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MULTI-CRITERIA DECISION MAKING IN COMPLEX DECISION ENVIRONMENTS

BY
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Multi-Criteria Decision Making in Complex Decision Environments

Ph.D. Dissertation

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We are rebellious in spirit, and desire paths are a physical manifestation of the untamed parts of us that defy control by external systems. This PhD thesis is about regaining control in decision making - working towards systems that fit our spirit rather than our spirit being confined to fit a system.

Fig. 1: A picture of a desire path taken from a walk at the University of Moratuwa campus in Sri Lanka

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CV

Alex Elkjær Vasegaard has a MSc in Math and Economics from Aalborg university, Denmark. Before graduation he worked as a student worker in the Operations research group and continued after as a Research assistent after graduation in 2019. He had a semester abroad at Royal Melbourne Institute of Technology in 2018. From 2020 he officially transitioned into a PhD fellowship in the Operations research group at Aalborg university. During his PhD study, he has had research stays abroad at Seoul National University in 2021 (South Korea), University der Bundeswehr Munich in 2021 to beginning of 2022 (Germany), University of Morotuwa (Sri Lanka) in 2022, and lastly at Polytechnique Montréal in 2022 (Canada).

His research interest by area include operations research, systems engineering, decision support systems, and multi-criteria decision making with a focus on integrating human preferences, while by topic they include the space and drone industry.

Abstract

In the future, many decisions will either be fully automated or supported by autonomous system. Consequently, it is of high importance that we understand how to integrate human preferences.

This dissertation dives into complex decision environments which we define as decision problems with an underlying large-scale NP-hard multi-objective optimization problem with uncertainty stemming from the stochastic environment or fuzzy preference knowledge of decision makers, all while the computation has to be performed in near-real time. The last charateristic leaves it infeasible to introduce a decision maker in operation, and automated approaches to solve and introduce preferences is therefore investigated. The dissertation approaches this through the investigation of two different problems domains, namely; the Satellite Image Acquisition Scheduling Problem (SIASP) and the Unmanned Aerial Vehicle Routing Problem (UAVRP) with emphasis on the search and rescue domain.

The dissertation is based on the foundations of operations research, but is essentially a multidisciplinary research field within decision theory, mathematics, computer science, economics, and psychology. This manuscript consists of an extended summary of the six research papers produced through the PhD work, denoted from Paper A - Paper F.

In Paper A, an exploration of regular evaluation methodology is introduced, investigating the application of MCDM approaches to manage the multi-objectivity and uncertainty in the SIASP. Different problem formulations are proposed, search heuristics are designed, discussed, and tested, and preference articulation schemes are evaluated based on the customizability, robustness, intuition, and explainability. In Paper B, the bi-objective optimization environment of UAV-based path finding is investigated in the context of smart cities. Here, we present the A priori decision framework to significantly decrease the complexity, but also showcase the complexity of identifying a proper preference structure, as a a weight setting through scalarization and the WSA is very scenario dependent, and with inexperienced decision makers therefore can seem completely arbi-

trary. In Paper C, results from different pre-processing configurations are investigated, concluding that the pre-processing has a significant effect on the performance of solution approaches for the SIASP. In Paper D, the UAVRP is investigated through an a priori preference integration framework assuming the corresponding score of visiting a node to emulate the importance that decision makers assign it. The research is focused on the design of a heuristic based approach and comparing the promising results with exact solvers. In Paper E, the implications from a decision maker standpoint are highlighted, which in case of the satellite operator are promising. Moreover, an extended sensitivity analysis is conducted to evaluate the preference space, which additionally lays the foundation for a significance test framework, that can be used to tune the decision maker defined preference structure. In Paper F, the decision stages of the SIASP is investigated in greater detail, leading to an analysis of the collaborative decision-making effects obtained from pricing schemes and preference structures of the satellite operation. An autonomous decision-making scheme is presented based on VIKOR and Shannon entropy to automatically suggest settings of pricing and preference structures.

In short the entire dissertation delves into the research field of a priori preference integration frameworks in order to further the transition towards autonomous decision making in complex decision environments. A discussion on pairwise and setwise preference articulation methods is also undertaken to further showcase the shortcomings of regular a priori frameworks. With this, attainable features and fitting decision frameworks are proposed, in order to consequently lay a roadmap towards the ultimate goal of a setwise preference articulation method.

Resumé

Dansk Titel: multi-kriterie beslutningsmodeller i komplekse beslutingsmiljøer

I fremtiden vil mange beslutninger enten være fuldt automatiserede eller understøttet af autonome systemer. Derfor er det af stor betydning, at vi forstår, hvordan man integrerer menneskelige præferencer.

Denne afhandling dykker ned i komplekse beslutningsmiljøer, som omfatter beslutningsproblemer med underliggende storskala NP-hårde fler-objektiv optimeringsproblemer med usikkerhed stammende fra det stokastiske problemmiljø eller fuzzy præferencekendskab hos beslutningstageren, samtidig med at beregningen skal udføres i nærreal tid. Den sidste karakteristik gør det umuligt at have en beslutningstager i drift, og derfor undersøges automatiserede tilgange til at løse og introducere præferencer. Afhandlingen arbejder med to forskellige problemområder, navnligt Satellite Image Acquisition Scheduling Problem (SIASP) og Unmanned Aerial Vehicle Routing Problem (UAVRP) med fokus på den første del af søgning- og redningsområdet.

Afhandlingen er baseret på viden produceret inden for forskningsfeltet operationsanalyse, men er i sin essens et tværfagligt forskningsfelt inden for beslutningsteori, matematik, datalogi og psykologi. Dette manuskript er en udvidet sammenfatning af de seks forskningsartikler, der er produceret gennem ph.d.-arbejdet, betegnet fra Paper A til Paper F.

I Paper A introduceres en regelmæssig evalueringsmetodologi, hvor anvendelsen af MCDM-tilgange til at håndtere flerobjektivitet og usikkerhed i SIASP undersøges. Forskellige problemformuleringer foreslås, søgeheuristikker designes, diskuteres og testes, og præferenceartikulationsskemaer evalueres ud fra tilpasningsdygtighed, robusthed, intuition og forklarlighed. I Paper B undersøges den biobjektive optimeringsmiljø for UAV-baseret ruteplanlægning i smarte byer. Her identificerer vi a priori beslutningsrammen for at reducere kompleksiteten markant, men vi viser også kompleksiteten ved at identificere en passende præferencestruktur, da vægtsætning gennem skalarisering

og WSA er meget scenarieafhængig og kan virke helt arbitrært for uerfarne beslutningstagere. I Paper C undersøges resultaterne fra forskellige konfigurationer af preprocessing til SIASP, hvor det konkluderes, at forbehandlingen har en betydelig effekt på præstationen af løsningsmetoder til SIASP. I Paper D undersøges UAVRP igen gennem en a priori præferenceintegrationsramme, hvor den tilsvarende score for at besøge en knudepunkt anvendes til at efterligne den vigtighed, som beslutningstagere tillægger det. Forskningen fokuserer mere på designet af en heuristikbaseret tilgang og sammenligning af lovende resultater med nøjagtige løsere. I Paper E fremhæves implikationerne fra et beslutningstagervinkel, hvilket i tilfælde af satellitoperatøren virker lovende. Der udføres desuden en udvidet følsomhedsanalyse for at evaluere præferenceområdet, hvilket yderligere lægger grundlaget for en signifikansprøvningsramme, der kan bruges til at finjustere den af beslutningstageren definerede præferencestruktur. I Paper F undersøges beslutningsstadierne i SIASP i større detaljer, hvilket fører til en analyse af de effekter, der opnås fra prissætningsordninger og præferencestrukturer for satellitdriften. Der præsenteres en autonom beslutningsproces baseret på VIKOR og Shannon-entropi til automatisk at foreslå indstillinger for prissætning og præferencestrukturer.

Kort sagt dykker hele afhandlingen ned i forskningsfeltet for a priori præferenceintegrationsrammer for at fremme overgangen til autonom beslutningstagning i komplekse beslutningsmiljøer. Der foretages også en diskussion om metoder til parvis og sætvis præferenceartikulation for at yderligere vise begrænsningerne ved regelmæssige a priori rammer. Med disse funktioner og passende beslutningsrammer foreslås der en vejledning mod målet om en sætvis præferenceartikulationsmetode.

Contents

Thesis Details

Thesis Title:	Multi-criteria decision-making in complex decision environments
Ph.D. Student:	Alex Elkjær Vasegaard
Supervisors:	Assoc. Prof. Peter Nielsen, Aalborg University
	Ass. Prof. Subrata Saha, Aalborg University

The core of the dissertation comprises the following papers.

[A] Vasegaard, A. E., Picard, M., Hennart, F., Nielsen, P., & Saha, S. (2020), "Multi criteria decision making for the multi-satellite image acquisition scheduling problem", *Sensors*, 20(5), 1242.

[B] Saha, S., Vasegaard, A. E., Nielsen, I., Hapka, A., & Budzisz, H. (2021), "UAVs Path Planning under a Bi-Objective Optimization Framework for Smart Cities", *Electronics*, , 10(10), 1193.

[E] Vasegaard, A. E., Picard, M., Nielsen, P., & Saha, S. (2023), "Towards an autonomous system for the satellite image acquisition scheduling problem through multi-criteria decision-making and the extended longest path algorithm" *Working paper - not submitted yet*

[F] Vasegaard, A. E., Moon, I., Nielsen, P., & Saha, S. (2022), "Determining the pricing strategy for different preference structures for the earth observation satellite scheduling problem through simulation and VIKOR" *Flexible Services and Manufacturing Journal*, 1-29.

In addition to the main papers, the following publications have also been made.

[C] Elkjaer Vasegaard, A., & Nielsen, P. (2021, March), "An improved pre-processing method for cyber physical systems-as illustrated in the earth observation satellite scheduling", *5th International Conference on Robotics, Control and Automation*, pp. 102-106.

[D] Pedersen, C. B., Nielsen, K. G., Rosenkrands, K., Vasegaard, A. E., Nielsen, P., & El Yafrani, M. (2022), *A GRASP-Based Approach for Planning UAV-Assisted Search and Rescue Missions*, Sensors, 22(1), 275.

This dissertation has been submitted for evaluation as a partial fulfillment of the requirements for the PhD degree. It is based on the scientific papers submitted or published, as listed above. The extended summary of the thesis incorporates elements from these papers, either directly or indirectly. In the assessment process, co-author statements have been provided to the evaluation committee and are accessible at the Faculty.

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None of this research would have been possible if it had not been for the giants before me laying the foundation for the decision making methods in use and under research at this moment. As our world becomes increasingly complex and interconnected, the ability to make informed and effective decisions has never been more critical. It is my hope that this dissertation will not only contribute to the existing body of knowledge but also inspire others to explore the fascinating realm of decision making and its profound impact on individuals, organizations, and society as a whole.

Thank you to my parents, Solvej and Søren, my siblings, Marc and Claire, my girlfriend, Sophia, and the rest of my family for accompanying me throughout the ups and downs, supporting and motivating me to do better, and for being an ever present reminder on what life is all about.

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Thank you to the operations research group at Aalborg university for your insights into research but also for being not just co-workers but friends. And a Special thanks to my PhD co-supervisor, Subrata Saha, your ideas have helped me improve my way of understanding research but also of understanding life. Thank you to My PhD supervisor

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Lastly, thank you to my friends all around the world for exploring the world with me. With friends like you, the world is nothing but a piece-of-cake.

Alex Elkjær Vasegaard
Aalborg University, June 29, 2023

Abbreviations

MCDM - Multi-Criteria Decision Making
SIASP - Satellite Image Acquisition Scheduling Problem
UAV - Unmanned Arieal Vehicle
VRP - Vehicle Routing Problem
UAVRP - Unmanned Arieal Vehicle Routing Problem
SAR - Search And Rescue
AI - Artificial Intelligence
DSS - Decision Support System
WSA - Weight Space Analysis
DM - Decision Maker

Part I

Dissertation

Chapter 1

Introduction

Autonomous systems already carry the weight of the world, and with the current outlook on the capability trends of labour automation (e.g., robotics, NLP) [54], data collection (e.g., sensors on automated systems) [8], connectivity (e.g., 6G, space-based communication), computing (both for local and cloud solutions) and general decision making, the weight is only getting heavier, and it is getting heavier fast. The increased automation seen in the manufacturing settings of the industrial revolutions is set to spill over into all lines of work [115]. The next frontier of automation covers all of human capability, most recently seen with the development of AlphaTensor and AlphaDev that moved into the territory of algorithm design for matrix multiplication and sorting, which is a field of research only thought to belong the fiercest of creative mathematical humans [28, 68]. Consequently, the transition of problems otherwise considered human-only property has to be conducted in a safe and ethical way [66].

Simultaneously, certain problems are not necessarily well-prepared for the regime of machine learning approaches, as trustworthiness and robustness reigns supreme. Especially, if the Decision Maker (DM) or group of DMs does not know or understand their preferences or the intricacies of the solution space particularly well and correspondingly needs a great deal of support to make a decision. Of these problems, the two that are investigated in this PhD dissertation are the Satellite Image Acquisition Scheduling and Unmanned Aerial Vehicle Routing Problem (SIASP and UAVRP, respectively) as these have similar characteristics and the knowledge gained from tackling them will be widely applicable.

With New Space, the recent change in the global space ecosystem, the private sector has entered the space race. Most notably seen with SpaceX developing reusable boosters that has decreased the price of payload-to-orbit and thereby increased the access to space for a lot of companies developing their own satellite systems [81, 140]. Simultaneously, the use of space-based systems in agriculture, communication, maritime and urban surveillance, search and rescue missions, environmental monitoring, climate change, military intelligence, traffic monitoring, business and finance has seen an explosion in interest and usage. Consequently, the problem of scheduling satellites is of high interest to both business and academic communities [140].

As competition in the access to space increases, so does the competition for developing more efficient satellite systems. Especially for the larger EOS systems like that of the Airbus D&S-owned PLEIADES or SPOT. The ability to acquire more data in greater detail with higher quality to the right customers in due time is of apparent necessity for their continued success [88, 97, 126]. Fig. 1.1 illustrates the complexity and scale of identifying the best satellite schedule, capturing the highest number of high quality images, while considering criteria of varying nature (e.g., emergency, customer type, cloud coverage, sun elevation, depointing angle, and profits). Simultaneously, as communication between in-orbit objects and ground stations is only feasible for certain periods, updating the satellite schedule based on new information is not always possible. Consequently, you want to have information that is as new as possible when developing a schedule. This means, either to re-schedule just prior to execution with no degrees of flexibility on the deadline or to place the decision making onboard instead of on-ground. Ultimately, this comes with the challenge of local optimality rather than global optimal plans, and whether the onboard intelligence has the trust of the satellite operation.

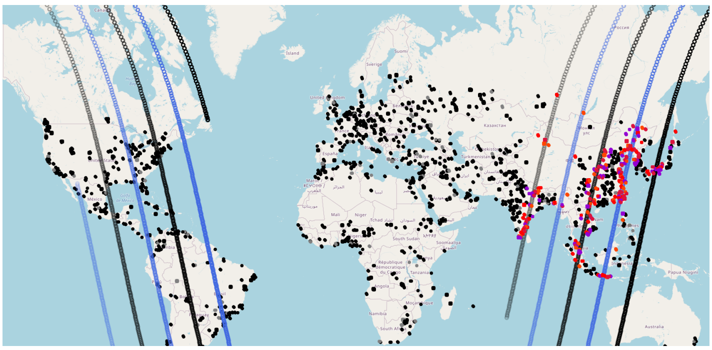

Fig. 1.1: A map representation of a SIASP scenario generated with the EOSpython framework briefly presented in Paper E

Equal to the revolution of New Space, the promised land of the Unmanned Aerial Vehicle (UAV) platform and the accompanying technology of its payload features faster delivery and pick-up in all levels of the supply chain for goods and services. Everything from improving the efficiency of supply chains within a factory environment [111], acquiring agricultural intelligence to increase efficiency of crop production [106], different search-and-rescue environments [36], to overcoming geographical pitfalls in vaccine delivery [37] are on the table. However, especially for use cases differing from logistics, the objectives and preferences of the DM start to fuzzify, as maximising the utility of the assets become of higher priority than minimizing the total distance travelled. This implies the need to evaluate the trade-off between visiting and omitting certain nodes of interest in ones graph, and quantifying the importance of different acquisitions.

Multi-criteria decision making (MCDM) is a field of research that deals with evaluation and design problems influenced by multiple criteria or objectives - with conflicting characteristics s.a. profits, quality, and sustainability. As future problems become increasingly more complex, it is important that we optimize for the correct balanced set of objectives to avoid everything from harmful bias and inconceivable costs to issues concerning transparency, reliability, and trust. The biggest example of today is the flawed focus on short term profits, that has caused the world to spiral towards a climate catastrophe.

