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Abstract

Search and rescue (SAR) missions in disaster sites are complex operations with the top priority of the first responders to find as many survivors as possible within a limited time window. In these missions, autonomous robots can assist the responder teams by providing essential information about the SAR environments without putting human resources in danger. Thus, a robot's ability to efficiently explore and navigate an unknown environment is the main requirement for an autonomous search and rescue robot. Currently, a common approach to this problem is to incrementally increase the robot's knowledge about the exploration space by directing it to the regions which border currently unexplored areas, called frontiers. However, deciding on where to move next when multiple candidates are present introduces an additional layer of complexity as the robot must make real-time decisions with limited and possibly inaccurate information. Also, imprecise robot movements and imperfect input data characteristics provided by robot sensors can impact the candidate assessment process and, therefore, should be addressed while designing autonomous search and rescue robots.

The dissertation consists of an introduction, three main chapters, general conclusions, and a list of references. The first chapter performs a literature review on autonomous navigation and environment exploration strategies and formulates the dissertation's objectives. In the second chapter, a novel adaptive approach that implements the fuzzy logic controller is proposed for the autonomous navigation and environment exploration process. Also, two novel extensions are developed for the state-of-the-art WASPAS multi-criteria decision-making method and applied to determine the most suitable frontier considering the current robot state and the discovered environment information. These extensions are modelled under the interval-valued neutrosophic and m-generalised q-neutrosophic environments and referred to as WASPAS-IVNS and WASPAS-mGqNS.

The third chapter evaluates the proposed autonomous navigation strategies and presents the results. The case study results highlight how the proposed approach could be applied to minimise the probability to damage the robot while maximising the size of the area searched by the robot. By addressing the estimated inaccuracies in the input data characteristics, the proposed decision-making framework provides additional reliability when comparing and ranking candidate frontiers. The obtained results also indicate the increased efficiency when comparing the proposed adaptive candidate assessment strategies to the standard candidate assessment-based strategies.

Reziumė

Paieškos ir gelbėjimo (SAR) misijos nelaimės zonose yra sudėtingos operacijos, kurių metu pagrindinė gelbėtojų užduotimi tampa per tam tikrą laiko tarpą aptikti ir padėti kaip įmanoma daugiau nukentėjusiųjų. Viena aktualių mokslinių tyrimų sritis šiame kontekste yra žmogaus ir roboto bendradarbiavimas, nes autonominių robotų naudojimas SAR operacijose gali padėti gelbėjimo komandoms surinkti nežinomos aplinkos informaciją, nerizikuojant žmonių gyvybėmis ar sveikata. Šiuo atveju, itin svarbus reikalavimas, taikomas autonominiam robotui, yra gebėjimas efektyviai ištyrinėti nežinomas ir, galimai, pavojingas aplinkas. Šiuo metu nežinomos aplinkos tyrinėjimo uždaviniui spręsti dažnai yra taikoma roboto nukreipimo į regionus tarp žinomos ir nežinomos erdvės (angl. *Frontiers*) strategija. Tačiau sprendimas, kur robotas turėtų judėti toliau, kai tyrinėjamoje erdvėje yra keletas galimų kandidatų, yra sudėtingas, nes dažnu atveju robotas privalo priimti tik pusiau optimalius sprendimus dėl nepakankamų ar nepatikimų sprendimui priimti reikalingų įvesties duomenų. Be to, netikslus roboto judėjimas ir netobuli sensoriai sukuria situacijas, kai įvesties parametrai nėra tikslūs, tad į šią problemą turėtų būti atsižvelgta kuriant autonomines nežinomos aplinkos tyrinėjimo strategijas.

Disertaciją sudaro įvadas, trys pagrindiniai skyriai, bendrosios išvados ir literatūros sąrašas. Pirmame skyriuje atliekama literatūros apie autonomines navigacijos strategijas, grindžiamas nežinomos aplinkos tyrinėjimu, apžvalga ir suformuluojamos darbo užduotys. Antrame skyriuje aptariama siūloma adaptyvi neraiškiosios logikos valdiklį naudojanti sprendimų priėmimo strategija. Taip pat, pasiūlyti du klasikinio WASPAS daugiakriterinių sprendimų priėmimo metodo plėtiniai, kurie taikomi siekiant nustatyti vertingiausią kandidatą, įvertinant esamą roboto būseną ir atrastą tyrinėjamos vietovės informaciją. Siūlomi WASPAS plėtiniai sumodeliuoti taikant intervalines neutrosofines aibes ir m apibendrintas q neutrosofines aibes, o nauji metodai atitinkamai pavadinti WASPAS-IVNS ir WASPAS-mGqNS.

Trečiame skyriuje įvertinama siūloma autonominės navigacijos strategija. Tyrimų rezultatai parodo, kaip siūloma strategija gali būti pritaikyta siekiant sumažinti tikimybę pažeisti robotą ir kartu padidinti atrastą aplinkos informacijos kiekį. Lyginant su standartiniais metodais, siūloma adaptyvi navigacijos strategija suteikia galimybę įvertinti netikslius įvesties parametrus ir yra efektyvi, lyginant ją su klasikinėmis kandidatų vertinimu pagrįstomis strategijomis.

Notations

Symbols

P_f – candidate frontier set.

$p_f(x, y)_i$ – candidate frontier.

U – utility score of a candidate.

$U(p_f(x, y)^*)$ – candidate frontier with the highest utility score.

W – the set of criterion weights.

w – the criterion weight value.

w_s – the criterion weight value when the membership is considered as strong.

w_v – the criterion weight value when the membership is considered as weak.

C – criteria set.

c – the value of a single criterion.

ST – the set of candidate assessment strategies.

St – a single candidate assessment strategy.

s_j – comparative importance of average.

k_j – characteristics of the comparative importance.

q_j – intermediate weight.

X – a set of objects.

x – a single object.
$T(x)$ – truth membership.
$I(x)$ – indeterminacy membership.
$F(x)$ – falsity membership.
λ – real number.
N_{sv} – a single-valued neutrosophic number.
N_{iv} – an interval-valued neutrosophic number.
N_{mq} – m-generalised q-neutrosophic number.
N^c – the complementary neutrosophic number.
$S(\ )$ – the score functions.
$a(\ )$ – the accuracy functions.
$c(\ )$ – the certainty functions.
$p(\ )$ – the degree of possibility.
D – The decision matrix.
$[d]_{ij}$ – a member of a decision matrix.
$[\bar{d}]_{ij}$ – a member of a decision matrix in a neutrosophic form.
$Q_i^{(1)}$ – the first objective of the WASPAS method.
$Q_i^{(2)}$ – the second objective of the WASPAS method.
Q_i – the joint generalised value of the first and second objectives of the WASPAS method.
$E(s)$ – distance to the hypothesised survivor.
$E(d)$ – distance to the dangerous area.
R – the computed path to the candidate.
wp_i – a single waypoint in the computed path to the candidate.
t – the time needed to reach the candidate.
p_α – the corner between the robot and the candidate.
α – the corner between the waypoints in a planned path.
v_m – the robot's movement speed.
v_r – the robot's rotation speed.
δ – the constant value representing the width of the door.
l_d – width of the detected drive-through region.
P_i – the sum of the penalty received by the robot for crossing dangerous regions.
d_p – the partial penalty value received by the robot for crossing dangerous regions.
O_d – the set of currently known dangerous areas.
o_d – the dangerous area.
d_d – distance from the waypoint to the dangerous area.
d_v – distance from the waypoint to the detected survivor.
φ – the number of sampled cells that are yet to be discovered.

Abbreviations

ANOVA – the procedure of analysis of variance.

CF – Closest Frontier.

DA – Danger Avoidance strategy.

EU – European Union.

IG – Information Gain strategy.

IVNS – Interval-Valued Neutrosophic Set.

MCDM – Multi-Criteria Decision-Making.

mGqNS – m-Generalised q-Neutrosophic Set.

MULTIMOORA-SVNS – Multi-Objective Optimisation by Ratio Analysis method, modelled under the Single Valued Neutrosophic Set.

ROS – Robot Operating System.

RS – Reach Survivor strategy.

RRS – Restrictive Reach Survivor strategy.

SAR – Search and Rescue.

SIG – Standard Information Gain strategy.

SVNS – Single Valued Neutrosophic Set.

UAV – Unmanned Aerial Vehicle.

UGV – Unmanned Ground Vehicle.

USV – Unmanned Surface Vehicle.

UUV – Unmanned Underwater Vehicle.

WASPAS – Weighted Aggregated Sum Product Assessment method.

WASPAS-IVNS – the WASPAS method, modelled under the Interval-Valued Neutrosophic Set environment.

WASPAS-mGqNS – the WASPAS method, modelled under the m-Generalised q-Neutrosophic Set environment.

WPM – Weighted Product Model.

WSM – Weighted Sum Model.

Contents

Introduction

Problem Formulation

Application of autonomous and semi-autonomous mobile robots in disaster sites for search and rescue (SAR) missions can increase the awareness of the first responders, allowing them to collect on-scene information about the unknown and, often, dangerous areas in the search site without putting human resources at risk (Pfitzner & Merkl, 2013; De Cubber et al., 2017). As such, robots are expected to accomplish multiple high-level objectives without any (or with minimal) intervention from the robot operators (Bahadori et al., 2015; Sheh et al., 2016). For example, robots can be tasked to explore and create a map of the initially unknown environment, visit a number of pre-set landmarks, detect and mark dangerous objects (e.g., radiation or fire source), detect and contact the survivors, and deliver sustenance and medication to the trapped or injured (Jacoff et al., 2003).

However, imprecise or incomplete information about the disaster site introduces additional complexity to the autonomous environment exploration problem. If no initial information about the geometrical structure of the environment can be presented to the robot in advance, an offline route planning approach cannot be applied, and an optimal solution cannot be found simply due to the absence of problem-related information. This issue can be solved by developing an efficient online navigation strategy, which enables the robot to autonomously decide where to move next (Amigoni, Basilico & Quattrini Li, 2014).

Currently, multiple strategies can be applied in autonomous navigation and environment exploration tasks. However, a prevalent approach to this problem is a frontier-based approach proposed by Yamauchi (1997). This strategy can be improved by applying the next-best candidate assessment strategy, which considers the mission optimisation priorities modelled by weighted criteria set. Due to the inherent multi-criteria nature of this environment exploration strategy, the multi-criteria decision-making methods (MCDM) can be applied to solve this next-best candidate selection problem. Thus, the main focus of this thesis aims to improve robot decision-making capabilities in search and rescue missions when multiple competing optimisation priorities are present, and the input data characteristics are inaccurate.

Relevance of the Thesis

Autonomous navigation and environment exploration strategies define how robots move and collect information in a completely unknown (or little known) environment. The common approach to this problem is to apply the candidate assessment-based (next-best-view) environment exploration strategies. As the decision on where the robot should move next requires balancing multiple competing optimisation priorities, developing a flexible, transparent and efficient decision-making system is an important issue that should be considered. Moreover, imprecise robot sensors and environment representation models can provide inaccurate input data characteristics used in the candidate assessment process. Therefore, autonomous environment exploration strategies that allow for the possibility to address these issues and ensure the stability of the decision-making process in SAR environments are a prominent study subject.

Research Object

The object of the thesis is autonomous robot navigation strategies based on the candidate assessment by a multi-criteria decision-making approach.

Aim of the Thesis

The thesis aims to improve the candidate-assessment-based navigation strategies applied by the autonomous search and rescue robot when the decision on where to move next is made by considering only the current state of the robot and the environment and having inaccurate input data characteristics.

Tasks of the Thesis

To achieve the aim of the thesis, the following problems had to be solved:

1. To review common navigation and environment exploration strategies applied by the autonomous robots and determine the shared limitations of these strategies in search and rescue missions.
2. To develop novel candidate assessment strategies considering the common limitations of the candidate-assessment-based autonomous navigation strategies.
3. To develop an adaptive autonomous navigation strategy that allows switching between the rules that govern the candidate assessment process.
4. To develop novel extensions of the multi-criteria decision-making methods capable of considering the inaccurate input data characteristics.
5. To evaluate the performance of the developed multi-criteria decision-making method extensions.
6. To investigate the performance of the proposed autonomous navigation strategies in the simulated search and rescue missions.

Research Methodology

This thesis applied literature analysis methods for the investigation of the existing autonomous environment exploration strategies and problem formulation. Fuzzy logic, neutrosophic set theory and multi-criteria decision-making methods were applied to develop an adaptive online autonomous environment exploration strategy for search and rescue missions. The quantitative and qualitative evaluation methods were used for the assessment of the proposed autonomous navigation strategies.

Scientific Novelty of the Thesis

This thesis introduces the following scientific novelty:

1. The state-of-the-art WASPAS, multi-criteria decision-making method, is proposed two novel extensions, which utilise the neutrosophic set logic and enable the assessment of the inaccurate input data characteristics; i.e., WASPAS modelled under the interval-valued neutrosophic set environment (WASPAS-IVNS); and WASPAS modelled under the m-generalised q-neutrosophic set environment (WASPAS-mGqNS).
2. The novel egoistic, altruistic and impartial candidate assessment strategies are proposed for autonomous robot navigation in the search and rescue environments.
3. A novel adaptive approach is developed for autonomous search and rescue robots, which combines fuzzy logic controller with multi-criteria decision-making methods.

Practical Value of the Research Findings

The research findings can be useful when developing and extending autonomous navigation and environment exploration strategies applied by autonomous mobile robots. Practical application of the proposed strategies can be valuable in collecting on-scene information about dangerous search and rescue sites without putting humans at risk. The proposed method allows robots to make decisions in real-time and choose different rules of operation, depending on the dynamic environment information. For example, while navigating, robots can apply an egoistic behaviour model and avoid danger, an altruistic model and prioritise reaching survivors, or an impartial behaviour model that could be useful in situations where area mapping is the most important task. The proposed criteria set that define distinctive navigation strategies are flexible and not exhaustive. Therefore, by introducing new criteria or adjusting the weights of the applied ones, the proposed strategies can be easily extended to consider new navigational requirements and, thus, be adjusted to specific real-world situations. The results also include the developed WASPAS extensions under the interval-valued neutrosophic environment (WASPAS-IVNS) and the m-generalised q-neutrosophic environment (WASPAS-mGqNS). These modern methods can be applied to consider vague input data characteristics that are often present in real-world situations due to the imprecise sensor readings and various measurement errors in the criteria assessment process. Therefore, these MCDM method features can be applied not only in the context of autonomous robot navigation tasks but can also be applied in multiple decision-making problems where there is a possibility of uncertain criteria values.

Defended Statements

The following statements based on the results of the present investigation may serve as the official hypotheses to be defended:

1. The developed WASPAS method extensions under the interval-valued and m-generalised q-neutrosophic sets are stable and capable of considering the inaccurate input data characteristics.
2. The developed autonomous navigation and environment exploration strategies that consider the issues of robot safety, visitation of the detected survivors, exploration around the priority locations of the autonomous robot, define different egoistic and altruistic robot behaviour models and are more effective when compared to the baseline strategies that assess only the common cost–benefit models.
3. The developed adaptive autonomous navigation and environment exploration strategy that combines the fuzzy logic controller and MCDM methods enables the robot to effectively switch between the rules that govern candidate assessment strategies and increase the performance of the autonomous robot.

Approval of the Research Findings

Research results on the dissertation topic were published in six scientific publications. Four were published in the reviewed scientific journals, which are indexed in Web of Science databases (Semenas & Bausys, 2022; Semenas, Bausys & Zavadskas, 2021; Semenas & Bausys, 2020; Bausys, Cavallaro & Semenas, 2019); and two were published in proceedings of international conferences (Semenas & Bausys, 2021; Semenas & Bausys, 2018).
The author made three presentations at international scientific conferences:

- 2nd International Conference on Communication and Intelligent Systems (ICCIS 2020), India, 26–27 December 2020.
- 10th International Workshop Data Analysis Methods for Software Systems (DAMSS 2018), Druskininkai, Lithuania, 29 November – 1 December 2018.
- Open Conference of Electrical, Electronic and Information Sciences (eStream), Vilnius, Lithuania, 26 April 2018.

The Structure of the Dissertation

The scope of the dissertation consists of an introduction, the three main chapters, general conclusions, a reference list, and the list of publications by the author. The scope of the thesis is 121 pages, 57 equations, 23 figures and 22 tables. A total of 126 thesis-related research references are made.

1

Overview of the Autonomous Robot Navigation Strategies

This chapter reviews the autonomous navigation and environment exploration strategies applied by autonomous search and rescue (SAR) robots. It discusses common applied autonomous navigation strategies and issues that must be considered when designing entirely autonomous SAR robots. The presented approach centres on the online candidate assessment strategy by multi-criteria decision-making methods (MCDM). This chapter concludes by formulating the main objective and tasks of the present investigation.

Parts of this chapter were published in articles (Semenas & Bausys, 2018; Bausys, Cavallaro & Semenas, 2019; Semenas & Bausys, 2020; Semenas & Bausys, 2021; Semenas, Bausys & Zavadskas, 2021; and Semenas & Bausys, 2022).

1.1. Search and Rescue by Autonomous Robots

The level of real-world disasters can vary from small and localised (such as fires in an industrial complex) to large-scale and covering vast habitable areas (e.g., earthquakes, floods and tsunamis) (Memon et al., 2016; Nagatani et al., 2013).

Disasters usually result in human casualties, health risks in affected communities, and economic and environmental damages (Jorge et al., 2018).

However, the introduction of autonomous search and rescue robots in such events can help to mitigate some of the mentioned problems by providing the on-scene information to responder teams, enabling them to react faster and make better decisions. By increasing the situational awareness of the first responders, more tasks can be accomplished in a shorter span of time. Also, the high-risk areas that need to be avoided or require more safety precautions before sending humans to such locations can be determined in advance (De Cubber et al., 2017).

Therefore, in search and rescue missions, autonomous robots are expected not only to create the representative map of the disaster site but are also tasked to complete a set of other high-level objectives of varying complexity, such as safely navigating in disaster sites with complex terrain and multiple obstacles (Luneckas et al., 2021b), finding and contacting survivors, visiting specific landmarks or locating dangerous objects and events (Jacoff et al., 2003). These high-level objectives and the assumed space of operation are the defining factors that influence the autonomous robot design (e.g., it can be an autonomous flying aerial vehicle (Kikutis, Stankūnas & Rudinskas, 2019) or a walking hexapod robot (Luneckas et al., 2021a), just to name a few). Thus, search and rescue robots can be classed as:

- Unmanned Aerial Vehicles (UAVs) (San Juan et al., 2018) that can be used for aerial-based search in harsh or vast environments, such as mountains (Silvagni et al., 2017; Karaca et al., 2018) or above the bodies of water (Zheng, Hu & Xu, 2017);
- Unmanned Surface Vehicles (USVs) that operate above the surfaces of water bodies to assist water-stranded boats or people (Jorge et al., 2018);
- Unmanned Underwater Vehicles (UUVs) that operate in deep-sea missions or are applied in flooded environments.
- Unmanned Ground Vehicles (UGVs) that are used in many situations, such as exploring disaster sites after an earthquake and assisting detected survivors (Sahashi et al., 2011; Kruijff et al., 2012) or operating in mining site disasters (Murphy et al., 2009; Reddy, Kalyan & Murthy 2015);

Although autonomous robots in search and rescue missions can provide many benefits, their application in real-world tasks is currently limited due to the high robustness and stability requirements. Thus, it is more common for SAR robots to perform alongside humans, forming human–robot teams (Sheh et al., 2016) and leaving the important decisions (e.g., confirmation of the detected survivor) to the human operators. Currently, there is no globally-recognised standard that describes how the decision-making modules of such robots should be designed.

Many initiatives have been taking place around the globe to address this problem and to establish globally-recognised guidelines for SAR robot development (performing autonomously or in human–robot teams). For example, the Center for Robot-Assisted Search and Rescue (CRASAR) was established in the United States of America. The main mission of this organisation is not only to support and promote the development and application of autonomous robots in disaster response but also to prepare trained specialists capable of working together with autonomous robots in search and rescue scenarios (CRASAR, 2020). It is also worth noting that this organisation has participated in the 9/11 response, providing on-the-ground assistance by rescue robots.

The European Union (EU) has also supported many initiatives related to the use of autonomous robots in search and rescue operations (De Cubber et al., 2017). One of such EU funded efforts was the NIFTi project which was active for four years starting in 2010 and focused on human–robot interaction in search and rescue missions (Kruijff et al., 2014). By focusing on the aspects of optimisation and separation of human and robot task loads, forms of communication and alignment with human rescue teams, NIFTi aimed for stronger robot cooperation with human rescue teams. The results of this project were successfully applied after the 2012 earthquake in Northern Italy (Kruijff et al., 2012).

Another EU funded project — TRADR — is a direct successor of NIFTi. The project was active for four years, starting in 2013 and focused on human–robot team interaction and cooperation in search and rescue scenarios (Kruijff-Korbayová et al., 2015). TRADR’s main goal was to develop robust user-centric strategies for long-term SAR missions involving UAVs and UGVs with different levels of autonomy.

INACHUS was one more EU project that could be considered a successful investment. It has been active since 2015 and has also continued for four years. This project was directed at developing solutions for urban search and rescue missions, enabling the rapid assessment of structural damage to the disaster site and providing tools to efficiently plan the actions of the first responders. The project includes modern sensor systems and communication solutions for survivor localisation (e.g., mobile phone signals, chemical sensors etc.) (Rigos et al., 2018), a snake-type robot design, which can navigate through rubble and other small spaces, decision and planning strategies for casualty and damage estimation.

In Asia, Japan and South Korea are also working on search and rescue robots. For example, in the 2011 Fukushima Daiichi event, robots were used to inspect structures with high collapse risk and to search for tsunami victims (Nagatani et al., 2013). Motivated by this event, the 2015 DARPA Robotics Challenge presented similar disaster site conditions to provide a platform for testing robots in performing common SAR objectives. In this event, the South Korean team won first place by developing a search and rescue robot capable of performing all of the required tasks of driving a vehicle, opening doors, climbing ladders and other challenges important in real-world SAR missions (De Cubber et al., 2017).

One notable global event that provides a testing ground for new autonomous robot design and environment exploration strategies for search and rescue missions is RoboCup Rescue Robot League (Akin et al., 2013; Sheh et al., 2016; RoboCup Rescue, 2020). This competition provides a testing ground suitable for the assessment of the robot's ability to navigate and explore disaster sites, create representative environment maps, locate the survivors and assess their condition, and deliver or extract various objects. Such an annual competition-based approach enables the modelling of good robot design practices, identification of effective navigation and environment exploration strategies, creating a globally-recognised approach (Aghababa et al., 2019) for testing autonomous robot capabilities, and measuring the overall progress of autonomous search and rescue robots and strategies throughout the years.

The autonomous navigation and environment exploration strategies applied by the SAR robots are affected by many different factors, including how the underlying high-level objectives are modelled. And the modelling of these objectives can involve many different stakeholders, such as medical staff, police officers, firefighters, disaster survivors, local authorities and journalists, just to name a few. Each of these stakeholders can have a set of unique expectations or requirements for the deployed autonomous robot, introducing value tensions that should be addressed to achieve not only the given mission goals (Harbers et al., 2017) but also to create a transparent and trusted autonomous system.

For example, in search and rescue missions, firefighters can prioritise the robot to construct a map that represents the layout of the disaster site and mark the locations of dangerous events that may hinder the rescue process. Medical staff can prioritise the monitoring of the detected survivors, and survivors can prioritise their own well-being. Also, robots are expensive tools that could be modelled to egoistically protect themselves from harm instead of achieving some of the given short-term goals.

As autonomous SAR robots can be involved in decision-making situations that directly affect humans, an efficient robot decision-making strategy must balance the set stakeholder requirements while also addressing real-world legislative and ethical design requirements (Veruggio & Operto, 2008) applicable to the intelligent systems. Therefore, several papers have emerged to address these issues. For example, Murphy and Woods (2009) addressed the inherent flaws of the fictional Asimov laws (Asimov, 1950) and proposed three laws of responsible robotics. Amigoni and Schiaffonati (2018) considered the application of an ethical framework to search and rescue robot design and development. Vanderelst and Winfield (2018) tested an ethical behaviour model in physical robots, providing proof of the concept that robots can be enforced to behave socially acceptably.

Bogue (2014) reviewed the ethical and legal issues of several existing and emerging classes of robots, and Alaieri and Vellino (2016) published a paper discussing the issue of unpredictable robot behaviour and the liability transferring from the robot to its designers and users (although it should be clarified that in SAR scenarios, important decisions that impact the survivors are currently always entrusted to the humans). Boddington et al. (2017) discussed a collection of recent works that tackle ethical concerns in artificial intelligence.

Several global initiatives have also been started to develop a globally-recognised standard for the development of intelligent autonomous systems. IEEE has recently launched its global initiative on the ethics of autonomous and intelligent systems to advance the public discussion by proposing the concept of ethically aligned design (Chatila & Havens, 2017). The European Union institutions addressed the rising concerns by preparing a legislative analysis for devising civil law rules regarding the smart autonomous systems (Nevejans, 2016) and, in 2019, presented ethical guidelines for trustworthy artificial intelligence (AI HLEG, 2019), which can also be applied when designing autonomous SAR robots. However, the discussed research initiatives do not define exact operative rules to follow but rather provide abstract guidelines that should be considered when practically designing autonomous robot systems. Therefore, the practical development of a decision-making strategy, including how the criteria and their relative importance are determined, is still an immense challenge due to the complexity of real-world situations. Moreover, the incomplete information about the environment and uncertainty that is associated with such information (Yager, 2020) introduce additional complexity to the task, requiring a flexible approach for modelling robot navigational behaviour in SAR missions.

The strategies that enable the flexible adjustment of autonomous SAR robot navigational behaviour could be based on the ethically adjustable design model proposed by Contissa et al. (2017). In general, by extending this design, the robots can be dynamically adjusted to adopt different behaviour models and, therefore, a more flexible approach can be exploited to solve complex navigational problems. This behaviour-based approach was somewhat indirectly tested in the research by Roesner et al. (2019), which proposes a controller for UAV-type swarms. In this research, agents either assist a detected survivor (act in an altruistic manner) or prioritise exploration and increase the robot’s operational time enabling it to act in an egoistic manner, highlighting the possibility of different robot behaviour model development. Also, if the previously discussed EU guidelines for trustworthy intelligent systems are considered (AI HLEG, 2019), the approach of modelling explicit altruistic and egoistic navigation strategies can provide a solid foundation for flexible, autonomous navigation strategy due to the inherent transparency of this approach.

1.2. Environment Exploration Strategies for Autonomous SAR Robots

As a robot must navigate in an unknown environment, an important factor becomes not how the robot moves between the spatial targets (specifically, not how the concrete movement trajectories are planned (Ning et al., 2012)), but rather where it moves (what spatial targets the robot should select and reach) considering the high-level objective (Amigoni, Basilico & Quattrini Li, 2014). One can define the two common objectives given to the autonomous mobile robots as the coverage and the exploration of the environment. In coverage objectives, autonomous robots are required to navigate so in a known environment that would allow them to observe (or physically visit) all of the available locations within (Choset, 2001; Galceran & Carreras, 2013), whilst in the environment exploration tasks, autonomous robots are required to explore the initially unknown environment by discovering its features.

In general, environment exploration strategies define how autonomous robots navigate and gather information within the given operating environment. The main factors that define the complexity of these strategies are the amount of the initially available information, the success conditions of the high-level objective, and the additional requirements that the robot must address during the exploration process (e.g., to create a representative map of the exploration environment, visit specific locations or landmarks, detect a number of task-related objects, deliver items to specified locations, etc.). It is also important to note that if search and rescue missions are considered, the primary objective is usually not to build an accurate environment map but rather to find as many survivors as possible within a limited time (Basilico & Amigoni, 2011).

One of the main factors that define the applicability of autonomous navigation and environment exploration strategy is the amount of initially available information that could be provided to the exploring SAR robot. Depending on this parameter, the applied strategy can either be classed as offline or online (Amigoni, Basilico & Quattrini Li, 2014).

In situations where the layout of the environment and other objective-related information is known in advance, global optimisation (offline) path planning strategies can be applied to find the optimal or near-optimal solution to the exploration process (Amigoni, Basilico & Quattrini Li, 2014). These methods can include classical approaches, such as A* or Dijkstra, sampling-based methods or bio-inspired neural networks (Kulvicius et al., 2021). Certainly, there are cases where path planning methods can compute every possible outcome for a finite number of actions and determine the optimal path. However, this depends on the complexity of the high-level objective and the supplementary tasks that the autonomous robot must complete. According to Galceran and Carreras (2013), even the simplest path planning tasks for coverage objectives are related to the covering salesman problem and, therefore, are NP-hard. This means that in many scenarios, only the near-optimal solutions to the exploration problem can be achieved if the autonomous robot system is required to perform in real-time (online).

Considering the environment coverage tasks, the computation of guided paths is a fast and simple framework that can be applied by the robot designer to enable autonomous robots to systematically cover the exploration environment by following pre-computed paths (e.g., spirals with an increasing radius (Choi et al., 2009)). Some other examples of path planning methods can include strategies that define a set of priority locations (Roa-Borbolla et al., 2017) to be visited or avoided and strategies that implement wall following (González et al., 2005; Katsev et al., 2011). Although strategies that apply guided coverage paths are moderately easy to implement, their efficiency is arguable in situations where none or only partial information about the environment and its conditions can be presented to the robot in advance. In such cases, hybrid frameworks that incorporate environment exploration methods or a multiple robot cooperation approach can be applied to achieve better results. Several examples of such terrain coverage strategies can be found in the research of Zheng et al. (2005) and Senthilkumar and Bharadwaj (2008).

However, in many real-world navigation and environment exploration scenarios, the application of offline global path planning and optimisation strategies is hardly possible. Due to the lack of initial information, the complete set of possible candidate locations for the robot to visit is unknown in advance, meaning that the decision-making module cannot optimise the robot's path. Nevertheless, autonomous SAR robots are expected to explore the unknown environment and complete the given high-level objective without any (or only with minimal) intervention from human operators (Calisi et al., 2007; Akin et al., 2013). To solve this problem, robot designers can utilise a variety of online autonomous navigation and environment exploration strategies, in which the initially unknown environment features are discovered by iteratively directing the autonomous robot to visit and observe the unknown portions of the search space.

These online environment exploration strategies are commonly based on the greedy next-best-view approach, which interprets the robot-constructed map to determine a set of candidate locations within the partly explored search space and choose the one that should be visited by the robot (Basilico & Amigoni, 2011). By applying these strategies, the decision on where the robot should move next is made on the go and therefore depend only on the current state of the robot and the known environment information. In other words, instead of trying to optimise the exploration path globally by considering every possible outcome, the next-best-view analysis and decision-making approach tries to optimise short-term decisions by searching for the local maximums that best correspond to the given high-level objective at each decision-making step. The underlying idea of such navigation strategies is to increase the robot's partial knowledge about the search space to make better decisions on where to move next. The general concept of such environment exploration strategies can be defined as provided in Fig. 1.1.

