A Cyber Physical Architecture for Symbiotic Multi-robot Fleet Management

Daniel Mitchell, Yue Gu, Jamie Blanche, Samuel Harper, Blair Archibald, Michele Sevegnani, and David Flynn

Abstract The Metaverse is transforming the way we interact with robots, sensors, environments, and humans, via the creation of a digital domain that is inter-operable, unified, and co-created by many collaborators. Several sectors have identified that robots are valuable for optimizing current processes. However, robotic platforms face challenges in the environments they are deployed in, requiring a diverse range of capabilities and roles. A Multi-robot (MR) fleet presents opportunities via the leverage of attributes of diverse robot types. Symbiotic interactions are established via collaborative robotics for the completion of objectives and ensuring mission resilience. The Metaverse provides distinct opportunities for a human-in-the-loop to engage with an MR-fleet via cyber physical platforms including simulation and mixed reality. This chapter presents a Symbiotic Multi-Robot Fleet (SMuRF) and Operational Decision Support Interface (ODSI) which co-ordinates the orchestration and deployment of an MR team within an autonomous inspection, maintenance and repair mission, and where the ODSI provides a human-in-the-loop with a holistic overview of the robotic platforms at run-time. In addition, we demonstrate how formal methods, in the form of probabilistic models to address mission success probabilities, can be verified during run-time alongside the SMuRF. This improves

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Y. Cai et al. (eds.), *Virtual and Augmented Reality Technology-Enhanced Learning*, Gaming Media and Social Effects, https://doi.org/10.1007/978-981-96-2332-7_17

overall situational awareness and validates decisions made by the human operator in real-time and in advance of an autonomous mission to provide foresight.

Keywords Cyber-physical system · Multi-robot fleet · simulation · mixed reality

1 Introduction

Humanity is responding to several challenges which can be tackled if we improve the productivity, safety and resilience for autonomous systems. These challenges include: (A) the global climate crisis where robots are being designed to inspect, maintain and repair the complex renewable assets via autonomous deployments. (B) Operation and maintenance challenges in nuclear facilities and decommissioning of legacy facilities to ensure the safety of human workforce and examine/explore areas which may be subject to radioactive chemicals. (C) How the metaverse can be used to improve procedures and evaluation in healthcare. (D) How customers can improve their interactions with products within the Metaverse and real world. Several opportunities are created within cyber physical systems (CPS) to improve current procedures that exist within the software (cyber component) and hardware (physical component) of the systems.

Of the previously discussed overhead challenges, next we discuss more focused challenges inhibiting regular deployments. Current robot deployments include individual platforms within specific short-term inspection and maintenance activities all within controlled environments. Whilst the deployment of robotics in the field is a valid next step, this brings challenges due to the requirement for a dedicated team of at least two deployed human engineers per robot. As presented in Table 1, a human may be required for teleoperation, to intervene when challenges are faced and also in the analyzation of engineering results [1–3]. These different tasks all represent different skillsets which can be trained but also require years of experience (e.g. validation of inspection). Intervention may seem like an easy solution; however, when the robots are positioned in dangerous environments, this creates substantial risks [2]. For example, if a robot faces a challenge in a confined space and a human is required to rectify sensed and unsensed problems which inhibit mission completion. A risk assessment would be required for the confined space and robot, a human would be required to intervene and an additional human would be required to be on standby to help if anything went wrong. However, these dangerous scenarios can also include working at height and radioactive environments too. To summarize, the deployment of robots should not present an additional operational hazard, which detracts from human productivity, therefore, autonomy within inspection missions require operational governance. This is important for even the most basic mission in the real world alongside the ability for a robot to complete a range of functional tasks according to its capability.

The Metaverse unlocks opportunities that can benefit from dynamic, real-time and remote interaction across a host of different digital models and technologies

Table 1 List of different human roles required during a single teleoperated robotic inspection mission

Human role	Description	Problem
Teleoperation	To teleoperate the robot into position to complete inspection	This leads to three distinct roles which require different training for the deployment of a robot (1) Learning how to teleoperate a robot safely (2) Years of experience learning about inspection faults (3) Safe human intervention and accessing potentially dangerous areas (confined space training)
Engineering expertise	To validate the inspection or re-pair process via their engineering knowledge	
Intervention	To assist the robot in overcoming challenges when these are faced. These can include trip hazards, reliability failure, mapping failure, etc.	

[4]. This creates an ecosystem which is agnostic to digital technology, models and methods of interaction with the aim to enhance individual and collective human-team experiences [5, 6]. Digital twins is a method currently in development within the robotics community which can be further enhanced by the metaverse [7]. There are different types including digital model, shadows and twins [8]. Within this, we also have different levels of functionality and intelligence which is all driven by the capability challenge in addressing operational decision-making, planning and knowledge capture [9]. In summary, the digital twin acts as an information integrator to enable and enhance operational decision-making for a digital representation of an in design or real-world asset. This can improve validation, verification, reduce costs and risks whilst maximizing the exploration of different factors.

In relation to robotics, the metaverse promotes opportunities to further develop the relationships which occur across humans, digital twins and robotic platforms. In the example where there is a facility where robots are used for operation and maintenance. The metaverse enhances the digital version of the real asset where a human can interact and view real data of an asset and compare this with the digital version as shown in Fig. 1. This allows the human observer to 'teleport' to different areas of the digital plant seamlessly to view different areas with adaptability between a holistic and close-up view of the facility. The digital twin also allows for increases in productivity. Current procedures can be easily adapted to validate and verify different approaches to view for productivity, efficiency and safety improvements. This allows for these approaches to be verified ahead of running them onboard the real asset.

The connection of robots to the metaverse promotes agile systems and approaches, enabling smart nuclear, smart warehouses, novel medical applications and agile energy infrastructure. How each sector utilizes the metaverse will differ in terms of lists of priorities. However, as robots and autonomous systems are iteratively introduced into current procedures, the key metrics will remain the same. These include the following:

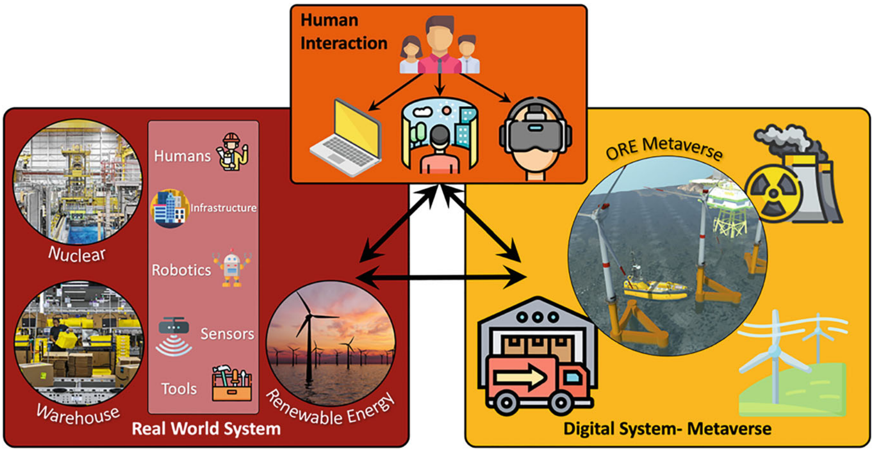

Fig. 1 Representation of the key components linked to the digital system in the Metaverse consisting of real-world system, digital system and human interaction

Level of current capability—The ability of a system to complete a designed task, e.g. inspection, maintenance or repair.
Type of deployment—Levels of autonomy from fully autonomous to teleoperation [10].
Metrics to gauge value—Validation of the value created for operators when handing over systems for operations can be measured in cost reductions, safety, resilience and productivity improvements.

This paper aims to enable for an improved understanding of the state-of-the-art to identify how the cyber and physical roadmaps converge to become a cyber physical system. Enable for improved understanding of the concepts required to improve multi-robot fleets and the types of technology being applied within several sectors including nuclear, logistics, military and renewables. The chapter subheading structure can be viewed within Fig. 2.

1.1 Trends and Imperatives

The robotics market is a market which will positively disrupt sectors due to economic benefits and reduction in the intensiveness of labour [11]. Globally, the robotics market is expected to grow at a Compound Annual Growth Rate (CAGR) of 22.8% between 2021 and 2030 to reach $214.8 billion. It is expected that this growth will be established due to the adoption of artificial intelligence and robotics across defence, security, manufacturing, electronics, automotive, and healthcare domains. The industrial share of the robotics market is expected to grow at a CAGR of 14.3% from 2020 to 2027 to reach a value of $30.8 billion. In addition, within the healthcare sector,

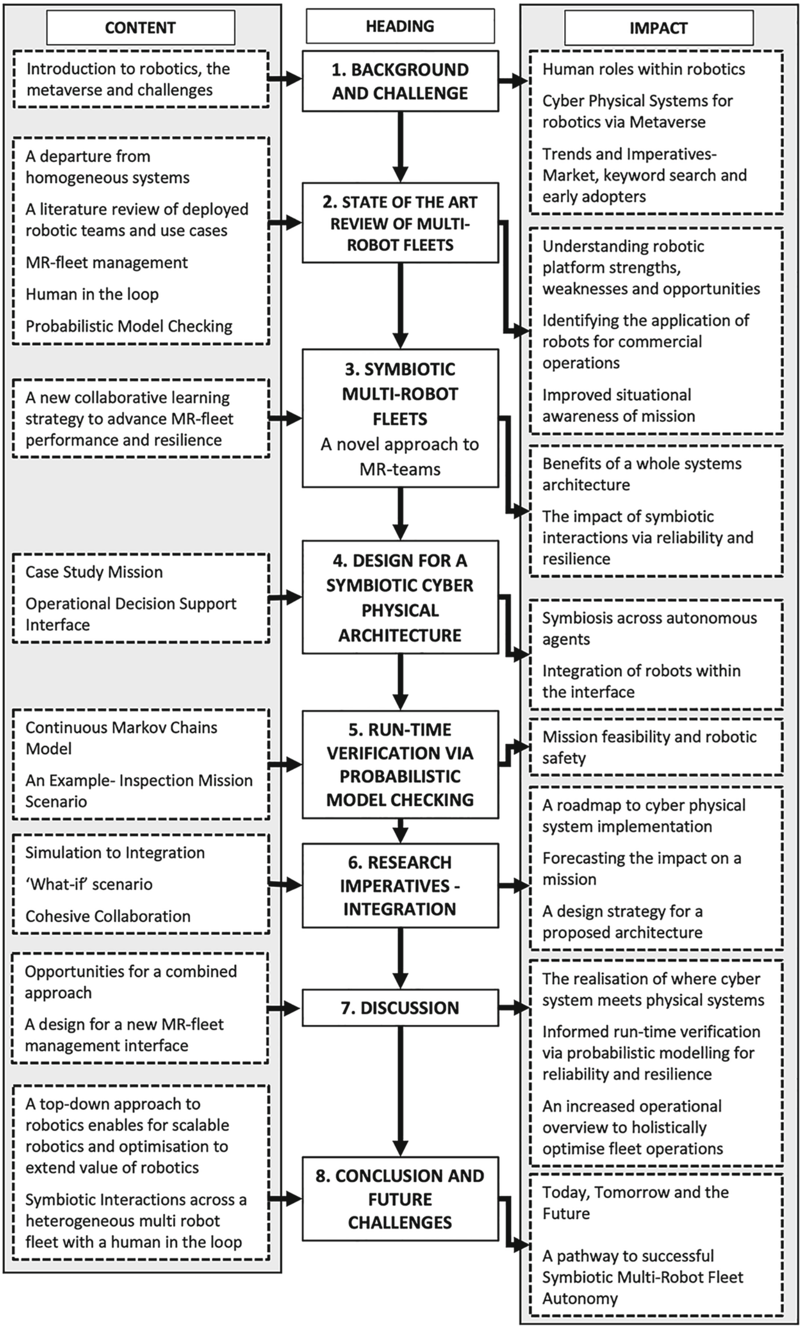

Fig. 2 Paper structure highlighting content and impact from each subheading in the chapter

