Development of a Multi-robotic Exploration System for Power Plants

A thesis submitted to The University of Manchester for the degree of

Master of Philosophy

in the Faculty of Science and Engineering

2020

Si-Hai An

School of Electrical and Electronic Engineering

Robotics for Extreme Environments Group

Contents

Word count: 24988

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Nomenclature

Abbreviations:

O&M	Operation and Maintenance
GA	Genetic Algorithm
OSH	Occupational Safety and Health
DEM	Distance Estimate Module
HTF	Heat-Transfer-Fluid
PCC	Parabolic Cylinder Collectors
UAV	Unmanned Autonomous Vehicle
ERF	Exponential Risk of Fault
VR	Virtual Reality
GPS	Global Positioning System
BWW	Boiler Water Walls
RFID	Radio-frequency Identification
SA	Simulated Annealing
PSO	Particle Swarm Optimisation
ACO	Ant Colony Optimization
MRDS	Microsoft Robotics Developer Studio
3D	3 Dimension (al)
V-REP	Virtual Robot Experimentation Platform
API	Application Programming Interface

Scalars:

A	exploration system used Greedy and the general charging method
B	exploration system used GA and the general charging method
C	exploration system used GA and the predicted charging method
R1	exploration robot #1
R2	exploration robot #2
T0	initial position of the robot team
T1~T6	different exploration targets in a power plant
C	charging station
E_m	the energy consumption of robot in real-time, J
m	the energy consumption of Pioneer p3-dx robot, 1.43 J/m
T_d	robot's past-path lengths in real-time, m
$\mathrm{D_b}$	the robots' remaining amount of energy stored in battery, m
$\mathrm{D_{rc}}$	distances from the robot to the charging station, m
$\mathrm{D_{nc}}$	distances from the robot's next exploration target to the charging station, m
$\mathrm{D_n}$	distances from the robot to the next inspected target, m
$\mathrm{D_{r1}}$	distances from the robot to the last inspected target, m
D1	summed distances of $\mathrm{D_n}$ and $\mathrm{D_{nc}}$, m
C1~C…	different chromosomes inside the GA
L_p	real-time robot's total shaft revolutions
D_w	the diameter of the robot's wheels, m

Abstract

On-site exploration is an important procedure in scheduled Operation and Maintenance (O&M) in power plants. Currently, the efficiency of O&M work is challenging due to human reliability and the limitations of the deployed robots. Thus, the goal of this project is to develop an enhanced robotic exploration system for on-site data collection of power plants. Specifically, this project focuses on developing an efficient coordination method for a multi-robotic exploration system, with the aim of maximising utilisation of the limited onboard energy of exploration robots to accomplish on-site inspection tasks with high efficiency.

In the exploration scenarios, this project considered using a limited number of robots to conduct continuous exploration of multiple targets. Two modes were specifically considered for on-site exploration at a power plant: (1) temporary exploration, whereby the robots are required to conduct the exploration as quickly as possible to diagnose faults zone-by-zone, and (2) long-term exploration, whereby the robots are required to use their limited energy resource to maximise the number of inspected targets explored.

In the exploration system's development, this project considered two factors for optimal exploration-efficiency: (1) scheduling of an optimal exploration plan, and (2) appropriate charging controls. Consequently, three multi-robotic exploration approaches were developed in this study: (1) the Greedy algorithm and general charging method for temporary exploration, (2) the Genetic Algorithm (GA) and general charging method for long-term exploration, and (3) the GA and predicted charging method for exploration system improvement.

A comparison of these three approaches showed that the developed Greedy based method was suitable for temporary exploration tasks to diagnosis faults zone-by-zone. However, the developed GA based method had more advantages in long-term exploration. Finally, it was found that the predicted charging method could save energy and increase inspection efficiency of the exploration system. In application, these developed exploration approaches can be used for different scenarios inside a power plant, and can be applied to other similar domains, such as cooperate rescue, farming or cleaning.

Declaration

No portion of the work referred to in the thesis has been submitted in support of an application for another degree or qualification of this or any other university or other institute of learning

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Acknowledgements

First and foremost, I would like to express my sincerest thanks and gratitude to my supervisors, Dr Simon Watson and Dr Farshad Arvin, for their continuous support during my research. Their knowledge, understanding, motivation and enthusiasm were vital to my progression in this process and I would not have been able to complete this thesis without their professional guidance and encouragement.

I would also like to express a special thanks to Prof. Barry Lennox for making time for me to suggest further research opportunities. In terms of the power plant O&M data, I would like to thank the following people for their information: Jingrui Ai, Hongliang Zheng, Caiwen Niu, Xue Wang, Jianxin Wang, Guoxiang Wei, Yu Chen, Meichao Zheng, Mingyuan Wang, Muzhuo Zhang, Zichao Li, Chunyu Li, Shucheng Shi, Xinpei You, Jianguo Li, Gang Liu, and Fu Li.

In terms of the various problems I encountered during this research, I would like to express my deepest appreciation to the following people for always being willing to lend me a hand: Dr Mingzhu Chen, Dr Fei Wang, and Lu Wang from Technological University Dublin; Dr Zhengyi Jiang, Dr Yibin Peng, Dr. Lujia Wang, Yao Shi, Xiaojia Li, Bo Liu, David Felipe Morales Aldana, Okechi Onuoha, and Hilton Tnunay from the University of Manchester; Dr Gang Chen, Sasha (Shixue) Shen from the Gengdan Institute of Beijing University of Technology.

Outside of this research project, in terms of my professional development, I am very thankful to my life mentor, Prof. Xiuping Tian, for her constant encouragement and recommendations. In addition, my appreciation also goes to my sponsor, the Gengdan Institute of Beijing University of Technology, for securing the funding required for my advanced studies in both Ireland and the UK.

Finally, I would like to express my deepest thanks and gratitude to my sister, Xiaomeng Luo, for her continued love and support during my studies and most importantly, I would like to thank to my parents, Fumin An and Jiuxia Liu, for their unwavering support and belief in me! If it was not for you, I would not be where I am now!

Chapter 1

Introduction

1.1 Research Background

Exploration using robotic platforms for extreme environments has become an important research topic in recent years. These areas include petroleum [1], chemical industry [2], underwater [3] or lunar and planetary environments applications [4]. In terms of the use of a single robot for exploration, this has been proposed for visual inspection of nuclear power plants in [5]. The developed robot can reduce human involvement in inspections of radioactive nuclear areas. In a recent study [6], an exploration robot was developed to inspect an aircraft fuel tank, which decreased the workload of the aircraft crew and improved maintenance efficiency. In addition to these individual exploration robots, multi-robotics can be used as an alternative to solve complex exploration tasks. As an example, monitoring of a jet engine turbine used miniature swarm robots as proposed in [7] and in another study, an application of swarm robotics in crops inspection for precision agriculture was proposed in [8]. Hence, a customised robotic exploration system using multiple robots can be a reliable solution for different applications.

On-site exploration in power plants to inspect equipment is an indispensable process for the site's sustainability and maintenance. Currently, the inspection task is generally conducted by human inspectors who operate in hazardous areas where they are exposed to high temperatures, electric shock, dust, noise, and extreme weather. It is clear that these engineers experience great challenges in their Occupational, Safety and Health (OSH) [9][10]. This is likely to become even more prevalent in the future as the number of renewable energy generation facilities in remote locations is likely to increase in the future [11]. In this context, the associated costs of accessing these remote sites has inspired the deployment of advanced robotic systems for exploration of these facilities.

1.2 Research Motivation

Continuously monitoring of power generation devices for maximum power generation is a requirement of different power plants. The most common maintenance method to diagnose faulty devices is on-site manual exploration in cooperation with sensor networks [12][13]. However, the reliability of this maintenance method is not very high due to human involvement, large number of sensors required and the sensor's stability, which has lead to difficulty in the precise O&M of a power plant. Upgrading a complete set of the sensor networks in old operating facilities to an advanced configuration will lead a power plant shutdown with a certain time, and this process also results in a considered cost [14].

Using exploration robots is an alternative and versatile method instead of manual on-site exploration to enhance the quality of monitoring, such as its accuracy and efficiency. Only a few robotic projects have been successfully commercialized to assist power plants conducting on-site exploration works [12]. This indicates that the performance of these robots needs to be improved, such as their effectiveness, or applicability for those different power plants. This has also lead to another concern, which is that due to these unmatured exploration robots, manual operation for on-site exploration still exists in various power plants, which poses a threat to the safety of engineers.

Therefore, there is a necessity to determine the characteristics of on-site exploration tasks for different power plants, and recognise the limitations of current exploration platforms to develop a general-purpose and effective robotic exploration system for the precise O&M of power plants.

1.3 Aims and Objectives

The premise of sustainable electricity in any power plant is that the equipment’s health is inspected and maintained to allow full-time operation under the designed operating conditions. This project inspired by current robotic explorations' limitations in its efficiency and its applicability in case of on-site exploration works. Thus, this project aims to develop an enhanced robotic exploration system using multiple mobile robots. The main objectives of this research are:

(1) To determine the characteristics of on-site exploration tasks in different kinds of power plants.
(2) To recognise the challenges of human inspectors working on-site and to discover the significance of using on-site exploration robots.
(3) To identify the limitations of current deployed robotic exploration for as the inspection requirements summarised in Objective 1, and to develop effective exploration methods to deal with different conditions.
(4) To develop exploration scenarios and evaluation metrics for dynamic testing of the developed robot exploration system.

1.4 Scope of the Work

This project is a prototype work which contributes to development of an exploration system. The system will use multiple limited robots for covering on-site exploration tasks in power plants. The proposed system was implemented using simulation software. For the overall scope of this project, see Figure 1.1.

In addition to the development of the exploration algorithm, the simulation of the system is performed using the following three stages:

(1) Develop a multi-layered framework for the robot's main controller. In detail, high, middle, and low-level behaviours were developed to accomplish multi-robot task allocation, robot motion control, and conduct exploration. For further details, see Section 4.2.
(2) Develop an exploration platform for a multi-robotic exploration system. In detail, three auxiliary sensors were developed and integrated into the selected platform: (1) an approximate sensor to avoid collisions, and (2) an encoder system and (3) a Distance Estimation Module (DEM) for the robot's motion control. For further details, see Section 4.3.
(3) Develop four different configuration maps for the exploration system evaluation. To be more specific, two small size maps (25×25 m^2), with 10 and 20 exploration targets, and two large size maps (300×250 m^2), with 10 and 20 exploration targets, respectively, were developed. Thus, based on the different scales maps, but with same exploration targets configuration, the performance of the computational system can be checked accordingly. For further details, see Section 4.4.

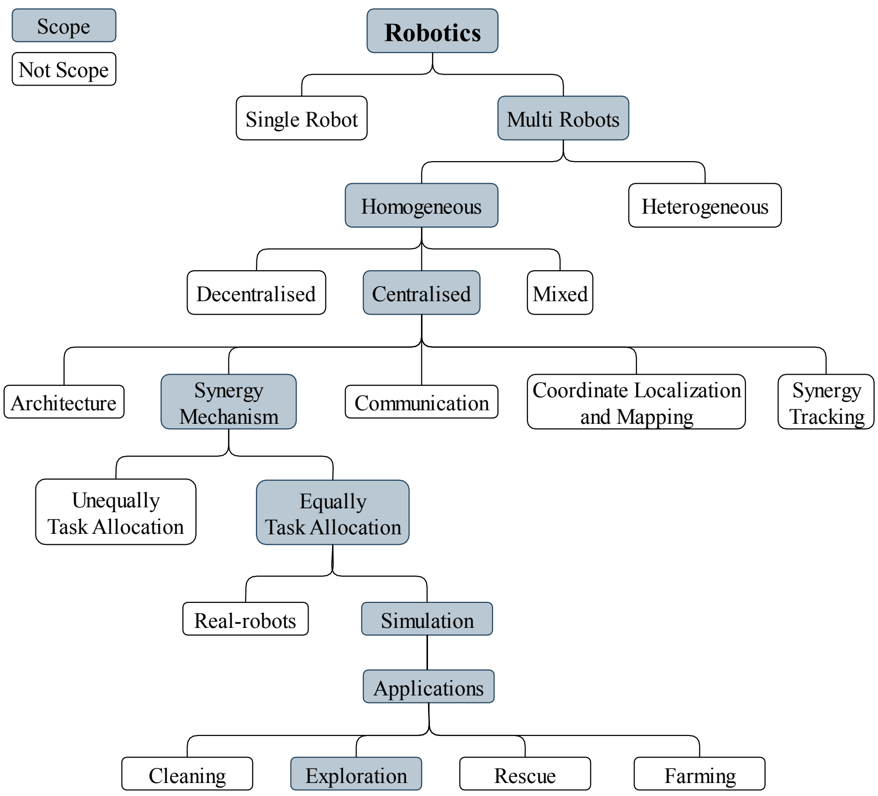


Figure 1.1: Scope of this thesis.

1.5 Novelty and Contributions

The novelty of the developed multi-robot exploration system is twofold: (1) the exploration system is customised for application in a real power plant, based on the two exploration modes (temporary and long-term) that may occur in a power plant, and (2) the exploration system considers the impact from both the scheduling of the exploration strategy and the different charging mechanisms for multi-robotic exploration system optimisation. The contributions of this research are as follows:

(1) This project establishes a good foundation for further work on the development of a robot exploration system for power plant:

- The characteristics of on-site inspection in different power plants is determined via a literature review and through interviews with engineers from power plants, which is demonstrated in Section 2.1.1;
- in addition, the limitations of the current human-based sensor network for O&M of power plant, and the significance of using robotic exploration system are provided in Sections 2.1.2 and 2.1.3;

- the limitations of the most recently developed robot for on-site exploration of power plants is outlined in Section 2.2;

(2) This project develops a multi-layered framework between Matlab and V-REP for multi-robot synergy control, which can be directly adapted in the power industry as it has universal applicability, and saves robot limited on-board computation resources, which is presented in Section 4.2;

(3) This project discusses the general requirements of on-site inspection at power plants, and develops an exploration platform, which contributes to the overall body of knowledge in exploration system formulation. This is described in Sections 4.3.1 and 4.3.2;

(4) This project provides a new, easy and reliable method (via an encoder) to solve real-time measuring robot past-path lengths issues in V-REP simulator. The contribution of this method for V-REP simulator is twofold: (1) it is generally applicable as it can be used to measure wheeled robots' past-path lengths in real-time for any type of path-planning algorithm; and (2) there are no requirements to study the principles of these algorithms and complex mathematical works to capture robots' past-path lengths. This is demonstrated in Section 4.3.3, and Section 5.2;

(5) Power plant modelling works are based on real power system constructions. In addition to two small-scale power plant models, this project provides another two real-sized power plant models, which are explained in detail in Section 4.4. These models present the general lay out of power generation devices in a power plant, which can be used in further research, e.g. route situation-based multi-robot task allocation;

(6) The V-REP path planning library – the Open Motion Planning Library (OMPL), was tested based on limited computer configuration, where nineteen state-of-the-art path planning algorithms are evaluated, while the further use and development recommendations using OMPL are detailed in Section 5.1;

(7) The multi-robotic exploration systems developed in this study can conduct inspections and charging tasks, and these systems are optimised via the developed predicted charging mechanism. These exploration systems are adaptable for temporary or long-term exploration modes for enhancing precise

O&M in power plants, and these contributions are demonstrated in Chapter 3, and Sections 5.3, 5.4, respectively.

1.6 Thesis Structure

This thesis is divided into six chapters and one additional appendix. Following the introduction, Chapter 2 reviews the various current exploration techniques used in power plants. The characteristics of on-site exploration in different kinds of power plants, and the significance of using exploration robots to replace human inspectors are discussed in this chapter. Following that, fifteen of the most recently developed power-plant exploration robots, and five multi-robotic exploration methods are analysed. At the end of this chapter, three robot simulation software are described. In Chapter 3, details of the developed multi-robotic exploration methods are outlined. The first two sections of this chapter explain the function of the exploration robot and the two charging methods, while the last two sections describe two different multi-robot exploration approaches for temporary and long-term exploration modes. Chapter 4 outlines the experimental configurations for implementation of these developed exploration methods. The first two sections of this chapter discuss the experimental setup and robot control framework and, following that, the development works of the exploration robot platform are presented. The final two sections of this chapter describe the exploration scenarios and evaluation metrics, before Chapter 5 demonstrates the experimental results and discussions. Finally, Chapter 6 demonstrates the conclusion and further works and Appendix A details information on the investigated power plants.

Chapter 2

Literature Review

Manual and robotic are two methods for on-site exploration of power plants, which will be reviewed in this chapter. This chapter is divided into five sections. Firstly, Section 2.1 reviews the manual explorations solutions in power plants, before, in Sections 2.2 and 2.3, reviews of the most recently developed power-plant exploration robots and multi-robotics exploration methods are explained. Following that, Section 2.4 reviews three robot simulation packages before finally, Section 2.5 summaries the chapter.

2.1 Exploration in Power Plants

This section aims to discover the characteristics of on-site exploration tasks in different power plants, and identifies the significance of using robots for exploration. In this section, general reviews of exploration requirements in different power plants are described, before discussion on human reliability in power generation industry. Then, this section will briefly discuss the places that can be served by exploration robots and how robots benefit the power plant industry. Finally, this section summarises the challenges of developing a generally applicable exploration robot for these power plants.

2.1.1 Manually Inspection

There are two types of power plants operated around the world: conventional and renewable. Conventional power plants have been in use for many years, using fossil fuels to generate power, such as coal/gas-fired power plants. Recently, however, the use of renewable energy has increased, such as wind farms and nuclear, solar, or hydropower plants, and so on. These plants play a role in generating electricity for the world and their proportion of the energy mix is likely to increase in the future. However, whether a conventional or renewable plant, manual inspections still exist in all power plants. This is verified by recent exploration projects and 11 different O&M engineers from nine power plants. The details of this review are as follows:

(1) *Solar power plant:* In a solar power plant [15], the manual exploration-efficiencies for check the dust cover rate on solar panels is poor. This is because thousands of solar panels are generally deployed in a large area. In another solar power plant [16], inspector safety was threatened when they inspected the pipes because the liquid inside these pipes is of very high temperatures.
(2) *Wind farms:* In [17], there was a challenge of efficiently monitoring wind farms by manual inspection as the difficulty in reaching the top of the wind turbines. In addition, in other wind farms [18], the difficulty of monitoring of the wind turbines for making sure it is running under designed conditions has been recognised, as these turbines have a vulnerable sensing system. Generally, when these turbines are deployed over the long-term to face uncertain weather, the turbines are turned off even with pitch position sensor errors.
(3) *Nuclear:* In [19], on-site inspection of a nuclear power plant occasionally requires human involvement, which is considered dangerous due to the radioactive materials and multiple exploration targets. In [20], the decommissioning of a nuclear power plant faced the same problem as human inspectors had to experience extreme environments to gather on-site data.
(4) *Thermal and Hydropower:* In [21], manual inspection of a thermal power plant was considered time-consuming due to these exploration tasks are repetitive generally. In addition, the on-site inspector’s safety is at risk due to power plant’s reliability. In [22], manual inspection of underwater structures in a hydropower plant is ineffective due to underwater visibility and the multiple exploration targets.
(5) *Additional investigation of real power plant engineers:* a total of 11 O&M engineers from nine different power plants are invited for providing the on-site exploration information (ten from thermal power plants, one from a hydropower plant). From the results, on-site exploration is a basic O&M requirement in these plants, and human inspectors carry out this work. The two most common modes for on-site exploration are: (1) in cooperation with a main station to conduct a temporary inspection for fault diagnosis, and (2) periodic exploration (long-term) to inspect the health of equipment in different zones. Details of these engineers are

listed in Appendix A. In relation to the on-site inspection/O&M of power plants, these engineers were mainly concerned about professional risks due to the power plant’s reliability. Thus, potential on-site risks and some sample exploration targets are also summarised from the interviews with engineers, which are demonstrated in Tables 2.1 and 2.2.

From the reviews above, it is clear that the phenomenon of manual on-site inspection in different power plants exists. In this context, the next sections of this chapter will discuss human reliability in power generation.

Table 2.1: List of subsystems and faults that may occur in a power plant, as summarised from interviews with engineers (for further details, see Appendix A).

Power plant subsystem	Function	Potential problem	Consequence
Raw material handling system	Convert raw fuels to useful small pellets.	Dust explosions, self-ignition, off-gassing of bacteria, fungi	Fire, Explosion, Worker fatalities, Loss of production, Poison, Power plant destruction, Human operator's OSH, Gas/steam turbine or generator damage, Large-scale electricity black-out, Unexpected maintenance
Fuel storage system	Storage of the raw/converted fuels.		
Feeding system	Delivery of the treated pellets.	Noise	
Carbonisation system	Removal of the different moisture content from coal pellets.	Self-ignition	
Air booster system	Pump the compressed air to gasification or gas turbine.	High temperature, pressure	
Gasification system	Transfer the solid fuel to a gas fuel.	Syn-gas leakage, explosion-prone	
Tar removal system	Remove the tar from syn-gas.	High temperature, pressure	
Syn-gas purification system	Remove the ash and impurities from syn-gas.	Combustible leakage	
Gas power system	Generate electricity via gas turbine.	Excessive vibration and overheating, tube corrosion, leakage, noise	
Steam power system	Generate electricity via steam turbine.		
Heating system	Recovery of waste heat from power cycle for heating requirements of terminal users, such as hot water supply.	Output water temperature fault	
Refrigeration system	Recovery of waste heat from power cycle to support cold requirements.	Refrigerator fault	
Back-up system	Support power can be generated when maintaining on some devices.	Back-up system starts time delay	

Table 2.2: Details of the exploration samples of a power plant, as summarised from interviews with engineers (for further details, see Appendix A).

Mainly Task	ID	Service Zone	Case Study	Example Fault Phenomenon
On-site exploration	1	Boiler system	Steam pipe leakage	Leakage
	2		Steam temperature faults	Overheat
	3		Feedwater leakage	Leakage
	4		Boiler safety valve faults	Steam leakage, high-frequency leakage
	5		Boiler air pre-heater faults	(1) loose pipe; (2) water leakage
	6		Drum water level indicator	(1) mica leakage; (2) lack water
	7		Boiler ash leakage	Leakage
	8		Forced draft fan faults	(1) unusual noise; (2) lubricant leakage
	9		Coal mill	Pulverised coal leakage.
	10	Turbine system	Booster pump faults	Overheat and lack of lubrication
	11		Electrical feed pump front pump faults	Oil leakage
	12		Oil filter faults	Oil leakage to the hot tube resulting in fire
	13		Generator faults	Generator overheat
	14		Condenser vacuity faults	Air leakage
	15		Pipe faults	Pipeline crack/corrosion
	16		Refrigeration system faults	H_2 leakage
	17		Valve faults	Valve cracks at water source
	19	Electrical unit	Motor faults	Overheat or fumes
	20		Generator mechanical faults	Overheat or unusual noise
	21		Electrostatic precipitator faults	Voltage gauge has more error than normal
	22		Coal feeding faults	Fuse broke
	23		Sewage pump faults	Cannot start or relay action fault

2.1.2 Human Reliability

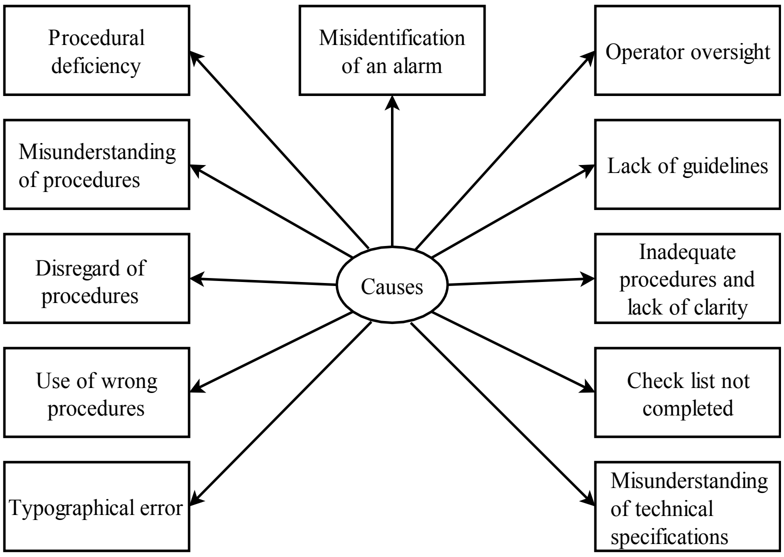


Figure 2.1: Some accident caused by operator error in a power plant, adapted from [23].

