MASTER'S THESIS

Multi-Domain Conflict Comparison Support Model

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Multi-Domain Conflict Comparison Support Model

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"Rest at the end, not in the middle." — Kobe Bryant

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SUMMARY

In the last couple decades, the warfare paradigms have changed significantly and the operations are no longer only conducted in the air, on land and in the maritime domains. The domain of cyber security is now being explored by the adversaries in order to challenge the military forces in competition or during conflict. The usage of multiple domains during warfare is called the Multi-Domain Battle paradigm.

During the execution of a Multi-Domain Operation, the targeting process is used in order to target adversaries and achieve an advantage in battle. As a part of the targeting process, different engagement plans, also known as courses of action, are evaluated and compared to each other by the commander and its staff. The evaluation and comparison are done with the use of the Military Decision Making Process methodology which allows the commander and its staff to have a better understanding of the mission and eventually decide which course of action provides the best result. It should be stated that the evaluation of engagement plans is a subjective process since the commander relies on his own experience and knowledge.

Results from earlier conducted research show that different techniques were used in the development of models that could provide support during the course of action comparison process. However, the interiors of these models were not accessible to the decision makers that were using these models. Making it more difficult for the users to understand the model and then properly use it. In other domains than the military domain, the Bayesian model is used which does provide an explainable and transparent model. The Bayesian model does so by representing the causal relations between variables and incorporating the uncertainties that arise within the decision making process.

With use of the available scientific and military doctrines, the features are determined that can be used in evaluating which course of action is best to use during an operation. In order to do a Bayesian Network analysis, a causal graph in the form of a directed acyclic graph is constructed. This structure displays the causal relations between the different features. Each of the nodes in the bayesian model are assigned a condition probability table with use of the point-allocation method. The values of the weights are based on the real incident information from the Russia-Ukraine war. When selecting a course of action, the proposed model shows the influence of the choice on the different features. This information can be used in the analysis of courses of actions and provide support in the decision making process. The proposed model does not have the capability to directly compare multiple courses of action and only shows the influence of a choice.

The model is demonstrated with the use of three illustrative created scenarios that were based on different events of the Russia-Ukraine war. The result of the demonstration showed that the model is applicable to the military domain.

It is concluded that the proposed model provides is a transparent model that can be understood by its users and properly used. Therefore, the decision makers are in a better position to consider the human aspect during Multi-Domain Operations. The model is still considered limited in its capabilities, therefore, a list of recommendations and future work is provided.

SAMENVATTING

Over de laatste jaren zijn de paradigmas die gebruikt worden voor het voeren van oorlog enorm verandert. De operaties vinden niet langer alleen plaats in de lucht, op land of in het maritieme domein. Het cyber security domein is ook erg in trek bij tegenstanders om zowel in competitie of tijdens een conflict de strijdkrachten uit te dagen. Het gebruik van meerdere domeinen in oorlogsvoeren wordt ook wel het Multi-Domain Battle paradigma genoemd.

Tijdens het uitvoeren van een Multi-Domein operatie wordt het targeting proces toegepast om gericht tegenstanders aan te vallen en zo een voordeel te behalen in de strijd. Als een onderdeel van het targeting proces vergelijkt en evalueert de commandant en zijn staf de verschillende aanvalsplannen. De evaluatie en vergelijking wordt gedaan door middel van de Military Decision Making Process-methodiek. De commandant en zijn staf krijgen met gebruik van deze methodiek een beter begrip van de missie waardoor er uiteindelijk besloten kan worden welke aanvalsplan het beste resultaat oplevert. Hierbij moet wel opgemerkt worden dat de evaluatie van aanvalsplannen een subjectief proces is, aangezien de commandant vertrouwt op zijn eigen kennis en kunnen.

Resultaten uit eerder onderzoeken hebben laten zien dat er verschillende technieken gebruikt zijn in modellen die ondersteuning bieden tijdens het evalueren van aanvalsplannen. Hoe de modellen precies in elkaar zatten was echter niet bekend bij de gebruikers van de modellen. Hierdoor is het moeilijker voor gebruikers om het model te begrijpen en het vervolgens op de juiste manier te gebruiken. In andere domeinen wordt het Bayesiaanse model gebruikt dat wel een verklaarbaar en transparent model geeft. Het Bayesiaans model toont de causale relaties tussen variabelen en neemt onzekerheden mee in het besluitvormingsproces.

Met behulp van de beschikbare wetenschappelijke literatuur en de militaire doctrines worden de kenmerken bepaald die van belang voor het evalueren van de beste aanvalsplan. Om een Bayesiaans analyze uit te kunnen voeren wordt een causale diagram, in de vorm van een gerichte acyclische diagram, geconstrueerd. Deze structuur geeft de causale verbanden tussen de verschillende kenmerken weer. Elke kenmerken in het Bayesiaans model krijgt een conditiewaarschijnlijkheidstabel toegewezen met behulp van het point-allocation methode. De waarden van conditiewaarschijnlijkheidstabel zijn gebaseerd op incident informatie van echte gebeurtenissen in the Rusland-Oekraïne oorlog. Bij het kiezen van een aanvalsplan laat het model zien wat de invloed van de keuze is op de andere kenmerken. Deze informatie kan dan gebruikt worden bij de analyze van aanvalsplannen en biedt ondersteuning bij het besluitvormingsproces. Het voorgestelde model geeft niet de mogelijk om meerdere courses of action te vergelijken maar toont alleen de invloed van een keuze.

Het model wordt gedemonstreerd met behulp van drie gecreëerde scenario's die gebaseerd zijn op de verschillende gebeurtenissen in Rusland-Oekraïne oorlog. Het resultaat van de demonstratie toont dat het model toepasbaar is in het militaire domein.

Er wordt geconcludeerd dat het voorgestelde model een transparent model is dat door de gebruikers kan worden begrepen en daardoor op de juiste manier kan worden gebruikt.

Hierdoor zijn de gebruikers in een betere positie om het menselijke aspect van Multi-Domein operatie mee te nemen in hun besluitvormingsproces. Het model kan als beperkt worden beschouwd, daarom is er een lijst van aanbevelingen gedaan.

1

Introduction

Since the Cold War, the warfare paradigms and strategies have significantly changed and the military operations that are conducted are no longer only carried out in the air, land and maritime domains, but also in the cyberspace domain. A problem that results from the domain expansion is that an increasing number and range of actors is able to further deny or disrupt access to and action within the domains from extended distances. The different adversaries are, therefore, able to challenge the ability of a Joint Force, a military force composed of two or more military entities operating under a single commander, to achieve military and political objectives. These kind of problems will continue to increase as adversaries are finding new ways and means to keep challenging the military forces.

As a result of being challenged by adversaries in multiple military domains, the shift was made to the to the Multi-Domain Battle (MDB) paradigm [1]. The most recent example is the Russia-Ukraine war that is ongoing. Ever since the maiden large demonstrations in 2014, the Revolution of Dignity and the formation of a new government in Ukraine who wants to strengthen its relations with Europe, tensions have been increasing between Russia and Ukraine but also in Ukraine between its own people. As a result of the escalating situations, Russia decided to launch a military operation which led to the annexation of Crimea and the establishment of the self-proclaimed breakaway states Donetsk and Luhansk. The tensions kept building up the last few years, but escalated into a full-blown war when Russia decided to attack and invade Ukraine [2] [3].

Even though the war is still ongoing, it has shown signs of the Multi-Domain Battle (MDB) paradigm [4] where military forces challenge each other across multiple military domains [1]. The MDB framework that was introduced consists of several aspects that address the operational challenges, such as being contested in all domains and isolated from help by friendly forces with both lethal and nonlethal means. The approaches that are presented within the framework are in many manners evolutionary as the concept is build upon relevant past and present doctrinal practices. The MDB paradigm can be used in competition, where the military forces are actively campaigning to advance or defend national interests without violence, or in armed conflict, where a large-scale of violence, in contrary to competition, is used [5].

During the execution of a Multi-Domain Operation (MDO), an operation conducted during MDB, armed forces conduct the military targeting process [6] [7] [8] in order to target adversaries that will contribute to gaining a political and/or military advantage. As a part of the targeting process, the different courses of action (CoAs), different extensive solutions to an identified problem from which the best is selected, to engage a target are considered and further compared [6]. In order to solve well-structured problems, the Military Decision Making Process (MDMP) methodology is used. With the use of the MDMP, different activities are performed by the commander and its staff in order to have a better understanding of the mission and to decide which CoA provides the best result regarding the situation at that time [9] [10].

Over the years, opposing states have developed capabilities that can challenge the military forces across all domains and impose a complexity on the armed forces that makes it harder to gain advantage in battle. Among these developments is the increasing usage of Artificial Intelligence technologies within different applications. By using Artificial Intelligence enabled capabilities, the activities of adversaries can be countered more efficiently and faster than was previously possible [11]. The application of Artificial Intelligence or/and Machine learning (AI/ML), a combination of multiple AI techniques, to the CoA analysis phase of the MDMP has tremendous potential in providing decision making support for battle spaces that are becoming highly contested and more complex [12]. While the use of AI enabled capabilities increase effectiveness of the military forces, the human aspect is still to be considered highly. Therefore, an intelligent model should be transparent and explainable to the users so it can be properly understood and correctly used [13] [14] [15].

1.1. Problem Statement

As described previously, adversaries have continued developing technologies and techniques that can be applied in MDO through the years and have shared this knowledge with other states. Therefore, it could be the case that adversaries own capabilities that are superior to the technologies owned by the military forces. If the enemy is able to converge these capabilities across multiple domains, this will impose complexity on the armed forces and will make it harder for them to gain an advantage in battle.

In order to counter the activities of opposing parties and to achieve the strategic objectives in battle, the armed forces should be able to apply the joint capabilities efficiently, faster and with greater agility than it previous could. According to [1] and [5], the need for AI-enabled capabilities is growing since the machines will support the human users in their tactical tasks. The assistance of AI-enabled application will help human users by minimizing their biases and cognitive constraints in order to improve decisions while shortening decision cycles to match and outmaneuver the adversaries.

This research will focus on the comparison of CoAs within the MDMP. The MDMP is an iterative planning methodology were different activities are conducted by the commander, staff, subordinate headquarters and other friendly partners in order to better understand the situation and mission, develop and compare CoAs, decide which CoA provides the best result with regards to the mission, and produce an operation plan [10]. The findings of this research can mainly be used in two phases of the targeting process, phase IV: decision making, force planning and phase V: assignment and the phase mission planning and usage of force.

A multidisciplinary approach is required by this research since military operations will take place in multiple domains and require different expertise, such as military, software engineering and AI. To best of our knowledge, the research direction of AI support within

MDMP in MDO is novel, the aim of this research is to investigate this matter, design and build an implementation of a model that is able to provide support in CoAs comparison process.

1.2. Research Objective

The aim of this research is to explore how to design and implement a model that is able to show the influences of a selected CoA choice while targeting the assets of an adversary. It is crucial that the model considers the human aspect, such as the lives of civilians, while executing a multi domain operation. By providing a transparent model to the users, the model can be correctly understood and used when executing such an operation. To the best of our knowledge and from the conducted literature review (see Chapter 4), it was noticed that the research direction is novel.

As mentioned before the research objective is to design and implement a model that can provide support in the comparison of CoAs in MDB, in order to solve the research problem a solution needs to be found for the following research question:

How to design a model for CoAs comparison in Multi-Domain Operations?

In order to achieve the set research objective, the design science research methodology is chosen. This approach focuses on the creation of designs and implementations of artifacts that have a societal purpose. The main research question is divided into several sub research questions that are presented in Chapter 3.

1.3. Thesis Outline

The remainder of the paper is structured as follows. The second chapter describes the needed background information about the topics that are being discussed in this paper. The third chapter presents the approach that was applied to this research in order to achieve the established research objective. The fourth chapter describes the conducted literature review that was done in order to gain knowledge about the AI techniques that were used in the military domain, but also other domains. The fifth chapter discusses the definition of a CoA within MDB, the features that were used for the proposed model, the causal graph that represents the relations between these features, and the implementation of the proposed model. The sixth chapter presents the scenarios that are based on real incident data from the Russia-Ukraine war, the selection of a scenario, the results that the model provides about the influence of the choice on the features, and the interpretation of the results. The seventh chapter describes the conclusions on all the sub research question, the answer to the main research question, the limitations of the current research, and the directions that could be taken in future research.

2

BACKGROUND

This chapter provides the relevant background information that was required in order to conduct the research. This chapter starts by providing an introduction of the military discipline with the focus being on Multi-Domain Battle, and the different processes that are used in order to create an operational plan that can be executed during a Multi-Domain operation. Both the targeting process and the MDMP are discussed in their own sub section. The second section describes the concept of Artificial Intelligence and the different learning paradigms within the sub-field of Machine Learning. The final section of the chapter describes probabilistic/Bayesian modelling. This section is divided into two subsections which discuss Bayes' Theorem and Bayesian Belief Networks.

2.1. MULTI-DOMAIN BATTLE

The strategies used in warfare have changed significantly over the last few decades. Military operations are not only carried out in the air, land, and maritime domains, but have also moved to the cyberspace domain. By using the multiple domains, enemies want to create a strategic and operational stand-off that separates the units of the armed forces in time, space, and function. Armed forces are willing to use different kinds of means to achieve their campaign objectives. For instance, military forces use access and denial systems to cause incredible losses on the enemies and its allies. However, the armed forces could also utilize propaganda and influence people their political decision making through different media outlets, such as local news, but also social media [5] [16] [17].

The execution of operations across multiple domains, also called multiple domain operations (MDO), can either be conducted in competition or while being in armed conflict. When being in competition, military forces increase the competitive space by countering the adversaries persuasion of other parties, unconventional warfare, the usage of special operations forces, local paramilitaries, proxy forces and activists for destabilizing target governments and the control of those governments on a certain area or population. Various non-lethal capabilities are employed by the armed forces in order to provide the population with information and to create a believable narrative and eventually achieve a military objective [5]. In armed conflict, however, armed forces will create a physical stand-off and defeat aggression by employing operations across all domains where violence and lethal methods are used in order to create a favorable strategic and political outcome. The use of violence will most likely result in casualties on both sides. In return to competition, the military forces will concentrate their efforts on preventing the regeneration and re-establishment of adversaries forces within the obtained area and will assist the establishment of a regional order that has the same military objective [1].

The central idea of conducting MDO's is to succeed in competition and only when absolutely necessary, MDO's will be executed in conflict which results in the military forces penetrating, corrupting, and destroying anti-access and area denial systems. The armed forces will then be able to further maneuver, achieve strategic objectives and force adversaries to return to competition on favorable terms [5].

While engaging in Multi-Domain Battle(MDB), military forces do so by using three interrelated principles, calibrated force posture, Multi-Domain formations and convergence, in order to reduce the problems that are induced by adversaries. Calibrated force posture is the combination of position and the ability maneuver across strategic distances. In order to create a window of opportunity, the strength of military forces is shown off by using multiple Multi-Domain formations that can independently operate within the expanded operation area. Convergence is rapidly and continuously applying all the available capabilities on the adversaries across all different domains during the MDO.

