale de Lausanne, please see http://www.swarm-bots.org.

Swarm Engineering

Swarm engineering aims to provide a systematic means of operationalising swarm systems and behaviours. First posed by Kazadi (2000) and formally defined in the seminal paper by Winfield, Harper, and Nembrini (2005), swarm engineering aims to achieve 'the design of predictable, controllable swarms with well-defined global goals and provable minimal conditions' (Kazadi, 2000). Swarm engineering can often be challenging due to the, at times, non-intuitive translation of atomic to emergent behaviour, making overall design and verification inherently difficult (Winfield et al., 2005). As Brambilla et al. (2013) discussed, swarm engineering remains in development, with many distinct fields of research receiving various levels of attention.

Figure 3 depicts the scope of this paper and focuses on the fundamental concepts of design, analysis, and verification of swarm engineering. More comprehensive reviews can be found in Brambilla et al. (2013) and Winfield et al. (2005).

Figure 3: Key concepts in swarm engineering



Design Methods

Swarm behaviour design defines atomic agent behaviours and algorithms to realise emergent behaviour within a swarm. Swarm behaviour can be broadly separated into behaviour-based and automatic design approaches.

Behaviour-Based Design Methods—Probabilistic Finite State Machines

Behaviour-based design methods achieve emergent behaviour by applying expert knowledge (a human designer) to explicitly define atomic agent behaviours in a generally iterative process (Brambilla et al., 2013; Cheraghi et al., 2022). Probabilistic Finite State Machines (PFSM) are one primary behaviour-based design approach. First proposed by Minsky (1967), PFSMs represent agent behaviour through a collection of 'states' containing specific algorithmic behaviour. Agents stochastically transition between states, with transition probability either fixed or conditional on external factors, encouraging exploration within a behavioural state space and, by extension, in the environment (Brambilla et al., 2013; Cheraghi et al., 2022). PFSMs have been used to create swarming behaviours such as aggregation, collective transport, and foraging (Gioioso, Franchi, Salvietti, Scheggi, & Prattichizzo, 2014; Majid et al., 2022). For example, Garnier et al. (2005) show that aggregation can be achieved in cockroach-inspired swarms with just two states, a 'stay in cluster' state and a 'leave cluster' state. Transition probability from 'stay in cluster' to 'leave cluster' is inversely proportionate to the cluster size, meaning that agents tend towards larger clusters, eventually creating a single large aggregation (Garnier et al., 2005).

Behaviour-Based Design Methods—Virtual Physics

Virtual physics is a widely used alternative method for behaviour-based design. In this approach, each agent is treated as a 'particle' under the influence of force vectors from other agents and the environment (like a magnet surrounded by magnets) as defined by an expert-designed rule. The resultant total force vector acting on the agent dictates future movement (Spears, Spears, Hamann, & Heil, 2004). Agents only require a single (designed) rule to translate neighbouring agents' direction, heading, and distance into a future motion vector, simplifying agent design (Brambilla et al., 2013). Virtual physics methods have been used in many swarm behaviours, including aggregation and collective movement (Brambilla et al., 2013). The boids model presented by Reynolds (1987) is a notable example of a virtual physics model used to demonstrate swarm flocking behaviour. Like PFSMs, virtual physics methods can require 'tuning' to achieve suitable performance and are considered a bottom-up design approach.

Automatic Design Methods—Evolutionary Robotics

Automatic design methods seek to automate and optimise elements of behaviour-based design methods while facilitating the development of more complex behaviours. Prominent approaches include evolutionary optimisation methods and reinforcement learning. Evolutionary methods take inspiration from Darwinian evolution. Specifically, a population of 'chromones' is first initiated, with a chromosome encoded representation of the agent control law, such as a PFSM or virtual force law (Doncieux, Bredeche, Mouret, & Eiben, 2015; Francesca & Birattari, 2016). Chromosome fitness is then evaluated using a user-defined metric. High-fitness chromosomes subsequently pass-through genetic operators such as recombination, mutation, and selection to mimic the biological evolution (Doncieux et al., 2015; Mukhlish, Page, & Bain, 2018). Due to the large task iteration requirements, this process is often completed offline using simulation. Recent developments in evolutionary design methods include the introduction of a diversity promotion mechanism to alleviate premature convergence partially and stagnation (Lehman, Risi, D'Ambrosio, & O Stanley, 2013), multi-objective optimisation to improve sub-task performance (Francesca & Birattari, 2016) and the incorporation of a learning mechanism through an 'epigenetic' layer in the evolutionary process to improve optimisation performance and robustness in dynamic environments (Mukhlish et al., 2018).

Automatic Design Methods—Reinforcement Learning

Automatic swarm behaviour design has also been achieved using reinforcement learning (RL) methods. In RL, trial and error optimise an agent's policy (the agent controller) based on rewards from and interaction with the environment (Sutton & Barto, 2018). Policies are often implemented using artificial neural networks. They are trained using a combination of actor-critic, Q-learning, and policy gradient descent methods (T. Nguyen, Nguyen, & Nahavandi, 2020), learning from human instruction (apprenticeship learning) (Gee & Abbass, 2019; H. T. Nguyen, Garratt, Bui, & Abbass, 2019), and a combination of RL and evolutionary algorithms (Li & Tan, 2019). Given sufficient training, RL has produced highly capable policies in strategic settings, as displayed in AlphaGo Zero's success against a world champion Go player (Silver et al., 2017). For example, Hüttenrauch, Šošić, and Neumann (2017) successfully demonstrated RL in a swarm application, training a swarm of eight homogenous agents using a deep 'guided' RL approach. The guided

RL approach posed by Hüttenrauch et al. (2017) can be generalised to the Multi-Agent RL (MARL) paradigm, where agents can actively account for the learning and dynamic policies of other agents during training to improve overall policy performance (Foerster et al., 2018; Kim et al., 2021). MARL can also be used for cooperative, competitive and mixed settings, increasing overall flexibility, such as swarm versus swarm engagements where cooperation and competition are necessary for success (T. Nguyen et al., 2020). In general, MARL is considered a difficult paradigm to apply effectively due to inherent partial observability, environment non-stationarity and the credit-assignment problem (Gronauer & Diepold, 2021; T. Nguyen et al., 2020). In addition, like evolutionary methods, MARL typically requires significant computational resources. It cannot guarantee the production of adequate solutions; however, it nonetheless represents substantial potential in understanding and designing the interaction between multiple intelligent agents.[9]

Analysis

Simulation

Computational simulation is the most common method of developing and testing swarm systems and behaviours. It can be separated into microscopic and macroscopic approaches (Brambilla et al., 2013). Microscopic approaches generally use agent-based simulation and model individual agent-agent and agent-environment interactions. Microscopic methods allow the swarm designer to simulate individual agent controllers while incorporating probabilistic agent mechanics and environmental effects such as disturbances and noise for a more representative simulation (Brambilla et al., 2013; Cheraghi et al., 2022). However, as agent-based simulations are numerical and generally stochastic, analysis can require many simulations before statistically significant trends become evident (Ling, 2020).

Many 2D and 3D swarm agent-based simulation platforms have been developed, focusing on scalability and fidelity. ARGoS (Pinciroli et al., 2012) is a widely used software offering subsystem-level model integration, preinstalled models of popular experimental platforms (such as e-puck and kilobot), and a modular design allowing for the simultaneous simulation of up to 10,000 agents (Dorigo et al., 2021). ROS-Gazebo (Isaacs et al.,

9 Please see Gronauer and Diepold (2021) for a more comprehensive review of MARL.

2020) and SRIMMAGE (DeMarco, Squires, Day, & Pippin, 2019) offer other open-source solutions. Munoz (2011), Schuety and Will (2018), and Padgett (2017) all develop custom different UAV asset defence simulations to train, test and analyse swarm behaviours rapidly. Solutions such as those presented by Porter (2019) offer high-fidelity aircraft modelling simulations to explore swarm behaviour. A more extensive list of simulation software can be found in (Cheraghi et al., 2022).

Macroscopic simulation focuses on directly simulating whole-of-swarm dynamics. This simulation method can model spatial swarm system dynamics using stochastic differential models and the Fokker-Plank equation, and swarm behaviour state dynamics using rate and differential equations (Dorigo et al., 2021; Elamvazhuthi & Berman, 2019). In principle, these methods can model any swarm collective behaviour, provide a systematic way of transforming microscopic to macroscopic behaviour, and verify swarm behaviours through stability and robustness analysis (Dorigo et al., 2021). However, using these methods can be difficult in practice due to analytical constraints, excessive computational demand, and difficulty in modelling inter-agent communication (Brambilla et al., 2013; Dorigo et al., 2005).

Experimental Platforms

When developing and validating swarm systems, experimental platforms are employed to provide real-world validation. Disparate swarm platforms have been designed to operate across the land, maritime and air domains. Kilobot, one example of a widely used ground-based platform (Dorigo et al., 2021), is known for its cost-effectiveness and simplicity. Kilobot swarms of up to 1,024 agents have been demonstrated (Wyss Institute, 2017). More complex behaviours have been shown with the e-puck, one of the most widely used swarm research platforms (Mondada et al., 2009). As a generic platform, e-puck allows for more complex proofs of concept. However, swarms of more than 30 agents have proved challenging. Outside of individual laboratories, Swarmie, the NASA Swarmathon robot, has been used to test foraging behaviours for planetary exploration (Ackerman et al., 2018). Maritime swarms have also been experimentally demonstrated, as seen in the CoCoRo project, presenting a swarm of up to 40 heterogenous uninhabited underwater vessels (UUVs) (European Commission, 2015; Schmickl et al., 2011), and the CORATAM project, a homogenous uninhabited surface vessel (USV) swarm (Christensen et al., 2015). These projects explored environmental monitoring swarm solutions.

Substantial work has been completed with aerial swarm platforms such as CrazyFlie 2.0, a non-quadrotor UAV used to achieve indoor aerial swarms of up to 49 agents (Giernacki, Skwierczyński, Witwicki, Wroński, & Kozierski, 2017). The Zephir II gen-7 fixed-wing UAV used in the ARSENL program is considered the most notable outdoor aerial swarm platform, achieving swarms of up to 50 agents (T. H. Chung et al., 2016; Escamilla, 2020).

