A Multi-Robot Platform for the Autonomous Operation and Maintenance of Offshore Wind Farms

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Blue Sky Ideas Track

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ABSTRACT

With the increasing scale of offshore wind farm development, maintaining farms efficiently and safely becomes a necessity. The length of turbine downtime and the logistics for human technician transfer make up a significant proportion of the operation and maintenance (O&M) costs. To reduce such costs, future O&M infrastructures will increasingly rely on offshore autonomous robotic solutions that are capable of co-managing wind farms with human operators located onshore. In particular, unmanned aerial vehicles, autonomous surface vessels and crawling robots are expected to play important roles not only to bring down costs but also to significantly reduce the health and safety risks by assisting (or replacing) human operators in performing the most hazardous tasks. This paper portrays a visionary view in which heterogeneous robotic assets, underpinned by AI agent technology, coordinate their behavior to autonomously inspect, maintain and repair offshore wind farms over long periods of time and unstable weather conditions. They cooperate with onshore human operators, who supervise the mission at a distance, via the use of shared deliberation techniques. We highlight several challenging research directions in this context and offer ambitious ideas to tackle them as well as initial solutions.

KEYWORDS

Extreme Environments; Wind Farms; Autonomy; AI Planning; Explainability; Robotics; Multi-agency

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1 INTRODUCTION

Pressured by the need for sources of energy alternative to conventional ones (e.g. fossil fuels), there is an increasing trend of developing technology that can be used for renewable energy collection.

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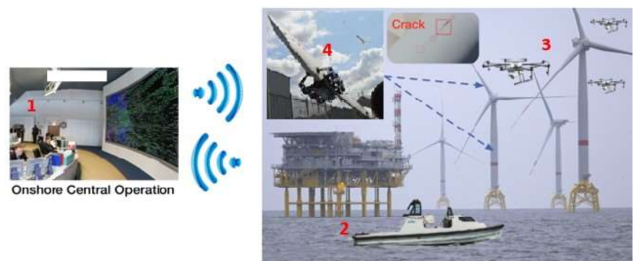

Figure 1: Conceptual overview of the system architecture.

One such a trend is the use of turbines, which can be positioned onshore or offshore, for capturing wind energy. Offshore wind turbines are preferable as their location provides the opportunity to exploit stronger winds and larger areas for deployment, and minimizes potential conflicts of interests with other aspects of society (e.g. visual disturbance) [5]. However, the cost of maintaining offshore wind farms to allow them to perform at their optimal level over 25 year of service can be one fourth of the wind turbine installation costs [14]. A recent report [16] values the global wind operation and maintenance (O&M) market at $12 billion in 2018 and predicted it would rise to $21 billion by 2025.

O&M involves inspecting components of a wind turbine that might become faulty and repairing them. Early identification of faults leads to significant reduction in O&M costs [11]. Inspection and repair missions on wind turbine blades are typically performed by rope-access technicians, often working in extreme conditions and during restricted weather windows. Using this approach, the length of turbine downtime, and hence lost energy production, is high, while daily use of crew transfer vessels makes up a significant proportion of wind farm O&M costs.

Recent advances in the development of robotic platforms and autonomous systems have opened up new opportunities for deploying semi/fully autonomous systems for the O&M of offshore wind farms, with the benefit that health and safety risks associated to human operators can be removed [17, 18]. One of the best-known examples of robotic platforms widely used in this area are semi-autonomous drones launched from boat vessels. Although drones can be useful to speed up inspection missions, the turbines must be shut down for the drones to operate reliably, causing loss of revenue generation. Moreover, given the non-contact nature of the drones' modus operandi, they cannot perform nondestructive testing (NDT) inspection and repair tasks, which are then left to the rope-access technicians with all the associated risks.

In this paper, we present an intelligent, collaborative, unmanned, multi-robot platform designed for the autonomous inspection, maintenance and repair (IMR) of offshore physical assets, including offshore wind farms and oil & gas infrastructures (see Fig. 1). We envisage an autonomous mothership, equipped with a robotic crew of drones and crawling robots, sailing to the offshore assets and carrying out continuous inspection, maintenance and repairing of them for extended periods of time and under various weather conditions. Being the mothership augmented by an accurate, moving imaging system, the turbine will be shut down only when maintenance and repairing need to be carried out, considerably reducing downtime. After an in-depth study of the market, we argue that no similar integrated, comprehensive robotic solution for offshore O&M is currently in use worldwide. Its adoption would be a major step-change in the offshore and oil & gas industries. By leveraging an heterogeneous team of fully autonomous and intelligent robots, our system can (1) Remove the need to shut wind turbines down to carry out blade inspections; (2) Remove the need to send humans offshore to carry out blade IMR tasks; and (3) Reduce the risk of using autonomous vehicles offshore to carry out asset IMR tasks.