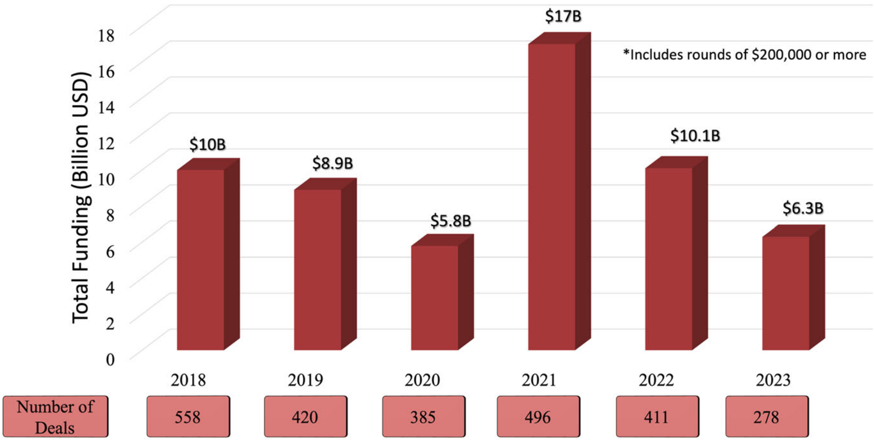

Fig. 3 Funding in robotics including pre-seed, seed and all venture rounds (last updated November 2023) [14]

surgical robots are expected to grow by 19.3% within 2022–2030 to reach $18.2 billion [12], with key developments in orthopaedics, neurology, urology and gynaecology [13]. In 2022, funding in robotics reached record highs with over $17 billion being invested in venture capital robotic start-ups. This tripled the investment when compared with 2020 as displayed within Fig. 3 [14].

A keyword search was conducted within robotics to provide valuable insights into the target applications and trends which exist within the last decade. When conducting the keyword search, Scopus was utilized to search for words within the title, abstract and keywords sections of publications. The terms included "*Robots*" AND "*keyword*", where the keywords can be identified within Fig. 4 ('*Team*', '*Swarm*', '*Multi-Robot*', '*Heterogeneous*' and '*Homogeneous*'). 'Swarm' is typically used within nature to describe a large or dense group of flying insects, however, '*swarm robotics*' is used within research as a collective term for multiples of the same ground, aerial or subsea robots, and with an approach to the coordination of the robots as a system [15]. The results of the search indicate a rise in publications in the last 5 years for '*Multi-Robot (MR)*', '*team*', '*swarm*' and '*heterogeneous robotics*'. This represents research focusing on gaps which exist in creating scalable robot teams that have value for operators to coordinate, collaborate and optimize partnerships with robots, humans and facilities. Whilst heterogeneous and homogeneous keywords are used less, this is mainly due to a collective consensus in the preference of terms which are more easily defined, especially by the wider public. Current research is oriented towards homogeneous robotics however, we identify a gap in research that exists across a diverse MR-fleet, which can include commercial off the shelf and bespoke platforms connected with a human operator to oversee activities. This will operate as human–machine teams, where the operator can designate tasks to robots and the robots can work together to complete tasks whilst updating the human-in-the-loop and allowing them to focus on more complex tasks.

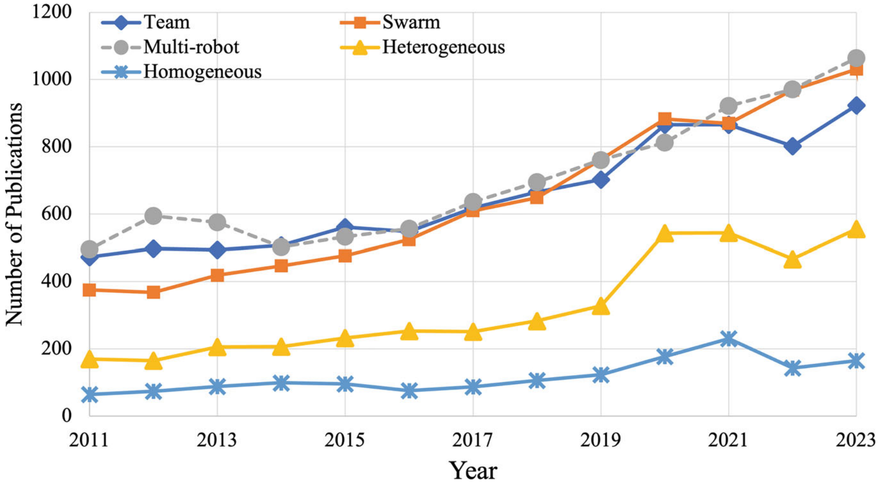

Fig. 4 Number of publications each year identified within Scopus using keyword search terms ‘robot and keyword term’ (last updated April 2024)

Early adopters within industry are taking advantage of ground-up capabilities from robots, where an MR-fleet approach is allowing them to excel within their operations. As identified in the introduction, there is a shift from single robot deployments to robots that can operate within a facility more regularly. For persistent autonomy to occur, a facility operator must remove the current requirement for a robot to be operated by a team of human operators as this removes the key value from having a robot on site in the first place. This creates opportunities in fleet management as, once a single robot is implemented within a digital twin, it can be easier to scale to multiple robots of the same type. This allows for a single dashboard where a diverse MR-fleet can be operated by a single operator to coordinate the team. Hence, the reason for an increase in publications using these keyword terms. The remainder of this subsection discusses three use cases: inspection of energy facilities, warehouse operations and the Ministry of Defence UK.

Energy Robotics

Energy Robotics represent a company which helps operators of oil and gas, chemical and power and utilities facilities to capture key information from a robotic fleet. Their aim is to improve inspection via the creation of a digital dashboard to display data (Fig. 6a) from a range of ground-based robots, including Boston Dynamics SPOT, ExR-2 and Rover robots (Fig. 6b), to complete a range of inspection tasks. These robots have a range of standard, well-proven sensors onboard, such as LiDAR, visual cameras, thermal cameras, gas sensors and microphones. Whilst each robot supports different combinations of payloads, the key objective of their service is to collect high-quality data and present this within a user interface to digitalize inspection. Case studies include the inspection of a Shell plc operated Oil Refinery in the Netherlands, where a SPOT and ExR-2 are used to complete regular routine inspection around well-defined routes [16]. This allows humans to focus on more complex tasks. Advantages of their digitalization tool are as follows:

1. Robot control: A user can manually control robots live during a mission (teleoperate).
2. Robot health status: Key status elements such as robot latency, battery %, mode of operation (driving, stopped etc.), types of sensors implemented and emergency stop.
3. Teachable inspection missions: Robots can be manually teleoperated around a route with sensors aimed at different locations throughout a route. The robot can then repeat this mission and feedback data to the digital tool.
4. Inspection reporting: An automatic report is generated for a human operator with a visual representation of robot, map and key inspection points visualized in graphs or images.

This CPS highlights key elements which are required for a human operator at a facility to extract the key value from robotics and automated systems. This identified approach highlights the key requirement for a multi-robot fleet and the management required as a fleet of robots increases around a facility. This highlights the need of the research approach within this chapter where key improvements in future could include robots which can autonomously work together to complete objectives of the mission, e.g. by sharing sensing payloads. In addition, the inclusion of more robotic platforms such as unmanned aerial vehicles (UAVs) can improve the holistic inspection of a site.

Amazon Fulfilment Centre

In 2012, Amazon announced that they would purchase Kiva Systems-which interconnect hardware and software to streamline the process of picking, packaging and shipping e-commerce products for $775 million [17]. In June 2022, Amazon announced their first autonomous warehouse robot named Proteus (Fig. 6c). This robot uses a powerful hydraulic lift to convey tall, wheeled cages containing packages around a warehouse. This allows for efficient and effective delivery of items to personnel to be sealed into cardboard boxes before postage. The robotic platforms, which are more effectively defined as swarm ground robots (several of the same robots working together to a common objective) are built and tested alongside their own diagnostics with the aim to support growth which enables more jobs due to the humans which build, support, interact and deploy them [18].

In terms of fleet management, robots and cages are spread out at random locations on the warehouse floor. There is no assigned cage specifically for each item. This reduces the amount of time it takes to get an item to the picking station on the warehouse floor. The algorithms also monitor popular items which are being sold and moves the cages with these items closer to the picking station location to allow for a reduction in time. To keep track of the robots there is a grid system on the ground using a series of QR codes which allows the units to work together to clear paths for each other to retrieve items as efficiently as possible. Cameras onboard the robots identify if any items fall out of the cages and notify a human to retrieve the objects. When things go wrong, a robot technician is permitted to enter the warehouse floor provided they are wearing a vest which sends a signal to nearby robots to stop. This allows a human to collect items which may have fell onto the shop floor or complete maintenance on the robotic platforms [19]. Whilst this may be implemented, there is no mention of how issues in robotic fleet maintenance are identified. Algorithms in future could be used to self-certify a robotic platform and ensure it can extend its remaining useful life ahead of key maintenance periods.

Ministry of Defence: British Army

The British Army released their approach to robotics and autonomous systems in 2022, which included a vision to 2035 where the central idea consists of creating an operational advantage for land forces by integrating adaptable robotic and autonomous systems within human machine teams, with the aims to generate mass and tempo (as defined in Fig. 5) whilst reducing risk [20]. This can be used to create an operational advantage in real time on the battlefield and within mission support to aid decision-making. Human machine teaming is a key element of the deployment of robots alongside soldiers (Fig. 6d, e) [21]. This will include a large amount of real-time fleet management and coordination via increased mass whilst reducing human density in close combat roles.

In September 2022, a successful deployment of swarm UAVs was conducted alongside military exercises where the soldiers themselves deployed multiple live drones. The first key result included an improvement in the regulation of UAVs as this was the first time the Military Aviation Authority issued a categorization of this

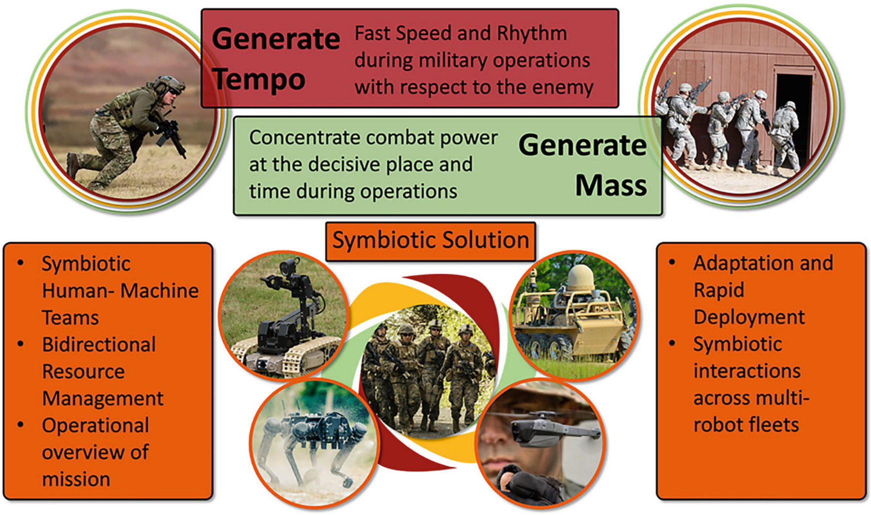

Fig. 5 Overview of key military definitions and how a symbiotic robotic approach can improve military operations

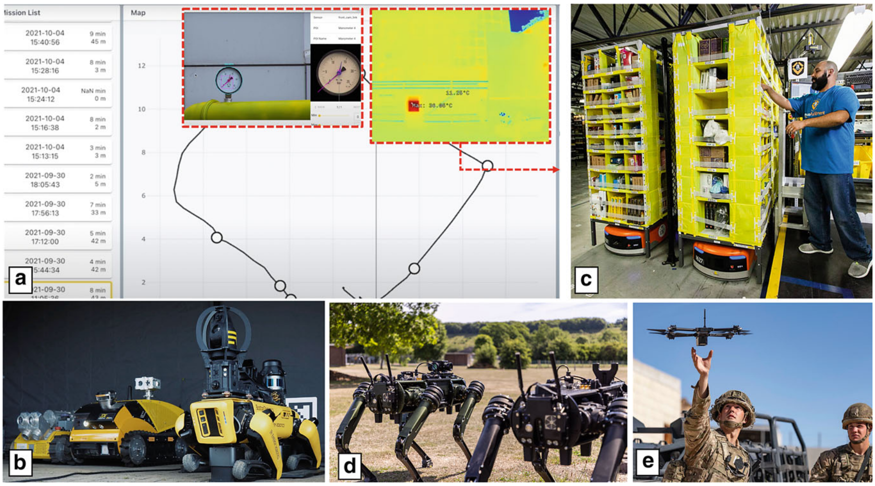

Fig. 6 Early adopters of swarms and multi-robot fleets highlighting Energy Robotics with their software interface for multi-robot fleet management (**a**) and multi-robot fleet (**b**), Amazon warehouse robots (**c**) and early tests of robotics within the British Army for reconnaissance (**d**, **e**) [16, 22–24]

type of swarm to be operated by a single operator. Of the UAVs and equipment demonstrated, the company Atlas, presented the capability for a single operator to control four drones using a tablet with the creation of manual mission taskings. Elbit Systems UK Ltd. performed a second demonstration, which included one operator having the ability to task 6 drones via autonomous missions. This allowed for an operator to task multiple drones with the same mission or various missions for the swarm [25].