Dorigo et al. (2021) noted that most experimental swarms may present scalability issues due to the arduous charging and software management requirements for individual agents. Dhanaraj et al. (2019) partially alleviated this drawback in a laboratory setting by applying a simulated decentralised hardware approach. To alleviate software upload requirements while preserving swarm behaviour, Dhanaraj et al. (2019) employed fully connected robots controlled by a centralised server that emulated the decentralised controllers of all agents.

Verification

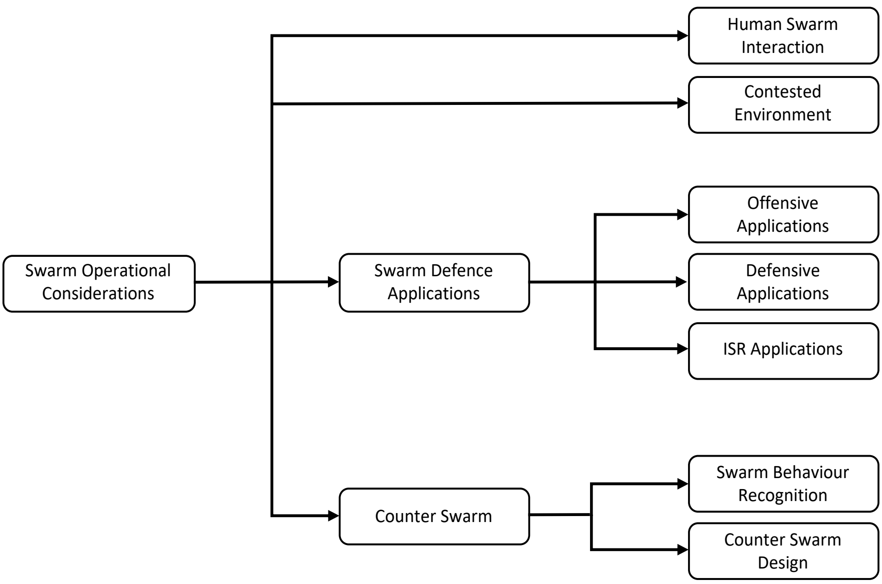
Swarm engineering aims to guarantee and verify stability in swarm behaviours before deployment to ensure robust and predictable performance. Swarm performance is generally hard to verify because swarm behaviours and tasks are not set by universal standards or definitions. (Winfield, 2009). In foundational work, researchers have attempted to verify the overall stability of swarm behaviour, ensuring that the swarm will not suddenly disperse or exhibit unwanted (emergent) characteristics during its operation.

Analytical efforts to prove the stability of virtual force controllers include the Lyapunov and control theory methods (Gazi & Passino, 2003; Himakalasa & Wongkaew, 2021). Kouvaros, Lomuscio, Pirovano, and Punchihewa (2019) and Lomuscio and Pirovano (2020) successfully verified PFSM behaviour using alternating time temporal logic and extended verification activities to open and probabilistic systems. Revill (2016) investigated UAV swarm performance in a search and rescue mission from a failure mode perspective outside of formal behaviour stability analysis. This work examined potential failure mode combinations in the swarm, including loss of navigation capabilities and communications in an agent. This research highlighted several negative impacts on emergent behaviours and overall mission success. Revill (2016) discovered and rectified all undesirable emergent behaviours by adding fail-safe behaviours to the state machine.

Operationalising Swarms

Figure 4 depicts the state of recent research conducted into how swarm technologies can be operationalised within the defence context. This research includes how a military member or team may interact with a swarm to achieve directed operational effects and how the contested environment influences swarm design and operation. There is also considerable interest in how swarm systems may be used effectively in offensive, defensive and ISR applications. Research into counter-swarming technology has also been conducted to defend against an adversarial swarm.

Figure 4: Primary Swarm Operational Considerations



Human-Swarm Interaction and Interfaces

When utilising swarm capabilities, human operators must be able to interact with the swarm to realise sufficient situational awareness and efficient control. Contemporary research focuses more on Human-Swarm Interaction (HSI), a variation of Human-Machine Interaction. It serves to explore and develop more efficient and effective methods of interacting with intelligent swarm systems to achieve the desired outcome (Abbass, Petraki, Hussein, McCall, & Elsawah, 2021; Kolling, Walker, Chakraborty, Sycara, & Lewis, 2016).

Cummings, Clare, and Hart (2010) note that humans and swarms excel at different activities. Swarms are more capable at lower-level activities such as foraging, whereas humans excel at more abstract activities such as future state prediction and task verification (Hocraffer & Nam, 2017). HSI seeks to leverage the high-level supervisory intent from a human operator to guide the swarm's behaviour. A human-swarm system combines a swarm with supervisory control provided by a human operator (Kolling et al., 2016). In such a system, information flow is bi-directional. Specifically, the swarm sends situational awareness and status updates to the operator, and the operator sends high-level control input to the swarm (Hocraffer & Nam, 2017).

Researchers have proposed several high-level HSI architectures. Hepworth et al. (2021) present the Human Swarm Teaming Transparency and Trust Architecture (HST3), a generic swarm and swarm interface framework for transmitting, interpreting, and acting on human intent. In this model, the swarm can *converse* as an independent agent with the operator to provide transparency in its decisions and actions. The human operator shares their intent with the swarm and can then *question* the swarm about how it will achieve the desired goal (Hepworth et al., 2021). HST3 aims to achieve a state of symbiomemesis, a term that describes the symbiotic human-machine relationship, which features a persistent and stable form of logical coupling (Abbass et al., 2021). HST3 and symbiomemesis directly contrast with the conceptual framework of Hasbach and Bennewitz (2021), who favour a 'Swarm Amplified Human' (SAH). In SAH, the swarm is considered an extension of the human operator's nervous system and inherently subordinate to the operator. Transparency in logical intent is not directly addressed in this model; however, the conceptual architecture aims to make interaction as intuitive as possible.

Many swarm interface methods have been proposed and explored, including graphic interfaces, touch screens, voice recognition, smartwatches, gloves, augmented reality, and smart clothing (Vaidis & Otis, 2021). In addition, gesture commands and eye movement recognition through computer vision technologies have also been explored (Vaidis & Otis, 2021). Cillis, Oliva, Pascucci, Setola, and Tesei (2013) have presented a method of interaction using a Microsoft Kinect camera to identify 12 distinct actions for control of several robots. Further, Haas et al. (2010) used touch and voice commands to control a heterogenous swarm in supporting a simulated convoy support mission. Voice commands operated slightly more effectively throughout the experiment; however, both were effective at interfacing with the swarm. Both Cillis et al. (2013) and Haas, Hill, and Stachowiak (2009) emphasised the importance of rapid corrective action (changing swarm action) throughout the swarm interaction, demonstrating that interfacing methods must be intuitive and responsive to be effective (Haas et al., 2010; Haas et al., 2009).

Several other platforms and experiments have been developed to aid HSI. Douglas, Carraway, Mazzuchi, and Sarkani (2020) presented a method for testing and understanding human cognitive load in HSI scenarios. Douglas et al. (2020) used several platforms, most notably the real-time strategy game StarCraft II. In parallel, Dhanaraj et al. (2019) developed the Adaptable Platform for Interactive Swarm-robotics (APIS) to rapidly prototype and evaluate interaction methods. This system was constructed using 50 small robots on a table with easily extensible software architecture, allowing operators to focus on HSI design (Dhanaraj et al., 2019).

Swarm Operation in an Adversarial Environment

Adversarial environments are typical in a defence context. These may include harsh environments where general conditions may be unfavourable, hazardous to the agent, or difficult to operate within (Wong, Yang, Yan, & Gu, 2018). Other contested environments may include those in which an adversary may wish to degrade or destroy the swarm capability (Sargeant & Tomlinson, 2018). Wong et al. (2018) presented an overview of autonomous robotics within harsh environments. They identified key challenges to swarm operations within such environments, including localisation difficulties caused by limited GPS connectivity, dynamic obstacle avoidance, and path planning (Wong et al., 2018).

Fraser, Hunjet, and Szabo (2017) investigated the effects of degraded wireless communication on swarm emergent behaviour through network analysis. By applying agent-based simulation, Fraser et al. (2017) showed that the fundamental attraction-repulsion algorithm used for intra-swarm localisation could be severely affected through reduced bandwidth and signal attenuation. Phillip Smith, Hunjet, and Khan (2018) aimed to minimise this sensitivity through machine learning methods. Using a semi-stochastic action selector, Phillip Smith et al. (2018) learned to transfer data between agents in a contested environment efficiently and thereby improve overall swarm performance.

Sargeant and Tomlinson (2018) and Du, Cao, Yin, and Song (2020) explored potential attack methods against a swarm in a contested environment. Multiple attack vectors were identified and discussed, including a replay attack (re-using previously eavesdropped information to transmit false information), physical tampering, software attacks and incorrect interface information display where the swarm interface was altered to present incorrect information. In intelligent and learning swarms, adversaries could also modify the environment to manipulate swarm learning and cause undesired adaptation within the swarm behaviour, known as adversarial Artificial Intelligence (AI) (Du et al., 2020).

According to Sargeant and Tomlinson (2018), communication attacks, further categorised as data-modification, interference, prevention, collision and exhaustion attacks, constitute a large portion of potential disruption methods, due to a swarm's reliance on communications. Masquerade attacks, for instance, when an adversary integrates as a member of the swarm, pose a particular concern (Sargeant & Tomlinson, 2018). Masquerade attacks allow for eavesdropping and manipulation or degradation of the swarm through misinformation tactics. Hence, swarm systems must implement sufficient intrusion detection and cryptographic communication algorithms to avoid adversarial manipulation (Du et al., 2020). Blockchain is one recently suggested framework to achieve secure communications (Castelló Ferrer, 2019; Du et al., 2020).

Without perturbing hardware, software or communications, there are many attack vectors to manipulate collective swarm motion. This is achieved through a process known as adversarial control (S. Chung, Paranjape, Dames, Shen, & Kumar, 2018). Shepherding is the best-known example of this type of control, using external adversarial agents to guide the swarm by relying on internal collision avoidance and collective motion behaviours of the swarm (S. Chung et al., 2018; N. K. Long, Sammut, Sgarioto, Garratt, & Abbass, 2020).

Defence Swarm Applications

Substantial work has been conducted on swarming for specific defence applications, ranging from offensive and defensive strategies to implementing swarm systems to achieve ISR and communication capabilities.