This dissertation focuses on two decision problems residing in the Complex Decision Environments of remote sensing, which in the context of this dissertation are characterized by the following properties:

1. *Large-scale optimization problem*: for practical reasons, the problem scenarios are always characterized by a large number of variables and constraints, which make them computationally intensive and time-consuming. Large-scale optimization problems arise in various domains, such as engineering, finance, logistics, and transportation, and they require a mixture of advanced and novel optimization algorithms and high-performance computing resources [21, 79, 138].

2. *Complexity of NP-hardness*: NP-hardness refers to the computational complexity of a problem that belongs to the class of problems known as NP (nondeterministic polynomial time) problems. An NP-hard problem is one for which there is no known algorithm that can solve it in polynomial time [93]. Examples of NP-hard problems include the traveling salesman problem, the knapsack problem, and the graph coloring problem.

3. *Multi-objectivity (if not many-objectivity)*: Multi-objective optimization problems involve optimizing two or more conflicting objectives simultaneously. The goal is to find either find a single solution accommodating the preferences of the DM or a set of non-dominated solutions [108, 124]. Many-objective optimization problems involve optimizing many objectives simultaneously [19]. Multi-objective and many-objective optimization problems are common in real-world applications, such as engineering design, financial portfolio optimization, and supply chain management [69]. The preferences of the DM determine how the different objectives are compared. In a safety-critical environment, certain objectives are of much higher priority than others [78].

4. *Near real-time computation requirements*: This characteristic refer to the need to solve a problem within a specified time constraint [42]. Near real-time applica-

tions require fast and efficient algorithms that can deliver results within minutes, seconds, or even milliseconds. Examples of near to real-time applications include autonomous vehicles, robotics, and financial trading systems.

5. *Uncertainty from either the environment or the DM*:

   In the environment imposed domain, the uncertainty refers to the stochastic behaviour that may or may not follow a known probability distribution [116]. In general, this stems from unknown or indescribable factors that influence the decision-making process. These factors may include changes in market conditions, fluctuations in demand, or unexpected disruptions in supply chains.

   In the domain of the DM, the uncertainty refers to the inherent limitations and biases of the DM, that can affect the optimization problem [58]. These limitations can include incomplete information, incompetence, cognitive biases, and personal preferences that may not align with the stakeholder preferences in terms of defining optimality [20]. Generally, this entails dealing with knowledge that is fuzzy and considering it as such, rather than enforcing through a crisp framework [47].

Combined, these properties make it very unlikely that the solution approach will yield an optimal solution, as some trade-offs have to be made on the basis of optimality, feasibility, robustness and explainability. A set of attractive features beside optimality for the obtained solution is robustness and explainability. Not necessarily seen as conflicting, but as complementing traits.

1 Motivation

1.1 Practical Perspective

We are at the dawn of the cybernetic era, pushing towards software 2.0, and leaving increasingly more humans redundant in different applications of the OODA loop (Observe, Orient, Decide, Act) [86]. Increased computational capabilities and the ever-increasing amount of available data [102] allows for the inclusion of beneficial information to the decision process. However, this additional information dramatically increases the complexity of the decision environments, and it is therefore important that the developed methods increase the transparency of the decision process. Accuracy and interpretability have for a long time been contrasting features of one's model, but the success of ensemble methods (XGboost with all its variants, random forrest), neural networks (MLPs, RNNs), and kernel based methods (support vector machines) in this accelerated world have re-sparked the hunt for interpretability [12, 39, 72, 84, 104]. Not only in the relationship between the feature space and solution space, but also in its connection to the preference space. However, for certain automated processes, solution search methods with a lack of transparency are not feasible alternatives due to the high variation in problem scenarios and the need for trust in the system [15]. This includes the so-called black-box methods of deep neural networks, but in general methods where explainability is a function of the size of the model. As an example, decision trees are generally very explainable, but larger decision trees, and extended versions of these like the popular XGboost method, are too complicated to deem explainable [18]. Consequently, these methods are not feasible for these situations, especially, when the act of allowing the DM to impose their preferences is of high importance.

To point in a direction with the practical perspective, a question for the complex decision environments is therefore: *Why are the correct preferences often omitted in the design of solution approaches to large-scale NP-hard optimization problem with near real-time computation requirements?*

1.2 Theoretical Perspective

For an automated decision-making scheme to be successful, we have five entities that we want to overlap as much as possible. see illustration in Fig. 1.2. Here an overlap signifies the level of control and understanding, that one entity has over the other. The corresponding entities are the DM, the preference structure, the problem formulation, the final solution, and the solution characteristics. The functionality of an overlap are signified by the processes of preference elicitation, preference articulation, solution search, and a simulation or testing phase. Note, the order with which these processes take place is not fixed.

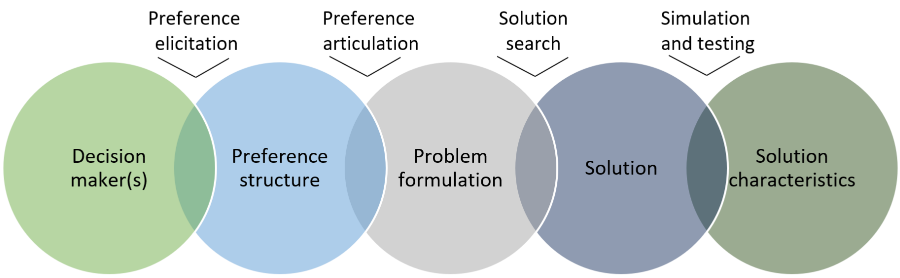

Fig. 1.2: Holistic illustration of an automated decision-making procedure with focus on the relationship between the DM, the final solution, and the solution characteristics. Note, the left to right ordering does not imply any ordering, as the solution search also can be performed before or during the preference elicitation. The ordering depends on the design of the system (see section 2.2 on place of articulation).

Today, a great deal of decisions can be represented mathematically as optimization problems, but due to the scale and available computing power, multiple objective/criteria aspects are often neglected or omitted, leaving a sub-optimal solution to be produced that ultimately does not fit to the preference structure of the DM. However, since Daniel Kahneman won the 2002 Nobel prize in economics for his work on behavioural economics, the notion of human behaviour has gained traction, and research communities have moved towards integrating human factors into decision-making problems [49]. This all with the goal of improving explainability, flexibility, robustness, and transparency of the decision environments, but also to alleviate bias and integrate the inherent incompetence, indifference, and uncertainty of the DM. An example for the push in this direction, is the newly defined terminology of Industry 5.0, which seeks to reintegrate humans and sustainable human values into industry [77].

Despite the push to integrate the correct preference structures [46, 64, 133], when dealing with large-scale NP-hard problems in time constrained environments the comparison of different solutions on the obtained Pareto front is of high likelihood to not lay on the actual Pareto front [63, 119], and consequently the additional computing power spent to identify additional solutions could have been used more effectively. Additionally, in real-time computation requirement environments, the act of allowing a DM to evaluate a Pareto front is often completely infeasible. Especially, if the Pareto front is generated in a many-objective environment where practically every feasible solution can be Pareto optimal.

A general theoretical question for the complex decision environments is therefore: *Which problem formulation scheme and solution approaches are applicable to integrate the preferences of the DM in a large-scale NP-hard stochastic multi-objective optimization problem with real time computation requirements?*

1.3 Philosophical Perspective

In the future every decision will be automatable, and it will have to be an active choice for humans to participate, contribute, finetune, alter or oversee decision processes. Consequently, it is imperative that we understand how human preferences can be articulated, integrated, and taught.

In order for the autonomous system to properly make or suggest solutions that fit our preferences, the underlying problem needs to integrate multiple objectives and/or criteria that properly reflect the real-world scenario. Any single objective/criteria representation of the real world is nothing but a naive reflection of the truth. Nevertheless, some naive reflections can be very useful, but in general, the more complex a problem gets, the more naive a single objective representation is. Even in the event that only profit is to be considered, the actual objective would be long-term profit, which is extremely difficult to quantify as quality, customer satisfaction, company image, even employee satisfaction and climate impact has a great impact on the long-term profits of the company. Surely, considering these other criteria has a negative impact on short-term profits, and the important thing is therefore to assert the correct balance between the different objectives and/or criteria. After all, humanity is playing a (seemingly) infinite game where the objective is to ensure participation rather than to win [14].

Rather than playing within the constraints of the game, we are playing with the actual constraints.

Furthermore, as a philosophical remark to the motivation of this PhD dissertation, the works of Mercier et al. [73] showcase that the origin and real use of reason is a social ability, rather than an ability that allows us to obtain better decisions. As a consequence, reason and thereby decision-making tools are moreso utilized to better reason for the decision that we make towards others [123]. Before complex decision-making tools are easily available, it is therefore very understandable that decisions explained by simple and very transparent reasoning like metrics such as profit, will be accepted as the best one. Therefore, due to the increased amount of available data and with the development of more intuitive decision-making tools, it is very plausible that a direct consequence is improved sustainability, improved employee happiness, health, and customer satisfaction. Simply put, a direct consequence of the improved decision-making methods is, that bad decisions more clearly will stand out as what they are - bad decisions.

We humans have the power to destroy all life on earth within a couple of hours, and we have had that since the invention of the atomic bomb. Einstein famously said that *"The release of atomic power has changed everything except our way of thinking..."*. Before we transition completely to the cybernetic era, it is important that we either change the way we think or develop tools that improve our thinking. I hope this work contributes to the latter.

2 Research Gaps

The research gaps are identified based on the two representative problem domains; the SIASP and the UAVRP, where the majority of work is done within the SIASP.

The following research gaps and corresponding research objectives are identified:

1. Some problems, which are fundamental MCDM problems, are not considered as such in the literature and business due to the added complexity. One goal is therefore to present efficient and robust methods that efficiently integrate and analyse the multi objectivity of the problem in order to benefit from the added flexibility that this yields. The SIASP is a great example as most papers on the matter focus on the scheduling sub-problem, and in turn seek to optimize e.g., expected number of images, expected profit, or average cloud cover without considering the collective multitude of objectives existing within the satellite operation [9, 42, 91, 120]. **How can this be integrated in a manner that does not significantly increase the complexity of the solution approach?**
   Additionally, the MCDM problems with implicitly known alternatives will only to a very low degree allow the DM to incorporate their preferences, and often through a very rigid weight setting scheme [42, 67]. **How can this be extended**

such that operators can incorporate their preference structure more precisely and take advantage of the system flexibility?

2. The same problems often neglect the fuzzy and stochastic nature of the decision environment, examples on these uncertain conditions in the SIASP are:

    - Uncertainty in cloud coverage information – directly impacts the quality and therefore quantity of acquired data.
    - Uncertainty imposed by the incompetence of the DM when defining the preference structure.
    - Uncertainty in terms of the accuracy of the imposed preference structure.
    - Uncertainty in long term effects of the different preference structures. The realization and understanding that the ultimate objective is changing in relation to time and/or decision environment.

    How can uncertainty be incorporated in the solution approaches without increasing the complexity of the decision environments greatly?

3. The current plethora of MCDM methods developed for the evaluation problems focus on problems where alternatives have to be selected, ranked, or sorted [2, 56, 131]. However, there does not exist a method for choosing between different subsets of alternatives that incorporate the true preference of the DM. For complex decision environments, the matter of understanding the different alternatives sometimes extend the selection, ranking, and sorting goal of regular MCDM approaches. This could be in the process of selecting the best subset of image acquisitions available. Recent work by J. Figueira et al. [30] suggest to make strides towards the set wise selection problem with their ELECTRE-score method, but when incorporating preferences they are only implementing the preferences on the single element level.

3 Research Questions

From the research gaps, the corresponding research questions are:

RQ1 *Which decision-making framework is applicable to integrate the multi-objectivity of complex optimization problems without a significant increase on the computational load of the solution approach?*

RQ2 *How can the approaches from the evaluation methodology be converted to accompany and mitigate explainability and transparency issues in design problems, while allowing for a customizable integration of the preference structure?*

RQ3 *How can the different types of uncertainty be integrated in the solution approach?*

RQ4 *How can setwise preference information be elicited, integrated, and utilized?*

The goal with these questions is, besides addressing the identified gaps, to develop novel solution methodologies for integrating multi-criteria decision making in complex decision environments, as well as contribute to both MCDM literature and the literature on the different problems. The focus and coverage of the research questions in terms of an automated decision-making procedure can be seen in Fig. 1.3. Additionally, RQ1 is specifically answered in detail in Section 1, RQ2 in Section 2, and RQ3 in 3. The last research questions is answered with a discussion and a proposed roadmap in Section 4.

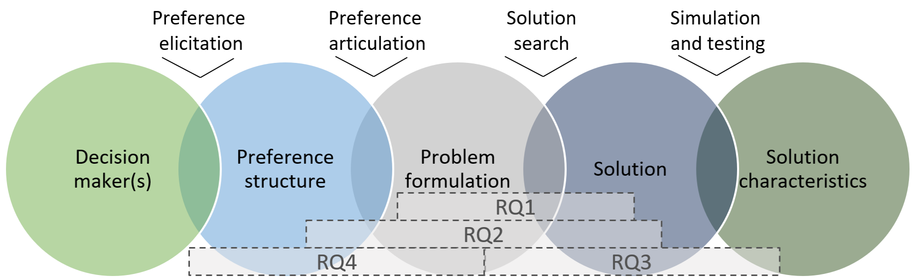

Fig. 1.3: Holistic illustration of an automated decision-making procedure with focus on the relationship between the DM and the computed solutions. The corresponding coverage of the posed research questions posed in Section 3 can also be seen illustrated.

Holistically, this means the DMs will occupy the role of customers in the system. This PhD study focuses on the preference articulation in the automated decision-making procedure, but will also cover the phases of solution search and simulation, while the preference elicitation is only briefly described.

4 Research Methodology

Validating the results of the devised solution approaches is in some ways trivial when the objective is clear, as the procedure of modelling the problem (See Fig. 1.4) in order to obtain a real-world solution are comparable with other real-world solutions a posterior. Following a scientific research method rigorously will lead to robust results, and not doing so will consequently show in the results. However, for the sake of repeatability and later re-applicability, the utilization and description of the used research methodology is crucial. Especially, as the devised methods at a later point is expected to either directly or indirectly be used to generate applicable knowledge for the industry.

Knowledge creation relies heavily on the presupposed assumptions of that knowledge about the world. Often these are referred to as the ultimate presuppositions, which serve

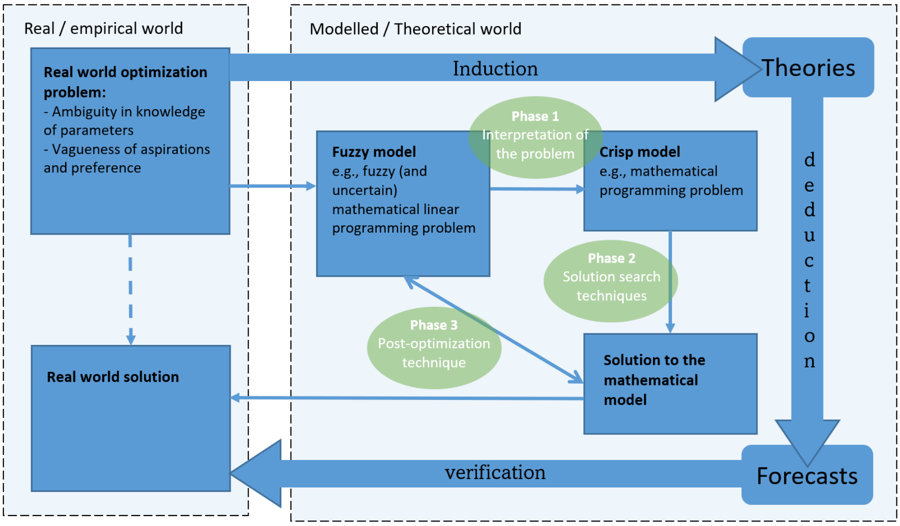

Fig. 1.4: Illustration of the conceptual background when modelling a real world problem and the three phases of interpretation, solution search, and sensitivity analysis. The figure is adapted from M. Inuiguchi et al. (2002) [47] and based on the cyclical nature of creating knowledge with the analytical view in Arbnor et al [5].

as the foundation in determining how facts are realized, interpreted and aggregated [5]. If a "worldview", P, is challenged, the supporting arguments, Q and R, are now not just supporting but the new bearing arguments, and to upheld these, new supporting arguments, S, T, U, and V, have to be posed. Consequently, a person who presupposes that reason is the ultimate test for truth, must at some point base even the simplest of arguments on a set of axioms, that may or may not presuppose the actual truth [25].