Of key importance to the military is trust and explainable AI, whilst the robot is what we see visually, there are multiple algorithms, AI and data sharing occurring in the background, which allows for these robots to become effective trustworthy partnerships within a Human–Machine Team. This is where the value is created from robotics and autonomous systems. In future, we shall see more iterations of demonstrations which include autonomous ground vehicles for transport of ammunitions, UAVs for reconnaissance missions, quadruped robots completing reconnaissance ahead of soldiers and rescue evacuations via large drones [22, 23, 26–28].

2 State-of-the-Art Review of Multi-robot Fleets

2.1 Departing Homogeneity

The characteristics that define a swarm are: decentralized control, limited inter-robot communication, use of local information streams, and the emergence of global behaviour patterns. These have typically consisted of several simple robotic platforms, with swarming techniques beginning to be applied to more complex robots and fleets [29]. Applications of swarm robotics to date, however, are limited to proof-of-concept studies under highly controlled conditions. These swarms are also characterized by homogeneity of the robotic platform [30]. An MR-fleet shares many of the attributes of a swarm, but with the added advantage of the inclusion of more than one type of robotic platform. This results in a larger degree of flexibility in the MR-fleet due to the differing capabilities of the platforms used, allowing for the leveraging of capabilities for maximum benefit. With swarms and MR-fleets exhibiting relative merits, the need for resilient and trustworthy autonomy demands flexibility in operations, a criterion that is better suited to the varied capabilities of an MR-fleet.

2.2 Applications of Multi-robot Fleets

Warehouses

The use of robotics in the industrial and commercial sectors is well-established, where facilities are advancing further in warehouses designed to accommodate the needs of a robotic fleet [31]. Warehouses are excellent examples of use cases for wheeled robotic agents due to smooth concrete flooring and due to the predictable and managed operating conditions, which are optimized further to facilitate the robot operations. However, the practical application of robotic systems in unmanaged dynamic environments require run-time path planning capable of identifying a safe route for navigation through areas less suitable for robotic operations [32]. Accounting for environmental dynamism in path planning for Robotic Autonomous Systems (RAS), while an established field, places a focus on object detection and collision avoidance as part mobile Simultaneous Location And Mapping (SLAM) operations [33]. An identified area of improvement includes an emphasis on research to identify the safe passage of a robot through an area with uncertain ground conditions that would otherwise impede RAS operations.

Termed "*Robotic Mobile Fulfilment Systems*" (RMFS), robotically operated smart warehouses play a key role in maintaining the efficiency and smooth running of the logistics sector worldwide. Typical robot activities undertaken include lifting cargo pods from a pick-up area and delivery to a manual sorting station, with these missions including a MR-fleet working towards the same goals. Ensuring this efficiency drive is MR task allocation, which assigns tasks to each platform and is aimed at reducing the total cost of tasks, while also minimizing the number of robots used. Task allocations can assign multiple tasks to a single robot for consecutive execution or, for more complex objectives, instruct the platforms to form coalitions where required. At run-time, the addition of new tasks due to dynamic operational requirements can extend mission parameters and result in reallocations/re-tasking as a situation develops [34].

Offshore

The offshore energy sector is operationally complex, with high capital and operational expenditure costs associated with both the extraction/generation and transmission of energy to markets. With the energy markets currently supporting the offshore renewables sector, the offshore environment will remain a key operational area for many decades to come, with research being undertaken to optimize robotic platforms for safe and resilient offshore operations. Robotics in the offshore sector remains an emergent field, with the vast majority of research conducted focused on submarine systems that are designed to inspect and repair submarine structures, which is beyond the scope of this chapter. This section will focus on non-aquatic systems operating above the waterline, commonly termed as "*topside*".

Taurob: Designed with ATEX (equipment for potentially explosive environments) compliant electronics, Taurob has been developed, in partnership with Total, since 2019. A tracked unmanned ground vehicle (UGV) design, Taurob (Fig. 7a) was designed from inception as a mobile robotic platform for offshore platform environments for the O&G sector and is capable of climbing stairways up to 45°, while carrying a range of environmental sensors [35]. The Taurob brand has since diversified into the chemical, power generation, emergency response, security and surveillance sectors.

MIMREE/Bladebug: The Multiplatform inspection, Maintenance and Repair in Extreme Environments (MIMREE) project utilized a multi-robot system to automate the delivery and recovery of robotic inspection devices for the maintenance of offshore wind farms. The delivery system comprised of an autonomous surface vessel (ASV) and UAV, which is deployed once the ASV arrives at the offshore site.

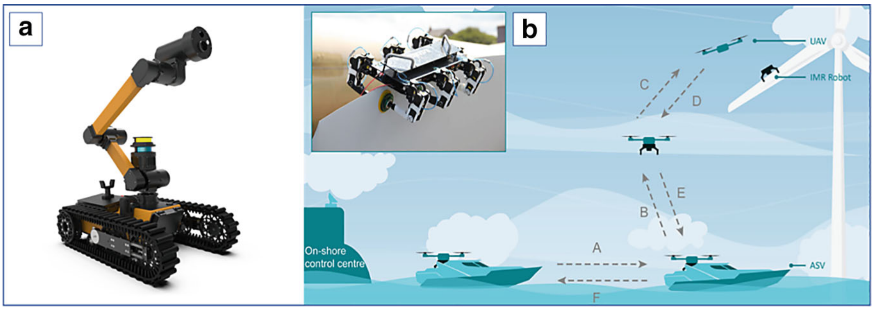

Fig. 7 **a** Taurob ATEX compliant robotic platform [36]. **b** MIMREE/Bladebug; A vacuum-based inspection robot that is delivered to a WT blade via a combination of UAV/ASV carrier robots. The Bladebug (inset) moves around the blade on an inspection mission. Adapted from [37]

The UAV, carrying the inspection robot as a payload, then delivers the payload to the site of interest. The inspection robot, Bladebug (Fig. 7b inset), is an insect-like design that utilizes vacuum pads for adhesion and locomotion. Figure 7b shows the operational process as A) the ASV and UAV deploy with the payload robot, as commanded by a remote operations centre. B) The UAV deploys with the payload robot, where it is delivered to the asset at point C). Following completion of the inspection mission, the payload robot is collected from the wind turbine blade surface at point D) and returned to the ASV at point E). The ASV is then reassigned or returns to base at point F) [37]. In the duration of this project several challenges were addressed, however, since the close of the project, Bladebug is the only outcome which has continued development and deployment [38, 39].

The ANYbotics ANYmal robot (Fig. 8) is a quadrupedal autonomous system used for proof-of-concept robotics for offshore substation/platform operations. Intended for residency on an offshore site, this system (and the similar SPOT system from Boston Dynamics) has been tested in environmental operating analogues and has also been deployed in an offshore environment [40, 41]. Though clear advancements have been made, with demonstrations given, in late 2019 to industry representatives at Port of Blyth, of quadruped, UAV, AUV, ASV and wheeled robotic designs, it is clear that these systems have not yet reached the level of non-intervention required for extended periods of autonomous offshore service [42]. Anybotics recently improved their robotic platform releasing an ANYmal X which includes ATEX-certified equipment allowing it to be operated within hazardous and potentially explosive environments. The robot has the ability to inspect using visual and thermal cameras with the ability to navigate over unstructured, complex terrains.

Consequently, in spite of the hazardous environment and high intensity labour requirements imposed by the offshore energy sector, the use of robotics systems offshore is in its infancy and limited to the inspection of offshore, subsea structures via remotely operated vehicles (with some automation but mainly teleoperation by a human operator) [36]. Ground-up improvements include improving manipulation

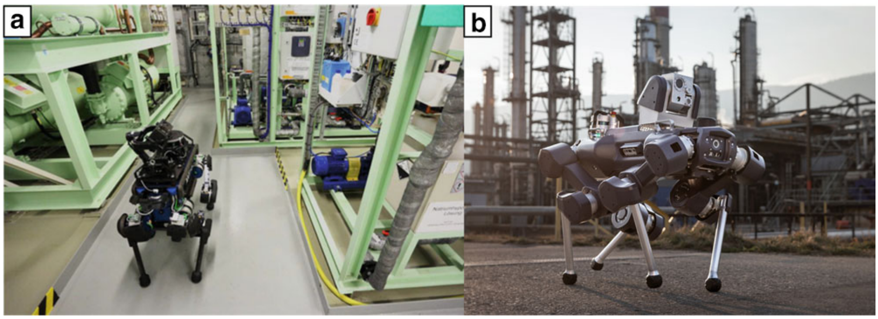

Fig. 8 ANYmal: **a** Quadrupedal system used for proof-of-concept robotics for offshore substation/platform operations [36]. **b** Anymal X Ex-certified robot [43]

activities which robots can complete alongside robots being used further for maintenance and repair activities. While research continues towards MR-fleets, resilient operations and trusted autonomy in beyond visual line of sight environments, with promising results, the nature of the high consequence environment offshore means that progress is slow. This is due to regulation in ensuring safe deployment of robotic platforms within facilities and with the capabilities from both ground-up and top-down challenges.

Nuclear

Robotics in a nuclear environment is a complex topic due to the severity of reactions when procedures are not followed. The nuclear sector has clear and well-documented origins in the wake of the worst nuclear accidents/incidents in the history of the sector [44]. It is therefore necessary to limit this discussion to mobile robotic platforms that utilize autonomy, rather than teleoperation, and to systems that return data other than visual/camera feeds.

The state-of-the-art in edge dynamic path planning has resulted in autonomous mobile robots that can account for uncertainty in the conditions of its operational environment, with navigational decisions made based on information from a suite of sensors [45, 46]. Costmaps, grid map representations of risk used in 2D path planning and navigation, can provide semi-autonomous systems with awareness of the position of static and mobile obstacles in an environment using sensors, such as Lidar or depth cameras [47]. Path planning algorithms then use this information to avoid areas where a collision may occur [48]. This costmap approach provides robots with a spatially resolved representation of risk, which can be expanded to a range of sensing modalities and threats. An example is the integration of ionizing radiation sensing with UGVs to map radiation levels in deployment areas where human presence is denied due to the radioactive environment [49]. This places greater emphasis on edge sensing to both detect and map high-risk areas, in addition to safeguarding the robotic platform by preventing a condition of irretrievable failure. The consequent evasion of highly localized radiation levels improves mission resilience and advances the RAS capacity for non-intervention in a hazardous environment.