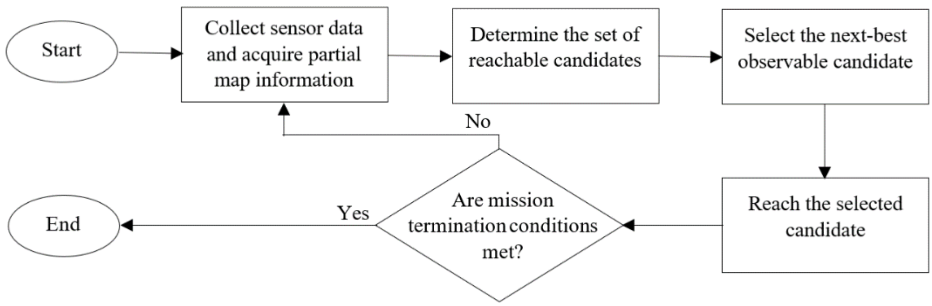


Fig. 1.1. Schematical representation of a common autonomous robot navigation strategy

At the start of autonomous navigation, the robot utilises the environment perception sensors and collects information about the environment features, such as physical obstacles and structures in its field of view. The newly acquired data is then stitched to the robot-constructed environment representation model. The robot applies self-localisation techniques and determines its position on the constructed map. This partial environment map is also used to determine a set of candidates that could be reached from the robot's current position. The candidates are then compared based on the given high-level optimisation requirements. The highest-ranked is then chosen as the next goal for the robot to reach. Then, the autonomous robot moves to the selected candidate by applying path-planning and obstacle avoidance algorithms. This process is repeated from the first step until the mission termination conditions are met, e.g., there are no more unvisited candidate locations left, the robot battery is depleted, or the high-level objective is completed.

In the context of this thesis, the most important segment of the online environment exploration process can be identified in the second and third steps of the navigation loop. To make an effective decision on where to move next, the robot has to build a list of reachable candidates, compare these candidates with each other and choose the most valuable one.

Many different strategies can be applied to assess the candidate locations. For example, Yamauchi (1997) proposed a popular and easy-to-implement approach commonly used as a baseline for algorithm improvement and testing (Gomez, Hernandez & Barber, 2019; Juliá, Gil & Reinoso, 2012). It is based on determining the distance to the frontier (the boundary region between the already explored and unknown space) and selecting the closest one. By following this approach, every time the robot reaches the selected frontier, newly discovered environment information is added to the robot-constructed map. Then, the list of available frontiers is updated, and the process of decision-making and moving to the selected goal is repeated.

In theory, the simple approach of leading the robot to the closest frontier would be sufficient in eventually covering the whole exploration space. However, as the complexity of the task increases, so does the complexity of the candidate frontier assessment. For example, in tasks where the exploration speed and the size of the robot-observed environment are important conditions for the overall success of the high-level objective, the robot operators could prioritise visiting candidates that are expected to provide more information about the environment while also minimising the time needed to reach the candidate frontier. Therefore, in such cases applying a single criterion to determine where to move next is not sufficient when considering the complexity of these tasks. A more efficient approach could be assessing candidate locations by balancing several competing criteria that define the underlying high-level objective. In other words, multiple and often competing criteria can be applied to assess the candidate frontiers. Therefore, this problem can be viewed as a multi-criteria problem, where each candidate is evaluated by combining a set of task-related criteria to determine the one with the highest utility. This candidate frontier is then chosen by the robot as the next-best location that the exploring robot should reach.

Several papers address this problem by introducing varying strategies for assessing the candidates. For example, González-Baños and Latombe (2002) proposed to assess the utility of a candidate location by measuring the distance between it and the robot while also estimating how much new information would be gained by reaching it. Makarenko et al. (2002) proposed to assess the candidate locations by the sum of the three utilities: the information gain utility, which is measured by estimating the amount of free grid-map cells around each candidate frontier; the utility of the cost of driving from the robot’s current location to the candidate location; and the localisation utility, which defines the expected precision of robot localisation in the candidate location. Amigoni and Gallo (2005) proposed considering the map overlap parameter, and Visser and Slamet (2008) also proposed expanding the criteria list for candidate assessment by considering the probability of communication. DasGupta et al. (2006) introduced an aggregation/refinement-based object search approach in which the exploration space is divided into a finite number of regions. In this strategy, each region is treated as a graph vertex with a set cost and reward value. A strategy on criteria value assessment for evaluating candidate locations is discussed by Potthast and

Sukhatme (2014), who proposed a probabilistic method to estimate the information that could be gained in extremely cluttered environments.

Basilico and Amigoni (2011) implemented a frontier-based environment exploration strategy and proposed to assess the utility of a candidate by estimating a set of commonly applied criteria, i.e., the distance to the candidate frontier, the estimated information gain, the probability of the robot to communicate (send information) after reaching the candidate frontier. Gomez et al. (2019) also introduced a frontier-based approach that incorporates semantic (transit area importance), geometric (size of the frontier) and topological (the distance that the robot has to travel) criteria for selecting the next candidate frontier.

Ström et al. (2017) proposed a prediction-based exploration approach for autonomous navigation in enclosed environments, and Wang et al. (2018) proposed a collaborative environment exploration approach, in which aerial and ground robots are deployed for fast environment mapping objectives. However, the latter researchers applied a standard candidate frontier assessment methodology for evaluating the expected information gain versus the cost needed to obtain this information.

Although different candidate assessment strategies can be employed in autonomous navigation and environment exploration tasks, the expectations triggered by autonomous systems and their applicability in no-win situations (that are typical in search and rescue missions) highlight that a clash of prioritisation ordering between competing options is inevitable in some real-world situations (McGrath and Gupta, 2018). In other words, the decision-making process is dependent on the assessment of multiple competing technical, social, economic, environmental, cultural, and religious belief-based criteria. As such, in the context of autonomous robot systems, candidate assessment problems can be thought of as multi-criteria decision-making problems that involve several competing optimisation priorities set by the robot designers or operators.

In this thesis, the exploration of the search and rescue environments is considered when the environment information, such as the location of survivors and the current state of the exploration space, is unknown in advance. By considering the commonly applied next-best-view approach for exploring initially unknown environments and the criteria-based nature of the candidate assessment and selection problem, it can be argued that multi-criteria decision-making methods can be applied as an effective way of combining and comparing competing criteria sets that correspond to the underlying high-level objective. Therefore, the application of MCDM methods in autonomous navigation and environment exploration tasks is discussed next.

1.3. Multi-Criteria Decision-Making Approach for Autonomous Environment Exploration

Considering decision-making problems typical in the real world, there can be an essentially unlimited number of competing criteria with different levels of importance that need to be assessed to make an optimal (or, in many real-world cases, just near-optimal) decision (Aruldoss et al., 2013). In other words, it is common that the dominant solution to the problem does not exist, and one must choose the best alternative from the available list while assessing the set of preferences and their importance to the high-level objective.

With a finite number of alternatives to choose from and each alternative assessed by a finite number of task-related criteria, the problem can be simplified to the selection of the best alternative. In this sense, some assessment problems can be solved by linearly combining a set of criteria and assigning a crisp score value to each alternative. However, when the complexity of the task increases and the number of competing criteria is too big to handle, multi-criteria decision-making methods come into the spotlight. And throughout the years, many different MCDM methods and their extensions were proposed (Mardani et al., 2017), such as AHP, TOPSIS, ELECTRE, PROMETHEE, WPM, WSM, WASPAS, MULTIMOORA, COPRAS, VIKOR (Aruldoss et al., 2013; Kumar et al., 2017; Mardani et al., 2017; Zavadskas et al., 2012), just to name a few.

Multi-criteria decision-making methods are exceptional tools that are commonly applied when aiming to model and solve complex decision-making problems in the economic, social, energy and engineering fields. For example, the problem of selecting a location for the waste incineration plants by the WASPAS MCDM method is discussed by Zavadskas et al. (2015a). The design selection problem of lead-zinc flotation circuits is considered by Zavadskas et al. (2016). The MULTIMOORA method was applied to a house-shape evaluation problem by Juodagalvienė et al. (2017). Stojić et al. (2018) proposed a methodology for supplier selection for manufacturing chains, and more recently, an MCDM-based safety evaluation methodology for urban parks was introduced by Zavadskas et al. (2019). The industrial robot selection problem was discussed by Keshavarz Ghorabaee (2016). Chandrawati et al. (2020) proposed to apply the WASPAS MCDM method to determine the most efficient evacuation route in the case of flooding disasters.

As the MCDM methods are extremely flexible tools, there are also MCDM method application examples when considering real-world problems in the field of robotics and autonomous mobile systems. For example, a method for selecting an automatically guided vehicle for warehouse automation is proposed by Zavadskas et al. (2018). The problem of selecting the most appropriate manoeuvre for autonomous city vehicles is considered by Furda and Vlacic (2010) and solved by applying the Simple Additive Weighting Method. Martín Ramos et al. (2010) applied MCDM methods for path selection for an autonomous mobile robot. Similarly, Jeddisaravi et al. (2016) proposed to utilise the ELECTRE I framework for time-limited environment coverage and exploration task. The proposed approach utilises the multi-criteria decision-making methods to select the pre-computed route that maximises area coverage and minimises the visibility field overlap of the waypoints. However, the latter approaches by Martin Ramos and Jeddisaravi are a bit different in the sense that the decision-making method is applied for selecting the path that was computed by the offline strategy, rather than proposing the online autonomous navigation and environment exploration strategy.

The explicit navigation strategy for the autonomous robot by multi-criteria decision-making methods for criteria combination and deciding on where to move next is proposed by Amigoni and Gallo (2005). Basilico and Amigoni (2011) propose to extend this research by applying the Choquet fuzzy integral for criteria combination to determine the best position to move to in search and rescue missions. The candidates are assessed by applying the standard criteria set of the expected information gain, the ability to communicate after reaching the candidate location, the distance to the candidate location, and the time that is needed to reach the candidate. The results of this research highlight the efficiency of MCDM methods when applied in the online decision-making approach compared to the standard ad hoc strategies.

Following this research, a PROMETHEE II outranking method is proposed by Taillandier and Stinckwich (2011) to improve the robot's decision-making ability. As in the previous research, the standard criteria of the distance to the candidate location, the ability to transmit information and the estimated amount of new information that would be gained after reaching the candidate were applied in the assessment process. In the recent research, the author of this thesis introduced several strategies for candidate frontier assessment by also considering robot safety-related criteria for the assessment of the candidate locations in the robot's local space (Bausys, Cavallaro & Semenas, 2019). Polvara et al. (2020) proposed a strategy that, along with the set standard criteria, also considers battery status, sensing time and radio frequency identification (RFID) tag information gain. However, the latter method is created specifically for environment coverage problems for the discovery of RFID tags. Lastly, Zagradjanin et al. (2022) applied TOPSIS, SAW and COPRAS MCDM methods for selecting a candidate to be reached by the robot next.

Although online next-best-view environment exploration strategies allow for the possibility to balance criteria that support the given high-level objective, the multi-criteria decision-making method application capabilities in complex scenarios are yet to be exhaustively studied, especially if search and rescue missions are considered. Another prominent issue is unstable robot navigation and path planning performance, computation of the imperfect environment representation model and inaccurate robot sensors. Thus, the ability to consider the uncertain or imprecise input data characteristics applied to decide where the robot should move next in a partially explored environment is a prominent issue that prompts researchers to look for modern techniques when modelling such data in complex decision-making problems.

1.4. Conclusions of Chapter 1 and the Formulation of the Thesis Tasks

The key observations and conclusions were formulated following the literature review:

1. Search and rescue missions are complex tasks in which autonomous robots can be used to collect on-scene information and reach additional objectives (e.g., establish communication with the detected survivors or mark dangerous events in the area) to increase the safety and efficiency of rescue teams, enabling them to make more informed decisions. However, it is common that in real-world situations, none (or little) a priori information about the environment can be provided to the robot, meaning that only the near-optimal solutions to the autonomous navigation and environment exploration problem can be achieved. Thus, a popular approach to this problem is the application of online candidate assessment strategies.
2. The candidate assessment problem can be viewed from the multi-criteria decision-making perspective. Specifically, the competing optimisation priorities (or high-level objectives) that define the core of the candidate assessment strategy can be modelled by a group of maximised and minimised criteria. Then, the multi-criteria decision-making methods can be applied to assess the utility of each candidate. However, generally applied candidate assessment strategies fail to address the issues of the inaccurate input data characteristics when deciding on where the robot should move next. Therefore, effective methods that can consider this decision-making issue are needed.
3. Presently, common candidate assessment strategies are based on the cost–benefit approach that considers mainly the technical environment exploration parameters, including the distance from the robot to the candidate, the time needed to reach the candidate, the ability to transmit information after reaching the candidate, and the estimated amount of new

information that could be discovered. However, these strategies fail to consider the safety, social and other factors of the autonomous SAR missions. Also, as international organisations require to ensure the transparency and flexibility of autonomous systems, novel autonomous navigation and environment exploration methods that would consider these requirements are needed.

4. Additionally, commonly applied candidate assessment strategies are modelled on the notion that the rules governing the decision-making process do not change throughout the environment exploration. Therefore, an adaptive autonomous navigation strategy capable of switching between the rules that govern the candidate assessment process could show potential in SAR missions.

Based on the performed literature survey, the following tasks were formulated to achieve the aims of the study:

1. To develop novel candidate assessment strategies considering common limitations of the candidate-assessment-based autonomous navigation and environment exploration strategies.
2. To develop an adaptive autonomous navigation strategy that allows switching between the rules governing the candidate assessment process.
3. To develop novel extensions of the multi-criteria decision-making methods, able to consider the inaccurate input data characteristics.
4. To evaluate the performance of the developed multi-criteria decision-making method extensions.
5. To investigate the performance of the proposed autonomous navigation strategies in simulated search and rescue missions.

2

Neutrosophic Multi-Criteria Decision-Making Methods for Autonomous Robot Navigation

This chapter discusses the environment exploration strategy based on multi-criteria decision-making (MCDM). It defines the candidate assessment problem and introduces novel extensions for the state-of-the-art WASPAS MCDM methods, i.e., the WASPAS-IVNS method modelled under the interval-valued neutrosophic set environment, and the WASPAS-mGqNS method modelled under the m-generalised q-neutrosophic set environment. Also, the chapter introduces the approach for switching between the strategies governing the candidate assessment process and, finally, offers conclusions.

Parts of this chapter were published in articles (Bausys, Cavallaro & Semenas, 2019; Semenas & Bausys, 2020; Semenas & Bausys, 2021; Semenas, Bausys, & Zavadskas, 2021; Semenas & Bausys, 2022).

2.1. Autonomous Robot Navigation using Multi-Criteria Decision-Making Approach

As motivated in the previous section of this thesis, the proposed autonomous navigation and environment exploration strategy is based on the robot's ability to make an effective decision on where to move next. This decision is made by applying an online approach to evaluate the discovered environment information, robot state and the candidate's performance according to the considered optimisation priorities. Thus, the preliminaries of the proposed environment exploration strategy are presented, and the approach to the candidate assessment is discussed from the theoretical perspective. As the considered environment exploration approach extends the frontier-assessment-based strategy (Yamauchi, 1997), the candidates the robot can reach can also be referred to as frontiers.

Considering the developed environment exploration strategy, the decision on where to move next is made by measuring the utility U of each candidate frontier $p_f(x, y)$. This value is computed by applying a group of unique, problem-related criteria $C = \{c_1, c_2, \dots, c_n\}$ and their relative weights $W = \{w_1, w_2, \dots, w_n\}$, corresponding to the optimisation priorities given to the autonomous search and rescue robot. In other words, the optimisation priorities can be defined by a collection of competing functional, economic, social, ethical, environmental or other requirements, which are either maximised or minimised. By measuring the utility of each candidate, the robot can then choose the next short-term goal.

A group of candidate frontiers $P_f = \{p_f(x, y)_1, p_f(x, y)_2, \dots, p_f(x, y)_m\}$ is determined in the proposed approach whenever new environment information is added to the partial environment representation model. Thus, each time the robot discovers new information (e.g., a new frontier, a survivor or a dangerous object), criteria values are recalculated, and the utilities of candidate frontiers are re-assessed. As the map is updated once every second by attaching newly discovered information, new frontiers may be discovered at this frequency. Therefore, in this thesis, frontier detection and utility assessment processes are performed at persistent time intervals. This approach helps to reduce the number of computations during runtime, to prevent indecisive robot behaviour, and also enables the robot to change its movement direction if a frontier with higher utility is detected while moving to the previously selected candidate.

Throughout the frontier assessment process, a vector of optimisation-related criteria values $c \in C$ is mapped to the candidate frontier $p_f(x, y)_i$ as $p_f = \{c_1(p_f(x, y)_i), c_2(p_f(x, y)_i), \dots, c_n(p_f(x, y)_i)\}$. Then, by applying multi-criteria decision-making methods, utility $U(p_f(x, y)_i)$ of a candidate frontier $p_f(x, y)_i \in P_f$ is assessed, and the one with the highest utility $U(p_f(x, y)^*)$ is selected as a new goal for the autonomous robot to reach.

2.2. Criteria Weight Assessment by SWARA Method

In general, criteria weights indicate the direction of optimum prioritisation and showcase how the importance of one criterion is compared to another. Thus, the deliberate criteria weight assessment is essential to efficiently solve the given decision-making problem (in the context of this thesis, deciding where the robot should move next). As different stakeholders can prioritise different criteria (Harbers et al., 2017) in these scenarios, the Stepwise Weights Assessment Ratio Analysis (SWARA) method can be applied to normalise tensions between the stakeholders and determine criteria weights. This process can be defined by the six following steps (Keršulienė et al., 2010):

1. The list of objective-related criteria is constructed.
2. The criteria are ranked by their significance in descending order.
3. The comparative importance of the average value s_j is measured.
4. The characteristics of the comparative importance are determined by $k_j = s_j + 1$.
5. Then, intermediate weights are determined by $q_j = \frac{q_{j-1}}{k_j}$.
6. The final weights are determined by $w_i = \frac{q_i}{\sum_{j=1}^{n} q_j}$.

2.3. Proposed WASPAS Method Extensions for Candidate Assessment Task

The original Weighted Aggregated Sum Product Assessment method, namely WASPAS, was first proposed by Zavadskas et al. (2012). This state-of-the-art multi-criterion decision-making method aggregates the Weighted Product Model (WPM) and the Weighted Sum Model (WSM) to construct a universal decision-making strategy. However, as researchers pushed to develop new methods for the assessment of incomplete or uncertain input data characteristics, the original WASPAS method was extended several times by applying fuzzy sets, as the fuzzy set theory (Zadeh, 1965) is considered an efficient method to model input data characteristics and found many applications in practical and theoretical studies (Kalibatiene & Miliauskaite, 2021). In fuzzy sets, a single input data object x is modelled as a value $\mu(x) \in [0,1]$ that represents its membership degree in the object universe X (Wang et al., 2005). However, the classical fuzzy sets are limited when the decision-making problems with the inaccurate input data characteristics are considered, as the input values can be modelled not only by membership and non-membership degrees.

The intuitionistic fuzzy set was introduced by Atanassov (1986) as the generalised fuzzy set incorporating the hesitation degree. This approach allows considering situations in which the sum of membership and non-membership degrees are unequal to one. Methods that are based on the fuzzy set theory were further extended when Pythagorean fuzzy sets were introduced by Yager (2013) to address the issue of imprecise membership degrees in the decision-making problems, and the q-Rung orthopair fuzzy sets (Yager, 2017) were introduced to increase the space of the acceptable values in membership degrees of the input data characteristics.

The neutrosophic sets and the neutrosophic set logic were first proposed by Smarandache (1999) as the generalisation of fuzzy and intuitionistic fuzzy sets. In neutrosophic set logic, the input data characteristics are defined by the truly independent truth membership degree, T, indeterminacy membership degree, I, and falsity membership degree, F. The inclusion of the indeterminacy membership degree and the ability to model these memberships independently differentiates the neutrosophic set from other fuzzy sets. Due to these advantages, neutrosophic sets and neutrosophic set logic were successfully applied in multiple real world decision-making problems, where the ambiguity and inaccuracy of the input data characteristics are considered (e.g., Zavadskas et al., 2015; Zavadskas et al., 2020b; etc.). However, as argued by Smarandache (2019), the neutrosophic set also generalises the intuitionistic fuzzy set, spherical and n-hyperspherical fuzzy sets, the Pythagorean fuzzy set, and the q-rung orthopair fuzzy set. Therefore, it is possible to unite these fuzzy sets under the m-generalised q-neutrosophic set (mGqNS) and implement all the benefits of the generalised fuzzy sets. This generalisation could then be applied to model flexible strategies for real-world decision-making problems (Saha et al., 2020; Zavadskas et al., 2020a).

As neutrosophic sets (Wang et al., 2005) allow to deal with incomplete or uncertain input data characteristics in a more flexible way, and the membership degrees can be modelled independently, two novel state-of-the-art WASPAS method extensions that include these modern neutrosophic sets are proposed for the considered candidate assessment task. The WASPAS method is chosen as a base for the proposed improvement due to the stability and wide application of this MCDM method in multiple real-world decision-making tasks (e.g., Zavadskas, Kalibatas & Kalibatiene, 2016; Zavadskas, Đalić & Stević, 2021). Further sections of this thesis discuss the preliminaries of the proposed WASPAS extensions by the interval-valued neutrosophic set (IVNS) (Zhang et al., 2014) and the m-generalised q-neutrosophic sets (mGqNS). Also, the state-of-the-art WASPAS method, modelled under the single-valued neutrosophic set (SVNS), is presented.

2.4. Single-Valued Neutrosophic WASPAS Method

In 2014, the WASPAS extension modelled under the interval-valued intuitionistic fuzzy sets was developed by Zavadskas et al. (2014) and referred to as WASPAS-IVIF. Zavadskas et al. (2015b) also proposed an innovative approach to consider the uncertainties in the input data characteristics and improve the accuracy of a decision-making process by introducing the Weighted Aggregated Sum Product Assessment method with grey attribute scores, namely WASPAS-G. In the same year, Turskis et al. *(*2015) proposed a fuzzy multi-attribute performance measurement method allowing to naturally model the qualitative parameters under uncertainty. Lastly, a novel extension to the WASPAS method, modelled under the single-valued neutrosophic environment (WASPAS-SVNS), was proposed by Zavadskas et al. (2015a) to provide the tools for modelling the uncertain input data characteristics.

2.4.1. Preliminaries of the WASPAS-SVNS Method

First, the definitions of neutrosophic set logic applied by the WASPAS-SVNS method are presented:

Definition 1.1. The neutrosophic set NS is defined by the three independent membership functions: truth membership function, T, indeterminacy function, I, and the falsity function, F.

Definition 1.2. Let the set of objects in the decision-making problem be denoted by X, where $x \in X$ is a single object. Specifically, X defines a set of criteria applied for candidate frontier assessment and x is a measure of a single criterion. Thus, the single-valued neutrosophic set (SVNS) is defined as:

$$SVNS = \{\langle T_{sv}(x), I_{sv}(x), F_{sv}(x)\rangle : x \in X\}, \tag{2.1}$$

where the three membership functions follow the conditions of:

$$0 \leq T_{sv}(x), I_{sv}(x), F_{sv}(x) \leq 1; \tag{2.2}$$

$$0 \leq T_{sv}(x) + I_{sv}(x) + F_{sv}(x) \leq 3. \tag{2.3}$$

Definition 1.3. The single-valued neutrosophic number (SVNN) is defined as follows:

$$N_{sv} = \langle t_{sv}, i_{sv}, f_{sv}\rangle. \tag{2.4}$$

Definition 1.4. In this thesis, the neutrosophication of sensor input data is achieved by applying the methodology defined by Zavadskas et al. (2015a).

Definition 1.5. If $N_{sv_1} = \langle t_{sv_1}, i_{sv_1}, f_{sv_1} \rangle$ and $N_{sv_2} = \langle t_{sv_2}, i_{sv_2}, f_{sv_2} \rangle$ are two single-valued neutrosophic numbers, then the summation operation between them can be defined by:

$$N_{sv_1} \oplus N_{sv_2} = \langle t_{sv_1} + t_{sv_2} - t_{sv_1} t_{sv_2}, i_{sv_1} i_{sv_2}, f_{sv_1} f_{sv_2} \rangle. \quad (2.5)$$

Definition 1.6. If $N_{sv_1} = \langle t_{sv_1}, i_{sv_1}, f_{sv_1} \rangle$ and $N_{sv_2} = \langle t_{sv_2}, i_{sv_2}, f_{sv_2} \rangle$ are two single-valued neutrosophic numbers, then the multiplication operation between them can be defined by:

$$N_{sv_1} \otimes N_{sv_2} = \langle t_{sv_1} t_{sv_2}, i_{sv_1} + i_{sv_1} - i_{sv_1} i_{sv_2}, f_{sv_1} + f_{sv_2} - f_{sv_1} f_{sv_2} \rangle. \quad (2.6)$$

Table 2.1. Neutrosophication grades applied in this thesis (Zavadskas et al., 2015a)

Crisp normalised terms	SVNNs
Extremely good (EG) / 1.0	(1.00, 0.00, 0.00)
Very very good (VVG) / 0.9	(0.90, 0.10, 0.10)
Very good (VG) / 0.8	(0.80, 0.15, 0.20)
Good (G) / 0.7	(0.70, 0.25, 0.30)
Medium good (MG) / 0.6	(0.60, 0.35, 0.40)
Medium (M) / 0.5	(0.50, 0.50, 0.50)
Medium bad (MB) / 0.4	(0.40, 0.65, 0.60)
Bad (B) / 0.3	(0.30, 0.75, 0.70)
Very bad (VB) / 0.2	(0.20, 0.85, 0.80)
Very very bad (VVB) / 0.1	(0.10, 0.90, 0.90)
Extremely bad (EB) / 0.0	(0.00, 1.00, 1.00)

Definition 1.7. If $N_{sv_1} = \langle t_{sv_1}, i_{sv_1}, f_{sv_1} \rangle$ is a single-valued neutrosophic number and λ is a real number that follows the condition of $\lambda > 0$, then the multiplication operation between them can be defined by:

$$N_{sv} \cdot \lambda = \langle 1 - (1 - t_{sv})^{\lambda}, i_{sv}^{\lambda}, f_{sv}^{\lambda} \rangle. \quad (2.7)$$

Definition 1.8. If $N_{sv_1} = \langle t_{sv_1}, i_{sv_1}, f_{sv_1} \rangle$ is a single-valued neutrosophic number and λ is a real number which follows the condition of $\lambda > 0$, then the power operation between them can be defined by:

$$N_{sv}{}^{\lambda} = \langle t_{sv}^{\lambda}, 1 - (1 - i_{sv})^{\lambda}, 1 - (1 - f_{sv})^{\lambda} \rangle. \quad (2.8)$$

Definition 1.9. If $N_{sv_1} = \langle t_{sv_1}, i_{sv_1}, f_{sv_1} \rangle$ is a single-valued neutrosophic number, then the complementary neutrosophic number component can be defined as follows:

$$N_{sv}{}^{c} = \langle f_{sv}, 1 - i_{sv}, t_{sv} \rangle. \tag{2.9}$$

Definition 1.10. The score value *S(N)* is determined by:

$$S(N_{sv}) = \frac{3 + t_{sv} - 2i_{sv} - f_{sv}}{4}. \tag{2.10}$$

2.4.2. Formulation of the WASPAS-SVNS Method

Following the general form of the original WASPAS method, the WASPAS-SVNS method can be defined by the following seven steps (Zavadskas et al., 2015a):

Step 1. The decision matrix D_{sv} is constructed from a set of available candidate frontiers in accordance with the criteria set by the high-level objective. Members of this matrix can be denoted as $[d_{sv}]_{ij}$, where $i = 1, 2, \ldots, n$ are indexes of the candidate frontier and $j = 1, 2, \ldots, m$ are the indexes of the criteria.

Step 2. To compare different input data objects, one must first normalise the members of the decision matrix by applying the vector normalisation approach as follows:

$$[d_{sv}]_{ij} = \frac{[d_{sv}]_{ij}}{\sqrt{\sum_{l=1}^{m}([d_{sv}]_{lj})^2}}. \tag{2.11}$$

Step 3. The members of the decision matrix are converted to the neutrosophic form by applying the conversion table presented in definition 1.4. After this step, matrix members obtain the general SVNN form of $[\bar{d}_{sv}]_{ij} = \langle t_{sv_{ij}}, i_{sv_{ij}}, f_{sv_{ij}} \rangle$ as presented in definition 1.3.

Step 4. Values of the first objective of the m-generalised q-neutrosophic WASPAS method are determined for each candidate frontier by applying the following equation:

$$Q_i^{(1)} = \left(\sum_{j=1}^{O_{max}} [\bar{d}_{sv}]_{ij} \cdot w_j\right) + \left(\sum_{j=1}^{O_{min}} [\bar{d}_{sv}]_{ij} \cdot w_j\right)^{c}. \tag{2.12}$$

Here, O_{max} and O_{min} represent the set of maximised and minimised criteria, respectively. And c represents the complementary set member.

Step 5. Values of the second objective of the m-generalised q-neutrosophic WASPAS method are determined for each candidate frontier by applying the following equation:

$$Q_i^{(2)} = \left(\prod_{j=1}^{Omax}([\bar{d}_{sv}]_{ij})^{w_j}\right) \cdot \left(\prod_{j=1}^{Omin}([\bar{d}_{sv}]_{ij})^{w_j}\right)^c. \quad (2.13)$$

Here, the equation definitions correspond to the ones presented in Step 4.

Step 6. The joint generalised value that incorporates the results obtained from steps 4 and 5 is determined by the following equation:

$$Q_i = 0.5Q_i^{(1)} + 0.5Q_i^{(2)}. \quad (2.14)$$

Step 7. The final rankings of candidate frontiers are assessed by applying the score function presented in definition 1.10. The candidate frontier with the highest utility is then considered as the next location the robot should visit.

Next, the developed extensions of the state-of-the-art WASPAS MCDM method are discussed.

2.5. Interval-Valued Neutrosophic WASPAS Method

One of the major issues in the decision-making process by autonomous robots is the incomplete and imprecise sensor data (e.g., measurement errors introduced by the sensors or errors in the environment representation model) used to determine the utility of candidate frontiers. The proposed WASPAS extension modelled under the interval-valued neutrosophic set environment, namely WASPAS-IVNS, enables the robot to consider the inaccurate input data characteristics. By considering this issue, the proposed WASPAS extension is expected to provide additional reliability when comparing similar candidates.