Theorists of science, have developed a large suite of "conceptual languages", that relates the ultimate presuppositions with the area of study. The chosen "language" represents the research methodology, that enables knowledge creation to rest on a bedrock of presuppositions on which other research also rests. The paradigm is that common set of assumptions and orientations which a research community shares - and with the paradigm, specialization flourishes [57]. The progression of a research community can be identified based on the state of the paradigm. Either multiple different "worldviews" exist situating the research field in a pre-paradigmatic period, a single agreed upon paradigm can be identified classifying it as a normal science, or an anomaly has been identified that cannot be explained with the current set of presuppositions throwing the state of the science into chaos, called the revolutionary science period. Later, due to a new paradigm being identified that explains the anomaly, the science is yet again in a state of normal science. Until a new anomaly is identified or a broader, more inclusive model is identified [57].

The Analytical View

In Arbnor et al [5], three methodological views are presented, namely the analytical view, the systems view, and the actors view. The crux of their differentiation happens at the posed ultimate presuppositions, where the analytical view sees the information of the whole as factive and equal to the summed information of its parts. Here information can be both objective and subjective, and lastly the parts are explained through verified judgements [5]. In the analytical view, the research methodology utilize and investigate cause-effect relations (as an ideal), logical models, and pose representative cases. As a critique to the analytical view, both the systems view and the actors view state that the whole is not equal to the sum of its parts. Many other theories have appeared as a critique to the analytic view, e.g., the actor-network theory.

In Fig. 1.4, the analytical view on knowledge creation is in full effect. From the empirical and real world, the theories are induced. With these theories, (fuzzy and eventually) crisp models are designed and formulated. Based on the models and theory, we deduce a solution or make a prediction about the real-world, which then is verified and compared through real-world experimentation. Note the connection to Fig. 1.2, where phases 1 and 2 in Fig. 1.4 correspond to the design of the problem formulation and solution search.

Assuming the state of the optimization research community being in its normal science period, this PhD dissertation utilizes the standing paradigm and hereunder research method by the analytical view. Combining results from the standing theoretic contributions from multi-objective research community and the expert knowledge generated on the designated problem domains to infer and deduce new solution methods. To deduce results from existing theory, we develop the scheme presented in figure 1.5. This is a personal work paradigm designed to suit the research topics, but it is heavily inspired by the mixed research method [141], perspectives on the scientific method [122], and the Rapid Application Development method [71]

In stage 1 for each problem domain, a focused literature study is conducted to explore the utilized problem formulations, solutions approaches with the edge of utilized MCDM methods, and furthermore to investigate specifics and peculiarities to the problem. In stage 2, the problem specific information is identified for the problem environment, e.g., relevant criteria, operational constraints, and objectives to consider. Additionally, the stochastic and uncertain elements or conditions to account for in the decision environment is identified.

In stage 3, we collaboratively design and implement the solution search algorithms and the MCDM algorithm.

The natural next step in stage 4 is to develop a scenario generator or a simulation tool that generate problem scenarios. That is, to generate simulated real world data to which the solution approaches can be compared and validated experimentally. For the

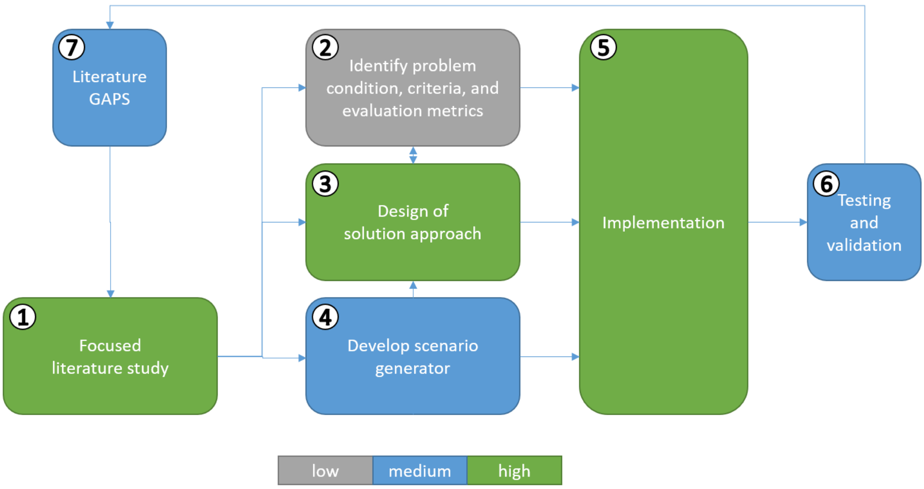

Fig. 1.5: Overview of the adapted research methodology with the different stages. The colors present a combined view of the different levels of workload and novelty required to execute the different stages.

SIASP, that is, cloud coverage, which leads to develop either a cloud forecast generator or to retrieve real-time forecasts of the location of customer requests, and to utilize those forecasts. Moreover, the uncertainty induced by the DM due to both incompetence and their literal uncertainty towards the actual preferences is investigated. Note the applicability of the scenario generator highly depends on the inputs from industry experts. This development procedure coincides with the development of evaluation metrics. Likely they can be implemented directly from the literature study as the results can serve as a means of comparison with other research results. Hereafter, we implement the solution approach and the scenario generator in stage 5.

In stage 6, solution approaches are then experimentally verified through a thorough simulation phase, and those results are then discussed to present proposals that can fill the the identified literature gaps in stage 7. Note the dissemination in stage 7 will again activate the first stage in order to do a second focused literature study that thoroughly puts the proposed results into context. Consequently, the developed research methodology is an iterative process.

5 Structure of the Dissertation

The PhD dissertation consists of two distinct parts; the actual dissertation and the collection of papers. Additionally, the dissertation is split into three chapters; the remainder of Chapter 1 briefly presents the publications and work done through the PhD period. Chapter 2 explains the practical and theoretical background for the problem domains and the field of MCDM. Chapter 3 functions as a comprehensive summary and discussion of the developed methods and lessons learnt with a road map for future work sketched out.

5.1 Publications and Submissions during the PhD Study

Table 1.1: Overview of the papers

Paper A: Multi-criteria decision making for the multi-satellite image acquisition scheduling problem **Summary:** With this paper we investigate the effect and explainability of different scoring methods for the SIASP, namely TOPSIS, ELECTRE-III, and WSA. Along developing a simple scenario generator, we formulate the problem as a binary programming problem and deploy the large-scale exact GLPK algorithm to obtain a solution. We find the solution approach to do great on small problem scenarios, but struggle when the scenarios get larger. We found the ELECTRE-III approach to show high levels of customizability and allowed the DM to discriminate between customer priorities in an intuitive direct way, which the common weight articulation methods did not. The research objectives are to: • showcase the applicability of evaluation methodologies as scoring approach (a priori) in satellite scheduling problem • introduce ELECTRE-III, TOPSIS, and compare with the naïve weight setting • showcase the direct vs indirect preference structure articulation **Reference:** Vasegaard, A. E., Picard, M., Hennart, F., Nielsen, P., & Saha, S. (2020). Multi criteria decision making for the multi-satellite image acquisition scheduling problem. Sensors, 20(5), 1242.
Paper B: UAVs Path Planning under a Bi-Objective Optimization Framework for Smart Cities

Continued on next page

Table 1.1 – continued from previous page

Summary: In this paper we showcase a framework for the integration of multiple objectives in UAV path finding problem. Along with investigating the issues of doing so through regular weight setting approaches. We also devise a 2-stage VNS approach to combat the high complexity issues of the path finding approach, where a scenario almost randomly can be too complex for other approaches to solve. The research objectives are: • Investigate the issue of multi-objective formulation in path finding problem only indirect preferences • Investigate the scenario size effect on solution approach: Exact vs devised heuristic (VNS) **Reference:** Saha, S., Vasegaard, A. E., Nielsen, I., Hapka, A., & Budzisz, H. (2021). UAVs Path Planning under a Bi-Objective Optimization Framework for Smart Cities. Electronics, 10(10), 1193.
Paper C: An improved pre-processing method for cyber physical systems-as illustrated in the earth observation satellite scheduling **Summary:** This conference paper showcases some of the learnings and possible improvements found when dealing with the pre-processing method of the SIASP. One takeaway is the seemingly free improvements on running time. We also investigate the effects of modifications made in the pre-processing on small reformulations of problem. **Reference:** Elkjaer Vasegaard, A., & Nielsen, P. (2021, March). An improved pre-processing method for cyber physical systems-as illustrated in the earth observation satellite scheduling: Pre-processing method for cyber physical systems. In 2021 the 5th International Conference on Robotics, Control and Automation (pp. 102-106).
Paper D: A GRASP-Based Approach for Planning UAV-Assisted Search and Rescue Missions **Summary:** In this paper the UAV path finding problem is investigated in the setting of the UAV-assisted Search and Rescue problem (SAR). The paper walks through the later part of the design process of a fully-autonomous decision system, where the hotspots are simulated on a real-world map, a network is inferred and simplified to combat the complexity, and a grasp-based heuristic is developed and deployed to yield feasible routes. The system is compared to an exact approach and analysed through experimentation for different problem settings.

Continued on next page

Table 1.1 – continued from previous page

Reference: Pedersen, C. B., Nielsen, K. G., Rosenkrands, K., Vasegaard, A. E., Nielsen, P., & El Yafrani, M. (2022). A GRASP-Based Approach for Planning UAV-Assisted Search and Rescue Missions. Sensors, 22(1), 275.
Paper E: Towards an autonomous system for the satellite image acquisition scheduling problem through multi-criteria decision-making and the extended longest path algorithm **Summary:** This paper is a direct extension to the identified problems found in Paper A. We reformulate the problem into a DAG in order to decrease the complexity of large-scale problem scenarios, and develop the greedy algorithm ELPA that takes advantage of the satellite network knowledge. We further continue the analysis of the ELECTRE-III scoring approach and present two decision support tools in the heatmaps and the significance tests to support decisions on changes. The research objectives are: • Reformulation of SIASP as a DAG with interdependent and allowed nodes, and introduce the ELPA method • Performance analysis of ELPA vs exact approach (GLPK) • Weight space analysis and hypothesis test as decision support tool for the DMs to accompany ELECTRE-III **Reference:** Vasegaard, A. E., Picard, M., Nielsen, P., & Saha, S. (2023). Towards an autonomous system for the satellite image acquisition scheduling problem through multi-criteria decision-making and the extended longest path algorithm. *Not submitted*
Paper F: Determining the pricing strategy for different preference structures for the earth observation satellite scheduling problem through simulation and VIKOR

Continued on next page

Table 1.1 – continued from previous page

Summary: With this paper we extend the analysis of the SIASP to cover the collaborative decision making that is feasible with the MCDM framework. An in-depth analysis of the stakeholders and DMs in the SIASP and the market tendencies are used to reason why the pricing strategies are soon to see a change. We deploy the VIKOR method and the Shannon entropy weight elicitation method to automatically retrieve the best compromise solution in terms of a pricing strategy and preference structure. The results indicate significant benefits of collaborative decision-making strategies when devising the decision process. Mainly to: • Investigate dependencies in decision process of SIASP, i.e. integrating pricing strategy decisions on the schedule decisions • Automatic preference structure selection through VIKOR and Shannon's entropy weight elicitation method **Reference:** Vasegaard, A. E., Moon, I., Nielsen, P., & Saha, S. (2022). Determining the pricing strategy for different preference structures for the earth observation satellite scheduling problem through simulation and VIKOR. Flexible Services and Manufacturing Journal, 1-29.

The overall connections between the appended papers can be seen in Fig. 1.6, where three different subgroups have been showcased; namely main contributing papers, and supporting papers for the two problem domains. Note research questions 1-3 are investigated in all four papers of the main contribution, while research question 4 is answered in the dissertation. However, RQ1 is especially investigated in Papers A and B, RQ2 is investigated in all of the main papers, while RQ3 especially is investigated in Paper E and F.

6 Research-related Work

This section showcases all the work I have done in relation to the PhD. In the appendix in Section S-1, one can find a more detailed overview of conferences and workshop participation, teachings, supervisions, and examinations, as well as PhD related course work.

6.1 Abroad Research Stays and other Research Projects

The research has been conducted in collaboration with Airbus Defence & Space, Seoul National University (SNU), and Universität der Bundeswehr Munich (UniBWM), University of Morotuwa (UoM), and Polytechnique Montreal.

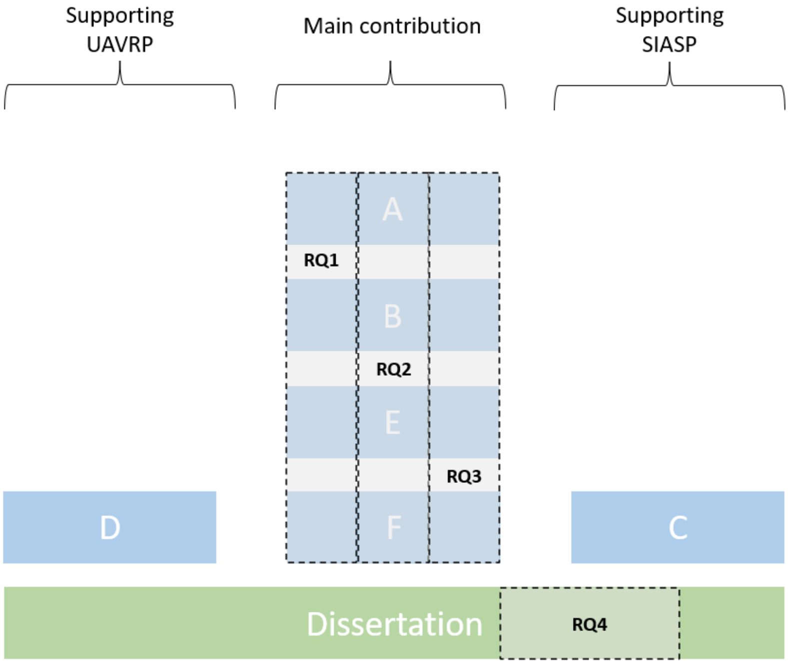

Fig. 1.6: Overview of the contributions and their connections to the research questions shown

At the industrial engineering department at Seoul National University under Prof Ilkyeong Moon the focus was on diving deeper into the decision structure of the SIASP, while initializing future collaborations on the drone applications. Under Prof Rose at the the Simulation and model building group at the computer science department of UniBwM, the focus was specifically on mission planning. At the Supply chain operations group of UOM the collaboration with Dr. Amila Thibbotuwawa and Dr. Niles Perera was focused on drone applications and on completing a literature study on the SIASP. With Prof. Pellerin and the team from the department of Mathematical and Industrial Engineering at Polytechnique Montreal the research work was focused on UAV deployment in the context of Search-and-rescue setting with real-world historic data from the tornado environment of Oklahoma.

The results of these collaborations is that there is a paper under preparation with Sean Grogan and the research group from Polytechnique Montreal on exactly prioritized UAV routing under tornado Search and rescue mission planning. Similarly there is a systematic literature review paper under preperation with Buddhi Weerasinghe and the research group from UoM. Finally, further papers are in preparation in collaborations with the research group from SNU and UniBwM on UAV deployment.

Chapter 2

Background and State-of-the-Art

In this chapter we unfold the practical and theoretical background of the investigated problem domains in Section 1 and thereafter the landscape of MCDM in Section 2 with a special emphasis on the applicable solution approaches.

1 Background of Problem Domains

As mentioned in the introduction, the following two problem domains both have high degree of membership to each of the identified characteristics that define a complex decision environment. The following explanations on the two problem domains will take the perspective of why they have a certain membership to each of the characteristics, and how the literature have dealt with it, separately.

1.1 Satellite Image Acquisition Scheduling Problem

The satellite image acquisition scheduling problem has been mathematically formulated as an optimization problem for decades. Bensana et al. [9] were likely the first to formulate the problem as a linear programming problem. Since, a great deal of extensions have seen the light of day with knapsack problem formulations [120], maximum clique problem formulations [67], exact and inexact solution approaches [61, 121], single to multi-objective formulations [11, 108], and different specifications of the real-world problem in constellation to single satellite [48], hyper-agile to non-agile [61], single-user to multi-user platform [11].

Large-scale Optimization Problem

The problem scenarios are usually of very large scale characteristic. Beside the high number of reasons for increased customer demand, the business case of sending high-resolution imaging satellites to orbit do not function without having a large set of customers to service. Otherwise, pseudo-satellites or other aerial platforms provide a great alternative. The benefit of orbiting image satellites come exactly in the form of their ability to acquire high quality images, to acquire large amounts of data, fast, and with high revisit frequency [4].