2.3 Fleet Management

A multi-robot fleet is a relatively new concept due to the approaches from roboticists and engineers when addressing challenges. Many approaches look to design methods for ground-up capabilities which include aspects of the capabilities of robots, such as traversing difficult terrain, manipulation of valves, identification of data within gauges and teleoperation of robotic platforms. However, a new approach is required which creates additional value when these ground-up capabilities are regularly deployed within a facility, which includes fleet management and task coordination of a diverse multi-robot fleet to capture the true value and optimization.

This can be especially difficult as designers of robotic platforms often work in independent silos, making it difficult to orchestrate robots in shared environments and monitor multiple robots within a single systems view [50–52].

The operation of multiple robots within a mission space requires coordination and monitoring. These tasks are typically performed by a Fleet Management System (FMS), which is a centralized control system that issues commands and processes communications to and from robotic elements within a fleet or swarm [53, 54]. The role of the FMS (and similar systems) is to enable optimized task allocation to the fleet/swarm to reduce cost, energy expenditure and increase productivity for a given set of mission objectives [34, 55–57]. As discussed earlier, Energy Robotics utilize an FMS where data can be visualized within this system alongside the deployment of the robotic platforms also. Formant also presents an FMS for robotic platforms which can access robotic software development kits to allow for autonomous missions and teleoperation of a robotic fleet. Their interface can be summarized under operation (remote control of a robot), analytics (data management) and observe [58, 59]. However, in general for all RAS, it can be said that autonomy in its current form is unable to solve all problems and often requires human intervention when circumstances leave the autonomy envelope. This leads to human-in-the-loop optimization.

2.4 Human in the Loop

The human-in-the-loop (HITL) represents a pathway to the real world, where a robot (or fleet) is operating in a particular environment to perform a task or set of tasks, with a virtual world model (a digital twin) of the operating area detailing information gathered by the robot on mission parameters and the operating space. Under a fully autonomous paradigm, the robotic fleet will be given instructions via the Digital Twin (DT), and any amendments to mission planning or task allocation are issued by the DT [60].

The realities of commercial and industrial deployments of robotic fleets in warehouses, such as those optimized for robotic systems at Amazon, Nimble, Plus One, Waymo and Zoox, are such that impediments to task progress, and where robots are deemed to be at risk, require human intervention by a teleoperator/HITL to rectify. Using machine learning and AI, it is possible to train a robot fleet to improve its operational efficiency by self-correcting for common problems without the need for repetitive human interventions. This optimizes the use of HITL time and focus for less common errors [61].

As such, optimization of HITL time has become a priority in autonomy research and incorporates advances in perception capability to improve the accuracy and fidelity of human–robot interaction. The future of industrial autonomy will require significant levels of fleet automation to remain flexible and adaptable enough to maintain task efficiency, even when conditions depart those optimized for operations [62]. This is especially important to enable market growth by increasing the speed of

MR-fleet operation, while lowering operating costs. Thus, collaborative autonomy in dynamic and less predictable operating conditions, including the presence of humans, will continue to be a major research imperative for robotics [63, 64].

Whilst a human would be able to validate the success of a mission, as MR-fleets become larger, it is more effective for probabilistic modelling to validate and verify mission success in real time. This allows a human operator to focus on more complex tasks and as artificial intelligence is better suited to cognitively validate the rate of success of a mission. Additional benefits also include human factors where a human may disregard the state of a robotic platform to perform a mission (even though it is damaged etc.) to ensure that they meet targets, etc. Therefore, probabilistic modelling ensures that a fleet is used properly and responsibly.

2.5 Probabilistic Model Checking

Despite the advantages of multi-robot fleets, the increased complexity in unknown environments makes it difficult to reason about and guarantee the properties of the overall system when deploying robots in critical missions (e.g. inspections). Human operators are often paired with the robot fleets to improve the decision-making but only if the operator maintains situational awareness—understanding of the current state—as well as anticipating future states of the system and the environment [65]. Previous studies have shown that a strong awareness significantly improves human performance [66], while humans with poor awareness may have problems detecting and intervening in abnormal behaviours of robots [67, 68].

Formal methods that use mathematical models for the analysis and verification of systems have been widely applied to support the development of software and hardware systems, such as data refinements, code verification, and industrial applications [69]. Model checking is a formal technique to assess whether a given system satisfies certain properties. It has been used to provide insights into multi-robot systems (e.g. swarms) and analyzes the robustness [70] (e.g. fault-tolerance in robotic swarms) and security [71] (e.g. verification of security protocols in multi-agent systems). Considering the probabilistic nature of real systems, such as unpredictable failures, probabilistic model checking is designed to formally verify stochastic systems against quantitative properties. A typical approach to solving the probabilistic model checking problem involves the construction of mathematical models of the system (i.e. possible system states, transitions between states and the likelihood of these transitions) and an iterative examination of all possible executions of the system model to compute the exact numerical measure [72].

Many tools have been developed to perform probabilistic model checking. For example, PRISM [73] supports different types of mathematical models, including discrete-time Markov chains (DTMCs), Markov decision processes (MDPs) and continuous-time Markov chains (CTMCs). It is applicable and expressive enough to perform an exhaustive analysis of the system under study [73]. A core component of PRISM is a probabilistic model checker that quantifies all possible behaviours of a system, e.g. asking the probability that a system succeeds. It has been successfully used in a wide range of domains, from real-time probabilistic communication protocols (e.g. IEEE 802.3 CSMA/CD [74]) to biological systems (e.g. complex biological pathways [72].

Instead of verifying a system before deployment, run-time monitoring [75], also known as run-time verification, uses formal methods to dynamically analyze the execution traces that a system generates at run-time. It has grown actively in the last decades and numerous practical tools have emerged. Falcone et al. compare and classify 60 tools in different dimensions, including their specifications and deployment [76]. Current tools rely on two main activities to perform the verification: creating monitors from specifications and receiving observations (system state updates) from the monitored system [77]. Monitors are static, once created and only the observations are updated at run time. These tools are broadly applied to verify agent-level properties, e.g. safety, but it is challenging to analyze mission-level properties, such as the success of human-in-the-loop system, where the system evolves over human interactions.

In this work, we investigate using run-time probabilistic model checking to model and analyze mission-level properties when human operators are in the loop. We allow formal models to evolve at run time to account for system dynamics and human interactions. The models are then used to perform model checking against properties of interest. By modelling, we don't only monitor the process, but also predict the possible effects of interactions to improve situational awareness. Our previous studies have applied similar techniques to predict failures in a multi-sensor lift system [78] and to provide valuable insight into the delivery mission of the UAV swarm [79]. We specifically focus on the human factors: how human interventions might affect the running system (and hence model checking results) and how the formal information aids human operators in making decisions. In our latest work, a user study was conducted on the UAV swarm scenario and showed that the formal information increased human-swarm performance without affecting the workload and system usability [80].

3 Symbiotic Multi-robot Fleets

As identified in the trends and imperatives section, there exist trends to reach regular autonomous deployment. These include MR teams and increased human–robot interaction via agile cyber physical systems. Robots are currently being deployed as single robots for single use cases such as within an inspection role. As facilities continue to realize the potential of robotics, there will be an increasing number of robots and types of robots being deployed within operational facilities sector-wide. To further enable the value from robotics this will require several methods for humans to interact with robotic platforms, autonomous systems and other types of sensors. Cyber physical systems will allow for digital tools to: synchronously allow for query-based logic, adapt missions and work alongside robots to increase productivity by allowing humans to work on more complex tasks.

To achieve this, key steps include MR-fleets which can be considered as a wide range of robots (quadruped, wheeled, UAV, amphibious vehicles etc.), deployed to complete O&M activities as individual robots or partnered together. To realize this ambition, there will be necessary steps for resilient robots which can autonomously overcome day-to-day challenges due to environmental conditions such as terrain, weather conditions and mission profiles. Reliability will also be a key component of MR-fleet management, where robots are capable of self-certification of onboard systems to validate safety procedures. Additionally, MR-fleet management allows for humans to allocate tasks and coordinate the autonomous MR-fleet to ensure productivity [81].

A Symbiotic Multi-Robot Fleet (SMuRF) provides a new collaborative learning strategy to advance robot team performance and resilience for autonomous missions. This also features improvements in cyber physical coordination, management and deployment of MR-fleets via a holistic system of systems approach. A whole systems architecture is presented within Fig. 9, which includes three key layers: RAS, data and digitalization and personnel. People are core to the success of technology, this is mainly due to how they interact, communicate and ensure safe operation of both robotics and humans. Digitalization of a cyber physical system allows for personnel to visualize and co-create, resulting in a partnerships across human–machine teams. This also establishes increased visualization, where remote operators can access key information to visualize the robot within the environment and to interact effectively with autonomous missions. Data is a powerful tool within a CPS, and where inaccurate data can result in inaccuracies within a system of systems approach, especially as this feeds into autonomy. Within the RAS layer, this can be summarized alongside infrastructure, sensors, autonomy, AI and robotics. These systems have been paired together as they all require similar architectures and all feed data into the lower layers within Fig. 9. In most cases, it is often the autonomy and AI (software) which lets down the physical robotics platforms performance. Therefore, resilience and reliability within autonomy are especially important in future to ensure problems which robots face can be overcome when in an autonomous mode of deployment. Currently, many problems which autonomous systems face simply require teleoperation to overcome, therefore this would minimize this. Symbiotic interactions feature across all three segments allowing for the whole system architecture to co-create and mutually optimize missions. Examples of symbiotic interactions are discussed in the following segment.

A requirement for an effective SMuRF includes a diverse MR-fleet, where an example is displayed in Fig. 10, representing a nuclear facility. The environment displays an area which could not be fully inspected via a single robotic platform. This represents the first key motivation supporting a SMuRF, where a ground robot can be used to inspect low areas, aerial vehicles can inspect high areas and robots can work together to complete inspection objectives. To expand on teamwork, symbiosis represents the second motivation, where robots mutually benefit from cooperating with each other to complete mission objectives. This can include requesting different

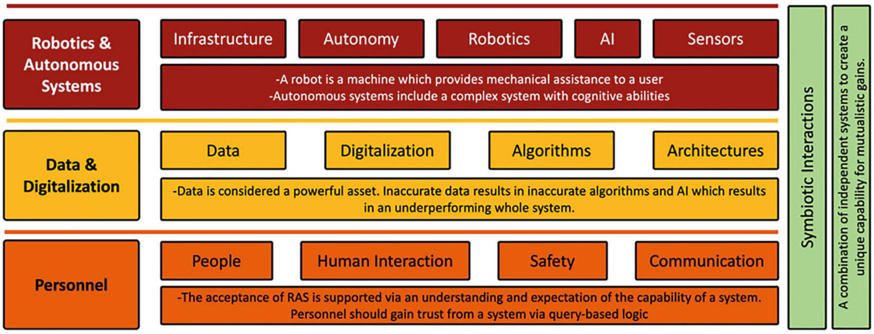

Fig. 9 Whole systems architecture featuring symbiotic interactions

robots due to different payloads to ensure the most effective inspection of an area. The third motivation includes fleet management and digitalization where robots can be coordinated via a HITL and information transfers to the human about the SMuRF missions.

Fig. 10 Composite image of a SMuRF within a nuclear setting, consisting of ground-based robots (Clearpath Husky, Boston Dynamics SPOT), aerial platforms (Intel Falcon, DJI Tello) and infrastructural sensors (Limpet sensor) [82, 83]

4 Design for a Symbiotic Cyber Physical Architecture

The transition from semi to persistent autonomy requires robots working alongside humans. These resident robots must demonstrate safety compliance and decision-making to preserve safety and maintain the trust of humans in shared and dynamic workspaces. Designing for a symbiotic CPS allows a MR-fleet to perform missions while increasing the chance of mission success through considering factors which affect the resilience and reliability of the fleet. An example of such a mission is given in the case study which follows.