In order to impose their will and assure dominance during MDB, armed forces use the targeting process to engage the assets of adversaries in effort to overcome the challenges posed upon on the military forces. For the engagements of targets, plans of actions are developed with the use of the Military Decision Making Process methodology. The literature review (see Chapter 4) that was conducted shows that AI-enabled capabilities are needed in order to stay competitive within conflict and eventually gain advantage during conflict. By using an AI model as assistance to human decision makers in the targeting process (see Section 2.1.1) and MDMP (see Section 2.1.2), the military forces should be able to better determine how to attack the enemy and what means should be used during the engagement.

2.1.1. Targeting Process

The targeting process is an extensive procedure that consists of planning and execution, including the selection of prospective targets, the gathering of information in order to determine if the attack on a particular object, person, or group of persons will meet the military, legal and other requirements, the selection of the weapon that is going to be used for attack, the execution of the attack, including those who have to make the decision on short notice and have a minimal opportunity to plan [6] [7] [8]. The targeting process consist of the following steps:

Phase I - Analysis of commander's intent:
The objectives for the mission are determined and the parameters by which the objectives can be achieved are defined. This is done by considering the political and strategical direction.

Phase II - Target development:
By analyzing the enemy's areas of greatest dependence, targets are identified and selected which give the advantage to the military forces in order to achieve their mission.

Phase III - Analysis of capabilities:
The military capabilities, both lethal and non-lethal, are then matched to the selected tar-

gets in order to achieve the objectives set in phase I while minimizing undesired effects.

Phase IV - Decision making, force planning and assignment:
The information and result from the first three phases are then gathered and are delegated to specific forces/units for further planning and execution of the mission.

Phase V - Mission planning and usage of force:
The mission is further planned at a tactical level and is prepared for target engagement while determining if the target is positively identified. Other information checks and the minimization of collateral damage is also conducted.

Phase VI - Mission assessment:
The mission is evaluated according to the gather information with regards to the produced effects and the achievement of the military objectives.

The MDMP, which is described in the next subsection, is applied within the targeting process in order to ensure that the required actions are taken in order to engage the selected target.

2.1.2. Military Decision Making Process

The MDMP is an iterative planning methodology that combines the activities of the different entities within the military force in order to understand the situation and mission better, developing and comparing target engagement plans, determine which plan will best accomplish the mission and produce an operation plan which can then be used for execution [9]. Considering the military targeting process (see Section 2.1.1), the MDMP can be applied to phase IV, when decisions need to be made about the engagement plan of the selected target and it needs to be made sure that the target is correctly identified. Since time is critical within operations, the MDMP is used in order to ensure that required actions are taken in advance and that military forces are in position before the execution of the operational plan. The MDMP consists of the following steps [10]:

Step I - Receipt of Mission:
The MDMP is started by commanders when a mission is anticipated. The purpose of this step is make sure that all participants are notified, determine how much time is available for planning, and determine which planning approach is going to be used.

Step II - Mission Analysis:
The staff analyzes the plans and orders of the headquarters about the mission in order to have a full understanding of the mission, the intention, available resources, limitations and specified tasks. The evaluation criteria of the engagement plans and the importance of these criteria are also determined by the commander and the staff during this phase.

Step III - Course of Action Development:
After the situation is fully analyzed and understood, different solutions for follow-on analysis and comparison are generated that meet the requirements set by the commander based on it's intent and planning guidance.

Step IV - Course of Action Analysis:
The analysis of courses of action allows for the staff to identify the problems that it might encounter with coordination and determine the outcome of each planned action for each individual CoA. CoA analysis, also called wargaming [18], is considered a disciplined process with rules and steps that try to visualize the progress of a still to be executed operation.

Step V - Course of Action Comparison:
The comparison of CoA is an objective process in which CoAs are evaluated against one another, but also against a set of evaluation criteria in order to determine which CoA has the highest probability of success. The selected CoA will then be used for further developed in an operation plan.

Step VI - Course of Action Approval:
The commander selects the CoA that best accomplishes the mission. When none of the CoA are selected by the commander, the process of CoA development, analysis, and comparison is reiterated. When a proposed CoA is slightly adjusted, the staff needs to redo the CoA analysis step and provide the commander with the results and a recommendation. The approved CoA is used in the final planning guidance.

Step VII - Orders Production, Dissemination, and Transition:
The operation order that is produced as a result of the final planning guidance will serve a directive for the military units participating in the mission.

The focus of this research is to develop an intelligent model that is able to provide support in the process of CoA comparison within MDMP. According to the doctorines [1] [5], the operational environments are becoming more lethal, hyperactive and, therefore, require operational decisions to be made faster than was previously needed. In order to do so, the need for Artificial Intelligence (see Section 2.2) enabled capabilities that can assist human users in making decisions while considering all environment factors is growing.

2.2. Artificial Intelligence

Artificial Intelligence (AI) is the science and engineering of creating intelligent systems that simulate human Intelligence and are able to think and act in the same manner. The ideal characteristic of AI is the ability to rationalize and to take actions in order to achieve a specific goal [13]. An AI can be classified (see Section 2.2.1) as either SuperIntelligence, General, Broad, Limited or Narrow [19]. One of the approaches that is considered to be critical in order to achieve human-like reasoning and decision making is machine learning (see Section 2.2.2). Machine learning refers to computers having the ability to learn without being explicitly programmed to do so [20].

2.2.1. Artificial Intelligence Classification

In a Narrow AI, the type of the input data and the decision that is going to be made is fixed. The AI model is taught to produce a certain output to a specific input, and is not able to accept any other types of input. A Narrow AI does not work well when the input does not match the assumptions that were used during the training process.

A Limited AI, is a combination of the outputs of multiple narrow AI's in order to solve a larger task. There are several approaches that can be used for the combining of Narrow AI, such as a complex graph structure or making the output of one AI the input of another. This solution provides the capability to map multiple inputs to a single or multiple outputs.

With Broad AI, the internal structure of the AI is adapted at the input data level itself. The AI is able to be trained on multiple inputs simultaneously and also has the capability to produce multiple outputs at the same time. The model can take any subset of the input data and produce any subset of the different outputs. Since the different inputs and outputs are considered during the creation of the Broad AI, the AI model is able to learn the relationships that exist between the different types of input, on the contrary to the Narrow AI and Limited AI models.

A General AI demonstrates learning and reasoning that is similar to that of human. A General AI would be able to independently identify new patterns, use new approaches to solve problems that it encounters, and understand the impact and trade-offs of its actions.

A SuperIntelligence AI is a model that is self-aware and has cognitive abilities that greatly exceed the abilities of humans.

This research will concentrate on the development of an AI model that can be classified as a Limited AI since various outputs will be connected to each other which will form a directed acyclic graph, also known as a Bayesian Belief Network (see Section 2.3.2).

2.2.2. Machine Learning

As described above, Machine Learning (ML) is the ability for a computer to execute a task and get better at it over time. In order to be more precise, the following definition of ML is provided:

> *"A program is said to learn from experience E with respect to some task T and some performance measure p, if its performance on the execution of T, as measure by P, improves with experience E."* [20]

The following self-learning algorithms are types of machine learning paradigms [13] [21] [22]:

- Supervised learning: Is a learning paradigm that is characterized by its use of labeled datasets to train algorithms that classify or predict outcomes. The supervised learning algorithm is trained by iteratively making predictions on the training data and adjusting the result while considering the correct answer. Within the supervised learning approach, human intervention is needed for the labelling of the data. A supervised learning algorithm requires a substantial amount of data in order to be well trained and accurately provide predictions. Supervised learning can be divided into the following sub-categories:
    - Regression: A regression algorithm provides a certain value as output when a certain input variable is provided to the model.
    - Classification: Based on labelled data, a classification algorithm makes a distinct separation between data samples and classifies these data samples into categories.

- Unsupervised learning: Opposed to supervised learning, unsupervised learning paradigm uses unlabeled datasets. The algorithm applies clustering to discover patterns and associations within the provided data. This is utterly useful when a human expert is unable to define any common properties within the data. With the unsupervised learning approach, human intervention is only applied to the validation of output data. It is possible that the algorithm provides groups of elements that should actually not be grouped together.

- Reinforcement learning: With the reinforcement learning paradigm, an algorithm is trained by executing several actions within a complex environment while trying to maximize the reward. The algorithm get either rewards or penalties when performing actions.

2.3. Probabilistic Modelling

Probabilistic modelling is a model-based machine learning approach that develops a model which is a simplified formulation of a system or a process. The models that are created with the use of probabilistic modelling can be utilized for both supervised learning and unsupervised learning (see Section 2.2.2). The probabilistic model consists of variables, the relevant parts of the system or process to be modelled, and the respective relations between these variables. Probabilistic reasoning is performed when a state is given to each variable, and subsequently the probability distribution, also called *inference*, is determined [23]. Depending on the purpose of the probabilistic model, the model can be used for a number of matters, such as for making predictions based on historical data, detecting possible anomalies within data, diagnosing existing issues, and binary decision making while dealing with uncertainty. A model is considered to be accurate and precise when the predictions made by the model are similar to real-world observations and, therefore, have a minimum error [24].

The model variables and relations can be displayed in a structure named the probabilistic graph model (PGM). There a number of different graphical models (see Figure 2.1), but this research focusses on the Bayesian network. A Bayesian network (see Section 2.3.2) is a model that is represented as a directed acyclic graph (DAG). Within the DAG the propositional variables are represented as nodes and the dependencies between the nodes are represented as edges [25]. As a result of this representation, the causal relations are described between the variables within the Bayesian network which provides an explainable and transparent model.

Bayes' theorem (see Section 2.3.1) is fundamental to Bayesian modelling and the Bayesian network. The inference in Bayesian networks differs from the inference in traditional methods since the uncertainty is preserved by the model. The Bayesian approach interprets probability as a measure of *belief* that a certain event will occur at some time. This is considered to be a more intuitive approach since human thinking is similar. Based on the information that is available to an individual, a belief is assigned to the occurrence of an event. The belief that is assigned might be different from individual to individual but this does not necessary mean that it is wrong. Humans employ this approach constantly while interacting with their environment. While only seeing partial truths, beliefs are formed based on the gathering of evidence. The belief that is originally assigned to an event is called the *prior probability*. The belief that is updated after the occurrence of an event and the

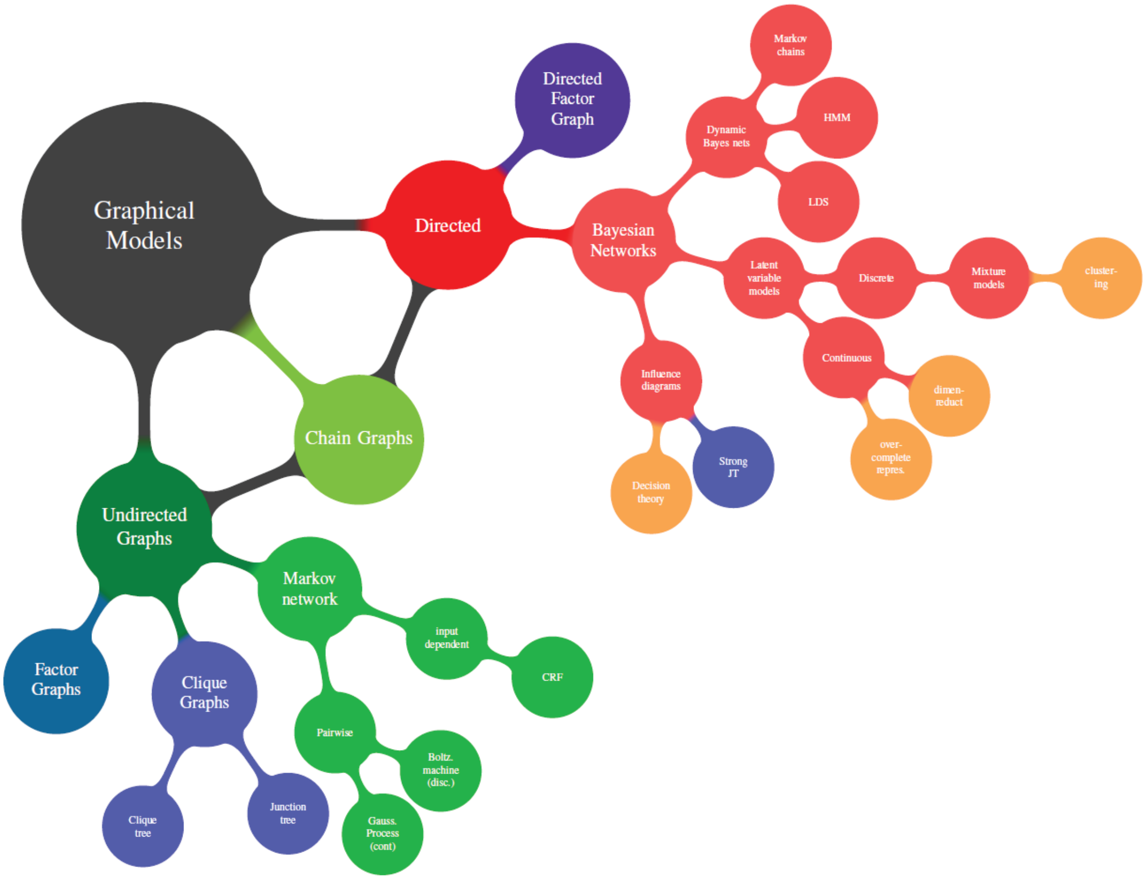

Figure 2.1: The family of graphical models. Each node is a specialization of its parent nodes [23].

gathering of new information is called the posterior probability. The process of updating the prior probability model variables into *posterior probability distributions* is called *conditioning*. The Bayesian model, therefore, learns after it is provided with newly available data [24] [26].

2.3.1. Bayes' Theorem

Bayes' theorem is mathematically defined as followed:

$$p(H|D) = \frac{p(D|H)p(H)}{p(D)} \tag{2.1}$$

Where H and D are variables in a certain space S and are, therefore, a subset of S. The variables H, which stands for hypothesis, and D, which stands for data, are considered to be events. The conditional probability function $p(\cdot)$ is assigned to each of the variables H and D. The probability function of D in Equation (2.1) is $p(D) \neq 0$ [27].

The elements in Equation (2.1) have certain names and are defined as followed:

- p(H) and p(D) : are the probabilities while observing event H and D. The probabilities are also known as prior probabilities or marginal probabilities.
- p(D|H) : is a conditional probability of event D occurring when H is true. It is also be defined as the probability of D given a fixed H. This probability is also known as the

likelihood.

- p(H|D) : is a conditional probability of event H occurring when D is true. This probability is also known as the posterior probability since the hypothesis probability is updated after the collection of new data.