The SIASP has evolved from considering EOS with no degree of maneuverability to the realm of hyper-agile EOS [126]. The natural consequence of this is that a larger pool of requests can be reached as an acceptable depointing angle usually lies around 15-20 degrees unless otherwise specified. Another consequence is the inter-request agility, meaning a multi-strip request can be managed by the same satellite in the same orbit.

Moreover, as satellite projects are long term investments, companies will usually manage a larger fleet of heterogeneous satellites. This diversity of imaging payloads roaming on the satellites means the satellites can cover multiple different visual bands and therefore depending on which objective the imaging request has, serve multiple different types of customers. In the scheduling procedure, the satellite fit for the task will complete it - and the set of capable satellites are with this setup usually overlapping [4].

Complexity of NP-hardness

The generalized version of the problem is of NP-hardness complexity with certain specifications shown to be NP-complete. In the knapsack problem formulation, a big reason for the scaling of the problem is the interdependencies between the decision variables and the number of decision variables scale indirectly with the number of satellites, number of requests, and time resolution of the satellite path. Similarly, this interdependency is the main reason in the maximum clique problem formulation. Here it is however easy to visualize its scaling by the explosion of added edges as graphs in the EOS case usually is dense. That is, close to the maximum number of edges. See figure 2.1 for an illustration of different scenario sizes.

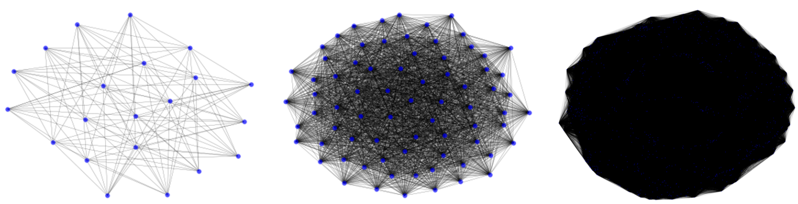

Fig. 2.1: The graph density showcased for the maximum clique problem of the SIASP for the three scenarios: 2 requests, 7 requests, and 15 requests, all with a time granularity of 9 seconds.

Multi-objectivity

The SIASP is fundamentally a many-objective optimization problem, that often is simplified to only consider a select few set of objectives [9, 79, 119]. Commercial satellites have only one long term objective in profit. However, as discussed in Paper E, the quantification of what long term profit entails is a difficult problem, and this means generally, that one classifies the total set of objectives into three different sets that focus on each of their aspects:

The political agenda: It prioritizes customer types in order to align with the company and stakeholder's policy. These are the immediate qualitative and quantitative effects that would decrease the likelihood of a satisfied customer [119].

The qualitative agenda: This deals with all the qualitative criteria that is connected to acquiring an EOS image. E.g., Sun elevation, depointing angle, and cloud coverage [116, 119, 125]. Perhaps, images above a certain quality is good enough, but in a competitive market having a comparably better quality is always of preference [129].

The operational agenda: This conveys the changing value of attempts relative to the remaining time until expiration of requests, the uncertainty of cloud coverage, and the multi-strip or stereo request completion [108]. Ultimately, it portrays the utility of completing certain request through time.

There is a general overlap between all of these aspect, and they all have to be weighted by the DM. E.g., the acquisition of a high number of images will naturally effect the quality of images, and a decreased quality can mean a loss of future customers. The EOS operator may desire to service as many customers as possible, but still want to ensure to service the highest priority customers. However, what if the acquisition of a high priority customer early in the process means a complete loss of a lower priority customer that has been waiting for their image for an extended period?

This is also where the critical dilemmas of the decision environment comes into play. Simultaneously, the priority of emergency requests have to be made with care, especially if multiple emergency requests are conflicting. Naturally emergency organizations will present their requests through a specialized platform, but ensure that the intricate priority is ethical is very difficult.

In Fig. 2.2, the entirety of the relevant criteria is showcased. The figure also illustrates the importance between criteria, and, if multiple objectives were to be considered, where to aggregate criteria to reach a certain total of objectives. Note, there are five different categories; weather, quality (satellite perspective), operational (effect on total schedule and future schedules), emergency, and customer related. The DM can ultimately analyse and quantify the trade-offs by evaluating different settings of the criteria.

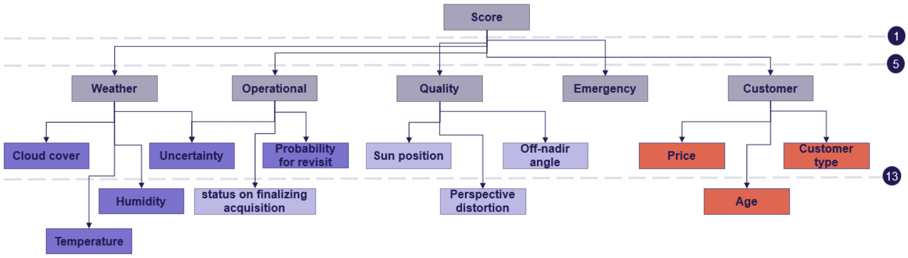

Fig. 2.2: A hierarchical representation of the criteria affecting the operational decisions of the EOS

Near real-time Computation Requirements

The real-time requirements of the scheduling stem from the utilized information. When weather conditions influence the decision-making process, inclusion of newer information leads to less uncertainty [116]. Additionally, it often happens that new customer requests will be added at the very last minute (e.g., emergency request), and consequentially, the intricacies of the customer pool makes it likely that the new optimal schedule is completely different than the one for the previous pool. A phenomena, that in evaluation problems without the consideration of the satellite network, is known as the rank reversal problem [127].

In continuation to the previous multi-objectivity characteristic, three different decision frameworks can be shown in Fig. 2.3. The left one represent a multi-level decision-making structure where certain data are considered first. The benefits of this decision-making scheme is that the scores are easy to compute, implement, and correspondingly to understand. However, with this it is required to construct a pre-defined axiom with which one can evaluate the image attempt and corresponding data against. The elicitation procedure for these axioms can be very difficult, biased, and as the axioms are defined for each objective independently, the collaborative effect can easily be missed.

In the middle in Fig. 2.3, the multi-level decision-making scheme is omitted and all data for the request is considered simultaneously. However, it is still necessary to build some pre-defined set of axioms to evaluate ones image attempts up against as the information considered to produce a score is assumed independent from the intricacies of the other requests.

The right side in Fig. 2.3, shows a representation of the complete opposite decision scheme. Here all data for all image attempts is considered simultaneously to produce a score. It is here not necessary to utilize a pre-defined set of axioms, despite it being possible. The benefits are that all information can be considered to produce the correct score that represents the relative importance of the image attempts.

For certain preference structures the dependency in decision procedures are of zero importance, and consequentially, the most optimal decision-making framework could be the multi-level scheme (left), while for others it may not be so.

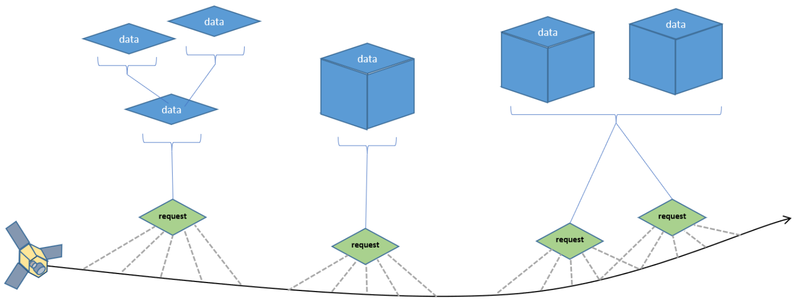

Fig. 2.3: The different modes of aggregating data into a score that represents the importance of the request and consequentially the image attempt. The decision-making process is either multiple independent processes (left), one process that considers all data for the single request dependent (middle), or one large decision-making procedure that simultaneously considers all intricacies of requests and satellite network (right).

For a complex decision environment of this character it is natural to consider data-based modelling schemes. However, due to the many-objective nature of the problem, these are rarely utilized due to transparency issues in defining preferences and the correlations in the data [72]. Otherwise, data based modelling is more used in the case of hyper-parameter tuning [65].

Lastly, the evolution of satellite agility and resolution means that the payload is used with as little downtime as possible, correspondingly designed to fit the demand. As demand increases, so does the need for real-time computation.

Uncertainty

The criteria in Fig. 2.2 have multiple different types of uncertainty; stochastic uncertainty in weather and satellite positioning, and the uncertainty of fuzziness in asserting the correct preference structure related to e.g., customer priority.

The literature has mainly focused on externally imposed uncertainty stemming from cloud coverage. Naturally, this is because of the stochastic element of which probability distributions are known. Consequentially, stochastic modelling frameworks have been proposed [116, 125, 126].

Recently, preference based approaches have been developed to incorporate exactly the uncertainty of decision-makers both from an a priori stand point [42, 136] and a posterior evolutionary algorithms or local search approaches [62, 108].

A system-based uncertainty can in the a posterior approach be seen as inherently considered. However, in the event that a decision-maker is introduced in the operational loop, the system will first of all be greatly delayed by the DM, and secondly the benefit of evaluating the Pareto front and produced set of solutions is not given due to the complexity and scale of the evaluation. Rather than evaluating operational decisions for each schedule, deeper analysis is, therefore, required in order to fine-tune an a priori preference structure by the DM for decisions of more strategic character. This naturally requires a great deal of trust by explainability and transparency in the system.

1.2 The UAV Routing Problem

The Vehicle Routing Problem (VRP) and the Traveling Salesman Problem (TSP) are two well-known combinatorial optimization problems that involve finding optimal routes [22, 34, 100]. The TSP, initially formulated in the 19th century, involves finding a Hamiltonian cycle with minimum distance in a complete graph, where each city represents a node, and the edges denote the distances between cities [60]. The VRP can be viewed as an extension of the TSP where additional constraints and complexities are introduced. Instead of a single agent, the VRP addresses multiple (potentially hetrogenous) vehicles, each with the ability to serve multiple customers [22]. The goal is to determine optimal routes for each vehicle, considering constraints such as vehicle capacity limitations, customer demands, time windows, and potentially other factors like real-time updates or multiple depots [34, 51, 100, 111]. The objective is to minimize the total distance traveled and/or other cost metrics while satisfying the given constraints.

Multiple different formal versions of the VRP has since been defined, e.g., VRP with profit maximization, which as opposed to the traditional VRP is posed as a maximization problem not required to visit all customers, but seek out the route that in total aggregated the most profit. The most investigated version of this variant of the VRP is refered to as the (team) orienteering problem [38, 87, 107].

The UAVRP is a recent addition to the problem domain and considers the added flexibility of a UAV operating in 3D space, while adding a new set of constraints to ensure safe operation [110, 111]. The ease of use, flexibility of the platform, and value it brings have consequently lead to a multitude of interesting problem domains being investigated for the UAVRP, e.g., the search and rescue scenario of Aalborg harbour (see Fig. 2.4).

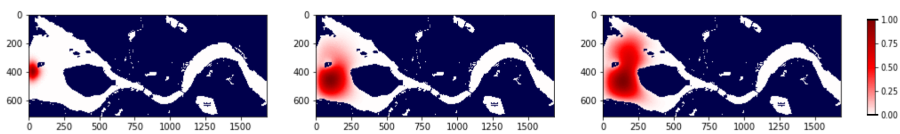

Fig. 2.4: Three instances of the evolution of a probability map generated for a lost object at the harbour of Aalborg.

Large-scale Optimization Problem

The VRP becomes a large-scale problem when dealing with UAVs due to several factors. UAVs can navigate through three-dimensional airspace and reach remote or inaccessible locations. This flexibility allows for a vast number of potential routes, increasing the solution space dramatically [83, 93].

UAV operations are especially affected by the dynamic and uncertain environment. Factors such as changing weather conditions, a non-linear speed-dependent fuel-consumption, different airspace restrictions due to safety concerns, and real-time traffic congestion require adaptability and dynamic decision-making [6, 111]. Incorporating these dynamic factors into the modelling of the UAVRP introduces additional complexity and computational requirements [41].

The number of UAVs used in a given application can vary significantly, ranging from a single UAV to multiple large fleets [111]. As the number of vehicles increase, the combinatorial nature of the VRP leads to an exponential growth in the potential solution space.

Additionally, as UAVs often require communication and coordination among themselves, ground stations, and other elements in the system, modes of sharing information, synchronizing movements, and avoiding conflicts adds additional complexity to the design phase of the solution approach [44, 95, 113].

Complexity of NP-hardness

The NP-hardness of the VRP has been extensively studied and proven in the literature [34, 111].

The formulation of the VRP consists of the subtour elimination constraint, which ensure that only one connected route is generated, as opposed to multiple non-connected routes [38]. There are two well-known formulations of the subtour elimination constraint, namely the DSF and MTZ [21, 75], to which there are no clear selection of which to choose for ones specific problem scenario and corresponding solution approach. This is because, the DFJ version creates an exponential number of constraints depending on the number of customers (one for all possible sets of customers), while the MTZ creates a polynomial number of constraints (one for each pair of customers), but the DFJ adds zero new decision variables while MTZ adds an entire new set. Consequently, the most suitable formulation stem from a collaborative effort of designing a fitting solution approach to the size of the problem scenario of interest that then again can manage the complexity of the problem formulation that is chosen [27, 87, 139].

Multi-objectivity

While the traditional formulation of VRP seeks to minimize a single objective, such as total distance traveled or total time, real-world VRP scenarios often involve multiple competing objectives [6, 41, 43].

The total duration of an plan is often dependent on multiple factors beside the total length of the route, e.g., the number of turns a route has to complete or the wind direction [40, 112]. Consequently, the shortest path is not always of highest priority.

In VRP, there is a trade-off between minimizing costs, such as fuel consumption or vehicle operating expenses, and maximizing service quality, which includes factors like customer satisfaction, on-time deliveries, or minimizing waiting times [3, 105, 113]. These objectives often conflict with each other, as reducing costs may result in longer routes or increased delivery times. The goal is to find a balance that optimizes both cost efficiency and service quality.

With growing concerns about environmental sustainability, reducing the carbon footprint and minimizing emissions have become important objectives in the VRP [109]. Balancing the reduction of vehicle miles traveled to lower emissions with meeting customer demands and optimizing other operational objectives is a multi-objective optimization challenge. It involves finding routes that minimize fuel consumption or emissions while still maintaining operational efficiency and service levels.

In certain VRP applications, risk management is considered as a critical objective [1, 59, 96, 130]. This includes minimizing the risk of disruptions or failures, ensuring robustness against uncertainties such as traffic congestion, adverse weather conditions, or vehicle breakdowns [34, 111]. Optimizing routes to minimize exposure to risk factors while considering other objectives, such as cost or service quality, introduces a multi-objective optimization dimension to VRP. Note, if a certain level of risk should be avoided, it is enforced as a constraint rather than an objective.

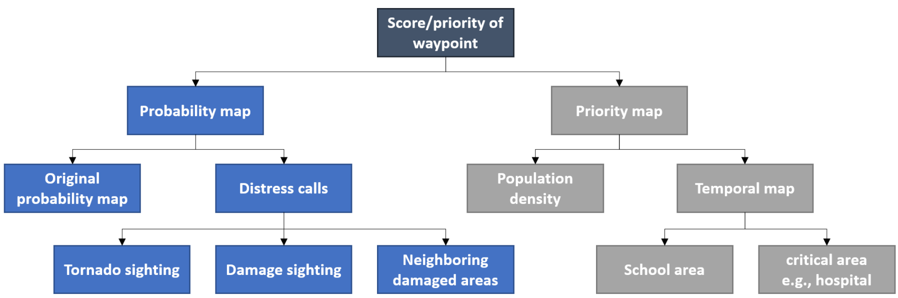

Fig. 2.5: A hierarchical setup of the criteria involved with a tornado Search and rescue scenario for the UAVRP. The blue indicate

In search and rescue settings, the application of the UAVRP introduces unique multi-objectivity considerations [10, 41, 50, 82, 93]. ultimately, one wants to locate the missing person as fast as possible and alive. This means balancing criteria, such as the importance of visiting different high probability areas, vs. visiting fatality-prone areas, all while considering the environment dynamics effect on the target location and whether ensuring not to miss a target (by outside-in search strategies) is more important than locating the target fast (by inside-out search strategies).

Additionally, in more specific land-based search and rescue problems like that of tornado emergency planning, one also has to consider different policies [35, 36]. E.g., the importance of infrastructure on the overall mission, the importance of ensuring the hospital and school areas, taking information from telephone calls into account and separating the information depending on tornado sighting or damage sightings due to the characteristics of the tornado. See Fig. 2.5 for an overview of the considered criteria in a tornado search and rescue scenario.