2.5.1. Preliminaries of the WASPAS-IVNS Method

The definitions of the applied interval-valued neutrosophic logic (Zhang et al., 2014), applied to model the WASPAS-IVNS method, are presented:

Definition 2.1. Following the properties of the single-valued neutrosophic set, the interval-valued neutrosophic set $IVNS$ is defined as:

$$IVNS = \{\langle T_{iv}(x), I_{iv}(x), F_{iv}(x)\rangle : x \in X\}, \quad (2.15)$$

where the three membership functions follow the conditions of:

$$T_{iv}(x) = [T_{iv}(x)^-, T_{iv}(x)^+] \subseteq [0,1]; \tag{2.16}$$

$$I_{iv}(x) = [I_{iv}(x)^-, I_{iv}(x)^+] \subseteq [0,1]; \tag{2.17}$$

$$F_{iv}(x) = [F_{iv}(x)^-, F_{iv}(x)^+] \subseteq [0,1]; \tag{2.18}$$

$$0 \leq T_{iv}(x)^+ + I_{iv}(x)^+ + F_{iv}(x)^+ \leq 3. \tag{2.19}$$

Definition 2.2. The interval-valued neutrosophic number (IVNN) is defined as follows:

$$N_{iv} = \langle [t_{iv}^-, t_{iv}^+], [i_{iv}^-, i_{iv}^+], [f_{iv}^-, f_{iv}^+] \rangle. \tag{2.20}$$

Definition 2.3. If $N_{iv_1} = \langle [t_{iv_1}^-, t_{iv_1}^+], [i_{iv_1}^-, i_{iv_1}^+], [f_{iv_1}^-, f_{iv_1}^+] \rangle$ and $N_{iv_2} = \langle [t_{iv_2}^-, t_{iv_2}^+], [i_{iv_2}^-, i_{iv_2}^+], [f_{iv_2}^-, f_{iv_2}^+] \rangle$ are two interval-valued neutrosophic numbers, then the summation operation between them can be defined by:

$$N_{iv_1} \oplus N_{iv_2} = \left\langle \begin{matrix} [t_{iv_1}^- + t_{iv_2}^- - t_{iv_1}^- t_{iv_2}^-, t_{iv_1}^+ + t_{iv_2}^+ - t_{iv_1}^+ t_{iv_2}^+], \\ [i_{iv_1}^- i_{iv_2}^-, i_{iv_1}^+ i_{iv_2}^+], [f_{iv_1}^- f_{iv_2}^-, f_{iv_1}^+ f_{iv_2}^+] \end{matrix} \right\rangle. \tag{2.21}$$

Definition 2.4. If $N_{iv_1} = \langle [t_{iv_1}^-, t_{iv_1}^+], [i_{iv_1}^-, i_{iv_1}^+], [f_{iv_1}^-, f_{iv_1}^+] \rangle$ and $N_{iv_2} = \langle [t_{iv_2}^-, t_{iv_2}^+], [i_{iv_2}^-, i_{iv_2}^+], [f_{iv_2}^-, f_{iv_2}^+] \rangle$ are two interval-valued neutrosophic numbers, then the summation operation between them can be defined by:

$$N_{iv_1} \otimes N_{iv_2} = \left\langle \begin{matrix} [t_{iv_1}^- t_{iv_2}^-, t_{iv_1}^+ t_{iv_2}^+], \\ [i_{iv_1}^- + i_{iv_2}^- - i_{iv_1}^- i_{iv_2}^-, i_{iv_1}^+ + i_{iv_2}^+ - i_{iv_1}^+ i_{iv_2}^+], \\ [f_{iv_1}^- + f_{iv_2}^- - f_{iv_1}^- f_{iv_2}^-, f_{iv_1}^+ + f_{iv_2}^+ - f_{iv_1}^+ f_{iv_2}^+] \end{matrix} \right\rangle. \tag{2.22}$$

Definition 2.5. If $N_{iv} = \langle [t_{iv}^-, t_{iv}^+], [i_{iv}^-, i_{iv}^+], [f_{iv}^-, f_{iv}^+] \rangle$ is an interval-valued neutrosophic number and λ is a real number that follows the condition of $\lambda > 0$, then the multiplication operation between them can be defined by:

$$N_{iv} \cdot \lambda = \left\langle \begin{matrix} [1 - (1 - t_{iv}^-)^\lambda, 1 - (1 - t_{iv}^+)^\lambda], \\ [(i_{iv}^-)^\lambda, (i_{iv}^+)^\lambda], [(f_{iv}^-)^\lambda, (f_{iv}^+)^\lambda] \end{matrix} \right\rangle. \tag{2.23}$$

Definition 2.6. If $N_{iv} = \langle [t_{iv}^-, t_{iv}^+], [i_{iv}^-, i_{iv}^+], [f_{iv}^-, f_{iv}^+] \rangle$ is the interval-valued neutrosophic number and λ is a real number which follows the condition of $\lambda > 0$, then the power operation between them can be defined by:

$${N_{iv}}^\lambda = \left\langle \begin{matrix} [(t_{iv}^-)^\lambda, (t_{iv}^+)^\lambda], [1 - (1 - i_{iv}^-)^\lambda, 1 - (1 - i_{iv}^+)^\lambda], \\ [1 - (1 - f_{iv}^-)^\lambda, 1 - (1 - f_{iv}^+)^\lambda] \end{matrix} \right\rangle. \tag{2.24}$$

Definition 2.7. If $N_{iv} = \langle [t_{iv}^-, t_{iv}^+], [i_{iv}^-, i_{iv}^+], [f_{iv}^-, f_{iv}^+] \rangle$ is an interval-valued neutrosophic number, then the complementary neutrosophic number component can be defined by:

$$N_{iv}{}^c = \langle [f_{iv}^-, f_{iv}^+], [1 - i_{iv}^+, 1 - i_{iv}^-], [t_{iv}^-, t_{iv}^+] \rangle\,. \tag{2.25}$$

Definition 2.8. The interval-valued neutrosophic numbers are compared by applying comparison functions: the score function denoted as $S(Q)$, the accuracy function denoted by $a(Q)$, and the certainty function denoted as $c(Q)$. These functions are defined as follows:

$$S(Q) = [t_{iv}^- + 1 - i_{iv}^+ + 1 - f_{iv}^+, t_{iv}^+ + 1 - i_{iv}^- + 1 - f_{iv}^-]; \tag{2.26}$$

$$a(Q) = [min\{t_{iv}^- - f_{iv}^-, t_{iv}^+ - f_{iv}^+\}, max\{t_{iv}^- - f_{iv}^-, t_{iv}^+ - f_{iv}^+\}]; \tag{2.27}$$

$$c(Q) = [t_{iv}^-, t_{iv}^+]. \tag{2.28}$$

Then, the comparison between the two IVNNs by score function can be completed by applying the following rules:

- If $p(S(Q_1) \geq S(Q_2)) > 0.5$, then $Q_1 \succ Q_2$, or Q_1 is superior to Q_2.
- If $p(S(Q_1) \geq S(Q_2)) = 0.5$ and $p(a(Q_1) \geq a(Q_2)) > 0.5$, then $Q_1 \succ Q_2$, or Q_1 is superior to Q_2.
- If $p(S(Q_1) \geq S(Q_2)) = 0.5$ and $p(a(Q_1) \geq a(Q_2)) = 0.5$, and $p(c(Q_1) \geq c(Q_2)) > 0.5$, then $Q_1 \succ Q_2$, or Q_1 is superior to Q_2.
- If $p(S(Q_1) \geq S(Q_2)) = 0.5$ and $p(a(Q_1) \geq a(Q_2)) = 0.5$, and $p(c(Q_1) \geq c(Q_2)) = 0.5$, then $Q_1 \sim Q_2$, or Q_1 is equal to Q_2.

Here, p represents the degree of possibility, determined by the following equation:

$$p\big(S(Q_1) \geq S(Q_2)\big) = \\ max\left\{1 - max\left(\frac{S(Q_2)^+ - S(Q_1)^-}{(S(Q_1)^+ - S(Q_1)^-) + (S(Q_2)^+ - S(Q_2)^-)}, 0\right), 0\right\}. \tag{2.29}$$

The comparison by accuracy and certainty functions are completed by applying an identical approach.

2.5.2. Formulation of the WASPAS-IVNS Method

Following the general form of the original WASPAS method, the proposed WASPAS-IVNS method is defined by the previously introduced seven steps:

Step 1. The decision matrix D_{iv} is constructed from a set of available candidate frontiers in accordance with the criteria set by considering the strategy optimisation priorities. Members of this matrix can be denoted as $[d_{iv}]_{ij}$, where $i = 1, 2, \dots, n$ are indexes of the candidate frontier and $j = 1, 2, \dots, m$ are the indexes of the criteria.

Step 2. The members of the decision matrix are normalised by applying the following normalisation approach:

$$[d_{iv}]_{ij}^{-} = \frac{[d_{iv}]_{ij}^{-}}{\max[d_{iv}]_{ij}\sqrt{m}}, [d_{iv}]_{ij}^{+} = \frac{[d_{iv}]_{ij}^{+}}{\max[d_{iv}]_{ij}\sqrt{m}}. \quad (2.30)$$

Step 3. The members of the decision matrix are converted to the neutrosophic form by applying the conversion table presented in definition 1.4. After this step, matrix members obtain the general IVNS form of $\left[\bar{d}_{iv}\right]_{ij} = \langle [t_{iv}^{-}, t_{iv}^{+}], [i_{iv}^{-}, i_{iv}^{+}], [f_{iv}^{-}, f_{iv}^{+}] \rangle$ as presented in definition 2.2.

Step 4. Values of the first objective of the m-generalised q-neutrosophic WASPAS method are determined for each candidate frontier by applying the following equation:

$$Q_i^{(1)} = \left(\sum_{j=1}^{Omax} \left[\bar{d}_{iv}\right]_{ij} \cdot w_j\right) + \left(\sum_{j=1}^{Omin} \left[\bar{d}_{iv}\right]_{ij} \cdot w_j\right)^{c}. \quad (2.31)$$

Step 5. Values of the second objective of the m-generalised q-neutrosophic WASPAS method are determined for each candidate frontier by applying the following equation:

$$Q_i^{(2)} = \left(\prod_{j=1}^{Omax} (\left[\bar{d}_{iv}\right]_{ij})^{w_j}\right) \cdot \left(\prod_{j=1}^{Omin} (\left[\bar{d}_{iv}\right]_{ij})^{w_j}\right)^{c}. \quad (2.32)$$

Step 6. The joint generalised value that incorporates the results obtained from steps 4 and 5 is determined by the following equation:

$$Q_i = 0.5Q_i^{(1)} + 0.5Q_i^{(2)}. \quad (2.33)$$

Step 7. The final rankings of candidate frontiers are assessed by applying the IVNN comparison methodology presented in definition 2.8. The candidate frontier with the highest utility is then considered as the next observation location.

2.6. m-Generalised q-Neutrosophic WASPAS Method

Next, the discussion focuses on preliminaries for m-generalised q-neutrosophic sets that are relevant to the proposed WASPAS-mGqNS method. The m-generalised q-neutrosophic set environment enables the robot operator to flexibly apply a number of different fuzzy sets for the assessment of candidate frontiers. This adjustment is made by defining m and q parameters. For example, the m value of 3 and q value of 1 define a classic fuzzy set (when I membership is disregarded), but m value of 1 and q value of 1 define the standard neutrosophic set.

2.6.1. Preliminaries of the WASPAS-mGqNS Method

Definition 3.1. Following the properties of the neutrosophic sets, the m-generalised q-neutrosophic set $mGqNS$ is defined as:

$$mGqNS = \{< T_{mq}(x), I_{mq}(x), F_{mq}(x) >: x \in X\}, \tag{2.34}$$

where the three membership functions follow the conditions:

$$T_{mq}(x), I_{mq}(x), F_{mq}(x): X \to [0, r], (0 \leq r \leq 1); \tag{2.35}$$

$$0 \leq (T_{mq}(x))^q + (I_{mq}(x))^q + (F_{mq}(x))^q \leq \frac{3}{m}; \tag{2.36}$$

$$m = 1 \ or \ 3; \ q \geq 1. \tag{2.37}$$

Definition 3.2. The m-generalised q-neutrosophic number (mGqNN) is defined as:

$$N_{mq} = \langle t_{mq}, i_{mq}, f_{mq} \rangle. \tag{2.38}$$

Definition 3.3. If $N_{mq_1} = \langle t_{mq_1}, i_{mq_1}, f_{mq_1} \rangle$ and $N_{mq_2} = \langle t_{mq_2}, i_{mq_2}, f_{mq_2} \rangle$ are two single-valued neutrosophic numbers, then the summation operation between them can be defined by:

$$N_{mq_1} \oplus N_{mq_2} = \left\langle \begin{matrix} \left(1 - \left(1 - t_{mq_2}^q\right)\left(1 - t_{mq_2}^q\right)\right)^{\frac{1}{q}}, \\ i_{mq_1} i_{mq_2}, f_{mq_1} f_{mq_2} \end{matrix} \right\rangle. \tag{2.39}$$

Definition 3.4. If $N_{mq_1} = \langle t_{mq_1}, i_{mq_1}, f_{mq_1} \rangle$ and $N_{mq_2} = \langle t_{mq_2}, i_{mq_2}, f_{mq_2} \rangle$ are two single-valued neutrosophic numbers, then the multiplication operation between them can be defined by:

$$N_{mq_1} \otimes N_{mq_2} = \left\langle \begin{matrix} t_{mq_1} t_{mq_2}, \left(1 - \left(1 - i_{mq_2}^q\right)\left(1 - i_{mq_2}^q\right)\right)^{\frac{1}{q}}, \\ \left(1 - \left(1 - f_{mq_2}^q\right)\left(1 - f_{mq_2}^q\right)\right)^{\frac{1}{q}} \end{matrix} \right\rangle. \tag{2.40}$$

Definition 3.5. If $N_{mq} = \langle t_{mq}, i_{mq}, f_{mq} \rangle$ is an m-generalised q-neutrosophic number and λ is a real number that follows the condition of $\lambda > 0$, then the multiplication operation between them can be defined by:

$$N_{mq} \cdot \lambda = \langle \left(1-\left(1-t_{mq}^{q}\right)^{\lambda}\right)^{\frac{1}{q}}, i_{mq}^{\lambda}, f_{mq}^{\lambda} \rangle \,. \tag{2.41}$$

Definition 3.6. If $N_{mq} = \langle t_{mq}, i_{mq}, f_{mq} \rangle$ is a single-valued neutrosophic number and λ is a real number that follows the condition of $\lambda > 0$, then the power operation between them can be defined by:

$$N_{mq}{}^{\lambda} = \langle t_{mq}^{\lambda}, \left(1-\left(1-i_{mq}\right)^{\lambda}\right)^{\frac{1}{q}}, \left(1-\left(1-f_{mq}\right)^{\lambda}\right)^{\frac{1}{q}} \rangle. \tag{2.42}$$

Definition 3.7. If $N_{mq} = \langle t_{mq}, i_{mq}, f_{mq} \rangle$ is a single-valued neutrosophic number, the complementary neutrosophic number component can be defined as:

$$N_{mq}{}^{c} = \langle f_{mq}, 1-i_{mq}, t_{mq} \rangle. \tag{2.43}$$

Definition 3.8. The score value $S(N_{mq})$ for mGqNS is determined by:

$$S\left(N_{mq}\right) = \frac{3+3t_{mq}^{q}-2i_{mq}^{q}-f_{mq}^{q}}{6}. \tag{2.44}$$

If $N_{mq_1} = \langle t_{mq_1}, i_{mq_1}, f_{mq_1} \rangle$ and $N_{mq_2} = \langle t_{mq_2}, i_{mq_2}, f_{mq_2} \rangle$ are two m-generalised q-neutrosophic numbers, the ranking of them is performed by:

$$\text{If } S(N_{mq_1}) > S(N_{mq_2}), \text{ then } N_{mq_1} > N_{mq_2}; \tag{2.45}$$

$$\text{If } S(N_{mq_1}) = S(N_{mq_2}), \text{ then } N_{mq_1} = N_{mq_2}. \tag{2.46}$$

2.6.2. Formulation of the WASPAS-mGqNS Method

Following the general form of the original WASPAS method, the proposed WASPAS-mGqNS method is defined by the previously introduced seven steps:

Step 1. The decision matrix D_{mq} is constructed from a set of available candidate frontiers in accordance with the criteria set by the high-level objective. Members of this matrix can be denoted as $\left[d_{mq}\right]_{ij}$, where $i = 1, 2, \dots, n$ are indexes of the candidate frontier and $j = 1, 2, \dots, m$ are the indexes of the criteria.

Step 2. The members of the decision matrix are normalised by applying the vector normalisation approach:

$$\left[d_{mq}\right]_{ij} = \frac{\left[d_{mq}\right]_{ij}}{\sqrt{\sum_{l=1}^{m}\left(\left[d_{mq}\right]_{lj}\right)^{2}}}. \tag{2.47}$$

Step 3. The members of the decision matrix are converted to the neutrosophic form by applying the conversion table presented in definition 1.4. After this step, matrix members obtain the general mGqNN form of $\left[\bar{d}_{mq}\right]_{ij} = \langle t_{mq_{ij}}, i_{mq_{ij}}, f_{mq_{ij}} \rangle$ as presented in definition 3.2.

Step 4. Values of the first objective of the m-generalised q-neutrosophic WASPAS method are determined for each candidate frontier by applying the following equation:

$$Q_i^{(1)} = \left(\sum_{j=1}^{Omax}\left[\bar{d}_{mq}\right]_{ij} \cdot w_j\right) + \left(\sum_{j=1}^{Omin}\left[\bar{d}_{mq}\right]_{ij} \cdot w_j\right)^c. \tag{2.48}$$

Step 5. Values of the second objective of the m-generalised q-neutrosophic WASPAS method are determined for each candidate frontier by applying the following equation:

$$Q_i^{(2)} = \left(\prod_{j=1}^{Omax}(\left[\bar{d}_{mq}\right]_{ij})^{w_j}\right) \cdot \left(\prod_{j=1}^{Omin}(\left[\bar{d}_{mq}\right]_{ij})^{w_j}\right)^c. \tag{2.49}$$

Step 6. The joint generalised value that incorporates the results obtained from steps 4 and 5 is determined by the following equation:

$$Q_i = 0.5Q_i^{(1)} + 0.5Q_i^{(2)}. \tag{2.50}$$

Step 7. The final rankings of candidate frontiers are assessed by applying the score function presented in definition 3.8. The candidate frontier with the highest utility is then considered the next observation location.

2.7. Adaptive Environment Exploration by Fuzzy Logic Controller

The proposed WASPAS-IVNS and WASPAS-mGqNS multi-criteria decision-making methods define only one part of the proposed environment exploration strategy. Differently weighted criteria groups can essentially define different optimisation priorities and, with this, different candidate assessment strategies (e.g., enable more altruistic or egoistic robot behaviour in SAR missions). Thus, a set of strategies that govern the proposed adaptive autonomous environment exploration approach can be denoted as $ST = \{St_1(C_1, W_1),\ St_2(C_2, W_2), \dots,\ St_k(C_k, W_k)\}$. Here, $St_i(C_i, W_i)$ defines a single candidate frontier assessment strategy and k is the number of strategies in the ST set. The decision on which strategy St to apply from the ST set is made by applying the fuzzy logic controller. The selected ST strategy is then applied by the designated decision-making method to assess the utility of currently available candidate frontiers. The proposed adaptive autonomous navigation and environment exploration strategy is schematically presented in Fig. 2.1.

It is also worth noting that the proposed approach differs from the similar approaches in the sense that a fuzzy logic controller does not directly control robot movements (e.g., Abiyev et al., 2016; Omrane et al., 2016; Chen et al., 2017)), but rather activates the set of rules (or in other words, strategies) that govern autonomous navigation process in SAR missions. Also, differently from the common approach of applying the same strategy at every decision-making iteration (e.g., Yamauchi, 1997; Taillandier & Stinckwich, 2011; etc.), the strategies are switched depending on the current state of the robot and the exploration space).

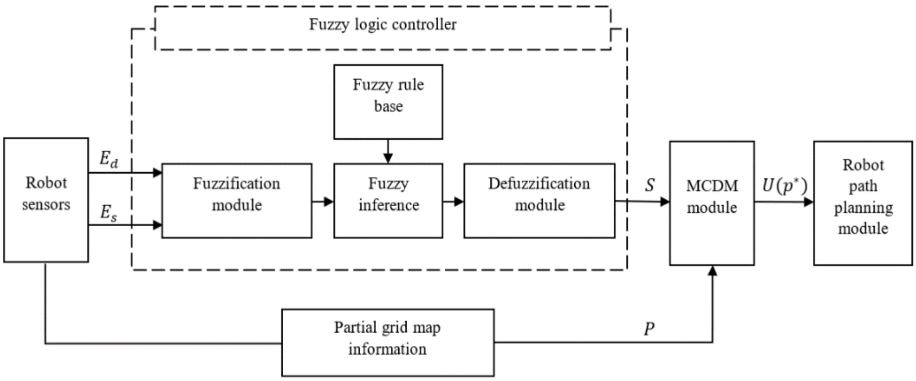


Fig. 2.1. Proposed adaptive environment exploration strategy. Here, $E(s)$ represents the distance from the robot to the hypothesised survivor, $E(d)$ represents the distance from the robot to the dangerous object, S represents the selected candidate assessment strategy, P is the list of available candidates and $U(p^*)$ is the utility of a candidate (Semenas & Bausys, 2021)

By applying the proposed environment exploration strategy, the autonomous robot starts the search and rescue mission at the set coordinate location $p_r(x{:}\,0, y{:}\,0)$. This location is a reference point around which the environment representation model is built. First, the input data from robot sensors is collected, as portrayed in Fig. 2.1. The obtained environment information is then added to the constructed partial map, and the robot estimates its position in relation to the physical obstacles and structures by applying the ROS provided gmapping package for laser-based self-localisation (ROS Gmapping, 2020). Next, the list of candidate frontiers is computed by detecting the connected chains of free grid-map cells that are adjacent to the cells that are yet unknown (undiscovered). Then, the centre point coordinates are calculated for each frontier $p_f\ (x, y)_i$, and any frontier that is considered as not reachable or too small to traverse by the SAR robot is discarded from the further utility assessment process.

The three main parameters considered in the next step are the distance from the robot to the hypothesised survivor, $E(s)$, the distance from the robot to the dangerous object, $E(d)$, and the list of currently available frontiers, P_f, which is computed by analysing the partial grid map information. The first two parameters are forwarded to the fuzzy logic controller, where their values are fuzzified, the fuzzy rule base is applied, and the output value is provided by the defuzzification module (which applies the centre of sums method). This value is then mapped to the environment exploration strategy St that is applied for candidate assessment by the search and rescue robot. Finally, the designated MCDM method is applied to determine the utility $U(p_f(x,y)^*)$ of each candidate frontier $p_f(x,y)_i \in P_f$ according to the selected strategy St.

When the decision on where to move next is made, the robot applies the path planning algorithm. Although there are many different methods to choose from (e.g., Kulvicius et al., 2021), this thesis applied the classical A* and Dijkstra algorithms that are provided within the ROS *Nav_core* package (ROS Nav_core, 2020) to determine the path to the selected frontier $R(p_f(x,y)^*) = \{p_r, wp_1, wp_2, \ldots, wp_l, p_f(x,y)^*\}$. Here p_r is the current robot position within the exploration space, wp are the waypoints returned by the path planning algorithm, and $p_f(x,y)^*$ is the highest valued frontier. If any new information about the environment is obtained during the movement process, the robot's decision-making module re-evaluates partial environment information and reassess utility values for all available candidate frontiers. This process is repeated until the exploration objective is completed or mission termination conditions are met. It is worth noting that although the proposed fuzzy logic controller and MCDM methods together define the proposed adaptive autonomous environment exploration strategy, they can also be applied separately or be transferred between different robot systems.

2.8. Conclusions of Chapter 2

1. The state-of-the-art WASPAS MCDM method is extended by modelling it under the interval-valued neutrosophic (WASPAS-IVNS) and m-generalised q-neutrosophic (WASPAS-mGqNS) environments. The WASPAS-IVNS extension is expected to enable the robot to consider inaccurate input data characteristics when deciding where to move next. The WASPAS-mGqNS method provides additional flexibility by

allowing the robot operators to choose between the generalised fuzzy sets applied in the decision-making process.

2. Different candidate assessment strategies can be defined by differently weighted and optimised criteria sets. This feature can be applied to model more altruistic or egoistic robot behaviour in SAR missions.
3. As multiple stakeholders can suggest different criteria weights to solve the same problem, the state-of-the-art SWARA method can be used to efficiently normalise the tensions between the stakeholders and determine criteria weights.
4. The decision on which candidate frontier assessment strategy to apply can be made by the fuzzy logic controller. Differently from the standard approach in which fuzzy logic is applied to control the robot movements, this approach does not directly control the movement of the robot but enables the robot to switch between the rules that govern the candidate assessment process. The proposed strategy is modelled to address the adaptivity requirements of the autonomous SAR robot.

3

Assessment of the Proposed Autonomous Robot Navigation Strategies

This chapter presents an investigation of the performance of the proposed adaptive environment exploration strategy and the novel WASPAS-IVNS and WASPAS-mGqNS methods introduced in the second chapter of this thesis. Novel candidate assessment and environment exploration strategies are developed to address multiple issues the SAR missions present, i.e., robot safety, detected survivor visitation, exploration around the prioritised environment areas, and the adaptability of an autonomous robot. The research results obtained by assessing the proposed environment exploration strategies are discussed in detail.

Parts of this chapter were published (Bausys, Cavallaro & Semenas, 2019; Semenas & Bausys, 2020; Semenas & Bausys, 2021; Semenas, Bausys & Zavadskas, 2021; and Semenas & Bausys, 2022).

3.1. Candidate Assessment Strategy by WASPAS-SVNS Method

The multi-criteria decision-making methods modelled under the neutrosophic set environment can be applied to extend standard navigation and environment exploration strategies that are based on the candidate assessment approach. However, this extension could be considered from the two viewpoints:

1. Criteria that are applied to decide on where to move next (in other words, what strategy is applied when assessing a candidate).
2. Criteria aggregation methods that are applied to measure the utility of a candidate.

At this time, prevalent strategies that are applied to decide on where the autonomous robot should move next are generally based on the technical navigation and environment exploration requirements, which consider the utility of a candidate only from the cost–gain viewpoint. For example, a common approach to the candidate assessment problem is to determine the ratio between the distance the robot has to travel (cost) and the size of the area that is expected to be discovered after reaching the candidate (gain). However, complex environment exploration tasks, especially those performed in disaster sites, introduce dangerous conditions that should be addressed when designing the autonomous navigation and environment exploration strategy. Strictly speaking, the strategy applied in the candidate assessment task should not only consider the technical parameters of the candidate assessment task but also be capable of determining if reaching the candidate is safe from the robot's perspective.

3.1.1. Candidate Assessment in the Robot's Field of View

The proposed novel candidate assessment strategy not only considers the standard cost and benefit aspects but also the safety factors of autonomous environment exploration. Also, the proposed environment exploration strategy is constructed on the premise that the decision on where to move next is made by considering only the information available within the robot's current field of view. This approach is expected to aid the robot in the assessment of its nearby environment and in making decisions on where to move next. The robot's field of view (which is 180° at a 15 m distance) is segmented into traversable zones that correspond to the currently visible spatial data. The candidate the robot could reach is thus placed at the centre of each traversable zone at the 1 m distance from the robot, as schematically presented in Fig. 3.1.

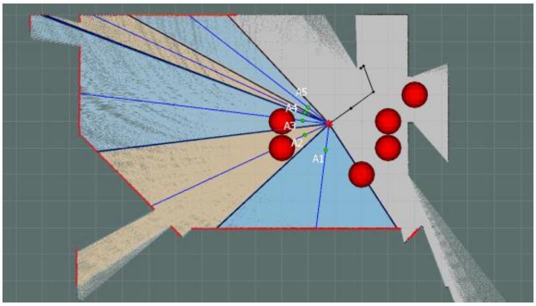


Fig. 3.1. Segmentation of the robot's field of view. Red markers represent dangerous objects. Green markers represent the assessed candidates. The computed traversable zones are marked blue and orange

The proposed candidate assessment strategy is constructed from two criteria sets: three standard criteria regularly applied for candidate assessment tasks and three new criteria constructed to specifically address the safety factors of an autonomous SAR mission. The first criteria set includes the criteria of the estimated amount of information that would be gained by reaching the candidate, the length of the collision-free path the robot could travel, and the battery consumption rate, which is modelled as the time needed to reach the candidate.

The estimated amount of new information that is expected to be discovered by the robot considers the discovered spatial information and the robot's field of view. An estimate of the information gain can be obtained by subtracting the size of the already-discovered area from the sampled area that would be visible to the robot after reaching the candidate location. However, it is worth noting that this estimate can differ from the actual results. These results strongly depend on how cluttered the environment is within the space that is not visible to the autonomous robot. Nonetheless, the criterion is maximised and is expected to direct the robot to the mostly unexplored areas.

The length of the collision-free path the robot could travel is measured by the Euclidean distance between the current robot position and the end of a centre line within the computed traversable zone. This criterion is applied and maximised to direct the robot to areas that are expected to lead the robot out of the current exploration space.

The time needed to reach the candidate can be minimised to balance the cost of reaching the candidate, and the expected maximum distance robot could travel. The introduction of this criterion is expected to normalise robot rotational behaviour when multiple traversable zones are detected with similar maximum collision-free paths. In this situation, the robot should continue following the previously selected movement trajectory. The criteria value is measured by the following equation:

$$t_i = \frac{d}{v_m} + \frac{p_\alpha}{v_r}, \tag{3.1}$$

where d is the distance to the candidate, p_α is the corner between the robot and the candidate. v_m and v_r are the movement and rotation velocities that are defined by considering the robot setup parameters.

However, although the discussed technical criteria are frequently applied in candidate assessment tasks, they are not sufficient for harsh-environment exploration. The inability to identify hazardous obstacles and evaluate their impact on the robot system is a major design flaw that could be addressed from the candidate assessment point of view. Therefore, in the context of this research, the candidate assessment strategy is expanded by introducing the criteria of the ratio between the detected drive-through region and standard door size, the distance to the detected dangerous obstacle, and the distance to the nearest vision-occluding object.

The ratio between the detected drive-through region and the standard door size is expected to support the length of the collision-free path criterion by estimating if the lengthy traversable zone could be, in fact, a doorway that leads to different areas of the explored environment. The criteria value is determined by applying the following equation:

$$c = \frac{\delta}{l_d}, \tag{3.2}$$

where $\delta = 0.762$ is a constant value, representing the width of a door, and l_d is the width of a detected drive-through. For computational purposes, the robot only uses l_d values that are larger than its width.

The distance to the nearest dangerous object is measured by the Euclidean distance between it and the assessed candidate. This criterion is proposed to model the safety concerns of the autonomous SAR robot. Although in real-world scenarios, there are numerous ways to damage the robot, in this model, a dangerous stationary object is considered. It is expected that by applying the proposed criterion, the robot will actively avoid any danger within its field of view. Similarly, the distance to the nearest vision occluding object is also considered in the proposed candidate assessment strategy, as the probability of colliding with the unseen dynamic object can also put the autonomous robot in danger. The criterion value is estimated by measuring the length of the sides of the adjacent traversable zones and referring to the shortest one. It is expected that by applying this criterion, the autonomous robot will keep further away from sharp corners, thus, leaving enough time for collision avoidance manoeuvres.

The complete criteria list applied in the proposed candidate assessment strategy is presented in Table 3.1.

Table 3.1. Proposed candidate assessment strategy

Criterion	Criterion name	Optimum	Weight
c_1	The distance to the nearest dangerous object, m.	Max	0.31
c_2	The ratio between the standard door size and the detected drive-through region width, %.	Max	0.26
c_3	The estimated amount of new information that could be gained, m^2.	Max	0.17
c_4	The length of a visible collision-free path, m.	Max	0.11
c_5	The time needed to reach the candidate frontier, s.	Min	0.08
c_6	The distance to the nearest vision-occluding object, m.	Max	0.07

The criteria weights and optimums presented in Table 3.1 are used in the candidate assessment task and are determined by applying the SWARA method introduced in the second chapter of this thesis. As the SWARA method is applied to determine the criteria weights in all of the considered experiments and strategy assessment tasks of this thesis, the example of the criteria weight computation process is presented in detail. The pairwise comparison of the relative importance of criteria is presented in Table 3.2.

Table 3.2. Pairwise comparison of the relative importance of criteria

Stakeholder	Pairwise comparison values of the relative importance of criteria				
	$c_1 \leftrightarrow c_2$	$c_2 \leftrightarrow c_3$	$c_3 \leftrightarrow c_4$	$c_4 \leftrightarrow c_5$	$c_5 \leftrightarrow c_6$
1	0.50	0.25	0.25	0.10	0.30
2	0.20	0.65	0.40	0.20	0.20
3	0.00	0.45	0.15	0.60	0.25
4	0.20	0.30	0.40	0.30	0.15
5	0.20	0.25	0.85	0.60	0.20
6	0.10	0.85	0.50	0.45	0.15
7	0.35	0.90	0.50	0.50	0.00
8	0.10	0.55	0.75	0.30	0.10
9	0.20	0.30	0.25	0.50	0.20
10	0.10	0.70	0.80	0.20	0.75

Then, the average value of comparative importance is determined. By applying the SWARA method, the final criteria values are computed and presented in Table 3.3.