The theorem of Bayes can be proved by deriving it from the conditional probability definition, where the conditional probability of event H is determined, given event D :

$$p(H|D) = \frac{p(H \cap D)}{p(D)}, \text{if } p(D) \neq 0 \tag{2.2}$$

The probability of both H and D, $p(H \cap D)$, occurring is the same as the joint probability *p(H,D)*. This results in the following formula, which is the probabilities product rule:

$$p(H, D) = p(H|D)p(D) \tag{2.3}$$

Considering that $p(H \cap D)$ is equal to $p(D \cap H)$, and, therefore, the joint probability of Equation (2.3) can be written as:

$$p(H, D) = p(D|H)p(H) \tag{2.4}$$

Since the joint probabilities are equal, Equation (2.3) and Equation (2.4) can be combined into:

$$p(H|D)p(D) = p(D|H)p(H) \tag{2.5}$$

When reordering Equation (2.5), the result is the definition of Bayes' theorem (see Equation (2.1)).

While working with conditional probabilities, it is necessary to understand that *p(H|D)* is not generally the same as *p(D|H)*. Mostly the probability event of D, given H, is greater or smaller. For example, the probability of clouds, given that it is raining outside is not the same as the probability of it is raining, given that the sky has clouds.

The hypothesis, H, is the joint distribution of model variables within a Bayesian Network (further explained in Section 2.3.2). The aim of Bayesian modelling is to update the model variables when new data is observed. The marginal probability $p(D)$ is also known as evidence.

2.3.2. Bayesian Belief Network

As stated in Section 2.3.1, a Bayesian Network, also called Bayesian Belief Network (BBN), is a definition of the joint probability distribution. The BBN provides a visual representation of knowledge and reasoning under uncertainty, but also the relationships between a set of variables [25]. Since the BBN is based on the knowledge and experience, the BBN is subjective in its nature [28].

The BBN is a directed acyclic graph (DAG) that consists of nodes that each have a corresponding conditional distribution, also called condition probability table (CPT). The connection between the nodes are called the edges and represent the causal, cause-effect, relationship among the variables [29]. As an example, the cause-effect from raining and a wet sidewalk can be represented as Figure 2.2, where the variable wet sidewalk is the effect of the parent variable rain which represents the cause.

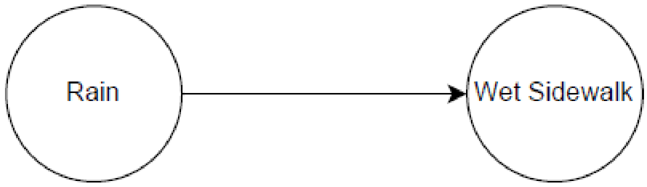

Figure 2.2: Statical representation of the cause-effect relation.

As an example, consider the joint distribution of three random variables a, b, and c. When using the product rule of probabilities (see Equation (2.3)), the joint distribution can be formulated as:

$$p(a,b,c) = p(c|a,b)p(a,b) \tag{2.6}$$

When applying the product rule for a second time on the $p(a,b)$ term of Equation (2.6), the joint distribution is defined as:

$$p(a,b,c) = p(c|a,b)p(b|a)p(a) \tag{2.7}$$

The formula of Equation (2.7) holds for all functional forms of the probability distribution. Considering the terms of Equation (2.7), a simple DAG can be constructed. For each of the variables a, b, and c a node is introduced and with their corresponding conditional distribution. The conditional distribution can be expressed as directed links between nodes corresponding to the variables on which the distribution is conditioned. This means that there are links between nodes a and b to node c for term $p(c|a,b)$ and no incoming links for term $p(a)$. The directed link from node a to node b determines that node a is the parent of node b and, therefore, node b is the child of node a.

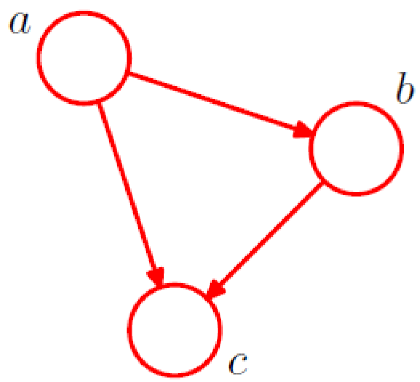

Figure 2.3: A directed acyclic graph that represents the joint distribution over variables a, b, and c [29].

The implicit chosen order of the variables resulted in Figure 2.3. If the particular order of variables would be different, a different decomposition of the joint distribution would have been obtain and hence a different DAG.

Considering the previous example with variables a, b, and c, the joint distribution is only determined over these variables. However, the joint distribution can be determined over a K number of variables by $p(x_1,...,x_k)$. By repeatedly using the product rule as shown with Equation (2.6) and Equation (2.7), the joint distribution can be formulated as a conditional distribution for each variable. The joint distribution over K variables can be written as:

$$p(x_1,...,x_k) = p(x_k|x_1,...,x_k-1)...p(x_2|x_1)p(x_1) \tag{2.8}$$

By choosing K variables, the decomposition of the joint distribution can be represented as a fully connected graph that has K nodes, one for each conditional distribution on the right side of Equation (2.8), and a link between each pair of nodes. The result can be applicable to any choice of distribution.

However, the absence of links between nodes in the graph is what actually holds information about the properties of the conditional distributions that the graph represents. As an example, the graph in Figure 2.4 is not fully connected since links are missing between the pair of x_1 and x_2, but also the pair x_6 and x_7 does not have a link between the nodes.

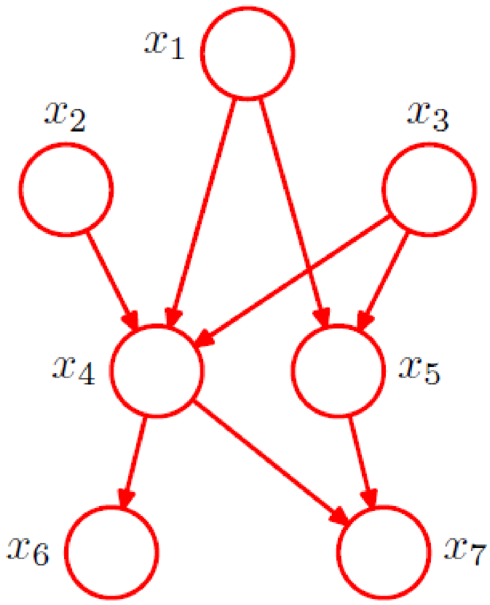

Figure 2.4: A directed acyclic graph that describes the joint distribution over variables $x1,...,x7$ [29].

The corresponding joint distribution of the graph can be written as a product of the conditional distributions. Each node will only be conditioned on the corresponding parents of that node in the graph. The joint distribution of Figure 2.4 can be written as:

$$p(x_1)p(x_2)p(x_3)p(x_4|x_1,x_2,x_3)p(x_5|x_1,x_3)p(x_6|x_4)p(x_7|x_4,x_5) \tag{2.9}$$

After considering Equation (2.9), a general description can be given for the relationship between a given directed graph and the corresponding joint distribution. The joint distribution that is defined by the graph is a product of the conditional distribution for each node conditioned by the conditional distribution of the parents of that node. This definition for a graph with K nodes can be formulated as:

$$p(x) = \prod_{k=1}^{K} p(x_k|pa_k) \tag{2.10}$$

The set of parent nodes of x_k are denoted by pa_k. The generalized equation Equation (2.10) expresses the joint probability distribution over a certain set of variables as a product of factors where each conditional distribution in the graph can be associated with the variables it depends on.

3
METHOD

This chapter discusses the research methodology (see Section 3.1) that was used in order to research the realization of an AI model that could support in the CoA decision making processes. The research required a multidisciplinary perspective since the military operations are taking place in multiple domains and different knowledge expertise, such as military, software engineering and AI, are combined.

Alongside the research methodology, this chapter also establishes the research questions (see Section 3.2) that were formulated in order to find a solution for the research objective (see Section 1.2).

3.1. RESEARCH METHOD

This research has adopted the Design Science Research approach [30] [31] [32] [33] [34] since it focuses on the design and implementation of artifacts with a societal purpose. The engineering cycle of the Design Science methodology can be found in Figure 3.1.

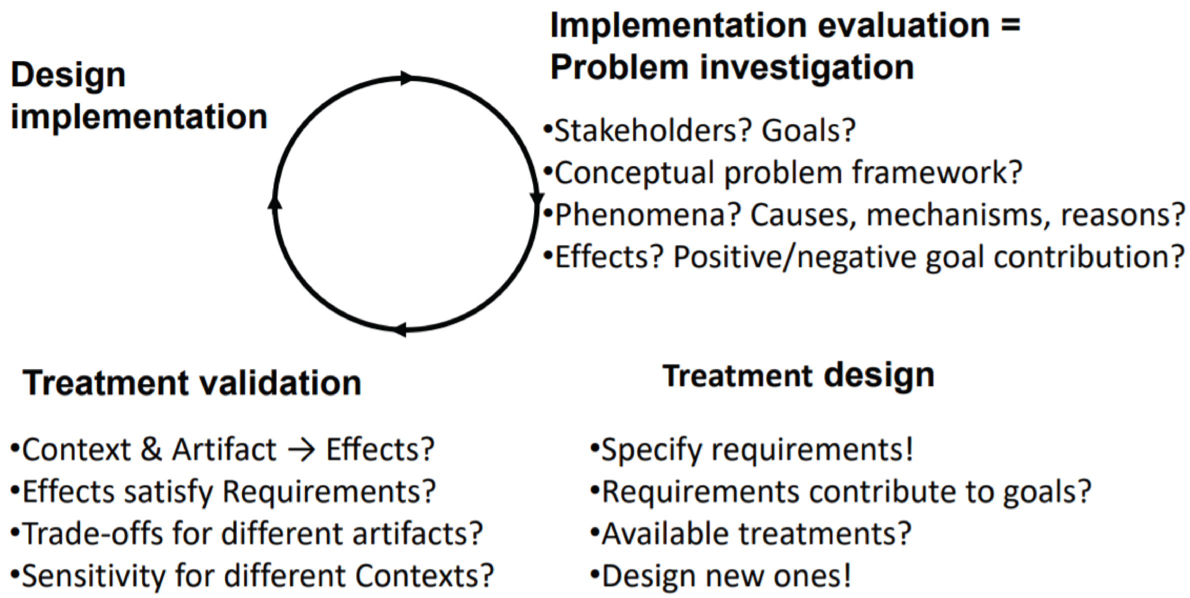

Figure 3.1: The engineering cycle in the Design Science Research methodology [31].

The following activities are carried out while using the Design Science Research methodology:

Activity I - Problem Investigation:

As stated before in Section 1.1, the engagement by adversaries across multiple domains is causing problems for the military forces in order to achieve a military advantage in battle. In order to counter the adversaries, the armed forces must be able to apply joint capabilities efficiently, faster, and with greater agility that previously was necessary across all domains. Therefore, the use of AI models that can assist humans in improving their CoA decision making processes are the topic of this research. Hence, an extensive literature review was conducted on the application of AI model in both the military domain and the non-military domain (see Chapter 4).

Activity II - Solution Objectives:

The aim of this research is to implement an intelligent model that apprehend the relations between the decision criteria and the decision itself in order to provide decision making support during the CoA comparison process.

Activity III - Solution Design and Implementation:

Since information is sensitive within the military domain and the accessibility to public data is not present, it is difficult to develop an AI model based solely on data. However, the military domain does provide expert knowledge and different sources of literature. In order to develop a model that is taking into account the human aspect while determining the influences a certain CoA, Bayesian reasoning was chosen as it provides a representation of knowledge where the causal relations between different features are shown. Thus, providing an explainable and transparent model which can then be properly understood and used by its users. The Bayesian model relies on knowledge and experience, which normally comes from experts, but is taken from scientific literature together with the military doctrines in this research.

In its nature, the Bayesian model is subjective since it developed on the knowledge and experience of experts [28]. Accordingly, the weights that are assigned to the states of the variables are done by using the point allocation method [35] where weights are directly assigned based on the subjective analysis of the ongoing Russia-Ukraine war.

The Bayesian model is able to update its belief when provided with evidence (see Section 2.3) and, therefore, considers the existing uncertainty that arises during reasoning. Once the choice was made for using the BBN as the development technique for building the model, then the design and implementation were created by using Genie modeler [36]. The proposed design and implementation of the Bayesian model can be found in Chapter 5.

Activity IV - Solution Evaluation:

The design science research methodology provides several methods in order to evaluate the developed artifacts, such as evaluation through expert knowledge, technical experiment and case study [33]. The development of CoA relies mainly on the experience and knowledge of the commander and its staff, resulting in a subjective model. Combined with this research being novel and not having an established structure would result in multiple models when consulting experts for their knowledge. Therefore, the evaluation of the model with the use of experts was not chosen. Since there are not any datasets available, it is not possible to do technical experiment on the proposed model.

With the recent war happening in Ukraine, there is a significant amount of real incident data that can be used for evaluation of the model (see Chapter 6). Thus, the proposed model is evaluated through demonstration on three build case scenarios based on the ongoing Russia-Ukraine war [37] [38]. By using the data of the most recent escalated conflict between Russia and Ukraine, the results that are produced by the AI model can be evaluated for the application within the military domain. The Russia-Ukraine war was chosen because the targets are engaged through multiple domains, it is a complex conflict that merges classical warfare methods with the modern, present methods and offers a lot of information that could be used for building the demonstration case scenarios [2] [4] [39] [40]. The targets were first engaged by Land and Air, but during the different operations Cyber was also used as an approach to gain a military advantage across all three domains.

3.2. Research Questions

The aim of this research is to explore how to design an intelligent model that can be used for CoA comparison decision making support MDO. In order to achieve this objective, the main research question is formulated:

How to design and implement a model that can support the CoA decision making process during Multi-Domain Operations?

The main objective of this research is divided into several sub-questions following a logical structure. Each of the sub-questions need to be answered so the main goal can be achieved.

SRQ1 : How can the comparison of COAs in Multi-Domain Battle be described?

This sub-question investigates the comparison process of CoA within MDB. It is then determined where the intelligent model should be designed for and where it can support the military decision-maker. This research question is divided into two sub research questions.

SRQ1a : What are COAs in Multi-Domain Battle?

This sub-question determines what COAs are in MDB.

SRQ1b : What are the features that can be used for CoA comparison decision making support in Multi-Domain Battle?

This sub-question addresses what features of COAs are used in MDB. The acquired features are used for the development of the intelligent model. By considering the military doctrines and expert knowledge shared through scientific papers, it is determined which variables, such as Minimum Impact and Civil Safety, are of interest for the model. This research does not consider the development and analysis process of COAs, but will only focus on the features that could be used for support in CoA comparison decision making processes.

SRQ2 : How to build an intelligent model that can be used for CoAs comparison decision making support?

This sub-question investigates the design and implementation of an intelligent model that will be used for CoA decision support. By considering the relationships between the different features (found in SRQ1b) and their causal impact on one another, the design for the proposed model is developed. The model is then implemented in Genie using the available data of the ongoing Ukraine-Russia conflict.

SRQ3 : What are the results of the intelligent model when demonstrated on three case scenarios?

This sub-question addresses the development of three case studies while using the data from the Ukraine-Russia conflict. The model is then evaluated through demonstration of the three different scenarios. The results are interpreted from both the military and the technical perspective.