Offensive Applications

Swarm technology poses several new opportunities to traditional offensive effects. General target engagement was presented by Nowak (2008) using self-organised genetic algorithms on simulated UAVs. Two swarming behaviours (flight formation and Bee-Inspired attack) were used to engage targets in various situations (Nowak, 2008). Gorrell, MacPhail, and Rice (2016) presented an initial discussion on the efficacy of using swarming effects to counter Anti-Access Area Denial (A2AD) envelopes within an operational setting. Williams (2018) extended this research using simulation to present a more generic *parallel attack* swarming tactic, which then developed four different swarming concepts of operation, including Swarm Breach, similar to the counter A2AD of Gorrell et al. (2016), Swarm Area Defence, Swarm Parallel Attack and Wide Area Recon.

The OFFSET program represents the most significant step towards an offensive swarm capability. The DARPA program has collaborated with many different industry partners to 'enable large-scale teams of air and ground robots to support unit forces in complex urban environments' (T. H. Chung, 2021). This work has created a readily extensible, open swarm architecture with many different swarm tactics (such as surveillance, motion, and loitering) and a human-machine interface for defence applications.

Defensive Applications

A number of swarm systems have been suggested for defensive applications. Munoz (2011) presented a preliminary analysis of a defensive swarm system to counter an adversarial uninhabited combat vehicle (UCAV) swarm. This analysis concluded that significant factors in mission success were blue agent characteristics, such as speed and endurance; the swarm system characteristics, such as blue agent launch rate; and the red agent quantity. Munoz (2011) concluded that these characteristics should be considered during swarm development and operation.

Munoz's (2011) premise was extended in the work of Escamilla (2020), which saw the development of a forward operating base defence capability using the ARSENL swarm capability from the NPS. This doctrinally based defensive framework could implement an arbitrary number of fixed-wing and quadcopter agents to fulfil several defensive roles, including perimeter surveillance, key area search, contact investigation and threat response. Simulations used five of each aerial vehicle in the swarm, with two 2020 flight tests physically demonstrating the capability in all roles (Escamilla, 2020).

In a separate defensive application, Holloway (2009) demonstrated a swarm solution to detect and respond to threats in a cyber network. Using online evolution to improve the swarm constantly, Holloway (2009) showed that the swarm could respond to several network scenarios, including detecting, engaging, assessing and responding to target intrusions and anomalies.

Intelligence, Surveillance and Reconnaissance Applications

Swarm-enabled sensor networks have been proposed for ISR capabilities. Early work (Barnes, 2008) displayed the potential capability of heterogeneous swarms for use in ISR, with physical testing demonstrating that small ground-based swarms could avoid obstacles while converging on a general target. Gulosh (2018) used a maritime-clearing mission simulation to highlight the benefit of swarm ISR systems in operation. While supporting a fire support team, a swarm composed of two subswarms of six drones resulted in a 200 per cent increase in targeted and engaged enemy combatants and a 50 per cent decrease in casualties compared to the baseline single-drone ISR capability. Nathan K Long et al. (2019) presented a swarm-based sea state estimation method using USVs. Based on biologically inspired shepherding principles, Nathan K Long et al. (2019) demonstrated that distributed and networked USVs could accurately estimate wave properties in simulation, providing insight into the effectiveness of swarm capabilities as a distributed data collection medium.

Counter-Swarm

Counter-swarm research has steadily increased recently, mainly focused on countering adversarial swarms. Counter-swarm requires operators to understand the adversarial swarm's underlying structure and possible intent, typically through mechanisms such as behaviour recognition and acting to nullify any potential adverse actions.

Behaviour recognition

Understanding swarm behaviour is critical to predicting and countering future actions (Park, Gong, Kang, Walton, & Kaminer, 2018). However, emergent behaviour can make it challenging to recognise swarm behaviour, with researchers having posed many diverse solutions. In most instances, behaviour recognition uses the motion of the swarm over time to characterise different features, such as the underlying C2 structure (Diukman, 2012), swarm interaction model (Gong, Kang, Walton, Kaminer, & Park, 2019; Park et al., 2018) or agent heterogeneity (Hepworth et al., 2020).

Some research focuses purely on identifying and quantifying the existence of emergent behaviour within a swarm. Brown and Goodrich (2014) used an *expressivity* model to identify clockwise and counterclockwise rotations in a loitering pattern, general swarming, and flocking behaviours. This framework only used local-based approximations and did not require knowledge of the whole swarm. Liu, He, Xu, Ding, and Wang (2018) used information theory to analyse a swarm's spatial density through time to detect emergent behaviour. Using this spatial density metric, Liu et al. (2018) were then able to identify jamming opportunities and overall effects on emerging behaviour within the swarm.

Other research focuses on interpreting a swarm's behaviour by identifying the underlying interaction mechanisms. For example, Diukman (2012) used communication theory and other analytical methods to classify the underlying control mechanism as established through the combination of the information source (local, global or hybrid), interaction type (with the environment, swarm and control unit), and level of communication integration. This method also allowed for an external swarm C2 module triangulation within space.

An alternative approach taken by Park et al. (2018) used control theory to estimate a set of parameters governing the adversarial swarm's assumed cooperation model. By injecting an intruding agent into the swarm and a perturbing swarm motion, Park et al. (2018) were able to determine the location of the swarm's 'virtual leader' and other interaction parameters using numerical observability methods. Gong et al. (2019) extended this work using partial observability numerical methods, allowing for the classification of a wider variety of adversarial swarms, including those with unknown numbers of agents, and swarms with different underlying mechanics.

Identifying behaviour differences among heterogeneous agents has also been explored. After perturbing the systems with a shepherd agent, (Hepworth et al., 2020)) used information theory on a heterogenous sheep-inspired flock (Strömbom et al., 2014) to classify the influential *leaders* and agent types within the swarm. Identifying different agents allowed for more targeted manipulation of an adversarial swarm by focusing on the *centre of influence* (swarm leadership), in contrast to the swarm centre of mass.

Counter-Swarm Technology

Swarm systems are believed to represent a significant risk to many operations, necessitating the development of counter-swarm technologies. Swarm robustness, scalability and adaptability make effective neutralisation highly difficult (Diukman (2012).

Most published counter-swarm literature focuses on aerial swarms. Notably, generic swarms can be countered using kinetic and non-kinetic means, such as exploiting the security concerns identified previously. Current aerial counter-swarming solutions include close-in weapon system (CIWS) gun adaptations, high-cost loitering interceptors and focused energy weapons. However, these are thought to be ineffective against future large-scale swarms (Diukman, 2012).

Alternative solutions aim to 'counter' swarming technologies through appropriate risk reduction activities. (Negron et al., 2015) developed the Swarm Risk Evaluation Tool to quantify swarm attack risk and risk factors. For example, during littoral environment discrete-event simulations, swarm risk depended on adversary UAV capability (speed) and quantity, ship to shore distance, meteorological conditions, and defensive capabilities. These findings highlight implicit methods to counter swarm risk.

Many counter-swarm methods require sufficient track information to track and target the swarm in more reactive measures. However, this can be difficult to achieve due to the presence of many agents. Louis, Benjamin, Michèle, and Maxime (2020) alleviated this problem using a Group Target Tracking framework to maintain a track of a swarm. This method modelled the swarm as a single, continuously evolving shape to reduce individual agent tracking requirements. Soylu (2012) implemented a swarm-tracking approach using friendly swarm and sensor fusion techniques to generate a common operating picture (COP), demonstrating the algorithm in a simulated 15v15 engagement.

Multiple centralised counter-swarm methods have been proposed following the tracking and recognition of swarm behaviour. Parsons (2020) developed an indirect fire capability within the existing Marine Corps group-based air defence. The solution targeted Electromagnetic Warfare (EW) vulnerabilities of the swarm by launching and deploying an EW jammer using a parachute to disrupt swarm communication. Grohe (2017) posited the utility of a low-cost missile-based interceptor; however, he did not disclose the style of submunition it would use. Pina (2017) investigated the use of directed energy weapons to disable swarm system agents. Pina concluded that a solution could incorporate both continuous laser waves to heat swarm platforms and pulsed microwaves to destroy electronic circuitry (Pina, 2017).

Other decentralised methods have also been proposed, such as using multiple coordinated effectors. Day (2012) and Tsatsanifos, Clark, Walton, Kaminer, and Gong (2021) countered an adversarial swarm using a team of coordinated defenders through an optimal control algorithm. Using the team swarm dynamics determined through the behaviour recognition work of Gong et al. (2019), Tsatsanifos et al. (2021) were able to successfully defend a high-value target against a swarm of 100 agents with 25 defenders. Walton, Kaminer, Gong, Clark, and Tsatsanifos (2021) further improved algorithm robustness by considering parameter uncertainties such as adversary swarm agent capabilities. Kolon and Schartz (2018) and Tsatsanifos et al. (2021) showed that it is theoretically possible to *capture* an adversarial swarm using a swarm-on-swarm collision, assuming both swarms follow a virtual physics flocking model. Here, intra-swarm coupling strength and communication time delays are important parameters in determining final collided-swarm behaviours.

T. H. Chung, Jones, Day, Jones, and Clement (2013) introduced a swarm versus swarm testbed competition within the ARSENL program to enable future competitive swarm research. Multiple behaviours were developed to allow for the engagement between swarms to be autonomously deployed throughout the trial (Strickland, Day, DeMarco, Squires, & Pippin, 2018). This program successfully demonstrated 10v10 swarm engagement of fixed-wing aircraft between two university teams over 13 missions and a total flight time of 10 hours (Buettner et al., 2017).

Swarming counter-swarm techniques have been enhanced through machine learning methods. For example, (Strickland et al., 2018) used simulation and a genetic algorithm approach to enhance behaviour selection in the ARSENL swarm team to produce a more effective counter-swarm solution. Three years later (Strickland, Pippin, & Gombolay, 2021) developed a reinforcement learning architecture for counter-swarm engagements and successfully demonstrated the capability in a 16v16 swarm engagement simulation.