The most critical building block for a fully autonomous, intelligent system to be deployed in this extreme environment is the integration of multiple robotic platforms into a single, coordinated system that is able to carry out the mission robustly as well as to cooperate with human operators located onshore. We use *AI planning* to underpin both the coordination of the platforms and the communication with the human operators. Those operators will be removed from dangerous environments, but will remain in charge of the mission remotely. The planning system will assist them in making decisions for the optimal use of the assets.

We believe that, if successful, our system will establish the business case for using autonomous robots for blade IMR and form the basis of collaborative remote systems for other relevant industries.

2 OVERVIEW OF MULTI-ROBOT PLATFORM

We now present an overview of the proposed integrated system, consisting of: (i) an onshore control center; (ii) an autonomous surface vessel (ASV); (iii) an unmanned aerial system (UAS) with multiple unmanned aerial vehicles (UAVs); and (iv) a blade IMR robot composed of a crawler robot and a repair arm manipulator.

2.1 Onshore Control Center

The Onshore Control Center assists human operators in planning, dispatching and executing the overall mission. The Control Center includes: (i) an AI mission planning tool for underpinning the autonomous behavior of all the robotic assets and their coordination in performing IMR tasks; and (ii) a Human-Machine-Interface (HMI), which allows the operator to remotely control the mission. These two components work together at the service of the operator.

There are two types of missions that the operator can dispatch: routine inspection missions, which need to take place regularly and in which the ASV is deployed together with the UAS; and repair

Figure 2: An example of ASV: Thales Halcyon ASV.

missions, which happen less frequently (only when intervention is needed) and involve the full crew, i.e. the ASV deploying both the UAS and the blade IMR robot. The human operator, via the HMI, specifies the high-level goals of the mission and leaves the AI planning system to deal with the details of how to best achieve them. We use general-purpose planning technology (e.g. the POPF-TIF system [15]), which we feed with a sophisticated temporal and metric PDDL [8] domain model representing all the actions that the different assets can perform and the coordination constraints between them. Our plan-based approach is very flexible because, when the mission changes because new assets are added to the robotic crew or new turbines are added to the farm, we only need to change the problem file, representing the specific mission, but not the domain file and the planning algorithm.

After the planning phase and through the HMI, the operator has the opportunity to review the plan, interrogate the planner on specific choices and make changes, if needed. Our goal is to develop a *joint, human/robot deliberation system* in natural language. We plan to combine planning with computational argumentation and natural language dialogue [6, 12]. Once the operator has validated and authorized the mission, the plan gets dispatched to the different robotic assets for autonomous execution. A cycle of *monitoring, executing and replanning* is implemented to deal with failures due to environmental conditions and other uncertainty factors. The operator maintains the ability to intervene via the HMI at any time during the unfolding of the mission. Data processing happens locally on the ASV via machine learning techniques and only valuable data are transmitted back to the operator for inspection. In such a way, the cognitive load of the operator is kept under control.

2.2 Autonomous Surface Vessel

The ASV acts as a fully autonomous hub for the unmanned transportation of IMR systems to offshore wind farms (see Figure 2). The hub contains storage and battery charging capabilities for both the UAS and the blade IMR robot. A stabilized custom imaging system provides remote visual inspection of the rotating blades, without the need to shut down the turbine. This is a unique feature of our system as existing imaging systems require the blades to be motionless to be able to inspect them. In the initial phases of the development of our system, the data gathered by the camera are transmitted to the onshore HMI for visualization and assessment by a human operator. Once the data has been processed, if a significant defect is identified, the operator has two options: recall the ASV to shore whilst a decision is being made regarding the appropriate interventions, or initiate a repair mission. The latter option

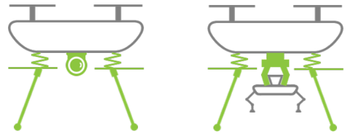

Figure 3: Inspection UAV and deployment UAV.

involves a UAV picking up the blade IMR robot and deploying it on the stationary turbine blades to carry out maintenance and repairs. In future developments, we plan to reduce the need for an operator in the loop for inspection analysis, defect categorization and IMR decision making, and to transfer these tasks to a machine learning system that will reside onboard the hub ASV.