From the reviews above, human-based/assisted on-site inspection still exists in different power plants. However, the reliability of these plants is at risk as most accidents reported are closely connected with human operations. For example, in the accidents reported in [9], in August 2016, 22 engineers were seriously injured as the human inspector failed to find the faulty device on-time.

In [23], the challenges of engineering maintenance arises from human reliability, error, and other factors in the manufacturing process have been summarised. These challenges are due to various causes as shown in Figure 2.1:

(1) procedural deficiency, the faulty device may not be checked on-time due to extreme cold or heat conditions;
(2) misunderstanding of procedures, resulting in an incorrect judgement of the device's health;
(3) disregard of procedures, resulting in a careless exploration;
(4) use of wrong procedures, such as exploration plan being delayed during a shift exchange; and
(5) typographical error, resulting in difficulty in analysing on-site information.

Therefore, there is a requirement to develop an on-site exploration technique to reduce the risks from human operation, such as an effective exploration robot system. Thus, the next section will discuss the significance of using exploration robots for inspection of power plants.

2.1.3 Exploration using Robots

The benefits of using exploration robots in the inspection of power plants are as follow:

(1) Guarantee of an additional feedback route. In [24], the performance of the current sensor network still had room for improvement. Two faults may affect the reliability of overall sensor networks: (1) a functional fault that leads to data loss, and (2) a data fault that may result in significant bias. This situation is particularly concerning in large-scale plants, which may be equipped with thousands of sensors nodes. The data from exploration robots can be used when calibrating or changing these fault sensors.

(2) Enhance the efficiency of fault diagnosis processes in case of old facilities. As is generally known, some power plants have been in operation for a number of years, meaning these plants may be equipped with a low-intensive sensor network. This situation might result in the health of the main power generation devices are well monitored, but not other subsystems. In this case, the diagnosis process is time-consuming, and experienced engineers are required. Thus, the historical data of these subsystems provided by exploration robots can be used as a reference for monitoring the device's health.

(3) Reduce the O&M costs for the power plant. Due to the different old/new conditions, sensor configurations and levels of automation, there are currently around 1.2 million O&M engineers working in power plants around the world [25]. Compared with the investigation results outlined in Appendix A (labour cost), a power plant may be assisted by hundreds or thousands of labours. Thus, using exploration robots to assist a few key engineers is an attractive solution compared to employing thousands of peoples.

(4) Protect the safety of on-site engineers. From the review, several flaws exist in power plant inspection, which may pose serious risks to the human operator's OSH [26]. Indeed, in August 2017, a human inspector received multiple injuries and large-scale burns after an accident in a power plant, and six weeks later, two human

inspectors were hurt at other power plants [26]. In addition, compared with the investigation results presented in Table 2.1, on-site inspection of a power plant can be regarded as an extreme environment where inspectors/O&M engineers face several risks. For example, inspectors/O&M engineers face threats to their health when inspecting fuel stocks due to dust or bacteria, or risk scalding when inspecting high-temperature pipework.

Thus, the use of robots for on-site exploration is an alternative solution that can help improve the precision of the O&M of power plants to optimise the plants' reliability.

2.1.4 Summary

From the review, it is clear that on-site inspection tasks exist in different types of plants. Thus, these plants are looking for a technology that could be used to cover the various on-site inspection tasks instead of human labour. At present, two exploration modes general exist: (1) temporary exploration where the human inspectors are required to operate as quickly as possible to find the faulty device, and (2) long-term exploration to inspect the health of equipment in different zones. However, the main challenge of using manual exploration in power plant inspection is the risks to the safety of these engineers when they work on-site. Thus, there is a requirement to develop an effective on-site exploration robot system with different exploration modes to inspect the health of equipment in power plants. The next section of this chapter will review the most recently developed power-plant exploration-robots and assess to what extent they meet this requirement.

2.2 Exploration Robots for Power Plants

The function of an exploration robot is to gather information in unknown or hazardous environments. In this section, the most recently developed robot exploration techniques for different types of power plants will be reviewed. The features and limitations of these projects are analysed and, following this review, the multi-robotic exploration system was chosen as the most appropriate approach for this project. The reasons for which will be outlined in this section.

2.2.1 Solar Power Plants

Figure 2.2: The developed pipeline detection robot for the solar power plant, adapted from [16].

Case study 1: Aitor et al. [16] developed an autonomous exploration robot to inspect pipe leakages of a solar power plant. In their study, two problems were recognised: (1) the inspectors' safety was threatened by high-temperature Heat-Transfer-Fluid (HTF) leakages from the Parabolic Cylinder Collectors (PCC), and (2) there was a difficulty of efficiently monitoring solar power plants by manual inspection as the exploration targets were generally laid out over a large area. An exploration robot was therefore developed to inspect HTF leakage from the PCC. Specifically, the developed robot was based on two parts: (1) a RobucarTT exploration platform with a ±0.2 m accuracy localisation system; and (2) a sensor and thermographic camera (attached with onboard manipulator) to detect leakages. The details of the developed exploration robot can be seen in Figure 2.2.

In terms of hardware configuration, the navigation problem of the robot was considered. This research attempted to keep the exploration on the pipeline, making sure the pipe remained in the robot's scanning range. Technically, the routes for exploration were planned via two processes: (1) Dijkstra's routing technology for computing the path on the topological graph; and (2) robot navigation through local metric maps and search-based algorithms. To be more specific, the global metric planner generated a path from the robot to the target, and the local metric planner then controlled the robot around the path generated from the first step to achieving navigation.

According to the test results, the exploration robot with the developed pipeline tracking system was able to conduct explorations of the solar power plant and the developed system could provide a high rate of success in pipeline position tracking with an acceptable error rate. The exploration was flexible as the leakage detection sensor could be adjusted by onboard manipulator. However, despite the usability of the developed robot, the performance of the developed robot was an issue when its exploration on thousands of PCCs.

Case study 2: Torsten et al. [27] developed a climbing robot for exploration of a receiver panel in a concentrated solar power plant. This system was developed because the receiver panels were vertically installed on a one hundred metres higher tower which was exposed to very high temperatures, meaning it was difficult to service by manual operation. A climbing exploration robot, based on a special mechanical and sensing systems, was therefore developed. In the mechanical system, a ‘six-legged’ structure was adopted whereby every leg was equipped with suction cups that helped the robot stick to the tower’s surfaces for climbing. In the sensing system, contactless sensors were used in the overall inspection processes to avoid damage to the detected device. The developed central-tower tube-exploration robot system can be seen in Figure 2.3.

In terms of exploration tasks, the robot was designed to conduct visual and eddy current tests to check the health of the receiver panel. These health conditions included three sides: (1) coating degradation, (2) coating thickness, and (3) corrosion inside the tube. In terms of the exploration methods, the developed exploration robot was controlled by human operators and to test the developed exploration robot, and an indoor mock-up solar tower receiver panel was developed in this study.

From the results, the developed robot was found to be able to perform the exploration tasks. The exploration period to inspect the entire receiver took 50 hours (with two sensors), and 16 hours (with eight sensors in parallel). After using the parallel inspection method, the efficiency of the exploration robot was enhanced. The main limitations of this robot are summarised as follows: (1) the solar energy conversion efficiency decreased as the receiver was covered by the exploration robot ($2.3\times1.6\times0.8\ m^3$); (2) the heavyweight of the exploration robot (280 kg) lead to energy consumption issues; (3) the evaluation processes were different compared with

Figure 2.3: The developed central tower exploration robot, adapted from [27].

reality, for example, the high-temperature surface of the heat exchangers meant the deployed suction cups would melt when the robot carried out an exploration; (4) the robot was manually operated; and (5) the efficiency of the developed robot needed to be improved.

Case study 3: Zhuo et al. [15] presented an idea to design a robot for monitoring and cleaning the photovoltaic surfaces of a solar power plant. In this project, the problem was recognised as the dust on the solar panels, which would lower the efficiency of power generation. In addition, monitoring and cleaning processes were manually conducted by human operators, which was time-consuming and labour-intensive. Thus, the project presented a novel idea to develop a multi-functioned robot platform to satisfy both monitoring and cleaning requirements. The robot was required to have the capability to jump the gaps between different solar photovoltaic pieces, and to run on these surfaces for inspection and cleaning. As a result, an Unmanned Autonomous Vehicle (UAV) was integrated with a split crawler as a robot platform for the maintenance of the photovoltaic surfaces. The proposed exploration and maintenance robot system is presented in Figure 2.4.

In terms of the robot's control, for exploration, thermal imaging infrared and cameras were used for on-site data collection. The exploration processes were customised via remote commands, such as take-off or exploration route planning. In terms of hardware configuration, dust cleaning and scraper cleaning devices were equipped to

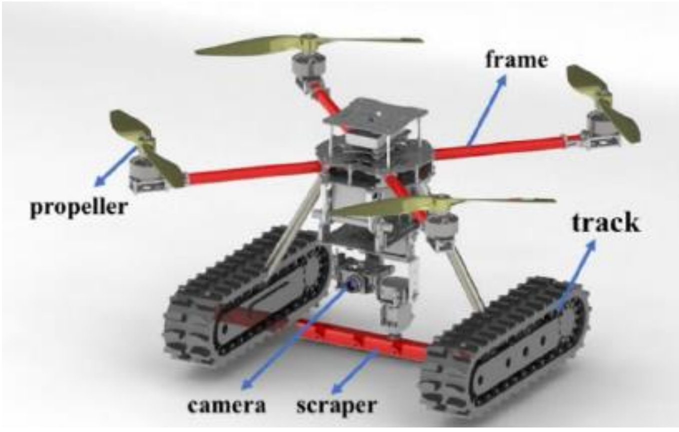


Figure 2.4: The proposed robot system for solar panel exploration and maintenance, adapted from [15].

the robot's onboard arms. This design allowed for adjustment of the scrapers to carry out the different cleaning requirements. The advantage of this design is that the exploration robot is multi-functioned, with the capability to both conduct inspections and clean the photovoltaic surfaces of the solar power plant. In addition, this exploration robot has a general-applicability in any type of power plant as it is contactless. For example, this exploration robot can be adapted in Case study 2 for exploration of a receiver panel in a concentrated solar power plant.

The main limitation of this study is that a real robot is still in development as all the details of the exploration robot provided above were imagined by the author. In addition, the endurance of this multi-functioned robot for continuously carrying out O&M tasks in a solar plant is a concern. This concern is because the robot is battery powered which means the robot has limited power to support its multiple functions.

2.2.2 Wind Farms

Case study 4: Netland et al. [17] presented a study to investigate the feasibility of a telerobot system for exploration of offshore wind farms. The inspiration for this project was twofold: (1) the difficulty of reaching the top side of the wind turbines manually which resulted in an exploration process that was poorly efficient; and (2) higher labour-costs due to turbine groups are required to be simultaneously checked with a certain period. Therefore, a rail-based robot exploration system was developed. This method allowed robots to be powered by ground stations, and avoided the

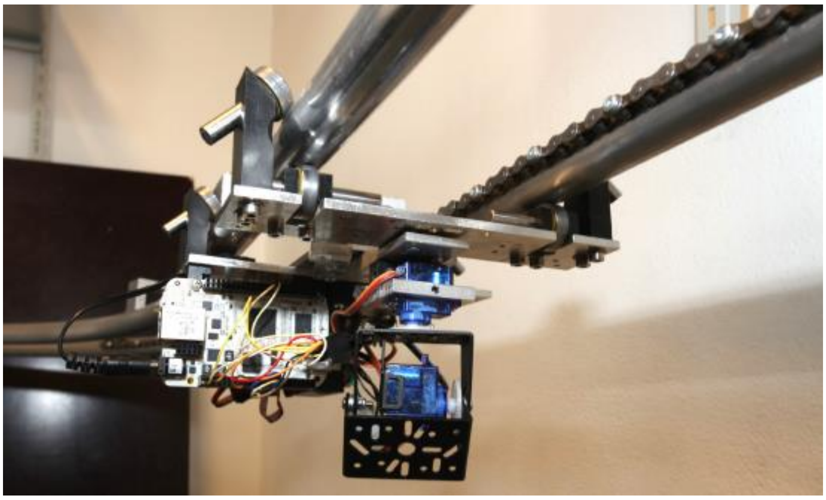


Figure 2.5: The proposed rail-way based inspection robot system for wind farms, adapted from [17].

exploration process being interrupted by limited onboard energy. The proposed rail-way based inspection robot system can be seen in Figure 2.5.

In terms of the sensing system, a camera was adapted for visual exploration. Regarding the motion system, the robot could move forward and backwards. In the overall exploration process, the developed exploration robot was wirelessly operated by the ground station and during usability tests, the satisfaction level of human-robot interaction process from these participants was evaluated. An indoor environment was used in the system's evaluation, where the robot was required to locate two faults in a distribution box: (1) a loose cable, and (2) a tripped fuse.

From the results, the developed robot was found to be able to locate the faults. However, participants were concerned about the flexibility of the proposed exploration robot, such as its ability to adjust to locate exploration targets but the robot's battery limitations were solved to allow exploration in the long-term. The main limitations of this project are summarised as follows: (1) skilled human operators are required as the robot is operated manually; (2) the test environment was idealised; and (3) it was expensive to build a railway route for real implementation.

Case study 5: Juntao et al. [18] carried out a study to develop a multi-robotic exploration system to monitor the health of wind farms. Currently, the precise O&M of wind farms is difficult due to extreme weathers. This because the reliability of the overall subsystem inside a wind turbine will suffer a great impact, such as the lifecycles of mechanical or sensor system are reduced. There was a necessity to develop another on-site exploration method which can be adapted to check these turbines healthy at any time. In general, the turbines in a wind farm are grouped and laid out over a large area. Therefore, this project considered using a multi-robotic exploration system to overcome the monitoring gap. This project involved two main steps: (1) developing a fault database for the turbines to formulate a potential risk assessment; and (2) developing a controller for scheduling an exploration strategy for a multi-robotic system.

For the fault database, Exponential Risk of Fault (ERF) concepts was proposed to quantify the damage of the defects. This helped the robot controller calculate the threat level for each exploration task. All ERF concepts from each robot were grouped together, which allowed the lowest-risks exploration plan for the robot team to be found. From there, the inspection strategy was formulated for the exploration system, which attempted to minimise the damage to a wind farm.

During testing, fault data from real wind farms were collected and used for ERF method assessment. From the results, the multi-robot system was found to be able to perform exploration tasks for wind farms with a low chance of serious accidents. This novelty of this project was its use of ERF as evidence for minimising operational risk for the development of the exploration system. However, the main limitation of this study was that the proposed multi-robotic exploration system was not fully developed.

Case study 6: Fabio et al. [28] carried out a study to investigate the usability of an exploration system for wind farms. In their study, the problem - the O&M technical inefficiency bothering the power generation capabilities of the wind farms – was identified. Thus, a risk-based method was considered and used to define the priority level of the inspection tasks to avoid serious accidents. In the development of the exploration robot system, two works were carried out: (1) an experienced dataset was built in the main station for diagnosis of the faults in wind farms; and (2) a fault

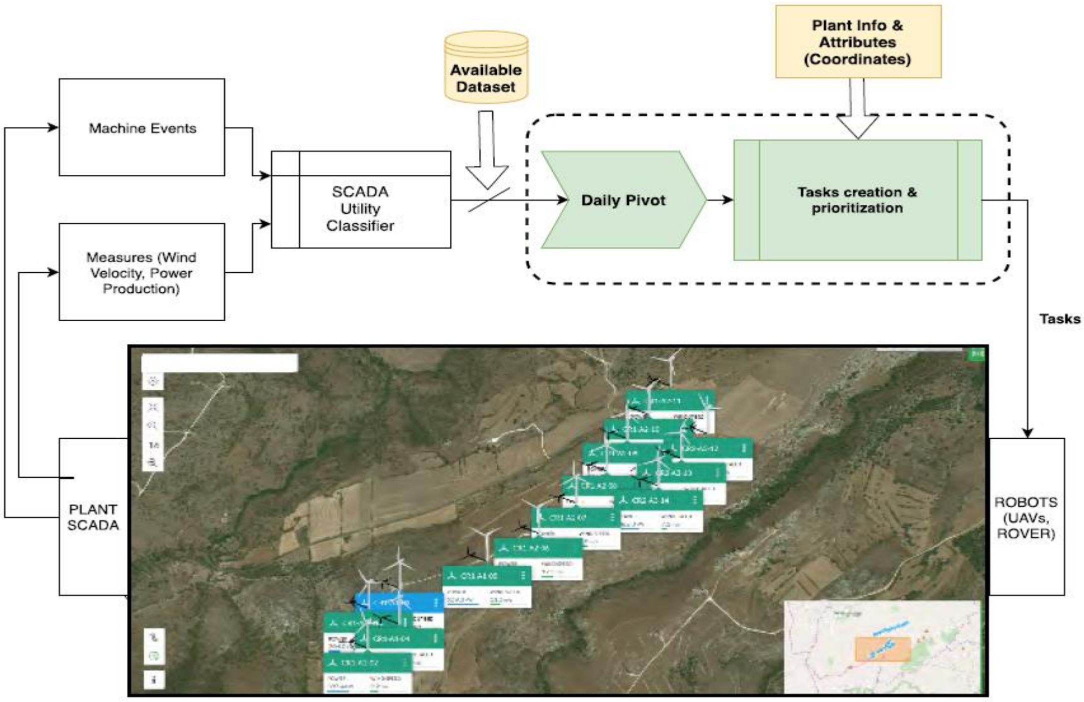


Figure 2.6: The proposed exploration system for wind farms in Greece, adapted from [28].

prediction model was proposed as evidence for scheduling the inspection strategy of the exploration robot, which contributed to minimising the damage to wind farms as much as possible. The proposed exploration system for wind farms can be seen in Figure 2.6.

In terms of dataset construction, one year of real data from a wind farm was collected. These data included the general situations of the wind turbines, such as their power generation, wind levels, gear temperature, and so on. In terms of the development of the predictive model, these collected fault data were classified into eight groups to represent the on-site situations and relative threat levels of damage. Furthermore, these threat levels were separated into two groups: (1) acceptance and (2) unacceptance. Thus, the exploration robot was able to recognise the priority levels of the inspection tasks.

After the experiments, the method developed for the robot exploration for wind farms reduced the chances for unscheduled maintenance of the wind farm. In addition, the power generation of the selected wind farm increased after adapting the developed robot system. The limitations of this project are summarised as follows: (1) the exploration efficiencies were limited by a single robot; (2) the predictive models for building the fault database required a large amount of experienced data, and this may have meant the developed exploration robot is not applicable to other facilities, such as a thermal power plant; and (3) the details of the exploration robot are not provided. This project considers generic agents and was interested in planning a low-level risks exploration strategy rather than the physical platform.

The contribution of this project is that it is strongly connected with the real power industry, and the exploration system that has been developed has been successfully deployed in a wind farm. In addition, this project also provides a key concept to exploration system development, which is that a developed exploration system should be able to adjust its exploration strategy based on different situations to minimise the possibility of shutdown of a power plant. Therefore, it is worth considering how to allocate exploration tasks to multi-robots to protect power plant as much as possible based on different exploration modes as concluded in Section 2.1.1.

2.2.3 Nuclear Power Plants

Case study 7: Qingsong et al. [29] developed a steam-generator exploration robot for a nuclear power plant. This study was inspired as a manual exploration of the steam-generator in a nuclear power plant was impossible due to the small spaces. Therefore, a remote-controllable exploration robot was developed for visual inspection tasks inside steam-generator. In this study, four subsystems were developed: (1) robot platforms, (2) sensing equipment, (3) assisting equipment, and (4) an operating system. The proposed exploration robot can be seen in Figure 2.7 left-hand side.

In terms of the development of the robot platform, magnetic wheels were adapted for the robot, giving it the capability to move and stick on the surface of the steam generator. To inspect the surrounding situation, four cameras were installed in the front and side of the exploration robot. One extra camera was attached to a built-in robotic arm to make detection more flexible. In addition, the distance from the robot to the target could be measured by the integration of distance sensors and a Virtual Reality (VR) system was adopted which allowed the human operator to see the robot’s position in the steam generator. In terms of the robot’s operating system, the exploration robot was controlled and monitored by a control panel and two screens.

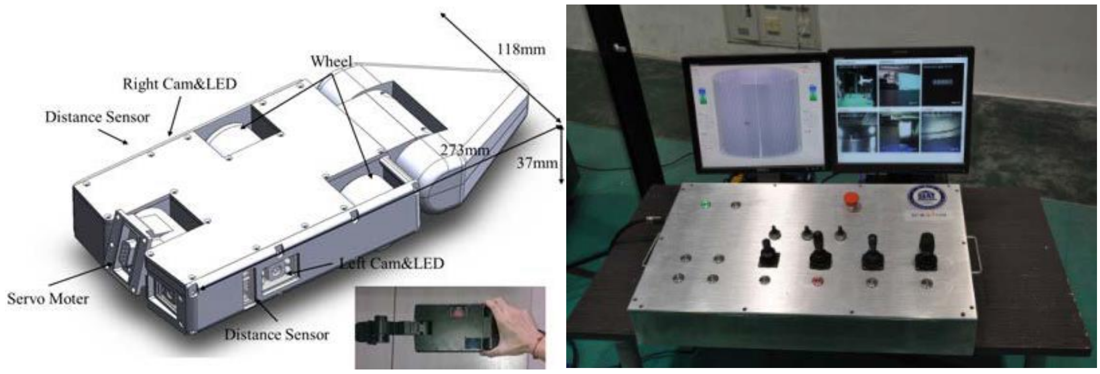


Figure 2.7: The robot system for exploration of a nuclear steam generator, adapted from [29].

The details of the VR system and control system can be seen in Figure 2.7 right-hand side.

In the experiments, the exploration processes were conducted on mocked-up models with the results revealing that the robot was able to perform exploration tasks inside the steam generator. The novelty of this project was that its utilised VR technology, which allowed operators to check on-site situations. The limitation of this study was that the robot was controlled via cables, which may mean the robot struggles with obstacles.

Case study 8: Dinesh et al. [20] carried out a study to apply a small quadrotor into nuclear power plants to gather on-site data for decommissioning. The inspiration for this project was twofold: (1) manual exploration of radiation areas for decommissioning or decontamination of nuclear sites is impossible, and (2) the robot’s navigation capability is challenged in this kind of unknown environment where might without GPS signal, or commands from a human operator. Thus, an autonomous exploration robot was developed to avoid human involvement in the exploration of nuclear sites. In addition, two external situations were considered: (1) the autonomous exploration capability when robot left with different battery are considered; and (2) robot are required to check situations for a narrow place, such as a primary containment vessel. Thus, a small quadrotor (diameter of 0.16 m) was selected as the exploration platform, which can be seen in Figure 2.8.

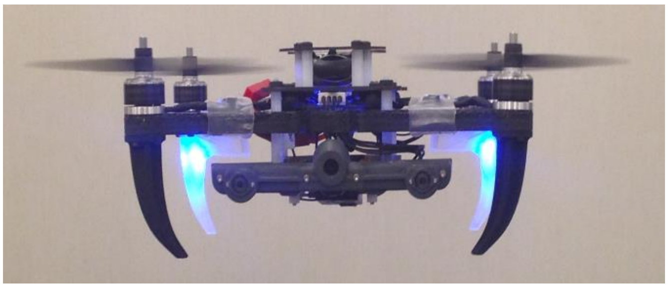


Figure 2.8: The proposed small UAV exploration platform for nuclear decommissioning, adapted from [20].

