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THESIS

ENHANCING MISSION ENGINEERING ROUTE SELECTION THROUGH DIGITAL TWIN DECISION SUPPORT

by

Boon Kien Eugene Lee

September 2021

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13. ABSTRACT (maximum 200 words)

This thesis presents a Model-Based Systems Engineering (MBSE) methodology for the development of a Unmanned Aircraft System (UAS) Digital Twin (DT) with the ability to demonstrate route selection capability with a Mission Engineering (ME) focus. It reviews the concept of ME and integrates it with an MBSE framework for the development of the DT. The methodology is demonstrated through a case study where the UAS is deployed for a Last Mile Delivery (LMD) mission and a route optimization module recommends an optimal route to the user. The optimization module is based on Multi-Attribute Utility Theory (MAUT), which analyzes predefined criteria that the user assessed would enable the successful conduct of the UAS mission. The thesis demonstrates that the methodology can execute an ME analysis for route selection to support a user's decision-making process. The discussion section highlights the key MBSE artifacts and also highlights the benefits of the methodology, which standardizes the decision-making process, thereby reducing the negative impact of human-factors that may deviate from the predefined criteria.

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ENHANCING MISSION ENGINEERING ROUTE SELECTION THROUGH DIGITAL TWIN DECISION SUPPORT

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ABSTRACT

This thesis presents a Model-Based Systems Engineering (MBSE) methodology for the development of a Unmanned Aircraft System (UAS) Digital Twin (DT) with the ability to demonstrate route selection capability with a Mission Engineering (ME) focus. It reviews the concept of ME and integrates it with an MBSE framework for the development of the DT. The methodology is demonstrated through a case study where the UAS is deployed for a Last Mile Delivery (LMD) mission and a route optimization module recommends an optimal route to the user. The optimization module is based on Multi-Attribute Utility Theory (MAUT), which analyzes predefined criteria that the user assessed would enable the successful conduct of the UAS mission. The thesis demonstrates that the methodology can execute an ME analysis for route selection to support a user's decision-making process. The discussion section highlights the key MBSE artifacts and also highlights the benefits of the methodology, which standardizes the decision-making process, thereby reducing the negative impact of human-factors that may deviate from the predefined criteria.

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Table of Contents

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List of Figures

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List of Tables

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List of Acronyms and Abbreviations

AI	Artificial Intelligence
AoA	Analysis Of Alternatives
DARPA	Defense Advanced Research Projects Agency
DOD	Department of Defense
DSTL	Defence Science and Technology Laboratory
DT	Digital Twin
HADR	Humanitarian Assistance and Disaster Relief
INCOSE	International Council on Systems Engineering
IOT	Internet-of-Things
IR	Industrial Revolution
LMD	Last Mile Delivery
MAUT	Multi-Attribute Utility Theory
MBSE	Model-Based Systems Engineering
MDMP	Military Decision Making Process
ME	Mission Engineering
MOE	Measure of Effectiveness
MOP	Measure of Performance
NASA	National Aeronautics and Space Administration
OECD	Organisation for Economic Co-operation and Development

OPM Object Process Methodology

OMG Object Management Group

ORBAT Order of Battle

PHM Prognostic and Health Management

RTS Return To Scale

SE Systems Engineering

SME Subject Matter Expert

SysML Systems Modeling Language

SoS Systems-of-Systems

UAS Unmanned Aerial System

UML Unified Modeling Language

UGV Unmanned Ground Vehicles

UK United Kingdom

U.S. United States

UUV Unmanned Underwater Vehicles

Executive Summary

The proliferation of 4th Industrial Revolution (IR) technology and the increased emphasis on digital transformation in the military industries has set the drive toward rapid development and adoption of DT and Mission Engineering (ME) in a Model-Based Systems Engineering (MBSE) paradigm. In recent years, there has been increased emphasis on digital transformation efforts for many military organisation across the world. In June 2018, the U.S. Department of Defense (DOD) released the "Digital Engineering Strategy" where one of the five goals was to "formalizing the development, integration, and use of models to inform enterprise and program decision making" [1]. As the military fields more autonomous systems, there is increase emphasis on the need for accurate models and decision support algorithms that enable users to better make use of these systems.

Mission routing is a combinatorial optimization research topic that has been extensively studied due to it application to many existent transportation challenges. In a military context, the decisions evaluate several variables such as potential for inclement weather and proximity of hazards that can impact the success of the mission. The ultimate goal is to select the route that would give the system the best chance of achieving mission success while being exposed to the potential threats along the routes. In this thesis, I argue that in a combat situation, with several operations happening at any given time in a dynamic environment, the use of DT may enhance the decision-making process for the mission planner. I suggest that a DT, armed with the requisite data inputs, is able to support the mission planner and provide valuable insights to the benefits and trade-offs for each route that are being assessed.