Table 3.3. Pairwise comparison of the relative importance of criteria

Criterion	Average value of comparative importance	Coefficients of comparative importance	Recalculated weights	Final weight
c_1	–	1.000	1.000	0.31
c_2	0.195	1.195	0.837	0.26
c_3	0.520	1.520	0.551	0.17
c_4	0.485	1.485	0.371	0.11
c_5	0.375	1.375	0.270	0.08
c_6	0.230	1.230	0.220	0.07
–			3.249	–

Once competing stakeholder opinions are modelled into a well-defined weight set, the proposed candidate assessment strategy can be applied by the autonomous robot to evaluate candidates located in its field of view. In this case, the key improvement of the proposed autonomous navigation strategy compared to the standard approach is the implementation of additional technical and safety-related criteria. This improvement is expected to enable the autonomous robot to better interpret discovered spatial information and assist it in avoiding dangerous objects without the additional navigation rules.

3.1.2. Evaluation of the Proposed Candidate Assessment Strategy in the Robot's Field of View

The considered candidate assessment strategy is tested in a simulated indoor environment by applying the dedicated Gazebo simulation software (Gazebo, 2021). The proposed strategy is implemented into the turtle-bot-like robot system, which is controlled by applying the Robot operating system ROS (ROS, 2020). The utility of each candidate is measured by applying the state-of-the-art WASPAS-SVNS method. The goal of this test is to determine if the inclusion of safety concerns in the applied environment exploration strategy can influence the robot movement trajectory. Thus, the example solution to one of the decision-making problems is provided. The initial decision matrix of the sample decision-making iteration is presented in Table 3.4. The utility of each candidate (denoted as A1, A2, …, A6) is measured by applying the WASPAS-SVNS method and presented in Table 3.5.

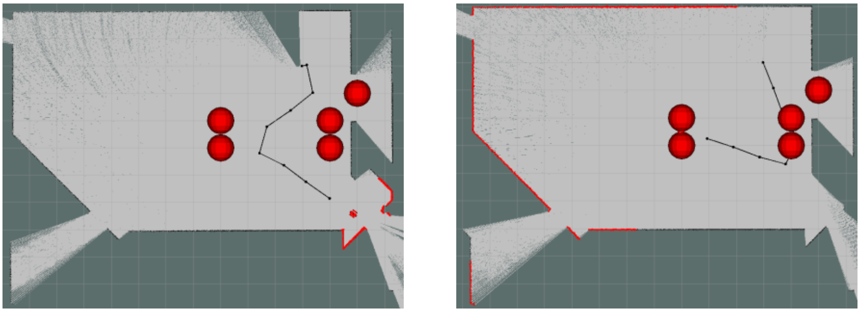
Table 3.4. Initial decision matrix of the sample iteration

Criterion	Candidate frontier					
	A1	A2	A3	A4	A5	A6
c_1	2.3608	2.2629	1.9455	1.2639	2.7165	3.9915
c_2	0.0100	0.8968	0.0995	0.0100	0.3886	0.4274
c_3	26.8296	43.6107	17.9941	9.7133	39.6498	5.3125
c_4	9.1394	12.5583	6.9450	4.4250	11.8150	2.7498
c_5	21.5175	20.7496	17.3396	6.7615	2.5623	17.7558
c_6	0.0100	8.7569	5.7627	0.0100	2.6942	1.3109

Table 3.5. Results provided by WASPAS-SVNS method for sample iteration

Method results	Candidate frontier					
	A1	A2	A3	A4	A5	A6
$Q_i^{(2)}$	(0.7195, 0.2986, 0.2805)	(0.8059, 0.1909, 0.1941)	(0.7526, 0.2435, 0.2474)	(0.8410, 0.1437, 0.1590)	(0.9268, 0.0745, 0.0732)	(0.7933, 0.1924, 0.2067)
$Q_i^{(2)}$	(0.0142, 0.9871, 0.9858)	(0.1042, 0.8944, 0.8958)	(0.0339, 0.9700, 0.9661)	(0.0085, 0.9927, 0.9915)	(0.0691, 0.9356, 0.9309)	(0.0431, 0.9581, 0.9569)
Q_i	(0.7235, 0.2948, 0.2765)	(0.8262, 0.1707, 0.1738)	(0.7610, 0.2362, 0.2390)	(0.8424, 0.1427, 0.1576)	(0.9318, 0.0697, 0.0682)	(0.8022, 0.1844, 0.1978)
$S(Q_i)$	0.7144	0.8277	0.7624	0.8498	0.9311	0.8089
Rank	6	3	5	2	1	4

The provided example demonstrates that the robot is capable of balancing the competing optimisation priorities modelled by the proposed criteria set. Considering the c_1 criterion that corresponds to the robot's safety, the candidate denoted as A5 is the second-best option within the list and A4 is last. However, the results obtained by applying the WASPAS-SVNS method indicate that A5 is ranked the best candidate and A4 is the second-best. In this case, the standard c_3, c_4 and c_5 criteria outweigh the proposed c_1 criterion. This result highlights how the optimisation priorities are balanced by applying the MCDM approach and indicates that robot safety issues can be effectively addressed when applying the proposed candidate assessment strategy. The robot's ability to evade dangerous objects is also illustrated in Fig. 3.2.



a) b)

Fig. 3.2. Robot movement trajectory: (a) the robot movement trajectory when applying the proposed candidate assessment strategy; (b) the robot movement trajectory, when applying only the c_3, c_4 and c_5 criteria. The red markers represent dangerous objects the robot should avoid, the black line indicates the robot's movement trajectory

The robot movement trajectory (black line in Fig. 3.2) suggests that by applying the proposed candidate assessment strategy, the robot is actively avoiding dangerous objects (red markers in Fig. 3.2). Also, the robot is attracted to areas considered to lead the robot out of the current exploration space.

Although the proposed method demonstrates stability and the ability to avoid dangerous objects, some improvements can be considered. For example, the assessment of the candidates that are only in the robot's field of view can reduce the efficiency of the environment exploration process as the decisions on where to move next might not be efficient on the global scale. Thus, further development of the environment exploration strategies is presented in the next chapters of this thesis.

3.2. Frontier Assessment Strategy by WASPAS-IVNS Method

Although the previously proposed strategy for candidate assessment in the robot's field of view shows potential, the application of the MCDM approach for the global candidate assessment task could increase the robot's performance when considering the size of the area that was searched by the robot. Differently from the previously discussed strategy, in this approach, the robot determines a set of possible candidates that could be reached by considering not the current field of view but rather all available environment information. Specifically, a frontier assessment-based strategy is considered (Yamauchi, 1997).

In general, a frontier can be defined as a region between the currently discovered and the unknown environment. By directing the robot to these areas, new environment information can be discovered and added to the partial environment representation model (in the case of this thesis, a grid map (ROS Gmapping, 2020)). Then, a list of reachable frontiers is determined once again, and the robot is directed to the one with the highest utility score, considering the applied candidate assessment strategy.

However, the imprecise robot movements and small measurement variations obtained by robot sensors can have a significant impact on the autonomous environment exploration quality and, therefore, should be addressed while designing environment exploration strategies. Thus, the proposed WASPAS method extension, modelled under the interval-valued neutrosophic environment (WASPAS-IVNS) is implemented into the autonomous robot decision-making module. The proposed decision-making method provides additional reliability when comparing and ranking candidate frontiers by addressing the plausible measurement errors in the input data characteristics.

3.2.1. Candidate Frontier Assessment Strategy

Compared to the previously discussed approach, the proposed novel candidate assessment strategy is developed to consider not only the technical and safety requirements of an autonomous robot but also the social aspects of the SAR mission. Also, each criterion measurement approach is adjusted to support the environment exploration strategy based on the frontier evaluation.

The proposed strategy is developed by combining six criteria that expand the standard environment exploration strategies, including the previously discussed safety requirements for SAR robots and address the situations in which survivors are detected. Thus, the candidates are assessed by applying the criteria of the estimated distance from the candidate frontier to the robot control station, the estimated amount of new information that is considered to be gained after reaching the candidate frontier, the estimated energy needed to reach the candidate frontier (measured by the time needed to reach the candidate), the distance from the robot to candidate frontier location, the estimated danger to the hypothesised survivor, and the estimated danger to the robot for following the computed path.

The first criterion, the estimated distance from the candidate frontier to the robot control station, is a technical criterion that defines the robot's ability to transmit information after reaching the candidate frontier (Visser & Slamet, 2008). If the maximum transmission distance is known in advance and the robot control station is located at the unchanging position $p_s(x, y)$, the criterion value can be estimated as the Euclidean distance between the control station and the candidate frontier $p_f(x,y)$ in P_f. This criterion can be minimised to prioritise frontiers that are close to the robot's starting location to perform more structured exploration while also enabling the robot to transmit the data to the robot operators. However, if this criterion is maximised, the further located frontiers will be preferred by the decision-making module. This can be applied to perform a faster environment exploration (nevertheless, robot operators should consider the possibility of losing communication with the robot and, thus, add restrictive rules that prohibit the robot from leaving the designated search area). Considering the operational parameters set to the simulated robot path planning algorithm, the estimated measurement variance for this criterion is set to ±1 m.

The estimated amount of new information considered to be gained after reaching the candidate frontier (expressed by the estimated length of the frontier) expresses the belief that the length of the frontier can be applied to estimate how much spatial information can be observed from the candidate frontier $p_f(x,y)$ (Gomez et al., 2019). Specifically, lengthier frontiers may indicate that they border wide-open spaces, whereas short frontiers could indicate their position near corners or cluttered spaces. When maximised, this criterion is expected to direct the robot towards the open spaces, enabling it to discover more of the search and rescue environment. Therefore, this exploration behaviour could be applied to quickly obtain the base layout of the environment, which, in return, can help the first responders to plan their actions (De Cubber et al., 2017). However, it is worth noting that the estimation can differ from the actual result. This strongly depends on the spatial information which is unknown to the robot. For example, the environment can be cluttered around the candidate frontier, shaping a dead-end structure. However, this clutter may not be visible to the robot before it actually moves to the frontier. Considering the deployed autonomous robot, in this research, the estimated measurement variance of this criterion is set to ±0.1 m.

The estimated distance from the robot to the candidate frontier is measured by the Euclidean distance between the current robot position $p_r(x,y)$ and the candidate frontier $p_f(x,y)_i$. The criterion is expected to direct the robot to the frontiers that are within the nearby exploration space.

The estimated time needed to reach the candidate frontier is applied to prioritise candidate frontiers that are reachable by straight and short paths. The criterion value is estimated by applying the approach proposed by Basilico and Amigoni (2011). More specifically, the criteria value $t(p_i)$ is determined by evaluating individual paths $R(p_f(x,y)_i) = \{p_r, wp_1, wp_2, \dots, wp_l, p_f(x,y)_i\}$ to each candidate frontier $p_f(x,y)_i$ in the currently available set P_f. Starting from the current robot position p_r to the candidate frontier $p_f(x,y)_i$, two connecting waypoints wp_l and wp_{l+1} create a path segment, returned by the robot path planning algorithm. Therefore, the distance between two waypoints can be denoted as $d(wp_{l-1}, wp_l)$ and the corner between two segments can be denoted as $\alpha(wp_{l-1}, wp_l, wp_{l+1})$. As such, the criterion value can be determined by the following equation:

$$t(p_f(x,y)_i) = \frac{\sum_{l=1}^{m} d(wp_{l-1}, wp_l)}{v_m} + \frac{\sum_{l=1}^{m} \alpha(wp_{l-1}, wp_l, wp_{l+1})}{v_r}, \tag{3.3}$$

where $v_m = 0.1\ m/s$ and $v_r = 0.1\ °/s$ are the minimum robot movement and rotation speed, respectively (here, the constant rotation and movement speed is assumed for criteria value estimation). Considering the robot operational parameters, the estimated measurement variance applied for this criterion is set to be equal to ±10 s.

Disaster sites can have objects threatening the autonomous robot (e.g., fire or radiation sources (Wang et al., 2017; Zakaria et al., 2017; Tsitsimpelis et al., 2019)), making it unable to continue the mission. Therefore, the criterion of the estimated penalty for following the computed path is introduced to address the robot's safety requirements. The penalty system is introduced to define the danger of following the planned path to the candidate frontier. The criterion value is determined by assessing the distance from the planned path to the nearby dangerous objects and converting the distances to a point-based penalty by the following equation:

$$P_i = \sum_{j=1}^{n} \sum_{i=1}^{m} d_p(wp_i, o_{dj}), \tag{3.4}$$

where $d_p(wp_i, o_{dj}) = 3 - d_d(wp_i, o_{dj})$ if $d_d(wp_i, o_{dj}) < 3$. The partial penalty is defined as d_p estimated by measuring the Euclidean distances between wp_i and o_{dj}. If this distance d_d from each waypoint wp in a path $R(p_f(x,y)_i)$ to all currently known dangerous areas in a set $O_d = (o_{d1}, o_{d2}, \dots, o_{dn})$ is greater than three meters, the robot receives no penalty. However, if the distance between wp_i and o_{dj} is two meters, the robot receives one penalty point. If the distance is 0.25 m, the robot receives a penalty of 2.75, and so forth. The considered measurement variance of this criterion is set to ±0.2.

Finally, one of the social aspects of SAR missions (namely, the robot's ability to consider the status tracking of the detected survivors) is proposed to be modelled by the estimated danger to the hypothesised survivor. This criterion is expected to attract the robot to the detected survivors and prioritise the ones who are in danger. To determine the value of this criterion, the Euclidean distance d_v from the planned route to the detected survivor is measured. If $d_v < 6$, the Euclidean distance d_d between the survivor and the nearest known dangerous area $O_d = (o_{d1}, o_{d2}, \dots, o_{dn})$ is measured. The criterion value is equal to $6 - d_d\ if\ d_d \leq 6$.

The criteria that define the proposed candidate frontier assessment strategy are presented in Table 3.6. The criteria weights are determined by applying the SWARA method, introduced in the second chapter of this thesis.

Table 3.6. Proposed strategy for the assessment of candidate frontiers

Criterion	Criterion name	Optimum	Weight	Estimated variance
c_1	The estimated distance from the candidate frontier to the robot control station, m.	Min	0.270	±1
c_2	The estimated amount of new information that is considered to be gained after reaching the candidate frontier (length of the frontier), m.	Max	0.217	±0.1
c_3	Estimated danger to the detected survivor, units.	Max	0.186	±0.2
c_4	Estimated damage for following the computed path, units.	Min	0.143	±0.2
c_5	Estimated time needed to reach the candidate frontier, s.	Min	0.099	±10
c_6	Distance to the candidate frontier, m.	Min	0.085	±1

It is worth noting that although the estimated variance of the criteria values is application-specific and modelled by considering the parameters of the deployed autonomous robot, it can be adjusted to consider the expected inaccuracies of the input data characteristics as defined by the experts or robot operators. Thus, this approach introduces additional flexibility when modelling input data characteristics applied by the autonomous robot in the candidate assessment task.

3.2.2. Assessment of Similar Candidate Frontiers

To highlight the practical application of the proposed WASPAS-IVNS method, an example solution to one of the autonomous robot decision-making iterations is presented. In this example, the indoor environment with a loop type topology is considered and presented in Fig. 3.3. Here, the dangerous areas and survivors are placed at random positions throughout the environment and are represented by the red and yellow markers, respectively. The multi-purpose Pioneer 3-AT robot platform is deployed in this example.

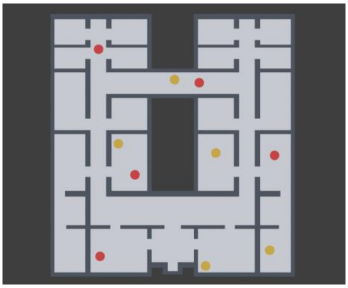


Fig. 3.3. Test environment with a loop type topology. The red markers indicate the positions of dangerous areas. The yellow markers indicate the positions of the survivors (Semenas & Bausys, 2020)

The area searched and mapped by the robot at the discussed candidate assessment example is provided in Fig. 3.4. In this example, one survivor and one dangerous object have already been discovered and marked by the yellow and red markers, respectively. The robot is located at the position marked by a black marker, and the black line represents its previous movement trajectory. The available frontier regions are depicted as blue lines, and the green markers represent candidate frontiers $a_i(x, y)$. At this iteration, the robot has to measure the utility of seven candidates.

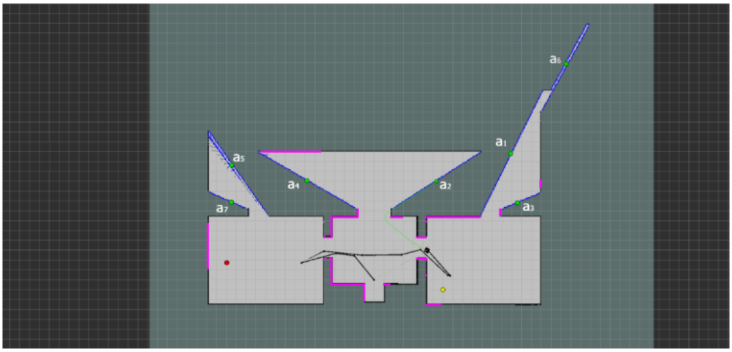


Fig. 3.4. Area searched and mapped at the considered candidate frontier assessment example. The blue lines indicate candidate frontiers $(a_1, a_2, \dots, a_7)$. The red and yellow markers represent the discovered dangerous object and survivor (Semenas & Bausys, 2020)

First, the criteria values are estimated for each candidate frontier. At this decision-making step, no new dangerous areas were detected around the candidate frontiers or survivors; hence, c_3 and c_4 criteria values are null. Although these criteria do not influence the decision-making process, it is highly recommended to change the null values to a small positive number to stabilise the numerical computational procedure of neutrosophic algebra. The constructed decision matrix for the sample iteration is presented in Table 3.7.

Table 3.7. Decision matrix of the considered candidate assessment example

Candidate frontier	Criterion					
	c_1	c_2	c_3	c_4	c_5	c_6
a_1	18.89	12.7	0.10	0.10	25.27	12.94
a_2	11.84	9.10	0.10	0.10	37.58	7.13
a_3	16.54	4.00	0.10	0.10	39.09	10.28
a_4	12.15	10.3	0.10	0.10	33.04	14.27
a_5	18.54	16.4	0.10	0.10	60.89	21.80
a_6	29.33	15.5	0.10	0.10	31.59	23.57
a_7	16.47	4.00	0.10	0.10	63.49	20.61

The utility of each candidate frontier is measured by applying the algebraic functions of WASPAS-IVNS introduced in the second chapter of this thesis. The same candidate assessment problem is solved by applying the WASPAS-SVNS method. Compared to the WASPAS-SVNS method, the modelling of candidate frontier evaluation problems under the interval-valued neutrosophic set provides additional tools for assessing similar candidates. Therefore, the proposed WASPAS-IVNS method enables the autonomous robot to make more accurate estimates when ranking the candidate frontiers. This difference is illustrated in Table 3.8, which represents the utility scores obtained by applying the WASPAS-SVNS method. In this example, the scores of the a_2 and a_4 frontiers are very similar. However, by applying the WASPAS-IVNS method, candidate a_2 is chosen as the next-best candidate the robot should reach.

Table 3.8. Candidate ranks by the WASPAS-IVNS and WASPAS-SVNS methods

Candidate frontier	WASPAS-IVNS		WASPAS-SVNS	
	$S(Q)$	Rank	$S(Q)$	Rank
a_1	[2.002, 2.286]	3	0.6655	3
a_2	[2.014, 2.312]	1	0.6708	2
a_3	[1.877, 2.172]	5	0.5982	5
a_4	[2.015, 2.306]	2	0.6719	1
a_5	[1.898, 2.174]	4	0.6171	4
a_6	[1.853, 2.117]	6	0.5812	6
a_7	[1.743, 2.027]	7	0.5193	7

The quality of the environment exploration strategy can be affected by the small variations in the input data characteristics present due to the imprecise environment representation model or faulty sensor readings. Therefore, the proposed WASPAS-IVNS method is introduced to address this issue. The assessment of the proposed method indicates that WASPAS-IVNS can be applied to solve complex decision-making tasks and show potential when applied in SAR missions. When compared to the standard WASPAS-SVNS method, the proposed WASPAS-IVNS method provides additional reliability when comparing similar candidates. This is achieved by considering the possible imprecisions in the input data characteristics.

3.3. Candidate Frontier Assessment by WASPAS-mGqNS Method

As the proposed candidate-assessment-based autonomous navigation and environment exploration strategies show potential in SAR environments, an additional candidate assessment strategy is proposed. This strategy considers the possibility of a priori information, which enables the robot operator to indicate the priority areas that should be explored. Also, a criterion that defines the spatial clutter around the candidate frontier is introduced to reduce the chance of selecting the frontier around which most of the information has already been discovered.

However, different real-world missions might require a slightly different approach when measuring the utility of a candidate. Therefore, a novel extension modelled under the m-generalised q-neutrosophic environment is proposed for the WASPAS method, namely, WASPAS-mGqNS. This extension enables the robot operator to shift between the fuzzy sets that govern the aggregation process of the applied criteria and introduces additional flexibility when modelling environment exploration strategies. Identically to the previously discussed frontier-based approach, the proposed candidate assessment strategy is applied by a simulated Pioneer-3AT robot. The obtained test results highlight how the proposed approach could be used to minimise the distance travelled by the robot and maximise the size of the area searched by the robot when the search must be performed around the several priority locations that are set in advance by the robot operator.

3.3.1. Priority-Based Candidate Frontier Assessment Strategy

The strategies discussed in the previous chapters of this thesis are applied in situations where no a priori information about the environment is known to the autonomous robot. Yet, considering some real-world situations, it is likely that robot operators can obtain some information about the environment and apply it to make more efficient decisions (e.g., as in Calisi et al., 2007; Roa-Borbolla et al., 2017). Therefore, for the candidate assessment problem, a novel strategy is proposed to enable the robot to explore areas around the set priority locations and reduce the amount of input data needed to filter the frontiers surrounded by mostly explored space. The main objective of the proposed strategy is to maximise the amount of discovered information around a set of priority locations while minimising the average distance travelled by the autonomous robot. Thus, the candidate frontier assessment strategy is modelled by applying six criteria, i.e., the distance from the robot to the candidate frontier, the estimated amount of new information that is considered to be gained after reaching the candidate frontier, the estimated time needed to reach the candidate frontier, the distance between the frontier and robot control station, the distance from the candidate frontier to the set priority location and the ratio between the number of unknown cells and the sample population size around the candidate frontier.

The distance from the candidate frontier to the set priority location is a novel minimised criterion introduced to enable more exhaustive exploration around the set priority location without directly moving the autonomous robot to the designated area. The main idea behind introducing this criterion is that in real-world search and rescue missions, it is very likely that the rescue teams can obtain some information about the environment and focus the exploration effort around the prioritised locations (e.g., Calisi et al., 2007; Roa-Borbolla et al., 2017). The criterion value is measured by the shortest Euclidean distance between each priority location and the considered candidate.

The ratio between the free cells around the frontier and the sample population is a maximised criterion that is introduced to reduce the chance of selecting frontiers that are unreachable or are surrounded by already discovered space (e.g., candidates that are detected near the corners of a room or, due to the faulty environment representation model, in the middle of the wall). This criterion is also applied to address the issue of inaccurate or noisy robot-constructed environment representation model (Zakiev et al., 2019). As the MCDM methods are vulnerable to numerical instability, this problem can have a notable influence on the performance of the proposed strategy. The criterion value is measured by sampling a total of 100 cells within a set radius around each frontier as presented in Fig. 3.5 (in the considered setup, the set radius is equal to 1.5 m) and applying the following equation:

$$c_6 = \frac{\varphi}{\lambda \cdot 2^n}, \tag{3.5}$$

where φ is the number of sampled cells that are yet to be discovered, λ is the real number, representing the sample population size and n is the number of sampled cells that are occupied. Although the approach of estimating the amount of free space that would be visible by considering parameters of robot perception sensors (Basilico & Amigoni, 2011; Taillandier & Stinckwich, 2011) can also be applied to determine the value of this criterion, this approach requires additional computational resources as more input data must be evaluated by the autonomous robot.

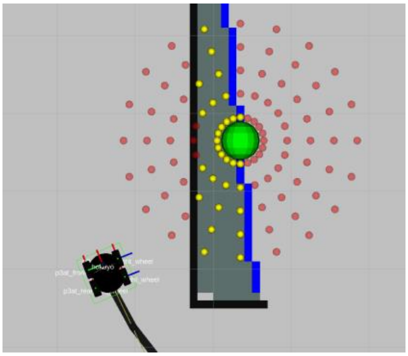


Fig. 3.5. Proposed cell sampling method. Here, the blue line indicates the chain of cells between the explored and unknown space. The green marker indicates the location of the candidate frontier $p_f(x, y)_i$. The red markers indicate samples that fall into the explored or occupied space. Yellow markers indicate samples located on the undiscovered cells (Semenas, Bausys & Zavadskas, 2020)

The proposed strategy for the assessment of candidate frontiers is presented in Table 3.9. The criteria weights are determined by applying the previously introduced SWARA method.

Table 3.9. Proposed (PS) candidate assessment strategy

Criterion	Criterion name	Optimum	Weight
c_1	Distance to the candidate frontier, m.	Min	0.07
c_2	The estimated amount of new information that is considered to be gained after reaching the candidate frontier, m.	Max	0.13
c_3	Estimated time needed to reach the frontier, s.	Min	0.24
c_4	Distance to the robot control station, m.	Min	0.04
c_5	Distance from the candidate frontier to the set priority location, m.	Min	0.37
c_6	The ratio between the number of unknown cells and the sample population size around the candidate frontier, %.	Max	0.15

To evaluate the performance of the proposed strategy (PS), two additional autonomous navigation and environment exploration strategies are considered, i.e., the direct control (WS) strategy and the information gain (IG) strategy, which is based on the cost–benefit candidate assessment approach, presented in Table 3.10.

Table 3.10. Information gain (IG) candidate assessment strategy

Criterion	Criterion name	Optimum	Weight
c_1	Distance to the candidate frontier, m.	Min	0.25
c_2	The estimated amount of new information that is considered to be gained after reaching the candidate frontier, m.	Max	0.30
c_3	Estimated time needed to reach the frontier, s.	Max	0.35
c_4	Distance to the robot control station, m.	Min	0.10

In this evaluation, the IG and the PS strategies are modelled by applying the frontier-based candidate assessment approach, in which the utility of a candidate is determined by applying the proposed WASPAS-mGqNS method. The direct control strategy WS is modelled by applying the approach in which the robot operator sets the order of priority locations to be visited, and the robot follows the shortest path between them.

3.3.2. Performance Evaluation of the Proposed Priority-Based Candidate Assessment Strategy

To highlight how the proposed priority-based candidate assessment strategy and the WASPAS-mGqNS method could be applied in autonomous navigation and environment exploration tasks, they are evaluated in a simulated search and rescue environment, presented in Fig. 3.6. Here, the white markers indicate four priority locations the autonomous robot is expected to visit and around which the robot should focus the exploration effort. The blue marker indicates the robot's starting position (considered as the robot's control station). The primary objective of the proposed candidate-assessment-based environment exploration strategy is to minimise the distance travelled by the robot and increase the size of the searched environment around a set of priority locations that are identified by the robot operators before deploying the autonomous SAR robot. The navigation and environment exploration task is terminated when the autonomous robot visits all four priority locations or the time limit of ten minutes is reached.

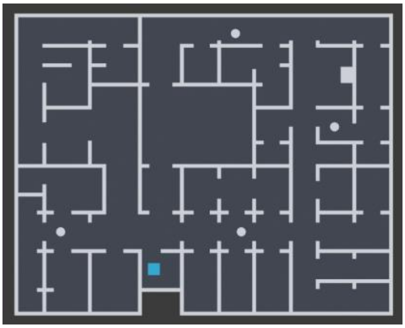


Fig. 3.6. Simulated indoor environment. White markers indicate the priority locations the robot is expected to visit. The blue marker indicates the robot's starting position (Semenas, Bausys & Zavadskas, 2020)

As in the previous tests, the autonomous robot deployed in a Gazebo simulator is controlled by applying the ROS robot operating system and using a similar navigation framework and sensor setup as discussed in the previous section of this thesis. The decision on where to move next is made, and the frontier with the highest utility is determined by applying the proposed WASPAS-mGqNS method. The performance of the three environment exploration strategies (PS, IG, and WS) is evaluated in this assessment. As the robot movement trajectories can differ between multiple simulations due to the inaccurate input data characteristics and errors in the environment representation model (which is used for path planning), a total of ten simulation runs were performed for each environment exploration strategy to obtain the averaged results. The results obtained in these tests are presented in Fig. 3.7.

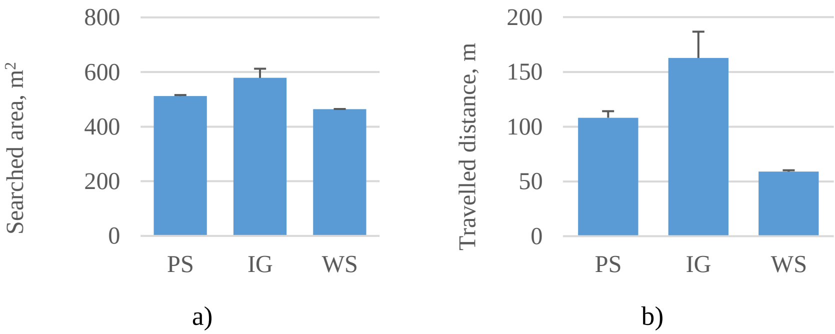
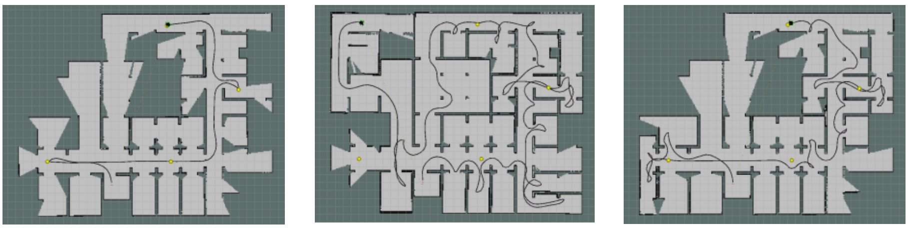


Fig. 3.7. Results of tested navigation strategies: (a) the size of the searched area, m^2; (b) the length of the distance travelled by the robot, m

Considering the average distance travelled by the autonomous robot, the WS strategy shows the best performance in the simulated environment. However, by applying this approach, the robot searched the smallest area when compared to the

IG and PS strategies. Considering the average distance travelled by the autonomous robot, the worst performance is observed when applying the IG strategy. Although this strategy enables the autonomous robot to search most of the exploration space, it also significantly increases robot backtracking and does not guarantee the visitation of all priority locations within the considered time window of ten minutes. As such, the addition of c_5 and c_6 criteria show potential in keeping the robot close to the prioritised locations while also minimising its chance to select the candidates that are surrounded by a previously searched environment.

These results are also represented by the robot movement trajectory presented in Fig. 3.8. For example, (a) represents the robot movement trajectory when the WS strategy is applied. In this example, the robot follows the shortest route between the set priority locations and finishes the exploration mission when the last priority location is visited. In contrast, it is common for the IG strategy to never visit all the priority locations and exhaustively explore the SAR environment until the given time limit is reached and the robot is stopped, as highlighted in (b). However, the proposed environment exploration strategy, presented in (c), indicates that the robot that applies the proposed candidate assessment strategy searched a lesser area when compared to the IG strategy. However, the robot is directed to the priority locations, enabling it to explore the frontiers around these positions and, thus, discover more environment information (when compared to the WS strategy) while simultaneously constructing a time-efficient navigation path (when compared to the IG strategy).



a) b) c)

Fig. 3.8. Robot movement trajectories when applying the PS, IG and WS strategies: (a) robot movement trajectory when WS strategy is applied; (b) robot movement trajectory when the IG strategy is applied; (c) robot movement trajectory when the PS strategy is applied (Semenas, Bausys & Zavadskas, 2020)

The obtained results indicate that the proposed candidate assessment strategy enables the autonomous robot to maximise the searched area around the prioritised locations while travelling a relatively short distance. Thus, the proposed MCDM method extension can be applied to solve such complex decision-making problems as candidate assessment tasks in autonomous environment exploration.