4.1 *Case Study Mission*

This case study reflects a real-world scenario involving autonomous interactions in a remote, dynamic and enclosed environment. A SMuRF is tasked with a routine inspection mission on an offshore asset. This is described graphically in Fig. 11. The grey baseline mission shows this routine inspection, involving an MR-fleet inspecting different areas depending on their capabilities (e.g., at height for the UAV). Symbiosis is demonstrated through an unplanned fault deviation from the baseline, this is shown by green line, and the level of symbiosis demonstrated by the increase on the Y-Axis.

The deviation begins when a wheeled UGV experiences a low battery warning. The operator is informed of this, then the rest of the fleet moves to assist autonomously. The UAV completes a short mission to corroborate a clear path via the onboard camera, then a legged robot UGV, equipped with a manipulator arm, moves to pick up and deposit a battery before all robots return to their starting points. This interaction is designed to prove the increase in resilience provided by a SMuRF, which increases the chance of mission success.

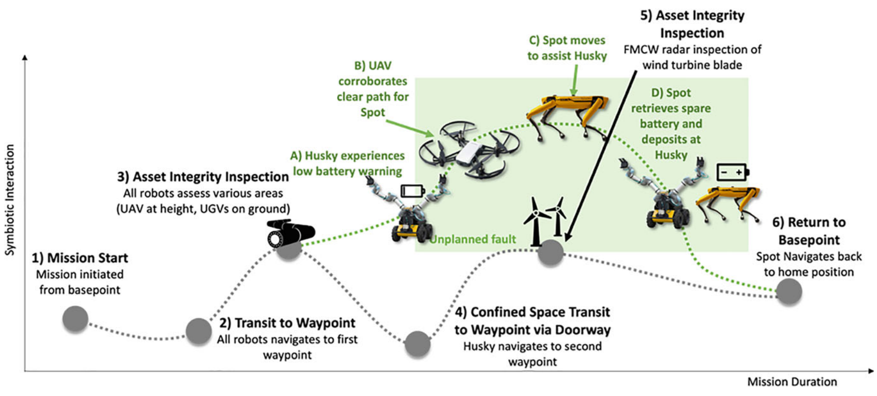

Fig. 11 Description of the MR mission plan. The grey line indicates the baseline mission, and the green line indicates the deviation upon fault detection

4.2 Operational Decision Support Interface

The Operational Decision Support Interface (ODSI) gives an operator a hyper-enabled overview of a SMuRF and allows for orchestration of the fleet. It is intended to be used as a tool to enable a human-in-the-loop to complete a successful autonomous mission with a SMuRF, via the provision of information and diagnostics on the robots in the fleet. To ensure cross-platform support across multiple devices, operating systems and input methods, the ODSI was created in Unity 2020.3.11f1. Unity allows the creation of an interface which can be adapted per-platform via layouts, text and buttons.

The ODSI allows for multimodal communications between devices and platforms, using USB, Wi-Fi and Ethernet connections. For this case study, the assets connected were as follows: DJI Tello (UAV), Boston Dynamics Spot (Quadruped UGV), Clearpath Husky (Wheeled UGV), 3 × webcams and Limpet (Multimodal sensor). A graphic depicting how these different assets were connected is shown in Fig. 12. More detail on each of these assets can be found in their relevant subsections.

The ODSI is shown in Figs. 13 and 14. All features are annotated A-J and all controls 1–15. The definitions of these are as follows:

ODSI Features:

A. Status of Husky (uptime, motor currents, battery voltages, driver temperatures, battery capacity and charge estimate)

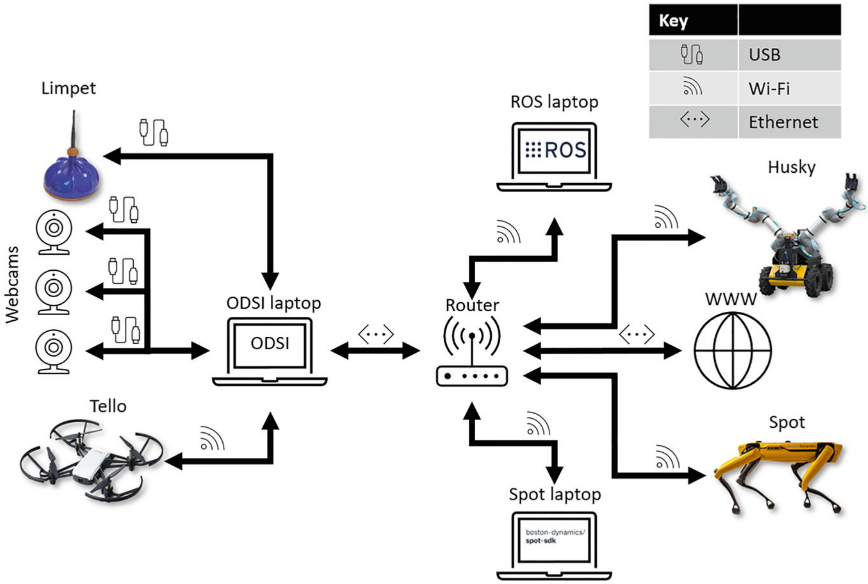

Fig. 12 Network layout of demonstration

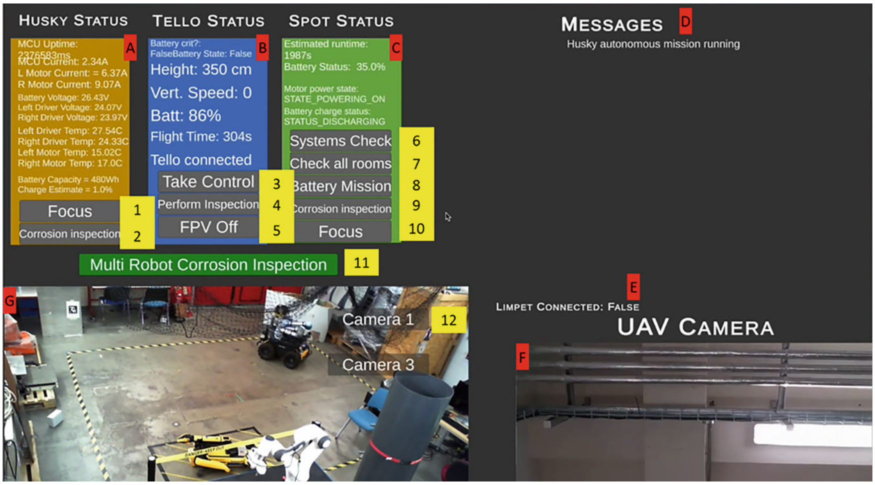

Fig. 13 Main control interface of the ODSI

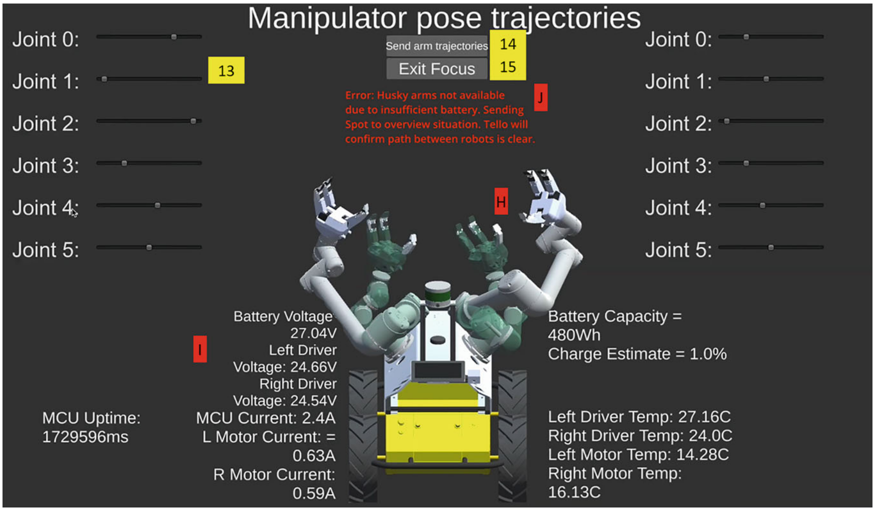

Fig. 14 Focus page of ODSI for the Husky robot

B. Status of Tello (battery criticality, battery state, height, vertical speed, battery charge, flight time and connection status)
C. Status of Spot (remaining run-time, battery charge, motor power state and battery status)
D. Messages from connected devices
E. Limpet connection status
F. Tello camera live feed

G. Webcam live feed
H. 3D model of Husky with ghost (current positions) and solid (projected positions) models
I. Status display similar to A
J. Error message sent from Husky.

ODSI Controls:

1. Focus screen for Husky
2. Perform Husky solo autonomous mission
3. Show teleoperation commands for Tello
4. Perform Tello solo autonomous mission
5. Toggle UAV Camera display (F.)
6. Perform Spot start-up sequence
7. Perform Spot room exploration mission
8. Perform Spot-Husky assistance mission
9. Perform Spot solo autonomous mission
10. Focus screen for Spot
11. Perform autonomous mission on all robots
12. Toggle camera feed
13. Manipulator joints desired positions, sliders control individual joint angles
14. Send arm trajectories to Husky
15. Exit focus screen.

4.3 Aerial Vehicle Within the SMuRF

Using a UAV within a SMuRF enables access to areas which cannot be reached by ground robots, including areas at height and over rough terrain. Additionally, the camera on a UAV allows the human operator to teleoperate and gain an overview of the work area. For use within this demonstration, a commercially available DJI Tello drone was chosen [84]. This platform has advantages in its low cost and small size allowing it to be flown indoors.

However, issues are presented with the limitations presented by the closed operating system onboard Tello and the size of the device. It is too small for any sensor payload beyond what is present on the device, consequently, the only practical application is for providing overviews of an environment through the onboard camera. Additionally, the lack of inbuilt sensors on the platform (only a height sensor and forward-facing camera) limits platform ability to perform autonomous missions that are more complex than hovering at a set height. There is also the requirement for a direct Wi-Fi communication between the operator and the UAV. Therefore, to implement the Tello within a SMuRF, accommodations must be made in the design of the network layout (see Fig. 12).

As the ODSI is built upon Unity, the '*TelloForUnity*' framework was cloned from GitHub [85]. This framework enables critical functions within ODSI for Tello, such as run-time telemetry, teleoperation and a live camera feed. It also handles communications between ODSI and the Tello through Universal Data Protocol messages.

4.4 Autonomous Ground Vehicles Within the SMuRF

A legged platform within a SMuRF allows access at ground level on uneven terrain or up/down staircases. Spot from Boston Dynamics was chosen as a commercially available platform for this operation. It is a quadrupedal robot capable of carrying a payload on its back, in this case a robotic arm which is used for manipulation of sensors and other objects [86, 87].

Limitations exist in its software accessibility—without a separate ROS PC, access to the systems of Spot is limited. A Python language Software Development Kit is provided for programming autonomous missions and functions, this was used to enable run-time communications of telemetry and mission status.

Limitations also exist in the creation of autonomous missions; Spot is capable of autonomous navigation but relies on fiducial markers placed in the environment and must be trained on a specific route through an environment before it is capable of traversing this route autonomously. Additionally, Spot must be able to locate at least one fiducial at any given time, which introduces challenges when assigning an autonomous route that passes through multiple rooms, e.g. all doors must be open for the mission. Spot is also capable of autonomous pick and place style operations with the robotic arm, but it must first be trained on the object which is to be manipulated through image recognition techniques. Each model is very large (> 5 GB) and only ensures detection in particular circumstances—the object must be at a similar angle with similar lighting in the same environment and position as the original training model.