In this thesis, I propose a methodology that aids mission planners in developing a DT model that is able to provide quantitative decision support analysis for UAS route selection. The method is based on Multi-Attribute Utility Theory (MAUT), and uses portions of the MagicGrid framework [2] and Bickford et al.'s framework [3]. Refer to Figure 1 for the proposed methodology.

A case study based on UAS LMD mission was used to illustrate the proposed method.The DT is developed using the Cameo-Enterprise Architecture software using Systems Modeling Language (SysML). The case study demonstrates that the DT decision support module can

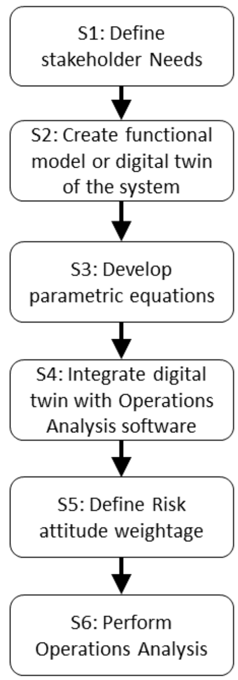

Figure 1. Proposed methodology

recommend the most optimal route, which is based on the operator's risk-attitude towards the mission criteria. Three mission criteria are used to select the route with the highest objective function. They are: (a) time to target, (b) remaining battery power and (c) threat probability. With the target location identified, the UAS shall be able to calculate potential routes to the target location. Each route is expected to have varying distance and threat probability; based on the MAUT, the operations analysis software or Artificial Intelligence (AI) software can calculate and recommend the most optimal route.

After building the functional model by developing the system's components in the MBSE software, the DT can then be integrated with other analytical software to demonstrate the route optimization capability. For this thesis, I use ModelCenter to conduct the simulations by extracting input data from the UAS DT and then perform the operations analysis, which in this case is route selection based on MAUT. In the subsequent step, the operator defines their weightage for each of the criteria. As the weightage sums up to 1, the operator is forced to prioritize between the criteria. I then integrate the model with ModelCenter to conduct the operations analysis. Using the Design-of-Experiment tool embedded within ModelCenter, I can simulate a variety of route distances and threat levels, and validate that the most optimal route with the highest objective value is selected.

Detailed analysis is conducted on the simulation outcome to validate the fidelity o f the simulation result. Route A is the shortest at 1000 m, yet with the highest threat probability of 0.4 due to exposure to the adversary's air defense assets. Route B, on the other hand, is the longest route at 15000 m but has the lowest threat probability at 0.001. Route C is 8000 m in distance, with a medium threat probability at 0.2005. The simulation recommends Route B as it has the highest objective function of 0.79569. In this case, Route B is selected despite the UAS having to travel a significantly longer distance and with 1500 percent longer duration compared to Route A. If the decision is left up to an operator without access to the proposed methodology described in this thesis, one would not be surprised if the operator would have selected Route A or C, which will take a shorter period of time to complete the mission. However, as a result of pre-defined thresholds and the fact that the same risk-attitude weightage is assigned to both Time to Target and Probability of Hit criteria, the recommendation is different.

The thesis has demonstrated the benefits of using MBSE methodology to develop a DT that can support route selection for a UAS conducting a LMD mission. In addition, the results also highlight three key observations. (a) The model enhances consistency in decision-making and reduces the effects of the human-factor in decision-making. (b) Utility of MBSE software for operations analysis. While MBSE software has expanded its capability to be able to conduct trade-studies, many users continue to rely on other external software to conduct operations analysis and simulations. (c) Lastly, the study highlighted the importance of data quality, which is fundamental for the decision-support module to produce a feasible solution that has operational benefit.

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CHAPTER 1:
Introduction

This chapter provides a background of the thesis, which is based on the key ideas of Digital Twin (DT) and Model-Based Systems Engineering (MBSE). This chapter explains the impact of 4th Industrial Revolution (IR) and how it is influencing the military in terms of the adoption and application of the these technologies. From the Systems Engineering (SE) perspective, implementing new technology is not just about acquiring new capability into our Order of Battle (ORBAT) – it is about how this technology can value add to existing processes and work flows. As captured in the Organisation for Economic Co-operation and Development (OECD)'s conference proceedings from the year 2000, innovation through existing technology such as electricity and automobiles have supported technological and societal growth to a large extent. Moving forward, a new generation of breakthroughs in areas such as computing, new materials, and environmental tools and systems will be required [1]. Fast forward twenty years to the arrival of the 4th IR, which has provided us the opportunity to leverage new technology to unlock further operational and efficiency gain. The rest of this introduction lays the foundation for this thesis and helps the reader understand Chapter 2, which is pending publication in the Multidisciplinary Digital Publishing Institute-Systems.