2.3 Unmanned Aerial System

The UAS contains a fleet of modular UAVs with reconfigurability onboard of the ASV. Depending on the task specifications, these UAVs can be reconfigured into either close-up inspection systems to examine wind turbine blades or deployment systems to deploy blade IMR robots on stationary wind turbine blades. As shown in Figure 3, for close-up inspections, the UAV is equipped with an imaging system that can record images of moving wind turbine blades; for repair missions, a gripping mechanism is used to deploy and retrieve an IMR robot on and from the turbine blade. There are a number of challenges in the development of the UAS. These include landing on a moving vessel in a harsh environment, autonomous navigation around wind turbines, landing safely and securely on a static but vibrating/oscillating blade without causing damage to it and locating and safely recovering the blade IMR robot once its mission is complete.

2.4 Blade IMR Robot

An autonomous crawling robot is deployed onto stationary wind turbine blades by the UAS to carry out subsurface NDT inspections, maintenance (e.g. conductivity testing of the lighting protection system) and repairs (e.g. to remediate cracks, delamination and leading edge erosion). The robot is able to perform autonomous navigation to reach the blade section that needs intervention, to carry an ultrasonic NDT payload and to perform general marinization. We plan to furnish the legs of the crawling robot with sensitive tactile sensors (*e-skin*) to improve the autonomous navigation over the blade surfaces. In developing this robot, the focus is on improving its capacity to carry out unmanned missions, high quality NDT inspections via a novel thermal imaging payload and blade repairs.

The IMR robot carries a *multifunctional, highly articulated arm* that can perform blade leading-edge surface treatments and repairs. Functionalities include cleaning, resin deposition or spray coating of damaged areas. The design of the repair arm integrates latest advances in soft materials, flexible electronics, advanced communication and manufacturing technologies in the construction process to fit the operational requirements of extreme offshore environments. This includes, for example, the ability of the arm to approach blade cracks from different orientations and to reach critical positions on the blade to carry out maintenance and repair works.

Figure 4: An example of crawling robot: BladeBUG robot.

There are a number of key challenges associated with the development of soft and flexible arms depending on the technologies employed for actuation and sensing. The actuation system must minimize disturbance to the physical placement and operation of the sensors integrated into the arm. The sensing system, on the other hand, should receive minimal signal interference from the rest of the system including electrical noises or magnetic fields.

3 CHALLENGES AND FUTURE RESEARCH

We now reflect on the major challenges posed by the development of the proposed multi-robotic systems and the research directions that seem more promising for its successful deployment.

3.1 Flexible and Robust Multi-Agent Autonomy

Autonomous decision making in mission planning and management is believed to be one of the most difficult problems to solve to achieve full autonomy [13]. Constructing a complete mission plan requires addressing multiple issues such as communication, coordination and cooperation, task and path (re-)planning, human-machine interfaces, and domain representation. We use state-of-the-art, general-purpose AI planners (e.g. [15]), which allow us to leverage the advancements achieved by a broad scientific community. Yet, we face several challenges. We discuss two of them.

The first open problem relates to *domain acquisition and representation* [4, 7, 9]. Formulating the domain knowledge necessary for an automated planner to produce high-quality plans requires an accurate domain representation of how the system works both in nominal conditions and in deviant environmental conditions. This is particularly difficult in extreme environments as they are characterized by a high level of uncertainty. Inaccurate domain modeling may lead to the wrong planning problems being solved and, in turn, to potentially catastrophic disruptions in the operation of robots in such environments. A general method for the automated refinement of pre-engineered domain models and problem formulation is necessary for AI planning in real world environments. We propose to use machine learning techniques to continuously monitor the discrepancies between the expected and the actual effects produced by a plan being executed and use these differences to drive the online refinement of the domain model.

The second challenge concerns *robustness in temporal planning*, which augments causal planning with temporal reasoning to handle synchronization and coordination constraints. Although temporal planning is considered essential for supporting real-world autonomous decision making, its progress has been slow and limited to simple scenarios. This is due to two intertwined factors: a large branching factor, deriving from considering sets of parallel actions, and the difficulty of crafting search control strategies in algorithms that contain such a high branching factor. Furthermore, temporal planning problems often come with a set of extra challenges such as required concurrency, timed and periodic state transitions and uncertainty in the execution time of the actions. Currently, no single planner can support all the features that are useful to model real-world problems and, at the same time, exhibit good performance. More research is required in this field to achieve robust temporal planning, which is fundamental to intelligent autonomous behavior.