Lastly, if a UAV has a higher altitude, the size of the area it can survey is higher, which consequently allows the mission of locating the target to be completed faster. However, the quality of the data gathered will also decrease with the altitude, as one has a higher risk of missing the target during a flyover [7, 26, 85]. Consequently, the altitude is highly dependent on the sensor and identification system quality and the corresponding environment that one searches in, and in order to maximise the ultimate goal of locating the missing target as fast as possible alive, one has to identify the optimal trade-off.

Near real-time Computation Requirements

In many VRP applications, the demands or service requests are dynamic and time-sensitive. For example, in delivery or emergency response scenarios, new service requests can arrive or change dynamically, requiring quick adjustments to the UAVs' routes. To ensure efficient and timely service, the UAVs' routes need to be computed or updated in near-real time to incorporate new demands and deliver the required services within the specified time windows.

UAV operations are subject to various uncertainties, such as changing weather conditions, traffic congestion, or unexpected events. These uncertainties can impact the feasibility and efficiency of planned routes. By performing near-real-time computations, UAVs can adapt to the dynamic environment, consider the latest information, and recompute routes accordingly. This allows for more robust and responsive decision-making, ensuring that UAVs can navigate safely and efficiently despite the changing conditions.

Uncertainty

Demand uncertainty refers to the unpredictability or variability of service requests or deliveries. In the UAVRP, the demand for services or deliveries can change dynamically, with new requests arriving or existing requests being modified or canceled.

Environmental uncertainty includes factors such as weather conditions, airspace restrictions, or other external factors that can impact UAV operations [110]. Weather conditions like wind, fog, or storms can affect the UAV's flight performance (including travel time and energy consumption), safety, and overall efficiency.

Traffic uncertainty relates to the unpredictability of ground traffic conditions that can affect UAV operations, particularly in urban or congested areas. Traffic congestion, road closures, or accidents can impact the UAV's ability to navigate efficiently or meet service time windows. Incorporating traffic uncertainty into UAV VRP involves utilizing real-time traffic data or predictive modeling to estimate travel times and optimize routes accordingly.

Operational uncertainty encompasses various operational factors that can affect UAVRP, such as equipment failure, limited resources (e.g., battery life or payload capacity), or unexpected events during missions. UAVs may experience technical issues, component failures, or unexpected changes in operational conditions, requiring adjustments in route planning, resource allocation, or contingency strategies.

1.3 Characteristic comparison of problems

In Table 2.1, one can see the comparison of the two problems in terms of the identified characteristics. In conclusion, the two decision environments are affected in a very similar manner. Especially, when considering the in-operation decision environment.

Problems	SIASP	UAVRP
Scale	Higly dependent on the design parameters such as time resolution, schedule horizon, number of satellites, satellite agility, and number of customer requests	Highly dependent on the resolution of the map and corresponding number of available waypoints, available distance, number of vehicles, and vehicle agility
Complexity	NP-hard	NP-hard
Multi-objectivity	Many-objective	Multi-objective, but for search and rescue settings it is a many-objective optimization problem
Computation	Near-real time, but with the ability to reschedule pre-computed solutions	Near-real time
Uncertainty	In operation, we see the environment imposed stochastics due to weather, decision-maker imposed uncertainty due to the complexity and fuzzy nature of the decision environment, and otherwise unexpected events.	In operation, it is the same, except for the induced uncertainty regarding vehicle agility.

Table 2.1: Characteristic similarities in the underlying optimization problem

2 MCDM and State-of-the-Art

In the realm of decision-making, the quest for an "optimal solution" is no more challenging than in MCDM, as exactly "optimality" is in question [70, 114]. Traditional approaches struggle to handle multiple conflicting objectives, leaving decision-makers with the daunting task of balancing trade-offs among various criteria. The concept of the Pareto front and non-dominance emerges as a powerful feature to navigate the intricate landscapes and aid in achieving informed and well-considered decisions.

The Pareto front, named after Vilfredo Pareto, an Italian economist, refers to a fundamental principle in MCDM that seeks to identify the best compromise solution(s) among conflicting objectives [117]. It represents a set of solutions where no alternative can improve upon one criterion without compromising another. That is, so-called non-dominated solutions. According to the Karush-Kuhn-Tucker conditions [70], the Pareto optimal set of an m-objective optimization problem is an $(m-1)$-dimensional piecewise continuous manifold. The ultimate goal is to identify a solution on that Pareto front that fits the preferences of the DM. By visualizing the trade-offs between conflicting objectives [46], the Pareto front provides decision-makers with invaluable insights into the available options and enables them to make informed choices based on their preferences and priorities.

The UAVRP and SIASP are interesting MCDM deployment opportunities to the MCDM community due to the complexity of the decision environment and the potential benefit for effective decision-making. Both problems involve multiple criteria and complicated trade-offs, making them suitable for exploring MCDM techniques, but certain characteristica of the problem domains could also inspire new insights to the existing literature. E.g. the non-linear nature to certain criteria settings in the SIASP (request age to quality) or the non-compensatory nature of the UAVRP in a SAR setting [36, 119].

In traditional optimization problems, decision-makers typically aim to optimize a single objective, seeking the best possible solution within a defined set of constraints [124]. However, in many real-world scenarios, decision-making involves numerous, often conflicting, objectives that must be simultaneously considered - setting the stage for multi-objective optimization [79, 132].

Many-objective optimization extends the concept of multi-objective optimization to scenarios with a larger number of objectives, typically three or more [62]. Again, the fundamental goal is to generate a set of solutions (i.e. the Pareto front) that represents the trade-offs between conflicting objectives.

Decision-makers face the daunting task of comprehending and effectively navigating this high-dimensional manifold to identify meaningful trade-offs and make informed decisions. To tackle many-objective optimization problems, various specialized algorithms and techniques have been developed. These approaches aim to explore and approximate the Pareto front efficiently while maintaining a good balance between convergence and diversity in the solution set [62]. Evolutionary algorithms, such as the Elitist Non-dominated Sorting Genetic Algorithm (NSGA-II) and the Strength Pareto Evolutionary Algorithm (SPEA2), are commonly used to address multi-objective optimization problems by combining selection, crossover, and mutation operators to evolve a population of candidate solutions [19, 23].

However, the intrinsic behaviour of volume and surface area in higher dimensions of convex shapes (assuming the feasible solution space to be bounded by one) leads

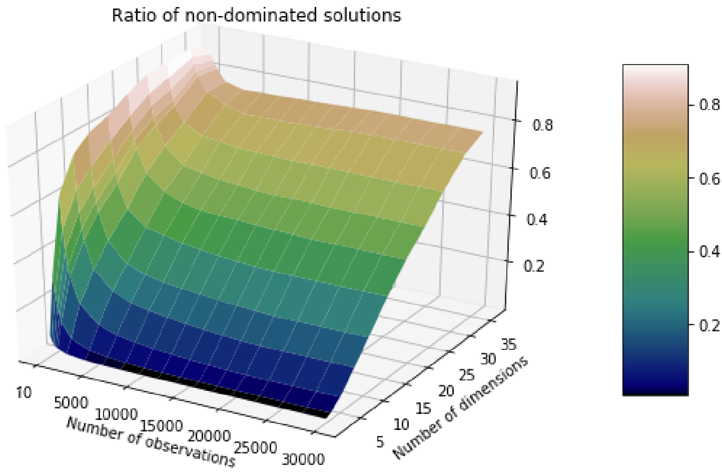

Fig. 2.6: Ratio of Non-dominated solutions randomly generated (observations) on the MaF1 benchmark problem [19].

to issues in evaluating many-objective optimization problems, as close to any solution evaluated in a high dimensional objective space will be non-dominated [101]. This is verified in Fig. 2.6, as it showcases the ratio of non-dominated solutions for different number of randomly generated solutions when evaluated on the objective function of the MaF1 benchmark problem with a different number of "activated" objectives [19]. In the extreme case with 30000 generated solutions (observations) and 35 objectives, approximately 80 % or around 24000 of the solutions are non-dominated. Consequently, when integrating the DM('s preferences) in these problems, it is necessary to do some (if not all) before the search (a priori).

2.1 Problem Typology

MCDM theory distinguishes between problems where alternatives or solutions are given either explicitly or implicitly, namely evaluation problems and design problems, respectively. In the works of S. L. Gebre et al (2021) [32] another taxonomy is given separating the problem domains between the characteristic of solution space being either discrete and continuous.

Evaluation Problems

For an evaluation problem, a set of explicitly given alternatives are present, i.e., $A = \{a_1, a_2, \ldots, a_{n-1}, a_n\}$, where n is the number of alternatives. Here, a set of criteria is

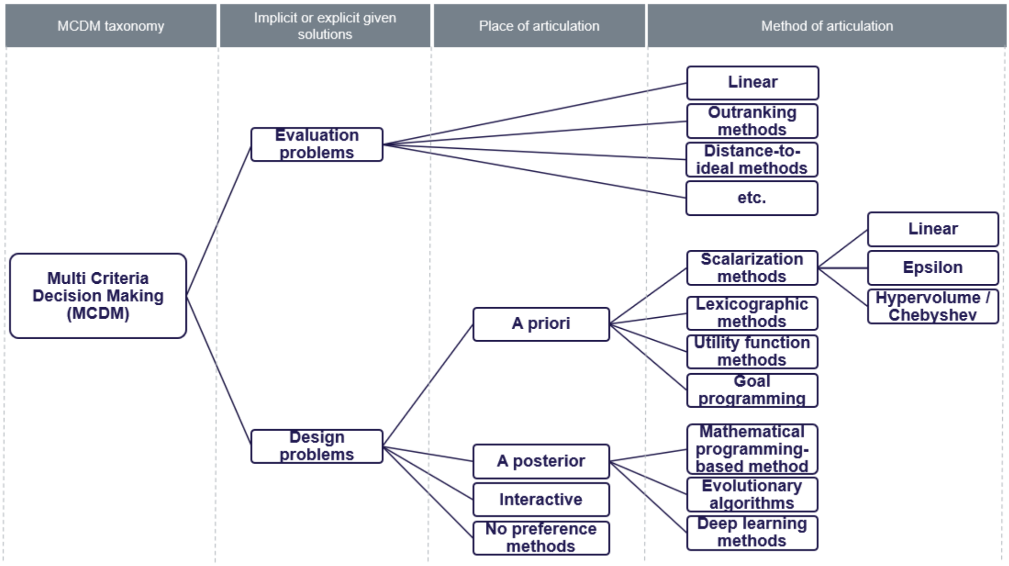

Fig. 2.7: Taxonomy of MCDM problems

then given for the alternatives to be evaluated against, i.e. $C = \{c_1, c_2, \ldots, c_m$ where m is the number of criteria. Usually, an evaluation matrix or performance matrix P is then given where the element P_{ij} yields the performance of alternative i for the jth criteria [45, 90].

The goal in evaluation problems can vary from selecting one alternative, to ranking all, or sorting them all based on predefined metrics. The method with which the set of alternatives are evaluated highly depends on the school of thought, and on the internal properties of the criteria. E.g., whether the performance of criteria are qualitative or quantitative or whether the performance data are specified by nominal, ordinal, interval or ratio scales [70]. But most importantly it depends on how the preferences of DM are incorporated for each criteria, e.g., for crisp or fuzzy data, whether they incorporate indifference, veto capabilities, or whether there are workload requirements for the DM, e.g., in terms of a representative model of preferences are to be defined rather than pairwise comparisons [16].

Some prominent examples are the french school of outranking, value or utility theory, distance to ideal point methods, and the structural approaches like analytical hierarchical process (AHP) or analytical network process (ANP) [16, 45, 80, 89]. See Fig. 2.7 for an overview of different solution methods.

Design Problems

For design problems, a set of objectives $F(x) = \{f_1(x), f_2(x), \ldots, f_m(x)\}$ and a set of constraints on the solution space are defined that implicitly yields a feasible region Q for solutions to roam within [92]. In general, the number of solutions is either infinite or much larger than for the case of evaluation problems. The goal of the problem is to either maximise or minimize the defined objectives over the feasible region on the solution space.

$$\begin{aligned} &\mathbf{Max}\ f_1(x), f_2(x), \ldots, f_m(x) \\ &\quad s.t. \\ &\qquad x \in Q \end{aligned}$$

Note, Q not only defines hard cut-off lines for each element in the solution, but it could also require the solution x to be e.g., binary or integer. Also, F can possibly consist of only a single objective.

In the case of multi-objective optimization and many-objective optimization problems the goal changes somewhat, as solutions can dominate each other with respect to different objectives. In this case the aim is to identify the Pareto front, which represents non-dominated or Pareto optimal solutions. Pareto optimal solutions are defined as solutions, where no improvement with respect to one objective is feasible unless a sacrifice is made in other objectives [13, 70]. Consequently, search algorithms need to take both solution diversity and solution performance into account.

Solutions for design problems can be represented through (variants of) the objective (or criteria) space and the solution space (for small dimensionality problems of x).

One can utilize a range of approaches to manage the multiple objective aspect of the problem. Some of the prominent examples are lexicographic approaches like goal programming, scalarization approaches that essentially collapse the multi-objective aspect before the search procedure, or general a priori approaches [17, 42, 94]. See Fig. 2.7 for an overview of different solution methods.

Remarks on the Typology

The focus of design problems are on the search methodology, while the actual integration of preferences often is provided in the end or completely neglected. This means, that solutions are not necessarily emulating the actual preference, or that it at least require a great deal of modification and tuning post the search procedure. In the case, where preference integration is considered, it is used as a secondary procedure to the Pareto front searching approach. E.g. in the work of Q. Yao (2019) where the NSGA-II algorithm is used to identify a pareto front whereafter a suite of evaluation methods are used to select a single solution from that Pareto front [137].

As alternatives are provided explicitly for evaluation problems, the main focus lies in capturing the preference structure of DM as correctly as possible, and then integrating it with as much transparency and explainability as possible. Lately, fuzzy extensions to otherwise asserted methods are appearing to incorporate the uncertain nature of DM preferences [109, 133]. Moreover, as showcased in the study of Gallistel et al. [31], the perception of uncertainty also varies greatly between decision-makers and consequently, the quantification through fuzzy extensions are of high interest.

Some design problems are, because of their complexity and scale, essentially multi-stage evaluation problems, where one iteratively seeks to rank current solutions based on accommodating the preference structure of the DM. Hence instead of ranking based on biased fitting functions, it would be beneficial to utilize some of the knowledge from evaluation problems [62, 69].

Similarly, integrating the characteristics for both human preference structures and general uncertainty would be of considerable value.

2.2 Place of Articulation

It is important to highlight the place of articulation when characterizing the problem. Articulation is a term borrowed from linguistics and phonetics. In the case of decision making, it deals with preference integration. For the design problem, A posterior approaches which build the Pareto front, only for the DM to afterwards make a decision on a solution that fit their preferences best have already been mentioned. Generally, one distinguishes between a priori, a posterior, and interactive approaches [13, 69, 124].

A Priori

For a priori approaches in design problems, the multi-objectivity is collapsed or aggregated through some approach prior to the search procedure begins [94]. A drawback of this, is the system induced uncertainty attached to complex optimization problems where problem scenarios can have different effect on how objectives are optimized. Another drawback is the lack of feedback on the solution space, as one basically allows a predefined setting to determine the final solution. Because of these, any a priori approach requires heavy sensitivity analysis.

For evaluation problems, this means a model of the preference structure is defined prior to the DM observing/analysing the alternatives. E.g. TOPSIS can be seen as an a priori evaluation method, as the DM prior to observing the set of solutions can elicit their preferences.

However, for extremely complex and large scale problems, the a priori method is often the only possible method to integrate preferences, as searching for Pareto fronts and integrating the DM to evaluate it is too time consuming. For example, if a firetruck requires a route to a burning building that minimises time till destination, as far as possible minimises the number of larger bumps, or time spent around school areas, etc. then waiting 5 minutes for a search heuristic to build a Pareto front and for the driver to evaluate all the different trade-offs regarding the different possible objectives is not feasible [53]. In the example, the a priori integration of preferences is needed, and therefore a simplistic formulation of preferences is often implemented.

A Posterior

The a posterior approaches are the most frequently mentioned multi-objective optimization method, where a Pareto front is searched for [13, 23]. The method highly depends on the representation of solutions.

The most popular representation is by far the criterion/objective space representation. Here solutions are computed and mapped with respect to the performance for the different objectives, while the best performing and most diverse solutions are iteratively improved. In the case of many-objective optimization problems, visualization methods, like scatter plot matrix, bubble chart method, parallel coordinates or 3D-RadVis, can be utilized [46].

Another representation is the solution space, where (if the dimensionality of the solution is sufficiently small) it is possible to reflect the performance. Often, one has more than three dimensions on the solution space, and in that case it becomes an issue of a higher dimensionality objective space representation.