However, it is worth noting that the robot's navigational behaviour strongly depends on the physical features of the explored environment. For example, if there is a lack of available frontiers in the space around the prioritised location, the autonomous robot might not increase the amount of the discovered environment information before the mission termination conditions are met.

3.4. Environment Exploration by the Adaptive MCDM Approach

Considering the complexity of the candidate assessment problem in SAR missions and the inherent complexity of real-world environments, it can be argued that an efficient autonomous robot must be capable of swapping between the rules that govern the candidate assessment task rather than applying the same rules for each candidate assessment iteration. Therefore, an adaptive environment exploration strategy is proposed, which implements the multi-criteria decision-making methods to decide on where to move next, and the fuzzy logic controller, which is applied to determine the most appropriate strategy for the candidate assessment problem. Differently from the previously discussed strategies, the proposed approach enables the autonomous robot to apply the most appropriate candidate frontier assessment strategy based on the currently discovered environment information and robot surroundings. Specifically, the decision on where to move next is made by applying one of the pre-set strategies defined by differently modelled criteria weights. The criteria are aggregated, and the utility of a candidate frontier is measured by applying the previously discussed neutrosophic WASPAS method extension, i.e., WASPAS-IVNS.

3.4.1. Fuzzy Logic Controller for Adaptive Environment Exploration

In general, a basic fuzzy logic controller can be constructed from the four core components: the fuzzification module, fuzzy inference machine, fuzzy rule base, and the defuzzification module (Klir & Yuan, 1995). The first component, the fuzzification module, is responsible for processing and mapping a set of crisp input data values to the linguistic terms, called fuzzy sets, and determining the degree of membership of each input data value in the unit interval of [0, 1]. A fuzzy logic controller is a popular approach to modelling autonomous robot systems that is successfully applied in many different designs (e.g., Din et al., 2018; Hong et al., 2012; Seraji & Howard, 2002; Singh & Thongam, 2018; Kahraman et al., 2020; Sreekumar 2016; and Khurpade et al., 2011, just to name a few).

The inference machine is applied to assess the fuzzified input data by a set of fuzzy IF-THEN rules (called the fuzzy rule base), which govern the output of the module. These rules can be defined by the experts, built on the knowledge base or just by referencing successful system tests. However, as there may be multiple rules that are activated due to the overlaps in the inference machine output, the defuzzification module is applied to convert the obtained results to a crisp output value. This value is further applied in selecting the appropriate candidate assessment strategy. The defuzzification process can be performed by applying several methods. For example, the centre of sums method (which is used in the proposed system), the centre of gravity method, first, last or mean of maxima, just to name a few.

The proposed fuzzy logic controller is applied to determine which candidate frontier assessment strategy should be applied considering the current robot's state and known environment information. It is also worth noting that the proposed fuzzy logic controller showcases applicational principles of the proposed adaptive strategy and is not aimed to define how the robot should realistically operate in every search and rescue mission. In this case, the proposed approach describes how the output value of the fuzzy logic controller can be assigned to the unique candidate assessment strategies. However, this process can be further extended by introducing a fully autonomous or rule-based approach. The fuzzy logic controller uses two input arguments, namely, $E(s)$ – the distance from the robot to the hypothesised survivor and $E(d)$ – the distance from the robot to the closest dangerous area. One output parameter is provided, namely, the candidate frontier assessment strategy St that should be applied by the autonomous robot at the current environment exploration step.

The input membership functions for the $E(s)$ are defined as contact (SC), near (SN), medium (SM), far (SF), and very far (SVF). The input membership functions of the distance to the $E(d)$ are defined as critical (DC), very near (DVN), near (DN), medium (DM), far (DF), very far (DVF), and safe to ignore (DSI). Here, triangular membership functions are used for the inputs as presented in Fig. 3.9 and Fig. 3.10.

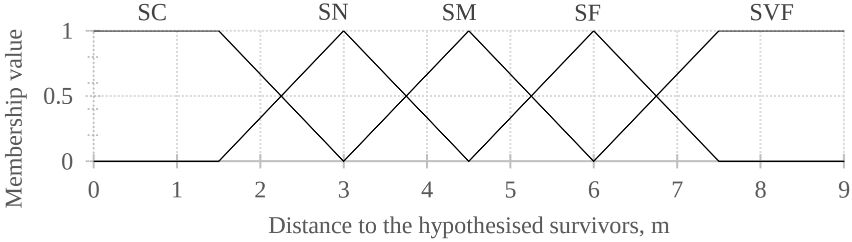


Fig. 3.9. Input membership function for the distance to the hypothesised survivors

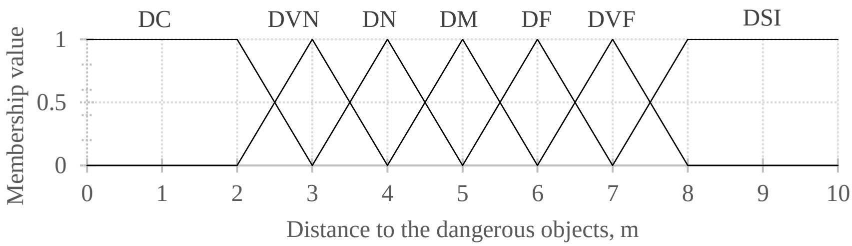


Fig. 3.10. Input membership function for the distance to the dangerous objects

In the proposed adaptive candidate assessment strategy, the output of the fuzzy logic controller is mapped to the candidate frontier assessment strategies, as presented in Fig. 3.11. Here, the proposed candidate assessment strategies are defined as the danger avoidance strategy (DA), which represents the egoistic behaviour model and is expected to direct the autonomous robot away from the dangerous paths and areas; the restrictive reach survivor strategy (RRS), which is expected to balance the robots survivability requirements with the need to explore the frontiers around the hypothesised survivor; the reach survivor strategy (RS), which represents the altruistic behaviour model and prioritises candidate frontiers that are relatively close to the hypothesised survivor; and the information gain strategy (IG), which is applied for directing the robot to the set prioritised locations. It is also worth noting, that the list of the proposed candidate assessment strategies is not finite and can be easily extended depending on the specific environment exploration task and the needs of robot operator.

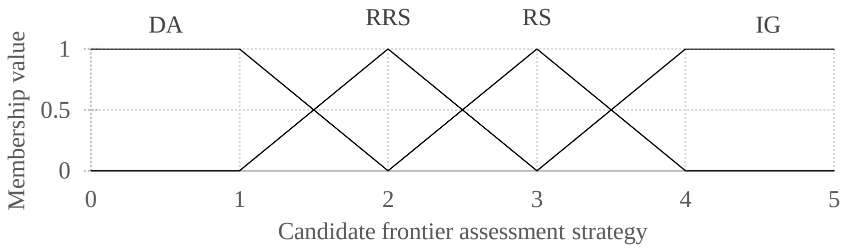


Fig. 3.11. Output membership functions for selecting the candidate frontier assessment strategy

Since five fuzzy membership functions are defined for $E(s)$ and seven fuzzy membership functions are defined for $E(d)$, the fuzzy rule base is constructed from a total of 35 IF-THEN rules which are presented in Table 3.11.

Table 3.11. Fuzzy rule-base for selecting candidate frontier assessment strategy

Membership terms	DC	DVN	DN	DM	DF	DVF	DSI
SC	DA	RRS	RRS	RRS	RS	RS	RS
SN	DA	RRS	RRS	RRS	RS	RS	RS
SM	DA	DA	RRS	RRS	RS	RS	RS
SF	DA	DA	DA	RRS	RS	IG	IG
SVF	DA	DA	DA	DA	RS	IG	IG

Several of the fuzzy rules applied by the proposed fuzzy logic controller are defined:

- IF $E(s)$ is SC AND $E(d)$ is DC THEN St is DA;
- IF $E(s)$ is SN AND $E(d)$ is DVN THEN St is RRS;
- IF $E(s)$ is SF AND $E(d)$ is DF THEN St is RS;
- IF $E(s)$ is SVF AND $E(d)$ is DSI THEN St is IG.

To determine the output value of the proposed fuzzy logic controller, the defuzzification step is performed by applying the centre of sums method. The obtained output value is then mapped to the candidate assessment strategies (that are presented in Table 3.13) according to the thresholded membership value. In this case, the obtained output value is applied to determine if the membership to the candidate frontier selection strategy is weak or strong. The membership is considered strong, and the selected candidate frontier assessment strategy applies the criteria weights represented as w_s, when the obtained output value St satisfies the following condition:

$$w_s \; is \; true \; if \; \begin{cases} St \leq b + 0.25 \\ St \geq b - 0.25 \end{cases}, \tag{3.6}$$

where b is the integer value, which is closest to the fuzzy controller output value St. Likewise, the membership is determined as weak, and the selected candidate assessment strategy applies the criteria weights represented by w_v when the obtained output value St satisfies the following condition:

$$w_v \; is \; true \; if \; \begin{cases} St > b + 0.25 \\ St \leq b + 0.5 \end{cases} \; or \; \begin{cases} St < b - 0.25 \\ St \geq b - 0.5 \end{cases}, \tag{3.7}$$

where b is the integer value, which is closest to the fuzzy controller output value St. Here, the four main candidate assessment strategies $ST(C, W)$ are modelled by applying the criteria presented in Table 3.12.

Table 3.12. Criteria applied to model the candidate frontier assessment strategy

Criterion	Criterion name	Optimum	Estimated variance
c_1	Length of the frontier, m.	Max	±0.6
c_2	The ratio between the number of unknown cells and the sample population size around the candidate frontier, %.	Max	±3
c_3	Distance from the robot to the candidate frontier, m.	Min	±0.3
c_4	Estimated time for reaching the candidate frontier, s.	Min	±1.2
c_5	Distance from the candidate frontier to the robot control station, m.	Max	±0.3
c_6	The estimated danger for following the computed path, units.	Min	±0.3
c_7	Estimated survivor hypothesis confirmation, %.	Min	±5

Similar to the previously discussed approach, the c_2 criterion is applied to determine if the frontier is surrounded by already explored areas or if it borders the edge of the unexplored space. However, in this strategy, the criterion value is estimated by sampling the grid map cells around the candidate frontier in the radius of 4 m with a sample population of 880. If the cell is thresholded as unknown, it is added to the sum of unknown cells, and the obtained result is divided by the sample population. As the applied WASPAS-IVNS method enables the robot to evaluate the possible inaccuracies in the input data, the considered variance of this criterion is set to ±3%.

The estimated survivor hypothesis confirmation is defined as c_7 and is an important criterion when considering autonomous environment exploration tasks in search and rescue missions. The criterion can be minimised to urge the decision-making module to choose a path to the frontier, which is near the detected hypothesised survivor. This feature can assist the rescue teams in determining if the detected object is a survivor that needs help and not a false positive. However, as human and dangerous object recognition introduces many problems that are out of the scope of this thesis, it is assumed that the robot can ideally recognise these objects when they are detected in the robot's field of view. In real-world situations, this can be achieved by recognising heat signatures to identify hot objects, such as humans (Cakmak et al., 2017), or Geiger-muller sensors to detect dangerous objects, such as radioactive substances (Zakaria et al., 2017), etc. The survivor confirmation rate is measured by the distance between the autonomous robot and the hypothesised survivor and increases (with an estimated variance of ±5%) as the robot approaches the detected object. The increase is measured by the linguistic fuzzy approach in which the distance between the robot and survivor is mapped to the percentage value. To address the specifics of neutrosophic sets, the default value of a criterion is set to a high randomised value. Later this value is switched to the exact measure whenever the survivor is detected. The 100% confirmation rate is achieved when the distance between the robot and the survivor is less than 1.5 meters (Aghababa et al., 2019).

The four distinctive frontier assessment strategies that are modelled by applying the proposed criteria set are provided in Table 3.13. The relative weights of criteria are determined by applying the SWARA method.

Table 3.13. Proposed set of candidate frontier assessment strategies

Criterion	Optimum	Candidate assessment strategy							
		DA		RRS		RS		IG	
		w_s	w_v	w_s	w_v	w_s	w_v	w_s	w_v
c_1	Max	0.15	0.14	0.08	0.09	0.10	0.10	0.12	0.12
c_2	Max	0.19	0.16	0.09	0.10	0.13	0.12	0.16	0.14
c_3	Min	0.08	0.09	0.06	0.07	0.09	0.09	0.11	0.09
c_4	Min	0.06	0.11	0.14	0.12	0.21	0.15	0.22	0.16
c_5	Max	0.05	0.07	0.05	0.20	0.05	0.07	0.25	0.21
c_6	Min	0.34	0.24	0.35	0.28	0.08	0.20	0.08	0.20
c_7	Min	0.13	0.19	0.22	0.16	0.35	0.28	0.05	0.07

It is hypothesised that the adaptive candidate assessment strategy will provide more balanced results when compared to the four individual candidate assessment strategies. As a result, the robot should evade dangerous areas while visiting detected survivors.

3.4.2. Evaluation of the Adaptive Candidate Frontier Assessment Strategy

As previously discussed, the fuzzy logic controller is the main component of the proposed adaptive environment exploration strategy, which enables the robot to select the appropriate frontier assessment strategy based on the current state of the robot and the discovered environment information. Thus, an example of robot movement trajectory when applying the proposed strategy is presented in Fig. 3.12. Here, the robot travelled path is represented by a black line. Dangerous areas are presented by the red markers. Yellow markers indicate survivors, and the white markers are the prioritised locations robot should visit. In this example, the proposed WASPAS-IVNS method is applied for the assessment of candidate frontiers.

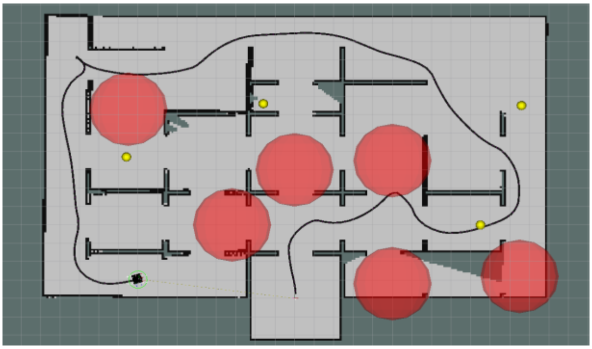


Fig. 3.12. Example of a robot movement trajectory by applying the proposed strategy and the proposed WASPAS-IVNS method. The black marker indicates the current robot position, red markers indicate dangerous areas and yellow markers indicate detected survivors (Semenas & Bausys, 2021)

The exploration process is managed by the online candidate frontier assessment and selection process, which is directly controlled by the fuzzy logic controller as schematically presented in Fig. 2.1. Considering the provided example of the robot movement trajectory, the input parameters for the fuzzy logic controller, namely, the Euclidean distance between the robot and the closest dangerous object $E(d)$, and the distance between the robot and the closest hypothesised survivor $E(s)$, are presented in Fig. 3.13.

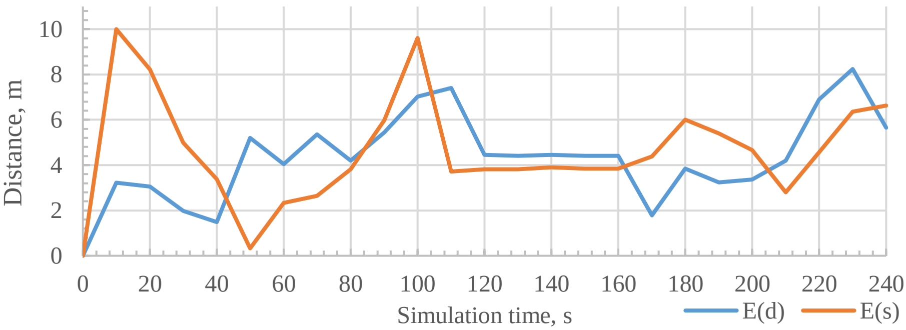


Fig. 3.13. *E(d)* and *E(s)* values over time in the considered environment exploration example

Each exploration sequence begins by applying the basic cost–benefit strategy IG that is switched to the more suitable one, depending on the output of the fuzzy logic controller. This strategy activation and de-activation process is presented in Fig. 3.14.

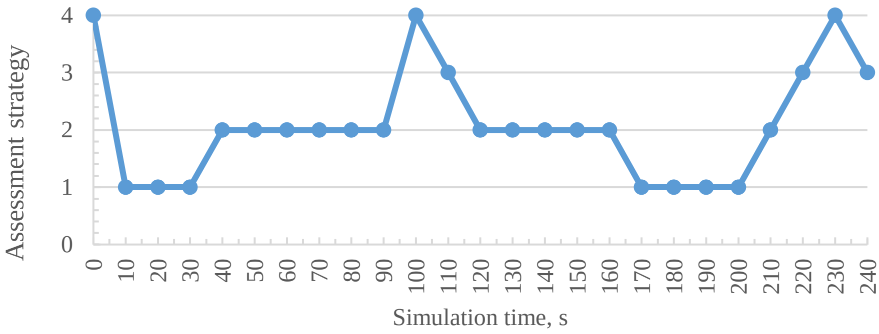


Fig. 3.14. Applied frontier assessment strategy over time. The index of 1 corresponds to the DA strategy, 2 – to the RRS strategy, 3 – to the RS strategy, and 4 – to the IG strategy

Here, "1" indicates that the danger avoidance strategy DA is applied for the assessment of candidate frontiers. Identically, the index value of "2" indicates the application of the RRS strategy, the value "3" indicates the application of the RS strategy, and the value "4" indicates the application of the IG strategy. The example shows that the proposed fuzzy logic controller allows the autonomous robot to swap between the candidate assessment strategies $ST(C, W)$ throughout the SAR mission.

The example suggests that the autonomous SAR robot that applies the proposed environment exploration strategy is actively avoiding the dangerous areas detected at the early stages of exploration. Also, the detected survivor attracts the robot to the candidate frontiers located on the right side of the simulated environment. The robot then explores nearby frontiers until the task termination conditions are met. However, in the considered example, one frontier that is located in the right-bottom area, between the two dangerous objects, was not visited during the exploration process. Although such behaviour in this situation reduces the amount of penalty received by the robot, it might also be unwanted in real-world SAR missions as the robot can ignore unsafe paths that could possibly lead to discovering more important environment features. Therefore, the autonomous robot operators should carefully consider how safely the robot should move in the environment and what are the effects of premature termination of the environment exploration process, as it may lead to situations where portions of the disaster site are not explored exhaustively.

The assessment of each strategy's performance considers the average penalty received by the robot for traversing dangerous areas and the average rates of the survivor hypothesis confirmation. Fig. 3.15 presents the results that indicate the amount of penalty received by the autonomous search and rescue robot when applying each of the proposed individual strategies (IG, RS, RRS and DA). The results obtained by applying the adaptive candidate assessment strategy are represented by FC.

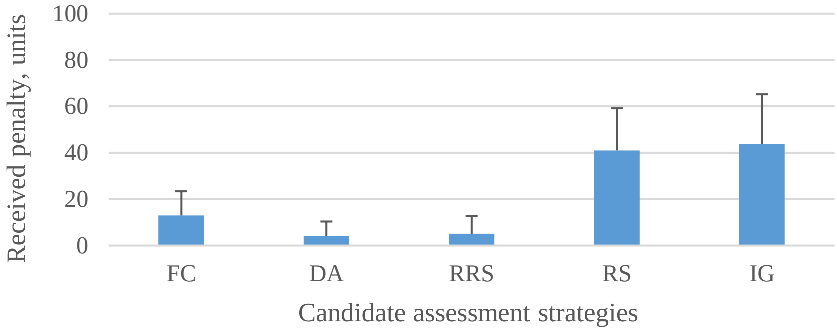


Fig. 3.15. Average penalty received by the autonomous robot when applying each candidate assessment strategy, units (Semenas & Bausys, 2021)

The considered test results indicate that the proposed adaptive environment exploration strategy (FC) shows more balanced results when compared to the four strategies that can be applied individually. For example, the FC method shows better performance when compared to the RS and IG strategies when the average of the received penalty is considered. In this case, the autonomous robot, operating by applying the proposed environment exploration strategy, reduces the received average penalty by 70%. However, the egoistic DA and RRS strategies that prioritise robot safety can reduce this average by up to 91%. The performed assessment also indicates that there is no noteworthy difference between the average percentage of survivor confirmation hypothesis (which reaches 80–83% by applying all four strategies) when comparing the proposed adaptive navigation strategy FC and the DA, RRS, RS and IG strategies.

This result can be explained by considering the topology of the simulated SAR environment. As the robot can discover all environment information within the given time interval, every survivor is detected. However, the proposed adaptive environment exploration strategy that can swap between the rules that govern the candidate assessment process actively directs the robot farther away from dangerous areas (when the DA strategy is applied) and leads it to the areas that are near the hypothesised survivors (when the RRS and RS strategies are applied). The proposed approach shows potential in providing more balanced robot behaviour when compared to the non-adaptive application of each strategy.

3.5. Generalised Autonomous Robot Navigation Strategy

As the proposed fuzzy logic controller shows potential in autonomous navigation and environment exploration tasks, the proposed strategy is further tested by developing a generalised candidate assessment strategy, which enables the evaluation of the previously proposed MCDM methods, namely, WASPAS-IVNS and WASPAS-mGqNS. The proposed autonomous navigation and environment exploration strategy is also compared to the common environment exploration strategies. The generalised environment exploration strategy for search and rescue missions is evaluated in three simulated indoor environments representing hypothetical SAR environments. The primary aims of this assessment are:

- To test the performance and stability of the proposed WASPAS-IVNS and WASPAS-mGqNS methods against the WASPAS-SVNS and MULTIMOORA-SVNS methods.
- To examine the capabilities of the proposed generalised navigation strategy in the simulated search and rescue mission and compare the results against the baseline candidate-assessment-based strategies, namely, the classical Closest Frontier (CF) strategy and the Standard Information Gain (SIG) strategy.

When applying the CF strategy, the autonomous robot evaluates the utility of the multiple candidates solitary on the estimated time needed to reach them. The SIG strategy is based on the multi-criteria decision-making approach and is derived from previously introduced candidate assessment strategies (Basilico & Amigoni, 2011; Taillandier & Stinckwich, 2011; Bausys, Cavallaro & Semenas, 2019; Visser & Slamet, 2008). The criteria and their relative weights that define the SIG strategy are presented in Table 3.14. The WASPAS-SVNS method is applied to aggregate criteria values and measures the utility of candidates when the SIG strategy is applied.

Table 3.14. Standard information gain (SIG) strategy

Criterion name	Optimum	Weight
The estimated length of the frontier.	Max	0.50
The estimated time needed to reach the candidate frontier.	Min	0.30
The estimated distance from the candidate frontier to the robot control station.	Min	0.20

Five parameters were considered to compare the proposed autonomous navigation and environment exploration strategy and the baseline candidate assessment methods. Three of them are measured on an ordinal scale: the robot travelled distance, the size of the searched area, and the amount of the received penalty for traversing dangerous areas. Two of them are measured in a ratio scale, i.e., the ratio between the robot travelled distance and the size of the searched area, and the ratio between the received penalty for traversing dangerous areas and the size of the searched area.

It is also worth noting that the autonomous robot will not necessarily display identical navigational behaviour in the same environment when considering the different simulation runs. This is due to the various robot movement imprecisions and the inaccurate environment representation model used by the robot to decide on where to move next. Therefore, each individual candidate assessment strategy is tested for a total of twenty simulation runs in a single environment, and the averaged results are considered.

3.5.1. Generalised Candidate Frontier Assessment

The key part of the proposed generalised candidate frontier assessment strategy is the adaptive decision-making approach applied to measure the utility of candidate frontiers. In this case, the utility is determined by applying one of the modelled strategies from a group of criteria and their relative weights that define different candidate assessment strategies. It is also worth noting that the proposed criteria list is not exhaustive and can be extended to include more objective-related requirements that are important when deciding on where the autonomous robot should move next.

As previously discussed, one of the possible approaches for modelling candidate assessment strategies is to embed the optimisation requirements by enabling the autonomous robot to make altruistic or egoistic decisions. This can be achieved by defining different criteria optimums and weights to the same criteria set. For example, by forcing the robot to prioritise the frontiers with the computed path that also enables the robot to reach and monitor detected survivors and minimise the robot’s priority to avoid penalties, the robot will essentially be controlled by an altruistic strategy that prioritises survivors over the safety of the robot. On the other hand, the egoistic frontier assessment strategy ensures that the robot prioritises its safety and survivability above other objectives. Therefore, in situations where the decision-making module must compare the safety of the computed path to the candidate frontiers and the ability to make contact with the survivor, the robot would prefer to select the safer alternative from the robot’s perspective.

These generalised behaviour models are not intended to exhaustively define how the robot should behave in realistic search and rescue missions but rather provide an example of how different behaviours can be modelled for candidate assessment tasks. As the author already highlighted in the previous chapters of this thesis, other frontier assessment strategies can be modelled to address the specific optimisation requirements by introducing differently modelled criteria groups and their weights.

In total, eight criteria are proposed for the frontier assessment task to model technical, social and safety requirements of search and rescue missions. The criteria set is built from the two key groups. The first group includes three criteria that were derived from the previously discussed next-best candidate assessment strategies (Basilico & Amigoni, 2011; Taillandier & Stinckwich, 2011): the amount of new information that could be obtained after reaching the candidate frontier (defined by the length of a frontier), the estimated cost of reaching the candidate frontier (defined by the estimated time needed to reach the frontier), the ability to transmit information from the candidate location to the robot control station (defined by the Euclidean distance between the robot and robot control station).

The second group includes five criteria that address the technical, safety and social aspects of search and rescue missions: the estimated penalty for following the computed path to the candidate frontier, the ratio between the free cells around the candidate frontier and the sample population, the distance from the candidate frontier to the closest priority location, the current lowest recognition rate of a hypothesised survivor near the robot-computed path to the candidate frontier, and the estimated overall recognition rate of the hypothesised survivors that could be monitored while following the computed path to the candidate frontier. The last criterion is maximised to prioritise paths that allow the autonomous robot to monitor the discovered survivors. As the physical state of the survivors can change during the search and rescue mission, it can be reasoned that the autonomous robot should prioritise paths that enable it to monitor detected survivors and provide the rescue team with the latest information about their physical condition. In the context of this thesis, the criterion value of the total recognition rate of survivors that can be monitored by following the computed path is estimated by measuring the Euclidean distance d_v from each waypoint wp_i in the robot-planned path to the known survivor locations. If $d_v < 3\,m$, it is assumed that the survivor is observable and can be monitored by the passing autonomous robot. The survivor recognition rates are summed to determine the value of a criterion. The final criteria set that defines the generalised candidate frontier assessment approach is presented in Table 3.15. The candidate frontier assessment strategies that define the adaptive environment exploration strategy are presented in Table 3.16.

Table 3.15. Criteria set for the generalised frontier assessment strategy

Criterion	Criterion name	Considered variance
c_1	The estimated length of the frontier, m.	±0.6
c_2	The estimated distance from the candidate frontier to the robot control station, m.	±0.3
c_3	The estimated time needed to reach the candidate frontier, s.	±7
c_4	The estimated penalty for following the computed path, units.	$\pm(n * 0.3)$
c_5	The total recognition rate of hypothesised survivors that could be monitored by following the computed path, %.	$\pm(n * 10)$
c_6	Current lowest hypothesised survivor recognition rate, %.	±10
c_7	Distance from the frontier to the closest priority location, m.	±0.3
c_8	The ratio between the free cells around the frontier and sample population, %.	±10

Table 3.16. Strategies that define the generalised environment exploration strategy

Criterion	Optimum	Candidate assessment strategy			
		DA	RRS	RS	IG
c_1	Max	0.056	0.029	0.043	0.213
c_2	Max	0.061	0.073	0.019	0.075
c_3	Min	0.197	0.203	0.131	0.322
c_4	Min	0.394	0.373	0.395	0.043
c_5	Min	0.037	0.039	0.065	0.033
c_6	Min	0.112	0.125	0.234	0.081
c_7	Min	0.078	0.070	0.025	0.137
c_8	Max	0.065	0.089	0.088	0.097

The generalised candidate assessment strategy is implemented into the autonomous robot decision-making module, as presented in Fig. 2.1. It is expected that the proposed strategy will provide a balanced robot movement trajectory, evading dangerous objects, visiting detected survivors and exploring around the priority areas.

3.5.2. Autonomous Robot Design

The proposed autonomous environment exploration strategy is employed by the simulated multi-purpose four-wheeled Pioneer 3-AT (P-3AT) robot platform (ROS Robots, 2020). The base parameters of the robot are set by considering the existing manual (MobileRobots Inc., 2006). The P-3AT platform is selected for its wide-ranging application in the context of academic autonomous mobile robot research, including the field of search and rescue missions. The Robot Operating System (ROS, 2020) libraries and packages are applied to set up the robot navigation stack and other essential components, including environment perception, localisation, movement and mapping modules. However, the robot navigation stack is extended by implementing the proposed generalised candidate frontier assessment strategy.

The simulated P-3AT robot is equipped with several simulated sensors that enable it to obtain environment information. The main sensor the robot uses to perceive spatial information (e.g., walls and other physical obstacles) is the Hokuyo laser range scanner sensor. This simulated sensor is mounted on the top-front part of the robot frame, enabling it to scan the environment at the 360-degree field of view at a 30-meter distance. The data obtained from this sensor is applied to build the partial map of the currently explored SAR environment. For this task, the simulated P-3AT robot applies the ROS-provided grid-map environment representation model (ROS Gmapping, 2020). In this model, the obtained spatial information is projected on a two-dimensional occupancy map, which is constructed from a set of equally-sized cells (in this thesis, the size of each cell is set to $0.1\ m^2$). In this case, each individual cell contains its estimated occupancy value, which can be thresholded as occupied (if the cell is considered to contain an obstacle), free (when the robot can traverse the cell freely) or unknown (if the corresponding search area was not yet observed by the autonomous robot). By applying this grid map model, frontier regions can be defined as the chain of connected free cells that are adjacent to the unknown cells. The centre cell of the frontier, denoted as a point $p_f(x, y)$, is considered a candidate frontier and all of the criteria values that are applied to determine the utility of the candidate are estimated according to this point.

It is also worth noting that object recognition and image analysis problems (such as survivor or dangerous object identification) pose a set of problems that are out of the scope of this thesis. Therefore, it is assumed that the simulated P-3AT robot can accurately identify and mark dangerous objects and hypothesised survivors whenever they are detected in the robots' field of view. However, in real-world situations, robots can additionally be equipped with thermal cameras or other heat sensors (Cakmak et al., 2017) and use vision-based recognition methods or other sensors and strategies for the identification of these objects.

3.5.3. Simulated SAR Environments

The simulated Pioneer-3AT robot platform, which implements the proposed candidate frontier assessment strategy, is deployed in three indoor environments, which have distinctive topology and are simulated in the Gazebo simulation software (Gazebo, 2021). These environments define clear exploration bounds for the autonomous robot. The different environment sizes and topology also provide bigger and more diverse sets of candidates that could be assessed when testing the proposed autonomous navigation strategies. Several of these environments were also tested in previously discussed results. The top-down structures of these SAR environments are presented in Fig. 3.16. Here, the blue marker represents the robot's starting location. The red markers represent dangerous areas that the robot must avoid during the navigation and environment exploration process. However, these areas must be marked on the built environment representation model for further use by the search and rescue teams. The yellow markers represent survivors that the robot should reach to enable a close-up evaluation of their physical status. The white markers represent priority locations that were set by the robot operators before the navigation process to direct the autonomous robot to the areas that are expected to provide important information for responder teams.

a) b) c)

Fig. 3.16. Simulated SAR environments: (a) the 1st environment with the 26 m by 17 m exploration space and an open topology; (b) the 2nd environment with the 32 m by 26 m exploration space and a separated area topology; (c) the 3rd environment with the 43 m by 28 m exploration space with a loop-type topology. The red markers indicate dangerous areas the robot should avoid, white markers represent priority locations, and yellow markers represent the position of survivors. The blue marker represents the robot's starting position (Semenas & Bausys, 2022)

As portrayed in Fig. 3.16, the first environment is 26 m by 17 m with dominant open spaces. This topology enables the robot to traverse exploration space without following the specific paths between the areas, meaning that the robot can cover the exploration space without the need to backtrack. Six areas are considered dangerous to the robot and, thus, should be avoided if possible. The locations of the four survivors are initially hidden from the robot's field of view. The two priority locations were set to direct the robot to the left and right sides of the map. Due to the location of the dangerous objects, it is expected that the proposed environment exploration strategy will first lead the robot to the right side of the environment.