3.2 Explainability

The more robots become autonomous, the less they require human intervention in their day-to-day tasks, in so releasing human operators from the burden of constant monitoring. However, cases might arise when the autonomous system does not meet the expectations of the operator. For example, in a wind farm inspection scenario, a UAV might quickly return to the ASV due to an unexpected plummeting of its battery capacity. Faced with this unanticipated behavior, the human operator might have troubles in understanding the behavior of the UAV, which in turn will have a negative impact on the trust towards it. This problem becomes more excruciating and the trust even lower when it involves remote robots compared to co-located robots [2, 10]. Therefore, it emerges as of crucial importance to equip autonomous systems with the capability to *explain* their behavior and the rationale behind it to the human operators. In extreme environments, where the stakes are high, interaction between humans and machines must be as fluid as possible and needs to happen at the cognitive level.

We argue that planning is ideally placed to fulfill the requirements of *intelligibility* and *accountability* of autonomous systems. Plans can be seen as 'certificates' of an agent's behavior both before and after execution. Hence, they can naturally enable collaboration between operators and robots. Currently, however, they are stored in the form of impenetrable and immutable low-level scripts, which makes it difficult to leverage them for explainability. We envisage that, for plans to become the centerpiece of a smooth exchange between the humans and robotic system, they need to be appropriately combined with other techniques, such as *computational argumentation* and *natural language dialogue* systems. Although this direction is promising and research on eXplainable Artificial Intelligence (XAI) has gained significant momentum recently, more research is needed in goal-driven XAI [1].

3.3 Acceptability

Another issue linked with explainability is the *acceptability* of highly autonomous robot systems. Although the goal of removing humans from extreme environments might seem noble and uncontroversial, this endeavor frequently meets strong resistance from the work groups who operate in such environments, not only because the workers fear to lose their jobs, but because they often take great pride in performing dangerous and complex tasks under pressure, as shown in research (e.g. [3]) and as we have experienced first hand in the renewable energy domain. Operators become more willing to be moved to work onshore if they feel that they can retain ownership of the mission by a close and meaningful collaboration with the robotics. To this end, we envisage the use of virtual and augmented reality to create a *virtual twin* of the wind farm onshore that the operators can inhabit with the robots.

3.4 Robust Communication

The Onshore Control System losing communication with the ASV while at sea or with the UAV while in flight could lead to possible collisions between the robots and offshore energy assets, ditching of the UAV into the sea, and loss of the ASV at sea. Adding several layers of safety and mitigation against such a loss of communication is of paramount importance. For instance, loss of communication by the UAS must automatically trigger a return-to-ASV automated procedure. In addition, the UAS will be equipped with a Proprietary Cellular Safety Solution (CSS), entirely separate from the on board electronics of the drones. CSS physically captures the UAS within the safety borders of the farm preventing any possibility of the UAVs escaping the site perimeter.

3.5 GPS accuracy

GPS based positioning may be at times inaccurate by tens of centimeters leading to potential collisions between the robots and the offshore energy assets. This may also affect the performance of the robots for conducting inspections and repairs. To improve both global and local positioning, we plan to use a real-time kinematics (RTK) enabled GPS receiver in combination with processing computer vision solution. These technologies should be installed on the ASV, UAS and the blade IMR robots.

4 CONCLUSION

In this paper, we present our vision to introduce a step-change in the O&M of offshore wind farms by deploying a fully autonomous multi-robot platform for the inspection, maintenance and repair of offshore wind turbine blades. The aim is to significantly reduce the costs and turbine downtime associated with these tasks and remove the health and safety risks of relying on rope-access technicians. In particular, we discuss a multi-robot platform encompassing an ASV that acts as the hub of an ecosystem of robotic assets such as UAVs and crawling robots with high-precision manipulators. An onshore control system based on AI planning technology brings together all those robots creating a concerted, joint behavior and maintains the human operators in the loop. Our system is unique in that it addresses all phases of the O&M of offshore wind farms autonomously thanks to the use of a tightly coupled system of heterogeneous robots and AI planning, which supports both the intelligent behavior of the robotic platforms and a fluid collaboration with the human operators in charge of the O&M missions.

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REFERENCES

[1] Sule Anjomshoae, Amro Najjar, Davide Calvaresi, and Kary Främling. 2019. Explainable Agents and Robots: Results from a Systematic Literature Review. In *Proceedings of the 18th International Conference on Autonomous Agents and MultiAgent Systems (AAMAS '19)*. International Foundation for Autonomous Agents and Multiagent Systems, Richland, SC, 1078–1088. http://dl.acm.org/citation.cfm?id=3306127.3331806

[2] W. A. Bainbridge, J. Hart, E. S. Kim, and B. Scassellati. 2008. The effect of presence on human-robot interaction. In *RO-MAN 2008 - The 17th IEEE International Symposium on Robot and Human Interactive Communication*. 701–706. https://doi.org/10.1109/ROMAN.2008.4600749

[3] J. L. Bellanca, ÂăL. R. Swanson, J. Helton, and M. McNinch. 2019. Mineworker-sâĂŹ Perceptions of Mobile Proximity Detection Systems. *Mining, Metallurgy and Exploration* 36 (2019).