In terms of the development of the autonomous system, this project was split into three steps: (1) the real-time status of UAV are collected for adjusts its flying pose; (2) the environments around the UAV were mapped via a stereo and a camera; and (3) a pre-generated map was used to plan the exploration path for the UAV. During testing, the system was evaluated under a mocked-up model.

From the results, the exploration robot was found to be able to be used in an unknown environment to conduct autonomous exploration without human intervention. However, battery consumption had a significant impact on exploration performance. To be more specific, in the case of low battery, the sensing system was affected as the exploration process was unstable, which caused the exploration robot to crash or drift in some instances. The main limitation of this study was that the robot was tested is in an indoor lab environment.

Case study 9: Benjamin et al. [19] carried out a study to investigate the feasibility of using autonomous exploration robots for general O&M of nuclear power plants. This project was inspired by the fact that manual monitoring of radiological materials inside a nuclear plant is generally considered dangerous, time-consuming, and repetitive. In this project, the significance of using an autonomous robot was discussed, with the conclusion that nuclear plants can benefit from the use of exploration robots in terms of the release of labour for more complex tasks, the double verification of equipment for the plant, reductions in costs, and so on. As a result, a fully autonomous exploration robot – CARMA – was developed, which can be seen in Figure 2.9.

Figure 2.9: The developed CARMA robot, adapted from [19].

The development was split into four steps: (1) radiation sources (alpha, beta, and gamma) in the nuclear plant were determined; (2) the exploration robot was developed, based on the robot platform (TurtleBot2) and relative sensing system (a thermal sensor package and navigation sensor). A spring arrangement was also developed to absorb the shock of the sensors when the robot operated on uneven surfaces; (3) the autonomous exploration system was developed based on simultaneous localisation and mapping techniques; and (4) the radiation avoidance algorithm was developed for planning the exploration path. To test the developed exploration robot, two experiments were carried out: (1) a computer simulation, and (2) the deployment of the developed system to a real nuclear power plant.

During testing, the developed robot system was found to be able to undertake exploration tasks and ran at a highly autonomous level. The contamination zone was identified by the developed exploration robot, and the exploration process was more reliable by the adoption of spring arrangements in the sensing system. The project developed radiation avoidance algorithms that could be used to compute a cleaning path for the robot, which allowed further maintenance and recycling if the robots were to be deployed in a real nuclear power plant. However, after a comprehensive review, a concern was the exploration efficiency of this robot when deployed to a large-scale site to inspect multiple targets.

2.2.4 Thermal Power Plants

Figure 2.10: The developed exploration robot for a thermal power plant, adapted from [21].

Case study 10: Yandong et al. [21] developed a robot for on-site monitoring of the equipment in a thermal power plant. This project was inspired by three reasons: (1) reliability and effectiveness of manual exploration is limited when inspectors face multiple and various exploration tasks in a thermal power plant; (2) on-site exploration in a power plant generally involves extreme conditions, such as high-temperatures, thus the engineer’s safety suffers great risks; and (3) labour shortages. Therefore, a robot system was developed to accomplish general on-site exploration tasks for thermal power plants and this robot can be seen in Figure 2.10.

In terms of the robot’s hardware configurations, three parts were developed: (1) an exploration platform, (2) sensing system, and (3) charging system. To cover the exploration tasks in large sites, the speed of exploration platform was designed to 1.3 m/s and its ability to climb 25° slopes. In addition, considering indoor and outdoor exploration requirements, the robot was developed to be able to work at conditions between -40°C ~ +70°C. For the sensing system, a camera was specially customised with a detection range of up to 30 metres and a shock absorption system was adapted to enhance the system’s exploration qualities. Obstacle avoidance was achieved by using an ultrasonic distance measurement radar. In terms of the charging system, the robot continuously monitored its remaining battery via an energy consumption evolution chip. During exploration, the robot navigated a fixed route.

According to the test results, the developed exploration robot was able to conduct explorations of the thermal power plant. For instances, it was used to check the gage pressure, thermometer, oil level, and valve status in the thermal power plant. However, limitations included the fact that the exploration robot navigated a pre-defined route, and the efficiency of the developed robots was an issue when multiple targets needed to be checked in a limited amount of time.

Case study 11: Jun et al. [30] developed a robot for exploration of Boiler Water Walls (BWW) in a thermal power plant. Current manual exploration of BWW is inefficient and results in a loss of power generation. This inefficiency is due to the highly complex and tough conditions inside a boiler. Thus, there was a requirement for quick maintenance of boiler systems to reduce O&M time. A wall-climbing robot was therefore developed to assist the engineers for conducting exploration inside a BWW. This robot can be seen in Figure 2.11.

In terms of the system's development, two main parts were considered: (1) the exploration platform, and (2) non-destructive testing. For the exploration platform, to accomplish exploration in a flexible way, the robot's body was made straight, with sideways walking parts that allowed the robot to move on a horizontal or vertical plane. In addition, the robot's power breaks problem was also considered because of robot might fall to lead the device got a secondary damaged. Thus, a magnetic adsorption system was deployed which was used to make sure the robot remained on the BWW. For the sensing system, cameras and an ultrasonic sensor were both installed for obstacle avoidance and tube exploration.

Experiments were conducted in a real power plant and in the experiments, it was found that exploration of the BWW could be easily conducted by the developed robot. In addition, the efficiency of the proposed exploration system was enhanced, as the robot was able to inspect six points in one-stop. However, the limitation was that the proposed robot was only suited to a boiler system.

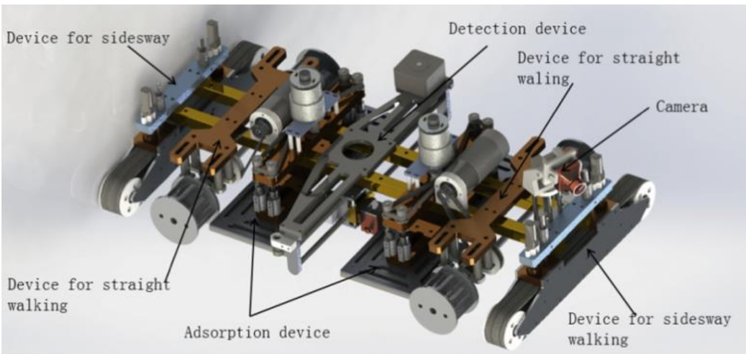


Figure 2.11: The proposed wall-climbing robot system for exploration of a thermal-plant boiler, adapted from [30].

Case study 12: Vikesh et al. [31] developed an exploration robot to monitor a thermal power plant's fuel feeding system. The inspiration for this project was twofold: (1) breakdown problems of the coal conveyor were identified as lowering the power production of the thermal power plant; and (2) manual exploration to prevent conveyor shutdown was challenging due to dusty conditions (because of the conveyor's open design, the pulverised coals are exposed directly). Thus, an exploration robot was developed to inspect the coal conveyor belt in this project.

In terms of the fault phenomenon of the conveyor system, two common faults were considered for the system's development: (1) the unusual temperature of the bearing system, and (2) unusual noise of the conveyor belt. Thus, an infrared temperature sensor and a sound level metre were adopted in the robot sensing system. In terms of exploration routes, Radio-Frequency Identification (RFID) labels were stuck on the conveyor belt where these RFID labels were far from each other with a certain distance for the robot to follow. In terms of fault diagnosis, the console received data via a wireless module from the exploration robot.

According to the test results, the exploration robot was able to check the conveyor instead of manual exploration. However, the proposed RFID system may be interrupted by coal dust, which could lead to the robot's loss of control or it missing 'hot spot' exploration points.

2.2.5 Robot Platforms for Exploration

Figure 2.12: The real exploration robot system deployed in Lanxi 500 kV substation, adapted from [32].

Case study 13: Lihui et al. [32] developed a robot platform to explore on-site device health in substations. The inspiration for this project was twofold: (1) cost-effective issues of manual exploration of substations, as exploration processes are repetitive and a certain number of inspectors are required; and (2) the fact that human inspectors may face challenges such as high voltage, high temperatures or extreme weather. Therefore, a mobile exploration robot was developed to undertake on-site exploration tasks in substations. This robot can be seen in Figure 2.12.

Firstly, the on-site exploration characteristics were determined as the exploration targets being various and laid out over a large exposed area. Therefore, a perception system was integrated with different onboard sensors for comprehensive exploring capability. For instance, the robots' had the ability to read the voltmetre or oil level gauge through a high-resolution camera; or it can check the temperature fault for different devices via the onboard thermal cameras, etc. During exploration, an RFID routing system was deployed to guide the robot's navigation. In addition, the charging task of the exploration robot was considered due to its limited battery. After finishing a one-period exploration task, the robot returned to the station for charging. The developed robot system was tested in a 300×200 m^2 real substation. During testing, two exploration robots were separately serviced for 500 kV, 220 kV, and 35 kV zones in the Lanxi substation.

The result was that the robot team was found to be able to effectively assist substation in carrying out on-site exploration tasks. In terms of the robots' efficiencies, three exploration periods can be guaranteed by two robots in one day. However, the main limitation of this study was that, due to the pre-fixed route of the RFID label, a large amount of labelling was required. In addition, in terms of the temporary exploration tasks, the robot may not fully be charged, meaning there was a necessity to develop a charging method to avoid the robots stopping, such as robots are required to get back to charging station once the battery left lower than a threshold value.

Case study 14: Hutter et al. [33] developed a quadrupedal robot platform to replace manual operation in harsh environments. In this study, due to the traditional wheeled robot structures, the mobility and versatility of these robots were limited in complex environments, such as climbing stairs. Thus, a novel robot dog – ANYmal – was invented to enhance operational capability in these challenging environments. The developed robot was 0.5 m high and weighed 30 kg and can be seen in Figure 2.13.

In this project, hardware and kinematic motion control of the robot were both studied. For the hardware, considering further maintenance was needed, the robot was designed to be fully reassembled by different units. As the robot was developed for harsh and unknown environments, ANYmal was customised to protect from dust ingress, and with capability to stay safe if it fell from 50 cm height. Environmental perceptions were based on three systems: (1) two industrial-levels lidars were equipped for robot localisation and mapping environments; (2) wide-angle cameras were used for on-site situation feedback; and (3) a pan-tilt head system was adapted to support different sensing packages that could be integrated for various cases. The overall test of the robot was carried out in a real industrial factory where ANYmal was required to conduct explorations to inspect different targets.

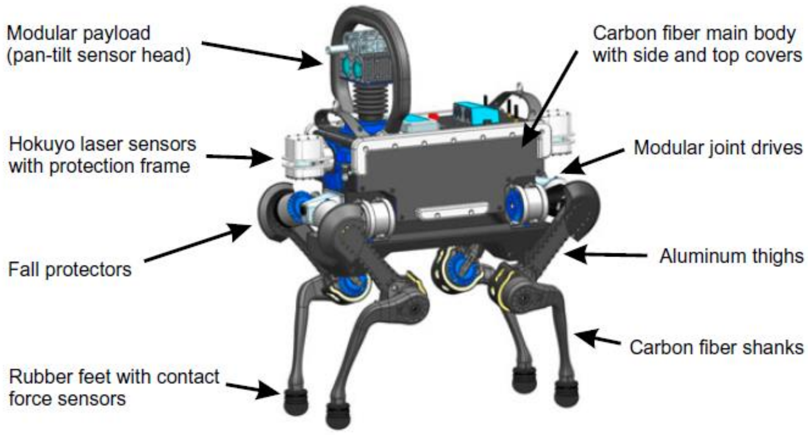


Figure 2.13: The invented robot dog, ANYmal, adapted from [33].

From the results, the proposed structure was found to be able to help the robot perform tasks in complex environments. This was because the robot was able to engage in normal walking, running, climbing stairs and jumping. Based on the developed perception system, the robot is successfully navigated which allowed the robot to avoid obstacles and arrive at targets successfully for exploration tasks. The novelty of this system was that, compared with a general wheeled robot, the mobility and dynamic locomotion of ANYmal was significantly improved. However, after review, this project was found to have two primary concerns: (1) the exploration efficiency of ANYmal when it is deployed in a large area for long-term exploration; and (2) legs of the ANYmal could stuck into floor gaps.

Case study 15: Romulo et al. [34] developed an autonomous robot to explore defects in civil infrastructure. This project was inspired as the safety of civil-infrastructure inspectors is at risk when they conduct exploration of ageing buildings. Thus, an exploration robot system was developed to undertake exploration tasks for these old facilities. The details of the developed exploration robot can be seen in Figure 2.14.

In this project, hardware configuration and exploration methods of the robot's development were considered. In terms of the exploration robot platform, a Husky robot platform was deployed with a high-resolution camera. While in terms of exploration methods, two main algorithms were developed to support the robot carry out explorations: (1) a crack detection algorithm was developed to locate defects in

Figure 2.14: The proposed autonomous robot system for monitoring civil structures, adapted from [34].

the buildings; and (2) a measurement algorithm was developed to quantify the level of damage. An indoor experiment with 14 different types of cracks (horizontal, vertical, curved, angled, etc.) was used to test this exploration system.

According to the test results, all cracks were successfully detected by the exploration robot, and the accuracy of crack measurement was as high as ±1.033% in terms of crack position, and ±5.48% in terms of crack dimensions. However, the usability of the developed robot was good, but the exploration-efficiency was not tested in this project, such as the time taken to conduct an exploration task to find all the defects in a room.

2.2.6 Summary

In summary, development of exploration robots for on-site inspection in power plants is a demanding area of research which is contributing the improve the reliability of these power plants. However, to provide a comprehensive analysis of these reviewed projects, a summarisation of these robots, such as their properties and their limitations against our investigation results from Section 2.1.4 (on-site inspection characteristics), are listed in Table 2.3. Overall, there is still room for improvement in these exploration systems from three aspects:

(1) Versatility, such as some invented exploration robots are too professional for a particular place or device. This was observed from Cases 1, 2, 7, 11, 12, 15. These

robots are difficult to apply in other domains, especially as this project looks for an exploration system that has the capability to cover general on-site exploration works in power plants;

(2) Effectiveness, the efficiencies of some reviewed exploration system were challenged when the robots had to face multiple inspection targets, and would worsen if the targets were laid out in large-scale power plants. This was observed from Cases 1-4, 6, 8-10, 14-15. As most projects attempt to use single robot platforms to conduct on-site exploration works, there is inefficiency in the exploration process when compared with multi-robots, thus increasing the difficulty for precise O&M for power plants;

(3) In all reviewed case studies, the charging impact on the exploration system's performance was not considered. Thus, there is a necessity to develop an appropriate charging/exploration mechanism for the improvement of the exploration system for the followed reasons. Firstly, as the ability of the cable support robot to conduct exploration restricts exploration flexibility, most projects use a battery to support the robot's exploration. The issue in these reviewed projects is that they did not consider how to balance charging/exploration requests for exploration system optimisation, e.g. providing a suitable condition for the robot to charge itself during exploration, but as much as possible reducing the impacts from the charging process on the efficiency of the exploration system.

Overall, from the review above, a multi-robot exploration method with the capability to undertake more complex tasks is an alternative solution to replace a single inspection platform. However, in the case of the limited robots and multiple exploration targets, there is a need to develop an optimal cooperative mechanism and a proper charging method for system optimisation. Thus, the next section will outline an optimal cooperative mechanism for the development of a multi-robotics exploration system.

Table 2.3: Summary of the different robot exploration platforms.

<table>
<tr><th rowspan="2">Case No.</th><th rowspan="2">Power Plant Types</th><th rowspan="2">Types of Robot</th><th rowspan="2" colspan="2">Robot Numbers / Mechanism</th><th rowspan="2">Exploration Functions</th><th colspan="3">Limitations</th></tr>
<tr><th>Usability</th><th>Efficiency</th><th>Power</th></tr>
<tr><td>1</td><td rowspan="3">Solar Power Plants</td><td>Wheeled robot</td><td rowspan="4">Single</td><td>Autonomous</td><td>Detect pipe leakages</td><td rowspan="2">Poor</td><td rowspan="4">Poor</td><td>Battery</td></tr>
<tr><td>2</td><td>Legged robot</td><td>Manually</td><td>Inspect health of the receiver panel</td><td>Cable</td></tr>
<tr><td>3</td><td>Wheeled, and drones together</td><td>N/A</td><td>Monitor and clean photovoltaic surfaces</td><td rowspan="4">Good</td><td>Battery</td></tr>
<tr><td>4</td><td rowspan="3">Wind Farms</td><td>Rail-based robot</td><td>Manually</td><td rowspan="3">Explore health of the wind turbine</td><td>Cable</td></tr>
<tr><td>5</td><td rowspan="2">N/A</td><td>Multiple</td><td>N/A</td><td>Good</td><td rowspan="2">N/A</td></tr>
<tr><td>6</td><td rowspan="7">Single</td><td>N/A</td><td>Poor</td></tr>
<tr><td>7</td><td rowspan="3">Nuclear Power Plants</td><td>Wheeled robot</td><td>Manually</td><td>Inspect the steam-generator</td><td>Poor</td><td>Good</td><td>Cable</td></tr>
<tr><td>8</td><td>Drones</td><td rowspan="3">Autonomous</td><td>General exploration of the plant</td><td rowspan="3">Good</td><td rowspan="3">Poor</td><td rowspan="3">Battery</td></tr>
<tr><td>9</td><td rowspan="2">Wheeled robot</td><td>Monitoring of radiological materials</td></tr>
<tr><td>10</td><td rowspan="3">Thermal Power Plants</td><td>General inspection of the plant</td></tr>
<tr><td>11</td><td>Legged robot</td><td>N/A</td><td>Inspection of the Boiler Water Wall</td><td rowspan="2">Poor</td><td rowspan="3">Good</td><td>Cable</td></tr>
<tr><td>12</td><td rowspan="2">Wheeled robot</td><td rowspan="4">Autonomous</td><td>Detection of the fuel feeding system</td><td rowspan="4">Battery</td></tr>
<tr><td>13</td><td rowspan="3">Robot Platforms for Exploration</td><td>Multiple</td><td>General inspection of substations</td><td rowspan="2">Good</td></tr>
<tr><td>14</td><td>Legged robot</td><td rowspan="2">Single</td><td>Exploration of harsh environments</td><td rowspan="2">Poor</td></tr>
<tr><td>15</td><td>Wheeled robot</td><td>Inspection of the health of buildings</td><td>Poor</td></tr>
</table>

2.3 Multi-robotics Exploration

As power plants are large-scale and involve multiple exploration sites, this project considered using multi-robotic exploration system for power plant inspection. In terms of using a limited number of robots to explore these multiple targets, the main challenge of the exploration system was to separate the exploration tasks to these robots appropriately, such as the formulated exploration strategy with capability to let robot team with the minimum travelling cost. This problem was regarded as a combinatorial optimisation problem. This kind of problem can be solved by adapting the optimisation tool, and the overall calculation process can be split into seven general steps as shown below:

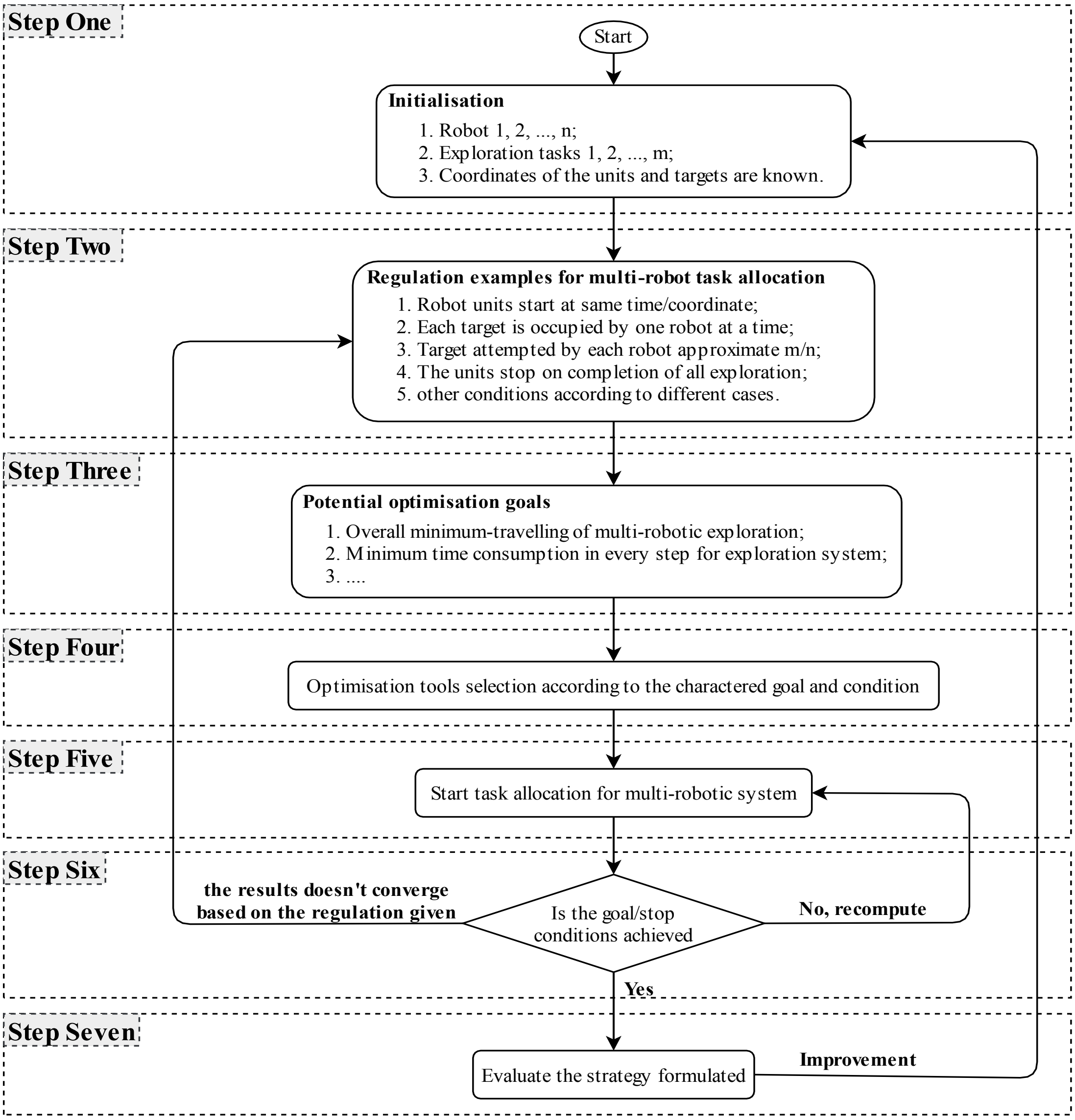


Figure 2.15: The general process to solve the combinatorial optimisation problem.

Step One: Initialisation

This is the first step to solve the combinatorial optimisation problem where the given conditions for multi-robot task allocation need to be collected. These conditions include the numbers of robots, tasks, and their positions.

Step Two: Exploration Rule Setup

This step clarifies the additional task details for the multi-robot system. For example, the robot exploration capability, the robot start location, exploration behaviours and so on.

Step Three: Optimisation Goal Setup

This step is based on setting up the optimisation goals for multi-robot task allocation. For example, the shortest exploration route for the exploration system, or minimum time consumption for exploration at every step of the exploration system.

Step Four: Select Optimisation Tool

At this stage, a suitable optimisation tool must be selected to solve this combinatorial optimisation problem – Multi-robot Exploration Task Allocation. The selection can be considered from two aspects: (1) determining the characters of the optimisation problem(s), e.g. local/global optimisation, computational cost; and (2) identifying the capabilities and drawbacks of the optimisation tools, e.g. convergence time required or usability against the conditions provided before.