Antifragility

To support counter-counter swarm technologies, the concept of antifragility[10] for swarm systems may be considered. While a swarm system may be robust, flexible, and scalable, unless it is able to learn from exposure to counter swarm techniques and technologies, it may be a fragile system. Simpson, Oosthuizen, El Sawah, and Abbass (2021) present the concept of Agile Antifragile AI-Enabled Command and Control (A3IC2), whereby traditional C2 models can become agile and antifragile through the implementation of AI to support feedback and overcompensation from new encounters. In the context of swarm systems, use of AI-enabled learning to enhance the swarm intelligence of the system has the potential to develop antifragile swarm systems. Implementation of A3IC2 for swarm systems would likely involve elements of HSI to ensure both the swarm system and C2 agents are able to leverage the strength of swarming tactics, swarm intelligence, and overall mission success.

10 Antifragility is a property of a system capable of thriving after exposure to stressors, shocks, volatility, noise, mistakes, faults, attacks, or failures (Taleb, 2012)

Part Two—Defence Applications, Considerations And Challenges

This part describes the current state of the publicly available swarm, counter-swarm and enabling research applications from the United States, the United Kingdom, Canada, New Zealand, and Australia. A range of future concepts, physical demonstrations and simulated experiments are explored for swarm and counter-swarm scenarios. The part then explores the state of Australian industry, including the key drivers that challenge industry's capability to deliver future swarming capability to Defence. This part concludes by considering the relevance of education, technology, application, and operations, establishing their influence on the force, capability, strategy, and technological uncertainty.

Swarming in Defence is often viewed through the lens of physical Uninhabited Aerial Systems (UAS); however, swarming applications are not limited to the sphere of UAS and may manifest across the physical and information domains. The following non-exhaustive list of applications aims to illuminate facets of the swarming spectrum across multiple application domains.

a. The conduct of offensive and defensive cyber operations, including specific applications for network intrusion detection (cyber-swarm).
b. Sensing and awareness applications for physical infrastructure protection, environment estimation, and surveillance.
c. Cross-domain applications, such as land-based maritime reconnaissance and surveillance (ASW, ASuW).
d. Guidance and control of autonomous UxVs, such as for logistic distribution, ISR and other enabling activities.

e. Information activities, such as social media exploitation (information swarm).
f. Human safety monitoring in large populations, including crowd control, traffic coordination, and air traffic routing applications.
g. Resilient communication networks in contested and congested environments (assured communications).
h. Asset management and monitoring, including fleet management and construction (physical security).
i. Optimisation and routing for the information and physical domains (planning).
j. Robust, scalable, and precision strike capabilities within physical and cyber domains (kinetic and non-kinetic).

International Military Environment Scan

The broad range of projects from partner nations outlined below are from publicly available sources. While the survey is not exhaustive of the topic area, the projects listed highlight the state of contemporary research into and analysis of swarming and enabling capabilities.

Future Concepts

Recent RAS and AI advancements have challenged contemporary offensive and defensive dynamics associated with massed forces. Autonomous Collaborative Platforms (ACPs) can be broadly described as any autonomous platform capable of collaborating with other inhabited or uninhabited platforms to achieve a common goal. ACPs are no longer bound by coordination and concealment difficulties, cumbersome logistics, C2, or sustainment difficulties. These days, ACPs could share information among teammates, among swarm members, or to a cloud in low-bandwidth settings, rather than depending upon large quantities of continuously streamed data. On these platforms, 'better detection, recognition and precision increases lethality and intensifies the imperative to identify, understand and target quicker than an opponent' (UK Ministry of Defence, 2018, p. 15).

The US Department of Defense has recently commenced a significant body of work to support developing 'Autonomous Swarm/Strike—Loitering Munitions'. In February 2021, the US Navy, through the Office of Naval Research (ONR), awarded Raytheon a contract to develop uninhabited surface and underwater ACPs as vehicles to launch drone swarms. This development was described as 'a rapid capability effort to achieve operational launch capability from a USV and a UUV. The intended concept of operations (CONOPS) and tactics, techniques and procedures (TTPs) are to provide intelligence, surveillance and reconnaissance (ISR) and precision-strike capability from maritime platforms' (U.S. Department of Defense, 2021). The High-Volume Long-Range Precision Strike (HVLRPS) from USVs and Fires (HVLRPF) from UUVs will leverage work that was previously undertaken to develop the Innovative Naval Prototype (INP) and the Mobile Precision Attack Vehicle (MoPAV). This work demonstrated the fitment of Coyote Block 3 drones in strategic locations for rapid deployment of drone swarms.

ACPs, swarming, and counter-swarming TTPs and CONOPS feature in concept papers across the international military communities. When judging the value of massed, low-cost systems, the broad utility of swarming already outstrips that of many mature technologies and TTPs, and is changing the idea of qualitative superiority from an attribute of the platform to an attribute of the force (UK Ministry of Defence, 2018, p. 46). Current concept papers discuss the prospect of delivering capability through a system of systems approach where autonomous swarms work together to increase survivability and lethality.

Swarming

In 2012, the US Strategic Capabilities Office (SCO) was created by the Secretary of Defense and partnered with Naval Air Systems Command (NASC) in a collaboration to develop advanced autonomous systems. In the following year, the SCO onboarded scientists and engineers from MIT Lincoln Laboratory to modify their 3D printed Perdix micro-drone for military use. The drones were designed to allow for rapid, modular software updates throughout testing and development. In the first operational test flight, conducted in 2014, the drones were housed in and launched from the flare canisters of an F-16 Fighting Falcon. Throughout 2016, 90 operational sorties were flown, culminating in demonstrating 103 Generation 6 Perdix drones successfully executing autonomous missions. While carrying out four individual missions, the swarm was launched from the flare canisters of three F/A-18 Super Hornets at Mach 0.6, demonstrating collective decision-making, adaptive formation flying, and self-healing. The near-term goal for the US SCO is to scale the swarm to 1,000 agents to enable more considerable swarm capabilities.

The US Navy's ONR commenced the Low-Cost UAV Swarming Technology (LOCUST) program in 2014 as a collaborative endeavour to research, simulate and demonstrate an innovative batch of swarming drones and a new way to launch them. LOCUST is intended to autonomously overwhelm an adversary in offensive and defensive operations with a large variety of mission profiles. In partnership with Raytheon, the program developed the Coyote drone, a small, expendable tube-launched drone capable of operating for up to one hour with interchangeable payloads. In 2017, Raytheon announced it was developing a new Coyote Block 2 version. In 2018, the US Army announced it was buying these versions of Coyote as counter-drone interceptors.

The US 2020 Advanced Technology Investment Plan (PEO Land Systems Marine Corps, 2020) detailed two LOCUST-related projects to further develop Coyote Block 3. The first will see ONR partner with the US Marines to demonstrate the next phase of heterogeneous platforms swarming with expeditionary systems, and the development of a LOCUST Expeditionary Launch Module. This includes experimentation efforts in support of the Marines' requirements to include 'Close-in Covert Autonomous Disposable Aircraft super swarm experimentation'.

While ISR has traditionally been the focus of the military application of swarm programs, the US Air Force Research Laboratory (AFRL) Vanguard Program initiated Golden Horde in 2019 to demonstrate Networked, Collaborative, and Autonomous (NCA) weapons. Golden Horde has successfully developed and tested a Collaborative Small Diameter Bomb (CSDB) integrated weapon system to enable a swarm of CSDBs to share data and execute coordinated behaviours. CSDBs are fitted with a collaborative autonomy payload that allows them to communicate locally through onboard radios to locate, identify, prioritise, and defeat targets.

In December 2020, two CSDBs were rack launched from an F-16 Fighting Falcon. They were able to establish communication links with each other, detect a target (GPS jammer), and coordinate an attack. Just two months later, a successful demonstration was achieved with four CSDBs. The development is led by AFRL and prime contractor Scientific Applications & Research Associates (SARA) through a contract. SARA developed the GPS jammer seeker technology. Supporting contractors included L3Harris, which provided the Banshee 2 networked software-defined radio; Georgia Tech Research Institute, which developed the radio antenna, collaborative autonomy processor and algorithms; and the Boeing Company, which integrated the new technologies into its SDB-I weapons (Air Force Research Laboratory, n.d.).

Following successful trials, Georgia Tech Applied Research Corporation has been awarded a contract to extend the collaborative payload to integrate with Raytheon's Miniature Air-Launched Decoy (MALD). The extension will see MALD developed as a flying, programmable, low-cost, expendable, air-launched decoy craft that deceives advanced enemy integrated air defence systems by duplicating the combat flight profiles and signatures of combat aircraft. It is intended to be capable of autonomous swarming behaviours.

The most recent development in the AFRL Golden Horde program is a swarm munitions virtual environment called the Colosseum. The Colosseum is a digital engineering pipeline encompassing software, hardware-in-the-loop, and surrogate UAVs (Air Force Research Laboratory, n.d.). It aims to rapidly integrate, develop and test transformational NCAs, swarming weapon capabilities, and air platform technologies for future military users.

In 2019, the United Kingdom's Defence Science and Technology Laboratory (DSTL) collaborated with engineering firm Blue Bear after the award of a contract to develop a sovereign heterogeneous swarm. The contract required the swarm to be capable of delivering multiple mission objectives, such as logistics resupply, medical assistance, and situational awareness. The collaboration culminated in a two-week exercise that successfully demonstrated a fully autonomous heterogeneous drone swarm controlled by a single operator. The swarm comprised 20 fixed-wing UAVs, with five different platforms (Blue Bear's Ghost, Ghost Modular, Red Kite, Cobra, and hand-launched flat pack system), carrying seven different payloads to deliver multiple effects. The exercise, which concluded with over 220 sorties, successfully demonstrated an operationally suitable capability (B Das, 2021).

The success of the exercise led to military trials in 2021, known as Autonomous Advance Force 4.0—Flexible Human-Swarm Teaming, focused on establishing how to team humans and swarms to gain a battlefield advantage. In this exercise, an array of autonomous systems teamed with UK Royal Marine Commando strike teams from Alpha Company of Taunton-based 40 Commando. The heterogeneous swarms were operated on land, subsurface and surface and in the air to increase the capabilities and effectiveness of the strike teams during raids on several complex adversarial positions, such as missile and RADAR installations. The swarm comprised six Malloy TRV150 all-weather drones for tactical resupply (capable of a 68 kg payload), multiple Anduril Ghost drones (mini-helicopters) for ISR, Remus underwater vehicles dropped into the sea by the Malloy TRV150s, the MADFOX vessel on the waves, and hand-launched fixed-wing Cobra drones in the air. This heterogeneous swarm demonstrated significant flexibility by switching roles to conduct reconnaissance, supply, and support for raids ashore and at sea. The military trials scrutinised tactics and enhanced knowledge about how swarms can—and cannot—be used to inform UK Commando Force operations in the future (Royal Navy, 2021).