In the case of a preference space representation, an example is to define some abstract importance on the different objectives through some weight distribution. Hereafter, an array of settings are tested and the resulting solutions and mapped on the preference space. The DM can then investigate the computed solutions and determine which weight setting that fits best [19, 46]. More generally, the parameters of the method with which objectives are collapsed can be used to investigate the flexibility and robustness of the method. Again, visualising this can become quite difficult, but often heatplots are utilized.

A general drawback of the a posterior approach is the demand for computation time to conduct the search, as well as analysis after to impose preferences and select a decision. However, integrating preferences becomes more precise as they are acted directly on the solution.

There are to the best of my knowledge, no evaluation methods that can be viewed as a posterior.

Interactive

The interactive approaches interactively integrate preferences by relying on the continuously monitoring of and change of direction from the DM. The queries exchanged between the system and the DM is dependent on which method to use. According to [135] the taxonomy of the interactive MO methods has four design factors:

1. Interaction Pattern: whether the interaction is during a run or after.

2. Preference information: Expectation (reference point method), comparison of objectives (through weights, trade-offs, classification of objectives, etc.), or comparison of solutions (pairwise comparison, classification of solution, or selection of preferred one)

3. Preference model: value function, dominance relation, outranking relation, decision rules

4. Search engine: Mathematical programming technique or non-mathematical programming technique

In the case of evaluation problems, the interactive approaches require the DM to directly evaluate preferences against alternatives, e.g., through the pairwise comparisons in AHP.

2.3 Preference Elicitation

Preference elicitation is the process with which information about the preferences is acquired from the DMs, while the preference structure is how this information is modelled [55, 124]. Note preference structure and preference model is interchanged throughout the literature. Again, the preference modelling is highly dependent on the place of articulation, and the elicitation strategy and preference structure is often very connected.

Note, here one must distinguish between direct and abstract preferences, as the DM either yield preference information with which a ratio and specific information can be asserted or some abstractly defined preference understanding through weights [6, 76, 98]. Quite distinctly, the abstract preference setting requires a substantial amount of understanding of the system to not be defined in an arbitrary and incorrect manner.

Preference Relations and Implicit Preferences

Preference relations between alternatives are often utilized as an elicitation method for obtaining preferences, e.g., for the AHP which asserts numeric values corresponding to the preference between pairs of alternatives [16]. In Table 2.2 the asserted preferences can be seen. Often a set of alternatives will then be compared in the following manner: $a_1 >> a_4 \approx a_5 > a_2 >> a_3$, showcasing a strong preference for alternative a_1 over the others. Methods of implicit preferences can then be utilized to extract a model that will rank similar alternatives in the same manner. In some sense emulating or automating value extraction from an initial preference ordering.

In general comparison terminology, the preferences are essentially an ordering on the set of solutions, the specific ordering can be based on different type of scales, either nominal, ordinal, interval, or ratio scales [98, 103, 114, 134]. Nominal refers to a sorting of the solution into different categories with no specific preference to either of the different categories, basically only an ordering based on naming. The ordinal scale refers to an ordering based on both name and quantity into predefined categories. Consequently, the difference between two categories means that one solution is regarded higher for some objective than solutions categorised to another category. However, one does not know anything about the ratio with which categories differ [55, 64]. With interval and ratio orderings the difference between different instances on the predefined scale can be quantified [16, 29, 30, 55]. That is, a given difference in one region will equal the same difference in another region of the scale. An example is the temperature scale, where a difference of 20 degrees means the same in all regions of the scale. Consequently, one can add more detailed information to the ordering of different instances. The difference in interval and ratio is that the later implements an actual zero to the scale, which refer to the complete absence of the measured or compared quantity.

Relation meaning	much more important	more important	equally important	not important	less important	much less important	do not care or know
Symbol	$\gg$	$\succ$	$\approx$	$\neg$	$\prec$	$\ll$	$\#$

Table 2.2: Ordinal preference relations between alternatives, as per H. Wang et al. (2017) [124]

These methods have been presented without taking into account the decision environments, which can vary greatly between the approach of a single DM or a group of DMs. Here it would be reasonable to refer to groupwise decision-making methods of consensus methods, voting based, or Delphi's method [76]. Additionally for preference relations, the ratio with witch one is preferred over other alternatives can be very hard to elicit, and as a consequence the Simos' procedure has been developed [29]. Here "playing cards" are added in the ranking to showcase an approximate ratio difference between alternatives.

Amount of Articulation

Finally, the amount of articulation, which also is a term borrowed from phonetics and linguistics, is a very important topic to cover when determining which preference model to utilize.

It varies greatly how much work is required to compute a preference structure and for some problems it is not feasible to do a complete pairwise comparison [16]. For this reason, design problems with infinite solutions are not evaluated through these. So once again, this is highly dependent on the choice of method.

In general, we split between exemplifying ones preference structure implicitly, yielding pairwise comparisons, or defining a model that emulate the preference structure. Additionally, hybrid versions can be posed, as e.g., the ELECTRE framework, despite enforcing pairwise comparisons, does it through a representative preference model [30, 89].

For small problem scenarios, it can be feasible to do pairwise comparisons, while it does not make sense to define a complete outranking model with all threshold values [16, 90]. Similarly, for large scale problems, pairwise comparisons are not feasible at all, as of why developing a representative model is preferred.

2.4 A Priori Preference Articulation Methods

As mentioned in H. Wang et al. (2017) [124], we distinguish between the modelling of preferences through weights, goals, utility functions, outranking relations, and reference vectors. See Table 2.3 for a overview of the ability accompanying the different preference articulation methods.

Transformation type	Preference articulation method(s)
Transforms the multi-objective framework of the problem	Weights, Goals, Outranking methods, and the utility function
Guides the search phase by a priori asserted preference to certain solutions	Outranking methods and the reference points

Table 2.3: The transformation type of the preference articulation methods

Scalarization

As previously mentioned, scalarization is a common approach in multi-objective decision-making. It involves assigning weights to each objective or criterion, allowing the decision-maker to express their relative importance. These weights can be represented as a set, denoted as $w = w_1, w_2, \ldots, w_m$, where w_i represents the weight assigned to the ith objective or criterion.

By employing scalarization, the multi-objective problem can be transformed into a single-objective framework using various aggregation methods. Two popular methods are the weighted normalized sum and the Chebyshev approach [33, 74]. In the weighted normalized sum, the individual objectives are combined according to their weights, resulting in a single aggregated objective that represents the overall performance of a solution. The Chebyshev approach, on the other hand, considers the worst deviation among the objectives and aims to minimize this deviation, effectively addressing the most critical objective.

The advantages of scalarization methods lie in their simplicity and ease of use. Decision-makers can assign weights to reflect their preferences and priorities, providing a straightforward approach to tackling multi-objective problems. However, a limitation of scalarization is the challenge of determining appropriate weights, especially in scenarios with significant variations. The abstract nature of weight settings may lack clear justification, potentially introducing subjectivity and arbitrariness [52, 128].

Goals

For multi-objective optimization problems, goals are extensively used as preference integration. Here soft constraints are defined with some objective threshold value desired to be met [13, 17]. Goal programming is perhaps one of the most popular multi-objective optimization methods, where this is implemented through a conversion of multi-objectivity into a single-objective programming model or through a lexicographic approach, that iteratively goes through objectives, and adds the former reached goal as a soft constraint. Ultimately, goal programming convert the maximisation of utility gained from each objective to a minimization of distance to the predefined goals of the set of objectives.

Goals are rather easy to define, but penalties on the other hand are extraordinarily hard to define [70]. Another drawback is the possibility of deriving Pareto-inefficient solutions [133]. Additionally, a large variety of human preferences are hard to adhere to through goal programming, most notably indifference.

Utility Function

In the field of Multi Attribute Utility Theory (MAUT), the goal is to develop a utility model that infers the utility of solutions rather than the preference [70, 103]. Often this is done by ranking a subset of solutions, in order for some method to infer a underlying model, e.g., through the additive value function.

The findings from economic theories like prospect theory are sought to be consolidated in MAUT, meaning the resulting model mimics real-world behaviour. The complexity of the model is however extremely difficult to administer as utility functions often neglect certain aspects of the preferences [70]. Ultimately, the same difficulties are observed in MAUT.

Outranking

Outranking methods are designed to establish relationships between alternatives by comparing their attributes. In this context, an alternative A is said to outrank alternative B if, after considering all available information, a majority of the attributes indicate that A is at least as good as B (concordance condition), while the opposition from the other attributes, known as the minority, is not excessively strong (non-discordance condition) [89, 90].

Outranking models introduce three threshold parameters: indifference q, preference p, and veto thresholds v. These thresholds enable decision-makers to define the level of tolerance for indifference, preference, and strong opposition. The veto threshold allows the minority attributes to exert a powerful opposition, effectively vetoing the preference of one alternative over another [20]. The ELECTRE framework, provides two indexes identifying the credibility in the outranking of alternative A over B, namely the concorrdance and discordance index. For the concordance, the following relations are posed:

$$\begin{aligned}
&\text{(A is strongly preferred to B in criteria i)} &&\Leftrightarrow && g_i(A) - g_i(B) > p \\
&\text{(A is weakly preferred to B in criteria i)} &&\Leftrightarrow && p \geq g_i(A) - g_i(B) > q \\
&\text{(A is indifferent to B in criteria i)} &&\Leftrightarrow && q \geq |g_i(A) - g_i(B)|
\end{aligned}$$

Outranking models are typically human-oriented, providing a high degree of customization. They are non-compensatory, meaning that an alternative cannot compensate for poor performance in one attribute by excelling in another. These models also have fuzzy extensions, allowing for the integration of uncertainty in problem input and decision-makers' specific incompetence or uncertainty [20, 99].

By incorporating outranking methods, decision-makers can capture nuanced relationships between alternatives and accommodate individual preferences and uncertainties. The flexibility and adaptability of outranking models make them valuable tools for MCDM, enabling decision-makers to address complex and diverse decision scenarios effectively [55].

Reference Point

Reference points or vectors play a crucial role in guiding the search phase of multi-objective optimization problems by providing an expectation or benchmark for the objectives. In many-objective optimization problems, where a multitude of non-dominated solutions can exist, the reference point method becomes particularly valuable in steering the search towards desirable regions of the solution space [132, 138].

The reference point method allows decision-makers to define reference points in either the objective space or the preference/weight space. These reference points serve as targets or aspirations for the optimization algorithm, guiding it to search for solutions that approximate or improve upon these benchmarks. In the objective space, reference points represent specific values or ranges that decision-makers aim to achieve for each objective. By setting reference points in the objective space, decision-makers can a priori guide the search towards solutions that align with their desired objectives [24, 62].

Alternatively, reference points can be defined in the preference or weight space. In this approach, decision-makers assign weights or preferences to each objective, indicating their relative importance or priority. These weights guide the search algorithm to explore solutions that optimize the objectives according to the defined preferences.

Reference points and weights are essentially two sides of the same coin, as they provide a means to express decision-makers' expectations and preferences. While reference points manifest in the objective space, indicating desired values for objectives, weights reflect the priorities assigned to each objective in the preference or weight space [24].

Chapter 3

Bridging the Gap: Solution Approaches for Complex Decision Environments

In a holistic manner, the solution approach for a complex decision environment covers the pre-processing, the computation of a solution, and the integration of the DM(s). Due to the time-constrained environment of deploying a solution, it is therefore important to look at all three components. In the conference Paper C, an investigation of the pre-processing and its effect on the overall performance was conducted. The paper documented the incremental improvements conducted through the work on the SIASP, but similar improvements are expected to be made in general for cyber-physical systems.

When designing a solution approach for a problem residing in the sphere of complex decision environment, trade-offs between the pre-processing, the computation of a solution, and the integration of the DM(s) have to be made. In the operational environments where the SIASP and the UAVRP are addressed, the computation of the solution approach took up most of the time, and consequently, leaving time for the DM to evaluate trade-offs on the Pareto front was deemed infeasible in practice [119]. This chapter investigates exactly decision frameworks that implement the preferences of the DM outside of the operation of the solution approach.

1 Decision Framework for Complex Decision Environments

A decision framework can be understood as a structured and systematic approach that guides the process of making decisions. It provides a conceptual framework and set of principles to organize, analyze, and evaluate available the information and options, facilitating the decision-making process. A decision framework typically includes components such as problem identification, goal setting, criteria development, alternative generation and evaluation, and decision implementation. It helps decision-makers clarify objectives, consider relevant factors and constraints, assess trade-offs, and ultimately arrive at a well-reasoned and informed decision. The framework serves as a roadmap, ensuring that decision-making follows a logical and transparent path, reducing biases and increasing consistency. It provides a structured approach to handle complexity, uncertainties, and conflicting objectives, enabling decision-makers to navigate complex decision environments more effectively and achieve optimal outcomes.

In Paper B [91], the bi-objective decision framework of minimizing deployment time and maximizing coverage is seen implemented through a linear scalarization approach. Despite the ease of implementation, a consequence of this framework is the difficulty of assigning weights of importance, where a seemingly arbitrary weight configuration will leave the UAVs to not investigate the grid at all due to the objective in minimizing deployment time being too significant.

Consequently, a natural solution to this problem is to completely avoid the multi-objective framework by only considering a single objective and implementing the other objectives through hard constraints as e.g., deployment time. This is done in Paper D [83], where the objective is to produce a set of routes that maximise the aggregated relative importance of the visited nodes in a SAR environment. Again, the relative importance of nodes is assumed calculated based on expert knowledge which brings us back to the main question of how to properly determine a decision framework for aggregating the objectives.

In Paper A, E, and F [118, 119], it is seen how the expertise of the DM is pushed into the modelling of the scenario generator. Here, all the considerations of the problem environment from different customer types, imaging types, satellite position and request location, to pricing scheme, is modelled. The different scenarios that the DM can expect to experience is tested with the different preference structures, which consequently allows the DM to determine a preference structure with the knowledge of expected outcomes.

1.1 The A Priori Decision Framework

In the realm of complex decision environments, where optimization problems involve multiple objectives and intricate trade-offs, selecting an appropriate decision-making framework becomes crucial. One key consideration is the integration of multi-objectivity in a manner that allows for near-real time computation and implementation of the solution. Here, having a DM evaluate a set of solutions through e.g., a Pareto front is simply infeasible in deployed operations. Consequently, the a priori preference integration frameworks emerge as a fitting solution to address this challenge.

A priori preference integration frameworks incorporate decision-makers' preferences and priorities before engaging in the optimization process. These frameworks aim to integrate multi-objectivity by explicitly considering decision-makers' preferences and guiding the search for optimal solutions accordingly.

The A priori preference integration method has been investigated through the appended papers A, B, E, and F [91, 118, 119]:

1. The work in Paper A [119] investigate three different transformation methods from the multi-objective framework to the single-objective framework. The different preference articulation methods are: TOPSIS, ELECTRE-III and the WSA method. From discussions with satellite operators, we identified the high value of customizability, interpretability, and explainability. As the individual performance results from the three frameworks are comparable, the control in terms of how preferences can be implemented was a deciding factor. The ELECTRE-III showed itself to be the most suitable method, especially when the decision-maker wanted to discriminate between different customer types, and basically enforce a hard hierarchical structure.

2. In the subsequent Paper E, we sought to build a decision support system allowing the DM to understand the consequences of the operationally implemented a priori preference structure. One can see this as an informed finetuning procedure through the analysis of performance heatmaps (signifying the estimated Pareto front) and a hypothesis tests that represent significant changes.

3. The work of Paper F [118], extended the analysis to employ an automated selection mechanism in the setting of collaborative decisions of pricing scheme and a preference structure of the satellite operation. A selection of different preference structures were implemented for the a priori decision framework combined with a selection of different pricing schemes. The solution approach utilized the distance to ideal method VIKOR and the Shannon information entropy method to elicit preferences.

4. In the UAVRP work of S. Saha et al. (2021) [91], a bi-objective optimization framework were defined and solved through linear scalarization. As mentioned previously, we investigated the difficulties of assigning the correct weights of importance.

By involving decision-makers upfront, the a priori preference integration framework alleviate the computational burden that can arise from extensive iterations and computations required by other approaches. Especially, as the investigated problems are large-scale and NP-hard, one can always come closer to optimality, and the additional computing power spent on implementing a posterior approaches and building Pareto fronts could have been utilized to build an overall better solution. Essentially, the trade-off lies in integrating the correct preference structure or obtaining the best solution.

A priori preference integration in a multi-objective setting presents inherent challenges due to the complexity and conflicting nature of multiple objectives. One difficulty arises from the need to accurately capture decision-makers' preferences. Assigning appropriate weights or priorities to each objective can be a complex task, as it requires understanding the relative importance of objectives and the trade-offs between them. Decision-makers may struggle to determine precise and consistent weights, particularly when facing conflicting objectives or when the importance of objectives varies across different decision scenarios. Additionally, a priori preference integration may encounter difficulties in cases where decision-makers' preferences are uncertain or subject to change over time. Furthermore, the potential for cognitive biases and inconsistencies in expressing preferences can further complicate the integration process.