Through these identified limitations, the scope to run a dynamic mission with Spot is narrow. Despite these limitations, the platform can still be used for routine inspection missions and assistance of other robots, e.g. through battery recovery, hence its application in this SMuRF.

To handle communications between Spot and the ODSI, a laptop running the Spot SDK in Python was connected to Spot through Wi-Fi. This laptop was, in turn, running a Python TCP client to send information to the TCP server in the ODSI. This allowed the ODSI to send commands to Spot and receive run-time telemetry information.

Wheeled platforms within SMuRFs allow access to confined spaces at ground level and have enhanced payload capability for sensors and manipulators. For this application, a Clearpath Husky was chosen as a commercially available platform. The Husky is equipped with a variety of positional and visual sensors, as well as two Universal Robotics UR-5 manipulators for various tasks [88].

Husky has advantages in terms of having an open software base, using the standard ROS system on its onboard computer. This gives the platform more flexibility in how it is implemented, and as a result means complex autonomous missions can be planned and executed. An additional advantage of this is it is possible to simulate failure modes to trigger recovery missions. The limitations of the platform are physical—it is unable to cross uneven terrain or inspect at height, additionally it is the heaviest of the three robots.

To enable autonomous navigation for this study, a laptop was connected to Husky via Wi-Fi to act as the ROSCore, to avoid making possible breaking changes to the platform's onboard computer. This laptop was in turn connected to the same Wi-Fi network as the ODSI. Communications between ROS and the ODSI were handled by a custom Python script. Unity has the capability of accepting a ROS connection, however the messages are large and frequent and contain information not necessary for the operations performed in this demonstration. Therefore, the custom client script will only send relevant robotic telemetry and mission started/stopped indicators.

4.5 Providing Overview for a Human in the Loop

To enable operator overview of the mission environment, USB webcams were deployed. The video feed from these can be switched in the ODSI.

A critical aspect of any SMuRF is the inclusion of infrastructural sensing. This can inform robotic decision-making through the early detection of adverse conditions. Limpet is an ROS-enabled integrated sensor platform for infrastructural condition monitoring, and was designed for mass production at low cost, allowing for deployment in an operating area in large collectives to monitor the environmental conditions on offshore installations [89]. Typically affixed to infrastructure via magnets, the Limpet has a robust protective housing to enable operation in harsh environments. It contains sensors for; time-of-flight, sound, pressure, temperature, humidity, hall-effect, acceleration, angular velocity and optics. The sensing module is inside a weather and impact proof shell for environmental protection and has an integrated magnet and sticking strip for attaching to surfaces. Consequently, the Limpet platform, albeit not a mobile robot, is useful for signal relay, navigation fidelity and situational/environmental awareness.

For this study, the Limpet is connected to the ODSI via a USB cable and communicates over a serial connection. This enables environmental effects to impact the SMuRF decision-making.

5 Run-Time Verification via Probabilistic Model Checking

Given the case study above, we focus on an example scenario to show how the probabilistic model checking can reason about the system and provide valuable insights into the mission at run time. We model the scenarios of each individual robot in the fleet and the operator's actions. As illustrated in Fig. 15, Husky operates to explore

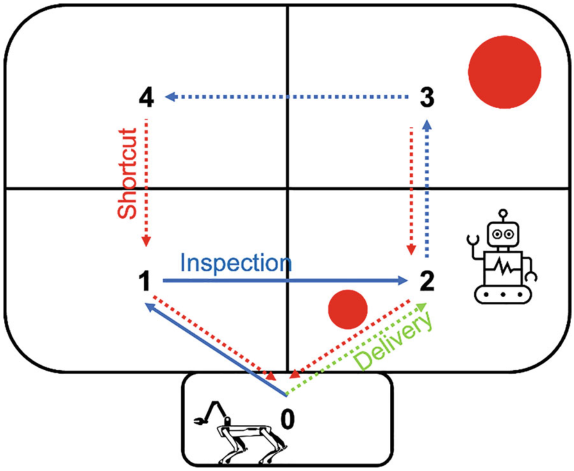

Fig. 15 Example scenario of the abstracted inspection mission: The continuous environment is discretized into a **2 × 2 grid** with numbered cells (0 being the **base** station, where robots are on standby.) Each cell might contain obstacles (**red** objects) with different sizes. Robots follow the pre-designed paths to perform **inspection**, **delivery** new batteries and return to base via **shortcuts**

the environment and identify obstacles whilst Spot is on standby to deliver batteries for Husky when there is a battery failure, or the operator asks to do so. We count the inspection as completed when Husky inspects all regions within the environment and all robots in the fleet safely return to the base station.

5.1 Continuous Markov Chains Model

As the multi-robot fleet operates in continuous environments, we take the form of (labelled) Continuous Markov chains (CTMCs) as our model. A CTMC is a triple $C = (S, R, L)$, where S is a finite set of states with a designated initial state, $R : S \times S \rightarrow \mathbb{R}_{\geq 0}$ is a rate matrix that represents a set of non-negative real numbers, and $L : S \rightarrow 2^{AP}$ is a label function that assigns atomic predicates with states, e.g. $s \mapsto \{\text{success}\}$. A transition occurs between two states s and s' only when rate $\lambda\big(s, s'\big) > 0$, in which case the probability of this transition being triggered within t time units equals to $1 - e^{-\lambda(s,s')\cdot t}$. Thus, transitions with higher rates occur more often. If $\lambda\big(s, s'\big) > 0$ holds for more than one state s', there exists a race between outgoing transitions from state s.

Rather than directly build a CTMC, we use the PRISM modelling language [73], a state-based language based on reactive modules [90], that supports high-level specification of processes. Processes are represented by modules consisting of non-deterministic choice over action-labelled guarded commands (which denote transitions); modules are composed of all common actions.

5.2 Properties

Properties of interest in PRISM are represented as an extension of the Continuous Stochastic Logic (CSL) [91], which is a temporal logic with probabilistic operators. In this work, we focus on the *eventually* temporal operator, that examines, for all paths, if a state labelled where is true can be eventually reached. PRISM allows us to quantify the properties via an operator that determines, not if a path exists where is true, but the *likelihood* of this being the case. A time boundary can also be added to require to be true within time units (domain-dependent, e.g. hours, minutes or seconds) through.

An essential property of the mission is *feasibility*, that is, how likely the inspection is to succeed based on the current state of the MR-fleet and the environment. Another important property to be concerned about is the *safety* of the robots, such as the likelihood of the robot failure over the next time units. Given the complexity and stochasticity involved during the mission, it is always difficult for operators to reach a conclusion about the feasibility and safety information by merely observing.

5.3 Implementation

As is typical in modelling, it is often necessary to abstract specific details of the scenarios, e.g. by discretizing continuous values, to maintain a meaningful trade-off between performance and accuracy. For our model, we aim to determine the likelihood that all robots make it from the base station to spatial regions and back to the base safely, where the failure can come from dead batteries or background failure (collisions etc.). Each robot has a battery level that we discretize to four values: *high*, *mid*, *low* or *critical*, similar to the method used in [92]. Batteries are charged at a fixed rate at the base. When robots are not at the base, their batteries drain at fixed rates corresponding to the current level, e.g. batteries near critical levels might discharge faster than those fully charged. A robot with a critical battery cannot continue with its current operation and needs to return to the base, and then resumes after its battery is fully charged. Meanwhile, the battery fails at a fixed rate based on its current level when robots operate outside the base, e.g. batteries near critical levels might fail more often than those fully charged. When its battery fails, a robot's movement also terminates.

As CTMCs are discrete state models (but with continuous transitions), they are not well-suited to modelling the continuous space. Therefore, to capture the movement of robots, we discretize the environment into a grid of cells, e.g. a 2×2 grid as shown in Fig. 15, allowing each cell to be identified using integers (with 0 being the base). When Husky operates inspection, it follows a pre-designed path (e.g. $0 \rightarrow 1 \rightarrow 2 \rightarrow 3 \rightarrow 4$) through all cells, and takes *shortcuts* on its way back (e.g. $4 \rightarrow 1 \rightarrow 0$, or $3 \rightarrow 2 \rightarrow 0$). Spot always moves following the shortcuts to ensure batteries can be delivered on time. Note that this can be determined ahead of time/ calculated by planning tools before running the model.

To each cell, except the base, we associate a background failure rate that captures unknown failures within that cell, e.g. hazards, and collisions, which is updated during the inspection of Husky, e.g. higher rates of failure if large obstacles are detected. Furthermore, a rate of movement determines how quickly robots move between adjacent cells, assuming higher rates for Spot than Husky in all cells.

During the inspection of Husky, the operator determines when and whether to send out Spot for delivering new batteries. Their action is modelled as the synchronization of the Husky module and the Spot module, where the process of Husky is paused to wait for the delivery process of Spot to be finished and resumed after that. We assume this synchronization always happens when the battery on Husky fails.

5.4 Example Scenario

Cells might contain obstacles with different sizes that are unknown to Husky and Spot before the inspection. The background failure rate associated with each cell is updated with knowledge of the obstacles acquired by Husky during the inspection. To show how our model can aid the operator in making decisions on whether to send out Spot to deliver new batteries for Husky, we present the following scenarios. Note that decisions can be made at any time step and the results below compare the effects with and without operator interference.

Scenario 1: Husky currently performs the inspection in cell 2, as shown in Fig. 15, and has a low battery level. Figure 16 shows how the success probability of the mission and the safety of robots change within the next time units with/without the operator request to send out Spot.
Scenario 2: Similar to Scenario 1, if Husky is currently in cell 3, the probabilities are presented in Fig. 16.

In both scenarios, sending out Spot increases the probability that Spot fails during the delivery. Especially in Scenario 2, Spot might face a high risk to fail as Husky detects a large obstacle in cell 3 and the background failure rate is increased accordingly. Therefore, sending out Spot might not be a smart choice as the success probability is already high in Scenario 2. However, it might be worth taking a small risk of losing Spot to improve the success probability in Scenario 1.

6 Research Imperatives—Integration

The previous example scenario in Sect. 5.2 serves as a template for verification of a SMuRF at run time, which means multiple robots can be involved in different tasks. As for the integration, the physical SMuRF can, at any point, provide all known

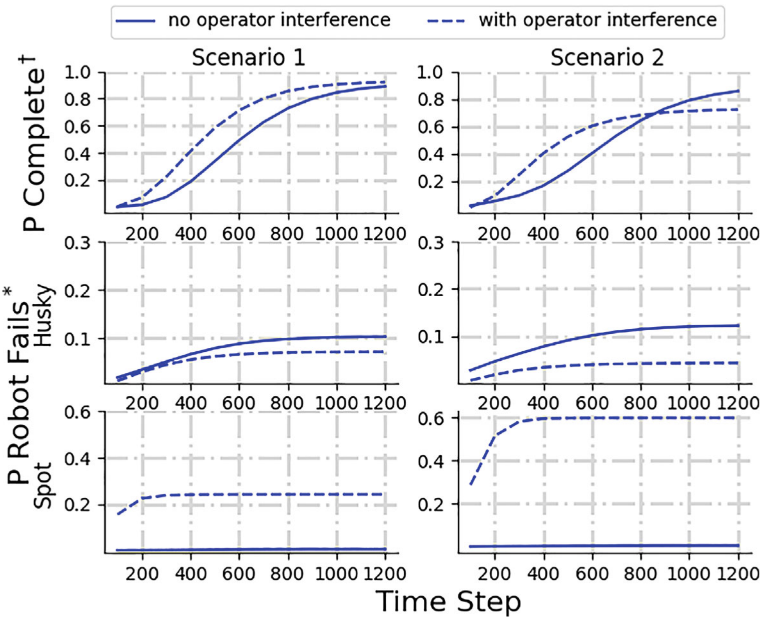

Fig. 16 Mission feasibility and robot safety: the probability changes within the next time units. Operator may interfere and ask Spot to deliver a new battery for Husky. † The probability of Husky completing the inspection and all robots being safe. * The probability of the robot failing due to the battery failure and background failures

information, including the knowledge of obstacles, and the status of robots (e.g. locations, battery levels), allowing the PRISM model to be constructed and updated accordingly and run for analysis in parallel. A key benefit of having a formal model is that we can run 'what-if' scenarios to give the operator more information before making decisions. A 'what-if' scenario can be described as a forecasted speculation about how a given situation (list of events during an autonomous mission), might occur by having a positive or negative impact on the key performance indicators of the mission. This can be displayed to an operator graphically in the interface, for example, an operator might query the trade-off between the feasibility of the mission and the safety of robots based on Fig. 16. Similarly, different what-if scenarios can be analyzed and large sets of properties can be abstracted by the upper and lower probability bounds, i.e. their envelopes of behaviour, to improve the situational awareness [93].