DARPA's Offensive Swarm-Enabled Tactics (OFFSET) program was initiated to enable rapid development and deployment of breakthrough swarm capabilities by leveraging and combining emerging technologies in swarm intelligence and human-swarm teaming. There were three main lines of effort. These included an advanced human-swarm interface to enable users to monitor and command up to 250 swarm system agents. There was also a real-time, networked virtual environment that supported a physics-based swarm tactics game to explore, evolve and evaluate swarm tactics. In addition, the program involved live experiments comprising three vignettes of increasing scale, complexity, and duration. Vignette I, conducted in October 2018 and June 2019, was a mission to isolate an urban object that comprised a swarm of 50, in an area of operations (AO) of approximately two square city blocks, for up to 30 minutes. Vignette II, conducted in December 2019 and August 2020, was a mission to conduct an urban raid that comprised a swarm of 100, in an AO of approximately four square city blocks, for up to two hours. The culminating event was vignette III, a mission to seize key urban terrain that was conducted in June and July 2021, which comprised a swarm of 250, in an AO of approximately eight square city blocks.

Table 2 presents a summary of physical swarm demonstrations discussed throughout Part One and Part Two. Swarm size and action complexity must be viewed together, as a perspective of swarm size in isolation does not adequately describe the efforts for progress in the field. The important deduction here is that the operational and environmental complexities have been continuously increasing, leading to the capstone 2021 DARPA tactical missions. We can expect to see further advancements across militaries globally to generate disparate swarm capabilities. Leveraging ongoing research in the field offers many opportunities to explore distinct capability and capacity mixes for physical swarms, such as swarm size, platform capability heterogeneity, and the applied tactical actions under consideration. Note that the demonstrations listed in Table 2 do not present a summary of ongoing research directions in other domains, such as cyber or space.

Table 2: Summary of swarm physical demonstrations discussed

Year	Organisation(s)	Swarm Size	Platform Type	Actions
2016	US Strategic Capabilities Office, US Naval Air Systems Command, and Massachusetts Institute of Technology	103	Gen6 Perdix	Autonomous mission profiles
2015	Naval Postgraduate School	50	Zephir II Gen-7 fixed-wing UAV	Concept development
2015	Universitaet Graz, Université Libre de Bruxelles, University of Stuttgart, Scuola Superiore di Studi Universitari e di Perfezionamento Sant'Anna, University of York	40		Heterogeneous autonomous underwater swarm
2017	Wyss Institute, Harvard University	1024	Kilobot 3.3 cm low-cost swarm robot	Collective self-organisation

Year	Organisation(s)	Swarm Size	Platform Type	Actions
2017	Poznan University of Technology	49	CrazyFile 2.0	Research-focused indoor non-quadrotor aerial swarm
2019	UK Defence Science and Technology Laboratory, BlueBear	20	Blue Bear's Ghost, Ghost Modular, Red Kite, Cobra, and hand-launched flat pack system	Heterogenous agents with distinct platforms, operational capabilities, and payloads
2018	US Defense Advanced Research Projects Agency	50		Tactical missions in urban areas, up to 30 minutes
2019	US Defense Advanced Research Projects Agency	100		Tactical missions in urban areas, up to 2 hours
2021	US Defense Advanced Research Projects Agency	250		Tactical missions in urban areas over 8 square city blocks

Counter-swarming

As swarm capabilities increase, with both state and non-state actors continuing to refine their TTPs in the efficient use of swarming technology, counter-swarming concepts require particular attention—specifically in the defence of large, static, or low manoeuvrability assets such as RADAR installations and battle groups. A swarm's capability to confuse, disorient and overwhelm conventional systems (such as anti-air, counter-rocket, artillery, and EW measures) presents a significant challenge to the prioritisation of threats and the achievement of effective responses. With increased numbers, and all-angle attacks (subsurface, surface, and air), contemporary weapon systems will likely struggle with the high rates of fire, magazine capacity, rapid discrimination, and targeting. This observation is supported by recently published concept papers in which analysis is refocusing towards potential counter options to cyber operations, EW, Directed Energy Weapons (DEW), and swarms to disrupt swarms (Naval Postgraduate School, n.d.; UK Ministry of Defence, 2017, 2018).

Through the Defence Technology Agency in New Zealand (DTA-NZ), counter-swarm capability research predominantly centres on the land and maritime domains. Through the Technical Cooperation Program (TTCP AER Group TP-12) and the ABCANZ Focussed Information Exchange Group on countering maritime UAS, and the Air Force Interoperability Council (AFIC), DTA-NZ seeks to achieve two outcomes. The first is to inform capability owners about plausible future threats to their systems from swarming—for example a ship, aircraft, or land formation. The second is to assist the capability acquisition community in the definition of feasible counter-swarming capabilities.

The Canadian Armed Forces are actively researching counter-UAS (C-UAS) systems that are easily and readily deployed, and capable of detecting, tracking, identifying and neutralising targets. There are two main lines of effort. The first is for fixed installations, and the second is for mobile vehicles. In both cases, the objective is to develop systems that are as automated as practicable to minimise training, user input, and level of human effort in performing C-UAS functions.

The NPS's 'Defence Strategies Against a Swarm Attack on a High-Value Target' paper details work in developing counter-swarm physics-based simulation. The NPS has used several tactics to successfully model engagements of up to 2,000 attackers and 200 defenders. These simulations have been used to calculate and optimise probabilistic attrition rates to help inform the type and quantity of defences required for a particular attack.

Human-Swarm Teaming

In future conflict situations, we posit, those who seek to gain the greatest military advantage will need to effectively establish human-swarm teams to realise the full potential of the promised capabilities. Humans, robotics, and AI will need to be integrated to exploit the capabilities of each to outperform their opponents.

> *Weak human + machine + better process was superior to a strong computer alone and, more remarkably, superior to a strong human + machine + inferior process … Human strategic guidance combined with the tactical acuity of a computer was overwhelming. (Kasparov, 2010)*

Operational situations that generate mass weight through swarming will likely lead to settings where a *human swarm supervisor* quickly becomes cognitively saturated with an increasing agent to human ratio. Current research has demonstrated that a human swarm supervisor can effectively control a swarm of up to 80 agents. As with present organisational structures, the span of command may need to be considered a constraint to ensure cognitive saturation is not experienced (UK Ministry of Defence, 2018).

Contemporary research focuses on increasing the capabilities of individual technologies, with a focus on the integration of technologies for human teaming a lower priority effort. Considerations as to how best to team humans and swarms cannot be regarded as a design factor for individual capability programs. This is due to the system and institutional impacts human factors have on defence (UK Ministry of Defence, 2018) and therefore requires focused effort to optimise capability outcomes.

Australian Industry

It is difficult to quantify the current level of focus within Australian industry on swarming and counter-swarming technologies. This is due, in part, to the lack of discriminatory indicators within the Australian and New Zealand Standard Classification of Occupations (ANZSCO) (Australian Burea of Statistics, 2019). The lack of descriptors could indicate that swarm and counter-swarm related technologies are yet to achieve critical mass and are still a nascent segment of Australian industry; however, this conclusion is presently not verifiable. A viable method to provide further insight would be to codify the technologies which enable the delivery of swarm and counter-swarm capabilities. Unfortunately, key technologies such as artificial intelligence and robotics also remain notably absent from ANZSCO's descriptors (Australian Burea of Statistics, 2019).

To help address the gap, this paper defines 14 key enabling technologies that directly support the development of swarm technologies for military applications. These enabling technologies are primarily subordinate to the fields of robotics and AI. They are nevertheless representative of the broad base of disciplines that have been, are presently, or are likely to contribute to the foundation of swarming and counter-swarming capabilities identified earlier in this paper. These 14 enabling technologies are presented in **Table 3**.

Table 3: Swarm Enabling Technologies

Ref	Enabling Technology	Description
1	Robotics and Uninhabited Vehicles (UxVs)	Focused on the design, manufacturing, and operation of platforms
2	Communication	Focused on information-sharing mechanisms for agent interaction
3	Sensing and Processing	Extraction of insights from sensor data and computation of this
4	Recognition	Detection and classification of patterns
5	Swarm Robotics Guidance and Control	Focused on algorithm design
6	Swarm Behaviours and Tactics	Formation and configuration for scenarios
7	Multi-Agent Artificial Intelligence	Focused on the organisation and interaction of multiple intelligent agents
8	Human x Interaction (HxI)	Interaction and communication between humans and machines/intelligent agents
9	Planning (Navigation and Goal-Oriented[11])	Focused on techniques to solve schedule and objective-based problems
10	Computer Vision	Deriving meaningful information from digital images and videos
11	Swarm System Architectures	Conceptual model to define structure and behaviour of the swarm system
12	Situation Awareness and Assessment	Knowledge understanding
13	Autonomy (General)	Focused on broad self-governing systems
14	Counter-Swarming (General)	Countermeasures to swarm systems

11 Goal-based reasoning is a system that is programmed to achieve human-defined goals and allowed to determine its own method of achieving these goals. Consequently, a goal-based reasoning system may consist of multiple agents that support the system in achieving goals.

To establish the maturity of Australian industry, an environmental scan was conducted of 24 companies operating in Australia[12] to gauge their level of focus on these 14 enabling technologies. Many of the companies surveyed have some level of international presence, in either a technology export capacity or with international parent companies. The environment scan was limited to 24 companies, based on publicly available information, and did not include research being undertaken by Australian universities. Notwithstanding these limitations, the environment scan did give rise to several notable observations.

The environment scan indicated the existence of industry awareness about the enabling technologies identified in **Table 3**. It also highlighted the sparsity of actual investment in swarming and counter-swarming capabilities. The primary focus for swarm technology development is contained in the aerospace domain, specifically UAS, with substantially lower representation across land, maritime, space and information domains. Outside of the defence sector in Australia, the industries investing in swarm technology research are predominantly agriculture and mining (Duff, 2021). Overwhelmingly, such companies are focused on enabling technologies related to robotics, UxVs and general autonomy. Sensing and processing, as well as interaction and communication, are well represented. However, the scan indicated that this area of focus was the result of operational necessity rather than research prioritisation. More specialised capability development, such as behaviours and tactics, and swarm robotics guidance and control, are poorly represented across Australian industry.