Previous IRs were enabled by technological advancements and new inventions. While the same could be said for the 4th IR [2], the 4th IR is unique in the sense that it is characterized by the merging of boundaries between biological, digital, and physical realms [3]. The Forbes Technology Council lists Artificial Intelligence (AI) and Data Analytics, amongst others, as the most important technological solutions that will influence businesses and consumers in 2021 and beyond [4]. As these technologies continue to mature, there is an opportunity for industries to change how things are done, and be more efficient and effective.

The same can be said from the military perspective. The Department of Defense (DOD) Inspector General recently released the top ten management and performance challenges for the fiscal year 2021 [5]. Amongst them are issues such as, "transforming data into strategic assets" and "building and sustaining the DOD's technological dominance." I assert that the employment of 4th IR technology and processes such as DT and MBSE will help to address the challenges highlighted by the DOD Inspector General. The military, being a high-risk industry due to exposure to life-threatening operations and environments, has traditionally applied the idea of "factors-of-safety" for design and certification of systems and in how decisions are made for operations. Further, the military's strong process-driven approach leads to compounding factors-of-safety at various stages of systems design and operation processes. This may lead to designs that are heavier than required and decreased performance, which could have indirect impacts on mission outcomes or safety [6]. The use of DT provides the benefit of being able to test and evaluate system designs and operational decisions beyond the physical limits thereby eliminating the use of "worse-case scenarios," which tends to sacrifice system performance yet comes with a higher cost.

The concept of MBSE is very much aligned to that of DT with the building of system models, incorporation of data, and simulations. This is echoed by Bickford et al. [7] where a MBSE methodology is used to develop a DT. With advancement in MBSE software packages which enable simulations and trade-studies to be conducted, an engineer is able to build system models and use them to support an operator's decision-making process during missions. As mentioned by Kranabitl et al., MBSE models are sources of knowledge and are the basis of good decisions [8]. I assert that MBSE in the military context plays an important role not just in supporting the acquisition process. If an engineer can operate models as a DT during the operational and support phases of a system's life cycle, the DT can also support operational decision-making.

This research embraces the ideas of DT and MBSE, and explores the methodology through a case study where a generic Unmanned Aerial System (UAS) DT is used. The methodology I develop in Chapter 2 is an extension of earlier DT concepts by Bickford et al., and is enhanced to include parts of MagicGrids' MBSE methodology [9]. Currently in review, Chapter 2 is a manuscript written for Multidisciplinary Digital Publishing Institute's Systems journal. This thesis is aligned with the approach described in the memo titled "System Engineering Theses: A Manuscript Option" [10] from the Systems Engineering Department at the Naval Postgraduate School. The aim of this research is to develop and demonstrate the proposed methodology for the development of a DT through a case study where a UAS is deployed for a Last Mile Delivery (LMD) mission and a route optimization module recommends an optimal route to the operator. The thesis demonstrates that the DT can execute operations analysis for route selection to support the operator's decision-making process.

CHAPTER 2:
Manuscript Submission

2.1 Enhancing Mission Engineering Route Selection through Digital Twin Decision Support

A version of this chapter is in review as: Lee, E.B.K.; Van Bossuyt, D.L.; Bickford, J.F, "Enhancing Mission Engineering Route Selection Through Digital Twin Decision Support," Multidisciplinary Digital Publishing Institute (MDPI) Systems. Submitted August 2021.

2.2 Introduction

The 4th Industrial Revolution (IR) has changed the way many industries work across the world in recent years. As described by Klaus Schwab, founder of the World Economic Forum, the 4th IR will be driven largely by the convergence of digital, biological and physical innovation [2]. One could understand the 4th IR as the blurring of boundaries between the digital, biological, and physical world. This is made possible with rapidly increasing computing power and data transfer rates. It brings about great potential to increase productivity, while communication will be easier and transportation will be faster [11], thereby enabling the proliferation of technology in the fields of Internet-of-Things (IOT), Artificial Intelligence (AI) and machine learning, 3D printing and genetic engineering to name a few [12]. Just as in other industries, the 4th IR has made its impact on the military. As Farrell and Terriff [13] identified, there are three drivers for military change including (1) pressure from senior leadership, (2) emulation of other professional militaries, and (3) an external shock . We argue that the 4th IR is fueling all three military change drivers with the pace and extent of the 4th IR proliferating across different technologies used by the military. For instance, United States (U.S.) Department of Defense (DOD) was reported to have increased its unclassified investments in AI from 600 million dollars in FY2016 to 2.5 billion dollars in FY2021 [14]. In the same light, China was reportedly planning to spend 21.7 billion by 2020 to develop a core AI industry [14]. Barno and Bensahel discuss that military operations enabled by these 4th IR technologies may transpire so fast that it requires human to be out of the decision-cycle [15]. In this regard, we expect the 4th IR to also drive rapid development and adoption of Digital Twin (DT) and Mission Engineering (ME) in a Model-Based Systems Engineering (MBSE) paradigm.