Future research imperatives include a symbiotic system of systems approach to enable for these technologies to work cohesively and collaboratively together [94, 95]. An overview of the systems required to achieve this is displayed in Fig. 17 where a human operator has access to a SMuRF deployed in the field. Moving from right to left, the human operator must have access to all elements of a robotic team whether deployed in the field or within simulation. To enable this at the hardware

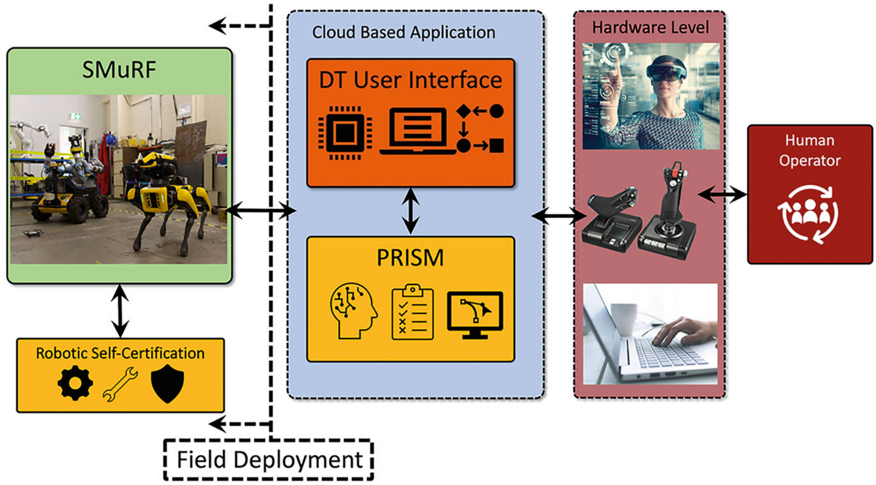

Fig. 17 Proposed design strategy of the positions of systems required where the SMuRF is deployed out in the field

level the human operator must have access to virtual reality headsets, joysticks and laptop to access the correct information. A virtual reality/augmented reality headset can enable for humans to position themselves in the digital world which can act as a representative of the real world. This can lead to improved decision-making during operations where a SMuRF is positioned remote in the field, the headsets can also act as effective tools in training and for presenting information to the human-in-the-loop in a more interactive approach [96–98]. A laptop can be used for any data analytics which is required to be done including accessing overviews from missions, completed objectives, errors, accessing cameras and other information from sensors. Finally, joysticks/controllers are effective tools for in the case where a robot is required to be teleoperated. This would be aided from a display or virtual reality headset for remote control of an autonomous vehicle [99–101].

The cloud-based application layer is where we would strategically position our digital twin in a future research imperative direction. This would be to enable several engineers to access the digital twin and to allow for add ons to be easily implemented. However, there are several definitions of digital twins available which can lead to confusion in the case of autonomous operations. There will certainly be different key performance indicators depending on the application and owner of the digital twin. As a reminder we define a digital twin as 'a software which acts as an information integrator to enable and enhance operational decision making for a digital representation of an in design or real-world asset'. The digital twin would include bidirectional information where the sensor data which the robots deployed in the field collect are transferred in real time to the digital twin to enhance the operational overview of the human operator via the relative hardware methods. This would allow for access to data related to inspection, environment and robot performance. Several add ons such as PRISM can enhance a digital twin to enable for forecasting of different events to further improve the verification and validation of a SMuRF deployed in the field.

Finally, we discuss the robots deployed in the field. Since, wireless communications in robotic missions cannot always be guaranteed, robots should have their own self-certification protocols onboard to safeguard against autonomous operation above its own physical limits, alongside cybersecurity in the case of a local threats [81, 102–105]. The robot team deployed in the field must strategically share information through each layer to the digital twin to minimize bandwidth issues, alongside inter and intra communication amongst the fleet to solve tasks related to inspection.

7 Discussion

To allow humans to focus on complex tasks, their role must adapt as robotic systems are scaled in the workplace. To date, up to three humans can be required to conduct an inspection using a mobile service robot due to the requirements to (1) teleoperate, (2) provide engineering expertise, and (3) intervene when things go wrong. This is disadvantageous due to both the cost of personnel, and increased risks from having more people working in a hazardous environment. Even as robotic platforms and autonomy improves, human roles will still be required in some scenarios, but with different approaches via different levels of autonomy, and improvements in persistent and trusted autonomy [10]. Full autonomy would be the first choice for inspection where, if the human-in-the-loop was not satisfied with results, they could teleoperate the robot to gain an improved understanding of the inspection area. This would be further enriched by metaverse applications to improve the perspective for the human via data insights [106, 107].

This chapter has investigated early adopters of multi-robot teams in industrial applications and described research areas and robotic platforms via our state-of-the-art literature review. We identified a shift away from homogeneity for inspection missions, due to the wide range of requirements that are faced in industrial environments. In many cases it is non-optimal to have a single robot to complete all inspection tasks, and the inspection capability from a diverse multi-robot fleet has substantial benefits to industrial facility operators. Human-in-the-loop remains an important feature within robotics due to the requirement to feedback information from inspections and for the human to understand the inspection mission. Probabilistic modelling was identified as an approach to allow measurements and predictions of key mission parameters which negatively impact or stop the mission. These can be simulated in advance of the real-world mission and compared against the real robot to ensure the success and recovery of a robot. A mixed SMuRF becomes even more important when considering ground, air, and subsea inspection modes.

An opportunity exists where a combination of both SMuRF and probabilistic modelling addresses resilience and reliability challenges for robots. This can be evaluated via simulation and physical robotic tests to comparatively evaluate the success rates of the robotic fleet to a number of variables which challenge the success of the mission. With a human-in-the-loop, the operator should be aware of the situation of robots and their operational environment which present critical hazards, such as working at height, weather conditions or radioactive dangers. Probabilistic modelling enables increased levels of awareness using validation and verification to present the human operator insight into the risk of future system failure. This should not overbear the operator requiring high levels of cognitive loads allowing them to easily identify whether the mission is achievable or not.

A combination of both approaches (cyber and physical) will be enhanced via the metaverse. Fleet management will enable information to be fed to advanced technologies such as virtual reality, mixed reality and augmented reality. This will reduce the requirement for laptops and mobile phones but still enable complete access. Digital twins already exist but will see significant advancement by giving humans the ability to teleport into a space for visualization purposes to oversee a mission. This data can be fed into a simulation that is representative of the environment and enhanced via real-time footage of robots corroborating the actions of the fleet.

Increased processing capabilities both onboard the robots, and via the cloud, enables a digital twin which uses informed run-time verification to inform on decision-making of autonomous systems. For example, systems should be designed so that if the mission success chance is above a set safety or reliability threshold the mission can continue automatically. Only if it falls below a set success chance, then the human-in-the-loop is notified (the mission continues, but the operator has the option to stop the mission) and if the threshold drops further then the human-in-the-loop is notified that the mission is being aborted. This enables mission critical updates to a human operator and can allow for the redesignation of tasks across a multi-robot fleet to ensure the mission is completed by another robot.

A multi-robot fleet creates opportunities for several types of missions across a myriad of sectors. However, the human-in-the-loop requires in-depth knowledge and information about each diverse robot to perform the necessary computations. This also includes the human operator having the knowledge to know which robots to deploy for different missions and know what their robotic capabilities are at the start and during the mission.

Coordinating a multi-robot fleet with a human operator requires an operational overview of facility, robotic assets and areas to be inspected. These can be accessed via a laptop or metaverse application overseen remotely by a human. Key performance indicators of the dashboard would include the following:

Task assignment: The ability for a human-in-the-loop to designate tasks to different robotic platforms via waypoints. These waypoints would include the positions of areas needing inspection. Although a human operator designates tasks, the robotic and autonomous systems would create their own decisions on how best to inspect the areas and if they are the most suitable robots to inspect the area (as in some cases the human may have deployed the wrong robot for the job).

Predicting and mitigation of failures: Robots face challenges daily which they may be able to or unable to overcome. Therefore, the autonomy in the system should be able to predict when a failure is going to occur and try to prevent the error or overcome the error once it has occurred.

Productivity: Comparisons of how other autonomous missions could be completed in parallel to the real-time autonomous mission. This would ensure that robots are operating optimally and productivity levels are maximized.

We propose a novel MR-fleet management system which could be created in the metaverse and used to oversee future robotic operations. The dashboard would incorporate sensing, robotics, infrastructural and environmental data, where the human operator can access desirable data to ensure the efficient operation of a facility. Additionally, it can display logbooks of historical results, warnings, and reliability issues within the fleet with different tabs. Figure 18 displays the design of a dashboard where the home page is displayed presenting a Clearpath Husky, Boston Dynamics SPOT and DJI Tello drone. The home screen allows for a rapid overview of the robots completing their different tasks alongside different tabs which can be opened via the top left. This displays an image of each robot, battery status, thumbnail of the navigation map/camera feed and overall mission updates.

The navigation tab is presented in Fig. 19. On the left-side a summarized view is displayed for both UAV and SPOT robots (these views can be expanded). The right-side displays a more detailed view for the Husky robotic mission. The human-in-the-loop has access to a mission summary, live feed from cameras and the option

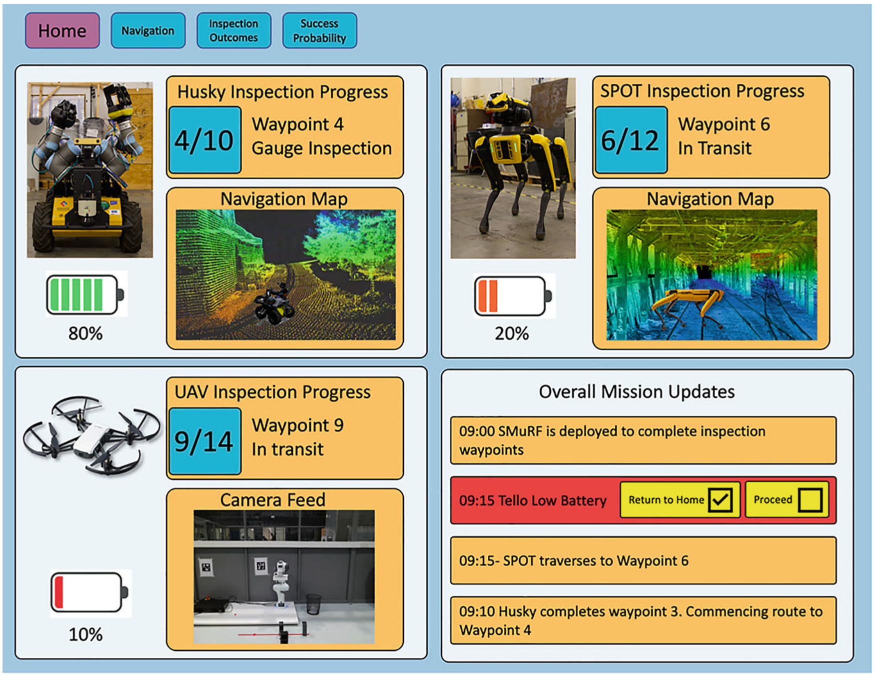

Fig. 18 Home screen tab displaying three robotic platforms and key information [108, 109]

to teleoperate if necessary. For safety purposes, each robot has an emergency stop (E-STOP) button.