The outcomes of the environmental scan conducted for this paper are broadly consistent with previous analysis conducted by the Australian Centre for Robotic Vision (ACRV) (2018). In the ACRV's scan, 1,000 companies were identified as undertaking research and development related to robotics. If it is accepted that approximately 9.5 per cent of companies undertaking robotics work in support of the Defence enterprise (Global Industry Analysts Inc, 2021), this would mean that only around 100 of these companies conducted defence-related work.

12 The selection methodology for inclusion and exclusion of industry companies was an environment scan. Companies were assessed based on their declared work against one or more of the enabling technology areas. Resulting from the low-density industry working on swarm and related technologies, no direct statistics are provided, although thematic summaries are reported.

The scope of the activities undertaken by these industry operators spanned the functions of production, distribution, integration and advisory (Australian Centre for Robotic Vision, 2018). The key relevant technologies identified in the *Robotics Roadmap for Australia 2018* by the ACRV were cognitive machines, trust and Human-Autonomy Teaming (HAT) (Australian Centre for Robotic Vision, 2018). The roadmap noted that key use-cases for robotic systems included situational awareness; intelligence, surveillance and reconnaissance; and targeting, noting the future requirements to migrate from robotic platforms to situations where 'autonomous systems operate in teams with humans in complex and contested environments' (Australian Centre for Robotic Vision, 2018).[13]

Defence is an acknowledged end-user stakeholder for robotic systems (Australian Centre for Robotic Vision, 2017). Defence requires cheap and modular platforms, with tailored effects for mission requirements, noting that at the time of publication these specific requirements are yet to be defined by Defence and communicated to industry (Australian Centre for Robotic Vision, 2018). While robotics and UxVs are likely to remain a dominant enabling technology for the military in the physical domain, there remains a paucity of robotics capability within Australian industry (Duff, 2021).

In an example of the lack of attention to military applications for robotic systems, the 2019 CSIRO Data61 AI Roadmap (Hajkowicz et al., 2019) did not identify Defence as being part of the 'high potential areas of artificial intelligence specialisation for Australia' (Hajkowicz et al., 2019). Instead, the potential domains identified as being relevant were (1) health, ageing and disability, (2) natural resources and environment (including agriculture and mining), and (3) cities, towns, and infrastructure (including safety and efficiency outcomes).

13 Note that this section of the report was contributed to by current and former Department of Defence staff.

Defence applications may be different in nature to other domains—due, for instance, to operations in threat settings. While there was a lack of representation of defence and related sectors in the AI Roadmap, the discussion of agriculture and mining is nevertheless relevant as both sectors share similar operational considerations with Defence. These include austere environments with extreme conditions; communication challenges over substantial distances, signal interference (noise) and high bandwidth requirements; complex human-machine interactions; and a range of unique high-level specific mission profiles and tasks, such as determining crop states (reconnaissance and surveillance tasks) or underground exploration for various mineral and metal profiles (search and locate tasks) (Duff, 2021). The complementary nature of these industry sectors, including possible dual-use technology applications, offers a range of opportunities to Defence (Hajkowicz et al., 2019). Where dual-use technology opportunities exist, additional work will be required to safely integrate them into the Defence domain, beyond a direct transfer of technologies 'as is'.

Considerations and Challenges

There are several pressures that prevent the realisation of enabling technologies, including their integration with each other and their human operators. These pressures encompass access to a skilled workforce, investment continuity, sovereign manufacturing, resource prioritisation and a high barrier to entry which limits industry participation. The Army RAS Strategy (Australian Army, 2018) identifies swarming as a generator of mass that has the potential to enable fewer humans to achieve greater output capacity than is possible today. In this context, the challenges that Defence faces fuse broader AI and robotic challenges with the added complexities associated with raising, training, and sustaining a workforce with the specialisations necessary to achieve the desired capability end state.

a. **Skilled workforce.** Research indicates that there will be 161,000 roles related to AI and Machine Learning (ML) nationally through to 2030 (Hajkowicz et al., 2019). Given the low density of defence and related robotic AI companies as a proportion of the national workforce, there may be upwards pressure on Australia's Science, Technology, Engineering and Mathematics (STEM) workforce for Defence. A recent Engineering Australia article (Stapleton, 2021) stated that there are insufficient domestic PhD students to support Australia’s research and development industry, noting that more scholarships exist than qualified and experienced candidates to undertake them. The upshot may be a situation in which Defence is unable to generate sufficient sovereign knowledge to design, implement, and protect our systems.

b. **Investment continuity.** Limited prioritisation of swarm and related technologies by Defence may have contributed to a lack of investment by industry and academia. Defence strategies seldom detail the granular transition pathway for technologies from research and development (R&D), through proof of concept (POC), to a mature delivered capability. This oversight amplifies the workforce constraints that hinder scale design and manufacturing for product delivery.

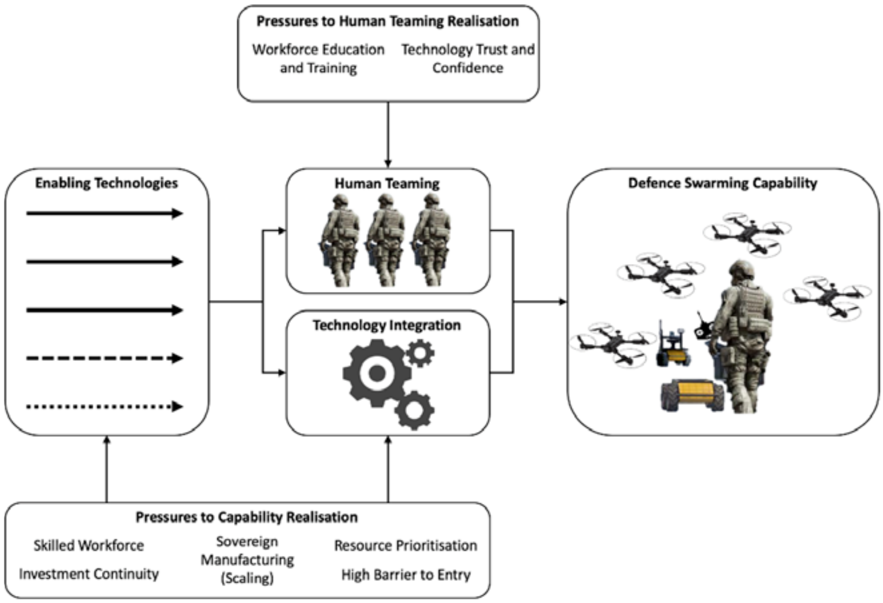
c. **Sovereign manufacturing.** Based on an analysis conducted by the International Federation of Robotics, Australia has been ranked 30th in terms of global automation production, while simultaneously Defence was identified as a ‘critical sector’ to a national robotics advantage (Australian Centre for Robotic Vision, 2017).

d. **Resource prioritisation.** Defence has yet to articulate swarming and counter-swarming technologies as priority investment and target technology areas, beyond inferred detail in the Sovereign Industrial Capability Priorities (SICP). The demand for industry to focus on swarming and counter-swarming capabilities directly is yet to be signalled (Duff, 2021).

e. **High barrier to entry.** There may exist substantial initiation costs to physical R&D and POC demonstrations for industry, and where physical swarming research is not within traditional academic teaming research (Duff, 2021). Typically, simulations are completed with high granularity. However, these can lack the fidelity experienced in real-world environments.

Figure 5 describes a system of technology and human challenges to generate a future Defence swarming capability. The identified pressures complicate the realisation of such a desired end state, regardless of the application domain or mission profile. Options to address these pressures are outlined in the following part.

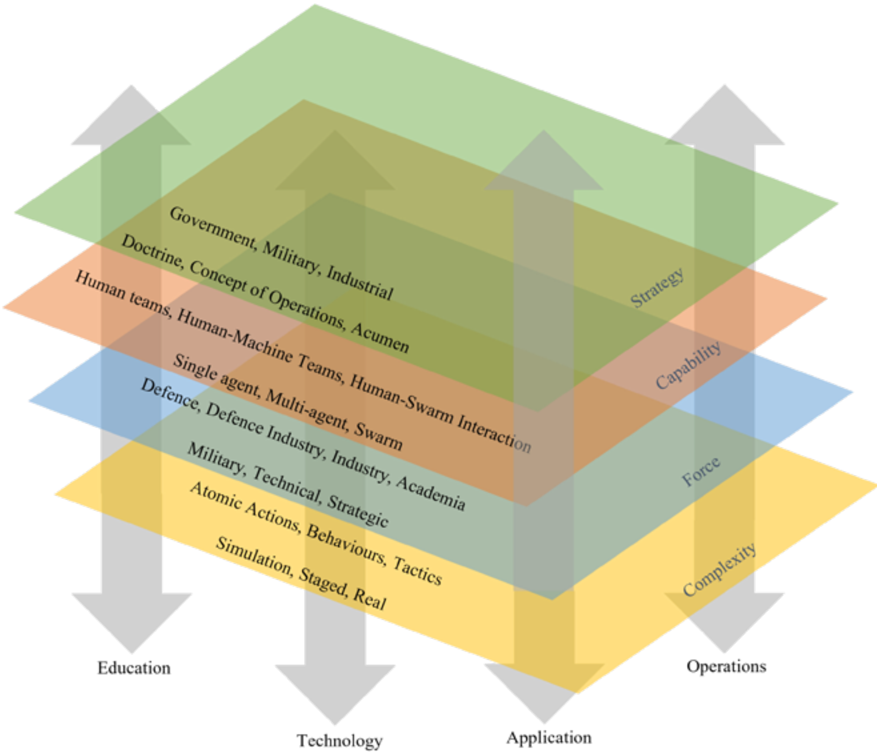
Figure 5: The identified Defence swarming pressures on capability realisation. This designed conceptual framework offers a demand signal for resource apportionment to generate capability and capacity portfolio options.



Swarm Capability Enablers

The key capability enablers highlighted by the literature, defence and industry scan were identified as education, technology, application, and operations. To illustrate how Defence could realise swarm and counter-swarm capability, the conceptual interface between capability enablers and their influence on the elements of Strategy, Capability, Force, and Complexity are illustrated in **Figure 6**.