Step Five: Multi-robotic Exploration Task Allocation

In this step, the conditions, exploration rules, optimisation goal and tool are ready. Thus, this step attempts to schedule an exploration strategy for the multi-robot system based on the limitations outlined above. The exploration strategy formulated can be, Robot #1 with Exploration Target 1, 3, 5, while Robot #2 with Exploration Target 2, 4, 6.

Step Six: Formulated Exploration Strategy Optimisation

This step requires adjusting the formulated exploration strategy for optimisation. This step may face two conditions: (1) successfully formulate an exploration strategy for the multi-robot system, thus this step checks the performance of different formulated strategies by comparing them at the end of the calculation; and (2) failure to formulate an exploration strategy several times, meaning improper conditions and optimisation goals are used, or a problem occurs in optimisation tool set up. Thus, it is necessary to re-assess the conditions used in *Steps Two ~ Five* to create a useful exploration strategy for the multi-robot system.

Step Seven: Formulated Exploration Strategy Evaluation
This step assesses each previous of the steps to optimise the overall multi-robot task allocation process. The improvement is based on evaluation of the final exploration strategy formulated for the multi-robot system. This step requires a comprehensive analysis of each step to find out the areas for improvement for multi-robot task allocation. For example, re-definition of boundary conditions, or improvement of the selected optimisation tool by modifying the framework or parameters.

The methodology to solve combinatorial optimisation problem has been outlined before, so now we must check and select suitable optimisation tools to schedule an appropriate exploration strategy for the multi-robotic system. Thus, a general review of optimal task allocation methods for a multi-robot system was carried out. In total, five approaches were reviewed: (1) Simulated Annealing, (2) Particle Swarm Optimisation, (3) Ant Colony Optimisation, (4) Greedy algorithm, and (5) Genetic Algorithm. After a comprehensive review, the Greedy and Genetic Algorithms were selected to solve temporary and long-term exploration tasks in power plants.

2.3.1 Simulated Annealing

Method 1: Simulated Annealing (SA) is an approximate approach to solve combinatorial optimisation problems [35]. Technically, the annealing process includes heating and cooling a metal so that its internal structure reaches or approaches equilibrium status to obtain machined metals with the desired performance. SA simulates this process and the equilibrium status of the machined metal is determined from the procedure of its internal crystal formation. In general, a machined metal is heated to a temperature and then, at a very slow cooling rate, its internal atoms are rearranged from being irregularly laid-out to a more regular pattern. From there, the inside of the machined metal contains regular crystals with a high density and low energy properties. Therefore, the internal structures of this metal achieve equilibrium status and the annealing process can be seen as successful. This also means that the optimal global solution has been found inside the SA. In contrast, if the cooling rate of the machined metal is too fast, the atoms of the machined metal are rearranged within a short period which may result in the internal structure of this machined metal being irregular. Therefore, the machined metal generally contains high energy non-crystals, which means the system stays unstable and is a suboptimal solution inside the SA. In this unstable case, like the annealing operation, the SA will repeat the heating and cooling procedures for the machined metal to rearrange its internal atoms to formulate the regular crystals. This process will help the formation of the internal crystals of the machined metal approach equilibrium status and abandon the suboptimal solution.

In [36], the combinatorial optimisation problem – single-model stochastic assembly line balancing of parallel stations – was solved by SA. However, one serious drawback of SA is it generally accepts inferior solutions which result in the repeat selection of past solutions, which wastes limited computation resources.

2.3.2 Particle Swarm Optimisation

Method 2: Particle Swarm Optimisation (PSO) is a swarm intelligence algorithm inspired by natural evolution [37]. One typical natural evolution process that has inspired PSO is the cooperation of birds when hunting to locate food. PSO models this kind of process and uses it to find the optimal solution in a group. In PSO, the problem is described in an n-dimensional space, and different particles (representing potential solutions) fly inside this space. These particles simulate human social behaviours, such as remembering the best solutions (the food's location) during hunting with groups, and then share this information with other particles. Most importantly, particles will learn from others to adjust their run status for purchasing global optimal solution that can be used to benefit all the group members. For instance, changing direction or flight speed to approach the current global optimal solution. The overall process will through serval iterations which contributes to keeping search the optimal global solution from every individual particle.

In [38], this paper reviewed the improvement of 46 different PSO techniques. In a general PSO model, the parameter setup must be used very carefully. Otherwise, the PSO may easily track or identify partial optimism, thus leading to speed and directional bias, ignoring the optimal global solution. For example, improper adjustment of the velocity of particles may lead all group members with the same velocity. As a result, the last global optimal solution recorded will also remain the same, meaning PSO will keep searching for solutions in the space, and will not converge in the local area.

2.3.3 Ant Colony Optimisation

Method 3: Ant Colony Optimisation (ACO) is a probabilistic approach for searching for optimal solutions in a party [39]. Similar to the PSO model, the ACO method is inspired by the hunting behaviour of ants, which, although almost blind, are able to establish the shortest route to find food and return to the nest. It was found that collective behaviours exist in an ant colony. For example, every individual ant will contribute to helping others ants hunting food via releasing pheromone trails. This information is then used as the guidelines to determine the further hunting direction for other ants. For example, food is found by the first ant, and during the search for food, different quantities of the pheromone will be released by this ant to the entire party. In this way, when another ant finds the pheromones left by the first ant, it will likely to follow this route, while releasing more pheromones to reinforce the trail for others. Therefore, the probability of finding food with the shortest path is increased and the entire population of ants benefits from this method of cooperation.

In [40], a survey of ACO's application, limitations and further research recommendations was conducted. ACO was found able to be used to solve many different combinatorial optimisation problems, such as the travelling salesman problem, or multiple knapsacks. However, in use of ACO, the computation processes for convergence an optimal solution is generally within an uncertain time. In addition, in areas of multi-objective problems, much more research is required, such as the evaluation functions of multiple objectives to increase the quality of the solution, or develop a parallel ACO for the optimisation of effectiveness.

2.3.4 Greedy algorithm

Method 4: The Greedy algorithm is a common method used to solve multi-robot task allocation problem [41]. As the name suggests, every operation in a Greedy algorithm is based on selecting the best solution, such as the shortest distance in global or the minimum time in local, etc. In a Greedy algorithm, two steps are generally taken: (1) greedy selection of the best solutions, then removal of the solution selected from the list, and (2) iterating this process again, until all tasks are allocated to members to formulate an optimum solution.

Due to the ease of implementation, the Greedy algorithm has generally been adopted to schedule an exploration strategy of a multi-robot system. In [42], the Greedy algorithm based multi-robot task allocation method was developed for industrial plant inspection. As a result of the greedy based exploration method for multi-robot task allocation, the computation times were saved by more than 10% in total. While in [43], a new multi-robot task allocation method – vacancy chain scheduling – was developed, where the tasks were allocated by a greedy selection of the optimal interaction behaviours of robots.

2.3.5 Genetic Algorithm

Method 5: Genetic Algorithm (GA) is a heuristic search scheme that simulates biological evolution processes to solve combinatorial optimisation problems [44]. In simple terms, GA abandons unqualified solutions and picks the best for further evolution to determine optimal solutions. The GA generally consists of five steps: (1) generating random solutions in a gene format; (2) checking the performance of these solutions by different evaluation metrics (also called fitness function); (3) evolution of these processes to generate a smarter population; (4) elimination of unqualified solutions; and (5) repetition of the previous processes until the acceptable answer emerges.

Use of the GA to solve combinatorial optimisation problems is beneficial from multiple perspectives [45]. For instance, GA reduces the possibilities of local minimum trapping due to its parallel computation mechanism. In addition, GA evaluates the solution by itself via a function called ‘fitness’ so that no requirement to use the auxiliary functions. GA has shown good performance and has been widely adapted for multi-robot system development. For example, in a previous study [46], GA was used to schedule an exploration strategy of a multi-robot system for manufacturing process exploration. While in [47], GA was adapted for planning exploration paths of a centralised multi-robot system in continuous environments.

Finally, in [48], GA was applied to solve coverage path planning problem for the multi-robot system, the completion time is minimised.

2.3.6 Summary

This section provides a summary of the different technologies which can be used to solve the combinatorial optimisation problem. To easily compare these methods, Table 2.4 below demonstrates their usability, and limitations.

Table 2.4: Summary of the reviewed optimisation technologies.

<table>
<tr><th>Problem</th><th>Method</th><th>Usability in Multi-robot development</th><th>Key Notes</th></tr>
<tr><td rowspan="5">Combinatorial optimisation problems</td><td>SA</td><td rowspan="3">Poor</td><td>SA generally accepts inferior solutions [36], which wastes limited computation resources</td></tr>
<tr><td>PSO</td><td>PSO may easily track or identify partial optimism to ignore the optimal global solution [38]</td></tr>
<tr><td>ACO</td><td>the computation processes for convergence an optimal solution is generally within an uncertain time [40]</td></tr>
<tr><td>Greedy</td><td>Good [41][42][43]</td><td>Support both local/global optimisation, and easy implementation</td></tr>
<tr><td>GA</td><td>Good [46][47][48]</td><td>GA reduces the possibilities of local trapping opportunities due to its parallel computation mechanism [45]</td></tr>
</table>

Overall, SA, PSO and ACO methods have their own limitations which significantly impacts the computation process and results. Thus, it is difficult to create a stable exploration system by using these methods without carefully setup. In contrast, Greedy and GA methods are deemed most adaptable in temporary and long-terms exploration modes for a power plant, for the following reasons.

Greedy for Temporary Exploration:

Firstly, two places are worth mentioning in the case of temporary exploration: (1) inspection efficiency request: in this case, exportation robots are better suited to provide the best exploration efficiency as every additional inspected target will reduce the possibility of power plant shutdown; and (2) the robot may be left with limited power but has to satisfy unscheduled temporary exploration requests for the power plant, thus the exploration capability of the robot is limited in this case.

Therefore, it is very clear that an exploration system for temporary exploration requires a robot with high exploration efficiency but based on a limited amount of battery. Thus, the Greedy method is suitable for temporary exploration compared with the other four reviewed technologies, for the following reasons:

(1) SA, PSO, ACO, or GA methods are all customisable for complex problems. Thus, using these methods for temporary exploration may waste computation resources. In addition, these methods may be able to schedule a global optimal exploration strategy for robots, but they may require robots to travel long-distances in some steps, thus these methods can not 100% guarantee more inspected targets in a short period of time compared to the Greedy method.

(2) In contrast, using the Greedy method to purchase local steps optimisation will allow the robots to as quickly as possible convert their limited energy to the exploration targets. The Greedy method allows the robot to examine, with little energy consumption, one zone after the other. Therefore, in addition to guaranteeing more inspected targets in a short period of time, the Greedy method is also able to systematically diagnose faults for power plants zone-by-zone.

GA for Long-term Exploration:

In terms of long-term exploration, two places are worth mentioning: (1) the exploration strategy is under scheduled, and exploration behaviours cover general on-site inspection tasks for an overall power plant; (2) the robot exploration system is continuously deployed on-site for maximum protection of device health.

A long-term exploration mode requires the exploration system to conduct on-site exploration tasks periodically. Therefore, it is necessary to formulate an optimal exploration strategy that means the exploration robots travel minimal distances to save energy consumption. Thus, the GA method should be used in a long-term exploration system for the following reasons:

(1) The GA method is widely adopted in other multi-robot developments, see Section 2.3.5 and Table 2.4 for examples;
(2) Of the reviewed global optimisation methods – SA, PSO, ACO, Greedy, and GA – the advantages of the GA method are obvious compared with the other four methods. For example, the GA method has the capability to parallel calculate the solution to reduce the local trapping opportunities. In addition, the GA method evaluates the solution by itself via a function called ‘fitness’ so that there is no requirement to use auxiliary functions.

However, as the exploration robot development requirements summarised in Section 2.2.6, in the selected Greedy and GA methods, the charging impact on the exploration robot performance was not considered. Thus, there is a necessity to develop a system with the capability to conduct both exploration and charging tasks for further optimisation. Also, there is a necessity to analysis of the performance of Greedy-based or GA-based exploration systems when they work for temporary exploration mode and long-term exploration mode. This analysis can be used as a judgement for further switching the suitable exploration strategy to satisfy different situations, such as using temporary exploration mode for rescuing an engineer zone-by-zone inside a power plant, or using long-term exploration mode for robot accomplish exploration tasks with high performance in energy-saving, effective exploration efficiency.

2.4 Robot Simulation Software

As the implementation of a robotic system is a time-consuming and costly process, a computer simulation was selected to develop the multi-robotic exploration system in this project. Three simulation packages were reviewed: (1) Microsoft Robotics Developer Studio (MRDS), (2) Gazebo, and (3) V-REP. Following a comprehensive review, the justifications for selecting the V-REP in this project are summarised as follows:

Simulator 1: MRDS is a Windows-based programming environment simulator for constructing robotic applications [49]. The main functions of MRDS are 3D simulation, visual programming, access to robot components (actuators, or sensors) for creation, control and debugging. The default programming language is C#. In addition, the implementation of the developed system on a real robot is available via the MRDS framework [50]. However, as of March 2012, there is no update or patch available for MRDS.

Simulator 2: Gazebo is an open-source tool for simulating robots running in indoor and outdoor environments [51]. It can be used to control a robot, relative sensor devices, and the dynamic environment. 3D simulation is allowed in Gazebo, and a physical engine has been developed to guarantee more realistic simulation. In addition, Gazebo is specially developed for single robot interaction in an environment, which would otherwise require plenty of time for the development of a multi-robot system [52].

Simulator 3: V-REP is a Coppelia Robotics product for developing a robot system. It is an open-source package for education and can be run in Windows, Linux or Mac environments. Seven programming languages are supported in V-REP, and there are two simulation modes allowed: (1) general, and (2) accelerated. The accelerated mode helps to reduce time-consumption in experiments. There are 48 different types of robots available in V-REP’s library for different applications. Most importantly, the different number and types of robots can be run simultaneously in V-REP [53].

Thus, V-REP was selected in this project to develop the multi-robotic exploration system, for the following reasons:

(1) It was tested by [54], and compared with Gazebo, the simulation performance of V-REP outperformed Gazebo.

(2) It is a versatile and scalable simulation framework with the capability to satisfy the requirements of the development of a complex system [55].

(3) Plugins are allowed by its integrated Application Programming Interface (API) function. The API function allows the user to easily implement or customise a simulation by themselves [56].

2.5 Summary

This chapter has reviewed different exploration techniques and robot simulation software. In Section 2.1, a brief review of manual exploration in the different power plant was presented. The characteristics of on-site exploration tasks in different power plants and the significance of using exploration robots were discussed in this section. In Section 2.2, the most recent exploration robots were reviewed and the limitations of these project were discussed according to the on-site exploration characteristics summarised in Section 2.1.4. The alternative solution – a multi-robotics system – was selected compared with a signal robot system due to the multi-robotics system's capabilities to finish multiple, various inspections tasks in a short time. The performance of the multi-robot system can be improved from two aspects: (1) scheduling of an optimal exploration strategy, and (2) appropriate charging control. In Section 2.3, five multi-robotic exploration methods were reviewed and justifications were provided for exploration robots using the Greedy and GA methods to conduct exploration in temporary and long-term modes. In Section 2.4, after reviewing three simulation packages, the justifications for using V-REP as the simulation platforms were outlined. In the next chapter of this paper, considering the temporary and long-term exploration modes, and combining with different exploration and charging methods, three multi-robotic exploration approaches will be demonstrated in detail.

Chapter 3

Methodology

In this chapter, the multi-robotic exploration approaches that have been developed will be presented. This chapter mainly consists of five sections: Firstly, Section 3.1 presents the exploration scenario of the development exploration robot system. Next, Section 3.2 describes the two different charging methods. Then, Section 3.3 and 3.4 explain the applications of Greedy and GA methods for temporary and long-term exploration modes for power plant exploration, before, finally, Section 3.6 summaries the chapter.

3.1 Exploration Scenario

Research Assumptions: In all developed exploration approaches, three assumptions are proposed:

(1) the map and target information are known in advance, without consideration of obstacles, and the task allocation process for the multi-robot system is in a static environment,
(2) the levels of priority of the exploration tasks and the change of exploration sequences are ignored,
(3) every exploration robot has the same number of inspection tasks, and every task can only be checked by one robot at a time.

Exploration Targets: In the investigated power plants, the main subsystem for power generation consists of a boiler, turbine, and electrical and auxiliary units. Generally, human inspectors carrying out an exploration go through these main subsystems. In this project, in the same way as a human inspector, the exploration robots are designed to undertake monitoring tasks for these different zones. To be more specific, the exploration robots are designed to inspect ten and twenty randomly laid out targets (from Table 2.2) in a scenario. These developed exploration scenarios are illustrated in detail in Section 4.4.3.

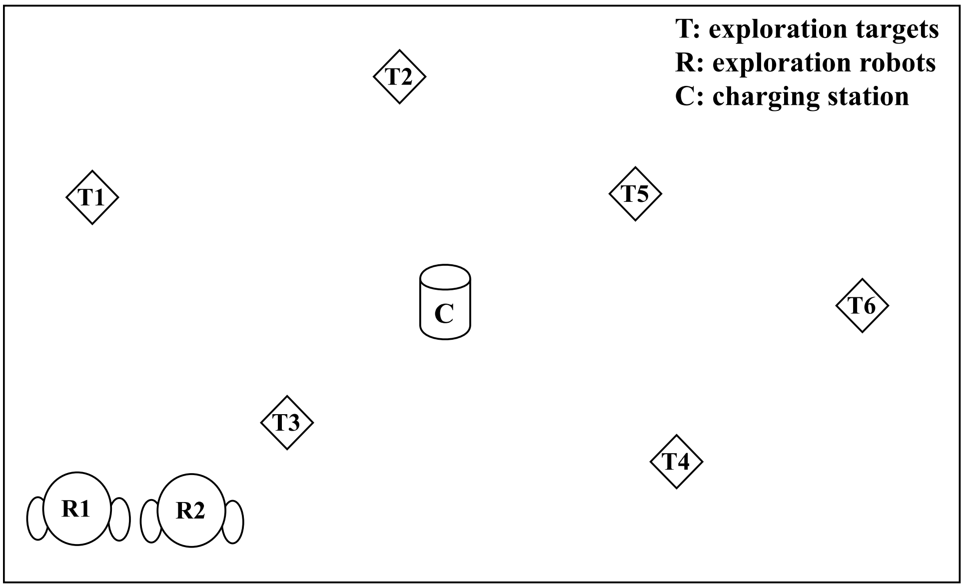


Figure 3.1: The sample configuration of the experiments.

Definition of Robot Exploration and Charging Tasks: The sample configuration of the experiments is presented in Figure 3.1. Two exploration robots are shown as *R1* and *R2*; the charging station is presented as *C*; and the sample exploration targets are illustrated as *T1~T6*. These targets are required to be continuously monitored by the exploration robots. The tasks of these robots when deployed on-site are pre-defined with four sequenced steps, which are as follows:

(1) the exploration robots start from an initial place, and then head towards the targets to conduct their exploration,

(2) the exploration robots go to the charging station if their remaining battery is lower than the threshold value (this value is based on the two developed charging methods, which will be demonstrated in the next section),

(3) the exploration robots are designed to return to their initial places after finishing their periodic exploration tasks,

(4) go back to step (1).

3.2 Robot Charging Methods

In terms of the robots' charging operation, their past-path length is used to manage the robots, stopping their exploration and return for charging after a certain point. Thus, once the past-path lengths of the exploration robots go over the threshold value, the inspection tasks switch to a charging task. In this project, the movement capability of the exploration robots was limited to 100 metres (for an explanation of this, see Section 5.1). In addition, to check the energy consumption of these robots at different times, the method in [57], for converted the robots' past-path lengths to their energy consumption is used here, which demonstrated as the following formula (3.1):

$$E_m = m \cdot T_d \,, \tag{3.1}$$

where m is the running cost of the selected exploration robot, 1.43 J/m [57] in this project, T_d is the past-path lengths of the exploration robot in metres.

3.2.1 General Charging Method

This method is a general charging method. In more detail, the exploration robot is required to charge itself until its amount of energy stored in battery is only able to support its return to the charging station. This works based on monitoring the distances between the exploration robot and the charging station (for details of the distance estimation modules, see Section 4.3.3). For example, as described in Figure 3.2, if a robot is conducting exploration from *Target 1* to *Target 2*, the charging task of the exploration robot will commence when the amount of energy stored in battery ($\mathrm{D_b}$) can only satisfy the charging requirements ($\mathrm{D_{rc}}$). After charging, the robot will then head towards *Target 2* from the *Charging station* ($\mathrm{D_{nc}}$).

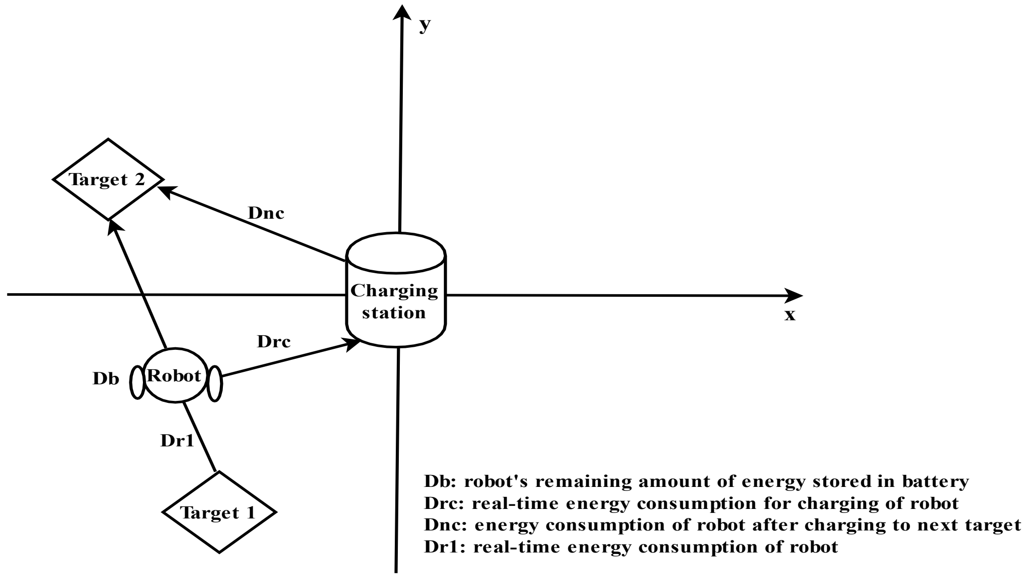


Figure 3.2: A schematic of the proposed General Charging Method.

3.2.2 Predicted Charging Method

This method is a predicted charging method. This method was inspired by [58], whereby the effective prediction of the energy consumption of a robot will benefit decision making for the formulation of a potential optimal strategy. In the general charging method proposed above, a problem may occur where the inspection tasks are interrupted in the middle of the inspection as the exploration robots run out of power. Thus, in this situation, as illustrated in Figure 3.2, the energy requirement for the continual exploration of *Target 2* is, D_{r1}+D_{rc}+D_{nc}.