The inspection tab is presented in Fig. 20 where a detailed overview of condition of inspections can be identified. The tab offers the opportunity to view warnings in a 3D environment where photographs of the inspection can be accessed. The metaverse allows for engineers to use virtual reality to inspect areas in the 3D model to ensure safe procedures can be in place ahead of rectifying issues in the real world.

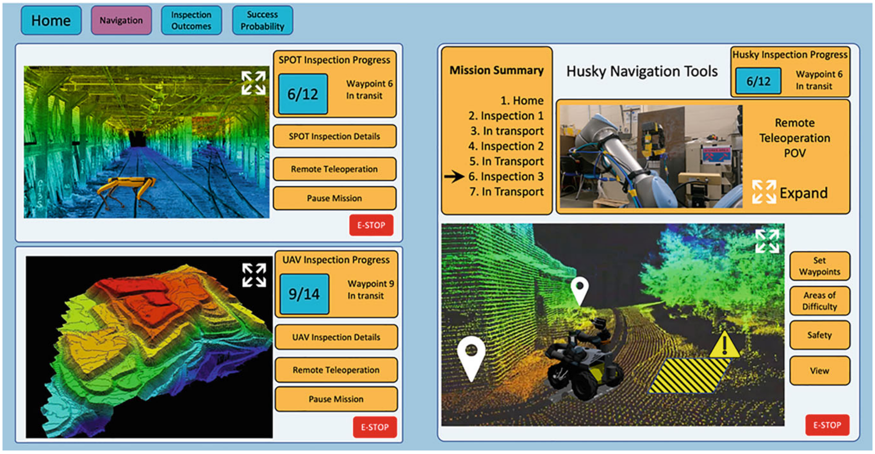

Fig. 19 Navigation tab displaying the navigation results for all of the conceptualized robotic missions [110]

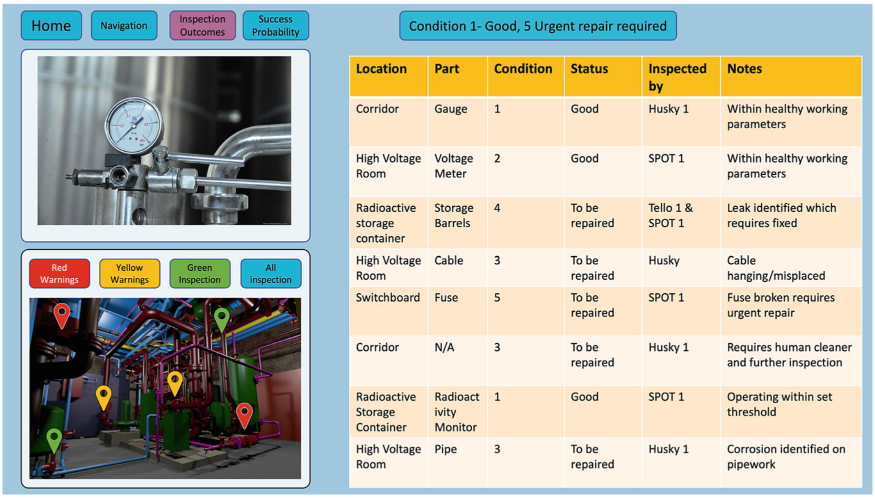

Fig. 20 Inspection outcomes tab highlighting the results from sensing methods onboard robotic platforms [111]

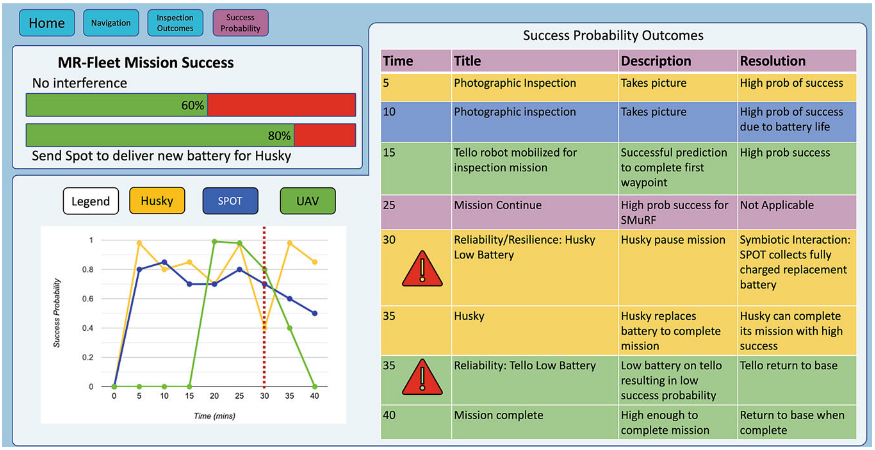

Fig. 21 Success probability tab presenting the success probabilities where the red dashed line indicates a symbiotic interaction which takes place for the Husky robot to increase the success probability of the robotic mission

The success probability tab presented in Fig. 21 gives an overview probability of the SMURF completing the mission with and without operator interferences (e.g. sending another robot for assistance). This is predicted ahead of the current process and updated at run time. Each tab for the robot presents the success probability over time using line graphs and highlights the symbiotic interaction points and other important events for the operator in a tabulated overview. Overall, the success probability dashboard gives the human-in-the-loop reassurance that the robot can complete a mission or that the robot needs task reassignment. Secondly, pressure to meet deadlines in the workplace can lead to human error via strict deadlines. This can lead to robotic failure and loss of an asset due to irresponsible management of inspection tasks resulting in extended timelines and costs. In this case, the success probability predicts the effects of possible interferences to assist the operator in making decisions.

8 Conclusions and Future Challenges

To conclude, robotics and autonomous systems are advancing rapidly in addressing improvements in capabilities required to conduct inspection (manipulation, sensing and autonomous missions). However, this improvement is limited for facility operators if they are unable to scale a couple of robotic platforms to a coordinated multi-robot fleet. This will allow for a wide range of inspections to be conducted leading to productivity improvements for both robots and human engineers who can focus on more complex tasks. Digitalization and metaverse applications are a necessary requirement in the coordination of multi-robot fleet deployments as a human must have access to high levels of interaction to gain the information they require and must not be limited by wireless communications or robot platform agility/mobility in accessing an area, e.g. attaining the required photograph or limited teleoperation due to communication bandwidths. Whilst ground-up applications of single robotic platforms are developed and deployed for different applications, the scaling includes a step to multi-robot fleets where a human-in-the-loop can coordinate a wide range of individual robotic platforms. A route towards optimized symbiotic multi-robot autonomy for today, tomorrow and the future is presented within Fig. 22. Currently, robotic platforms are teleoperated in the field with large teams of engineers to ensure they operate as intended. If a range of robots were deployed in a state-of-the-art facility, this would require a team for each robot which would not be feasible. The next advancement includes a meeting of the top-down and ground-up capability challenges where we can trust robots to operate as intended and coordinate them from a centralized interface where data can be transceived to each robot individually. The future advancement includes the symbiotic multi-robot fleet where the cognitive load on the human-in-the-loop is reduced via symbiotic interactions. This occurs when robots can request assistance to overcome challenges with resilience, reliability or safety during run-time in a mission. The creation of symbiotic multi-robot fleets where individual robotic platforms can adapt with respect to each other's mission profiles to provide assistance and improve overall mission quality. Many research and commercial parties are realizing the potential of a scaled robotic team for different applications within the nuclear and energy sectors, therefore a review on the emergent technologies and multi-robot fleets was required to improve the understanding, inform knowledge in robotics, and realize the potential in coordinating remote robots. Finally, we contribute to the state-of-the-art via the discussion of a symbiotic multi-robot fleet deployed in an offshore substation analogue scenario alongside the opportunities for probabilistic modelling to improve the reliability and resilience of autonomous missions.

Artificial intelligence is more widely being known to rapidly overcome challenges via its advantages of becoming highly adaptable in different scenarios. Some research is being conducted on robots which can learn from human engineers such as within small-scale agriculture [106] and applying artificial intelligence to robots that provide a service via communication and interaction [112]. This also has benefits for probabilistic modelling and a symbiotic multi-robot fleets. In future, this could enable to autonomous learning of how to do tasks, how to improve task accuracy and overcome resilience challenges by using the intelligence from the robotic platform. In addition to understanding and detecting cognitive overload by the human operator leading to shared control of information and key information fed to the human-in-the-loop.

This chapter provides a guide of how the metaverse can be applied to cyber physical systems for symbiotic multi-robot fleet management. An in-depth review of the state-of-the-art and how the cyber and physical roadmaps converge is discussed. Key concepts and technologies are discussed and how these can be applied to real-world applications are discussed too. Probabilistic modelling for the self-certification of robotic platforms is discussed alongside validation of mission success.

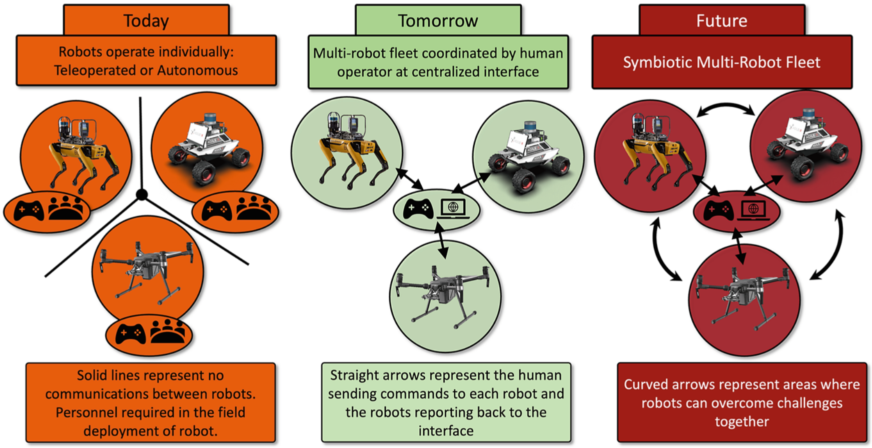

Fig. 22 Today, tomorrow and future pathway to optimized inspection and autonomy via robotics and autonomous systems

The contribution of this work provided a timely, academic-led review of cyber physical architectures for multi-robot fleets and a pathway for further development for robots conducting inspection activities in commercial, operational environments. Firstly, the background and challenge are presented where human roles within robotics and cyber physical systems via the metaverse alongside trends and imperatives for robotics are discussed. Secondly, a state-of-the-art review of robotic platforms for commercial activities and multi-robot fleets are discussed. A new approach named a symbiotic multi-robot fleet for inspection, maintenance and repair is introduced which features the whole systems architecture and discusses the key benefits of symbiotic interactions to improve reliability and resilience challenges in autonomous missions. In Sect. 4, the design for a symbiotic cyber physical architecture is presented alongside the robots which are part of the symbiotic multi-robot fleet and mission environment. Next probabilistic modelling with run-time verification is presented discussing mission feasibility and robot safety. The chapter then highlights key analysis from the chapter via a research imperatives section which focusses on the integration and a route to a cyber physical system which is deployed as a cohesive package. The discussion section is presented in Sect. 7 where the design for a novel multi-robot fleet management tool is presented to enable for multi-robot fleet coordination and overviews of autonomous missions. Finally, we present the conclusions of the book chapter.

Our work shows that most projects focus on the ground-up applications of robotic platforms (autonomous mission, manipulation, showcasing data to a human-in-the-loop) however, there is a need to realize that robots will require scaling and coordinated with a top-down view of the multi-robot fleet. To minimize cognitive overload, many decisions to overcome safety, resilience and reliability issues can be made by the autonomous systems themselves which leads to symbiotic interactions across a multi-robot fleet where information can still be fed to the human-in-the-loop via mission priorities.

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