4

Related Work

This chapter provides the literature review that was conducted in order to find relevant publications about decision making algorithms within the military domains, but also about techniques that are used outside of the military domain. The research is multidisciplinary and consist of multiple disciplines such as military science, AI, decision making and software engineering.

The results of the conducted literature research provide an insight into the techniques that were already used within the military domain. It also provides information about the other techniques that are available but have not been applied to the decision making problems within MDMP. The acquired knowledge was used in the design and implementation of the model (see Chapter 5).

4.1. Decision Making Algorithms within Military Domain

Over the years different AI approaches were taken when building a tool that could be used for generating strategies and evaluating the tactics in complex operation environments. One of the first used techniques was the genetic algorithm (GA) in combination with an agent based approach and was primarily focussed on land operations [41] [42]. Schlabach et al. developed a decision support tool where the GA was used for generation and evaluation of different kinds of engagement plans, also called CoAs, for military maneuvering [43]. In order to generate different COAs, the algorithm uses an abstraction of the terrain, also called the maneuver box for the agents to move on. Since not all information is needed for the generation and evaluation of COAs, certain details of the terrain are not considered. On this map the different units/agents, combat units and combat support units, maneuver towards a goal location in order to gain an advantage in combat. However, while maneuvering, the units also need to consider the units of the adversary which can have a negative effect on that specific battle. The fitness function, a function that determines how good a candidate/solution is when applied to a certain problem, of GA determines which COAs are best applied to certain situation and these COAs are grouped into a population. During each iteration, a random COA is paired with another COA. Between the COAs, parameters are being swapped. Not only does the swapping of the parameters take place, but parameters are also randomly mutated with new values. This results in the creation of two new child COAs. The newly created COAs are then again evaluated by the fitness function and selected on their quality [41]. This process is repeated a number of times according to the configured iteration value. While judging the selection of COAs, the niching strategy makes sure that the COAs in the final population are distinctively different from one another. The parameters that are considered during evaluation are based upon force ratio of opposing units and the combat rules which decide the next move of a unit.

The Artificial Intelligence COA recommender (AICR) that is proposed by Schwartz et al. uses a GA for COA comparison while executing a MDO [12]. The algorithm that is described is similar to the one that is previously elaborated upon by Schlabach et al.. However, the selection process of the newly created COAs is different, since Schwartz et al. are more concerned with the runtime of the algorithm. In order to speed up the runtime and have a faster performing algorithm, the quality score of each individual COA is subtracted with the minimum fitness score of that population. This reinforces the improvement of populations between iterations since there is a higher probability that the better performing COAs are selected. Even though Schwartz et al. used the GA for the development of the solution, newer AI techniques and approaches are available, such as Deep Reinforcement Learning, that could have a positive effect and enhance the ability of the AICR.

The Agent-Based Modeling and Simulation (ABMS) approach can be specifically applied to land and sea domain in order to have optimal use. Each agent is an autonomous individual with a specific set of characteristics, behaviors and decision-making capabilities, that interacts with its environment and other agents [44]. It is possible that an agent's behavior is driven by its explicit goal but this not necessarily an objective that is used to assess the effectiveness of its actions since its decisions are primarily based on its environment and the behavior of other agents.

Several concepts are available to be used in combination with ABMS, such such as using a neural planner to generate multiple paths on the map [45], a graph that consists of nodes that represent the different path intersections also called the decision waypoints, the interpretation of these decision waypoints as a Markov Decision Process, and different learning/execution approaches for a Multi-Agent model [46]. The methods that are discussed are, centralized Multi-Agent Reinforcement Learning, independent learners with centralized training, and independent learners with learned communication. With Centralized Multi-Agent Reinforcement Learning, all agents communicate with a centralized system which makes decisions about what each agent should do. Even though, there are multiple agents, the "hive mind" can be considered a single agent [47]. The independent learners with centralized training differs from the previous approach. During the training the agents depend on a global state but during the execution each agent is on its own and only depends on their local state. The concept independent learners with learned communication optimizes its method through determining what agents should communicate with each other, what information should be shared between agents and how many times the information should be shared [48]. The learning that is used in this method is done through relational graph learning and this is described by Chen et al. and Sun et al. [49] [50].

Another technique that was used for the supporting anti-terrorism planners in drawing conclusions about the risk of a terrorist attacks, was the knowledge-based Bayesian network. Hudson et al. describe the initially creation of a tool that can be used for assessing the terrorism threat while using a vastly large amount of information that contains an irreducible amount of uncertainties [51]. The Bayesian network approach allows users to manage large collection of threat/asset pairs and update its beliefs when provides with new evidence. The implemented network combines evidence from different analytic models, simulations, historical data and user judgments.

Within the military cyber domain, a multi-layered fuzzy model was proposed that estimates and classifies the effects while assessing the proportionality of the operation in order to provide support in targeting decisions. Since limited datasets of cyber operations are available, Maathuis et al. based their model design and implementation by analyzing real and virtual realistic cyber operations combined with the interviews of technical/military experts [7]. This research will use the current Russia-Ukraine war in order to design and implement an intelligent model for decision making support.

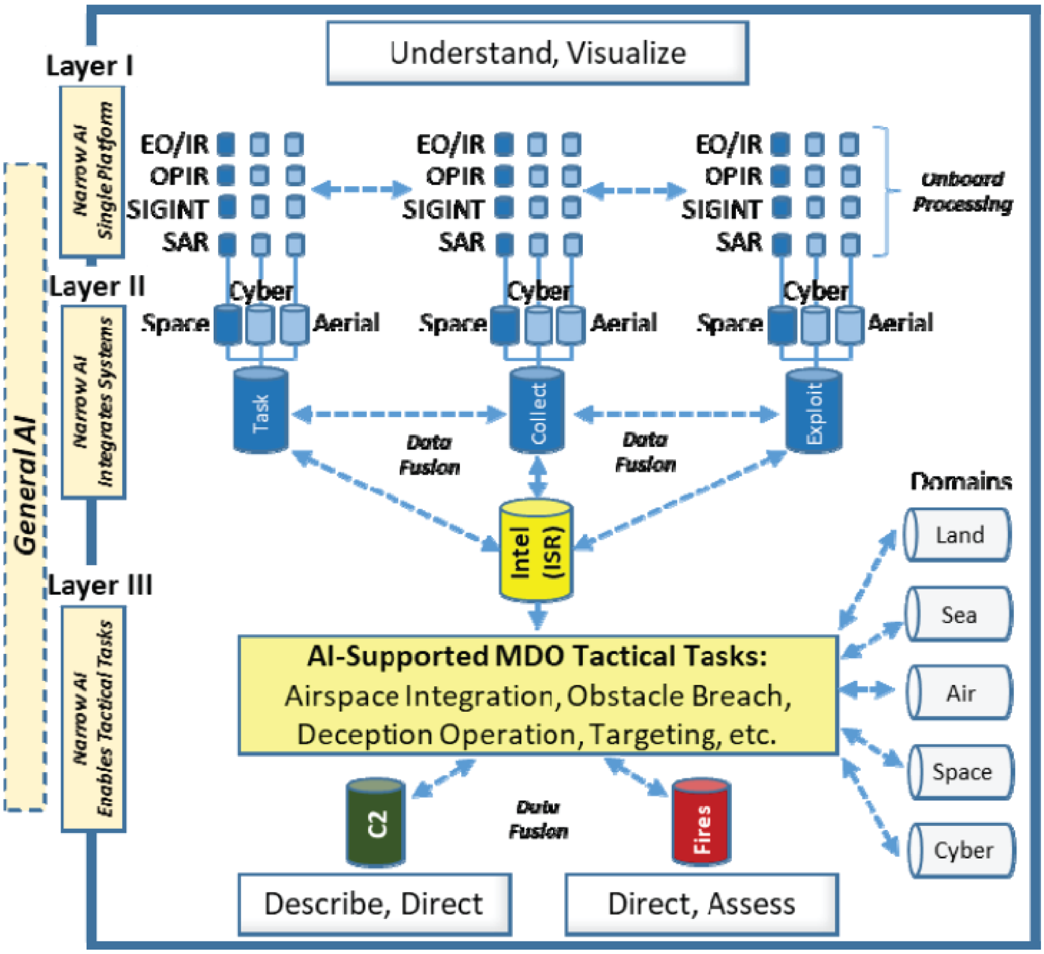

Figure 4.1: Potential Networked AI framework. This figure was directly taken from the article [11].

In order to solve and be able to provide decision making support in MDO, Spencer et al. propose a multilayered AI architecture [11]. An overview of the proposed AI architecture can be found in Figure 4.1. The AI architecture can execute MDO tactical tasks such as intelligence (ISR), command and control (C2) and fires. The intelligence function is expanded into the activities intelligence/task, surveillance/collect, and reconnaissance/exploit. The layers on the left side of the image indicate the layers of solutions for Narrow AI, AI that is able execute a specific task. The small cylinders in Layer I represent ISR tasks for space, cyber, and air domains that are conducted by different kinds of sensors. Another layer of Narrow AI is required in order to fuse the data within a joint function across all the systems that responsible for tasking, collecting, and exploiting within a the ISR function. The final layer integrates data outputs from Layer I and II across functions to enable the execution of a complicated MDO task. By combining multiple AI models that execute a single task and the fusing of data between layers, the AI framework could potential solve a complex problem such as COAs comparison.

Considering the different models and techniques that were previously described, it is clear that there is a lack of transparency within the different models. All the model except the Bayesian network can be regard as a black box. Maathuis and Gunning and Aha advocate for AI solution that are being used in the cyber domain targeting operations to be transparent so the models can be properly understood and used by its users Maathuis [15]. Which will result in the increasing trust of users in AI systems.

The focus of research within the military domain has primarily been on models that support decision making in single domain operations. These models would use agent-based model in combination with GA. This method is also applied to MDO, but concern is more with the runtime of the GA algorithm. The knowledge-based Bayesian model was used for decision support with assessing the risks of terrorist attacks, but the application has been used for CoA decision making support in MDO. In order to move from models that assess target engagement plans in single domain operations, multiple layer architectures are introduced so different algorithms can be combined to solve the decision making problems that arise within MDO. All the different techniques and models that were discussed, except for the Bayesian network, can be considered closed systems that do not provide any transparency to their users.

4.2. Decision Making Algorithms in other Domains

In order to deal with the lack of data and the uncertainties that arise during the multiple-criteria decision making process, other domains, such as construction management, risk management, cyber risk management and quality assessment, Bayesian networks are used opposed to the military domain where this technique is not widely applied (see Section 4.1).

The main goal of doing a risk management on a project is to determine, evaluate, and control the risks in order to let a project be successful. Lee et al. presents a risk management procedure that uses a BBN in order to identify the risks for large engineering projects and applied the model to the shipbuilding industry in Korea. Since there are many stakeholders and the criteria during the duration of the projects are changed, a BBN is used to represent the relationships between the different criteria that are of influence on the success of the project. The main advantages of using a BBN for the risk management process is that it can be used on small and incomplete datasets, combine different knowledge sources, deal with uncertainty within the model and support for decision analysis [52]. Considering safety of autonomous guide vehicles, Duran et al. identified the undesired events and sequences of events leading up to a catastrophic accident in order to design a BBN that can obtain the probabilistic estimation of safety of the system [53]. Within the cyber security domain, Yeboah-Ofori et al. describe how a BBN can be used for identifying the factors of different cyber attacks. These factors can then be used in order to effectively act against attacks and reduce cyber crimes on cyber physical systems (CPS). The research was novel and its contribution consisted of many uncertainties in the development of a BBN since there was a lack of expert knowledge and a lack of attack modeling concepts. The conclusion of the research was that a BBN considers these uncertainties and, therefore, is able to make accurate predictions during the event of a cyber attack on CPS [54]. Atoum and Otoom proposes a similar causal belief network for cyber security threats that arise when executing frameworks. The potential threats are reduced at an early phase of security implementations by giving a clear overview of the relationships between the frameworks components [55]. Moreover, Forio et al. provide a model that can predict the ecological water quality in a multifunctional river basin. By modelling the water resources and the related factors of change, the models are used to improve and protect the water quality of the river basins. The BBN models were constructed by using field data, expert knowledge and science literature [56]. In order to create a BBN structure, Mukhopadhyay et al. propose a Copula-aided BBN that will be used to assist the decision making process of what utility of cyber-insurance products should be used and to what degree. The essence of the Copula model is to express the function of the joint distribution of random variables as a function of marginal distributions. This establishes the correlation between the random variables which is captured in pairs, using the measures of association or dependence [57]. Mohammadfam et al. gathered knowledge about the causal relationship between the different variables of interest since the the use of structure learning algorithms require a high amount of data [58]. A combination of the previous mentioned approaches is used in this research. The criteria of interest are first identified and determined as variables of the model, then the relationships between the criteria are determined and, therefore, the structure of the model is established. Both are done with the available science literature and the military doctrines. The gained information is then further used in the design of the intelligent model.

In order to create a functioning bayesian model, the weights of the variables CPT's need to be determined. There a variety of techniques available that can be used in order to determine the weights of the CPT's within the models that are used for multiple-criteria decision support [59] [60]. Erdogan et al. propose the use Analytical Hierarchy process (AHP) method [62] in order to determine the weights of a BBN that is used for the assessment of contractors in construction management [61]. By using a decision making matrix, which is based on the Saaty scale [63], the weight is assigned to each criterion [61].

The use of Bayesian Best Worst Method (BWM) is another method that is used for a group decision making problem. The BWM method considers only the preference of a single decision maker when determining the optimal weights for a set of criteria [64]. By using the Bayesian model and ranking system, named credal ranking, the final distribution, can be computed while considering the weight distribution of each individual in the group. Mohammadi and Rezaei used the approach in the proposed model that supports decision making based upon the preference of a group of decision makers [65]. The approach Point allocation described in the overview of Odu determines that the weights of a variable are directly assigned according to the priority of the criteria [35]. In this research, the weights are assigned based on the subjective point allocation method since the BBN is also subjective in its nature (see Section 2.3.2). The priority of the features is a result of the analysis of the operations that are currently taking place in the Russia-Ukraine war. The features receive a weight of m/n where m is the importance of the criteria from $1..n$ and n is the number of states that a variable has.

Both Kornecki et al. and Maathuis build use case scenarios that are used in order to demonstrate the proposed models [37] and [38]. With the use of these use case scenarios, the applicability of the models are shown. In this research the building of use case scenarios is used in order to provide results and show the application of the model within the military domain.

4.3. Advancement of Research

Previous research within the military domain (see Section 4.1) shows models that only provide decision making support in single domain, such as land, maritime, operations. The solutions that assist in the decision making process primarily used GA in combination with an agent-based model and other techniques were not widely applied. The knowledge-based Bayesian model was used for decision support in the assessment of risks with terrorist attacks, but not for CoA decision making support in MDO. All models that were previously used within the military domain, except for the Bayesian network, are considered closed systems that do not provide a explainable and transparent model to their users. Making it difficult for the decision makers to properly understand the model.