The predicted charging method is based on the same conditions as mentioned previously, but in this scenario, the exploration robot is designed to hold at *Target 1*, and then head towards the *Charging station* directly. This means that the robots' energy consumption for accomplishing inspection tasks is, D_{rc}+D_{nc}. As we can see, in addition to the energy consumption from *Charging station* to *Target 2* (D_{nc}), the travelling consumptions of the *Robot* to the *Charging stations* in predicted charging method is D_{rc}, which is always smaller than the general charging method, of D_{r1}+D_{rc}. As a result, every charging operation of a robot using the predicted charging method will help the robot retain a certain amount of energy stored in battery when it returns to the *Charging station*. In contrast, the charging operation of a robot using the general

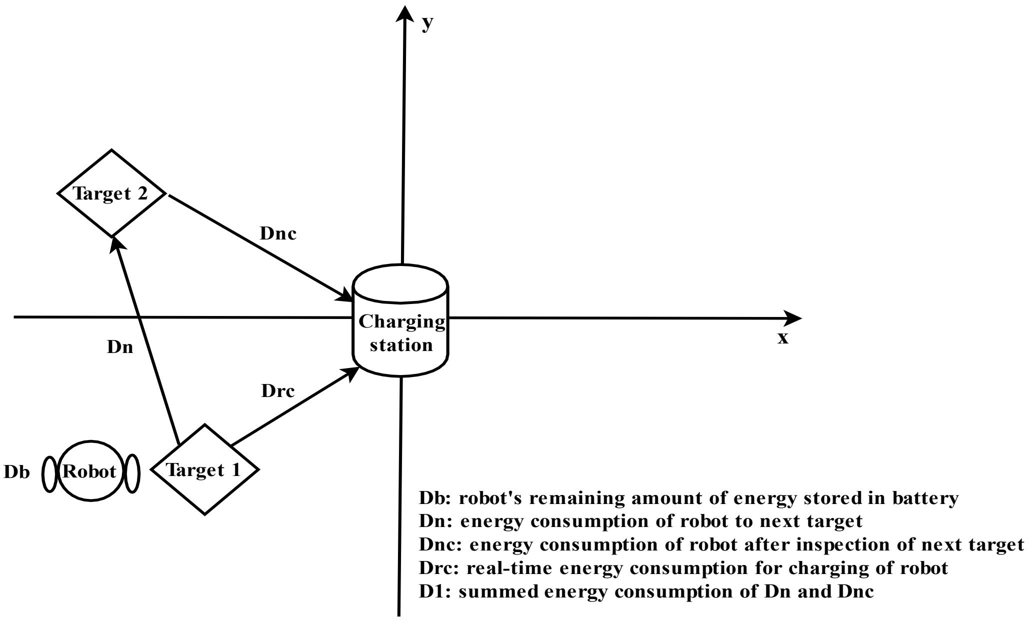


Figure 3.3: A schematic of the proposed Predicted Charging Method.

charging method will cause the robot to run out of power when the robot returns to the *Charging station*. Therefore, in theory, the predicted charging method outperforms the general charging method in terms of the avoidance of energy waste.

The implementation of the predicted charging method is illustrated in Figure 3.3. Assuming the exploration robot has finished its inspection task at *Target 1* and holds at that position to judge whether to go to the *Charging station* or keep exploring *Target 2*, the charging task of the exploration robots will commence if two conditions are met:

(1) if $D_b < D1$, where D_b is the exploration robots' remaining amount of energy stored in battery, D1 is the summed robot's energy consumption of D_n and D_{nc}, D_n is the exploration consumption of the robots to the next target, and D_{nc} is the charging consumption of the robots after inspection of the next target,

(2) if $D_b > D_{rc}$, where D_b is the exploration robots' remaining amount of energy stored in battery, D_{rc} is the real-time charging consumption from exploration robot to the *Charging station*.

3.3 Temporary Exploration using the Greedy algorithm

Temporary exploration contributes to finding potential problems in a power-plant as quickly as possible. Thus, the goal of the robot system is to as quickly as possible debug the faults in the power plant zone-by-zone. In this case, at every step, the nearest target to the exploration robot was selected by the Greedy algorithm and set as a goal for inspection. An advantage of this design is that limited robot sources will be concentrated in a certain area of a power plant to be able to diagnose faults zone-by-zone.

3.3.1 Principle of Greedy-based Temporary Exploration

In order to clarify the proposed Greedy-based temporary exploration, mathematical formulation has been implemented as follow.

Given Conditions, and Exploration Behaviours:

a) Robot team, $R = \{R_1,\ R_2,\ R_3,\ \dots,\ R_p\}$;
b) Exploration tasks, $T_{total} = \{T_1,\ T_2,\ T_3,\ \dots\ ,\ T_q\}$, $T_q > R_p$ and $R_p | T_q$;
c) Each exploraiton task T_q, can be checked by one robot R_p at a time, and each exploration robot R_p has the same exploration capabilities, which means the number of exploration tasks for each robot is $n = \frac{T_q}{R_p}$;
d) Robot team R are required to explore all tasks listed in T_{total} to complete one exploration cycle;
e) Each robot starts/stops its exploration from the same place;

Optimisation Objective — Local Optimal, and Methodology:

a) Local optimal allows each robot R_p to arrive at an exploration task with minimum time;
b) The Greed-based task allocation method for multi-robots, which requires each robot R_p to select the nearest exploration task (from task list T_{R_p}) as the next exploration target.

Mathmatical fromulation of the Greedy-based task allocation method for multi-robots:

1. Based on the given conditions, the known maximum number of exploration tasks

for each robot is n, thus, the Greedy-based method allocates T_{R_1} exploration tasks to R_1 robot, the details of which are as follows:

a) Define the start/end place as target a';
b) Robot R_1 starts its exploration from target a'; estimates the distance from target a' to all remaining targets $n-1$; selects the nearest target from target a' as the next exploration target for R_1 robot, and defines this selected target as target ${b_1}'$; thus, the travlling distance of Robot R_1 in this step can be stated as $d_{a',{b_1}'}$;
c) Robot R_1 continues its exploration from target ${b_1}'$; estimates the distances from target ${b_1}'$ to all remaining targets $n-2$; selects the nearest target from target ${b_1}'$ as the next exploration target, and defines this selected target as target ${c_1}'$; thus, the travlling distance of Robot R_1 in this step can be stated as $d_{{b_1}',{c_1}'}$;
d) …..
e) The same mechansim is used to allocate the remaining targets for R_1 robot. Robot R_1 continues its exploration from target ${j_1}'$; estimates the distance from target ${j_1}'$to all remaining targets $n-j_1$; selects the nearest target from target ${j_1}'$ as the next exploration target, and defines this selected target as target $(j_1+1)'$; thus, the travlling distance of Robot R_1 in this step can be stated as $d_{{j_1}',(j_1+1)'}$;
f) Again, the travlling distance of Robot R_1 from target $(n-1)'$ to the last exploration target n' is can be stated as $d_{(n-1)',n'}$;
g) Finally, the travlling distance of Robot R_1 when it returns to target a' from target n' can be stated as $d_{n',a'}$;
h) Therefore, the exploration task list T_{R_1} is fully allocated to Robot R_1; the overall travlling distance of Robot R_1, $L_{T_{R_1}}$ can be calculated using the followed formula (3.2):

$$L_{T_{R_1}} = d_{a',{b_1}'} + \sum_{j_1=b_1}^{n-1} d_{{j_1}',(j_1+1)'} + d_{n',a'} \tag{3.2}$$

2. According to the same task allocation mechansims methioned in Step 1, the

Greedy-based method allocates T_{R_i} tasks for Robot R_i which are the same as the tasks allocated for Robot R_1. Thus, the overall travelling distance of Robot R_i, $L_{T_{R_i}}$, can be calculated using the followed formula (3.3):

$$L_{T_{R_i}} = d_{a',b_i'} + \sum_{j_i=b_i}^{n-1} d_{\,j_i',(j_i+1)'} + d_{n',a'} \tag{3.3}$$

Notes:

a) $i = (1, 2, 3, \ldots, p)$;

b) The maximum number of exploration tasks n for Robot $R_1, R_2, R_3 \ldots$or any Robot R_p are the same, each exploration robot R_p has the same exploration capabilities;

c) The exploration task T_{total}, which includes every individual robots' task list $T_{R_1}, T_{R_2}, T_{R_3}, \ldots, T_{R_p}$, thus, $T_{total} = (T_{R_1}, T_{R_2}, T_{R_3}, \ldots, T_{R_p})$; In addition, as every exploration task in T_{total} can be only examined by one robot at a time, each individual robots' task list $T_{R_1}, T_{R_2}, T_{R_3}, \ldots, T_{R_p}$ is different;

3. Overall, in terms of using the Greedy-based task allocation method for a robot team, the overall travelling consumptions $L_{T_{greedy\ total}}$ of robot team R to complete an exploration cycle of the exploration task T_{total}, can be stated by the followed formula (3.4):

$$L_{T_{greedy\ total}} = \sum_{i=1}^{p} (d_{a',b_i'} + \sum_{j_i=b_i}^{n-1} d_{\,j_i',(j_i+1)'} + d_{n',a'}) \tag{3.4}$$

Where $i = (1, 2, 3, \ldots, p)$.

3.3.2 Implement of Greedy-based Temporary Exploration

To avoid all nearest targets being examined by a single robot, the task assignment process of these robots is alternated. This means that after one task is allocated to *Robot #1*, task assignment will be transferred to *Robot #2*. This process continues until all tasks are allocated to the robots. The overall Greedy-based multi-robotic exploration process for the temporary exploration mode is described in detail in Figure 3.4, and split into four main steps:

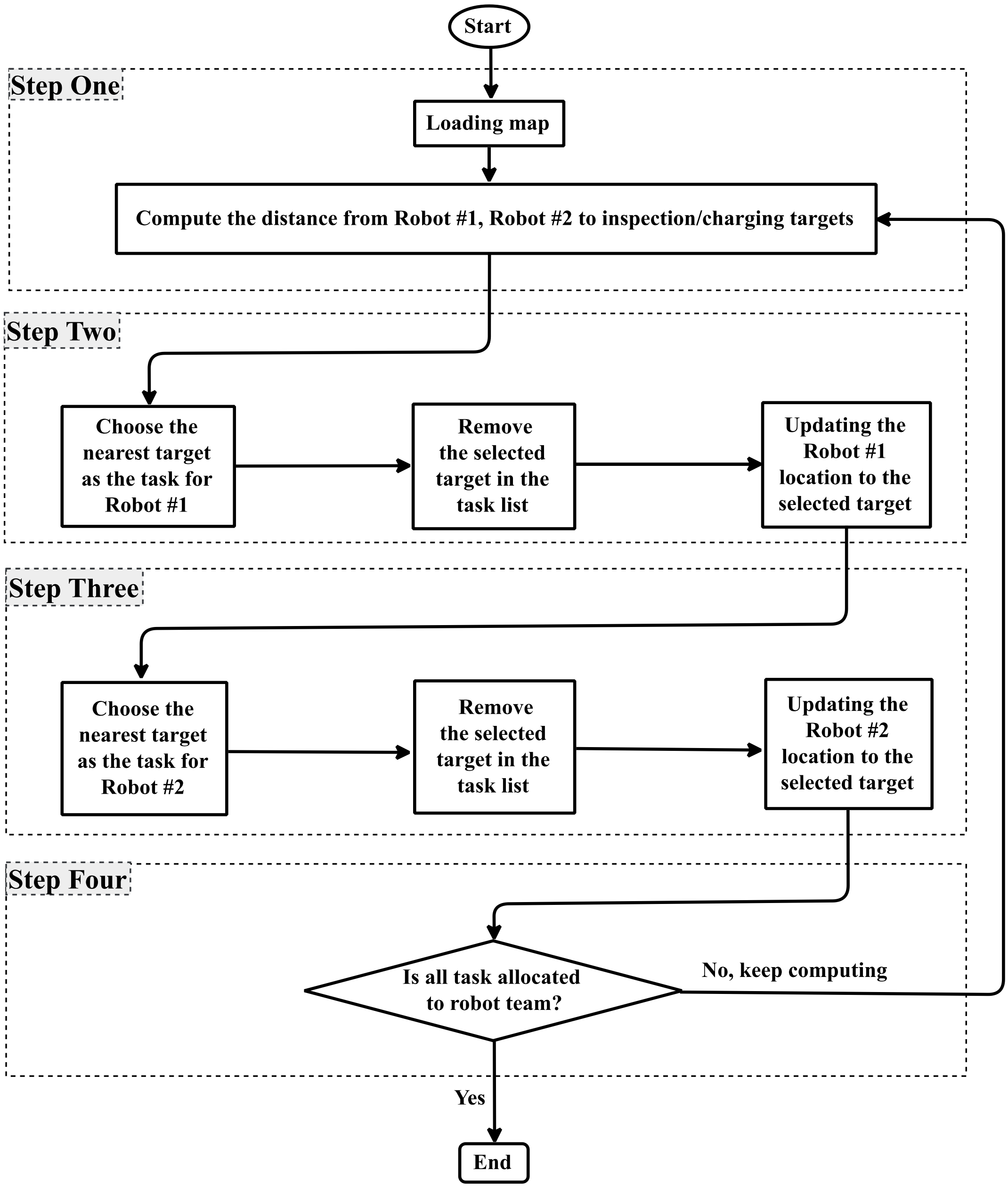


Figure 3.4: The Greedy-based multi-robotic exploration system for temporary exploration.

Step One: Loading the map and calculating the travel distances

Map information is loaded to generate travel consumption information, which is the distances between the exploration robots, the exploration targets and the charging station. Pythagorean theorem is used to calculate the travel consumption for two reasons: (1) the map and target information are known in advance, and (2) as stated in the hypothesis, obstacles in the map are ignored.

Step Two: Task allocation for *Robot #1*

The nearest inspection-target is selected by *Robot #1*, and removed from the exploration task list to avoid repeat selection by *Robot #2*. Then, *Robot #1* virtually updates its location to the currently selected target position to prepare for selection of the next exploration target.

Step Three: Task allocation for *Robot #2*

This step allocates the next exploration task to *Robot #2*. At this time, *Robot #1* stops calculating its exploration task and the same task selection process as described in *Step Two* is followed for *Robot #2*, allocating it the nearest inspection target, while updating its location to the currently selected target position.

Step Four: Best strategy searching for exploration system

In the final step, the Greedy algorithm checks the remaining tasks. If there are exploration tasks left, calculation processes are repeated from the first step of this process; if all tasks have been allocated to the multi-robotic exploration system, the exploration plan is then sent to these exploration robots.

The Greedy-based temporary exploration system developed in this study attempted to purchase local optimisation rather than purchase global optimisation for exploration system. The contribution differences between the developed Greedy-based temporary exploration system comparing with other projects, such as [42] is that additional charging impact to exploration optimisation has been considered in this project.

In terms of the multi-robotic exploration system’s development, it is necessary to think about how to balance different objectives and to explore the relationships behind these different optimisation objectives. For example, will minimum travel for an exploration system have minimum maintenance risks for a power plant.

3.4 Long-term Exploration using the Genetic Algorithm

Long-term exploration means using an exploration system to service a power plant over a long time period. Thus, the goal of a long-term exploration system is for the robots to use their limited onboard energy to service as many of the inspected targets as possible. In this case, the Genetic Algorithm is used to schedule an overall optimal inspection strategy for the multi-robotics system.

3.4.1 Principle of GA-based Long-term Exploration

Again, like the Greedy-based temporary exploration mode, to demonstrate the GA-based long-term exploration mode, mathematical modelling works for the overall GA multi-robot task allocation process. The given conditions and exploration behaviours of the multi-robot are the same as for the Greedy-based temporaray exploration.

Optimisation Objective — Global Optimal, and Methodology：

a) Global optimal allows robot team R with a minimum travelling consumption $L_{T_{global\,best}}$ to complete one exploration cycle of exploration task T_{total}.

b) As multiple exploration tasks can be allocated to different robots, this means that many different task allocation methods exist, thus, all possibile task allocation methods are defined into K_{total}; the GA-based task allocation method attampts to attempt all methods listed in K_{total}, to allow robot team R with a minimum travelling consumption $L_{T_{global\,best}}$ complete one exploration cycle of exploration task T_{total};

Mathmatical formulation of the GA-based task allocation method for multi-robots：

1. Based on the given conditions, the known maximum number of exploration tasks for each robot is n, thus, the GA-based method allocates T_{R_1} exploration tasks to R_1 robot, the details of which are as follows:
   a) Define the start/end place as target A'；
   b) Robot R_1 starts its exploration from target A' and randomly selects the next exploration target from all reamining targets $n-1$; and then defines this selected target as target $B_1{}'$; thus, the travelling distance of Robot R_1 in this step can be stated as $d_{A',B_1{}'}$;

c) Robot R_1 starts its exploration from target $B_1{}'$; then randomly selects the next exploration target from all remaining targets $n-2$; and defines this selected target as target $C_1{}'$; thus, the travelling distance of Robot R_1 in this step can be stated as $d_{B_1{}', C_1{}'}$;

d) …..

e) Following the same task allocation mechanism, Robot R_1 starts its exploration from target $J_1{}'$; then randomly selects the next exploration target from all remaining targets $n-J_1$; and defines this selected target as target $(J_1+1)'$; thus, the travelling distance of Robot R_1 in this step can be stated as $d_{J_1{}', (J_1+1)'}$;

f) Again, as in the last exploraiton task where Robot R_1 travelled from target $(n-1)'$ to target n', the travelling distance of Robot R_1 can be stated as $d_{(n-1)', n'}$;

g) Finally, the travlling distance of Robot R_1 when it returns to target A' from target n', can be described as $d_{n', A'}$;

2. According to the same task allocation mechansims methioned in Step 1, the GA-based method allocates T_{R_i} tasks for Robot R_i which is the same as the task allocation for Robot R_1;
3. Repeating Step 1 and 2 to generate a group of task allocation method $K_{initial}$ for robot team R; thus these different methods can be defined as, $K_{initial} = \{K_1, K_2, K_3, \ldots, K_v\}$; Note, as the maximum number of exploration tasks in T_{total} is T_q, therefore, in terms of all possibile task allocation methods K_{total} for robot team R is $T_q!$, which means $K_{total} = \left\{K_1, K_2, K_3, \ldots, K_{T_q!}\right\}$; However, the GA method only generates a subset of task allocation method $K_{initial}$ for robot team R when compared with K_{total}, thus $K_v < T_q!$, this means that $K_{initial} \in K_{total}$;
4. As it is clear that different task allocation methods in $K_{initial}$ are known, this step calculates the overall travelling distance of robot team R, $L_{T_{total}}$, for the different task allocation methods in $K_{initial}$:

a) The maximum number of exploration tasks for R_1 is n, thus, the overall travelling distance of Robot R_1, $L_{T_{R_1}}$ can be stated in the following formula

(3.5):

$$L_{T_{R_1}} = d_{A',B_1'} + \sum_{J_1=B_1}^{n-1} d_{\,J_1',\,(J_1+1)'} + d_{n',A'}$$

(3.5)

b) Again, the overall travelling distance of Robot R_i, $L_{T_{R_i}}$ can be stated in the following formula (3.6):

$$L_{T_{R_i}} = d_{A',B_i'} + \sum_{J_i=B_i}^{n-1} d_{\,J_i',\,(J_i+1)'} + d_{n',A'}$$

(3.6)

Where $i = (1, 2, 3, \dots, p)$.

c) Overall, the overall travelling distance of robot team R, $L_{T_{total}}$, which is based on one task allocation method K_v, and can be calculated by following formula (3.7):

$$L_{T_{total}} = \sum_{i=1}^{p}(d_{A',B_i'} + \sum_{J_i=B_i}^{n-1} d_{\,J_i',\,(J_i+1)'} + d_{n',A'})$$

(3.7)

Where $i = (1, 2, 3, \dots, p)$.

d) However, the formula disscussed in Step c) only describes one task allocation methods' travelling distance of robot team R; thus, to evaluate the performance of different task allocation methods, here, we import the variable x to represent the ID of different task allocation methods; therefore, the overall travelling distance of robot team R is $L_{T_{total}}$, which is based on different task allocation methods K_v, and can be calculated by using the following formula (3.8):

$$L_{T_{total_x}} = \sum_{i=1}^{p}(d_{A',B_i'_x} + \sum_{J_i=B_i}^{n-1} d_{\,J_i',\,(J_i+1)'_x} + d_{n',A'_x})$$

(3.8)

Where $x = (1, 2, 3, \dots, v)$.

5. In this stage, every task allocation methods in $K_{initial}$ and theirs $L_{T_{total_x}}$ are known, thus it is possibile to find out the best task allocation methods $L_{T_{local\,best}}$

in $K_{initial}$, the details of which are described in the following:

a) Compare the overall travelling distances $L_{T_{total_x}}$ of each task allocation methods K_v in $K_{initial}$;

b) Identify the best task allocation methods $L_{T_{local\,best}}$ in $K_{initial}$, where $L_{T_{local\,best}}$ is able to allow robot team R to travel a minimum distance to complete exploration task lists T_{total}, thus this comparation can be carried out using the following formula (3.9):

$$L_{T_{local\,best}} = \min_{1 \le x \le v} \sum_{i=1}^{p} \left(d_{A',B_i{}'_x} + \sum_{J_i=B_i}^{n-1} d_{J_i{}',(J_i+1)'_x} + d_{n',A'_x} \right) \tag{3.9}$$

Where:

$i = (1, 2, 3, \dots, p)$;

$x = (1, 2, 3, \dots, v)$.

6. This step aims to optimise the best task allocation strategy $L_{T_{local\,best}}$, as $K_{initial}$ only attempts a part of the task allocation methods from K_{total}, which means $L_{T_{local\,best}}$ may not be the best task allocation method $L_{T_{global\,best}}$:

a) Based on the current best task allocation method $L_{T_{local\,best}}$ and GA's own evaluation mechansim, GA is able to generate more adaptable task allocation methods $K_{initial'}$. This work is carried out in Steps 1~3;

b) Based on the GA's evaluation mechansim, GA then selects some/all of the task allocation methods from $K_{initial'}$, and using these selected methods, GA can then replace the old task allocation methods generated which are listed in $K_{initial}$;

c) GA identifies the best task allocation method $L_{T_{local\,best_{\mathrm{I}}}}$ from different iteration $\mathrm{I} = (1, 2, 3, \dots, \mu)$, and then GA generates a group of new task allocation methods $K_{initial'}$, This work is carried out in Steps 6, a) and b);

7. Finally, GA repeats the overall process from Steps 1~6 to try all possbile task allocation methods in $K_{total} = \left\{K_1,\ K_2,\ K_3,\ \dots,\ K_{T_q!}\right\}$ to find the best task allocation method $L_{T_{global\,best}}$.

3.4.2 Implement of GA-based Long-term Exploration

In terms of the construction of the GA, a classical GA framework developed in [59] was adopted in this project. The adapted GA was split into five steps, details of which can be seen in Figure 3.5.

Step One: Loading the map and calculating the travel distances

In this case, GA uses the overall shortest distance of the robot team as evidence for exploration strategy selection. Like the Greedy-based exploration method, the travel consumption distances between the exploration robots, the exploration targets and the charging station are required. Thus, as outlined in Step One in Figure 3.5, the positional information of the robots and exploration targets are collected in advance, and used with the Pythagorean theorem to compute the travel distances of the exploration robots.

Step Two: Initialisation of the exploration strategies of the robot team

This step intends to formulate a group of inspection strategies randomly for the multi-robotic exploration system. These strategies are coded in a digital format inside the GA. An example of the coding of an inspection strategy is according to Step Two in Figure 3.5. Every exploration target is then pre-defined with an ID, such as exploration *Target 1*, marked as *T1*. If *Robot #1*'s exploration started from *T0*, before inspecting *T1*, *T2*, *T5*, and finally returning to *T0*, *Robot #1*'s exploration strategy is coded as *0,1,2,5,0* inside of GA. The same mechanism is used for *Robot #2*, its exploration strategy coded as *0,3,4,6,0*. Thus, the overall inspection strategy of the exploration system, in this case, is *0,1,2,5,0,0,3,4,6,0*, and this kind of formulated strategy is called *Chromosomes* in GA. For example, *Chromosome 1* is demonstrated as *C1* in Step Two of Figure 3.5. Different *Chromosomes* (*C1, C2, C3, C…*) formed one group, called *Population* in GA, which is used to represent a group of exploration strategies for a multi-robot system.