2 Implementing the Evaluation Methodology into the Decision Framework

In the a priori preference integration frameworks, the integration and tuning of preferences play a crucial role in achieving effective long-term decision-making. However, as showcased in Paper B, it is very difficult for the DM to assign weights of importance to different objectives due to the indirect and abstract nature of the decision framework. This issue is repeating it self in all methods of articulation for a priori articulation (See the MCDM taxonomy in Fig. 2.7). Therefore, it is natural to investigate evaluation methodology for solution approaches with a more clear preference articulation. That is, methods that encourage decision-makers to explicitly articulate their preferences directly in a non-abstract manner.

Several strategies can be employed to facilitate the integration and fine-tuning of preferences within these frameworks:

1. Elicitation Techniques: Various techniques can be used to elicit the DM's preferences, such as interviews, surveys, interactive sessions or by simply just gathering information on the behaviour of the DM in certain scenarios. These techniques aim to extract information about the relative importance of objectives, trade-offs, and any constraints or preferences that decision-makers may have. Elicitation techniques should be designed carefully to encourage accurate and consistent expression of preferences. In the work on the SIASP, the method was validated based on the internal objective function of the satellite operation in Airbus D&S. That

internal objective function was derived years back based on extraction from operational experts. It has however not been updated in any timely manner and they were consequently very positive over the intuition behind the proposed method. However, due to confidentiality issues the results cannot be directly included.

An iterative processes that involve feedback and learning loops can enhance the integration and tuning of preferences. Decision-makers review and refine their preferences based on the outcomes generated by the framework. This iterative approach proposed in Paper E exactly allows decision-makers to progressively refine their understanding of the problem, make adjustments to their preferences, and converge towards more informed and consistent preference structures.

2. Pairwise Comparisons: Pairwise comparison methods allow decision-makers to assess the relative importance of objectives and criteria with respect to the different image attempts. By systematically comparing each objective against others, decision-makers assign direct numerical values representing their explicit preference or priority of one objective compared to another. These pairwise comparisons provide a structured approach to quantify and integrate preferences. This is exactly the foundation for the work in Paper E and F [118].

3. Sensitivity Analysis: Sensitivity analysis enables decision-makers to explore the impact of varying preferences on the final outcomes. By systematically adjusting the assigned weights or preferences and observing the resulting changes in the solution space, decision-makers can gain insights into the sensitivity of the decision to different preference settings. This analysis aids in fine-tuning preferences to align with decision-makers' aspirations and values and it is exactly what the heatplots and significance test in Paper E proposes.

4. Visualization and Decision Support Tools: Interactive decision support tools and visualizations can facilitate the integration and tuning of preferences. These tools provide decision-makers with a visual representation of the objectives, alternatives, and associated preferences, allowing them to gain a better understanding of the trade-offs and relationships. The work of E is a step towards such an iterative decision support tool. However, a much more detailed and novel scheme with relevant information and actions is needed. See Fig. 3.1 for a proposal towards such a method in the SIASP.

With the tuning and verification scheme presented in Fig. 3.1, the DM of the satellite operation will be able to both operate and verify the automatically generated satellite schedules. The operator will be able to modify the schedule based on two different evaluations; one on the level of the entire schedule and one on the individual request level. The modifications done by the operator should be collected for later tuning.

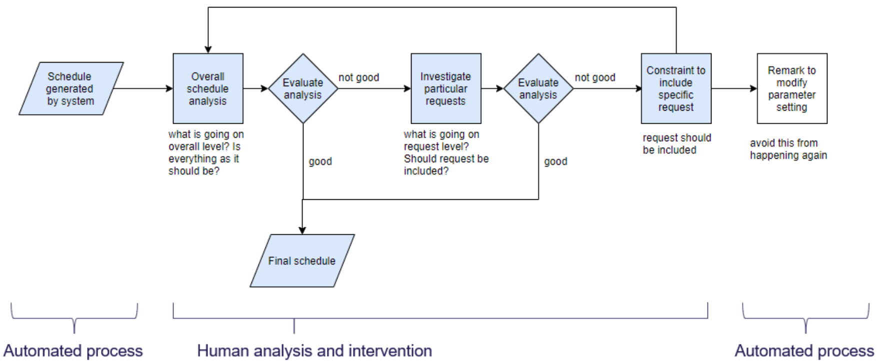

Fig. 3.1: A verification framework with two distinct interaction and evaluation procedures for the satellite operator to take control.

3 Integrating Uncertainty

Uncertainty is an inherent aspect of most real-world decision problems. It arises due to various factors, such as incomplete information, variability in data, and unpredictability of future events. In the SIASP, the main uncertain element stems from two sources; the stochastic element of the cloud coverage which upon acquisition deems certain imaging attempts invalid, and the fuzzy nature of the decision framework, where the DM is uncertain of the correct preference structure either because of incompetence or due to the complexity of the decision environment.

Often utilized solution approaches that deal with the stochastic element in the SIASP is that of stochastic programming formulation, dynamic modelling, or bayesian optimization frameworks. However, in the context of the complex decision environment with the characteristics of it being a large-scale NP-hard many-objective optimization problem with near real-time computation requirement, the added complexity of solving it through stochastic modelling methods and evaluating the uncertainty a posterior is deemed infeasible. Consequently, the uncertainty must be addressed a priori, which likewise means investigating which models yielded the better framework for doing so.

In Paper A [119], the three methods tested, TOPSIS, ELECTRE-III, WSA dealt with the stochasticity through a simple scoring procedure. Simply yielding a score that reflected the image attempts performance on all the objectives in an aggregated manner. That is, one objective being the corresponding standard deviation assigned to the predicted cloud cover estimate.

This approach was also utilized in Paper E [118], where doing so showcased signs of Braess' paradox in the sensitivity analysis. Here increasing the importance of cloud coverage led to a sudden increase in average cloud coverage, as it consequently decreased the relative importance of other objectives such as the uncertainty related to the cloud coverage forecasts.

The linear approach of WSA and TOPSIS treats the uncertainty objective as any regular objective and it is therefore very difficult to link it with the performance of the cloud cover objective, as they should be compared together. The outranking approach of ELECTRE-III does however implement a non-linear evaluation methodology through the veto, preference, and indifference threshold variables. Correspondingly, it is possible to state that differences between image attempts with a certain cloud coverage is so significant that one never want to acquire this over another image.

In the work of Paper F, the decision framework is extended to also consider the effect of pricing and preference structure, as these decisions collaboratively decide the final schedule. We focus on a set of different pricing segmentation schemes and a corresponding set of different preference structures. The uncertainty then lies in the complexity of the collaborative decision framework, as the pricing of satellite images precedes the high combinatorial complexity in the scheduling, as well as the multitude of evaluation criteria associated with customers' image requests. Similarly, any changes in pricing will inevitably impact the final schedule due to the intricate scheduling procedure and the preferences reflected in the scoring, making it challenging to fully comprehend and navigate the decision framework. The proposed solution approach of Paper F [118] utilizes VIKOR and Shannon entropy to automatically propose a combination of pricing and preference structure.

4 Rethinking Preference Integration

This section dives into setwise preference articulation and proposes a framework for a method that can elicit and articulate this characteristic in order to have alternatives or solutions evaluated based on ratio scales. Humans have a hard time to directly infer preferences based on a ratio scale, as the preference often is based on a the dependence of other factors. In satellite scheduling this hardship can refer to the articulated preference with an acquisition of a stereo image, where the acquisition of both image attempts to complete the stereo request is of high preference, while only the acquisition of a single image in the stereo request is of very little importance. With setwise preference articulation, one can in a more detailed manner elicit the overall ordering of preference on the image attempts.

Setwise preferences refer to a preference ordering of a set of items as a whole, while pairwise preferences refer to a preference ordering of pairs of items. For example, in pairwise preferences, a person might rank three items (A, B, C, and D) as $A > B$, $B > C$, $C > D$, which by assuming transitivity on aggregate leads to the preference ordering of $A > B > C > D$, indicating that they prefer A the most, B the second most, C the third most, and D the least. In setwise preferences, a person might compare the pairs of items (A, B), (A, C), (B, C), etc. and indicate which of each pair they prefer. This allows for a more detailed understanding of a DM's preferences, as they may have different levels of preference for different sets of items, than they have for them individually.

As an example, to continue the stereo imaging case of the satellite scheduling problem. If (A,B) represent a stereo image pair with the highest priority, and otherwise the two other image attempts (C,D) have a higher preference, then with the ability to at maximum capture two images from the entire set, the ordering is as follows:

$$(A, B) > (C, D) > (B, C) \vee (B, D) \vee (A, C) \vee (A, D) \tag{3.1}$$

This ordering is incompatible to the individual preference ordering, as the setwise ordering adds an "invisible bonus" in the preference of the combined acquisition of both image A and B. No mapping of preferences $U(.)$ on a ratio scale of the individual items A, B, C, and D, will lead to the above setwise ordering. That is, the setwise preference ordering cannot necessarily be directly inferred from orderings obtained from the individual level. Here $U()$ can also be refered to as the utility function known from economics, decision science, and multi-attribute utility theory [64].

This claim can be seen as the aggregation of individual preferences in Eq. (3.1) leads to ambiguities. Here $U(A, B) \neq U(A) + U(B)$ as:

$$(A, B) > (C, D) > (B, C) \vee (B, D) \vee (A, C) \vee (A, D) \tag{3.2}$$

$$\Downarrow$$

$$U(A, B) > U(C, D) > U(B, C) \vee U(B, D) \vee U(A, C) \vee U(A, D) \tag{3.3}$$

$$\Downarrow$$

$$\begin{aligned} U(A) + U(B) > U(C) + U(D) >& U(B) + U(C) \\ U(A) + U(B) > U(C) + U(D) >& U(B) + U(D) \\ U(A) + U(B) > U(C) + U(D) >& U(A) + U(C) \\ U(A) + U(B) > U(C) + U(D) >& U(A) + U(D) \end{aligned} \tag{3.4}$$

$$\Downarrow$$

$$\begin{aligned} U(A) + U(B) - U(C) - U(D) > 0 >& U(B) + U(C) - U(C) - U(D) \\ U(A) + U(B) - U(C) - U(D) > 0 >& U(B) + U(D) - U(C) - U(D) \\ U(A) + U(B) - U(C) - U(D) > 0 >& U(A) + U(C) - U(C) - U(D) \\ U(A) + U(B) - U(C) - U(D) > 0 >& U(A) + U(D) - U(C) - U(D) \end{aligned} \tag{3.5}$$

where the last inequation leads to $U(D) > U(B)$, $U(D) > U(A)$, $U(C) > U(B)$, and $U(C) > U(A)$, which then means the first inequeation does not hold. Again this means, the setwise scoring introduces a new level of preference to consider. Consequently, $U(A, B) = U(A) + U(B) + U(A \wedge B)$, where $U(A \wedge B)$ refers to the aforementioned "bonus" preference. Another way of stating this, is that preference mappings are build on the assumption of independece between all attributes of the preferences [124].

Another example is the ability to retrieve a more precise ordering based on setwise preference information. If A > (B, C) and B > C, we not only know that A > B > C, but also that from a ratio scale standpoint the difference with which A is preferred over B must be larger than the difference with which B is preferred over C, as the aggregate individual preference of both B and C expressed on a ratio scale is smaller than the preference of A expressed on the same scale.

A last example, is the difficulty of determining whether two high priority areas should be of higher priority than that of 10 lower priority areas. Essentially, allowing for a cross set level preference articulation.

The SIASP and UAVRP are essentially set selection problems, where we up until now have assumed the preference of each set to be equal to the aggregated individual preference of each image attempt or reached waypoint. Based on the above example, this is shown not to be the case, and it is therefore of high interest to identify a method with which setwise preferences can be elicited, articulated, and implemented. Ultimately, the setwise preference articulation for binary optimization problems, like that of the SIASP and UAVRP, can be implemented through the global solution evaluation, $\mathbf{U}(.)$ on the set of alternatives in ones solution $X \in \{x_1, x_2, \dots, x_N\}$. This can be described by the following telescoping sum:

$$\mathbf{U}(X) = \sum_{i=1}^{N}(u_i x_i + \sum_{j=1}^{N}(u_{ij} x_i x_j + \sum_{k=1}^{N}(u_{ijk} x_i x_j x_k + \dots \sum_{s=1}^{N}(u_{ijk\dots s} x_i x_j x_k \dots x_s)) \dots) \tag{3.6}$$

Where u_i is the preference as a ratio score assigned to the ith element of the binary solution space, and u_{ij} is the joint preference assigned to the acquisition of the ith and jth element of the binary solution space. If the preference space is symmetric, meaning $u_{ij} = u_{ji}$ then order of acquisition in the solution space is irrelevant, which means $U(x_i, x_j) = u_i + u_j + u_{ij} + u_{ji} == u_i + u_j + 2u_{ij}$. Consequently, the telescoping sum can be simplified dramatically as the number of different sets to consider in the different summations vary. That is, we do not sum from 1 up to N (See next section 4.1).

Note, the framework only consider the preferences of a single agreed upon preference structure. That is, we do not have to infer preferences of multiple DMs, as this opens up a new set of issues. See Arrow's impossibility theorem for one of these issues in terms of avoiding that no single DM can "dictate" the groups preference structure.

4.1 Amount of Articulation

In terms of the actual elicitation, the amount or work required by the DM is heavily affecting the success of the method. with N items, the setwise ordering can be elicitated based on a high number of feasible sets. There exist one large set consisting of all elements, then N sets consisting of all elements except for one, and then $C(N, 2) =$

$\frac{N!}{2!(N-2)!}$, which continues until only one element sets are counted. The behaviour can be described through this function:

$$\text{Number of feasible sets with N elements} := \sum_{r=0}^{N} \frac{N!}{r!(N-r)!} \tag{3.7}$$

On aggregate the behaviour sees a doubling plus one per increase in N, which leaves the number of sets to evaluate infeasibly large. Consequently, we need the proposed method to be of a representative mode. That is, a representative model should be extracted on which the actual performance of items can be evaluated and compared. Note, the performance should be evaluated based on the membership to all sets as in Eq. (3.6).

4.2 Modelling Features for Setwise Preference Articulation

The following discusses features for a method and the corresponding solution of a setwise preference articulation framework. Note, the section is not the exhaustive list of features.

Transitivity

Human nature is many times a paradox for logical and rational assumptions. It can be seen in the raven paradox that questions what type of information logically yields more information than before. And it can be seen in the Simpson's paradox where ungrouped and grouped data are telling different stories.

Transitivity is a logic statement to incorporate in models [124]. But the notion that an orange is preferred to an apple, an apple over a banana, and therefore an orange must also be preferred over the banana does not make much sense when people often buy all three fruits. Clearly, the preference on the single item level is often overshadowed when considering preferences on the set level. However, transitivity is a necessary statement in decision frameworks, because it helps maintain the logical coherence of preferences. If transitivity is violated, it can lead to inconsistencies or paradoxes in decision-making, and creating the risk of cyclic preference orders that defies logical reasoning.

Transitivity is therefore necessary when evaluating on the same level of set evaluations. That is, for sets of a certain size, all sets with that size, must follow the assumption of transitivity. At a first glance, the preference mapping on the single-element level seem to violate the transitivity of cross-level comparisons, and it is therefore an open question whether the framework should be transitive. A similar function to that of Eq. (3.6) could possibly be utilized.

Incomparability

Incomparability refers to situations where alternatives cannot be definitively ranked or compared against each other due to various reasons, such as conflicting criteria, lack of information, or subjective preferences. In the context of defining a decision framework, incomparability acknowledges the existence of cases where it is not possible or meaningful to establish a strict preference order among alternatives. Incorporating incomparability in a decision framework is essential because it recognizes the limitations of decision-making and allows for more realistic and flexible assessments. In the literature, it is also often referred to as commensurability.

In practice, decision frameworks handle incomparability in different ways. One approach is to introduce partial or weak preference relations, where alternatives are ranked or compared based on certain criteria, but incomparability is explicitly acknowledged for others. This approach allows decision-makers to express their preferences in a more nuanced and flexible manner. Another approach is to use preference modeling techniques that allow for fuzzy or linguistic representations of preferences. Fuzzy logic and linguistic variables provide a way to capture and represent imprecise or uncertain preferences, accommodating incomparability in decision-making. Decision frameworks that utilize fuzzy logic or linguistic variables enable decision-makers to express degrees of preference or uncertainty, providing a more comprehensive representation of their preferences. Based on the findings in the Papers A and E the later approach seems very appealing [119].