Research in other domains, such as construction management, cyber risk management, show the use of a Bayesian network that represents the causal relationships between variables and incorporates the uncertainties that arise within the decision making process. The Bayesian model provides an explainable model that can be understood and then correctly used.

5
Model Design

As a result of the literature research that was conducted, which can be found in Chapter 4, insights were gained about COAs and the comparison of CoAs in MDB. The modelling technique that will be used for an intelligent model that will provide support in the CoA decision making process is Bayesian reasoning. The Bayesian model is subjective in its nature since it is based upon knowledge (see Section 2.3.2) and provides a model that is transparent, explainable. The proposed model that is discussed in this chapter is not comparison model, but an influence model where the changed probabilities of features are evaluated based on the influence that a certain CoA has. This chapter aims at providing the answer/results to the first and second research questions (see Section 3.2).

This chapter will begin by addressing SRQ1A (see Section 5.1) by defining the definition of CoAs and where the comparison of CoAs takes places within the different processes that are executed during operation in MDB. The second section will address SRQ1B, where the different features that are used for decision support are specified (see Section 5.2). The third section and the fourth section will provide an answer to SRQ2. The third section describes how a causal graph was designed according to the gather information (see Section 5.3). The fourth section provides the implementation of the model in GeNieModeler (Section 5.4). The chapter ends by giving a short summary where the conclusions for CoA definition from Section 5.1 the selection of the features from Section 5.2 are summed up in order to provide a result for SRQ1 and SRQ2.

5.1. CoAs definition in Multi-Domain Battle

In order to counter react to being contested within multiple domains by adversaries, military forces execute Multi-Domain Operations in order to create an operational stand-off. The MDOs can either be executed in competition, where the armed forces are actively advancing or defending national interests without using violence, or in armed conflict, where a large-scale of lethality is used [1] [5].

While conducting a MDO, the military targeting process (see Section 2.1.1) is a crucial part of creating a strategic and operation stand-off. By selecting a target and engaging the selected target, military forces try to gain a political and/or military advantage on opposing parties. By using the iterative planning methodology MDMP (see Section 2.1.2), different activities of distinct entities within the military forces are combined in order to better understand the situation and mission, develop and compare target engagement plans, determine which plan will best accomplish the mission and produce an operation plan which can then be used for execution [10]. In every operation time is critical since the engagement of a target needs to be done as soon as possible before the factors of the environment change again. The usage of MDMP ensures that required actions are taken in advance and that military units are ready and in position before the execution of the operational plan. The application of the MDMP to the phases of the targeting process, phase IV: decision making, force planning and assignment, and phase V: mission planning and usage of force, support the armed forces in determining which target engagement plan is best to use in order to gain military advantage in conflict.

The previously mentioned target engagement plans are also known as the courses of action (CoA). A CoA is an extensive and well-defined plan on how to engage a selected target during the execution of a military operation [9] [10].

From the following military sources [9] [10], it was determined that CoAs should meet certain requirements in order for them to be used. The following list of requirements should, therefore, be considered when defining the CoAs in an MDO:

- A CoA should have a minimum impact on the military forces and the mission accomplishment.
- The CoA should assure that the armed forces will achieve the best posture for future operations.
- A CoA should give movement space for initiative by subordinates.
- The CoA should provide flexibility to deal with unexpected threats and opportunities.
- A CoA should provide a secure and stable environment for civilians living in the operational area.
- The CoA should be clear and easy to understand by subordinates.

List 5.1: Non-functional CoA decision support requirements [9] [10]

5.2. CoAs comparison features

In order to determine which CoA is best to use in the engagement of a selected target, a set of features will need to be established. These features and the weights of these features are determined by the commander and its staff during mission analysis (see Section 2.1.2) and will vary between mission personal. The features that are discussed in this section will be evaluated based on the influence that a particular CoA has. When the posterior feature probabilities are calculated for a particular CoA, weights should be assigned to each individual feature which establishes the importance of each individual metric relative to the other features in the decision making process [66]. By comparing the different features of a CoA and knowing the strengths and weaknesses of these engagement plans, it is more likely that the CoA with the highest success probability is to be selected and further developed for the operation. The selected CoA will then be used in order to gain an advantage in battle and hopefully achieve the desired effects. An example of the CoAs and the features used in order to determine which CoA is the best applied to the situation can be found in Figure 5.1.

Weight[1]	1	2	1	1	2	
Criteria[2] / **Course of Action**	Simplicity	Maneuver	Fires	Civil control	Mass	Total
COA 1[3]	2	2 (4)	2	1	1 (2)	8 (11)
COA 2[3]	1	1 (2)	1	2	2 (4)	7 (10)

Notes:
[1] The COS (XO) may emphasize one or more criteria by assigning weights to them based on a determination of their relative importance. Lower weights are preferred.
[2] Criteria are those assigned in step 5 of COA analysis.
[3] COAs are those selected for war-gaming with rankings assigned to them based on comparison between them with regard to relative advantages and disadvantages of each, such as when compared for relative simplicity COA 2 is by comparison to COA 1 simpler and therefore is ranked as 1 with COA 1 ranked as 2.

Figure 5.1: The features comparison of two different CoAs. This figure was directly taken from the article [9].

Based on the following military-related sources [9] [10] [43] [67] [68] [18] [69], the principles of war [70], the selection features from another domain [61], the requirements for CoAs (see List 5.1), and the similarities of features between the sources that are used for the comparison of CoAs, a list of features was identified. The subsequent list of features will be used to determine the influence of a choice in the CoA comparison process:

Variable names	***Variable states***	***Description***
M - Mass	• Concentrated • Thinly distributed • Dispersed	The developed CoA should consider the concentration/distribution of armed forces when engaging the enemy. Forces are either concentrated and closely placed to each other in a certain region on the battlefield, thinly distributed where the forces are nationally distributed on a operational area, or dispersed where forces are widely distributed and are located in different countries. By finding a balance in concentration and dispersion, the armed forces will have a better chance of confusing the enemy. However, the distribution of armed forces is not permanent and can change during the execution of the MDO.
Fi - Fires	• Lethal • Non-Lethal	The intended effect/outcome of a capability, either lethal or non-lethal, should be included when consideration of a CoA.

Fe - Flexibility	• High • Medium • Low	The CoA should include a degree of flexibility in the calculated movement that is needed in order to gain an advantage on the enemy. While maneuvering, the armed forces should be able to deal with unexpected threats and opportunities.
MI - Minimum Impact	• High • Medium • Low	The CoA should have a minimum impact on the force or the mission accomplishment.
CS - Civil Safety	• In Danger • At Risk • Safe	A CoA should contribute to the Safety of the civilians living in the operational area.
CC - Civil Control	• Chaos • Partially Controlled • Controlled	A CoA should make sure that control of the geographic stays within civil possession.
Si - Simplicity	• High • Medium • Low	When seeking for an advantage in competition or in conflict, engagement plans can naturally become complex. It is, therefore, critical that the developed CoA should be a clear, uncomplicated plan so the chances of confusion are minimal and it is ensured to be understood by subordinates.
T - Time	• Long Interval • Medium Interval • Small Interval	With emerging operational environments where smaller military forces fight on an expanded battlefield that is hyperactive and more lethal, it is critical for CoA to be executed within a certain time span in order to gain a military advantage.
O - Objective	• Achievable • Medium • Unattainable	When executing different tasks during military operations, there should be determined if the CoA achieves the desired result set by the commander.
Su - Sustainability	• Sustainable • Medium • Not Sustainable	The CoA should assure that the military forces will achieve the best posture for future operations.
Ch - Choice	• CoA1 • CoA2 • CoA3	The states of the CoAs will be determined in Chapter 6

Table 5.1: Selection Criteria Table.

5.3. CAUSAL GRAPH DESIGN

In order to do a Bayesian Network analysis, a causal graphical model that represents the different variables (see Section 2.3.2) needs to be constructed. Since the research on AI support within the comparison of CoAs is novel, there is no general structure available that can be used in order to evaluate the CoAs for comparison. During the process of CoA development, the commander determines the importance of the different features based on their own judgement and experience. The process of CoA comparison is considered to be largely subjective [9] [10] [28]. Considering the sensitivity of the Military domain and the lack of information, the structure of the model and the relations between variables can only be based on the non-functional requirements (see List 5.1) and the literature that was previously researched.

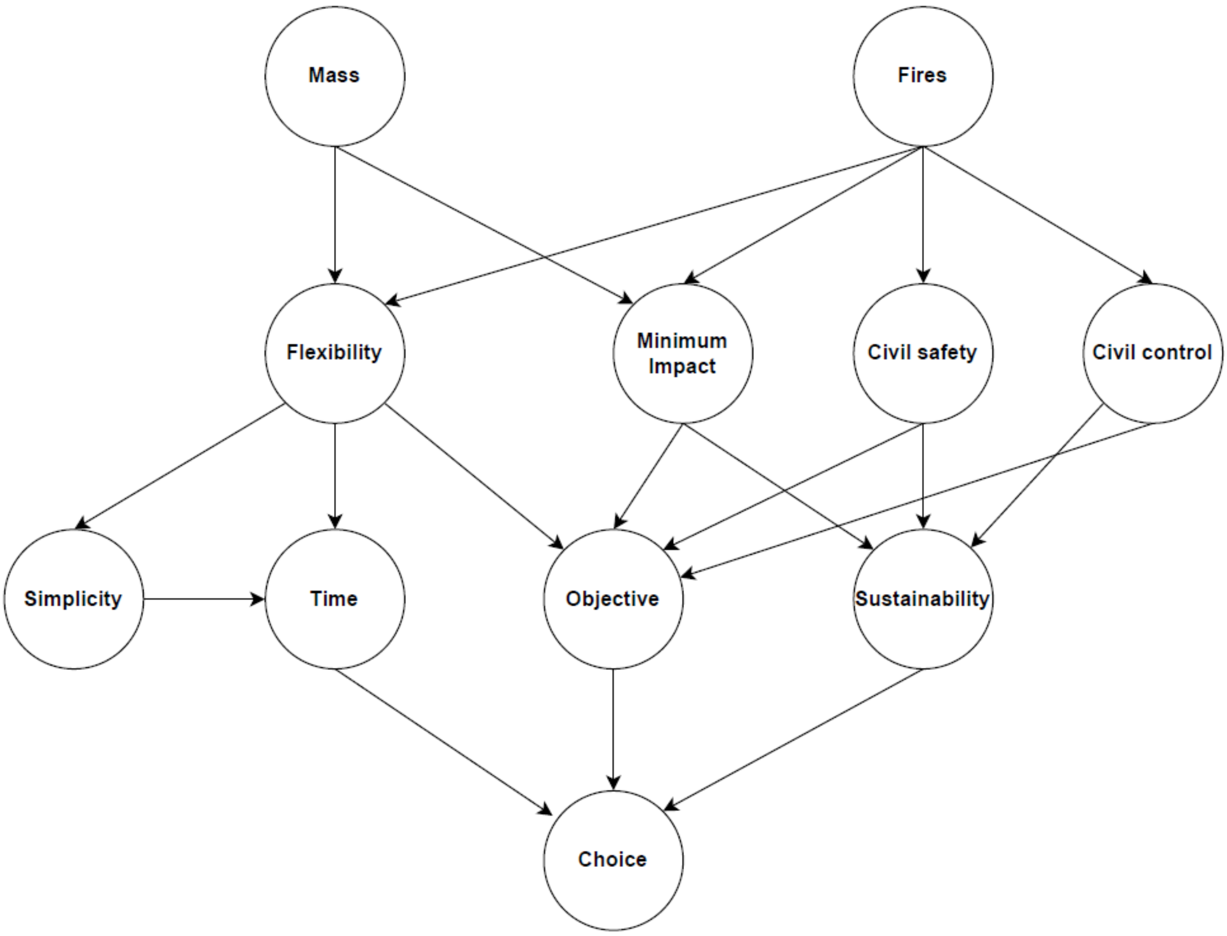

Figure 5.2: Causal Graph Design

The structure is consist of four layers which can be seen in Figure 5.2. The upper layer contains the Mass and Fires variables which are seen as the rout cause of the structure, since the commander has the most influence on these variables with respect to the choices that are made to accomplish the mission objective. The second layer contains the variables corresponding to the movement flexibility of the armed forces and the minimum impact on the forces which are both determined by the dispersion of the military forces and by the type of Fires that is used. Considering that the army forces are closely placed together and near a target, the type of Fires, lethal or non-lethal, can have negative effect on the movement and the impact that the capabilities has on its own forces within the operational area. The layer also contains the variables corresponding to Civil safety and civil control which are both an effect of Fires, since the type of capability determines if the civilians are going to be safe and if the group of civilians in the area can be controlled. The third layers consists of the variables corresponding to Simplicity, Time, Objective and Sustainability. The simplicity variable is affected by the movement flexibility since it can make an operation more difficult to execute when the military forces are restricted in their movement. The time of the duration of an operation is a result of both flexibility and simplicity since it can take the armed forces longer or shorter to act when a CoA is complex and the movement is reduced. The objective of the military operation is an causal effect of the impact on the military forces, the movement of the armed forces, the safety, and control of civilians since the accomplishment of the operation relies on the state of the military forces and the control it can hold within the operational area. If the armed forces or the civilians are heavily affected the mission objective might not be attainable. Both the minimum impact, civil safety and civil control variables establish how sustainable future operations are and determine if the operation is to achieve the best posture for future engagements. The choice between CoAs is determined by the time that an operation takes, if the mission objective is attainable and if the operation is sustainable for the near future. The final layer consists of a single variable named choice. This Choice variable is a causal effect of all the parent nodes that lie within the upper layers of the model and will influence its parents when updated with new evidence.

5.4. BBN IMPLEMENTATION

The implementation of the intelligent model is realized with the use of Genie Modeler [36] and is based on the causal graph design which is described in Section 5.3.

As described in Section 2.3.2, each node within the Bayesian model has a quantitative part, which is also known as the conditional probability table. Each of the nodes in the Bayesian model have their own states (see Table 5.1) and the sum of the different condition probabilities of the states will be 1, meaning that each state will either be one of the following values, zero, one or a fraction of the sum. The fraction weight is determined by m/n where m is the importance of the feature from $1..n$ and n is the number of states that a variable has. Considering the literature research (see Chapter 4), the lack of available data within the military domain and that the Bayesian model being subjective in its definition, the point-allocation method (see Section 4.2) is used to subjectively assign values to the conditional probabilities within the nodes. The values that are assigned to the variables states are based on the analysis of the situations that are occurring during the Russia-Ukraine war.

Since the model shows the different features, the relations between the features, and presents the probability of each feature, the solution can be explained and this allows the model to be understandable for the decision makers. Thus, strengthening the transparency of AI solution within the military domain.