Population size is one important parameter, which has significant effects on the GA results [60]. For instance, a smaller population size results in fast convergence; in contrast, a larger population size results in wasted computational resources. In [61], increasing the size of the population from 5 to 100 significantly improved the GA

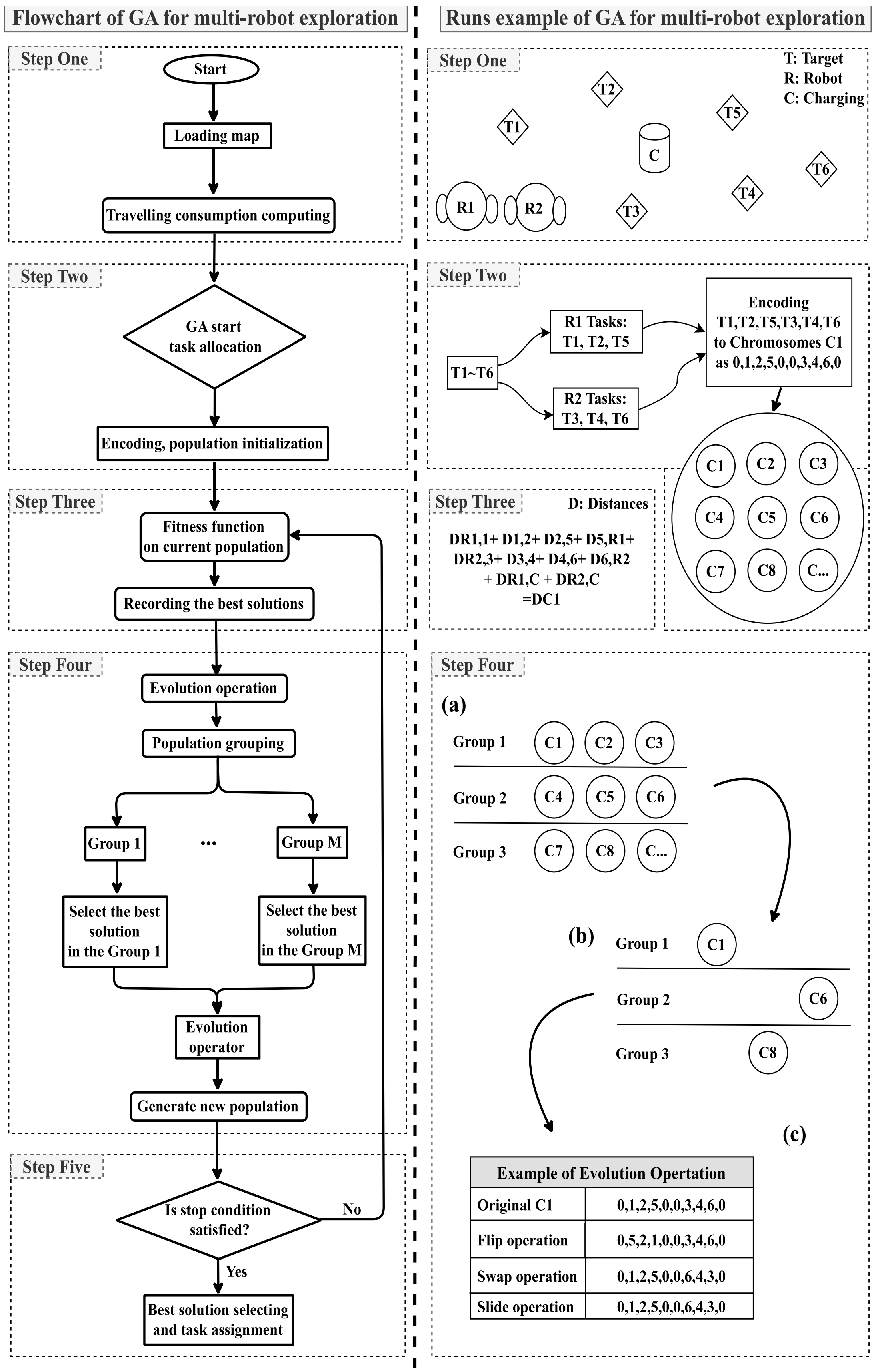


Figure 3.5: The GA-based multi-robotic exploration system for long-term exploration.

results. The accuracy of the results of the GA was almost the same when the population size was larger than 100 or around 100. Thus, in this project, an initial population size of 80 was selected.

Step Three: Evaluation of the formulated exploration strategies

The goal of this step is to determine the best exploration strategy for the current group (of the 80 different randomised strategies, as mentioned in *Step Two*). This is determined by selecting the minimum travel consumption of the multi-robotic exploration system. Inside GA, this evaluation work is based on a ‘fitness function’ as shown in Step Three of Figure 3.5; which attempts to add together all the travel distances for the multi-robotic exploration system. The overall travel distances calculated in this project refer to one exploration cycle of the robot system, which includes the robots travelling to exploration targets and charging station and returning to initial their position. Thus, the best exploration strategy in the current group can be selected, which is then recorded for further comparison.

Step Four: Optimisation of the formulated task allocation strategies

This step involves simulating the natural evolution process to generate an optimal exploration strategy for the multi-robotic system. This process mainly involves three stages:

(1) the formulated exploration strategy (*C1, C2, C3, C…*) from *Step Two* is separated into different groups, see Step Four (a) in Figure 3.5,
(2) the best exploration strategy from every group is selected for evolution, see Step Four (b) in Figure 3.5,
(3) the evolution operation is based on rearranging the target exploration sequence for these selected strategies. An evolution example for exploration strategy *C1* can be observed in Step Four (c) of Figure 3.5. In this case, four evolution operations on *C1* (*0,1,2,5,0,0,3,4,6,0*) are adopted: (1) retaining the original (*0,1,2,5,0,0,3,4,6,0*), (2) flipping (*0,5,2,1,0,0,3,4,6,0*), (3) swapping (*0,1,2,5,0,0,6,4,3,0*), and (4) sliding (*0,1,2,5,0,0,6,4,3,0*).

These new generated exploration strategies are then used to replace the first randomised population for further evaluation.

Step Five: Best strategy search

This step aims to search for the best exploration strategy among the different populations. This is achieved by repeating the previous steps and comparing the best strategy in every iteration until the designed iterations times are achieved. In [62], another combinatorial optimisation problems – multiple tasks being allocating to multicore processors – was solved by GA, in which 5,000 iterations were recommended in the calculation process. Thus, a 5,000 times iteration was used in this project.

3.5 Summary

This chapter has mainly outlined the details of the proposed exploration approaches in this study. Firstly, this chapter clarified the exploration scenarios and functions of the exploration robot in Section 3.1. The robots are deployed into environments for continuous monitoring of targets and are able to switch between exploration and charging tasks as required. Secondly, two charging methods were proposed in Section 3.2: (1) a general charging method, whereby the robots only go for charging when their remaining battery can only support their back to the charging station; and (2) a predicted charging method, whereby the system will consider whether the remaining battery is adequate to support both inspection and charging requirements; if it isn't, the robots will return to the charging station. Thirdly, the Greedy-based multi-robotics system for temporary exploration in a power plant, was explained in Section 3.3. This method contributes to a diagnosis of faults in the power plant zone-by-zone. Fourthly, the GA-based multi-robotics system for long-term exploration in a power plant, as described in Section 3.4. This method aims to iterate the overall optimal inspection routes for the robot team. Therefore, based on the different exploration and charging methods, three exploration methods were developed: (1) A, which uses Greedy and the general charging method for temporary exploration, (2) B, which uses GA and the general charging method for long-term exploration, and (3) C, which uses GA and the predicted charging method for exploration robot improvement. In the next chapter, details of the implementation of these three exploration approaches will be presented.

Chapter 4

Experimental Setup

This chapter outlines the configuration of the experiments. This chapter is organised in the following five parts: Firstly, Section 4.1 describes the simulation setup. Next, Section 4.2 and Section 4.3 presents the multi-robot control framework and exploration robots configurations, respectively. Then, Section 4.4 and Section 4.5 explain the evaluation scenarios and metrics, before, finally, Section 4.6 summaries the chapter.

4.1 Simulation Setup

The simulation work of the robot system is separated into two pieces of software: (1) MATLAB, and (2) V-REP. The reasons for using both of these packages are as follows:

(1) The first application of MATLAB is for control engineering, and its interface and the coding environment is very easy for developers [63]. In terms of the development of the exploration method, MATLAB can be used to schedule an exploration strategy for the multi-robot system. The problem for developing and testing the proposed exploration methods is, MATLAB lacks easy-to-use 3D physical simulations [64], meaning it is difficult to observe the performance of the proposed exploration approaches visually.

(2) In contrast, in terms of implementation of the exploration scenarios or the overall evaluation of the system, V-REP can be as an alternative solution because it supports 3D dynamic simulation [53]. In addition, it is possible to develop a charging management algorithm for exploration robot in MATLAB, but V-REP provides a more convenient means to do so. For instance, using V-REP, we can develop a simple sensor for recording the robots' past-path lengths to manage the exploration and charging tasks of the exploration robot.

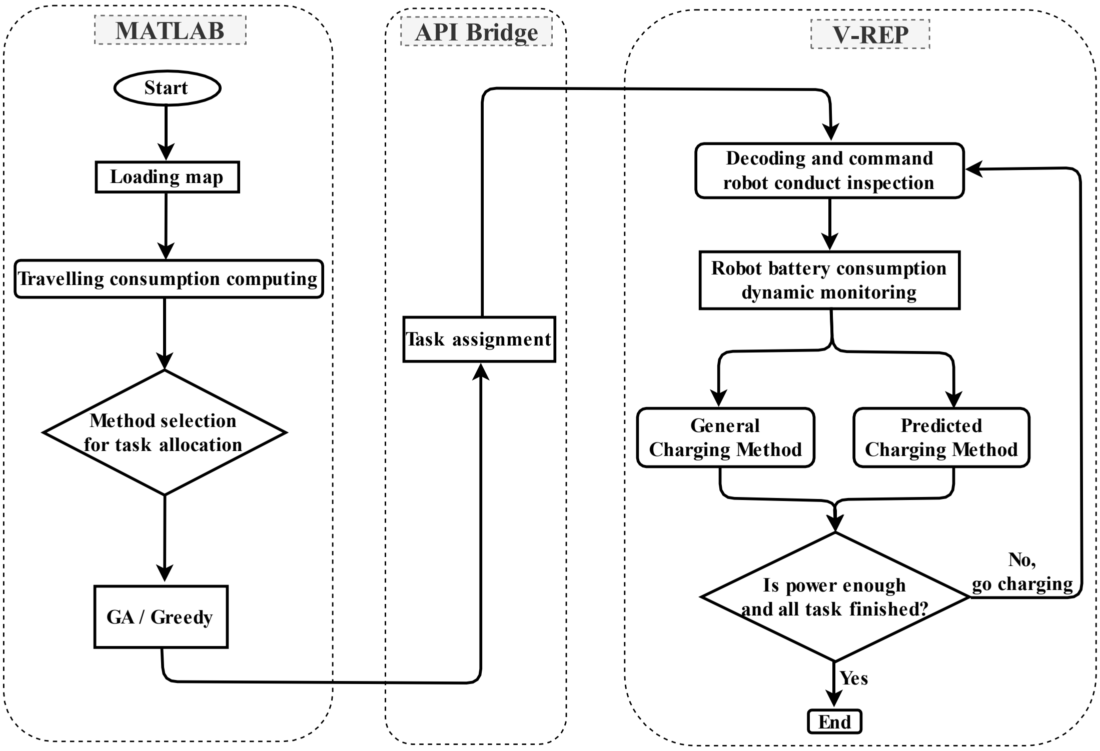


Figure 4.1: The simulation setup for the development of the multi-robotic exploration system.

As a result, the overall simulation setup is presented in Figure 4.1. MATLAB was selected for scheduling of the exploration strategy of the multi-robot system while V-REP was selected to simulate the multi-robotic exploration, charging, and exploration system test. The feasibility of using both MATLAB and V-REP was provided by [56], that is, the API function in V-REP allows data exchange between V-REP and other packages.

4.2 Control Framework

In terms of selecting a centralised multi-robot control mechanism for multi-robot control, this project aimed to develop an on-site exploration system to assist a power-plant control centre in recognising potential problems so that the task management of robots can be controlled by the power plant control centre. This control architecture will benefit both the power plant control centre and exploration robots. For example, the control centre can receive on-site data directly from the robots and adjust the exploration plan. In terms of the robots, each robot can use limited energy and processors to compute other tasks such as collecting information and route planning.

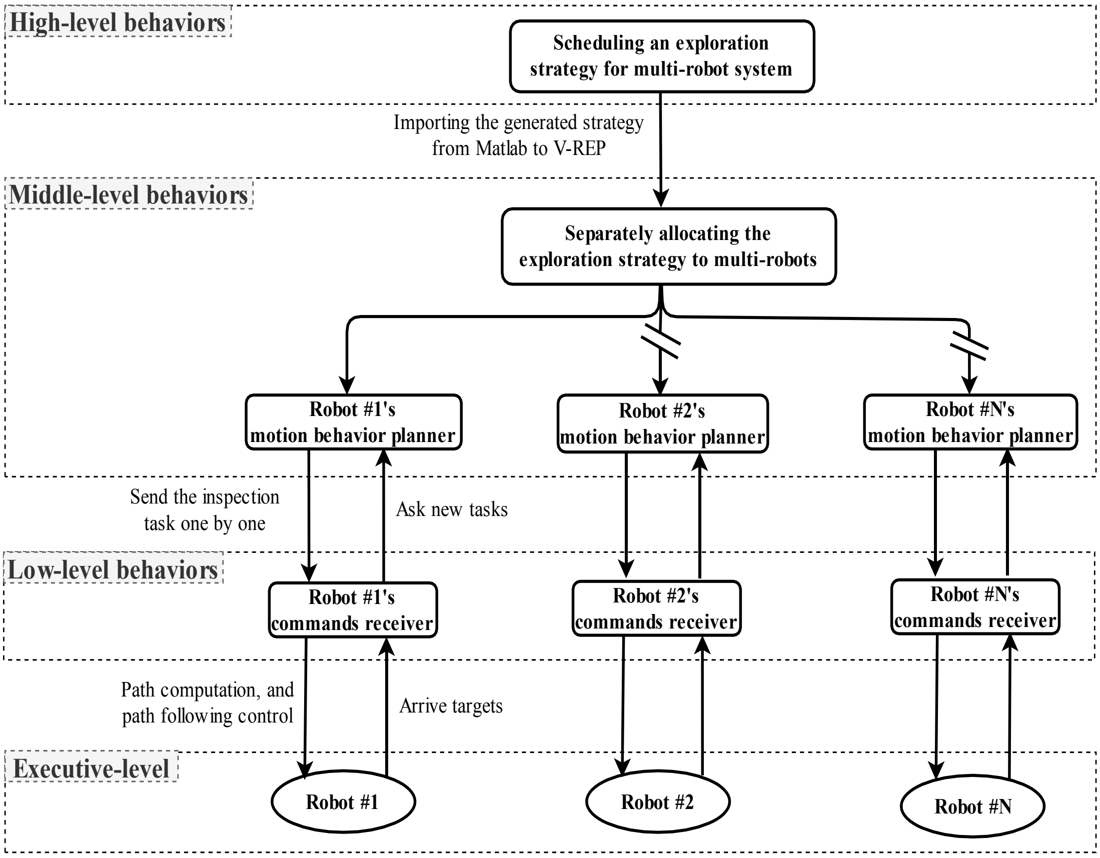


Figure 4.2: Work-load management of the developed robot.

The main functions of the control framework are threefold: (1) scheduling an exploration strategy for robots, (2) sending and separating the formulated exploration plan to robots, and (3) monitoring the robot battery in real-time and managing the robot for charging or exploration. As a result, three levels of robot behaviours – high, middle and low – were developed as presented in Figure 4.2.

(1) The high-level behaviours in MATLAB formulate an exploration strategy for the multi-robotic exploration system. This formulated strategy is then sent to V-REP via the API bridge.

(2) The middle-level behaviours in V-REP separate the exploration tasks to the different robots and manage their exploration tasks. For example, the middle-level behaviours manage a robot heading to *Target 1* and, after it finishes *Target 1*, it guides the robot to explore *Target 2*.

(3) The low-level behaviours in V-REP functions to help the exploration robot begin its movement for inspection or charging tasks. The robots' motion is achieved by

using V-REP's official path-planning module. In addition, this behaviour is also used to share the robots' real-time status (arrival at exploration target or charging station) with the middle-level behaviours, and then ask for new tasks.

At the executive-level (exploration robots), the robot's motion management is received from the low-level behaviours, but there is a requirement of these robots to feedback its real-time status to the low-level behaviours, so that it is going to an exploration task or finishing charging. Therefore, the next section will detail the configuration of the robot exploration platforms to satisfy these requirements.

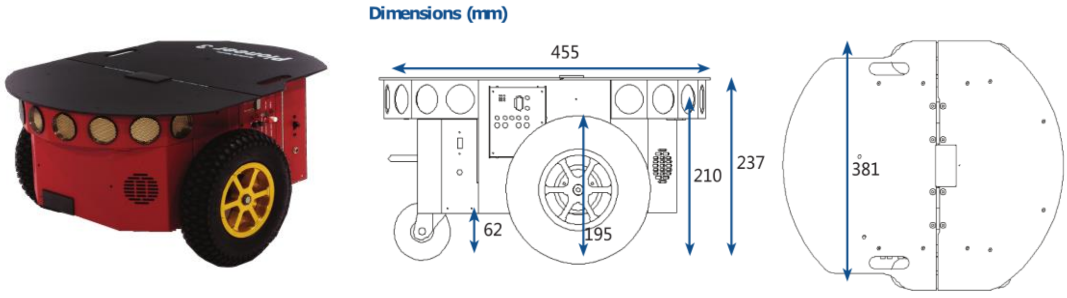
4.3 Robot System Formulation

This section presents the configurations of the developed exploration robots. The realisation of the exploration platform in this section is split into three stages: (1) the requirements of the exploration platform for on-site inspection at power plants are discussed, (2) the selected exploration robot model is explained, and (3) the developed auxiliary sensors are presented.

4.3.1 Robot System Requirements

In the case of on-site exploration of a power plant, exploration robots may face several complicated situations, such as various obstacles, faulty mechanisms, and so on. Thus, this section discusses the general requirements of an exploration robot for inspection of power plants. Based on the on-site characteristics of power plant exploration outlined in Section 2.1 and 2.2, the exploration platform used in this project was required to satisfy the following factors:

(1) Small and flexible so that the exploration robot can cover small areas,
(2) An open platform that allows various types of sensors to be added,
(3) A cheap platform for investors that allows a short payback time when these robots real deployed in power plants,
(4) Easy recovery for low maintenance.



(a) (b)

Figure 4.3: The schematic of the Pioneer p3-dx robot. (a) real Pioneer p3-dx robot. (b) the dimensions of the Pioneer p3-dx robot platform, adapted from [65].

4.3.2 Robotic Platform

In this project, the Pioneer p3-dx robot was selected as the exploration platform, and the real robot and its dimensions can be seen in Figure 4.3. The advantages of using the Pioneer p3-dx robot as the exploration platform are as follows:

(1) It is a platform with ready-to-use because it integrates with basic sensing systems, e.g. sonar sensors for locating targets. In addition, the robot's movement capabilities are 1.2 m/s. Thus, exploration time can be controlled within 30 minutes in the case of exploration of a power plant sized 500 m^2 of which the exploring path is 4×500 m.

(2) An open platform designed on its topside, which allows the robot to be integrated with various sensors for different applications. For example, in [66], a radar mapping system and relative support were integrated into the Pioneer p3-dx robot.

(3) The Pioneer p3-dx robot is priced at $4000 dollars [67], which represents the monthly earning of three human inspectors at an investigated power-plant. After setup, the robot can work continually to undertake exploration tasks.

(4) The Pioneer p3-dx robot is a light and small robot (9 kg). For the relative dimensions of the Pioneer p3-dx robot platform, see Figure 4.3 (b). The robot size in length and width are 45.5×38.1 cm^2 meaning it is easy recovery and suitable for exploration of narrow spaces.

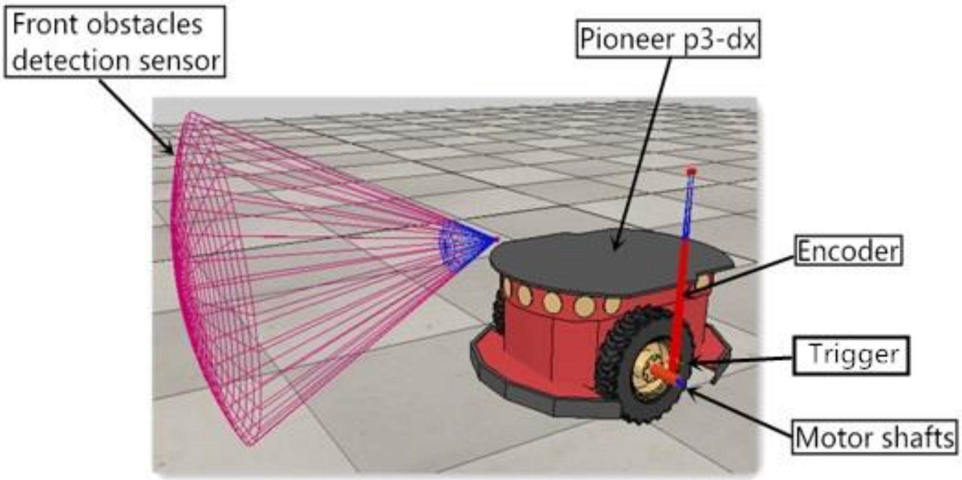


Figure 4.4: The developed sensing system on-board the Pioneer p3-dx robot, prepared in robot simulators, V-REP.

4.3.3 Auxiliary Sensor Development

This auxiliary sensor development work is because the Pioneer p3-dx robot model provided in V-REP simulator is a ‘pure’ model, the robot model is equipped with nothing on-board. Thus, three types of sensors were developed in this study to accomplish three objectives:

(1) Objective 1: real-time sensing of other robots to avoid collisions, this is due to the path crossing problem when these robots continuously deploy in scenarios;
(2) Objective 2: real-time recording of the robot’s past-path lengths in two places using: (1) the past-path lengths as evidence for switching between charging or exploration tasks for the robots, and (2) checking the energy consumption of these robots at different times for system evaluation;
(3) Objective 3: real-time measuring of the distances between robot and exploration targets/charging station to assist the low-level behaviours understanding the real-time robot’s status.

For details of these developed sensors for achieving Objectives 1, 2 and 3, see the following descriptions:

Objective 1: Proximity sensor

This work was necessary as there was a chance that the robots could collide with each other as the exploration strategy did not consider the path crossing problem. Therefore, these robots are suggested to have a front obstacle detection sensor to avoid collisions. This sensor (a proximity sensor) was configured with a detection range of 0.5 m in front of the robot and a 60° detection angle, which can be seen in Figure 4.4.

Objective 2: Encoder

This sensor was designed to record the robot's past-path lengths. This sensor is used in two places:

(1) To manage the charging and exploration tasks for the exploration robots. In this case, the movement capability of the exploration robots was limited to 100 metres (this was because the overall test took place in a small size map, see Section 5.1), meaning the exploration robots had to be charged before the battery ran out every 100 metres. In this case, the following formula 4.1 was used to calculate the robot's past-path lengths:

$$T_d = L_p \pi D_w \,, \tag{4.1}$$

where T_d is the real-time past-path length of the exploration robot in metres, L_p is real-time motor shafts revolutions, and D_w is the diameter of the exploration robot's wheels in metres.

(2) To evaluate the energy consumption of these robots at different times. In more detail, the real-time past-path lengths of the exploration robots were converted to energy consumption. This was done using formula 4.1 and formula 3.1.

The developed encoder was based on two parts as shown in Figure 4.4: (1) one detectable trigger was fixed on the motor shafts which turned with the motor shafts, and (2) two proximity sensors were separately laid out at a certain distance. Once the trigger arrived at the middle point between these two proximity sensors and was detected by the sensors, one revolution (L_p) was added in the recording system.

Objective 3: Distance Estimation Modules (DEM)

The objective of the DEM development was to help the low-level behaviours recognise the real-time robot's status (exploration or charging). To be more specific, the DEM continuously measures the distance from the exploration robot to the targets/charging station. Once the distance between the exploration robot and target/charging station is less than 0.5/0.8 metres, the status of the robot in its exploration or charging is regarded as finished. Following that, the exploration robot will conduct its next task(s) and the movement capability of robots after charging is then resettled to 100 metres as when fully charged. The development of the DEM was based on a V-REP's official distance-measuring modules.