Figure 6: Harnessing spectrum influences across the element factors for swarm capability



Education is an integral enabler for the realisation of new technologies or, in many cases, the synthesis of concepts to realise new capabilities. Evolving the education enabler using feedback from interface elements positions the future force to apply knowledge to scenarios that involve levels of complexity, innovation, capability, and strategy that are otherwise beyond planning horizons. Harnessing knowledge along the full spectrum of education could enable the acceleration of capability and strategy, while also minimising the potential impact of uncertainty. This paper presents a spectrum of education as:

a. General education: examples include the Australian national curriculum and *ab initio* curriculum for personnel within Defence and industry.
b. Professional education: examples include curriculums for specific professions, such as a STEM-based career, and mustering or category curriculums.
c. Research education: examples include postgraduate education, and research and development in different industries.

Technology has evolved throughout human history, with success realised when the technology is properly harnessed by the force implementing it to realise capability. To realise swarm capability, the force will need to be able to meaningfully interact with the technology to translate the technology to capability (Yaxley, Joiner, Bogais, & Abbass, 2021). Human systems engineering is used to graduate levels of autonomy in order to understand how force and capability interact with the spectrum of technology (Handley, 2021).

a. Tools: *user operates system*—humans use technology within the system, sometimes also performing fault correction to ensure the system remains functional.
b. Autonomy: *users monitor the system*—examples are human-machine teaming, where the human ensures ethical actions and decisions; and (evolving from this) *users are the system*, where human-machine teaming reflects monitoring of team interactions in human teams.
c. Swarms: a fusion of all elements, with meta, micro, and macro level interactions between humans and technology. HSI may be implemented as *users monitor the system*, allowing the humans to provide strategic guidance and monitoring to the swarm, and may extend up to *users are the system*, where the human teams with the swarm at the macro level to achieve an effect.

Application is a concept often recognised as defining technical readiness levels for technology or capability. However, to support the development of applied strategy, it is necessary to consider how doctrine may evolve in response to emerging capability. Currently, swarm simulations and scenarios have demonstrated success where human operators have well-developed strategic and tactical acumen (Kaminer & Clark, 2021). Consequently, to prepare the force for swarm capability, a review of strategy and doctrine is required to enable the capability to be harnessed at all levels of force design. Consequently, swarm capability and strategy may interact through the spectrum of applications as:

a. Theoretical: applying lessons from historical doctrine to inform future capability and strategy, such as the analysis developed by Arquilla and Ronfeldt (2000).
b. Prototype: abstracting strategy to current and future capability to inform curriculum design, preparing the force for the cognitive capabilities to combat complexity.
c. Actual: applying the strategy and capability in operations to gain experience and develop for complexity.

Operations are the situations that may be used to fuse the scenario, capability, and strategy for understanding the impacts of complexity. Each element of the operations spectrum may be explored using simulation, staged (for example, tabletop wargames), or real:

a. Training: may be targeted for an element of the Force (including individuals), capability, or overall joint strategy.
b. Exercise: an essential element of Force preparedness which provides a platform for safe risk-taking with an element of complexity. Examples include military exercises, technology challenges, and research projects.
c. Combat.

Part Three — Future Directions For Swarm Capabilities In Defence

This part outlines opportunities identified for swarm system realisation in Defence, as well as options Defence may consider in addressing the challenges and constraints identified in the previous part. Several options are presented which explore ways to address swarm technology adoption barriers, as well as plausible ways to accelerate future capability.

What Are the Barriers to Adoption?

In part two, this paper presented extant barriers that exist within Australian industry that limit the opportunities to exploit the different spectrums of Education, Application and Operations. During Australian industry growth, there may be increased opportunities to collaborate with partner nations and grow experience within Defence, as observed recently with distinct priority technology areas. Such collaboration has the added benefit of positioning Defence to articulate its requirements of Australian industry more clearly to realise future swarm capability.

The Defence innovation review announced by the Minister for Defence Industry in 2021 (Department of Defence Ministers, 2021) seeks to identify how to commercialise defence research in industry. Through harnessing experience gained through exercises and experiments, there may be an opportunity to accelerate the development of swarm capabilities in Australia. A domestic opportunity exists to capitalise on the spectrum of technology and applications that are already being used by non-defence Australian industries, extrapolating these lessons to build operational capability.

A combined method to address domestic technology limitations is for Defence to explore opportunities to improve both the education opportunities and operational capability. Collaboration with partner nations offers a viable pathway to support the development of capability and strategy, while offering experience to utilise emerging technologies that are not yet available domestically. Developing relationships with non-traditional partners in Australia may offer insights into how to accelerate operational preparedness, capability, and strategy. Enabling low-risk opportunities to demonstrate capability across the spectrum of operations may lead to more rapid technology, education, and application opportunities for Defence.

Proposed Swarm Capability Development Roadmap

The options identified in this part could be implemented in many ways. We present **Figure 7** and **Figure 8** as a considered initial proposal for a Swarm Capability Development Roadmap, combining several of the objectives identified by the options. The roadmap is separated into three overarching phases—explore, align, and exploit—the characteristics of which are discussed in further detail below. It is important to note that **Figure 7** presents a high-level proposal as a path forward and deliberately omits facets of leadership, participating organisations, and partner nations. We interpret the term *swarm system* in **Figure 7** to be thematically broader than the definition provided in Part One, including elements discussed in the previous two parts such as other domains (including non-physical, such as cyber swarming), concept development and experimentation, command and control integration, and HST integration. It will be important to ensure consideration is weighted towards the research directions identified in Part One and the military applications in Part Two, ensuring feasible objectives are set. This perspective considers a swarm system through the lens of distributed cognition,[14] blended across the spectrum of C5ISREW[15] capabilities.

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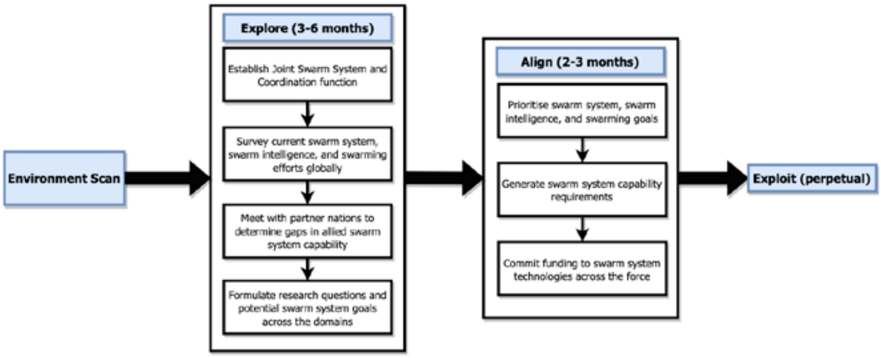
14 Distributed cognition is a concept introduced by the philosopher Andy Clark in the late 1990s, considering some types of knowledge as 'distributed over a community of individuals, rather than being represented in individual brains'. Please see (Clark, 1998) and (Carr, 2012) for further discussions.

15 The acronym C5ISREW expands as command, control, computers, communications, cyber, intelligence, surveillance, reconnaissance, and electromagnetic warfare.

Figure 7: Proposed swarm capability development roadmap

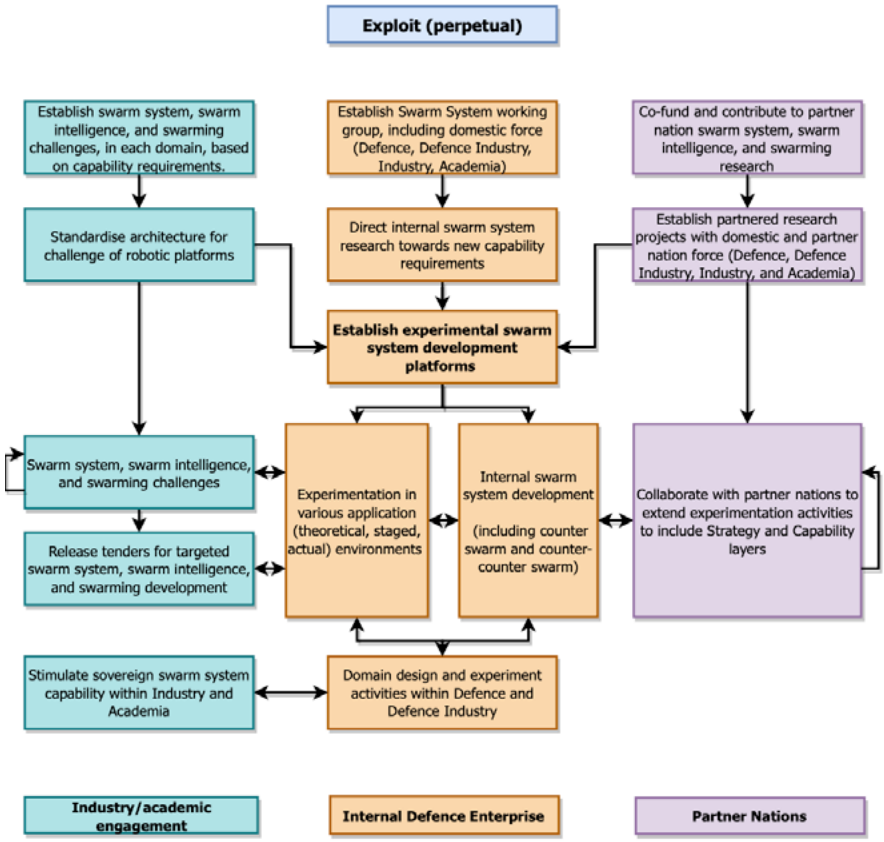


The 'Explore' phase enables detailed investigation into the four-element factors (presented in **Figure 6**) of swarm technologies. Initially, the Explore phase would focus on exploring the current strategy and force factors relevant to the achievement of swarm system capabilities. This could include examination of how each domain within Defence could apply swarm capability to realise specific outcomes, as well as a review of capabilities within the Australian Defence Force (ADF) and partner forces to exhaustively appreciate the context within which current swarm system capabilities are conceptualised and applied. The Explore phase would then identify key gaps and opportunities to inform the capability and complexity elements, thereby supporting the prioritisation of effort in the 'Align' phase.

The Align phase would direct prioritise swarm system development efforts for effects generation. Following the prioritisation of gaps and opportunities, swarm system capability requirements would be generated. Swarm system capability requirements and domain considerations help identify opportunities and threats to be considered within the Exploit phase.