The U.S. DOD has a long track record of embracing new technologies and incorporating them into DOD operational capabilities. In recent years, there has been much more emphasis and communication on the digital transformation strategy. In June 2018, the DOD released the Digital Engineering Strategy which laid out five goals including: "(1) formalizing the development, integration, and use of models to inform enterprise and program decision making; (2) provide an enduring, authoritative source of truth; (3) incorporate technological innovation to improve engineering practice; (4) establish a supporting infrastructure and environment to perform activities and collaborate and communicate across stakeholders; and (5) transform the culture and workforce to adopt and support digital engineering across a system's lifecycle" [16]. Of note to this paper is the first goal where the Digital Engineering Strategy mentions formally developing and integrating models to support engineering activities and decision-making across the system life cycle. With more intelligent weapon systems such as autonomous robotics and unmanned vehicles being fielded, there is increase emphasis on the need for accurate models and decision support algorithms that would enable users to better make use of these systems.

2.2.1 Specific Contribution

In this thesis, we propose a methodology that aids mission planners to develop a DT model that is able to provide quantitative decision support analysis for Unmanned Aerial System (UAS) route selection. The method is based on Multi-Attribute Utility Theory (MAUT), and uses portions of the MagicGrid framework [9] and Bickford et al.'s framework [7]. We provide insights on the steps and inputs required for the development of the DT model to support a deployed DT that supports operations analysis and routing decisions for a system.

2.3 Background and Literature Review

This section discusses concepts and recent related work that are relevant to the methodology we propose in this thesis.

2.3.1 Digital Twin

In 2012, National Aeronautics and Space Administration (NASA) defined DT as an "integrated multiphysics, multiscale, probabilistic simulation of an as-built vehicle or system that uses the best available physical models, sensor updates, fleet history, etc." [6]. In other words, DT is a virtual representation of the physical asset, based on onboard data installed on the asset, which then assists the user with maintenance, planning, and operational decisions among other activities. As described by Boschert et al. [17], DT can be characterized by the following features: (1) having a series of digital artefacts that are connected based on actual system operational data obtained from modeling and simulation. The models are created for a specific purpose which is often to study and solve for a particular problem in operation. (2) The DT is not a static model, it can be continue to be modified as the actual system continues to be develop and modified through its life-cycle. (3) The DT do not just replicate existing system behaviors, it can be used for testing and simulation which allows user to observe new behaviors and obtain solutions to address the user's problems.

Being in a virtual environment, a DT allows users the capability to test the system beyond its physical limits, which is something that often cannot be done easily and/or inexpensively with the physical system. This enables the user to better understand how the system behaves in different circumstances, and allows for further optimization of the system components [18]. Due to these advantages, DT can be applied to a multitude of applications. Examples include Prognostic and Health Management (PHM) as demonstrated by L'Her et al. [19] where a methodology is used to predict reliability failure probabilities for a nuclear power plant. Another example of the application is to validate system performance as demonstrated by Bachelor [20], where a model is used to compare the performance of different de-icing systems on an aircraft. Madni [21] mentions a list of applications for DT including those above as well as: (1) provide decision support to users through what-if analysis, and (2) discover new application opportunities and revenue streams through modifying and testing new system features and improvements.

The benefits of DT go beyond conducting test and analysis; DT is valuable in enhancing decision support. This is especially true in complex systems and challenging operating environments where multiple decisions have to be made by the human, often within a compressed timeframe with limited or incomplete information. As discussed by Kunath and Winkler, the ability for one to make a good decision depends on one's past experiences and the information that is made available to one [22]. In addition, if a decision is made based on manual calculations, the accuracy can be very low [22]. DT is well placed to overcome these issues. Marakas identifies three fundamental components of a decision support system as: (1) a knowledge base, (2) a decision context (model), and (3) an interface. DT meets all three criteria [23]. This is further evident in the many research applications where DT has been used. Some examples include, enhancing decision support for port operations [24] and improving management of logistic systems [25].

2.3.2 Mission Engineering

ME is defined as the "deliberate planning, analyzing, organizing, and integrating of current and emerging operational and system capabilities to achieve desired warfighting mission effects” [26]. The ME guide recently released by the U.S. DOD mentions that ME entails the employment of systems and Systems-of-Systems (SoS) in an operational context to provide information on system performance which can support decisions made by the users in pursuit of achieving mission success. Notably, the guide [26] describes ME as a data-driven approach to analyze key aspects of a mission to derive quantifiable trade-offs and make decisions. This enables one to test new concepts or tactics that have not been proven. Suffice to say, the concept of ME relies on 4th IR technology and the ability to exploit DT modeling and simulations.

An earlier perspective on ME is provided in Beam’s thesis, which depicts a notional framework for ME [27]. He explains that the various functions of ME (defining mission requirements, identifying mission concept of operation, mission design, and mission architecture) are used to optimize the mission solution. The mission solution serves to meet predefined stakeholder needs. While Beam’s definition are broad, it is aligned to that of the DOD.