The decision making outcome can be established by providing evidence to the Choice node. This means that a CoA, an engagement plan, needs to be selected in the implemented model. As a result of the causal relations between the variables of the different layers within the model and the different CPT's of the corresponding variables, the proba-

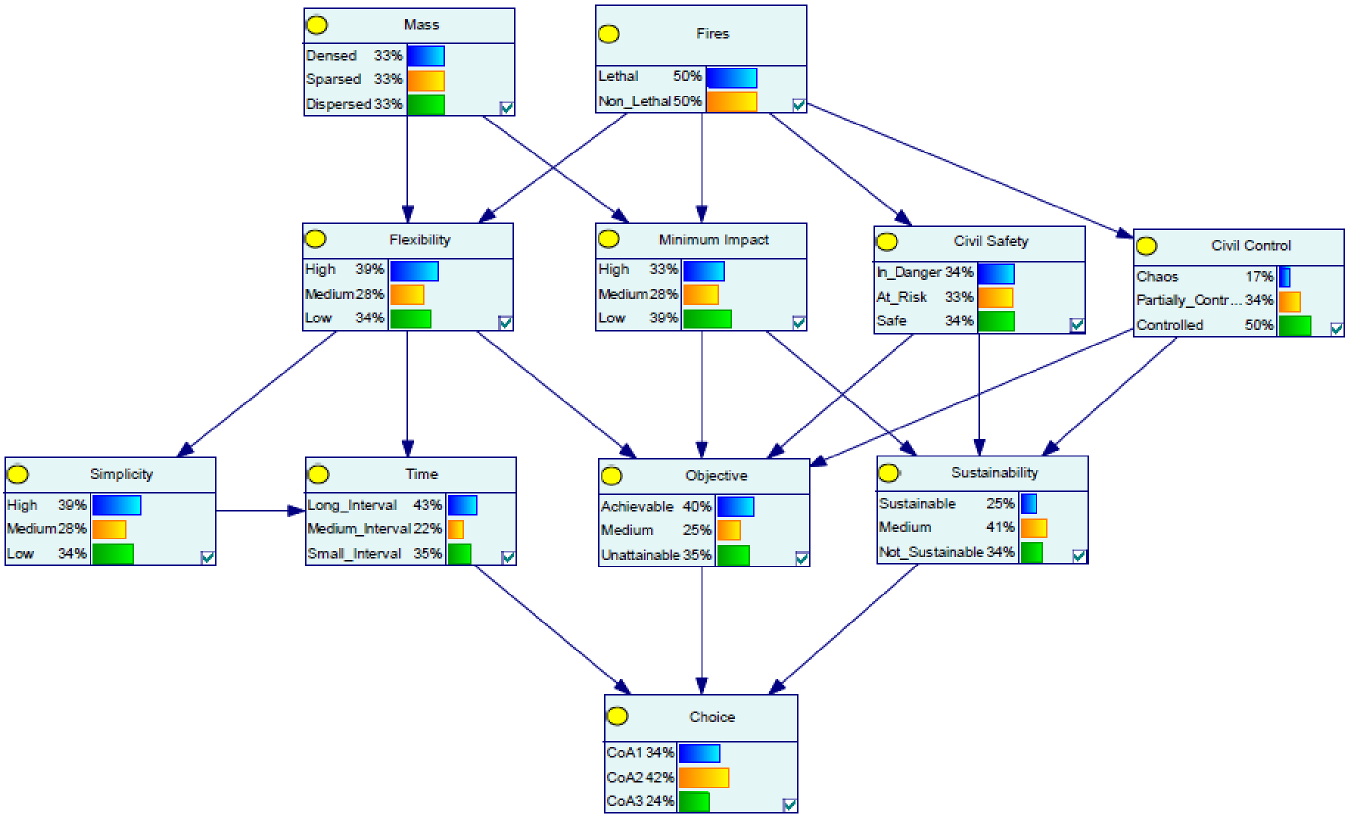

Figure 5.3: Implementation BBN with GeNieModeler.

bility of the features are updated accordingly and the influence of the selected CoA can be seen in the probabilities of the other features. The updated probabilities can then be used in order to determine if the decided upon important features have the required values so the set mission objective can be accomplished. The information that is produced by the proposed model can, therefore, provide support in the CoA comparison decision making process. Being a The provided model is not a comparison model but can be considered an influence model.

5.5. Conclusion

When being in competition or in conflict with an adversary, the military targeting process is used by the armed forces in order to select the target and determine the engagement of that target. During the military targeting process, different CoAs are developed by the commander and his staff on how to strike a target. The comparison of CoAs is done during phase IV: decision making, force planning and assignment, and phase V: mission planning and usage of force, of the targeting process. From the created CoAs, a single CoA needs to be selected that provides the best opportunity for the military forces to gain the upper hand in a MDO. The most suitable CoA is selected while considering the different defined evaluation features, which are minimum impact, simplicity, maneuver, fires, civil safety and control, sustainability, mass and time. During the evaluation of the features, the commander subjectively determines the importance of the different features.

With regard to doing a Bayesian Network analysis, a causal graph in the form of a DAG needs to be constructed. Since the research direction of the usage AI support in CoAs comparison is novel, the DAG is constructed as a result of the conducted literature review and gathered information (see Chapter 4). The constructed DAG displays the different causal relations between variables and is shown in Figure 5.2.

An implementation (see Section 5.4) of the causal design (see Section 5.3) is created with the use of Genie Modeler [36]. The states of each node from the Bayesian model are defined in Table 5.1. With the use of the point-allocation method, the values of the CPT's are assigned based on the gathered real incident information from the Russia-Ukraine war. Since the Bayesian model is a representation of the gathered military knowledge, shows the different features, the relations between the different features, thus making the model explainable and strengthening transparency. The proposed model is not a comparison model but an influence model.

In order to establish a decision making outcome, a state, a CoA, should be selected from the choice node. As a result of the causal relations between the variables of the different layers, the model provides variables with updated values and displays the influence of a particular CoA. These updated values then provide extra information when analyzing the different engagement plans and can, therefore, provide support in the CoA comparison decision making process.

6

Model Evaluation

As a part of the Design Science Research methodology, the created artifacts are to be evaluated (see Section 3.1). Since the development process of CoA relies primarily on the subjective input of the commander and its staff and there is no common structure that is used for such models, it was decided to not use expert's knowledge as an evaluation method because each decision maker would be provide an different answer. The lack of data makes the execution of a technical experiment evaluation not possible. Regarding the Design Science Research Methodology options for evaluation (see Chapter 3) and the conducted literature review (see Section 4.1), it was decided that the artifact, in this case an implementation of a model, is evaluated through exemplification. Therefore, the proposed model is demonstrated with the use of three created case scenarios. This chapter provides and discusses the results of the demonstration of the proposed model. The ongoing Russia-Ukraine war is used as an example of MDO and the gathered real incident data is used for the creation of the use case scenarios.

Ever since the fall and the collapse of the Soviet Union (SU) in 1991, Ukraine has been an independent state with it own president. However, Russia would maintain a significant influence in the country until the maiden revolution that took place in 2014 [71]. The maiden large demonstrations and civil unrest in Ukraine was sparked by the sudden decision of the government to not sign a free-trade treaty with the European Union, but instead would seek closer ties with Russia [72]. By using violent means, the government made the public even more angry which caused the escalation of the protests. This resulted in the Revolution of Dignity and the formation of a new government in Ukraine. After the creation of the new government, widespread protests escalated, both for and against the revolution, in several parts of Ukraine.

As a response to the escalated situation in areas of Ukraine, Russia decided to undertake a military operation which led to the annexation of Crimea and the creation of the self-proclaimed breakaway states Donetsk and Luhansk. The tension between Ukraine and Russia has been building up over the last few years [2]. While many experts did not believe and expect Ukraine would be invaded, the situation escalated extremely fast when Russia decided to attack Ukraine on the 26th of February 2022 [3]. Even though the war just started and is still on-going, it is shown that capabilities across different domains are used [4]. Military forces were first send by land in order to quickly conquer regions of Ukraine. After the armed forces were slowed down by the Ukrainian army, Russia resorted to aerial strikes and cyber attacks in order to hit certain high-profile targets that disrupt the communication between Ukrainian forces in the hopes of gaining back the momentum for the invasion.

From the analysis of the Russia-Ukraine war, an example situation is created where three illustrative scenarios are chosen in order to demonstrate the applicability of the implemented model (see Section 5.4) within the military domain. This chapter aims to providing an answer for the third research question (see Section 3.2).

This chapter starts by describing a military conflict where the goal is to invade an area of interest (Section 6.1). Next, the created scenarios are discussed where different capabilities are used in order to gain advantage during the battle (see Section 6.2, Section 6.3 and Section 6.4). The last section sums up the gathered results and provides a conclusion for SRQ3.

6.1. Scenario description

After a period of tensions building up and showing off the strength of the armed forces in a standoff, the situation escalated into an international armed conflict when forces started the invasion and making their way to the capital of the other country. The military forces have a single goal and that is overthrow the sitting government and install a new government that is friendlier to their own goals and interests. The target of the mission is the government building in the capital city.

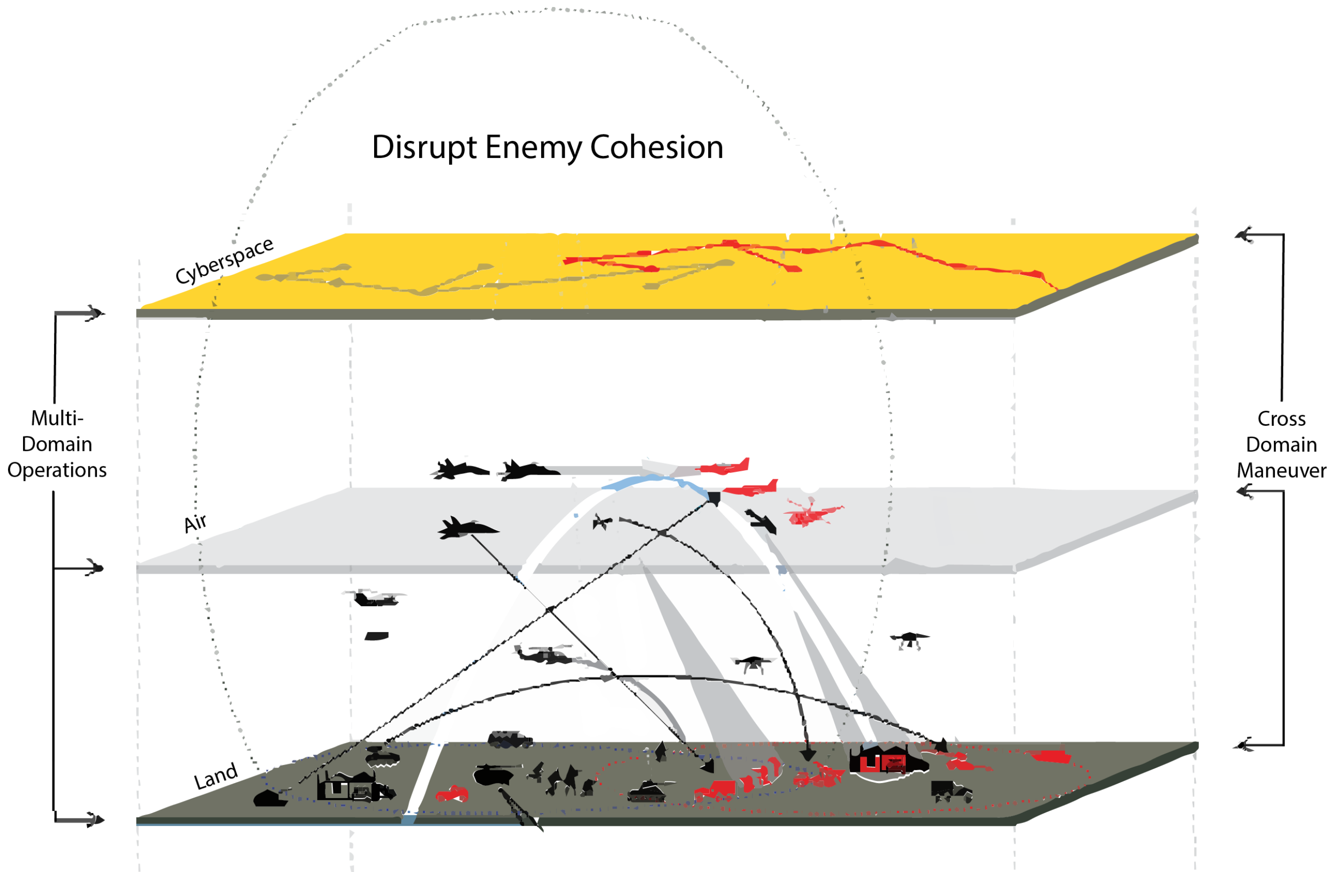

Figure 6.1: Scenario across three domains. This image was inspired by an image from [73]

In order to gain advantage in battle and create a strong posture for future operations, three scenarios are chosen which take place within the air, land and the cyberspace domain (see Figure 6.1). For the first scenario, a land operation was chosen as a CoA in order to achieve the mission objective of conquering and controlling the capital city. A aerial strike is chosen for the second Scenario, where the goal is to hit military facilities and weaken the enemy while achieving an advantage in battle. For the third and final scenario, a cyberspace attack was picked. During the cyber attack, the goal is to disrupt the systems of electricity companies in order to shut down systems needed for communication.

6.2. Land Operation Scenario

For the land operation, military forces are moving towards the capital government building and using artillery fire in order to gain control of the operational area around the target. The land operation scenario is based on the scenarios that are happening in Kyviv and Mariupol during the russian invasion of Ukraine. In Kyviv, russian troops used artillery fire in order fight opposition troops and gain control within the capital of Ukraine [74]. Another city that is desired by Russia is the city of Mariupol which is close to the sea and provides a tactical advantage. Russia has been using tanks and troops to surround the city and to conquer the city. Russia did not expect Ukraine to be much of an opponent and thought that the operations would be more effective. However, the failures have been resulting in a low morale among the russian military forces and the inability of Russia completing the invasion within a short amount of time [75].

When choosing the land operation as a plan to engage the target for feature Ch, the probabilities of the parent nodes are updated accordingly. Resulting in Figure 6.2 with different values for the probabilities as a result of the influence that the choice has on the model when compared to Figure 5.3. The results of the features are described in Table 6.1.

Variable names	***Description***
M - Mass	There is a higher probability of the military forces to be densely distributed across the operational area since different units need to approach to target for engagement.
Fi - Fires	The chance of the CoA to lethal has increased meaning that there is a higher probability that the land operation results in a lethal outcome for the target.
Fe - Flexibility	As an effect from the root nodes, Mass and Fires, there is an higher probability that the flexibility of the movement is low and, therefore, it is more difficult for the armed forces to navigate across the operational area.

MI - Minimum Impact	Since a the probability of the lethality has gone up and the probability of mass leans more towards densely distributed, there is a higher probability that the impact of the capability will have a negative effect on their own armed forces.
CS - Civil Safety	There is a higher probability that civilians within the operational area are within danger when using the aerial strike as an engagement plan.
CC - Civil Control	The control of the civilians in the area decreases because the capabilities used are more likely to be lethal.
Si - Simplicity	As a result of being less flexible in moving across the operational area, it is more likely for the CoA to be less simple in its execution.
T - Time	By being less simple in its execution and the effect of military forces being less mobile, there is a higher probability of the CoA taking more time to execute.
O - Objective	The objective of the mission is negatively affected since there is a higher probability of not attaining it as a result of the parent nodes.
Su - Sustainability	There is a slim chance that the CoA provides assurance for achieving the best posture for future operations.