The second environment represents the 32 m by 26 m exploration space, with multiple separated areas. This topology is expected to force the autonomous robot to apply backtracking behaviour as there is only one corridor that connects the separated areas. In this simulated exploration space, four areas are considered dangerous to the robot. The five survivor locations are initially hidden from the robot’s field of view, and the detection of three of them requires the robot to go out of its way and exhaustively explore further located parts of the environment.

The third environment represents the 43 m by 28 m disaster site with a mirrored loop-type topology. In the environments with this topology, the autonomous robot can visit multiple areas while moving between the interconnecting corridor loops. Eleven dangerous areas block multiple corridors, and seven survivors are distributed throughout the environment. In this scenario, it is expected that the autonomous robot will prioritise safe paths but will not avoid traversing dangerous areas if such a decision will enable the autonomous robot to monitor or reach detected survivors.

To simplify the simulations, it is assumed that the survivors do not change their positions and the dangerous areas do not expand. Also, several additional assumptions are made:

1. It is assumed that the robot operators have limited information that allows them to set the coordinates of priority locations that the robot should visit. However, no additional information about the current state of the environment is known to the autonomous robot or its operator in advance, meaning that the set location might be unreachable during the SAR mission. Hence, this information must be discovered by the autonomous robot at runtime.
2. No additional moving objects that could damage the robot are present in the environment. The robot’s field of view is also unobstructed by vision-obscuring objects or events, e.g., smoke, which can be a common issue considering the real-world search and rescue missions (Marjovi, Marques & Penders, 2009).
3. The autonomous robot must cancel its current task and reach the detected hypothesised survivor if it is nearby. The survivor is considered successfully reached, and its status can be evaluated when the distance between the survivor and the current robot position is less than 1.5 m (Aghababa et al., 2019).
4. The autonomous robot must also cancel its current task and reach the prioritised location if it is nearby. The prioritised location is considered successfully visited when the distance between it and the current robot position is less than 1.5 m. If there are two unvisited objects near the

exploring robot, specifically, the hypothesised survivor and the prioritised location, the robot will always prioritise the closest survivor.

5. The autonomous robot can change its navigation goal if a higher-valued candidate is detected while moving to the previously selected frontier. However, such decisions are made at constant simulation-time intervals to minimise the computational load on the robot decision-making module and reduce the likelihood of indecisive robot behaviour when several similar-valued frontiers are detected.
6. The autonomous robot continues the environment exploration process until one of the mission termination conditions is met. Specifically, if either the 10-minute simulation-time limit has passed or the robot has visited all of the priority locations set by the robot operators.

The final step in the proposed generalised autonomous navigation and environment exploration strategy is the assessment of candidate frontiers. However, as was previously discussed, there is a lack of flexible MCDM methods that allow assessing the inaccurate input data characteristics. This is a prominent issue, considering that inaccuracies can have a notable influence on the quality of the multi-criteria decision-making process and, consequently, on the proposed autonomous navigation strategy. Therefore, the proposed WASPAS-IVNS and WASPAS-mGqNS methods are applied and compared to the WASPAS-SVNS method to determine their computational stability and ability to consider the inaccurate input data characteristics.

3.5.4. Assessment of the WASPAS-IVNS and WASPAS-mGqNS Methods

The proposed WASPAS method extensions modelled under the interval-valued neutrosophic set and the m-generalised q-neutrosophic set enable the autonomous robot to consider the uncertainty of the input data characteristics. Thus, the performance of the proposed neutrosophic WASPAS method extensions, namely WASPAS-IVNS and WASPAS-mGqNS, are compared to the state-of-the-art neutrosophic WASPAS-SVNS and MULTIMOORA-SVNS (Stanujkic et al., 2017) methods.

The proposed method extensions are expected to introduce minor improvements and slight autonomous robot performance differences when comparing the previously discussed parameters of the average size of the area searched by the autonomous robot, the average penalty received by the autonomous robot for moving through the dangerous areas, and the average distance travelled by the autonomous robot. In other words, the result variations obtained between the three MCDM methods in the three simulated environments are expected to be generally insignificant, irrespective of the increased or diminished robot performance. The averaged simulation results obtained by evaluating the three MCDM methods are presented in Table 3.17.

Table 3.17. Average results obtained in the three simulated environments. The considered parameters: the area size searched by the robot, the received penalty for moving through dangerous areas, and the distance travelled by the robot

Environment	Method	Searched area, m^2	Penalty, units	Distance, m
1st	WASPAS-SVNS	367	5.47	66.11
	WASPAS-IVNS	367	7.20	68.92
	WASPAS-mGqNS	367	5.85	70.36
	MULTIMOORA-SVNS	366	7.49	67.23
2nd	WASPAS-SVNS	556	4.73	149.41
	WASPAS-IVNS	562	8.85	147.67
	WASPAS-mGqNS	557	6.03	151.14
	MULTIMOORA-SVNS	564	19.67	160.61
3rd	WASPAS-SVNS	643	14.47	137.03
	WASPAS-IVNS	644	11.70	130.94
	WASPAS-mGqNS	639	5.36	128.03
	MULTIMOORA-SVNS	628	33.54	131.63

Considering the results obtained in the simulated environments, it is observed that the autonomous robot applying the proposed WASPAS-IVNS and WASPAS-MGQNS multi-criteria decision-making methods provides similar results to the ones that uses the state-of-the-art WASPAS-SVNS and MULTIMOORA-SVNS methods.

When the developed WASPAS-IVNS and WASPAS-mGqNS methods are applied in the first simulated environment, the robot searches an almost identical sized area between the assessed multi-criteria decision-making methods. Also, in this environment, the autonomous search and rescue robot travelled a nearly identical distance (with a 4–6% increase between the average results). When the proposed WASPAS-IVNS and WASPAS-mGqNS methods were applied in the second simulated environment, the size of the searched area was increased by 0.3–1%, and the average distance travelled by the robot fluctuated from a 1% decrease to a 1% increase in value. When applying the proposed WASPAS-IVNS and WASPAS-mGqNS methods in the third environment, the autonomous robot travelled by up to 4.5–6.5% less distance when compared to the one that applied the WASPAS-SVNS method. However, the size of the searched area fluctuates up to less than 1% between the WASPAS-SVNS and the proposed WASPAS-IVNS and WASPAS-mGqNS methods.

As average results indicate similar navigational behaviour when applying the considered MCDM methods, the ANOVA test was performed to evaluate the significance of the observed variations between MULTIMOORA-SVNS, WASPAS-SVNS, WASPAS-IVNS and WASPAS-mGqNS. The obtained *p* values with a considered threshold of 0.05 indicate that there is no statistical significance between the averaged results of the size of the area searched by the autonomous robot. Also, there is no statistical significance between the distance travelled by the robot when applying WASPAS-SVNS, WASPAS-IVNS and the WASPAS-mGqNS methods. These results are stable in all three simulated environments.

When the proposed WASPAS-IVNS and WASPAS-mGqNS methods are compared to the state-of-the-art neutrosophic MULTIMOORA-SVNS method, the slight variations in the average distance travelled by the autonomous robot are observed. In the first simulated environment, the value of this parameter is increased by up to 4.6% when the WASPAS-mGqNS method is applied and by up to 2.5% when the WASPAS-IVNS is applied. A decrease of 3% is observed in the third simulated environment, and a decrease of up to 8% is observed in the second environment. However, the increase in the distance travelled by the autonomous robot does not notably affect the size of the searched area. A slight value increase of 0.2–2.6% can be observed in the first and third environments, as well as a reduction of up to 1% in the second environment. However, the observed variation is statistically insignificant in all simulated environments (with p values > 0.05).

Considering the average amount of penalty received by the autonomous robot for moving through the dangerous areas, the proposed WASPAS-IVNS and WASPAS-mGqNS methods show notable performance improvements in the second and third simulated environments when compared to the MULTIMOORA-SVNS method. These results indicate that the proposed WASPAS method extensions could be more suitable for candidate assessment tasks in autonomous search and rescue missions as they provide additional reliability when balancing between the set optimisation priorities. Considering the averaged results between the assessed MCDM methods, it could also be reasoned that when applied in environments with different spatial topologies, the proposed neutrosophic WASPAS-IVNS and WASPAS-mGqNS methods can provide as stable results as the WASPAS-SVNS method. The proposed extensions also allow the autonomous robot to consider the inaccurate input data characteristics that can be present due to the inaccurate sensor readings, imprecise environment model built by the exploring robot, and other errors in the criteria assessment process. Consequently, this ability can have a visible impact on the robot's long-term performance as it enables the autonomous robot to occasionally make better decisions when measuring the utility of similar candidates.

This ability is also highlighted by providing a computational example of the candidate frontier assessment problem presented in Fig. 3.17. In this example, the frontiers are presented by the blue chains of the connected grid map cells that are located between the known and the unknown exploration space. The green markers represent the candidate frontiers $p_f(x,y)_i$. The white markers represent the priority locations set by the robot operators. The red markers indicate dangerous areas the robot should avoid. The yellow markers represent the detected survivors. The autonomous robot is located at the position marked by a black marker, and the black line indicates the robot's movement trajectory.

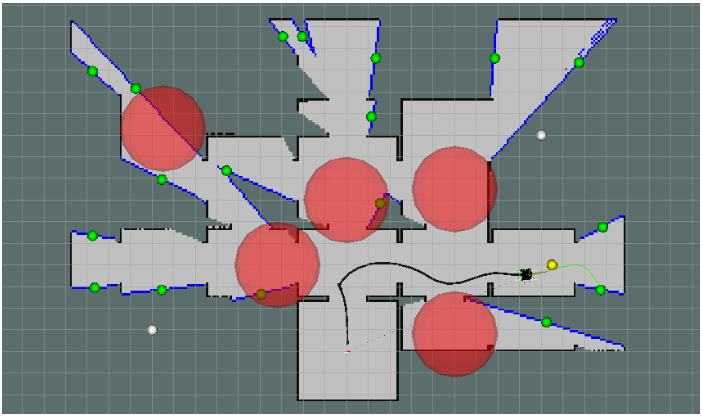


Fig. 3.17. Candidate frontier assessment problem. Frontier regions are defined by the blue lines, and the candidate frontiers $p_f(x,y)_i$ are marked by green markers. The white markers represent priority locations that should be visited by the robot. The red markers represent dangerous areas. The yellow marker represents the detected survivor (Semenas & Bausys, 2022)

In this example, the autonomous robot decision-making module has to assess 18 candidate frontiers and select the one with the highest utility. This frontier will then become the next spatial goal for the robot. In the current state of the environment exploration task, the autonomous robot is located near the detected survivor and is near the dangerous areas, meaning that the adaptive fuzzy logic controller will instruct the decision-making module to apply the RRS strategy for the candidate assessment task. Also, the prioritised location set by the robot operator is situated on the right side of the simulated environment. As the autonomous robot is expected to explore and map the area around the detected survivor, avoid the dangerous areas, and also reach the prioritised location, it is predicted that the robot will choose the candidate that allows it to get closer to the prioritised location.

The initial decision matrix that is constructed for the considered decision-making problem is presented in Table 3.18. In this instance, the autonomous robot is located very close to the detected survivor, and no other survivors are visible, meaning that there are no survivors that could be actively considered for the monitoring task. Therefore, in this specific candidate assessment example, the c_5 and c_6 criteria have no significant influence on the decision-making process. However, to address some specifics of the neutrosophic number normalisation, and avoid undecisive robot behaviour, the c_5 criterion value is set to a small positive constant, and the c_6 criterion value is set to a high randomised value.

Table 3.18. Initial decision matrix for the candidate frontier assessment problem

Candidate frontier	Criterion							
	c_1	c_2	c_3	c_4	c_5	c_6	c_7	c_8
$p_f(x,y)_1$	2.1	12.09	14.69	0.001	0.001	327.0	7.66	0.14
$p_f(x,y)_2$	2.0	13.17	20.49	0.001	0.001	423.3	5.12	0.28
$p_f(x,y)_3$	7.2	9.35	36.78	80.32	0.001	446.9	8.65	0.06
$p_f(x,y)_4$	8.8	17.14	50.12	111.1	0.001	494.9	3.78	0.57
$p_f(x,y)_5$	2.1	7.02	29.39	90.39	0.001	207.6	8.09	0.16
$p_f(x,y)_6$	3.5	15.18	43.72	111.1	0.001	324.1	4.15	0.50
$p_f(x,y)_7$	2.8	4.76	38.27	107.5	0.001	363.7	5.31	0.53
$p_f(x,y)_8$	1.5	10.91	47.15	91.15	0.001	298.8	7.89	0.01
$p_f(x,y)_9$	6.3	10.03	48.87	175.27	0.001	452.9	8.12	0.08
$p_f(x,y)_{10}$	3.8	9.01	50.78	135.26	0.001	389.1	1.90	0.51
$p_f(x,y)_{11}$	3.5	13.62	51.67	90.72	0.001	326.7	8.43	0.53
$p_f(x,y)_{12}$	3.9	11.68	58.89	128.5	0.001	204.3	6.96	0.51
$p_f(x,y)_{13}$	2.1	12.02	59.87	135.3	0.001	375.5	3.29	0.14
$p_f(x,y)_{14}$	3.1	14.69	53.34	91.08	0.001	468.9	11.95	0.46
$p_f(x,y)_{15}$	2.0	12.91	63.38	135.3	0.001	360.5	5.15	0.27
$p_f(x,y)_{16}$	6.3	15.58	75.24	258.8	0.001	280.2	11.18	0.15
$p_f(x,y)_{17}$	1.5	14.85	58.78	91.12	0.001	487.1	12.79	0.36
$p_f(x,y)_{18}$	2.2	17.49	89.78	258.6	0.001	410.1	12.26	0.62

After the initial decision matrix is computed, the criteria values are normalised and transformed to the neutrosophic numbers by applying the previously discussed methods. Then, the first and the second WASPAS objectives are computed for WASPAS-SVNS, WASPAS-IVNS and WASPAS-mGqNS methods. Then, the utility of each candidate frontier is measured and ranked by applying WASPAS-SVNS, WASPAS-IVNS and WASPAS-mGqNS score functions, introduced in the second chapter of this thesis. The candidate frontier with the highest utility is then chosen as the next goal for an autonomous SAR robot. The results of this step are presented in Table 3.19.

Table 3.19. Utility scores of the candidate frontiers

Candidate frontier	WASPAS-SVNS		WASPAS-IVNS		WASPAS-mGqNS	
	Score	Rank	Score	Rank	Score	Rank
$p_f(x,y)_1$	0.839	1	[2.467, 2.636]	2	0.711	1
$p_f(x,y)_2$	0.838	2	[2.492, 2.620]	1	0.707	2
$p_f(x,y)_3$	0.743	9	[2.181, 2.494]	11	0.607	6
$p_f(x,y)_4$	0.763	5	[2.354, 2.507]	6	0.604	7–8
$p_f(x,y)_5$	0.766	4	[2.325, 2.558]	4	0.632	3
$p_f(x,y)_6$	0.761	6	[2.352, 2.513]	5	0.609	5
$p_f(x,y)_7$	0.775	3	[2.384, 2.539]	3	0.623	4
$p_f(x,y)_8$	0.691	14	[2.119, 2.438]	15	0.586	12
$p_f(x,y)_9$	0.676	16	[2.049, 2.400]	16	0.558	16
$p_f(x,y)_{10}$	0.746	8	[2.338, 2.493]	8	0.598	9
$p_f(x,y)_{11}$	0.754	7	[2.331, 2.513]	7	0.604	7–8
$p_f(x,y)_{12}$	0.737	10	[2.321, 2.487]	9	0.590	10
$p_f(x,y)_{13}$	0.689	15	[2.174, 2.397]	14	0.568	14
$p_f(x,y)_{14}$	0.729	11	[2.278, 2.465]	10	0.587	11
$p_f(x,y)_{15}$	0.692	13	[2.219, 2.402]	13	0.566	15
$p_f(x,y)_{16}$	0.598	17	[2.057, 2.312]	17	0.522	17
$p_f(x,y)_{17}$	0.700	12	[2.208, 2.414]	12	0.572	13
$p_f(x,y)_{18}$	0.581	18	[2.068, 2.288]	18	0.516	18

When applying the WASPAS-SVNS and WASPAS-mGqNS methods, the candidate frontier $p_f(x,y)_1$ is considered to be the highest-valued frontier and the next goal the robot should reach. However, when the candidate is evaluated by applying the WASPAS-IVNS method, the frontier $p_f(x,y)_2$ is chosen as the next goal the robot should reach. A similar switch between the computed utility values is also observed when considering the frontiers ranked as the third- and the fourth-best candidate. This candidate assessment example showcases how the proposed WASPAS method extensions can address the issue of the inaccurate input data and, thus, make better assessments throughout the SAR environment exploration task when multiple similar candidates are present.

3.5.5. Comparison to the Baseline Strategies

The proposed generalised candidate assessment strategy, which applies the fuzzy logic controller and the proposed WASPAS-IVNS or WASPAS-mGqNS methods for measuring the utility of a candidate frontier, is compared to the two commonly applied strategies: the Closest Frontier strategy (CF) and the previously discussed standard information-gain strategy (SIG). It is hypothesised that the proposed generalised strategy will significantly increase the robot's performance when considering the size of the searched area, the distance travelled by the robot and the penalty received by the robot for traversing dangerous areas. To test this hypothesis, the examined strategies are applied in autonomous environment exploration tasks within the previously discussed simulated environments, and the averaged results are presented in Table 3.20.

Table 3.20. Averaged test results by the proposed environment exploration strategy when applying WASPAS-IVNS or WASPAS-mGqNS methods and the CF, SIG strategies

Environment	Method	Searched area, m^2	Penalty, units	Distance, m
1st	WASPAS-IVNS	367	7.20	68.92
	WASPAS-mGqNS	367	5.85	70.36
	SIG	360	57.32	77.18
	CF	365	55.72	77.84
2nd	WASPAS-IVNS	562	8.85	147.67
	WASPAS-mGqNS	557	6.03	151.14
	SIG	498	52.68	142.33
	CF	509	60.07	124.97
3rd	WASPAS-IVNS	644	11.70	130.94
	WASPAS-mGqNS	639	5.36	128.03
	SIG	569	95.74	113.30
	CF	521	93.18	97.98

When comparing the proposed adaptive generalised candidate assessment strategy that applies WASPAS-IVNS to the CF and SIG strategies, the discovered information in the first environment is increased by 1.8% and 0.5%, respectively. When comparing the proposed strategy that applies the WASPAS-mGqNS method to the SIG and CF strategies, the size of the searched area is increased by 1.8% and 0.5%. Such similar results can be explained by considering the topology of a simulated search and rescue space and the theoretical aspects of the frontier-based environment exploration strategy. As the simulated environment is relatively small and has an open topology, the autonomous robot can discover its spatial characteristics by visiting every available frontier within the set time limit of ten minutes. Therefore, in this type of environment, the ability to balance multiple optimisation priorities could be considered the most important performance evaluation metric of the proposed candidate-assessment-based autonomous navigation and environment exploration strategy.

When comparing the results of the proposed adaptive generalised strategy that applies the WASPAS-IVNS method to the results of the SIG and CF strategies, the penalty for traversing dangerous areas is reduced by 87.4% and 87.1%, respectively. This average is reduced by 89.8% and 89.5% when comparing the proposed strategy that applies the WASPAS-mGqNS method to the SIG and CF strategies, respectively.

When comparing the proposed environment exploration strategy, the robot travel distance in this environment is reduced from a minimum of 8.84% to a maximum of 11.5%. However, it is worth noting that this improvement strongly depends on the position of dangerous areas and the topology of the environment. In the considered SAR environment, the autonomous robot can reach most areas without backtracking, and this can significantly reduce the average distance travelled by the autonomous robot.

The increase in the average distance travelled by the autonomous search and rescue robot is also observed in the second simulated environment. As the considered exploration space is divided into multiple regions that are connected by a single corridor, the autonomous robot must backtrack to the previously discovered areas to reach the frontiers skipped in the early stages of environment exploration. Therefore, the total distance travelled by the autonomous robot is expected to increase when applying the proposed generalised candidate-assessment-based strategy. When comparing the results obtained by the proposed environment exploration strategy that applies the WASPAS-IVNS method to the results obtained by the SIG and CF strategies, the distance travelled by the robot is increased by 3.8% and 18.2%. When the results of the proposed adaptive strategy that applies WASPAS-mGqNS are compared to the results of the SIG and CF strategies, an increase of 6.2% and 21% is observed.

The average, minimum and maximum values of the area size searched in the second environment are presented in Fig. 3.18. The obtained results indicate that the maximum value obtained by applying the SIG strategy is somewhat above the average obtained by the proposed environment exploration strategy when applying the WASPAS-mGqNS method. However, the minimum size of the searched area by the proposed strategy when applying WASPAS-IVNS is above the average obtained by applying the baseline SIG strategy. In general, when the proposed generalised candidate-assessment-based navigation strategy is applied, the average size of the area searched by the autonomous robot is increased by a minimum of 9.5% and a maximum of 12.7%. These results highlight that the performance of the autonomous search and rescue robot is increased when applying the proposed navigation strategy.

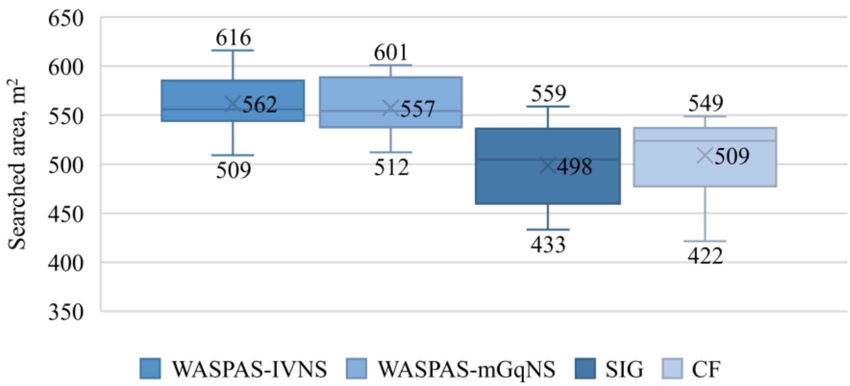


Fig. 3.18. Size of the searched area in the second environment, m^2

Considering the results presented in Fig. 3.19, it can be reasoned that the SIG and CF strategies display less stable navigational behaviour when compared to the proposed generalised adaptive environment exploration strategy. When comparing the results, the penalty received by the autonomous robot for crossing dangerous areas in the three simulated SAR environments is reduced by 83.2% and 85.3% when applying the WASPAS-IVNS method and by 88.6% and 89.9% when applying the WASPAS-mGqNS method. It can also be observed that the CF strategy is the least stable when considering the robot received penalty and provides the worst results among the examined methods. As the robot will always be directed to the closest frontier, small inaccuracies in the input data characteristics may lead to situations where between the different simulation runs, the robot movement trajectory is significantly different. This, in turn, can lead the autonomous robot into dangerous areas, forcing it to stay in a dangerous situation for unspecified periods of time.

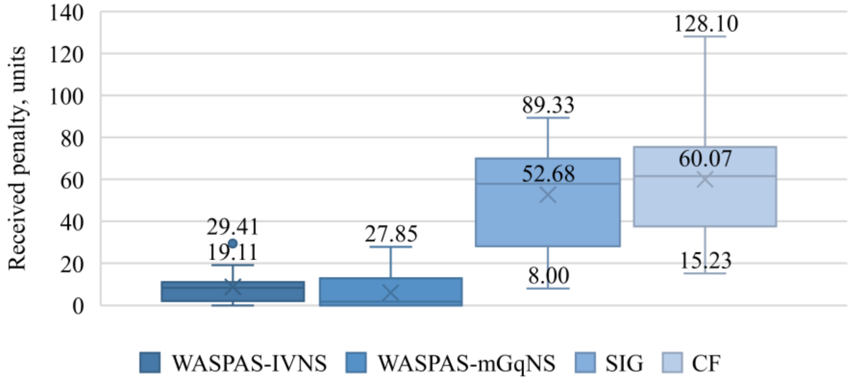


Fig. 3.19. Penalty received in the second environment, units

The results presented in Fig. 3.20 indicate that the average size of the searched area is increased when applying the proposed generalised strategy. Although the maximum size of the searched area when applying the CF and SIG strategies is close to the average presented by the proposed generalised strategy, these baseline methods show performance issues when considering the average of the multiple simulation runs. When comparing the results of the proposed environment exploration strategy to the results of the SIG and CF strategies, the amount of the discovered information is increased by 13.2–23.6% when applying the WASPAS-IVNS method and 12.3–22.6% when applying the WASPAS-mGqNS. This increase is also observable when considering the results obtained in other simulated environments, indicating that the robot performance is increased when the proposed generalised strategy is applied.

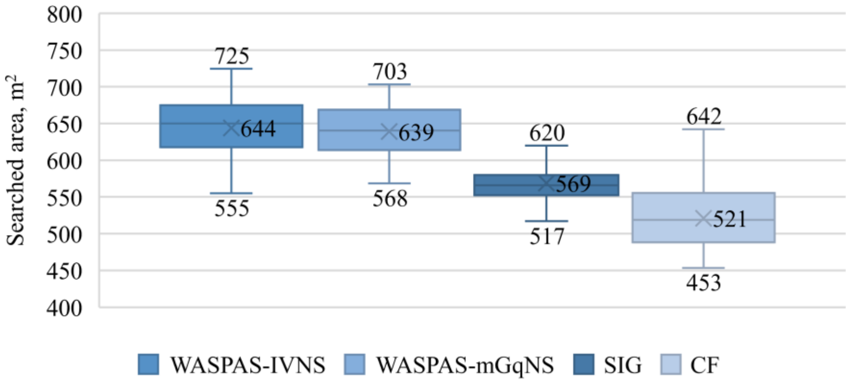


Fig. 3.20. Size of the searched area in the third environment, m^2

Considering the results presented in Fig. 3.21, the SIG and CF strategies display similar stability issues as in the other simulated environments. It can be reasoned that the baseline strategies are more sensitive to the inaccurate input data characteristics that are used by the autonomous robot decision-making module. This sensitivity can reduce the stability of the baseline methods, resulting in different navigational behaviour between the multiple simulation runs.

This issue is most noticeable when considering the average amount of penalty received by the autonomous robot for crossing dangerous areas. When comparing the results of the proposed environment exploration strategy to the results of the baseline SIG and CF strategies, a decrease of 87.8–87.4% and 94.4–94.3% is observed when the WASPAS-IVNS and WASPAS-mGqNS methods are applied, respectively.

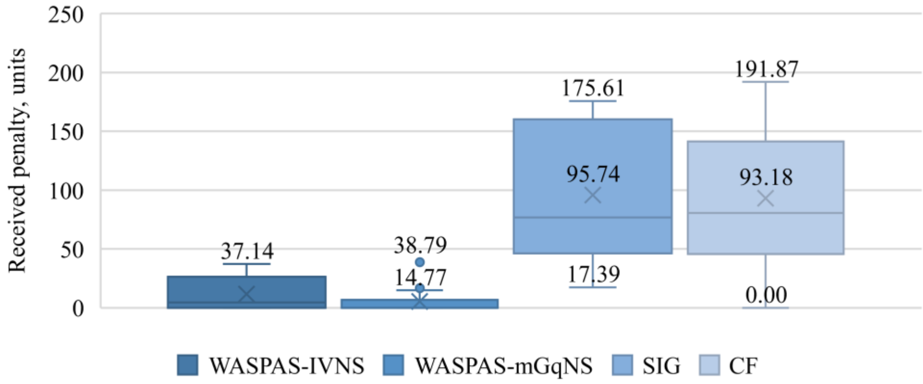


Fig. 3.21. Penalty received in the third environment, units

The obtained results provide that the autonomous robot performance is improved in all simulated environments when the proposed generalised autonomous navigation and environment exploration strategy is applied. However, it could be argued that the proposed strategy also increases the average distance travelled by the robot. For example, when comparing the results of the proposed environment exploration strategy to the results of the SIG and CF strategies, the average distance travelled by the robot was increased by 15.6–33.6% when the WASPAS-IVNS method was applied and by 13–30.7% when the WASPAS-mGqNS method was applied to deciding on where the robot should move next. Therefore, to determine the significance of the obtained results, the ANOVA statistical analysis test is performed. The p values were obtained when comparing the SIG and CF strategies to the proposed generalised autonomous navigation and environment exploration strategy. The considered threshold in this analysis is 0.05.

The test results allow maintaining that the increase in the average size of the area searched by the robot and the reduction in the distance travelled by the robot are equally statistically significant when the proposed generalised strategy is compared to the CF and SIG strategies in the second and third simulated environments (with p values < 0.05). The increase in the average distance travelled by the autonomous robot is also significant in the second and third simulated environments (with p values < 0.05) when the proposed strategy is compared to the CF. Also, improvements are statistically significant in the third simulated environment when compared to the SIG.

However, considering the experiment results, there is no notable increase in the robot's performance in the first environment. This lack of considerable performance improvements by the proposed autonomous navigation strategy when compared to CF and SIG strategies can be explained by considering the size and topology of the environment. As such result was achieved due to the small size of the first environment, which generally means that the list of candidates that is generated by the autonomous robot will also be small. Therefore, the autonomous robot is observing similar information during the navigation process and is computing similar lists of candidates that, if visited, will eventually lead the robot to all key areas. Thus, an almost identical amount of information is discovered, and similar distances are travelled by all the assessed autonomous navigation strategies.

However, in larger environments with multiple separated corridors and rooms (such as the second and third simulated environments), the autonomous robot movement trajectories start to differ from SIG and CF strategies, as the proposed generalised candidate assessment strategy is leading the robot to more valuable frontiers that are near the attraction zones, such as prioritised locations or detected survivors. It is also worth noting that this improvement can be considered dependable on the physical structure of the search and rescue environment and the position of the attraction zones and objects. Therefore, the proposed optimisation short-term decision-making could actually lead the autonomous robot to the dead-ends or dangerous areas, requiring the robot to backtrack. Nevertheless, the ability to balance competing criteria is an important factor of the proposed autonomous navigation strategy, which shows the potential of increasing the autonomous robot performance in environment exploration tasks.

To determine if the proposed generalised strategy is balancing between the optimisation priorities and the increased distance that is travelled by the autonomous robot is not significant, two additional parameters are taken into consideration. Namely, the ratio between the distance travelled by the robot and the size of the searched area and the ratio between the received penalty for crossing dangerous areas and the size of the searched area. These ratios are presented in Table 3.21.