The amount of factors that could impact a mission outcome is infinite, thus conducting an empirical study is a essential part of ME [26]. Hence, it is important to note that the utility of the analysis is a function of the data accuracy input to the model. Additionally, the practitioner must have good understanding of the mission objective to be able to define useful Measure of Effectiveness (MOE) and Measure of Performance (MOP) which quantify and measure the success of the system. These elements are critical for quantitative and subsequent qualitative assessment on the system being modelled.

2.3.3 Air Mission Planning

Mission routing is a combinatorial optimization research topic that has been extensively studied due to it application to many existent transportation challenges [28]. This is coupled with the rise in applications of autonomous vehicles such as UAS both in military and civilian industries. As mentioned by Thompson and Guihen, the route selection and recovery plans for an autonomous marine vehicle is a challenging one to consider with the various aspects of the mission. The magnitude of the challenges grows exponentially if the decision is to be made for a large fleet. Each vehicle will require a dedicated team to evaluate and plan its routing and recovery plans [29]. The same can be said for UAS.

Routing decisions are important especially in a military context, because the decisions analyze several priority variables such as potential for inclement weather and proximity of hazards that can impact the success of the mission. Notably, the cost of time for employing resources against the risk of exposure to threats is a key criteria to consider. In this regard, using a constant route time as an assumption can lead to poor route planning and inefficient use of resources [30]. A mission planner must consider several factors to ensure that the UAS has the best chance of completing the mission. In a military operating environment, every sortie allocated to the operator contributes to the overall chance of mission success. In a resource-tight environment, the ability to deploy assets optimally increases operational effectiveness contributing to the chance of mission success. Beyond the cost of each flight, in a military context, a system's survivability is often based on its ability to prevent detection and avoid threats. Aircraft survivability modus operandi were developed during the emergence of military helicopter operations in the 1950s, the procedures were based on two principles: 1) avoid detection, and 2) if detected, avoid being hit [31]. Hence, the mission planner ideally chooses a route that has the lowest threat probability. Considering all of the above, one can appreciate the importance of mission planning. We argue that in a combat situation, with several operations happening at any given time in a dynamic environment, the use of DT environment may enhance the decision-making process for the mission plan-ner. We suggest that the DT environment, armed with the requisite data inputs, is able to support the mission planner and provide valuable insights to the benefits and trade-offs for each route that are being assessed.

2.3.4 Model-Based Systems Engineering and Digital Twin

International Council on Systems Engineering (INCOSE) defines MBSE as "the formalized application of modelling to support system requirements, design, analysis, verification and validation activities beginning in the conceptual design phase and continuing throughout development and later life cycle phases" [32]. In recent years, there has been significant improvements in computational abilities and this is coupled with an increased emphasis on the application of Systems Engineering (SE) principles over a system's life cyle. This has led to the prominence of MBSE principles and methodology in the SE field. Bickford et al. mention that MBSE and the vision of DT are closely aligned, and if system models can be integrated in the operations and sustainment phase of a system's lifecycle, the integrated models can become a DT [7]. As such, a MBSE methodology can be employed to develop a system's DT.

The decision process of architecting the DT can be mapped onto the MBSE and SE processes [7]. In doing so, the system requirements can also be mapped across to drive the development of the DT achieving synergy as much of this data is normally specified in the system development process. Table 2.1 provides a view of the mapping of DT architecture with the MBSE processes. Bickford et al. categorize critical phases of the DT architecting process into: (1) concept exploration, (2) preliminary design, (3) detailed design, (4) implementation, (5) test and evaluation, and (6) operations and maintenance. Bickford et al. [7] further go on to present a case study of an unmanned surface vessel to described the process of building a DT for the purpose of predicting system failures, reliability performance and predicting the probability of successful conduct of the mission.

2.3.5 MagicGrid

There are many programming languages that are being used commercially such as JavaScript, Matlab, and Unified Modeling Language (UML). While these languages are versatile and capable of performing a wide range of automation and visualization task, they lack several features that directly support characterizing systems and supporting trade studies. Thus,Systems Modeling Language (SysML), a variation of UML, was created by INCOSE and Object Management Group (OMG) [33]. SysML is characterized by graphical artefacts that represents the data of the system stored in a database. Users are able to use SysML to conduct simulation, analysis and verification of the system of interest. In this regard, Kalvit [33] referred SysML as the “de facto modeling language” in the SE field. The MagicGrid framework is based on SysML. It consist of the “four pillars of SE”: Structure, Requirement, Parametric, and Behavior. The pillars are broken down into nine corresponding diagrams using SysML.