Table 6.1: Aerial Strike Results.

The results provided in Table 6.1 can be interpreted as a CoA that has a higher risk of putting their own military forces and civilians that are present within the operational area in danger because of the lethality that is being used within the land operation. When considering the human aspect in a MDO, it can be stated that this CoA's influence negatively affects this. The CoA does, however, provide a somewhat chance of having a strong posture for future operations. Even though, the chance is that the control will not be in the possession of the civilians. Since it is likely that the military forces are put closer together, the CoA is more difficult in its execution and takes longer to be executed.

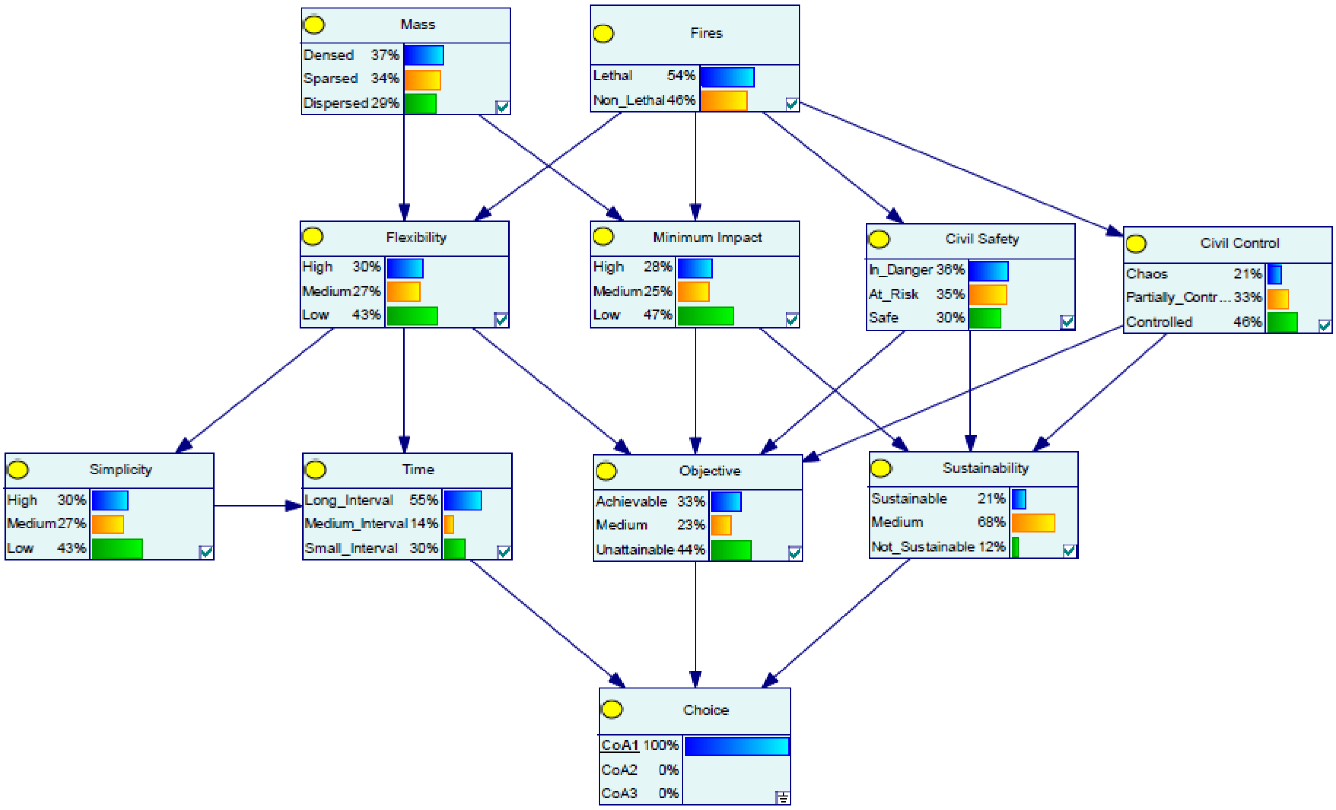

Figure 6.2: Land Operation Scenario BBN result

6.3. Aerial Strike Scenario

During the aerial strike scenario, facilities of interest are bombed in order to weaken the enemy and to make it easier to gain advantage in battle. The scenario for air strike is based on the scenarios that are currently taking place in Ukraine, where Russia started bombing cities such as Kyviv, Kharkiv, Mariupol and several others [76]. Russia aimed at destroying military facilities and infrastructure so it would be more difficult for the Ukraine army to fight back. The results of the air strikes were, however, more severe since hundreds of civilians died, essential facilities, such as hospitals, and essential infrastructure, such water supply, electricity, and heating networks were completely destroyed [77].

When choosing the aerial strike operation as a CoA for feature Ch, the conditional probabilities of the parent nodes would be updated. Resulting in Figure 6.3 with different values for the probabilities as a result of the choice influence when compared to Figure 5.3. The results of the feature probabilities are described in Table 6.2.

Variable names	***Description***
M - Mass	The calculated probabilities are almost evenly distributed, but slightly lean to densely distributed armed forces across the operational area.

Fi - Fires	The probability of lethality has increased meaning that there is a higher chance that the aerial strike results in a lethal outcome for the target.
Fe - Flexibility	As an effect from the root nodes, the probability distribution for the flexibility of movement is divided between highly flexible and low flexibility.
MI - Minimum Impact	Since a the probability of the lethality has gone up and the probability distribution of mass is distributed across all the states of the feature, the probabilities of the impact of the capability on their own armed forces is also evenly divided.
CS - Civil Safety	There is a higher probability that civilians within the operational area are within danger when using the aerial strike as an engagement plan.
CC - Civil Control	The control of the civilians in the area decreases because the capabilities used are more likely to be lethal.
Si - Simplicity	As a result of being less flexible in moving across the operational area, it is more likely for the CoA to be less simple in its execution.
T - Time	By being less simple in its execution and the effect of military forces being less mobile, there is a higher probability of the CoA taking more time to execute.
O - Objective	The objective of the mission is negatively affected but it seems to be probable that the mission objective can be achieved.
Su - Sustainability	The CoA is more likely to not provide assurance for achieving the best posture for future operations.

Table 6.2: Aerial Strike Results.

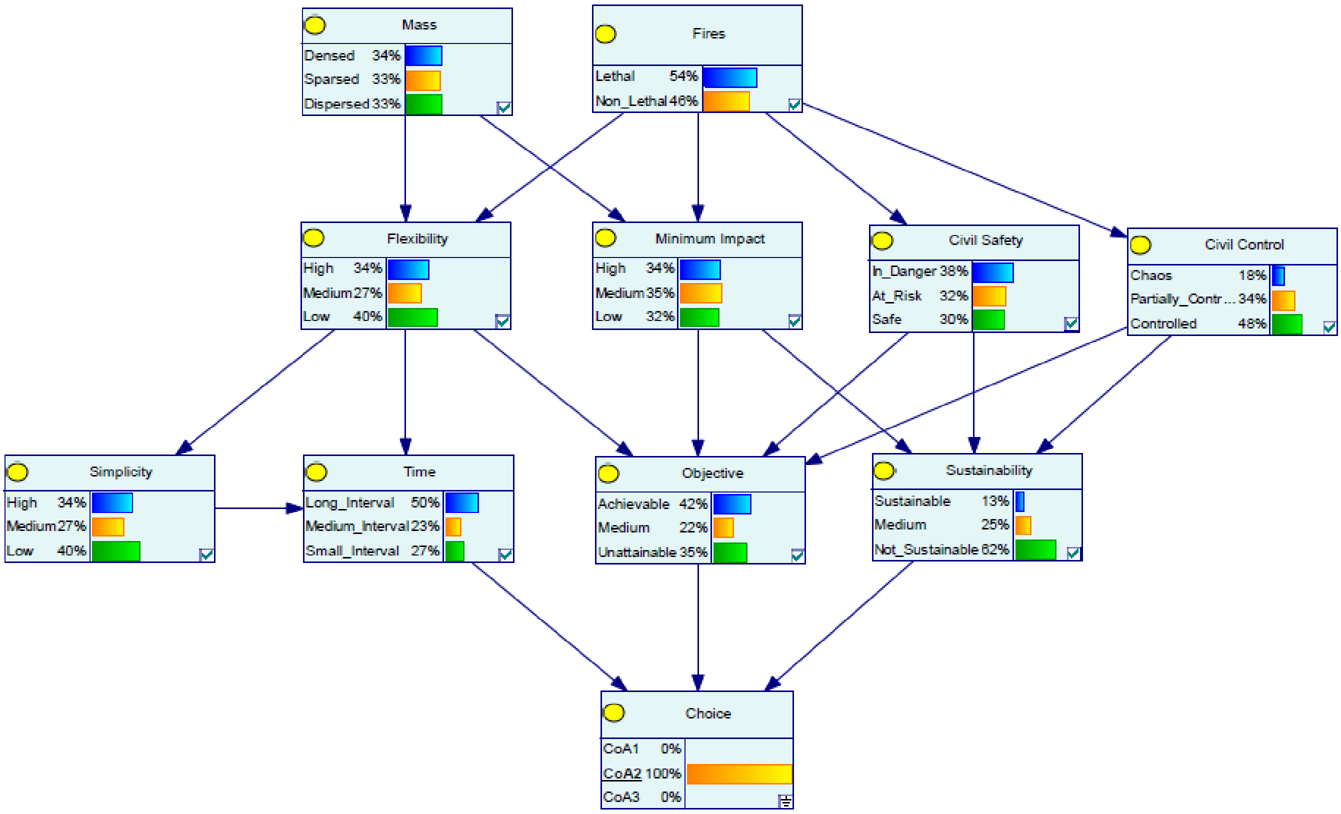

Figure 6.3: Aerial Strike Scenario BBN result

The results of the model in Table 6.2 can be interpreted in a similar sense as that of the land operation. There is a higher risk of the own forces and civilians to be in danger because of the lethality of the air strike. Therefore, the human aspect in the MDO is also negatively affected. The CoA does, however, provide a short term gain as it is not sustainable for future operations and does provide a strong posture. The military forces are still closely distributed across the operational area, and making it, therefore, longer in order to be executed.

6.4. Cyber Attack Scenario

During the cyber attack scenario, electricity companies are targeted in order to shut down the power grid and as a result shut down the systems needed for communication within the operational area. The cyber attack scenario is based on the scenario that took place in Belarus, where a hacktivist group took matters into their own hands and encrypted the servers of railway companies so the transportation of military forces was slowed down [78]. Another scenario is the cyber attack that happened in 2015, where electricity systems were targeted by hackers in order to cause outages [79].

When choosing the cyber attack operation as a CoA for feature Ch, the conditional probabilities of the parent nodes are updated accordingly. Resulting in Figure 6.4 with different values for the probabilities a result of the choice influence when compared to Figure 5.3. The results of the feature probabilities are described in Table 6.3.

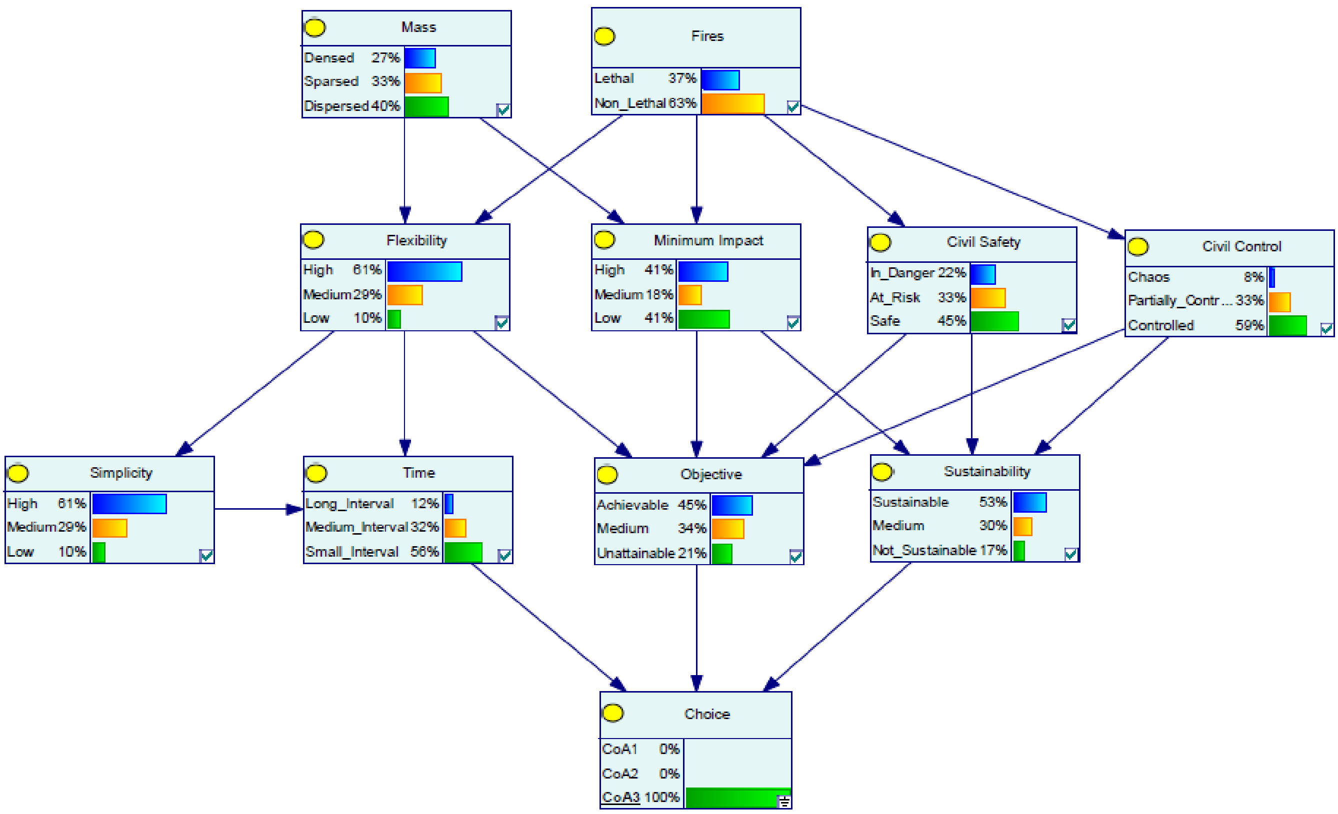

Figure 6.4: Cyber Attack Scenario BBN result

Variable names	***Description***
M - Mass	There is a higher probability that the armed forces are well dispersed and not densely put together on the operational area.
Fi - Fires	In opposite to the aerial strike CoA (see Section 6.3) and land operation CoA (see Section 6.2), the lethality probability has decreased and it is higher likely that a cyber attack will not be lethal for the target.
Fe - Flexibility	As an effect from the parent nodes, Mass and Fires, there is an higher probability that the flexibility of the military forces is flexible.
MI - Minimum Impact	The result of minimum impact is distributed between high and low. So there is a chance that the chose capability has little effect on the own armed forces or has a significant effect.