4.4 Multi-robotic Exploration Scenarios

This section presents the developed scenarios for three experiments:

(1) a scenario for the computer performance test. This test was carried out as we intended to evaluate the proposed exploration systems into a more realistic environment, such as a large size scenario laid out to replicate a real power plant. The problem is the computer's computation performance is unknown when the V-REP simulating robot runs in small or large size map;

(2) a scenario to test the accuracy and reliability of the developed encoder. This test was conducted to examine the encoder's accuracy and reliability, as the accuracy is critical for the successful completion of robot routine activities, e.g. record travelling path and plan the charging and/or exploration tasks;

(3) a scenario to evaluate the developed multi-robotic exploration system. This test was used to check the feasibility of using developed two exploration systems (Greedy-based, GA-based) for temporary exploration mode and long-term exploration mode in a power plant, and analysis the performance when exploration system using predicted charging method or general charging method.

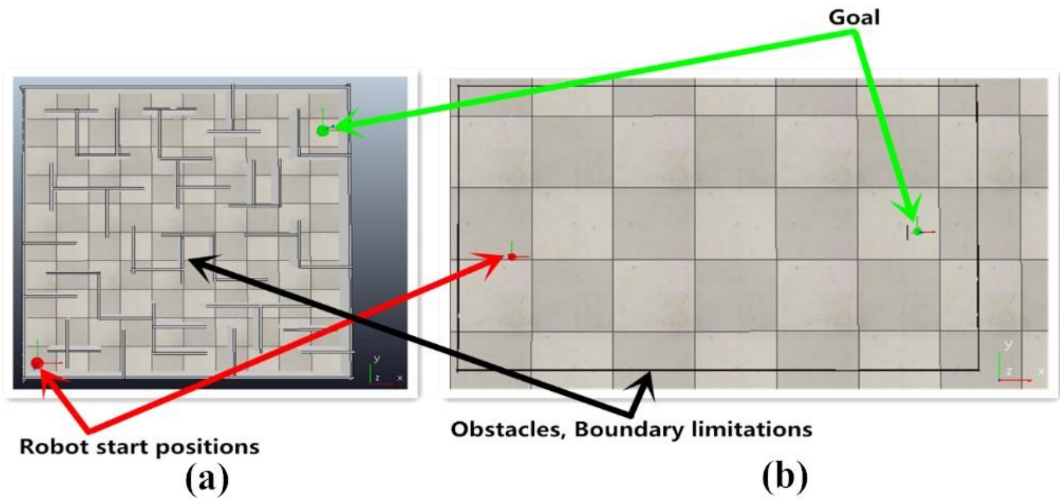


Figure 4.5: The configuration for the computer performance test, (a) 25×25 m^2 configuration, and (b) 300×250 m^2 configuration.

4.4.1 Computational System Performance

This work attempted to verify the feasibility of using V-REP to simulate the operation of the robot system in a large size map. The setup of the computer for these experiments was Windows 10 - 64bits with the following hardware: Intel Core i7 6-core CPU @3.2-4.6 GHz, 16.00GB RAM, and Nvidia Quadro P400 2GB graphics. In this experiment, computer performance was judged by one factor: does the deployed computer have the capability to calculate a useful path for the exploration robot in a small and large size map. Nineteen path-planning algorithms from the V-REP official library were adopted, and every algorithm was tested five times each in the small and large size maps. The details of these maps are as follows:

(1) A 25×25 m^2 map within a closed space, with irregular walls, see Figure 4.5 (a). There were at least one or more routes available for a robot.
(2) A 300×250 m^2 map within a closed space, with only one obstacle, see Figure 4.5 (b). The obstacle was located in front of the goal target; thus, one or more potential paths could be calculated.

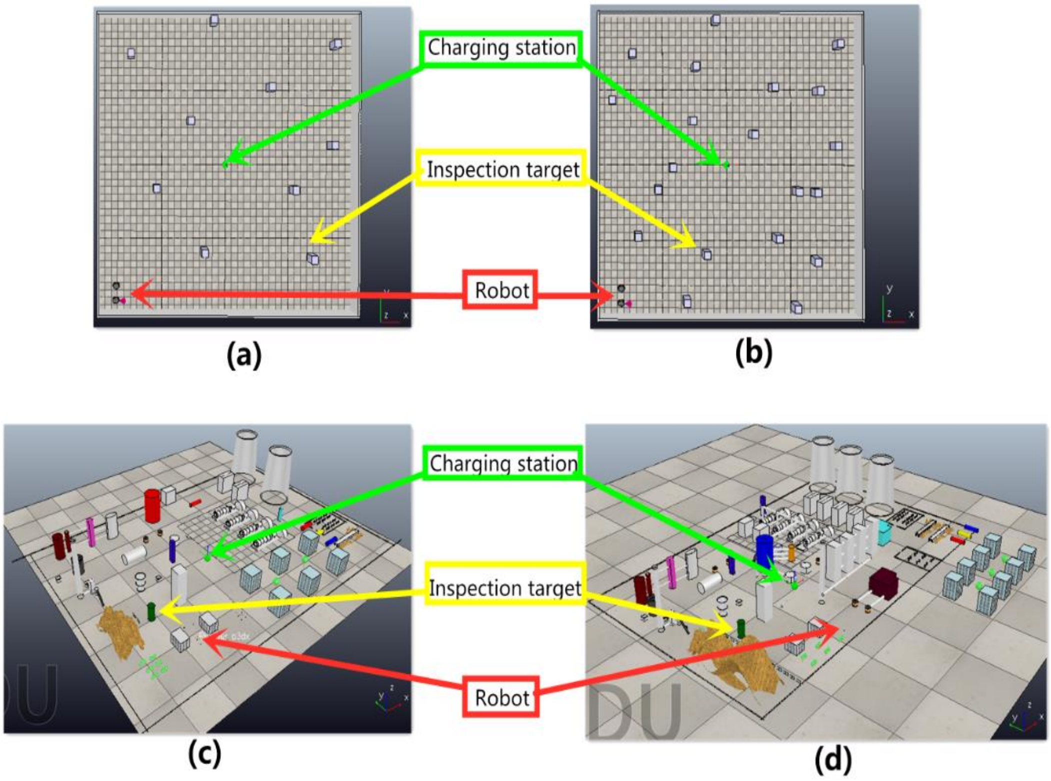


Figure 4.6: The developed power plant for robot exploration, (a) 25×25 m^2 configuration with 10 exploration places, (b) 25×25 m^2 configuration with 20 exploration places, (c) 300×250 m^2 configuration with 10 exploration places, and (d) 300×250 m^2 configuration with 20 exploration places.

4.4.2 Encoder Feedback Test

The accuracy and reliability test work of the encoder were split into two parts:

(1) the accuracy test of the developed encoder. One robot was deployed in a maze as presented in Figure 4.5 (a), where this robot was required to head to the goal target from an initial place. The total past-path length of this robot to the goal target was recorded.

(2) the reliability test of the developed encoder. Two robots were deployed in Figure 4.6 (a) and (b), where three developed exploration methods A, B and C were adapted for these robots. These robots are designed to continuous exploration of 10 or 20 targets and returned for charging as required. The energy consumptions of these robots were recorded at different times via formula 4.1 and formula 3.1.

4.4.3 Multi-robotic Exploration System

In this case, every test was attached with two exploration robots and one charging station. The tasks of these robots were performed as described in Section 3.1, where robots were required to continuously explore the targets, while properly switching between charging and exploration by themselves. To verify the robustness of these exploration methods, four maps were prepared:

(1) The first two configurations were based on a 25×25 m^2 map within a closed space, with 10 and 20 random exploration samples, see Figure 4.6 (a) and (b);

(2) The last two configurations were based on a 300×250 m^2 map within a closed space, with 10 and 20 random exploration samples, see Figure 4.6 (c) and (d).

4.5 Metrics

The evaluation metrics, for the proposed experiments, were consists of three: (1) metrics for examination of the computer performance, (2) metrics for verifying the accuracy and reliability of the developed encoder, and (3) metrics for evaluating the performance of the developed multi-robotic exploration methods.

4.5.1 Computational System Performance

In this test, the path-planning performances of the exploration robots were considered as the metrics for computer evaluations. The quality of a generated path for a robot may have faced three situations: (1) the right path, which could be used for the robots' exploration; (2) an incomplete path; and (3) an incorrect path, which may cause the robots to collide with obstacles.

4.5.2 Encoder Feedback

Accuracy test: The V-REP official path-length computation module was not adopted as the software cannot calibrate the robot-path recording in real-time. Although the robot path is recorded continuously, the record is updated by the software only when the robot has arrived designated areas. Thus, an adaptive robot management, i.e. continuous examination of charging and task exploring, is impossible to be achieved using V-REP official module. In this test, V-REP official module is used to examine the measurement accuracy of the developed encoder, i.e. the final travel distance of the robot recorded by the encoder is compared to the that by V-REP official module.

Reliability test: In this test, the robot's past-path lengths recorded by the encoder were converted to the relative energy consumption at different times. This was achieved by using formula 4.1 and formula 3.1. This reliability test was based on comparing the energy consumption of these robots at the same time. In theory, energy consumption at every stage in these exploration systems – A, B and C – should have been the same. This is because the robots are designed to continuously explore targets without a rest. In this case, the energy consumption of each robot was counted every 10 minutes, up to a total of 60 minutes.

4.5.3 Multi-robotic Exploration System

The evaluation of the developed exploration systems A, B and C was based on the small size map (see reasons for this in Section 5.1). These system tests were separated into two parts:

Inspection efficiency: Multi-robot evaluation by testing the number of inspected targets at different times. This test helped analysis the performance of the Greedy-based temporary exploration system and the GA-based long-term exploration system. The total number of inspected targets by the exploration system was counted every 10 minutes, up to a total of 60 minutes.

Energy-saving performance: Multi-robot evaluation by testing the number of inspected targets with different charging times. This allowed for evaluating the performance impact from the developed general/predicted charging method on the exploration system. The total number of targets inspected by the developed exploration system were counted at every charging task of the exploration robot. This test stopped once the numbers of charging task of each robot had reached five times.

4.6 Summary

This chapter has presented the details of the experimental setup and relative tests metrics. To be more specific, Section 4.1 discussed the simulation setup. MATLAB and V-REP software were selected in this project with the aim of developing a multi-robot exploration system with the capability to conduct inspection and charging tasks.

Section 4.2 described the robot's control framework. Three-layered behaviours between MATLAB and V-REP were developed, which contributed to scheduling an exploration strategy, assignment of exploration tasks, and management of charging and inspection tasks for these robots. Section 4.3 demonstrated the developed exploration platform. To be more specific, the robot platform model was selected considering the characteristics of on-site power plant exploration as determined in Section 2.1.4. Auxiliary sensors were also developed to assist the robots accomplishing exploration and charging tasks. Section 4.4 provided evaluation scenarios for three types of experiments: (1) the computer performance test when V-REP runs with small and large size maps, (2) the accuracy and reliability test of the developed encoder, and (3) the performance evaluation of the developed exploration methods. Finally, Section 4.5 presented the relative evaluation metrics of these experiments. In the next chapter, the results and discussions of these proposed experiments will be presented.

Chapter 5

Results and Discussion

This chapter presents three types of results: (1) computer performance for robot path planning, (2) the accuracy and reliability of the developed encoder, and (3) the performance evaluations of the three developed multi-robotic exploration methods. The encoder's reliability and the performance of the proposed exploration methods are described in box-plot. In a box-plot, the boxes represent the data range between the first and third quartiles. Inside the box, a horizontal line is used to describe the median value in the group, and the whiskers on the top and lower side show the data range in the group, which represent the maximum and minimum values.

5.1 Computational System Performance

The computer was tested for path planning of the robots in both the small (25×25 m^2) and large size maps (300×250 m^2), see Figure 4.5 (a) and (b). In total, nineteen different path-planning algorithms (provided by V-REP) were adopted [68], and every algorithm was tested five times. Three different qualities of path are presented with three colours in Table 5.1: (1) green represents the right path generated, (2) red represents the incorrect path generated, and (3) orange represents the incomplete path generated.

Based on the V-REP official recommended path planning module, for the small size map, the deployed computer was able to compute the correct path for a robot with a 94.7% success rate. In contrast, for the large size map, the deployed computer found it difficult to compute the right path for a robot. For example, wrong and incomplete paths were generated in 51 out of 95 experiments. In conclusion, due to the limited computer configuration, the small size scenario was more suitable for simulations of the developed exploration system conducting exploration tasks. In further usage of the V-REP simulation robot in the small and large size scenario, two suggestions can be

Table 5.1: The results of the computer performance test against standard algorithms provided by the Open Motion Planning Library in V-REP [68].

Map size	25×25 m^2					300×250 m^2				
Test ID	1	2	3	4	5	1	2	3	4	5
Algorithms	**Path generation results**									
BKPIECE1 [69]										
BiTRRT [70]										
EST [71]										
KPIECE1 [69]										
LazyPRM [72]										
LazyPRMstar [73]										
LazyRRT [74]										
LBKPIECE1 [69]										
LBTRRT [75]										
PDST [76]										
PRM [77]										
PRMstar [77]										
RRT [74]										
RRTConnect [74]										
RRTstar [73]										
SPARS [78]										
SPARStwo [79]										
STRIDE [80]										
TRRT [81]										

Right path   Wrong path   Incomplete

made: (1) in the small size scenario, using scaled parameters to approach reality should be considered, such as the robots' running speed; and (2) in case of the large size scenario, the experimental configurations should be carefully decreased to lower the computer hardware requirements, such as properly reducing the exploration targets. However, whether using small or large size maps, there was no effect on the multi-robots' evaluation in this project, which was because all robots were configured with the same parameters.

5.2 Encoder Feedback

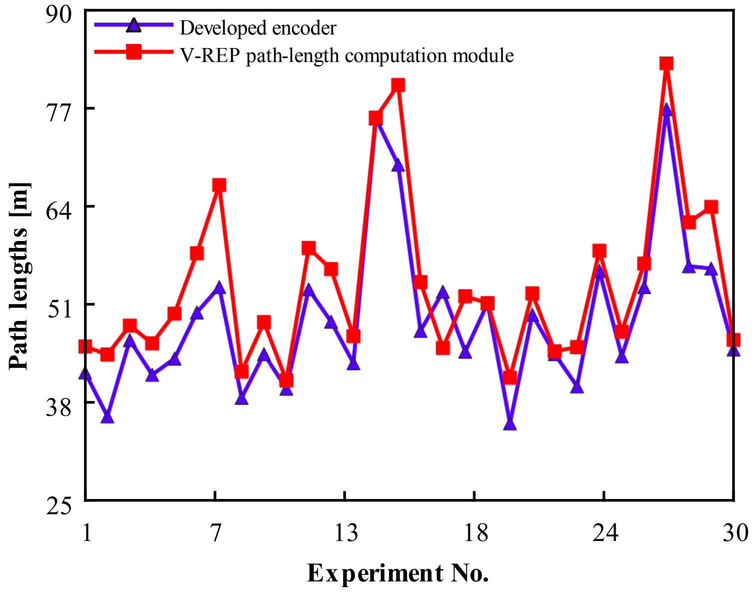


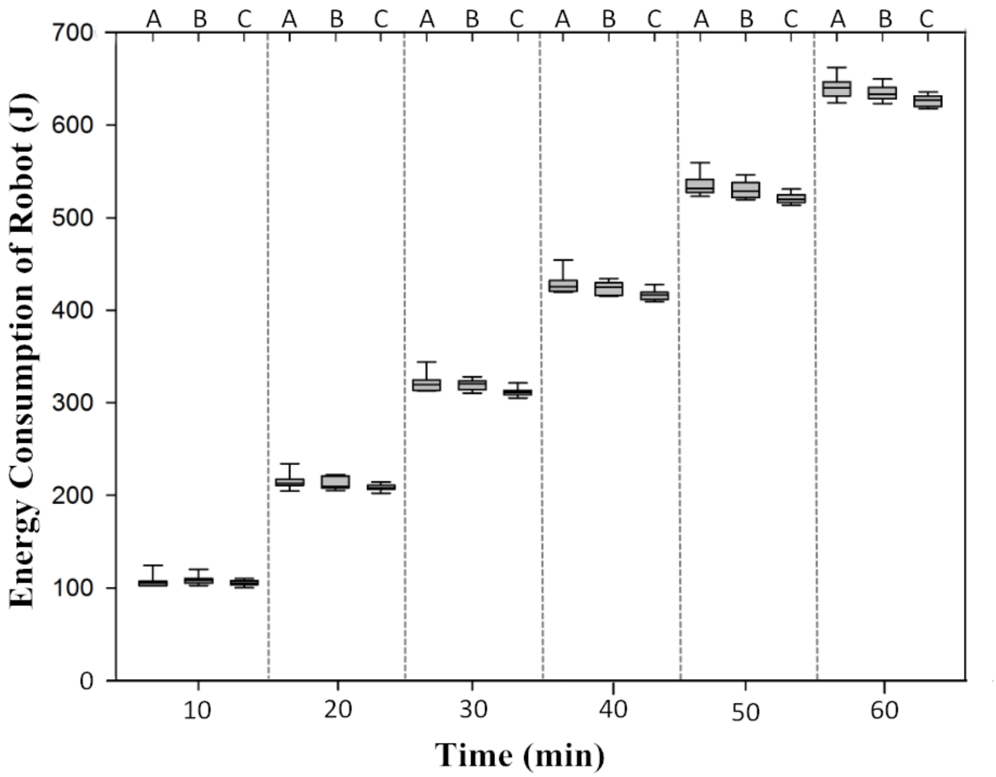
Figure 5.1: The results of the developed encoder test.

Accuracy test: A robot was equipped with a developed encoder, and tested 30 times in a 25×25 m^2 map, as presented in Figure 4.5 (a). The accuracies of the developed encoder were verified by comparing the difference(s) of the last total past-path lengths from the developed encoder and the V-REP official path-length computation module. This test results can be seen in Figure 5.1. The blue coloured line and red coloured line represent the results of the developed encoder and the V-REP official module.

From the results, it can be seen that the developed encoder was able to record the robot's past-path lengths with an acceptable error rate. Compared with the V-REP path-length computation module, 29 experiments out of 30 had an accuracy of more than 90%. The highest accuracy of the developed encoder was up to 99.89%. Errors occurred due to repeat counting when the robot adjusted its heading direction. To be more specific, the wheel (the one attached with encoder) would possibly move forward and backwards during testing, which may have triggered repeat counting by the detectors in some instances.

Reliability test: Two exploration robots were equipped with the developed encoder, and deployed into the 25×25 m^2 map, as shown in Figure 4.6 (a) and (b). Three multi-robotic exploration systems, A, B and C, were placed in 10 different initial positions and explored 10 and 20 targets in the map. The energy consumption of each robot was counted every 10 minutes. The total time allowed for the experiments was one hour, and the time error was controlled within ±0.01 s. Error control was achieved by a programme available in V-REP. The test results of the energy consumptions of each robot at different times can be seen in Figure 5.2 and Figure 5.3.

From the results, it can be seen that the energy consumption of each robot increased proportionally over time. In addition, whether 10 or 20 exploration targets, or *Robot #1* and *Robot #2*, the average energy consumption at a certain time in these different systems was almost same. From the data, in a total of 720 tests (every picture with 18 groups, and every group containing ten tests), comparing the average energy consumption of every exploration system with the overall average energy consumption of the three systems together at the same time, the maximum differences between these systems was 3.34%. This means the developed encoder is reliable in most cases for recording the past-path lengths of the robots.



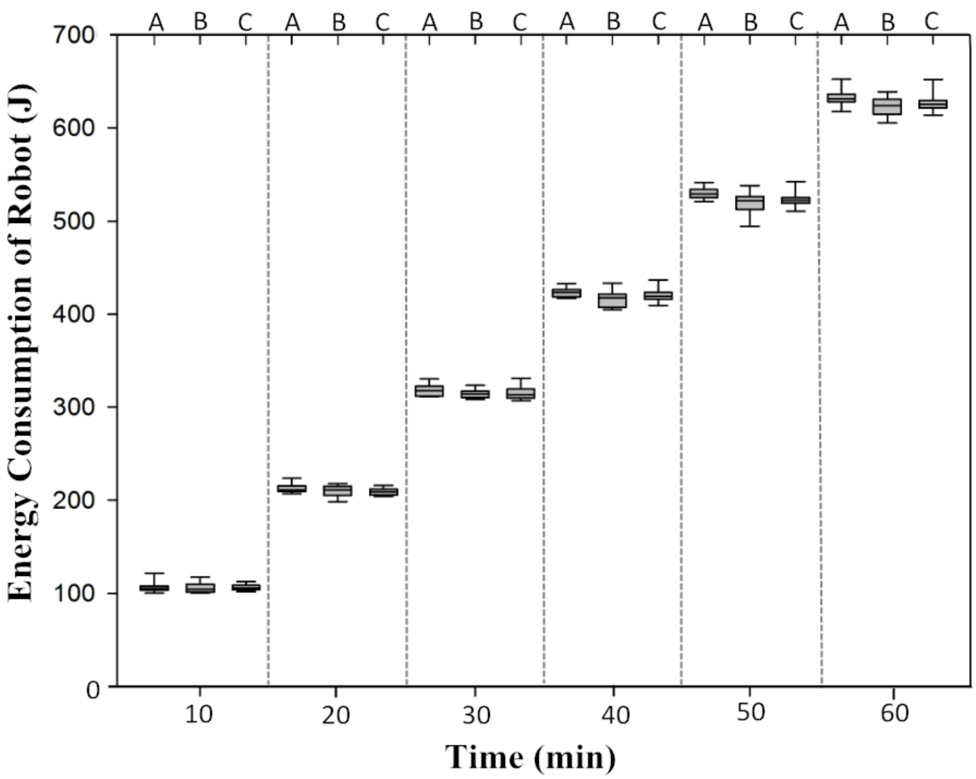


Figure 5.2: The energy consumptions results of individual robot, A: which used the Greedy and general charging method, B: which used the GA with general charging method, and C: which used GA with predicted charging method, (top) Robot #1 and (bottom) Robot #2 for 10 exploration targets.