The Requirement pillar depicts stakeholder needs. The system requirements capture the desired goal of the system and the objectives that it is expected to achieve. The component requirements encompass the requirements derive from the subsystems in order to support the higher-level system functions. The Behavior pillar covers the use cases for the system. Use cases are used to describe how the user or actor in SysML, would interact with the system. The inputs and peer systems required for the system to operate are expressed in the use case diagrams. Functional analysis describes the behavior of the system by decomposing every function performed by the subsystem. Component behavior demonstrates the detailed behavior of the subsystems. The Structure pillar includes the high-level interfaces required for the system to connect with its peer systems. The logical subsystems communication covers interactions between the various subsystems. The component structure depicts the physical interfaces between the component and its sub-components. Finally, the Parametric Pillar covers the MOE and physical characteristic of the system.

We assess that there are several similarities between the DT development framework proposed by Bickford et al. and the MagicGrid framework. Table 2.1 provides a comparison of Bickford et al.'s DT development process against the MagicGrid Process. In other words, what Bickford et al. describe using the SE process of Concept exploration stage to Detailed Design stage covers a large part of the MagicGrid framework of modeling a system using SysML with some disparities. Notably, we assess that MagicGrid specifically defines the system MOE as a key component of the MagicGrid framework. In Bickford et al.'s article, they highlight that DT developers should understand how each sub-component's performance contributes to the higher-level system performance. This can be achieved through working with the component original equipment manufacturer or Subject Matter Expert (SME). Having an appreciate of the relationship between the sub-component performance and system performance will aid developers in determining a suited performance parameters [7]. Having said that, Bickford et al.'s process is more practical than the MagicGrid process in that they take into consideration the requirements for data storage as well as the integration into physical design. This is an important consideration as the data is both a key resource and output for a DT.

2.4 Methodology

The following section describes the methodology for the development of the system DT and the operations analysis. Figure 2.1 shows the proposed six steps of the methodology for the creation of DT for route selection decision support.

2.4.1 Step 1: Define stakeholder needs

The stakeholder's requirement for DT should be clearly defined in two aspects. First, defining the physical design. That is, the capabilities and functions of the system of interest should be clearly defined. An accurate depiction of the sub-system interaction and use-cases enhances

Table 2.1. Comparison of Bickford [7] and MagicGrid's [9] processes for creating a DT

Systems Engineering Process	Bickford's Process	MagicGrid Process
Concept Exploration	Identify primary purpose	Stakeholder needs
	Identify DT algorithm Identify DT data input types Identify location of DT	System requirements Component requirements
Preliminary Design	Define DT architecture Define DT digital thread Integrate DT requirement into physical design	Use cases Functional analysis Component behavior System context Logical subsystem comms Component structure
	Identify source data Identify data storage requirement	*Not specifically covered
	*Not specifically covered	Measure of Effectiveness Component parameter

the accuracy of the model and the results obtained from subsequent operations analysis. Second, the goals of the operations analysis or the variable of interest should also be stated upfront. This ensures that all sub-systems related to the particular variable are captured upfront in the design of the DT. A similar approach is mentioned by Beery and Paulo [34], where the need for two parallel processes of creating the operational design and the physical design of system is essential for a MBSE analysis process.

2.4.2 Step 2: Create a functional model

Having defined the requirements, the DT equivalent of the system can now be developed. This can be done in various MBSE software such as CORE or CAMEO Enterprise Architecture. We recommend employing a software tool that is capable of using SysML. SysML's inclusion of Requirement and Parametric diagrams makes it more suitable for modeling system requirement and performance than many alternatives [35]. One may also use the Object Process Methodology (OPM) to represent the system architecture if one's organization is more accustomed to OPM. Both modeling languages are equally capable with subtle differences such as the OPM having only a single integrated model with objects, processes and relationships instead of different views as in SysML [35]. As we used the CAMEO Enterprise Architecture software in the case study, we chose to use the MagicGrid framework previously discussed in Section 2.3.5.

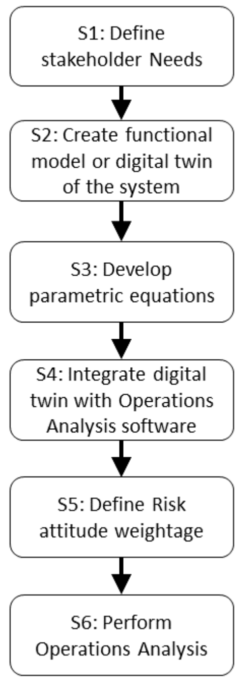


Figure 2.1. Proposed methodology.

2.4.3 Step 3: Develop parametric equation(s) for the variable of interest(s)

This step is derived from a subset of the MagicGrid framework [9], where the quantitative characteristics of the system are defined. The parameters can be derived from other subsystem parameters and mathematical expressions can be defined in the model. The model can also be verified to ensure that it meets the system requirements. This step is important as the defined variable of interest can subsequently be used for operations analysis either within the architectural software or other suitable analytical software.