CS - Civil Safety	The probability of the safety of civilians is higher since the capability has a higher probability of being non-lethal.
CC - Civil Control	The probability of controlling the civilians within the operational area increases.
Si - Simplicity	The execution of the CoA has a higher probability of being easy in its execution.
T - Time	Since the flexibility and the simplicity are high, there is a higher probability that the time needed in order to execute is the cyber CoA is less.
O - Objective	The objective of the mission is positively affected since there is a higher probability of attaining it.
Su - Sustainability	There is a higher probability that the operations gives the a better posture for future operations and, therefore, is sustainable.

Table 6.3: Cyber Attack Results.

The results provide in Table 6.3 can be interpreted as a CoA that can be used for long term achievements. When attacking electric companies through the cyber domain and disrupting communication among enemies, the military forces and civilians are less at risk of being in danger. Since this CoA uses non-lethal capabilities, the human aspect in the MDO is considered and provides a lower chance of human beings dying. The CoA seems to provide a strong posture that is sustainable for future operations as the cyber attacks can be constantly executed over a larger amount of time. The military forces can be distributed internationally and since the attacks are done through the cyber domain, it makes the execution of the CoA quick and fast.

6.5. Conclusion

While using the CoAs that are currently being used within the Russia-Ukraine war as an example, the model was evaluated for its applicability to the military domain through demonstration. The states of feature Ch consisted of CoA1 being a land operation where the military forces engaged the target by moving towards the target and attacking the target on land, CoA2 being an aerial strike where military facilities are bombed in order to weaken the adversaries and gain an advantage in battle, and the CoA3 being a cyber attack where military forces attack an electricity company in order to take out the power grid and disrupt communication systems among the enemy through the cyber domain.

As a result of setting the evidence of the Ch feature to the different CoA states, it can be seen that the probability of lethality increased for both CoA1 and CoA2 and there was also higher probability of the forces being closely distributed to one another. For CoA3 the opposite happened where the probability of lethality decreased and the military forces were distributed wider across the operational area. This can vary from nationally to internationally. The effect on the nodes, flexibility, minimum impact, civil safety and civil control was also different between the land operation/aerial strike and cyber attack. The calculated probability of the movement flexibility increased, the impact on the armed forces decreased, the safety and control of civilians within the operational area increased for CoA3, where the opposite happened for CoA1 and CoA2. This resulted in the probability increasing for the simplicity of the operation, it being highly probable that the execution of the CoA takes less time, it becoming more probable that the objective of the mission was attainable and that the operation would be sustainable for the future when using CoA3. For CoA1 and CoA2, the probability of the simplicity decreased, it became less probable that the CoA would be quickly executed, the objective of the mission becomes more difficult to attain and the sustainability of future operation decreased. Thus, making CoA1 and CoA2 effective for shorter term achievements, but do not provide the proper assurance for a strong posture for future operations.

Considering the model and the results mentioned above, it can be stated that the model is applicable to the military domain since it demonstrates the influence of selected CoA on the other features in the model. While determining the importance of certain features, it is up to the decision maker to determine which strategy is most appropriate when engaging a target.

7

CONCLUSION & DISCUSSION

This final chapter will present the conclusions of the research that were described in the previous chapters of this thesis. The limitations of the current proposed model will be provided and the directions for future work will be discussed. This chapter starts by presenting the answers to the sub research questions which are used in order to answer the main research question of this research. The research questions are described in Section 3.2.

7.1. CONCLUSIONS

In order to achieve the objective of exploring the design of an intelligent model that can be used for CoA comparison decision making support in MDO, Section 3.2 presented sub research questions which support in answering the main research objective. The answers to the sub research questions and main research question are provided below:

SRQ1 : How can the comparison of COAs in Multi-Domain Battle be described?

This research question was divided further into two separate questions, each focussed on a specific subject. The answers to those questions help in finding an answer for this research question.

SRQ1a : What are COAs in Multi-Domain Battle?

When being in competition or within a conflict with adversaries, military forces are constantly challenged across domains. In order to counter these actions and created an operational stand-off, armed forces execute Multi-Domain operations. The MDOs can either be executed in competition, where the armed forces are actively advancing or defending national interests without using violence, or in armed conflict, where a large-scale of lethality is used [1] [5].

The execution of the military targeting process (see Section 2.1.1) is an important part of creating a strategic and operational stand-off during a MDO. The armed forces try to gain a political and/or military advantage on enemies by selecting a target and strategically engaging the selected target. In order to strategically engage a selected target, an engagement plan needs to be developed. This is done with the use of the iterative planning methodology MDMP (see Section 2.1.2) where different entities within the armed forces execute different activities in order to to better understand the situation and mission, develop and compare target engagement plans, determine which plan will best accomplish the mission and produce an operational plan which can then be used for execution [10]. The operation time is critical since it is highly likely that the factors of the environment will change and, therefore, a different approach of the target is required. With the use of MDMP, the required actions are taken that ensure that military units are ready and in position before the execution of an operational plan. The application of the MDMP to the phases of the targeting process, phase IV: decision making, force planning and assignment, and phase V: mission planning and usage of force, support the armed forces in determining which target engagement plan, also called a CoA, is best to use in order to gain military advantage in conflict.

SRQ1b : What are the features that can be used for CoA comparison decision making support in Multi-Domain Battle?

The following features that can be used for the CoA comparison process are identified by reviewing military-related sources, the principles of war, scientific sources of other domains and the requirements of CoA (see List 5.1):

Variable names	***Description***
M - Mass	The developed CoA should consider the concentration/distribution of armed forces when engaging the enemy. Forces are either concentrated and closely placed to each other in a certain region on the battlefield, thinly distributed where the forces are nationally distributed on a operational area, or dispersed where forces are widely distributed and are located in different countries. By finding a balance in concentration and dispersion, the armed forces will have a better chance of confusing the enemy. However, the distribution of armed forces is not permanent and can change during the execution of the MDO.
Fi - Fires	The capability's intended effect, which is either lethal or non-lethal, should be considered when deciding on a CoA.
Fe - Flexibility	The degree of movement flexibility for the CoA is important in order to gain an advantage on adversaries, since the military forces should be able to deal with unexpected threats and opportunities.
MI - Minimum Impact	The impact on the military forces or mission accomplishment should be at a minimum.
CS - Civil Safety	The CoA should contribute to the safety of civilians living within the operational area.

CC - Civil Control	A CoA should contribute to keeping possession of control within the geographic in civilians hands.
Si - Simplicity	The engagement plans used in gaining an advantage in competition or in conflict can become complex in its nature. Therefore, it is critical for the developed CoA to be clear, uncomplicated so it can easily be understood when being executed by the subordinates.
T - Time	The execution of a CoA within a certain time span in order to gain a military advantage is critical since the emerging operational environments where smaller military forces fight on an expanded battlefield is hyperactive and more lethal than it previously was.
O - Objective	When executing different tasks during military operations, there should be determined if the CoA achieves the desired result set by the commander.
Su - Sustainability	The CoA should assure that the military forces will achieve the best posture for future operations.
Ch - Choice	States that define the different CoAs that will be used in order to engage the selected target. The states consist of CoA1 being the land operations where military unit move towards the selected target over land, CoA2 being an aerial strike where important facilities are taken out in order to weaken the adversaries, and CoA3 which is a cyber attack where the focus is on causing outages at electrical companies to disrupt communication lines between enemies.

Table 7.1: Selection Criteria Table.

With the answers provide to both sub questions, SRQ1 can be answered. When being in competition or in conflict with an enemy, the military targeting process is used so a target can be selected and it can be determine what the engagement plan for the target will be. As a part of the military targeting process, different CoAs are developed by the commander of the mlitary forces and his staff on how to attack a selected target. The comparison of CoAs is done during phase IV: decision making, force planning and assignment, and phase V: mission planning and usage of force, of the targeting process. From the developed CoAs, a single CoA needs to be selected that provides the military forces with the best opportunity to gain the upper hand during a MDO. Based on the defined evaluation features, which are minimum impact, simplicity, maneuver, fires, civil safety and control, sustainability, mass and time, the most suitable CoA is selected for the operation. During the features evaluation, the commander subjectively determines the importance of the different features and establishes which CoA is most suitable.

SRQ2 : How to build an intelligent model that can be used for CoAs comparison decision making support?

The process of CoA comparison is considered to be largely subjective [9] [10] [28] since it relies highly on the knowledge and experience of the commander and its staff. In order to deal with the lack of available data within the military domain, the subjective component of the process and to provide a transparent model to the users, a Bayesian Network is used as an approach in the development of an intelligent model which was developed with the use of scientific literature and the available military doctrines. A Bayesian model is able to update its belief when provided with new evidence, therefore, it considers the existing uncertainty that arises during reasoning. The design of the proposed model is constructed by analyzing the causal relations between the defined features (see Section 5.2). The causal graph (see Section 5.3) is designed based on the literature that is available within the military domain but also in other domains, such as risk management or cyber security domain.

The causal design is used for the implementation of the Bayesian model (see Section 5.4). Each state that was described in Table 5.1 is used in their corresponding variables. In the implementation, the values of the CPT's are assigned using the point-allocation method and the values are based on the gathered information of real events from the Russia-Ukraine war. The proposed model strengthens transparency and explainability of AI solutions in the military domain because the model represents the military knowledge through the features and relations between the features. The model is an influence model and not a direct comparison model.

By selecting a state, a CoA, from the choice feature, the influence of the CoA on the different features can be determined. The features are updated with new values for the probabilities of their corresponding states as an result of the CoA selection.These updated values provide extra information that can be used when different engagement plans are analyzed and support within the CoA comparison decision making process.

SRQ3 : What are the results of the intelligent model when demonstrated on three case scenarios?

The model was demonstrated for its applicability to the military domain by using situations from the Russia-Ukraine war as examples. The states of variable Ch consisted of CoA1 being a land operation where armed forces move towards the target while using artillery fire to weaken the enemy, CoA2 being an aerial strike where military facilities are targeted to be destroyed and CoA3 being a cyber attack where military forces attack electricity companies in order cause outages and disrupt communication possibilities among adversaries.

While updating the evidence of variable Ch to different CoA states, it can be seen that the possibility of CoA1 and CoA2 to be more lethal and there is a higher chance that forces are distributed closer together. For CoA3 on the other hand, the opposite happened where the probability of lethality decreased and the military forces were distributed wider across the operational area. This can vary from nationally to internationally. The effect on the nodes, flexibility, minimum impact, civil safety and civil control was also different between the land operation/aerial strike and cyber attack. When using CoA3, the probability of flexibility for movement increased, there is a higher chance that the impact on their own forces is low, there is a higher chance that civilians are safe and that civilians stay in control of the region. The opposite happened when CoA1 or CoA2 were chosen. This resulted in the probability increasing for the simplicity of the operation, it being highly probable that the CoA can be executed in a short time period, it becoming more probable that the objective of the mission was attainable and that the operation would be sustainable for the future when using CoA3. For CoA1 and CoA2, the probability of the simplicity decreased, it became less probable that the CoA would be executed in a quick manner, the objective of the mission becomes more difficult to attain and the probability of the operation being sustainable for the future decreased. Thus, making CoA1 and CoA2 effective for short term achievements, but do not provide the proper assurance for a strong posture for future operations.

Considering the results that are produced by the model, it can be stated that the model applies to the military domain because it shows the influence of a selected CoA through the changes in the probabilities of the other features. The decision maker determines which CoA is most appropriate when engaging a target through deciding which feature is more important than the other.

With the three sub research question being answered, the main question of this research can be answered. The main objective was formulated as:

How to design a model for CoAs comparison in Multi-Domain Operations?

It is highly likely that the usage of Artificial Intelligence in capabilities used in Multi-Domain Operations will keep increasing. With the use of AI, the military forces will be able to counter adversaries faster and more efficiently than the forces previously could [11]. However, it is crucial for the intelligent solutions to consider the human aspect in the executed operations. This can be achieved by providing a model that is explainable to the users, so it can be properly understood and used. Thus, strengthening the transparency of AI solutions instead of using black box models within the military domain [13] [14] [15].

By identifying the features that are used for CoA comparison in MDO, determining the relations between the features, a Bayesian model is created. The model cannot be used for the comparison of multiple CoAs but does show the influence that a CoA has on the other features within the structure. Thus, providing extra information when analyzing the different CoA options and, therefore, can provide support in the CoA comparison decision making process. The proposed model is evaluated through examplification which is one of the evaluation approaches that can be applied when using the Design Science Research methodology. The model was demonstrated with the use of three illustrative use cases consisting of a land operation, an aerial strike and a cyber attack. The produced results of the demonstration conclude that the model is applicable to the military domain because it shows the influence of the selected CoA on the different features.

The process of CoA comparison is a complex decision process within the military domain. By using a Bayesian model that provides representation of knowledge through features and the relations between the features, a transparent and explainable model is proposed that can be properly understood and applied by the users to an operation while still considering the human aspect.

Even though, the current model is able to show the influence of CoA on the other features, the model still has some limitations that will be discussed in Section 7.2.

7.2. LIMITATIONS

The result of the current research rely mainly on the created use case scenarios. Even though the data is taken from real incident events in the Russia-Ukraine war, the proposed model is only demonstrated but not validated. The lack of data does not make it possible to validate the structure but also the weights that were assigned to the different features using the point-allocation method.

Although the proposed model was able to produce some results, the current model can not be directly used in Multi-Domain operation since it is too limited in its capabilities. The model is only able to show the influence of CoA on the other features, but is not able to do a prediction about which CoA is best applied to the operation while considering more information and input.

As stated before, the developed model is not a comparison model but an influence model. Even though this is useful and can provide the decision maker with more information about a CoA and its effect, there is no real comparison made by the model where multiple CoA are compared to each other and the most suitable CoA is determined for the MDO at that time.

7.3. FUTURE WORK

With the conclusions and limitations being established for this research, it is possible to identify potential directions for the research of AI support within the CoA comparison process. All these recommendations are given based on the given answer to this research and the limitations that were previously discussed.

The validity of the current model can be increased by comparing the developed model to other structures. This can be done by gathering a large amount of datasets that can be used by structured learning algorithms in order to created models to which the current developed model can be compared to. Another step would be to consult experts within the military domain in order for them to provide models or for them to give their perspective about the proposed model.

Since the comparison of CoA in the military domain is a complex process and the proposed model is limited in its capabilities, it cannot be applied to MDO at this moment. Therefore, research should continue investigating the predictive modelling capabilities where datasets are used in order to train the model in making prediction about the outcome of a CoA. A next step for this direction would be to apply these predictive models to real situations and real operations.

Finally, the current model is able to show the influence of a CoA but does not do a comparison of multiple CoAs. Research should be done into a model that is able to compare multiple CoAs that are developed and provide the best CoA from that group of developed engagement plans in order to give the best advantage during MDO.

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