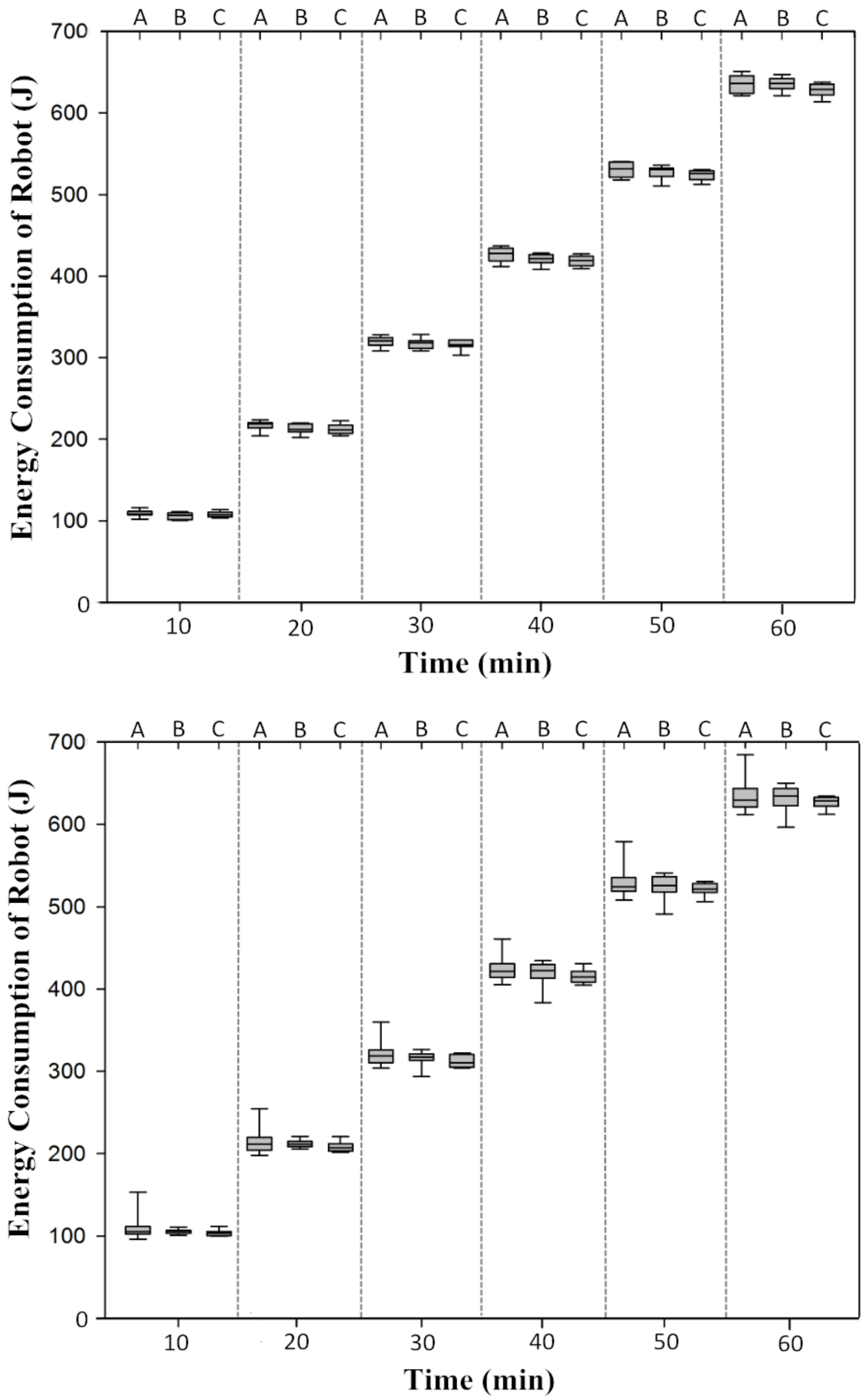


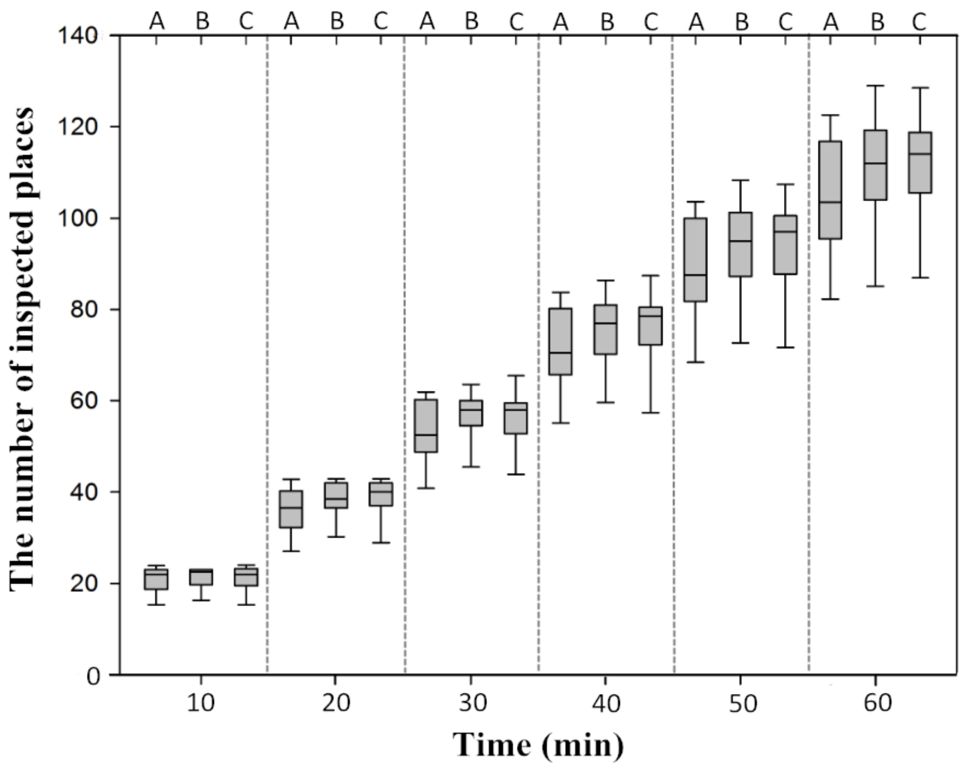
Figure 5.3: The energy consumptions results of individual robot, A: which used the Greedy and general charging method, B: which used the GA with general charging method, and C: which used the GA with predicted charging method, (top) Robot #1 and (bottom) Robot #2 for 20 exploration targets.

5.3 Inspection Efficiency

Three multi-robotic exploration methods, A, B and C, were tested for inspection of 10 and 20 targets. The robot teams were placed in 10 different initial positions in the experiments, and each test was one-hour in total, with the number of inspected locations counted every ten minutes. Time error was controlled within ±0.01 s, which was achieved by a programme available in V-REP. The results of the inspection efficiency of these developed exploration methods can be seen in Figure 5.4.

Greedy for temporary exploration mode: This inspection efficiency tested to evaluate the Greedy-based exploration system for temporary exploration mode, which had two limitations: (1) the evaluation metrics were not suitable. The original idea for the development of an exploration system for temporary exploration mode was that a robot team was designed to help the power-plant main station diagnosis faulty devices zone-by-zone. This means that evaluation work should focus on determining what percentage of exploration areas were checked by these proposed exploration systems at a certain time. In this study, we checked the exploration efficiency of this system in terms of the number of inspected targets rather than the percentage of exploration area cleaned by the system; in addition (2) the exploration tasks should halt after one complete exploration cycle. In theory, when these robots finished an exploration cycle task, these robots should be able to help the power plant find faulty devices. However, in this test, exploration method A was continuously deployed on-site when these robots finished one full exploration cycle.

In terms of further evaluating exploration method A, in the same way as for manual inspection operations, the exploration tasks in a power plant should be split into different zones. These different zones can be defined via the distances from the robot's initial location to the exploration targets. For example, *Zone 1*, with two exploration targets (10% exploration area), is far from the robot's initial location at less than 10m; *Zone 2*, with four another exploration targets (means 25% exploration area), is far from the robot's initial location at less than 20m (except *Zone 1*), and so on for other *Zones*. Thus, the performance of the Greedy-based temporary exploration method can be evaluated further by comparing the percentage of exploration areas serviced by these different exploration methods at a certain time.



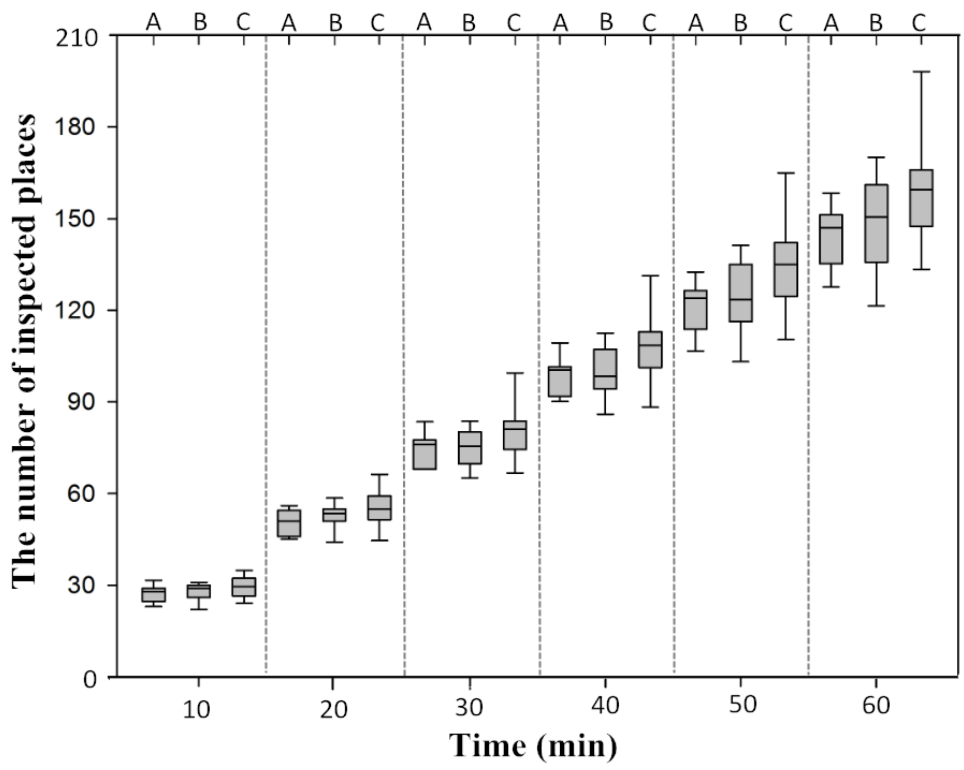


Figure 5.4: The results of robot team-work exploration efficiency, A: which used the Greedy and general charging method, B: which used the GA with general charging method, and C: which used the GA with predicted charging method, (top) Robot team for 10 exploration targets, (bottom) Robot team for 20 exploration targets.

However, in addition to inspection efficiency, the use of the Greedy-based exploration method (A) for temporary exploration mode was suitable compared with the GA-based exploration method (B), because robots used limited energy to debug faults for all the nearest targets zone-by-zone. In an application domain, this method can be adapted for emergency fault diagnosis.

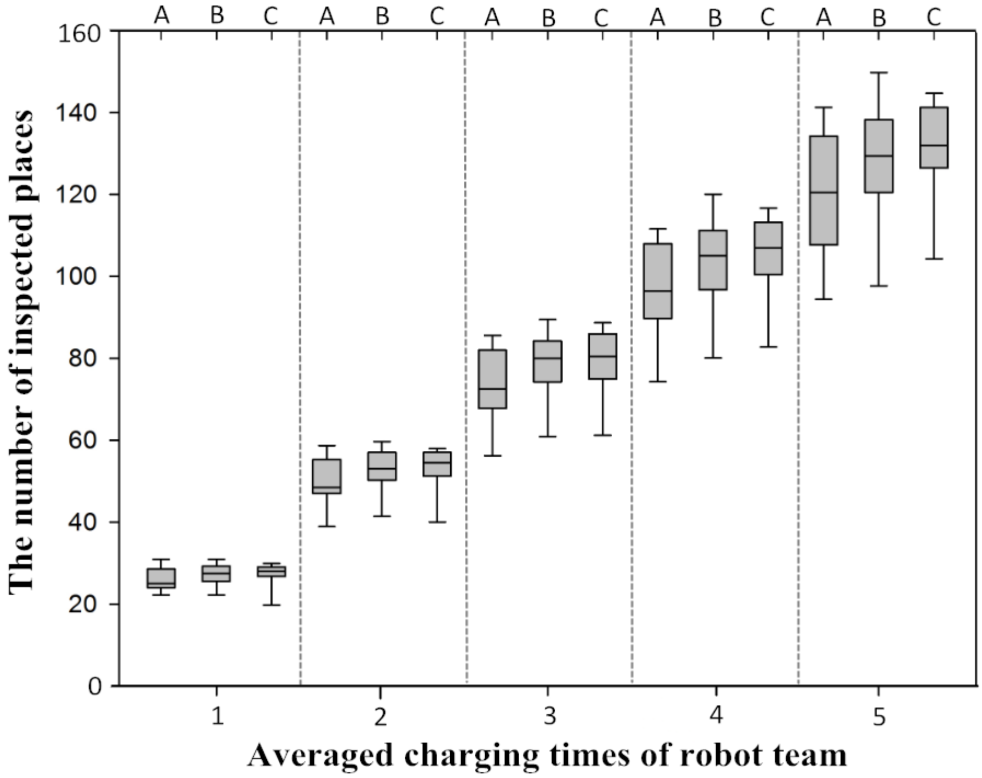
GA for long-term exploration mode: From the results, in the same charging method, using the GA-based exploration method (B) for long-term exploration was more suitable compared to use of the Greedy-based exploration method (A). As we can see, whether these systems explored 10 or 20 targets, the mean number of inspected targets from exploration method B outperformed exploration method A after 50 minutes of testing. From the data, we can see that in terms of the mean number of inspected targets, every hour test, exploration method B guaranteed 4~6 more inspected targets compared with exploration method A. This advantage will be more obvious if these exploration methods are deployed in a power plant for continuous tasks. Therefore, the GA-based exploration method (B) should be adopted for long-term exploration tasks in a power plant.

Charging method evaluation: From the results, exploration method C using the predicted charging method, outperformed exploration method A and B that used the general charging method. The average number of inspected targets in exploration method C was always higher than in exploration methods A and B since starting the tests. This advantage persists and becomes more obvious as the exploration target increases from 10 to 20. Therefore, this indicates that the developed predicted charging method is better than the general charging method for increasing the exploration robot's efficiency.

5.4 Energy-Saving Performance

This test used the same experimental configurations as explained in Section 5.3. Two robots were required to continuously explore 10 and 20 targets. In each test, the exploration robots were placed in 10 different initial positions. The relationship between charging times and exploration efficiency of the robot teams was examined in this test. To be more specific, every charging task of the exploration robot was used to count the number of targets inspected. This test stopped once the numbers of charging task of each robot had reached five times. The results of this energy-saving performance test for these exploration methods are presented in Figure 5.5.

Exploration methods evaluation: From the results, as the time and target number increased, whether 10 or 20 targets, the exploration efficiency of system B was better than that of system A. This has proved the long-term exploration strategy planning capability of GA outperformed the Greedy method. The Greedy-based exploration method may require robots to travel a long exploration cycle compared to the GA-based exploration method. This is because the travel consumption of the robot in the later exploration tasks may be too long compared with the GA-based exploration method, meaning the formulated exploration strategy is a suboptimal solution. In contrast, the optimal exploration strategy formulated by the GA is these robots to be separated and head in two different directions to finish exploration tasks in their own exploration areas. Therefore, the GA-based exploration method is suitable for long-terms exploration in a power plant, as it outperforms the Greedy-based exploration method in terms of its capability to allow these robots to effectively cooperate with each other, and scheduling a global optimal exploration strategy.



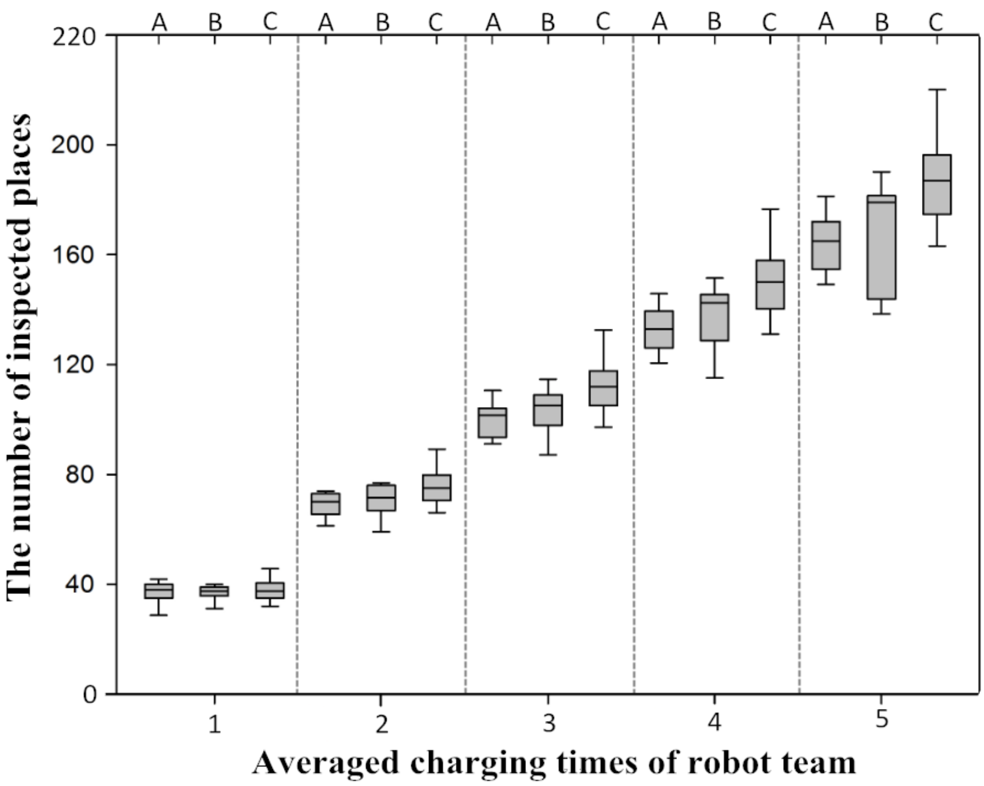


Figure 5.5: The different charging method results of multi-robot, A: which used the Greedy and general charging method, B: which used the GA with general charging method, and C: which used the GA with predicted charging method, (top) Robot team for 10 exploration targets, (bottom) Robot team for 20 exploration targets.

Charging method evaluation: From the results, it can be seen that the average number of inspected targets in exploration method C always outperformed exploration method A and B since starting the tests.

In the case of 10 exploration targets, after these robots finished five charging tasks, the extra exploration efficiency (the average numbers of inspected target) for exploration method C was guaranteed at 102.7% and 109.8% compared with exploration methods B and A. This advantage persists and becomes more obvious as the numbers of exploration targets increases from 10 to 20. In the case of 20 exploration targets, after these robots finish five charging tasks, the extra exploration efficiency (the average numbers of inspected targets) from exploration method C can be guaranteed at 111.0% and 114.1% compared with exploration methods B and A.

This directly proves that the developed predicted charging method can help the exploration robots save energy. The predicted charging method and general charging method both use the same limited energy for exploration, but the predicted charging method guarantees more numbers of inspected targets compared with the general charging method as the mean charging time increases. Therefore, an effective predict the energy consumptions of robots for properly switching the robot's exploration tasks to charging tasks, that can help robot avoid unnecessary energy waste, and improve the overall inspection efficiency of the exploration system.

5.5 Summary

This chapters presented three types of experimental results: (1) Section 5.1 demonstrated the feasibility of using V-REP simulation of robotic exploration on small and large size power plants; with the results of using small size scenarios most suitable based on the computer's limited configurations; (2) Section 5.2 tested the accuracy and reliability of the developed encoder; whereby it was found that the developed encoder was reliable for recording the robot past-path lengths within an acceptable error rate; and (3) Section 5.3 and 5.4 presented the evaluation results of the developed multi-robotic exploration methods; it was found that the Greedy-based method can be adopted for temporary exploration tasks with diagnosed faults zone-by-zone; the GA is more suitable for long-term exploration tasks with good exploration efficiency compared with the Greedy-based method; the predicated charging method has obvious advantages for optimising the inspection efficiencies and saves energy for the exploration system compared with the general charging method.

Chapter 6

Conclusion and Future Work

This project has recognised the gaps in existing on-site monitoring in various power plants, and has provided an effective multi-robotics exploration approach for further precision O&M at power plants. The exploration scenario considered in this paper used a limited number of robots to explore multiple targets. Two on-site exploration modes were proposed in this paper: (1) a temporary exploration mode where robots are required to diagnosis faults zone-by-zone in a power plant; and (2) a long-term exploration mode where robots are required to use limited energy to guarantee the inspection of more targets in long-term exploration.

In the development of these exploration systems, this project considered two factors for optimal efficiency: (1) scheduling of an optimal exploration strategy for these robots, and (2) appropriate charging control. Consequently, three multi-robotic exploration approaches were developed based on a combination of different exploration strategies (Greedy/GA) and charging methods (general/predicted). Implementation of these approaches are based on two works: (1) a multi-layered control framework was developed between MATLAB and V-REP for scheduling the exploration and managing the exploration/charging tasks of the multi-robot system; and (2) an exploration platform with auxiliary sensing devices (obstacle avoidance sensor, encoder) were developed in V-REP for exploration simulation and evaluations.

These systems were evaluated via three steps: (1) the feasibility of the V-REP simulated exploration robots in a mock-up power plant; (2) the accuracy and reliability of the developed encoder was evaluated, and (3) the developed multi-robotics exploration approaches for temporary and long-term exploration were analysed. From the results, it was found that using small scenarios for evaluation of the developed exploration systems was more suitable due to the computer’s limited configurations. The developed encoder was reliable for recording the robot’s past-path lengths with acceptable errors. This method has provided an approach to real-time monitoring of the robots’ past-path lengths in V-REP. The Greedy-based exploration method was found to be suitable for a temporary exploration task for diagnosing faults in a power plant zone-by-zone. The developed GA-based exploration method is suitable for long-term exploration tasks, which can guarantee more targets are expected after a certain period of time compared with the Greedy-based exploration method. In terms of the proposed general and predicted charging method’s impact on the exploration system performance, an effective prediction of the energy consumption of the exploration robot for properly switching its charging and exploration tasks, that is able to save energy and increasing the inspection efficiency for the exploration system.

This project is a prototype work, but contributes to the overall body of knowledge in research of the development of a multi-robotic exploration system for a power plant.

6.1 Limitations and Future Work

However, the multi-robotics exploration approaches proposed in this study are not perfect, and the limitations of these methods and direction for future research are summarised as follows:

(1) An optimal exploration strategy may not emerge in both the Greedy-based and GA-based exploration method. In terms of the Greedy-based exploration method, it will be challenging for a robot selecting the nearest exploration target for exploration tasks if the robot is equally far from two exploration targets. In further, the exploration details of these targets should be considered, such as these targets' exploration priority, the route, and so on. In terms of the GA-based exploration method, the evolution process of the GA is not fully optimised. In this case, different mutation processes can be attempted in future research to generate a more adaptable exploration strategy based on the proposed evaluation function.

(2) The scheduled exploration strategy of GA cannot be said to be representative in terms of long-term exploration. The GA-based exploration method only considered the first inspection loop for a static environment. Furthermore, there was a requirement to consider the travel consumption of robot teams from multi-inspection loops, or attempts on Artificial Intelligence (AI) techniques for exploration strategy scheduling of multi-robotic system in dynamics.

(3) Two different levels of behaviours separately manage the exploration and charging tasks. In future, the robot's travel consumption for charging tasks can be integrated into the exploration strategy scheduling stage.

(4) The accuracy and reliability of the encoder still have space for improvement. In future, based on current encoder design, one additional trigger-detection sensor can be established on opposite sides to avoid repeated counting, or counting should stop within a certain time after one detection.

(5) The developed predicted charging method does not consider the remaining battery before the robots' return to charge, and the remaining battery can be used to guarantee the additional number of inspected targets in further exploration.

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Appendix A

Investigation Details of The Real Power Plant

Table A.1: The interview details, as summarised from interviews with engineers.

Enterprise list	Scale (Mw)	Support Capability (4186 kWh/Year per person [82])	Approximate People hiring	Investigator
Sichuan Taipingyi Power Station, China Huaneng Group	320	600k users an hour	160	Investigator 1
Douhe Power Station, China Datang Corporation	1550	3000k users an hour	2600	Investigator 2
				Investigator 3
				Investigator 4
Huarun Power Station, CR Power Group	4600	9000k users an hour	580	Investigator 5
Hami Coal Electricity Co. Ltd, Shenhua Guoneng Group	2640	5100k users an hour	450	Investigator 6
Shouguang Power Station, China Shenhua Guohua	2000	3900k users an hour	1260	Investigator 7
Xibaipo Power Station, Hebei Xibaipo Electricity Co. Ltd.	2400	4700k users an hour	1680	Investigator 8
Hubei Jingmen Power Station	1840	3600k users an hour	1608	Investigator 9
Hebei Wangtan Power Station, China Datang Corporation	1200	2300k users an hour	960	Investigator 10
Datang Lusi Port International Power Generation Co. Ltd, DTP	2640	5100k users an hour	N/A	Investigator 11