Monotonicity

In the context of a decision framework, monotonicity refers to the property that increasing the performance or value of an alternative on a criterion should not decrease its overall desirability or ranking. It implies that improving an alternative's performance on a criterion should always lead to a better overall evaluation. In economic utility theory this is referred to as the "more is always better" assumption.

To have monotonicity in the decision environment means, a higher evaluation in the pairwise comparison matrix may not result in a lower score compared to before the increase. Non-monotonic models does allow for this change.

In Paper E, the issue of monotonicity was seen unfolding through the Braess' paradox, where a higher importance to cloud coverage above a certain threshold led to an overall decrease in the performance of said objective. This stems from the neglect of other relevant objectives, namely the corresponding uncertainty. Due to the difficulty in understanding when the non-monotonic behaviour initiates for different scenarios and different regions. Consequently, to ensure integrity and reliance on the preference articulation framework, monotonicity is a high-ranking trait.

Non-compensability

Non-compensatory refers to the idea that the performance on one criterion cannot compensate for a poor performance on another criterion. It implies that certain criteria or attributes are considered essential or non-negotiable, and a low performance on any of these criteria would lead to the rejection or elimination of an alternative, regardless of its performance on other criteria. Incorporating non-compensatory decision-making in a decision framework involves setting specific thresholds or requirements for each criterion, beyond which an alternative is deemed unacceptable or infeasible. This can be done by establishing minimum standards or cutoff values for each criterion, indicating the minimum acceptable level of performance [20].

Non-compensatory decision-making is particularly relevant in situations where certain criteria are considered critical or have higher priority than others. It allows decision-makers to prioritize specific attributes or requirements and ensure that they are met before considering other criteria. This approach is commonly used when dealing with safety-related considerations, legal requirements, or other non-negotiable factors.

However, it can introduce additional complexity to the decision framework as it restricts the flexibility of trade-offs between criteria. It may lead to a more conservative or stringent evaluation, potentially reducing the number of feasible alternatives. However, this trade-off is necessary to maintain the integrity and validity of the decision-making process, particularly when dealing with essential or non-negotiable criteria.

In the context of complex decision environments, the ability to impose non-compensability is of high relevance as discriminating between different image requests due to emergency traits is vital.

Rank reversal

Rank reversal refers to a phenomenon where the relative rankings or preferences of alternatives change when additional alternatives are introduced or when the evaluation is based on different subsets of criteria. It occurs when the rankings of alternatives (or preference structure) are not stable and can vary depending on the specific context or set of criteria considered [64]. Rank reversal is an important consideration in decision frameworks as it highlights the sensitivity of the decision-making process to the specific set of alternatives or criteria being evaluated. It implies that the relative superiority or inferiority of alternatives can change, leading to different rankings or preferences based on the particular context or subset of criteria under consideration.

One approach to manage rank reversal is through sensitivity analysis, where the stability and robustness of the rankings are examined under different scenarios or variations in criteria weights. Sensitivity analysis helps identify situations where rank reversal occurs and provides insights into the factors driving the variations in preferences. By understanding the causes and implications of rank reversal, decision-makers can make more informed and reliable decisions. Consequently, the decision framework needs to allow for extensive sensitivity analysis, which e.g., in the context of a fuzzy preference structure can be done with the aid of systems like stochastic multi-attribute analysis, which inspired the analysis in Paper E.

4.3 Roadmap towards Setwise Preference Articulation

Developing a setwise preference articulation framework involves several steps to design a robust and effective decision-making mechanism. The following is a roadmap that outlines the key stages in the development process addressing the challenges identified above in a structured manner.

1. Review preference elicitation techniques:
   - Investigate existing methods for eliciting preferences from decision-makers, including pairwise and setwise approaches. Additionally investigate the possibility for efficient sampling methods in preference elicitation.
   - Identify strengths and limitations of different techniques in capturing complex preferences, and consider their ability to allow for both incomparability and non-compensability.
2. Develop mathematical models for setwise preference articulation:
   - Establish mathematical frameworks to represent and manipulate setwise preferences, considering properties such as transitivity, incomparability, and monotonicity.
   - Explore techniques from decision theory and optimization to incorporate setwise preferences into the solution search process.
   - Create smaller benchmark problems for the model to be showcased and tested.
3. Investigate the place of articulation's effect on the ability to incorporate setwise preference:
   - Explore methods for integrating a priori preference information into the solution approach.
   - Develop approaches to incorporate a posteriori preference articulation during the optimization process to adapt to evolving decision-maker preferences.
4. Propose mechanisms that fine-tune preferences and the solution characteristics through testing and simulation:
   - Use testing and simulation techniques to refine the solution approach and its parameters.
   - Conduct sensitivity analyses to understand the impact of different preference settings on the solution outcomes.
   - Evaluate the sensitivity of the solution and preferences regarding incomparability, monotonicity, and rank reversal.

5. Implement a setwise preference articulation framework:
   - Develop software tools and/or algorithms that enable efficient elicitation and integration of setwise preferences.
   - Ensure usability and accessibility of the framework for both researchers and practitioners.
6. Validate the effectiveness of the framework:
   - Conduct case studies and experiments to evaluate the performance of the setwise preference articulation framework.
   - Compare the results against existing approaches and assess the framework's ability to capture complex decision-maker preferences.
7. Bridge the gap between research and practice:
   - Provide practical guidelines and best practices for implementing the setwise preference articulation framework.
   - Collaborate with industry partners to apply the framework in real-world decision-making scenarios and gather practical insights.
8. Foster collaboration and knowledge sharing for further refinement:
   - Facilitate collaboration between researchers, practitioners, and decision-makers to share insights and expertise.
   - Organize workshops, conferences, or forums to promote discussions on setwise preference articulation and its application in optimization problems.
   - Gather feedback from users and stakeholders to identify areas for improvement.
   - Incorporate new developments in preference elicitation, solution search, and evaluation techniques into the framework.

It is important to note that this roadmap provides general guidelines, and the specific steps and considerations may vary depending on the complexity of the decision problem and the context in which the setwise preference articulation framework is being developed. Flexibility and adaptability in the development process are crucial to accommodate the unique requirements and challenges specific to the decision domain.

Chapter 4

Conclusion and Future Work

Conclusion

In the design of solution approaches for large-scale NP-hard multi-objective optimization problems with near real-time computation requirements, the correct preferences are often omitted due to several reasons. The main reason is the fact that the complexity is already high in obtaining a solution, and consequently obtaining a solution that is near optimal and also near the correctly defined optimal setting is difficult. Consequently, complexity, robustness, and explainability are the driving forces behind the omittance.

Addressing the first research question (RQ1), the applicable decision-making framework for integrating the multi-objectivity of complex optimization problems without a significant increase in computational load is the a priori preference integration framework. This framework allows DMs to express their preferences by assigning weights to each objective or criterion outside of the operation of the system. Correspondingly, allowing for tactical tuning of the employed preference structure. It is however very difficult to elicit and integrate the correct preference setting, and correpsondingly it is of high importance to identify a scalarization method that is applicable, robust, and intuitive for the DMs. Versions of the weighted sum approach is despite their ease of use, very difficult to trust due to the abstract nature of the indirect preference articulation framework. The ELECTRE framework seems to yield an intuitive and robust platform for integrating preferences as the it has the ability to impose indifference, preference, and to discriminate between attempts. Moreover, does it provide a practical and computationally efficient way to integrate multi-objectivity for complex decision environments.

To tackle the second research question (RQ2), the approaches from the evaluation methodology can be adapted to address explainability and transparency issues in design problems. By incorporating customizable integration of the preference structure, DMs can have better visibility and understanding of how their preferences are considered in the solution approach. This customization allows DMs to align the solution with their specific requirements and helps mitigate transparency concerns. It is however important to understand the scales with which the different evaluation approaches compare alternatives, as they do not necessarily fit towards ratio-scaled use cases as those of design problems in complex decision environment.

The third research question (RQ3) revolves around integrating different types of uncertainty in the solution approach. Uncertainty arising from sources such as a stochastic environments or a fuzzy preference knowledge can be integrated a priori through the framework of ELECTRE-III, as different modes of stochasticity can be assigned a preference, while uncertain preferences can be expressed as such through the fuzzy outranking relation. It is important to notice, that the a priori framework does not concern the ability for futher decision cycles in operation, and consequently a comparison between longer planning horizons with outdated information and shorter planning horizons with newer information are the way one deals with aligning preferences to the corresponding stochastic environment. Further work is required to study efficient methods of stochastic modelling.

Finally, addressing the fourth research question (RQ4) regarding the elicitation, integration, and utilization of setwise preference information, an outcome of this dissertation is the revelation that setwise preference articulation methods indeed will alleviate a lot of issues regarding the correct preference setting. These methods allow DMs to express their preferences over sets of alternatives rather than assigning a single preference to the indivudual solution. Setwise preference information should be obtained through techniques like pairwise comparisons, ranking, or direct elicitation. By incorporating setwise preferences, the solution approach can provide more nuanced and comprehensive decision-making support in complex optimization problems. These methods are however rather cumbersome to produce and a roadmap towards defining an applicable framework is seen presented in Section 4.3. The roadmap indicates how the different aspects of the model can be implemented and how it can be tested and tuned. The implications of setwise preference are significant, but still a large challenge stands as a direct implementation of the corresponding score into standing solution methodology is not directly feasible. Firstly, due to the scale of the setwise preference space and the work required to elicit a fitting preference structure. Secondly, due to the bonus preference ocquirng when setwise preferences are considered as opposed to when only the single solutions are compared with each other.

Future Work

Ultimately, there are two different lanes to consider regarding the future work. The first one is the direct extensions of the work done throughout the PhD, while the second are all the spin-out projects that for different reasons are of interest to pursue. Firstly, the direct extensions:

- Follow the roadmap. One proposal to such a method is to synthesize results from multiple different solutions generated based on varying levels of a priori setwise articulation, and then adjust the preference structure based on orthogonal sampling approaches to accommodate the large scale of the preference space in a setwise preference framework. With this approach, one would approximate the setwise preferences without considerable load on both the computation and elicitation procedures.

- Conduct a computational performance comparison study, which directly approximates the final results obtained from a posterior articulation methods with a priori articulation methods, and finally evaluating the computational savings in doing so.

Secondly, the spin-out projects are more related to either the specific problem domains or the specific solution approach than a combination of both:

- look for related problem domains that could fall under the domain of complex decision environment to apply solution approaches. During my research stays, I have initiated work on the UAVRP for search and rescue in the usecase of tornados in Oklahoma, where the prioritization on how to use the search platforms depend on a large number of criteria. E.g., School areas, critical infrastructure, phone calls of tornado sightings or directly observation of damage. See Fig. 2.5 for a snippet of the work.

- Conduct a deeper study of the trade-off with allowing search and Rescue UAV platforms to monitor in different altitudes throughout a mission. This requires a deeper analysis of the sensor resolution and capabilities and the risk of missing targets at different altitudes.

- Use the EOSpython scenario generator framework to test different satellite specifications and provide insights into the value-addition moving towards hyper-agile platforms. This could lay the foundation for the design of future high-resolution satellite systems as the collective capability of the platforms in correspondence to their agility could be evaluated.

- For automatic preference articulation, a deeper (locus) exploration on the use of Shannon's information entropy to determine preference settings is required. Additionally, a comparative analysis of this approach to others is of high interest.

- Initiate discussions on the need for a measure that describes the amount of articulation required for different comparison methods. This would consequently mean a mapping between different problem domains and a fitting solution approach design regarding the place of articulation could be made. Moreover, it could be used to identify problems where the setwise preference articulation could bring the most value.

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Appendix

S-1 Related work

S-1.1 Conference and workshop participation

- ICRCA 2021: the 5th International Conference on Robotics, Control and Automation (Seoul, South Korea)
- Workshop and seminar for knowledge dissemination at University of Peradeniya 2022
- ISSC 2022: Interplanetary small satellite conference (San luis obituary, California)
- Toulouse 2022 space event
- Aalborg Robotics Challenge 2023

S-1.2 Teaching and supervision

I have lectured on the course Production management where I undertook the lecture "Forecasting and inventory modelling" for the sports science 9th semester 2020. I have also led two lectures in the course "Combinatorial Optimization Problems and Solutions for Autonomous Systems" on multi-objective optimization and multi-criteria decision making for the mathematics-economics 8th semester students 2023. Moreover, I held a workshop in that course on the NSGA-II algorithm. I have also undertaken a single lecture on "Characteristics of Remote sensing - Optical and radar imagery" in the course "Remote sensing image analysis (ID7.6)" in the Assets+ programme co-funded by the erasmus+ programme of the European Union.

I have supervised / am supervising the following math-econ master groups:

- Churn prediction in telecom industry (10.sem, 2020) (Telenor). The group utilized their master thesis to investigate and apply neural network and extreme gradient boosting classification methods for detecting unsatisfied customers.
- Storage optimization (7.sem, 2019) (Grundfos). The group devised zoning strategy to combat high complexity issues of larger problems instances.
- Demand forecasting (7.sem, 2020) (Grundfos).
- Data warehouse architecture (9.sem, 2020) (Telenor)
- Demand forecasting (10.sem) (Grundfos, 2021). Hierarchical time series analysis to infer information throughout the dependencies in predicting demand.
- Path planning for the UAV-assisted Search and Rescue mission (8.sem, 2021). The group investigated different network reduction methods and solution approaches to test their applicability to real world scenarios.
- Inventory management through path planning (7.sem, 2022) (Grundfos)
- Inventory management through Reinforcement learning (7.sem, 2022) (Grundfos)
- Introducing water temperature in path planning for the UAV-assisted Search and Rescue mission (9.sem, 2022).
- Garbage collection with IoT sensors (8. sem, 2023)
- Garbage collection with uncertain loads (8. sem, 2023)
- Garbage collection through CVRP and heuristics (8. sem, 2023)
- Forecasting of sales and inventory modelling of industry lubricants in expanding markets (10.sem, 2023).

S-1.3 Examination

Besides the above groups where I have participated as an examinator in the exam, I have participated in the following exams (and re-exams if necessary):

- Member of the Panel of Examiners of Research Degree Candidate - U.D.D.M. Dahanayaka from University of Moratuwa 2022 - Model the Vehicle Routing Problem to Optimize Freight Logistics Multiple Echelon Network
- Math-Econ 9th semester group fall 2022
- Linear Algebra (approx. 60 students) GBE 2 spring senester 2022
- Calculus (approx. 60 students) GBE 1 fall senester 2022
- Optimization and programming course (prepared written exam questions) - GBE 3 fall semester 2022

S-1.4 Course work

Courses	ECTS
Introduction to the PhD Study (Engineering/Tech), Spring 3 (2020)	0,5
From Timed Automata to Stochastic Hybrid Games (2019)	2,0
Academic Information Searching, Publishing and Management, Fall 2 (2020)	2,0
AI for the People (2020)	2,0
Applying the Danish Code of Conduct for Research Integrity to your Research 4 (2020)	1,0
Aspects of Advanced Analytics (2020)	2,0
Automated Planning Tools for Intelligent Decision Making (2021)	3,0
From Research to Business (2021)	2,0
Optimal Control (2020)	4,0
Project Management and Interpersonal Skills, Fall (2020)	2,0
Introduction to Stochastic Programming (2021)	5,0
International Scientific Networking - A (2022)	1,0
AI for defence	0,5
Conference participation	
ICRCA2021	2,0
ISSC2022	1,0
Space event toulouse 2022	1,0
Sri Lanka workshop	1,0
Total	32

Table 1: ECTS points gathered through the PhD work

Part II

Papers

1 Appended Papers

A Multi criteria decision making for the multi-satellite image acquisition scheduling problem

B UAVs Path Planning under a Bi-Objective Optimization Framework for Smart Cities

C An improved pre-processing method for cyber physical systems - as illustrated in the earth observation satellite scheduling

D A GRASP-Based Approach for Planning UAV-Assisted Search and Rescue Missions

E Towards an autonomous system for the satellite image acquisition scheduling problem through multi-criteria decision-making and the extended longest path algorithm

F Determining the pricing strategy for different preference structures for the earth observation satellite scheduling problem through simulation and VIKOR

SUMMARY

In the future, many decisions will either be fully automated or supported by autonomous system. Consequently, it is of high importance that we understand how to integrate human preferences correctly.

This dissertation dives into the research field of multi-criteria decision making and investigates the satellite image acquisition scheduling problem and the unmanned aerial vehicle routing problem to further the research on a priori preference integration frameworks. The work will aid in the transition towards autonomous decision making in complex decision environments. A discussion on the future of pairwise and setwise preference articulation methods is also undertaken.

"Simply put, a direct consequence of the improved decision-making methods is, that bad decisions more clearly will stand out as what they are – bad decisions."

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