Table 3.21. Averaged relative results obtained in the three simulated environments

Environment	Method	Distance / Searched area	Penalty / Searched area
1st	WASPAS-IVNS	0.19	0.02
	WASPAS-mGqNS	0.19	0.02
	SIG	0.21	0.16
	CF	0.21	0.15
2nd	WASPAS-IVNS	0.26	0.02
	WASPAS-mGqNS	0.27	0.01
	SIG	0.29	0.11
	CF	0.25	0.12
3rd	WASPAS-IVNS	0.20	0.02
	WASPAS-mGqNS	0.20	0.01
	SIG	0.20	0.17
	CF	0.19	0.18

The average results indicate that the penalty received by the autonomous robot for each travelled meter can be reduced from 85% by up to 90% when the autonomous robot applies the proposed generalised strategy. This performance improvement is notable in all the simulated environments. However, when considering the ratio between the distance travelled by the robot and the size of the searched area, this value is decreased by up to 12% in the first environment and increased by up to 9% and by up to 7% in the second and third simulated environments, respectively. The obtained results suggest that the application of the proposed adaptive navigation and environment exploration strategy can notably reduce the average of the robot received penalty relative to the distance travelled by the autonomous robot. Also, when the results of the proposed generalised strategy are compared to the results obtained by applying the SIG strategy, the increased average of the distance travelled in the third environment is not significant as the robot discovers more environment information.

The test results confirm that the proposed adaptive generalised autonomous navigation and environment exploration strategy can significantly increase the autonomous robot’s performance when compared to the baseline CF and SIG strategies. The robot’s ability to avoid danger while also increasing the size of the searched area is a significant feature that can be employed in search and rescue missions. However, it is worth noting that the results obtained by the online strategies strongly depend on the geometrical features of the exploration space and the positions of task-related objects that attract or push away the autonomous robot. For example, if the corridors or areas are blocked by dangerous objects, the robot will try to protect itself and choose to explore around the frontiers that are considered to be safer from the robot's viewpoint. However, such decisions may lead the autonomous robot to the dead-ends (as in the second environment, the top-left corridor) that require the robot to move back to the previously discovered locations, reducing the performance of the autonomous robot in the long run.

3.6. Conclusions of Chapter 3

Considering the results obtained by testing the proposed environment exploration strategies and WASPAS method extensions, the following conclusions can be drawn:

1. Introduction of non-standard cost–benefit criteria for a candidate assessment task shows the potential of increasing the robots' performance in SAR missions. By introducing safety requirements into the candidate assessment process, the autonomous robot is capable of avoiding dangerous objects present in its field of view without additional movement rules.
2. The developed WASPAS-IVNS method allows considering the issue of inaccurate input data characteristics when deciding on where the robot should move next. This improvement shows potential when the numerical criteria value differences are minimal between the two candidates.
3. The introduction of the area prioritisation criterion and the assessment of the occupancy around the candidate frontier show potential in enabling the robot to increase the size of the searched area (when compared to the direct control approach) while also reducing the distance travelled by the robot (when compared to the greedy cost–benefit frontier assessment strategy.
4. The introduction of the fuzzy logic controller enables the SAR robot to switch between the rules that govern the candidate assessment process. The development of four distinctive candidate assessment strategies highlights that different robot behaviour patterns (e.g., altruistic or egoistic) can be modelled and applied in SAR missions. The strategies that are modelled to prioritise the danger avoidance (egoistic) decrease the robot received penalty by up to 91% when compared to the ones that direct the robot to the detected survivors (altruistic). However, the adaptive strategy is capable of balancing between the egoistic and altruistic behaviours and thus receives 70% less penalty when compared to the altruistic ones.
5. The proposed neutrosophic WASPAS-IVNS and WASPAS-mGqNS methods show computational stability when compared to the WASPAS-SVNS and MULTIMOORA-SVNS methods. By applying the proposed candidate

frontier assessment strategy, a generally insignificant robot performance increase is observed, highlighting that the ability to deal with the inaccuracies in the input data characteristics enables the robot to make slightly better decisions which can have a long-term impact on the robot's performance in larger SAR environments.

6. When compared to the SIG and CF strategies, the proposed adaptive generalised autonomous navigation and environment exploration strategy that applies the proposed distinctive candidate assessment strategies and the WASPAS-IVNS and WASPAS-mGqNS methods provide notable improvements to the autonomous robot performance:
   6.1. When compared to the SIG strategy, the proposed generalised environment exploration strategy increases the average size of the searched area by up to 1.8%, 12.7% and 13.2% when applying the WASPAS-IVNS method, and up to 1.8%, 11.8% and 12.3% when applying the WASPAS-mGqNS method. The increase is significant in the second and third environments at the p values < 0.05.
   6.2. When compared to the CF strategy, the proposed generalised environment exploration strategy increases the average size of the searched area by up to 0.5%, 10.4% and 23.6% when applying the WASPAS-IVNS method, and by up to 0.5%, 9.5% and 22.6% when applying the WASPAS-mGqNS method. The increase is significant in the second and third environments at the p values < 0.05.
   6.3. Comparing the proposed generalised environment exploration strategy to the baseline SIG and CF strategies, the penalty received by the robot for crossing dangerous areas decreased by up to 87.1–89.8%, 83.2–98.9% and 87.4–94.4%.
   6.4. The increase in the distance travelled by the autonomous robot by up to 3.8–21% and 15.6–33.6% is observed in the second and third environments, respectively. However, considering the ratio between the distance travelled by the autonomous robot and the average size of the searched area, this increase is only noteworthy when compared to the CF strategy.

General Conclusions

1. The review of commonly applied online next-best-view environment exploration strategies, which measure the utility of each candidate goal by considering the given optimisation priorities, failed to address the inaccurate input data characteristics when deciding on where the robot should move next. Moreover, the applied candidate assessment strategies are commonly based on a non-adaptive approach that applies identical candidate assessment rules, disregarding the current state of the robot and the discovered environment information.
2. Extension of the candidate assessment strategy by non-standard cost–benefit criteria, namely the safety and social requirements of SAR missions, shows the potential of increasing robots' performance in SAR missions. Also, the introduction of area prioritisation and the assessment of the occupancy around the candidate frontier indicate the increased robot performance when compared to the standard cost–benefit strategies.
3. The developed adaptive autonomous navigation strategy that combines fuzzy logic controller with the proposed MCDM methods enables the SAR robot to switch between the strategies that govern the candidate assessment process in the environment exploration task, depending on the dynamic environment information. The proposed adaptive approach, which applies modern neutrosophic sets in the decision-making process, optimises the robot

navigation trajectories and increases the robot performance when compared to the non-adaptive application of the proposed individual egoistic, altruistic and impartial information gain strategies. The adaptive approach enables the robot to avoid dangerous areas and reduce the received penalty by up to 70% when compared to the altruistic strategies and the strategies that prioritise information gain. However, purely egoistic candidate assessment strategies can reduce the penalty received by the robot by up to 91%.

4. The developed WASPAS extensions modelled under the interval-valued neutrosophic set environment (WASPAS-IVNS) and the q-neutrosophic m-generalised environment (WASPAS-mGqNS) allow considering the inaccurate input data characteristics when deciding on where the robot should move next. This improvement shows potential when the numerical criteria value differences are slight between the two assessed candidates. The comparison between the proposed WASPAS-IVNS, WASPAS-mGqNS and the state-of-the-art WASPAS-SVNS and MULTIMOORA-SVNS methods indicates the computational stability of the proposed MCDM method extensions.
5. The proposed adaptive generalised autonomous navigation and environment exploration strategy introduce a notable performance increase when compared to the Closest Frontier (CF) and the Standard Information Gain (SIG) strategies:
   - 5.1. The quantitative comparison of the proposed generalised environment exploration strategy performance regarding the size of the searched area in the second and third exploration space shows an increase in the parameter value of up to 12.7–13.2% when considering the SIG strategy and up to 10.4–23.6% when considering the CF strategy.
   - 5.2. The quantitative comparison of the proposed generalised environment exploration strategy performance regarding the robot obtained penalty for traversing the dangerous areas shows a decrease in the parameter value of up to 94.4%. The highlighted performance is stable across the simulated environments.
   - 5.3. The increase in the distance travelled by the robot when applying the proposed generalised environment exploration strategy depends on the topology of the exploration space and the location of dangerous areas. Although the parameter value is increased by up to 33.6%, considering the ratio between the robot travel distance and the size of the searched area, the increase of the distance travelled by the robot more often increases the amount of obtained environment information.

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List of Scientific Publications by the Author on the Topic of the Dissertation

Papers in the Reviewed Scientific Journals

Bausys, R., Cavallaro, F., Semenas, R. (2019). Application of sustainability principles for harsh environment exploration by autonomous robot. *Sustainability*, *11*(9), 2518. [Science Citation Index Expanded (Web of Science)], [Index: 3,251 (2020, InCites JCR SCIE)], DOI: 10.3390/su11092518

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Summary in Lithuanian

Įvadas

Problemos formulavimas

Autonominių robotų naudojimas paieškos ir gelbėjimo operacijose gali padidinti gelbėjimo komandų efektyvumą ir saugumą, nes autonominės sistemos gali būti naudojamos nelaimės vietos žemėlapiui sudaryti, pavojingiems įvykiams identifikuoti, nukentėjusiems asmenims aptikti ir kitoms sudėtingoms užduotims atlikti (Jacoff et al., 2003; Pfitzner & Merkl, 2013; De Cubber et al., 2017). Tikimasi, kad robotai šias užduotis sugebės atlikti autonomiškai arba operatoriui tik minimaliai įsikišus (Bahadori et al., 2015; Sheh et al., 2016). Kita vertus, visiškai autonominių robotų taikymą apsunkina tai, kad aplinkos tyrinėjimo efektyvumas yra tiesiogiai priklausomas nuo robotui prieinamo pradinių duomenų kiekio. Pavyzdžiui, jei apie tyrinėjamą aplinką yra žinoma visa informacija, optimalus paieškos kelias gali būti sudarytas taikant išankstinio maršruto sudarymo strategijas. Tačiau, kai tyrinėjamos nežinomos aplinkos, šis uždavinys sprendžiamas taikant realiojo laiko navigacijos strategijas, kurios ieško artimo optimaliam sprendimo, remdamosi tik tuo laiko momentu žinoma aplinkos informacija ir roboto būsena.

Tokiam aplinkos tyrinėjimui galima pritaikyti įvairias strategijas, tačiau dauguma jų pagrįstos grafo arba tinklelio struktūros sudarymu ir analize. Viena iš populiarių aplinkos tyrinėjimo strategijų yra Yamauchi (1997) pasiūlyta roboto nukreipimo į artimiausią regioną tarp žinomos ir nežinomos erdvės strategija. Ši strategija gali būti išplėsta taikant kandidatų vertinimo metodiką. Kitaip tariant, sprendimas, kur robotas turėtų judėti toliau

(Amigoni, Basilico & Quattrini Li, 2014), gali būti priimtas pritaikius vykdomai užduočiai aktualią kriterijų aibę, kuri apibrėžia kandidatų vertinimo prioritetus. Kadangi kriterijų aibės dydis yra baigtinis, bet iš esmės neribojamas, sprendimams priimti galima taikyti daugiakriterinius sprendimų priėmimo (MCDM) metodus. Pagrindinis šios disertacijos tikslas – išplėsti autonominio roboto taikomas autonominės navigacijos ir aplinkos tyrinėjimo strategijas, grindžiamas kandidatų vertinimu, kai įvesties duomenys gali būti nepatikimi.

Darbo aktualumas

Autonominės navigacijos strategijos apibrėžia, kaip robotas juda ir renka informaciją nežinomoje erdvėje. Kadangi nežinomoje paieškos erdvėje neįmanoma numatyti ir įvertinti visų galimų roboto ir aplinkos būsenų, itin svarbia problema tampa efektyvios aplinkos tyrinėjimo strategijos sukūrimas ir roboto trumpalaikių sprendimų priėmimas, vertinant nepatikimus įvesties duomenis ir konkuruojančius optimizacijos prioritetus.

Tyrimo objektas

Disertacinių tyrimų objektas – autonominių robotų navigacijos strategijos, paremtos daugiakriterinių sprendimų priėmimo metodais.

Darbo tikslas

Išplėsti autonominio paieškos ir gelbėjimo roboto taikomas ir kandidatų vertinimu pagrįstas navigacijos strategijas, kai sprendimas kur judėti toliau, yra priimamas priklausomai tik nuo esamos roboto ir tyrinėjamos aplinkos būsenos, o sprendimui priimti naudojami įvesties duomenys gali būti netikslūs.

Darbo uždaviniai

Darbo tikslui pasiekti sprendžiami šie uždaviniai:

1. Išanalizuoti navigacijos ir aplinkos tyrinėjimo strategijas, taikomas autonominių robotų sistemose ir išskirti dažniausius šių strategijų trūkumus paieškos ir gelbėjimo uždavinių kontekste.
2. Suformuoti originalias kandidatų vertinimo strategijas, kai sprendimai, kur robotas turėtų judėti toliau, priimami remiantis tik tuo metu žinoma aplinkos informacija.
3. Sukurti adaptyvią autonominės navigacijos strategiją, kuri paieškos ir gelbėjimo robotui suteiktų galimybę pakeisti taikomas kandidatų vertinimo taisykles.
4. Sukurti naujus daugiakriterinius sprendimų priėmimo metodų plėtinius, kurie suteiktų galimybę įvertinti netikslius įvesties duomenis, taikomus sprendimų priėmimo procese.
5. Įvertinti siūlomų daugiakriterinių sprendimų priėmimo metodų plėtinių efektyvumą.
6. Įvertinti sukurtų autonominių navigacijos strategijų efektyvumą skirtingose simuliuojamose paieškos ir gelbėjimo operacijose.

Tyrimų metodika

Darbe taikomi literatūros analizės metodai, taikomi siekiant ištirti analizuojamą objektą. Autonominės navigacijos, daugiakriterinių sprendimų priėmimo, neutrosofinių ir neraiškiųjų aibių teorijos žinios buvo taikomos nežinomos aplinkos tyrinėjimo strategijoms kurti. Kiekybiniai ir kokybiniai vertinimo metodai buvo taikyti siekiant ištirti siūlomų navigacijos strategijų ir daugiakriterinių sprendimų priėmimo metodų efektyvumą.

Darbo mokslinis naujumas

1. Siūlomi du nauji klasikinio WASPAS (angl. *Weighted Aggregated Sum Product Assessment*) MCDM metodo plėtiniai, sukurti taikant neutrosofines aibes: WASPAS, modeliuojamas taikant intervalines neutrosofines aibes – WASPAS-IVNS, bei WASPAS, modeliuojamas taikant m apibendrintas q neutrosofines aibes – WASPAS-mGqNS.
2. Autonominiam paieškos ir gelbėjimo robotui siūlomos naujos egoistinės, altruistinės ir nešališkos kandidatų vertinimo strategijos, taikytinos autonominės navigacijos metu.
3. Autonominiam paieškos ir gelbėjimo robotui sukurta nauja adaptyvi autonominės navigacijos strategija, jungianti neraiškiosios logikos valdiklį ir daugiakriterinių sprendimų priėmimo metodus.

Darbo rezultatų praktinė reikšmė

Tyrimo rezultatai gali būti naudingi kuriant ir išplečiant autonominės navigacijos bei aplinkos tyrinėjimo strategijas, kurias taiko autonominiai robotai. Praktinis siūlomų strategijų pritaikymas gali būti naudingas siekiant surinkti duomenis apie pavojingas nelaimės vietas, nerizikuojant žmogiškojo personalo saugumu. Siūlomi autonominės navigacijos metodai leidžia robotui priimti sprendimus realiuoju laiku ir pasirinkti taikomas navigacijos taisykles. Pavyzdžiui, navigacijos metu robotas gali taikyti egoistinį elgsenos modelį ir taip vengti pavojaus, taikyti altruistinį modelį ir teikti pirmenybę nukentėjusių asmenų paieškai arba taikyti nešališką elgsenos modelį, kuris gali būti naudingas situacijose, kai skubus vietovės žemėlapio sudarymas yra svarbiausia roboto užduotis. Siūlomi skirtingas navigacijos strategijas apibrėžiantys kriterijų rinkiniai yra lankstūs ir nebaigtiniai. Įvedant naujus kriterijus ar koreguojant esamų kriterijų svorius, siūlomas strategijas galima nesunkiai išplėsti taip, kad būtų atsižvelgta į naujus autonominės navigacijos reikalavimus ir strategijos būtų pritaikytos konkrečioms realaus pasaulio situacijoms. Rezultatai taip pat apima sukurtus WASPAS-IVNS ir WASPAS-mGqNS daugiakriterinius sprendimų priėmimo metodus, kurie sumodeliuoti taikant intervalines neutrosofines ir m apibendrintas q neutrosofines aibes. Šiuos šiuolaikinius metodus galima pritaikyti, kai siekiama atsižvelgti į netikslias įvesties duomenų charakteristikas, kurios dažnai pasitaiko dėl netikslių sensorių rodmenų ir įvairių matavimo klaidų nustatant kriterijų reikšmę. Šios siūlomų metodų savybės gali būti pritaikytos ne tik autonominių robotų navigacijos užduočių kontekste, bet ir gali būti taikomos įvairioms sprendimų priėmimo problemoms spręsti, kai tikėtinos netiksliai nustatytos kriterijų reikšmės.

Ginamieji teiginiai

1. Sukurti WASPAS metodų plėtiniai, taikantys intervalines neutrosofines ir m apibendrintas q neutrosofines aibes, yra stabilūs, palyginti su klasikiniu WASPAS-SVNS metodu, ir suteikia galimybę atsižvelgti į neišsamius ar netikslius įvesties duomenis.
2. Sukurtos egoistinės ir altruistinės autonominės navigacijos ir aplinkos tyrinėjimo strategijos kurios įvertina roboto saugumo problemas, aptiktų nukentėjusių asmenų aplankymo reikalavimus, roboto gebėjimą prisitaikyti ir ištyrinėti prioritetines vietoves, yra efektyvesnės, lyginant jas su standartinėmis aplinkos tyrinėjimo strategijomis, pagrįstomis kainos ir naudos vertinimu.
3. Sukurta adaptyvi autonominės navigacijos ir aplinkos tyrinėjimo strategija, kuri sujungia neraiškiosios logikos valdiklį ir MCDM metodus, leidžia paieškos ir gelbėjimo robotui efektyviai tarpusavyje keisti taikomas skirtingas kandidatų vertinimo strategijas, šitaip padidindama autonominio roboto efektyvumą.

Darbo rezultatų aprobavimas

Tyrimų rezultatai disertacijos tematika buvo atspausdinti šešiose publikacijose. Keturi straipsniai atspausdinti recenzuojamuose moksliniuose žurnaluose, indeksuotuose WoS duomenų bazėse (Semenas & Bausys, 2022; Semenas, Bausys & Zavadskas, 2021; Semenas & Bausys, 2020; Bausys, Cavallaro & Semenas, 2019); ir dviejose publikacijose, atspausdintose pranešimo medžiagos pagrindu (Semenas & Bausys, 2021; Semenas & Bausys, 2018).

Tyrimų rezultatai buvo pristatyti trijose tarptautinėse konferencijose:

- „2nd International Conference on Communication and Intelligent Systems (ICCIS 2020)“, India, December 26–27, 2020.
- „10th International Workshop Data Analysis Methods for Software Systems (DAMSS 2018)“, Druskininkai, Lithuania, November 29 – December 1, 2018.
- „2018 Open Conference of Electrical, Electronic and Information Sciences (eStream)“, Vilnius, Lithuania, April 26, 2018.

Disertacijos struktūra

Darbą sudaro įvadas, trys pagrindiniai skyriai, bendrosios išvados, literatūros sąrašas ir autoriaus publikacijų disertacijos tema sąrašas. Darbo apimtis – 121 puslapis, tekste yra 57 formulės, 23 paveikslai ir 22 lentelės. Rašant disertaciją buvo pacituoti 126 literatūros šaltiniai.

1. Autonominių robotų navigacijos strategijų apžvalga

Šiame skyriuje apžvelgtos autonominių robotų pritaikymo galimybės ir nauda paieškos ir gelbėjimo operacijose, dažnai taikomos nežinomos aplinkos tyrinėjimo strategijos.

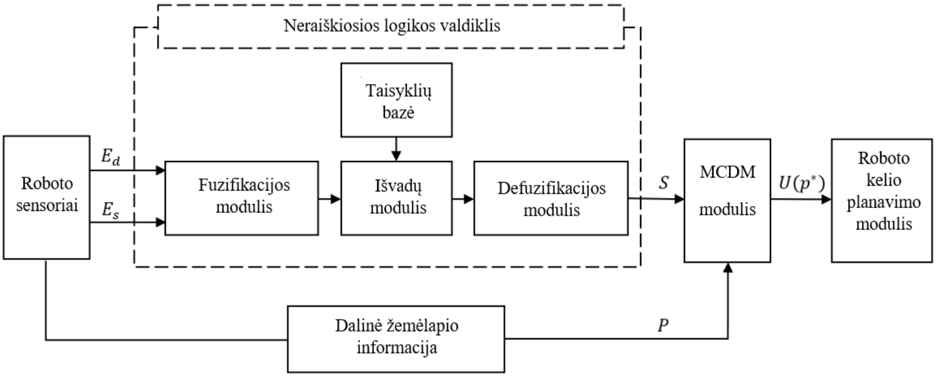
Atlikta nežinomų aplinkų tyrinėjimo strategijų, skirtų autonominiams paieškos ir gelbėjimo robotams, apžvalga parodė, kad dėl išankstinės informacijos trūkumo nežinomos aplinkos tyrinėjimo uždaviniams spręsti dažniausiai taikomos realiojo laiko sprendimų priėmimo strategijos (angl. *Online strategies*), grindžiamos ciklišku roboto nukreipimu į dar neištyrinėtas erdves. Taikant šias strategijas, kiekviename sprendimo priėmimo cikle robotas turi priimti sprendimą, kur judėti toliau, kai žinoma tik esama roboto ir tyrinėjamos erdvės būsena. Šiuo atveju sprendimą galima priimti taikant maksimizuojamų ir minimizuojamų parametrų rinkinį, kuris apibrėžia taikomą aplinkos tyrinėjimo strategijos tikslą (pavyzdžiui, padidinti navigacijos metu roboto ištirtą erdvę, kartu sumažinant jo nukeliautą atstumą).

Tokios sprendimų priėmimo problemos, kurių metu yra siekiama subalansuoti keletą kriterijų ir pasirinkti vertingiausią kandidatą, gali būti įvertintos taikant daugiakriterinių sprendimų priėmimo teoriją ir metodus. Visgi šiuo metu taikomos navigacijos ir aplinkos tyrinėjimo strategijos yra ne lanksčios ir paremtos tik techniniais kandidatų vertinimo kriterijais, neatsižvelgiant į kitus paieškos ir gelbėjimo operacijų aspektus. Be to, praktikoje dažniausiai taikomos kandidatų vertinimo strategijos neįvertina galimo įvesties duomenų nepatikimumo. Tikimasi, kad darbo metu suformuotos kandidatų vertinimo strategijos ir neutrosofiniai WASPAS sprendimų priėmimo metodo plėtiniai padės išspręsti šias literatūros analizės metu identifikuotas problemas.

2. Neutrosofinių daugiakriterinių sprendimų priėmimo metodų taikymas autonominių robotų navigacijoje

Antrajame darbo skyriuje detaliai aprašoma autoriaus siūloma nežinomos aplinkos tyrinėjimo strategija, taip pat sukurti neutrosofiniai WASPAS daugiakriterinių sprendimų priėmimo metodo plėtiniai, taikantys intervalines neutrosofines aibes (WASPAS-IVNS) bei m apibendrintas q neutrosofines aibes (WASPAS-mGqNS).

Siūlomos autonominės nežinomos aplinkos tyrinėjimo strategijos pagrindą sudaro Yamauchi (1997) pasiūlyta strategija, kuri paremta ciklišku roboto nukreipimu į regionus (kandidatus), esančius tarp jau ištyrinėtos ir dar neatrastos erdvės. Šiuo atveju roboto sukuriamas aplinkos modelis yra nuolat papildomas naujai atrasta informacija, o bet kuriuo metu paieškos erdvėje gali būti m kandidatų $P_f = \{p_1, p_2, \dots, p_m\}$, kuriuos robotas turi įvertinti ir pasirinkti vertingiausią. Siekiant optimizuoti šį procesą, kiekvieno kandidato $p_f(x, y)$ vertė U nustatytų prioritetų atžvilgiu apskaičiuojama įvertinant kriterijų rinkinį $C = \{c_1, c_2, \dots, c_n\}$, kuriame kiekvienam kriterijui yra priskirtas svorio koeficientas $W = \{w_1, w_2, \dots, w_n\}$. Kadangi skirtingi kriterijų svorio koeficientai ir optimumai apibrėžia skirtingas kandidatų vertinimo strategijas, ši savybė gali būti pritaikyta modeliuojant skirtingus roboto elgsenos modelius. Šių skirtingų strategijų rinkinys gali būti apibrėžtas kaip $ST = \{St_1(C_1, W_1), St_2(C_2, W_2), \dots, St_k(C_k, W_k)\}$, čia $St_i(C_i, W_i)$ – individuali kandidato vertinimo strategija, k nurodo, kiek strategijų yra rinkinyje ST. Sprendimas, kurią kandidato vertinimo strategiją pasirinkti, yra priimamas taikant siūlomą neraiškiosios logikos valdiklį. Skirtingai nei kiti praktikoje taikomi neraiškiosios logikos valdikliai, šiame darbe siūlomas valdiklis kontroliuoja ne roboto judesius, o nustato, kokia sprendimų priėmimo strategija turėtų būti taikoma, vertinant kandidatus, esančius P_f rinkinyje. Siūloma adaptyvi kandidatų vertinimo strategija schemiškai pavaizduota S2.1 paveiksle.



S2.1 pav. Siūloma adaptyvi kandidatų vertinimo strategija, taikanti neraiškiosios logikos valdiklį ir sukurtus neutrosofinius WASPAS metodo plėtinius. Čia $E(s)$ – atstumas tarp roboto ir aptikto nukentėjusio asmens, $E(d)$ – atstumas tarp roboto ir pavojingo regiono, S žymi parinktą kandidatų vertinimo strategiją, P – galimų kandidatų sąrašą, o $U(p^*)$ – apskaičiuotą naudingiausio kandidato vertę (Semenas & Bausys, 2021).

Viena pagrindinių problemų, su kuriomis gali susidurti autonominis paieškos ir gelbėjimo robotas, yra nepatikimi įvesties parametrų duomenys, kurie naudojami priimant sprendimus. Sukurtas WASPAS-IVNS metodas suteikia galimybę spręsti šią problemą skaičiavimų metu, įvertinant galimus įvesties parametrų nuokrypius. Toliau pateikiami pagrindiniai intervalinių neutrosofinių aibių apibrėžimai (Zhang et al., 2014), taikyti kuriant WASPAS-IVNS metodą.

S1 apibrėžimas. Intervalinė neutrosofinė aibė (IVNS) išreiškiama trimis intervalinėmis priklausomybės funkcijomis: tiesos funkcija – $T_{iv}(x)$, neapibrėžtumo funkcija – $I_{iv}(x)$, netiesos funkcija – $F_{iv}(x)$.

S2 apibrėžimas. Intervalinė neutrosofinė aibė gali būti išreikšta taip:

$$IVNS = \{\langle T_{iv}(x), I_{iv}(x), F_{iv}(x)\rangle : x \in X\}, \quad \text{(S2.1)}$$

čia trys priklausomybės funkcijos tenkina šias sąlygas:

$$T_{iv}(x) = [T_{iv}(x)^-, T_{iv}(x)^+] \subseteq [0,1]; \quad \text{(S2.2)}$$

$$I_{iv}(x) = [I_{iv}(x)^-, I_{iv}(x)^+] \subseteq [0,1]; \quad \text{(S2.3)}$$

$$F_{iv}(x) = [F_{iv}(x)^-, F_{iv}(x)^+] \subseteq [0,1]; \quad \text{(S2.4)}$$

$$0 \leq T_{iv}(x)^+ + I_{iv}(x)^+ + F_{iv}(x)^+ \leq 3. \quad \text{(S2.5)}$$

S3 apibrėžimas. Intervalinis neutrosofinis skaičius (IVNN) gali būti išreikštas taip:

$$N_{iv} = \langle [t_{iv}^-, t_{iv}^+], [i_{iv}^-, i_{iv}^+], [f_{iv}^-, f_{iv}^+]\rangle. \quad \text{(S2.6)}$$

S4 apibrėžimas. Intervalinius neutrosofinius skaičius galima palyginti taikant vertės $S(Q)$, tikslumo $a(Q)$ ir užtikrintumo $c(Q)$ funkcijas:

$$S(Q) = [t_{iv}^- + 1 - i_{iv}^+ + 1 - f_{iv}^+, t_{iv}^+ + 1 - i_{iv}^- + 1 - f_{iv}^-]; \quad \text{(S2.7)}$$

$$a(Q) = [min\{t_{iv}^- - f_{iv}^-, t_{iv}^+ - f_{iv}^+\}, max\{t_{iv}^- - f_{iv}^-, t_{iv}^+ - f_{iv}^+\}]; \quad \text{(S2.8)}$$

$$c(Q) = [t_{iv}^-, t_{iv}^+]. \quad \text{(S2.9)}$$

S5 apibrėžimas. Intervalinių neutrosofinių skaičių palyginimas gali būti atliktas taikant tikimybės laipsnį p, kurį apibrėžia šios taisyklės:

- Jei $p(S(Q_1) \geq S(Q_2)) > 0{,}5$, tada $Q_1 \succ Q_2$;
- Jei $p(S(Q_1) \geq S(Q_2)) = 0{,}5$ ir $p(a(Q_1) \geq a(Q_2)) > 0{,}5$, tada $Q_1 \succ Q_2$;
- Jei $p(S(Q_1) \geq S(Q_2)) = 0{,}5$ ir $p(a(Q_1) \geq a(Q_2)) = 0{,}5$, ir $p(c(Q_1) \geq c(Q_2)) > 0{,}5$, tada $Q_1 \succ Q_2$;
- Jei $p(S(Q_1) \geq S(Q_2)) = 0{,}5$ ir $p(a(Q_1) \geq a(Q_2)) = 0{,}5$, ir $p(c(Q_1) \geq c(Q_2)) = 0{,}5$, tada $Q_1 \sim Q_2$.

S6 apibrėžimas. Tikimybės laipsnis p apskaičiuojamas taikant nelygybę:

$$p\big(S(Q_1) \geq S(Q_2)\big) = \max\left\{1 - \max\left(\frac{S(Q_2)^+ - S(Q_1)^-}{(S(Q_1)^+ - S(Q_1)^-) + (S(Q_2)^+ - S(Q_2)^-)}, 0\right), 0\right\}. \quad \text{(S2.10)}$$

Kadangi vienas pagrindinių autonominių paieškos ir gelbėjimo operacijų aspektų, į kuriuos privalu atkreipti dėmesį, yra naudojamos strategijos lankstumas, m apibendrintų q neutrosofinių aibių taikymas robotų operatoriui suteikia galimybę pasirinkti, kokias neraiškiąsias aibes taikyti priimant sprendimą. Šis funkcionalumas realizuojamas pasirenkant atitinkamas m ir q parametrų reikšmes. Pavyzdžiui, klasikinės SVNS aibės taikomos, kai $m, q = 1$. Pagrindinius m apibendrintų q neutrosofinių aibių apibrėžimus galima pateikti taip:

S7 apibrėžimas. m apibendrinta q neutrosofinė aibė (mGqNS) išreiškiama trimis m apibendrintomis q neutrosofinėmis priklausomybės funkcijomis: tiesos funkcija – $T_{mq}(x)$, neapibrėžtumo funkcija – $I_{mq}(x)$, ir netiesos funkcija – $F_{mq}(x)$.