2.4.4 Step 4: Integration with operations analysis software

After developing the DT model in a virtual environment, one can then proceed to perform operations analysis with it. There are several types of analysis and the type of analysis chosen depends on the system behavior one is interested in exploring. In general, statistical analysis tools are used to observe interactions between variables and determine which of them has more impact on system performance [36]. Certain analyses such as Analysis Of Alternatives (AoA) can be done within system architecting software. However, for more elaborate analysis, many users turn to external simulation software packages such as ModelCenter [37], ExtendSim [34], or OpenModelica [20].

2.4.5 Step 5: Define Risk Attitude Weightage

We next use MAUT as the basis for the operator's decision support analysis. We suggest that MAUT is suitable for this purpose as it takes into account the multiple-attribute payoff which is often the challenge an operator faces in a dynamic environment [38]. The consideration for the use of MAUT is to be further discussed in subsection 2.5.2. Pertaining to the case study in this thesis, the operator must pre-define the risk attitude towards criteria. This is done prior to the route selection analysis to ensure consistency across the analysis. The risk attitude towards the particular mission affects the weightage the operator gives to each criteria used for route selection. Take for example, if the operator has a high-risk attitude, he/she will give a higher weightage towards criteria that supports the completion of the mission as compared to safety or reliability related criteria.

2.4.6 Step 6: Perform Operations Analysis

Now, the user is ready to conduct operations analysis with the DT through an external simulation tool. For an operational system with a fully modelled DT, the DT can also be integrated with AI capabilities which can help to enable autonomous decision-support based on the selected risk-attitude weightage in Step 5.

2.5 Case Study

We now introduce a case study that will be used to illustrate the proposed method in the subsequent sections.

2.5.1 UAS for Last Mile Delivery

Last Mile Delivery (LMD) in a military context is the "distribution of supplies from the last point of bulk disaggregation to dispersed forces in the theater of operations" [39]. The nature of warfare today is increasingly complex and dispersed, hence autonomous vehicles used for resupply are expected to make multiple stops on distribution missions to scattered forces [39]. In a contested environment, the delivery system is also exposed to the threat of being disrupted by adversaries which is in addition to system and environmental limitations such as weather conditions, battery or fuel limitations, and etc. All these factors must be considered by the operator especially for a UAS platform where humans are not constantly providing tactical judgement to system operations. Furthermore, the magnitude of the challenge is exacerbated if one is considering the use of multi-UAS or swarming operations, which has been an area of research by United Kingdom (UK)'s Defence Science and Technology Laboratory (DSTL) and Defense Advanced Research Projects Agency (DARPA) [29] among others. Hence, a decision support module of the system in a DT environment is valuable to the operator in managing multiple systems and multiple routes in a dynamic environment similar to that of military operations.

In the following subsections, we shall demonstrate the methodology with the development of a DT decision support module for a UAS on a LMD mission. The DT is developed using the Cameo-Enterprise Architecture software using SysML. Refer to Figure 2.2 for an illustration of a LMD mission for the UAS. In this case, the operator's mission is to deliver supplies to a forward deployed soldier. However, the potential routes for a UAS may entail exposure to adversary action. The case study shall demonstrate that the DT decision support module shall be able to recommend the most optimal route which is based on the operator's risk-attitude.

2.5.2 Multi-Attribute Utility Theory

MAUT is an established method for decision-makers to compare performance metrics and to determine trade-offs between them [40]. As discussed by Dyer [41], MAUT provides an axiomatic foundation for decisions that involves several criteria. The axioms impart rationale for quantitative analysis of alternatives. In the LMD case study, the operator or an AI software is expected to determine the most optimal route for the UAS based on a set of criteria determined by the mission lead. These criteria serve to allow the UAS a higher probability of success to complete the mission and return to base.

The additive value model is widely used by practitioners when conducting multi-objective decision analysis [42]. The following objective function from Parnell and Trainor [42] is

Figure 2.2. A LMD mission for the UAS to distribute supplies to frontline soldiers

used to evaluate each alternative routes:

$$v(x) = \sum_{i=1}^{n} w_i v_i(x_i) \tag{2.1}$$

where $v(x)$ refers to the value function of the alternative being considered. $i = 1$ to n is the total number of criteria used for the decision. x_i is the alternative's score on the i^{th} criteria. $v_i(x_i)$ is the single dimensional value of a score of x_i. Last, w_i is the weight for each of the i^{th} criteria. and $\sum_{i=1}^{n} w_i = 1$

The additive value model evaluates the trade-offs for the objectives by calculating the alternative's contribution to the value measures. Each value function $v_i(x_i)$ measures returns to scale based on the range of the value of measure and calculates a score x_i to a value. A value scale with the minimum acceptable value of measure: lower threshold, and the most desired value of the value of measure: upper threshold, should also be determined [43].