[4] Scott Sherwood Benson. 1996. *Learning action models for reactive autonomous agents*. Ph.D. Dissertation. stanford university PhD thesis.

[5] Lena BergstrÃűm, Lena Kautsky, Torleif Malm, Rutger Rosenberg, Magnus Wahlberg, Nastassja Åstrand Capetillo, and Dan Wilhelmsson. 2014. Effects of offshore wind farms on marine wildlife—a generalized impact assessment. *Environmental Research Letters* 9, 3 (mar 2014), 034012.

[6] Elisabeth Black, Amanda Coles, and Sara Bernardini. 2014. Automated Planning of Simple Persuasion Dialogues. In *Proceedings of the Fifteenth International Workshop on Computational Logic in Multi-Agent Systems (CLIMA-14)*.

[7] Bradley J Clement, Jeremy D Frank, John M Chachere, Tristan B Smith, and Keith J Swanson. 2011. The challenge of grounding planning in simulation with an interactive model development environment. (2011).

[8] M. Fox and D. Long. 2003. PDDL2.1: An Extension to PDDL for Expressing Temporal Planning Domains. *Journal of Artificial Intelligence Research* 20 (2003).

[9] Jeremy Frank. 2015. Reflecting on planning models: A challenge for self-modeling systems. In *2015 IEEE International Conference on Autonomic Computing*. IEEE, 255–260.

[10] Helen Hastie, Xingkun Liu, and Pedro Patron. 2017. Trust Triggers for Multimodal Command and Control Interfaces. In *Proceedings of the 19th ACM International Conference on Multimodal Interaction (ICMI '17)*. ACM, New York, NY, USA, 261–268. https://doi.org/10.1145/3136755.3136764

[11] Jan Helsen, Christof Devriendt, Wout Weijtjens, and Patrick Guillaume. 2015. Condition monitoring by means of scada analysis. In *Proceedings of European Wind Energy Association International Conference Paris*.

[12] S. Modgil. 2017. Dialogical Scaffolding for Human and Artificial Agent Reasoning. In *5th International Workshop on Artificial Intelligence and Cognition (AIC 2017)*.

[13] Yazan Mualla, Amro Najjar, Stéphane Galland, Christophe Nicolle, Igor Haman Tchappi, Ansar-Ul-Haque Yasar, and Kary Främling. 2019. Between the Megalopolis and the Deep Blue Sky: Challenges of Transport with UAVs in Future Smart Cities. In *Proceedings of the 18th International Conference on Autonomous Agents and MultiAgent Systems (AAMAS '19)*. International Foundation for Autonomous Agents and Multiagent Systems, Richland, SC, 1649–1653. http://dl.acm.org/citation.cfm?id=3306127.3331891

[14] J. Nilsson and L. Bertling. 2007. Maintenance Management of Wind Power Systems Using Condition Monitoring SystemsâĂŤLife Cycle Cost Analysis for Two Case Studies. *IEEE Transactions on Energy Conversion* 22, 1 (March 2007), 223–229.

[15] C. Piacentini, V. Alimisis, M. Fox, and D. Long. 2015. An extension of metric temporal planning with application to AC voltage control. *Artificial Intelligence* 229 (2015), 210–245.

[16] Zion Market Research. 2019. Wind Turbine Operations and Maintenance Market by Application (Offshore and Onshore): Global Industry Perspective, Comprehensive Analysis, and Forecast, 2018âĂŞ2025. *Zion Market Research Reports* (2019).

[17] Adrian Stetco, Fateme Dinmohammadi, Xingyu Zhao, Valentin Robu, David Flynn, Mike Barnes, John Keane, and Goran Nenadic. 2019. Machine learning methods for wind turbine condition monitoring: A review. *Renewable Energy* 133 (2019), 620 – 635.

[18] E Welburn, T Wright, C Marsh, S Lim, A Gupta, B Crowther, and S Watson. 2019. A Mixed Reality Approach to Robotic Inspection of Remote Environments. *Proceedings of the second UK-RAS Robotics and Autonomous Systems Conference* (2019), 72–74.