The Exploit phase sees the generation of swarm system capabilities for Defence. The roadmap option in Figure 8 uses an experimentally grounded approach to progress the swarm complexity factor towards the cyber-physical setting. Using this approach, initial Exploit activities would prioritise collaboration with academia, industry, defence industry, and our international partner community, informed by the outcomes of the swarm capability requirements.

Figure 8: The 'Exploit' phase of the swarm capability development roadmap



Collaboration may be facilitated through the conduct of 'swarm challenges', adopting a similar approach to the NASA Swarmathon (Ackerman et al., 2018). Such activities provide a forum to safely explore swarming capability (Ackerman et al., 2018) through a lower level complexity factor (simulation and staged) using participants from across the defence, industrial, and academic domains. To develop successful outcomes which have a meaningful impact and are sustainable, the considerations and challenges discussed in Part Two must be overcome. This includes the workforce and resources, as well as substantial commitments by defence, industry, and academia alike.

‘Exploit’ activities would ultimately inform the capability development and acquisition of a swarming platform system for experimentation in operational environments. Operationally relevant experimental insights would serve to accurately guide swarming capability across the technology spectrum towards a suitable Technical Readiness Level (TRL) for future capability. Force design activities would also be conducted to identify, explore, and integrate swarm system capability options into future force factor concept development. These activities would inform, and be informed by, swarming activities conducted at various levels of each of the four spectrums: education, technology, application, and operations.

How Can Defence Accelerate Future Swarm Capability?

The following levers are possible options for Defence to consider in accelerating technology development to realise a swarming capability.

Co-investment. This option sees Defence co-investment with industry and academia in infrastructure[16] to reduce the high barriers to entry previously discussed. This could result in a greater range of technology options proposed (exploration), as well as enabling deeper supply chain synthesis (raw material, design, systems integration) and manufacturing options. The objective of this option is to accelerate opportunities to explore, integrate and deploy sovereign swarming technologies supporting effects-based outcomes.

This objective could be achieved through a mechanism in which the barrier to entry for industry and academia is mitigated by Defence. Such mitigation measures could involve Defence providing experimentation platforms, dedicated facilities, and access to ranges. The upshot for Defence is that co-investment partners are enabled to focus on designing and implementing the AI and related advanced swarm functions. Moreover, asset and facility sharing may deliver a forcing function in which higher levels of collaboration between co-investment partners are observed, including the sharing of qualified and experienced personnel across projects. With Defence retaining ownership of provisioned platforms and equipment, integration control is maintained to ensure the prioritisation of initiatives such as the Generic Architecture program.

16 Infrastructure in this context is contextualised as the collective enabling functions for swarming development. This includes research resources, S&T and testing facilities and hardware platforms, secure ICT hardware and collaboration agreements.

Investment continuity. The necessary demand signal for industry and academia is yet to be achieved and will prioritise the development of swarm system capability and related technologies. This situation is likely to contribute to industry and academic hesitancy to invest. Combined with the high barrier to entry, smaller industry and academic partners may not wish to invest without resource certainty, although they possess the desirable abilities and experience in suitably qualified and experienced personnel. The objective of this option is to develop the baseline investment in swarm and counter-swarm technologies over a multi-year period. This option could be integrated into existing efforts, such as partnerships, co-investment and/or prioritised mission-based investment.

Partnerships. This option sees Defence collaborate and partner with industries to achieve technologies that yield dual-use outcomes, intended to reduce investment, and accelerate technology adoption. The objective of this option is to accelerate dual-use swarm system technologies to support the development of HSI capabilities, including workforce education and training, addressing skilled workforce and sovereign manufacturing challenges.

Agriculture and mining are identified as two promising industries for dual-use technology development for Defence. High pay-off areas identified for these industries are focused on natural resources and infrastructure development (Hajkowicz et al., 2019). There is an opportunity to investigate adoption challenges for Defence by leveraging existing research and technology development efforts, including concept demonstration activities. Co-investment with traditional and non-traditional Defence partners offers a compelling opportunity to expedite the adoption of swarm system capabilities across multiple domains.

Prioritised mission-based investment. This option sees Defence set mission-based objectives with key outcomes for industry and academia to deliver against, with solutions generated for specific use-case scenarios. The objective of this option is to increase industry and academic achievement of Defence outcomes against desired operational end states.

Defence should set the mission-based demand signal for how the ADF may need to operate in the future, both in swarm and counter-swarm scenarios. Defence operational and capability context concept scenarios should seek to prioritise resource apportionment and desired swarm system capabilities, augmenting the SICP. Industry and academic partners would present work to address these outcomes, focused on technology development and integration to meet the ADF's requirements. In this experimentation-based approach, Defence, defence industry, industry and academia would co-evolve understanding of how technology may be employed, possibly identifying novel operational concepts and tactical procedures throughout.

Defence applied workforce. A central challenge for Defence to adopt future technologies is the organisation's ability to develop the necessary skilled workforce to exploit them (Simmons, 2021). The Joint Professional Military Education (JPME) Continuum reflects a professional development paradigm for the achievement of expected operational demands, specifically where the level of complexity is relatively well known. As higher levels of the technology spectrum are employed, however, the teaming aspects of Defence will also evolve. In parallel, the cognitive capabilities required of 'the human in the system' will expand to require the exercise of professional judgement (*users monitor the system*) in multiple scenarios of increasing complexity.

To prepare for these expected cognitive demands, technological application competence must be raised across the workforce. Acclimation to technology needs to go beyond just exposure to the emerging technical and tactical systems; it also needs to expand these technologies into military strategy and capability. The objective of this option is to evolve the JPME Continuum to reflect the spectrum of education, while also considering career-broadening experiences to enhance workforce potential.

In updating and applying the JPME Continuum to better cater to the full spectrum of professional demands upon Defence, now and into the future, Defence should consider embedding personnel within industry and academia to gain early experience with the spectrum of enabling technologies that support capability development.

Defence and industry technical workforce. There is a paucity of suitably qualified and experienced technical personnel within Australia able to design, manufacture, integrate and maintain swarm and swarm-related technologies (see Part Two for a detailed discussion). This situation could present a substantial barrier to Defence's ability to adopt advanced technologies for in-service use. The objective of this option is to build capacity for the Defence and industry technical workforce. This option could see Defence establish additional technical degree and traineeship roles, at both civilian and military institutions, with guaranteed employment pathways upon completion of education programs. When considered in conjunction with the Defence applied workforce, education efficiencies could be achieved such as throughput scaling, as well as the development of a shared understanding between those designing systems and the end users employing a swarm capability. Expanding this aperture further could see agreements for common education establishments between Defence and partner nations. Existing arrangements like The Technical Cooperation Program (TTCP) and similar collaboration mechanisms could enable rapid workforce generation.

Counter-swarming. Defence will need to consider how an adversary will attempt to defeat a future swarm capability with various kinetic and non-kinetic countermeasures, across multiple domains. Such measures could identify if an agent is compromised, such as a swarm member negatively influencing the achievement of an objective. Through these lenses, novel countermeasures will be necessary to scale beyond current physical kinetic and non-kinetic approaches toward alternative methods. These may include shepherding and injection attack agents, which aim to directly exploit adversarial swarm mechanics (Hepworth et al., 2020). It is notable that research indicates that high-cost loitering interceptors and focused energy weapons are likely to be ineffective against future swarm capabilities (Diukman, 2012). The objective of this option is to identify technical methods irrespective of the technology stack to counter possible or likely future operational swarm capability TTPs. To ensure Defence has relevant technology options to apply in future warfighting scenarios, domain-specific research could be conducted on swarm countermeasures and counter-countermeasures. The TTCP offers a readily available mechanism to lead on this and doctrine experimentation efforts, having completed like bodies of work for distinct capabilities previously.

Sponsorship of enduring international efforts. This option seeks to partner with the international community, supported by the apportionment of resources and personnel, to address gaps, advance Defence priorities, and generate coalition-level capability. The objective of this option is to inform future capability development as a risk-reduction activity. By describing common technical specifications (shared platforms, hardware, software), interoperability objectives (independent and shared CONOPS), and TTPs, this option informs and de-risks future choices and decisions about swarming capability; leverages focused efforts on counter-swarming for near-term defence of assets; and accelerates swarm operational effectiveness.

Doctrine and TTP experimentation. For both swarm and counter-swarm systems, limited industry capacity may lead to few opportunities to develop Defence operational concepts and TTPs. In addressing this deficiency, Defence could consider prioritising service and joint experimentation campaigns which seek to generate strategy, capability, and force design principles. The objective of this option is to develop swarm and counter-swarm capability, strategy and TTPs for the objective Force.

This option could be achieved through engagement with strategic research partners, based in Australia and internationally, to establish a baseline for strategy-based research requirements. These include the conduct of operations (simulation-based analytical wargame scenarios, and exercises), applying doctrine from strategy-based research outcomes; collaboration with partner nation research institutions to conduct simulations of the doctrine to determine levels of effectiveness for allied operations; and partnering with industry to develop education and technology resources for defence and allied research.

Conclusions

As the adoption of new technology capabilities continues, both in the Pacific region and internationally, Defence must ensure that it has properly considered their potential impacts on our current capability portfolio. This task presents a significant challenge to ensure that the future capability and capacity mix meets the needs of the Objective Force and the spectrum of missions it may be assigned. Defence has already acknowledged the potential of swarm capabilities to generate a substantial warfighting mass that few, if any, of the extant capabilities could deliver. As new capabilities are deployed within Australia's near region which exploit the inherent advantages of swarm capabilities, Defence must consider how best to generate a capability overmatch for these technologies to mitigate the risk of unforeseen asset loss.

For Defence to effectively develop and deploy swarm and counter-swarm capabilities to achieve operational outcomes, it is essential to understand the current technology's limitations, as well as its future potential. This paper contributes to developing this understanding by examining the current state of global swarm and counter-swarm research efforts and technologies, reviewing current Australian industry capability and capacity, and exploring partner nation achievements. Based on this analysis, the paper has identified barriers to swarm capability adoption by Defence, as well as proposing potential feasible options to mitigate them. It is evident that Defence's capacity to capitalise on the operational potential of swarm and counter-swarm capabilities will require the adoption of new strategies, policies and procedures that support their design, development, and integration for a military context. Importantly, it will also require that Defence establish the means to raise, train and sustain a workforce capable of exploiting the technology for our national advantage.

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