S8 apibrėžimas. m apibendrinta q neutrosofinė aibė gali būti išreikšta taip:

$$mGqNS = \{\langle T_{mq}(x), I_{mq}(x), F_{mq}(x)\rangle : x \in X\}, \quad \text{(S2.11)}$$

čia trys priklausomybės funkcijos tenkina sąlygas:

$$T_{mq}(x), I_{mq}(x), F_{mq}(x): X \to [0, r], (0 \leq r \leq 1); \quad \text{(S2.12)}$$

$$0 \leq (T_{mq}(x))^q + (I_{mq}(x))^q + (F_{mq}(x))^q \leq \frac{3}{m}; \quad \text{(S2.13)}$$

$$m = 1 \,||\, 3, q \geq 1. \quad \text{(S2.14)}$$

S9 apibrėžimas. m apibendrintas q neutrosofinis skaičius (mGqNN) gali būti išreikštas šia išraiška:

$$N_{mq} = \langle t_{mq}, i_{mq}, f_{mq} \rangle. \tag{S2.15}$$

S10 apibrėžimas. Taikant m apibendrintas q neutrosofines aibes kandidatui parinkti taikoma vertės funkcija, kuri išreiškiama kaip:

$$S(N_{mq}) = \frac{3+3t_{mq}^{q}-2i_{mq}^{q}-f_{mq}^{q}}{6}. \tag{S2.16}$$

Originalus svertinės agreguotos sumos (WASPAS) metodas buvo sukurtas WPM (angl. *Weighted Product Model*) ir WSM (angl. *Weighted Sum Model*) pagrindu (Zavadskas et al., 2012). Toliau pateikiamas standartinio WASPAS metodo etapų aprašas, taikytinas sukurtuose WASPAS-IVNS ir WASPAS-mGqNS metoduose.

Pirmiausia kiekvienam galimam kandidatui yra apskaičiuojamos taikomą navigacijos strategiją apibrėžiančių kriterijų reikšmės ir sukuriama sprendimo matrica D. Matricos duomenys sudaryti iš $[d]_{ij}$ elementų, čia $i = 1, 2, \dots, n$ atitinka kandidato, o $j = 1, 2, \dots, k$ kriterijaus indeksus.

Tada atliekamas sprendimo matricos *D* normalizavimas. Taikant WASPAS-IVNS metodą normalizavimo funkcija išreiškiama taip:

$$[d_{iv}]_{ij}^{-} = \frac{[d_{iv}]_{ij}^{-}}{\max[d_{iv}]_{ij}\sqrt{k}}, \; [d_{iv}]_{ij}^{+} = \frac{[d_{iv}]_{ij}^{+}}{\max[d_{iv}]_{ij}\sqrt{k}}, \tag{S2.17}$$

o taikant WASPAS-mGqNS metodą naudojama tokia funkcija:

$$[d_{mq}]_{ij} = \frac{[d_{mq}]_{ij}}{\sqrt{\sum_{j=1}^{k}\left([d_{mq}]_{ij}\right)^{2}}}. \tag{S2.18}$$

Tuomet normalizuotos matricos elementai yra konvertuojami į neutrosofinę formą, taikant antrame šio darbo skyriuje pristatytą neutrosofikacijos lentelę (Zavadskas et al., 2015a). Po šio etapo matricos elementai įgauna atitinkamą neutrosofinę formą: $[\bar{d}_{iv}]_{\mathrm{ij}} = \langle [t_{iv}^{-}, t_{iv}^{+}], [i_{iv}^{-}, i_{iv}^{+}], [f_{iv}^{-}, f_{iv}^{+}] \rangle$ (taikant WASPAS-IVNS metodą) arba $[\bar{d}_{mq}]_{\mathrm{ij}} = \langle t_{mq}, i_{mq}, f_{mq} \rangle$ (taikant WASPAS-mGqNS metodą).

Kandidatų reikšmės apskaičiuojamos pagal pirmąjį WASPAS kriterijų, kuriame maksimizuojamų (O_{max}) ir minimizuojamų (O_{min}) matricos elementų $[\bar{d}]_{ij}$ reikšmės padauginamos iš svorių koeficientų w_j ir sudedamos:

$$Q_i^{(1)} = \left(\sum_{j=1}^{O_{max}} [\bar{d}]_{ij} \cdot w_j\right) + \left(\sum_{j=1}^{O_{min}} [\bar{d}]_{ij} \cdot w_j\right)^{c}. \tag{S2.19}$$

Kandidatų reikšmės skaičiuojamos pagal antrąjį WASPAS kriterijų:

$$Q_i^{(2)} = \left(\prod_{j=1}^{O_{max}} ([\bar{d}]_{ij})^{w_j}\right) \cdot \left(\prod_{j=1}^{O_{min}} ([\bar{d}]_{ij})^{w_j}\right)^{c}. \tag{S2.20}$$

Galiausiai apskaičiuojama apibendrinta funkcija:

$$Q_i = 0{,}5Q_i^{(1)} + 0{,}5Q_i^{(2)} \,. \tag{S2.21}$$

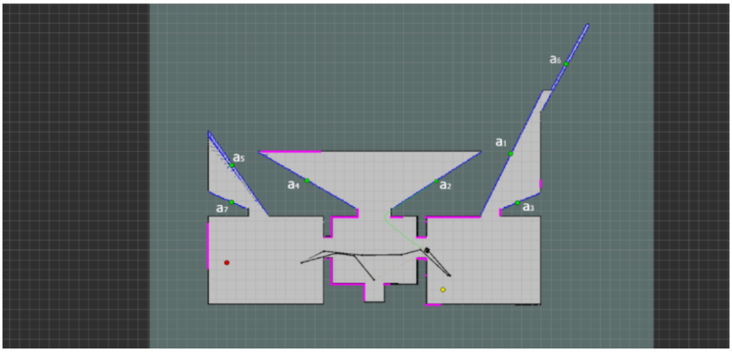
Taikant vertės funkcijas aprašytas S6 ir S10 apibrėžimuose, apskaičiuotos neutrosofinės reikšmės konvertuojamos į paprastuosius skaičius, kurie nusako kandidato vertę.

3. Siūlomų autonominių robotų navigacijos strategijų vertinimas

Trečiajame darbo skyriuje pateikti siūlomos autonominės roboto navigacijos nežinomoje SAR aplinkoje strategijos tyrimai. Darbo metu buvo atlikti penki tyrimai, kuriuose siūlomos skirtingos kandidato vertinimo metodikos, kai sprendimui priimti taikomi autoriaus siūlomi WASPAS metodo plėtiniai – WASPAS-IVNS ir WASPAS-mGqNS.

Pirmajame tyrime siūloma roboto matymo zonoje esančių kandidatų vertinimo strategija. Ji sudaryta modeliuojant šešių kriterijų rinkinį: atstumo nuo kandidato iki artimiausio pavojingo objekto, numatomos erdvės, kurią robotas gali ištirti pasiekęs kandidatą, galimo nukeliauti kelio ilgį, numatomo laiko, per kurį robotas gali pasiekti kandidatą, atstumo iki artimiausio roboto matymo lauką užstojančio objekto, ir santykio tarp aptikto pravažiavimo ir standartinio durų pločio. Siūlomų kriterijų optimumai ir svoriai nustatyti taikant SWARA metodą, o sprendimui, kur robotas turėtų judėti toliau, priimti taikomas klasikinis WASPAS-SVNS metodas. Tyrimo metu nustatyta, kad siūloma kandidatų vertinimo strategija gali padidinti roboto sprendimų priėmimo modulio efektyvumą. Standartinės kandidatų vertinimo metodikos išplėtimas integruojant roboto saugos kriterijus, paieškos ir gelbėjimo robotui suteikia galimybę aplinkos tyrinėjimo metu vengti pavojingų objektų, netaikant papildomų roboto judėjimo taisyklių ir padeda pasirinkti nustatytą strategiją atitinkančią judėjimo kryptį roboto lokalioje erdvėje. Nors siūloma strategija gali būti taikoma tyrinėjant nežinomą aplinką, svarstytini patobulinimai, kurie galėtų išplėsti esamos kandidatų vertinimo strategijos efektyvumą SAR aplinkose. Pavyzdžiui, pakeitus kandidatų aptikimo strategiją iš lokalios į globalią, robotas gali įvertinti kandidatus, atsižvelgdamas į visą atrastą aplinkos informaciją. Todėl antrajame tyrime siūloma globali navigacijos strategija, išplečiama atsižvelgiant ne tik į roboto saugumo reikalavimus, bet ir įterpiant nukentėjusių asmenų įvertinimo kriterijus.

Siūloma strategija sudaryta modeliuojant šešių kriterijų rinkinį: atstumo iki roboto valdymo centro, numatomos erdvės, kurią robotas galėtų ištirti pasiekęs kandidatą, numatomo laiko, reikalingo pasiekti kandidatą, atstumo tarp roboto ir kandidato, numatomo pavojaus aptiktam nukentėjusiam asmeniui ir numatomo pavojaus robotui, jei jis iki kandidato judėtų numatytu keliu. Kriterijų optimumai ir svoriai nustatyti taikant SWARA metodą. Sprendimas, kur robotas turėtų judėti toliau, priimamas taikant siūlomą WASPAS-IVNS metodą. Tyrimų metu nustatyta, kad dėl galimybės įvertinti galimas kriterijų reikšmių variacijas WASPAS-IVNS sprendimų priėmimo metodas yra tinkamas, siekiant efektyviai palyginti itin panašius kandidatus. Pavyzdžiui, S3.1 paveiksle pavaizduoti kandidatai $(a_1, a_2, \ldots, a_7)$ buvo įvertinti, klasikiniu WASPAS-SVNS ir naujai siūlomu WASPAS-IVNS metodais.



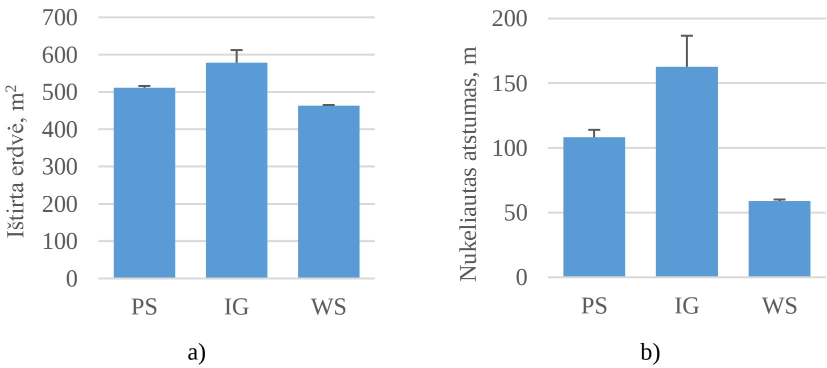
S3.1 pav. Pateikiamas kandidatų vertinimo pavyzdys. Robotas pažymėtas juodu kvadratu. Kandidatai pažymėti žaliais žymekliais ($a_1, a_2, \ldots, a_7$). Raudona spalva pažymėtas pavojingas objektas, geltona – aptiktas nukentėjęs asmuo (Semenas & Bausys, 2020)

Kandidatų vertinimo rezultatai, kurie buvo nustatyti taikant siūlomą WASPAS-IVNS ir standartinį WASPAS-SVNS metodus, yra pavaizduoti S3.1 lentelėje. Šiame pavyzdyje parodoma, kad WASPAS-IVNS metodas suteikia papildomus įrankius siekiant įvertinti itin panašios reikšmės kandidatus. Šiuo atveju pirmųjų dviejų kandidatų rangai apsikeitė vietomis. Nors, taikant WASPAS-SVNS metodą, a_2 ir a_4 kandidatų reikšmės yra itin artimos, robotas pasirinktų a_4 kandidatą, esantį toliau nuo esamos roboto pozicijos. WASPAS-IVNS šiuo atveju prioritetą teiktų artimesniam, a_2 kandidatui.

S3.1 lentelė. Kandidatų vertinimo rezultatai taikant WASPAS-IVNS ir WASPAS-SVNS metodus

Kandidatas	WASPAS-IVNS		WASPAS-SVNS	
	$S(Q)$	Rangas	$S(Q)$	Rangas
a_1	[2,002; 2,286]	3	0,6655	3
a_2	[2,014; 2,312]	1	0,6708	2
a_3	[1,877; 2,172]	5	0,5982	5
a_4	[2,015; 2,306]	2	0,6719	1
a_5	[1,898; 2,174]	4	0,6171	4
a_6	[1,853; 2,117]	6	0,5812	6
a_7	[1,743; 2,027]	7	0,5193	7

Trečiajame tyrime siūloma globali kandidatų vertinimo strategija sudaryta modeliuojant šešių kriterijų rinkinį: atstumo nuo kandidato iki roboto valdymo centro, numatomos aplinkos erdvės dydžio, kurią robotas galėtų ištirti pasiekęs kandidatą, numatomo laiko, reikalingo kandidatui pasiekti, atstumo tarp roboto ir kandidato, atstumo nuo kandidato iki artimiausio prioritetinio regiono bei santykio tarp nežinomų celių, esančių aplink kandidatą, ir mėginio dydžio. Skirtingai nei prieš tai pasiūlytos kandidatų vertinimo strategijos, ši strategija skirta situacijoms, kai roboto operatoriui žinomas nedidelis kiekis išankstinės informacijos apie SAR aplinką, kuris leidžia nustatyti prioritetinius paieškos regionus. Kriterijų optimumai ir svoriai nustatyti taikant SWARA metodą, o sprendimas, kur robotas turėtų judėti toliau, priimamas taikant sukurtą WASPAS-mGqNS metodą. Tyrimo metu siūloma aplinkos tyrinėjimo strategija (PS) yra lyginama su dviem strategijomis: standartine kainos ir naudos strategija (IG), ir trumpiausio kelio (tiesioginio maršruto sudarymo) strategija (WS), kurioje roboto operatorius nustato prioritetinių zonų aplankymo eiliškumą, o robotas jas aplanko, taikydamas trumpiausio kelio paieškos metodus. Tikėtasi, kad paieškos ir gelbėjimo roboto gebėjimas įvertinti užimtos erdvės, esančios aplink kandidatą, kiekį bei galimybė teikti prioritetą nustatytiems regionams leis padidinti roboto efektyvumą ištirtos erdvės dydžio atžvilgiu. Tyrimo metu surinkti rezultatai pavaizduoti S3.2 paveiksle patvirtina šią hipotezę. Tyrimo rezultatai išryškina, kad siūloma aplinkos tyrinėjimo strategija gali būti taikoma siekiant padidinti roboto ištirtą erdvę, sumažinti nukeliautą atstumą, ir kartu nukreipti robotą į prioritetinį paieškos regioną, kurį identifikavo roboto operatorius. Tyrimo metu daugiausia aplinkos erdvės ištyrė robotas, taikantis standartinę kainos ir naudos strategiją (IG). Tačiau, taikant šią strategiją, pastebimas ir ilgiausias roboto nukeliauto atstumo vidurkis. Priešingai, taikant trumpiausio kelio strategiją, autonominis robotas nukeliauja trumpiausią atstumą, tačiau ištiria mažiausiai paieškos erdvės. Taikydamas siūlomą kandidatų vertinimo strategiją, autonominis robotas elgiasi subalansuotai ir gali ištyrinėti erdves, esančias netoliese prioritetinių zonų, ir šitaip padidinti ištirtą paieškos erdvę (lyginant su WS strategija), bei sumažinti roboto nukeliautą atstumą (lyginant su IG strategija).



S3.2 pav. Navigacijos strategijų vertinimo rezultatai: a) roboto ištirta erdvė, m^2; b) roboto nukeliautas atstumas, m

Kadangi skirtingos kandidatų vertinimo strategijos nukreiptos į skirtingus autonominės navigacijos prioritetus, adaptyvi aplinkos tyrinėjimo strategija buvo sukurta siekiant suteikti robotui galimybę autonomiškai pakeisti kandidato vertinimo strategiją, atsižvelgiant į atrastą aplinkos informaciją. Sprendimas, kuri strategija turi būti pritaikoma vertinant kandidatus, yra priimamas taikant neraiškiosios logikos valdiklį, pavaizduotą S2.1 paveiksle. Kandidatams vertinti taikomos keturios skirtingos strategijos: pavojingo regiono vengimo strategija (DA), nukreipianti robotą nuo pavojingų regionų; atsargi aptikto asmens aplankymo strategija (RRS), prioritetą teikianti kandidatams, esantiems netoli aptiktų nukentėjusių asmenų ir toli nuo pavojingų regionų; aptikto asmens aplankymo strategija (RS), prioritetą teikianti kandidatams, esantiems netoli aptiktų nukentėjusių asmenų; informacijos paieškos strategija (IG), prioritetą teikianti roboto ištirtos erdvės padidinimui. Kandidatų vertinimo strategijos parenkamos įvertinant atstumus tarp roboto ir pavojingų regionų bei atstumus tarp roboto ir tyrinėjamoje SAR aplinkoje aptiktų nukentėjusių asmenų.

Vertinant tyrimo rezultatus, galima daryti išvadą, kad siūloma adaptyvi kandidatų vertinimo strategija aktyviai nukreipia robotą nuo pavojingų regionų ir traukią jį prie aptiktų galimai nukentėjusių asmenų. Roboto judėjimo trajektorija indikuoja, kad robotas nevengia pavojingų regionų tuo atveju, kai netoliese jų aptinkami nukentėję asmenys, ir patvirtina roboto gebėjimą subalansuoti skirtingus optimizavimo parametrus, vykdant kandidatų parinkimo užduotį. Vertinant individualių strategijų pateikiamus rezultatus, pažymėtina, kad egoistinių pavojingų regionų vengimui prioritetą teikiančių strategijų taikymas sumažina robotui skirtos nuobaudos kiekį iki 91 %, lyginant su RS ir IG kandidatų vertinimo strategijomis. Kitą vertus, siūloma adaptyvi aplinkos tyrinėjimo strategija yra pajėgi subalansuoti abu elgsenos modelius, o kartu ir sumažinti robotui skirtos nuobaudos dydį iki 70 %.

Siekiant palyginti sukurtus daugiakriterinius sprendimo priėmimo metodus, siūloma apibendrinta aplinkos tyrinėjimo strategija, jungianti potencialą rodančius kandidato vertinimo kriterijus ir kandidatų vertinimo strategijas, taikytas keturiuose aptartuose tyrimuose. Penktojo tyrimo metu buvo iškelti šie pagrindiniai tikslai:

1. Palyginti WASPAS-IVNS ir WASPAS-mGqNS metodų efektyvumą su klasikiniais WASPAS-SVNS ir MULTIMOORA-SVNS metodais.
2. Ištestuoti siūlomos autonominės aplinkos tyrinėjimo strategijos efektyvumą simuliacijoje ir gautus rezultatus palyginti su atskaitiniais, kandidato parinkimu grindžiamais metodais: artimiausio kandidato parinkimo metodu (angl. *Closest frontier* – CF), bei standartine aplinkos tyrinėjimo strategija (angl. *Standard information gain* – SIG).

Taikant CF strategiją, robotas parenka artimiausią galimą kandidatą, remdamasis tik tuo, kiek laiko prireiks robotui, kad pasiektų kandidatą. Taikant SIG strategiją, kandidatas parenkamas remiantis dažnai taikomu kriterijų rinkiniu (Basilico & Amigoni, 2011; Taillandier & Stinckwich, 2011; Bausys, Cavallaro & Semenas, 2019; Visser & Slamet, 2008), o sprendimas priimamas klasikiniu WASPAS-SVNS metodu. Siūloma apibendrinta kandidatų vertinimo strategija modeliuojama taikant aštuonis kriterijus, nukreiptus į roboto saugos, socialinius ir techninius SAR aplinkos tyrinėjimo aspektus: erdvės tarp žinomo ir nežinomo regiono ilgis (c_1); atstumas tarp kandidato ir roboto valdymo stoties (c_2); laikas, per kurį robotas gali pasiekti kandidatą (c_3); numatoma nuobauda robotui, jei kandidatas būtų pasiektas judant suplanuotu keliu (c_4); bendras nukentėjusių asmenų, esančių šalia suplanuoto roboto kelio, atpažinimo rodiklis (c_5); žemiausias nukentėjusio asmens, esančio netoli suplanuoto kelio, atpažinimo rodiklis (c_6); atstumas nuo kandidato iki artimiausio prioritetinio regiono (c_7); santykis tarp nežinomų celių aplink kandidatą ir mėginio populiacijos dydžio (c_8). Kandidatų vertinimo strategijas apibrėžiantys svoriai ir optimumai pateikti S3.2 lentelėje.

S3.2 lentelė. Kriterijai, apibrėžiantys apibendrintą adaptyvią navigacijos strategiją

Žymėjimas	Optimumas	DA	RRS	RS	IG
c_1	Max	0,056	0,029	0,043	0,213
c_2	Max	0,061	0,073	0,019	0,075
c_3	Min	0,197	0,203	0,131	0,322
c_4	Min	0,394	0,373	0,395	0,043
c_5	Min	0,037	0,039	0,065	0,033
c_6	Min	0,112	0,125	0,234	0,081
c_7	Min	0,078	0,070	0,025	0,137
c_8	Max	0,065	0,089	0,088	0,097

WASPAS-IVNS ir WASPAS-mGqNS metodai vertinti simuliuojamose aplinkose, pavaizduotose S3.3 paveiksle. Pirmoji SAR aplinka apima 26×17 m paieškos erdvę, antroji aplinka – 32×26 m paieškos erdvę, o trečioji – 43×28 m paieškos erdvę. Siekiant palyginti tyrimo metu surinktus rezultatus tarp siūlomos aplinkos tyrinėjimo strategijos, CF ir SIG strategijų yra taikomi penki parametrai. Trys parametrai yra matuojami ordinalioje skalėje: atstumas kurį nukeliavo robotas, roboto ištirtos SAR aplinkos erdvės dydis, ir nuobauda, kurią robotas gavo kirtęs pavojingais laikomas vietoves. Kiti du parametrai matuojami pagal santykinę skalę: santykis tarp roboto nukeliauto atstumo ir ištirtos erdvės dydžio bei santykis tarp robotui skirtos nuobaudos ir ištirtos erdvės dydžio.

a) b) c)

S3.3 pav. Simuliuojamos SAR aplinkos: a) pirmoji SAR aplinka, kuriai būdinga atvira topologija; b) antroji SAR aplinka, kurioje atskiros erdvės sujungtos centriniu koridoriumi; c) trečioji SAR aplinka, kuriai būdinga kilpinė topologija. Čia mėlynas žymeklis nurodo roboto pradžios poziciją, raudoni žymekliai – pavojingus regionus, kurių robotas turi vengti, geltoni žymekliai indikuoja nukentėjusių asmenų buvimo pozicijas, balti žymekliai – prioritetinius regionus, kuriuos turėtų aplankyti robotas (Semenas & Bausys, 2022)

Pirmoje aplinkoje, taikant WASPAS-SVNS, WASPAS-IVNS, WASPAS-mGqNS ir MULTIMOORA-SVNS metodus, roboto ištirta SAR aplinkos erdvė yra beveik identiška. Pagrindinis skirtumas šiuo atveju yra roboto nukeliautas atstumas, kuris yra padidintas nuo 4 iki 6 % taikant WASPAS-IVNS ir WASPAS-mGqNS metodus. Panašūs rezultatai matomi vertinant duomenis surinktus antroje ir trečioje aplinkose. Antroje aplinkoje roboto ištirta erdvė buvo padidinta iki 1 %, o nukeliautas atstumas, taikant WASPAS-IVNS ir WASPAS-mGqNS metodus, atitinkamai svyruoja nuo 1 % reikšmės sumažinimo iki 1 % reikšmės padidinimo. Trečioje aplinkoje roboto nukeliautas atstumas sumažintas iki 4,5–6,5 %, tačiau ištirta aplinkos erdvė buvo padidinta iki 1 %. Kadangi skirtumai tarp surinktų duomenų yra minimalūs, įvertinus šiuos rezultatus, galima daryti išvadą, kad siūlomi WASPAS-IVNS ir WASPAS-mGqNS metodai yra stabilūs, lyginant juos su klasikiniais WASPAS-SVNS ir MULTIMOORA-SVNS metodais. Be to, papildomas šių metodų funkcionalumas, kuris suteikia galimybę įvertinti sprendimui priimti reikalingų duomenų nuokrypius, gali sudaryti sąlygas pagerinti kandidatų vertinimo rezultatus. Pavyzdžiui, taikant WASPAS-IVNS ir WASPAS-mGqNS metodus, vidutinis robotui skirtos nuobaudos kiekis reikšmingai sumažėja, lyginant su MULTIMOORA-SVNS pateikiamais rezultatais.

Lyginant siūlomą aplinkos tyrinėjimo strategiją taikant WASPAS-IVNS ir WASPAS-mGqNS metodus, su bazinėmis CF ir SIG aplinkos tyrinėjimo strategijomis yra pastebimas siūlomos adaptyvios strategijos pranašumas. Pirmoje simuliuojamoje aplinkoje roboto rezultatai išlieka panašūs. Taikant siūlomą strategiją bei WASPAS-IVNS ir WASPAS-mGqNS metodus, roboto ištirta aplinkos erdvė padidinama iki 1,8 % lyginant su ištirta erdve taikant SIG ir CF strategijas. Rezultatų panašumą galima paaiškinti įvertinus santykinai nedidelį šios aplinkos dydį, jos atvirą topologiją ir taikomą kandidato vertinimu pagrįstą strategiją. Šiuo atveju robotas yra pajėgus padengti visą paieškos erdvę per paieškos ir gelbėjimo misijai skirtą laiko intervalą, nepaisant taikomos strategijos efektyvumo. Todėl pagrindinis strategijos vertinimo kriterijus tokiu atveju gali būti roboto gebėjimas subalansuoti užduoties reikalavimus, pavyzdžiui, gebėjimas užtikrinti roboto saugumą ir sumažinti nukeliautą atstumą. Taikant WASPAS-IVNS ir WASPAS-mGqNS metodus, pastebimas roboto surinktos nuobaudos sumažėjimas iki 89,80 %, o roboto nukeliautas atstumas pirmoje aplinkoje sumažinamas iki 11,46 %.

Lyginant SIG ir CF aplinkos tyrinėjimo strategijas su siūlomais neutrosofiniais WASPAS plėtiniais, pastebima, kad antroje aplinkoje nukeliautas kelias pailgėja iki 21 %. Kitą vertus, siūloma aplinkos tyrinėjimo strategija padeda robotui ištirti iki 12,7 % daugiau erdvės. Vertinant roboto nukeliautą atstumą ir ištirtos erdvės kiekį trečioje aplinkoje, šie parametrai padidėja atitinkamai iki 33,6 % ir 23,6 %. Atlikus ANOVA statistinės analizės testus, nustatyta, kad šie rezultatai yra statistiškai reikšmingi antroje ir trečioje aplinkoje, kai $p < 0{,}05$. Įvertinus santykį tarp roboto nukeliauto atstumo ir ištirtos erdvės dydį bei santykį tarp robotui skirtos nuobaudos ir ištirtos erdvės dydį, buvo nustatyta, kad, taikant siūlomą aplinkos tyrinėjimo strategiją, padidėjęs roboto nukeliautas kelias tiesiogiai veikia ir ištirto ploto dydį. Kitaip tariant, aplinkos tyrinėjimo metu robotas elgiasi subalansuotai.

Lyginant siūlomos strategijos ir SIG bei CF strategijų surinktą vidutinį nuobaudos dydį pastebimas siūlomos strategijos pranašumas. Lyginant SIG ir CF strategijas su siūloma aplinkos tyrinėjimo strategija, taikant WASPAS-IVNS metodą, maksimalus šio parametro reikšmės sumažinimas siekia 87,8 %. Taikant WASPAS-mGqNS metodą, pastebimas šios reikšmės sumažinimas siekia iki 94,4 %. Vertinant tyrimo rezultatus, galima daryti išvadą, kad siūloma nežinomos aplinkos tyrinėjimo strategija reikšmingai padidina autonominio roboto efektyvumą, lyginant ją su CF ir SIG strategijomis, o siūlomi WASPAS-IVNS ir WASPAS-mGqNS metodai yra stabilūs, lyginant juos su klasikiniu WASPAS-SVNS metodu.

Bendrosios išvados

1. Atlikta dažniausiai taikomų aplinkos tyrinėjimo strategijų apžvalga atskleidė, kad kandidatams vertinti taikomos strategijos neįvertina galimų nepatikimų įvesties parametrų, kai priimamas sprendimas, kur robotas turėtų judėti toliau. Be to, kandidatų vertinimas dažnai atliekamas taikant ne adaptyvias kandidatų vertinimo metodikas, kai sprendimui priimti taikomos tos pačios vertinimo taisyklės, neatsižvelgiant į esamą roboto ar aplinkos būseną.
2. Siūloma kandidatų vertinimo strategija, integruojanti roboto saugumo ir nukentėjusių asmenų įvertinimo kriterijus pagerina autonominio roboto rodomus autonominės navigacijos ir aplinkos tyrinėjimo rezultatus. Be to, kriterijų, įvertinančių užimtos erdvės, esančios aplink kandidatą, kiekį bei suteikiančių galimybę nustatyti prioritetinius tyrinėjimo regionus, integravimas sukuria efektyvesnę kandidatų vertinimo strategiją, lyginant ją su standartinėmis kainos ir naudos strategijomis.
3. Sukurta autonominės navigacijos strategija, jungianti neraiškiosios logikos valdiklį ir sukurtus MCDM metodus, leidžia SAR robotui navigacijos metu atsižvelgti į dinamišką aplinkos informaciją ir pakeisti kandidatų vertinimo strategijas. Siūloma adaptyvi autonominės navigacijos strategija, kuri priimant sprendimus taiko modernias neutrosofines aibes, optimizuoja roboto judėjimo trajektoriją ir padidina jo efektyvumą, lyginant su neadaptyviomis egoistinėmis, altruistinėmis ir nešališkomis kandidatų vertinimo strategijomis. Lyginant altruistines ir nešališkas kainos ir naudos strategijas su siūloma adaptyvia strategija, robotui skirtos nuobaudos dydis gali būti sumažintas iki 70 %, o su visiškai egoistinėmis strategijomis iki 91 %.
4. Sukurti neutrosofiniai WASPAS metodo plėtiniai, WASPAS-IVNS ir WASPAS-mGqNS metodai, suteikia galimybę įvertinti galimus nepatikimus įvesties duomenis. Ši galimybė užtikrina sprendimų priėmimo efektyvumą kai lyginami itin panašūs kandidatai. WASPAS-IVNS, WASPAS-mGqNS ir standartinių WASPAS-SVNS ir MULTIMOORA-SVNS metodų palyginimas parodė, kad siūlomi daugiakriterinių sprendimų priėmimo metodai yra stabilūs skirtingose paieškos erdvėse.
5. Siūloma adaptyvi apibendrinta aplinkos tyrinėjimo strategija yra efektyvesnė, lyginant ją su artimiausio kandidato strategija (CF) ir standartine aplinkos tyrinėjimo strategija (SIG):
   5.1. Kiekybinis rezultatų palyginimas tarp siūlomos apibendrintos aplinkos tyrinėjimo strategijos ir SIG strategijos parodė, kad, taikant siūlomą strategiją, autonominis robotas ištiria iki 12,7–13,2 % daugiau SAR erdvės. Lyginant siūlomą ir CF strategijas, robotas ištiria iki 10,4–23,6 % daugiau erdvės, kai taikoma siūloma strategija.
   5.2. Kiekybinis rezultatų palyginimas, kai vertinamas roboto surinktos nuobaudos dydis, rodo, kad, taikant siūlomą apibendrintą aplinkos tyrinėjimo strategiją, šis parametras sumažinamas iki 94,4 %. Šis reikšmės sumažėjimas yra stabilus visose simuliuojamose aplinkose.
   5.3. Taikant siūlomą apibendrintą aplinkos tyrinėjimo strategiją, roboto nukeliautas atstumas padidėja iki 33,6 %. Įvertinus santykį tarp roboto nukeliauto atstumo ir ištirtos erdvės dydžio, šis padidėjimas nėra reikšmingas, nes autonominis robotas kartu padidina ir ištirtą plotą.

Rokas SEMĖNAS

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BY MULTI-CRITERIA DECISION-MAKING METHODS

Doctoral Dissertation

Technological Sciences,
Informatics Engineering (T 007)

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TAIKANT DAUGIAKRITERINIUS
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