The weights plays an important role for the objective value of the function. As the summation for all the criteria comes up to 1, this forces the operator to prioritize between the criteria. For example if the Time to Target is the most important aspect of the UAS LMD mission, it should be given the highest weightage.

To obtain $v_i(x_i)$, a scaled scoring for the particular criteria should be calculated, we do this by using the following equation:

$$v_i(x_i), Scaledvalue = \frac{ActualValue - Lowerthreshold}{Upperthreshold - Lowerthreshold} \tag{2.2}$$

Having a scaled value of 1 means that the alternative achieves the goal value while a scaled value of 0 means that the alternative achieved the threshold value. The objective function is calculated and compared for each route to determine the preferred solution based on the weights or priorities set by the operator.

We note the additive value model may have its inherent weakness as it does not take into account the variation of the scales of the criteria [42]. Not using swing weights may result in the recommended alternative not being consistent with the stakeholders' preference [43]. While swing weights are important for the quality of the decision, our focus is on demonstrating the methodology of creating a DT, as such swing weights are not included in the case study calculations.

2.5.3 Route Selection Criteria

For the purpose of the case study, three criteria are evaluated to select the route with the highest objective function. They are: (a) time to target, (b) remaining battery power and (3) threat probability.

(1) Time to target

For the purpose of LMD, it is reasonable to assume that the time to target is a key criteria to determine the most optimal route. As highlighted by Thornton and Gallasch, potential use cases of LMD may include delivery of emergency resupply of ammunition or medical supplies [39]. As such, the utility curve for this criteria to the operator is determined to be a decreasing Return To Scale (RTS) concave; in other words, less is better. The operator prefers to reach the target in the shortest possible time. Beyond a certain time period, the case study assumes there is a steep drop in utility as the unit waiting for resupply could have already been overrun by an adversary. The time to target is assumed to be the straight-line distance divided by the speed of the UAS. The typical speed of UAS based on current technology and is assumed to be 20 meters per second [44].

(2) Probability of Hit

In a hostile environment, it is likely that there are adversarial threats along the routes to the target. The threats can impact the probability of success for the case study's LMD mission. In accordance with the Army Military Decision Making Process (MDMP), the operator should select the course of action that minimizes risk to the force and to mission accomplishment [45]. While the UAS is able to autonomously calculate potential routes, for threat data the UAS requires access to external resources with real-time updated threat information. The data of interest is the probability of hit, P_h. The probability of hit is the probability that every process of the engagement sequence is successfully completed [46]. As the probabilities are not correlated, i.e. each step has to complete before the next can begin, the probability of hit may be expressed as:

$$P_h = P_{Weapon} \times P_{Command} \times P_{Threat} \tag{2.3}$$

The P_{Threat} refers to the probability that the threat is active. $P_{Command}$ refers to the probability that the weapon has been commanded to engage the UAS. Finally, P_{Weapon} refers to the probability that the weapon is launched and detonates at the UAS. The utility curve for this criteria to the operator is determined to be a decreasing RTS concave, in other words less is better. The operator prefers to keep the probability as low as possible with a steep decrease in utility beyond a certain point.

(3) Remaining Battery life

System recoverability is a key aspect of system survivability [47]. The operator wants to ensure that the UAS has sufficient battery life to return to base regardless of the route selected. As such, the utility curve of this criteria is determined to be linear RTS, in other words more is better.

The main demand of the battery comes from the UAS's propulsion system. The percentage of battery energy remaining, B_R can be determined by the following equations [48]:

$$E_{demand} = P_M \times P_l \times t \tag{2.4}$$

$$E_{supply} = V_{batt} \times C_{batt} \times 3600 \tag{2.5}$$

$$B_R = \frac{E_{demand} - E_{supply}}{E_{supply}} \tag{2.6}$$

E_{demand} Energy demand is attributed to mechanical power to the propellers P_M, power loss P_l, multiplied by time of in operation. E_{supply} is obtained by multiplying the voltage and capacity of the model of battery in use [48].

2.5.4 Combining MAUT into the Methodology

Next, the MAUT is combined with the overall methodology shown in Figure 2.1. Refer to Figure 2.3 for the expansion of Step 6. With the target location identified, the UAS shall be able to calculate potential routes to the target location. Each route is expected to have have varying distance and threat probability, based on the MAUT described in Section 2.5.2, the operations analysis software or AI software can calculate and recommend the most optimal route. The equation below shows the overall function for the operator based on the mission criteria for route selection in 2.5.3.

$$v_{missionlead} = w_1 TimetoTarget_{score} + w_2 ProbabilityofHit_{score} + w_3 RemainingBattlife_{score} \tag{2.7}$$

2.6 Results Discussion

This section presents the results of each step of the proposed methodology for the case study laid out in the previous section.

2.6.1 Define stakeholder needs (Step 1)

First, we work with the stakeholders to understand their needs for the system. This can be done through interviews or surveys. The system requirement specification should be defined.

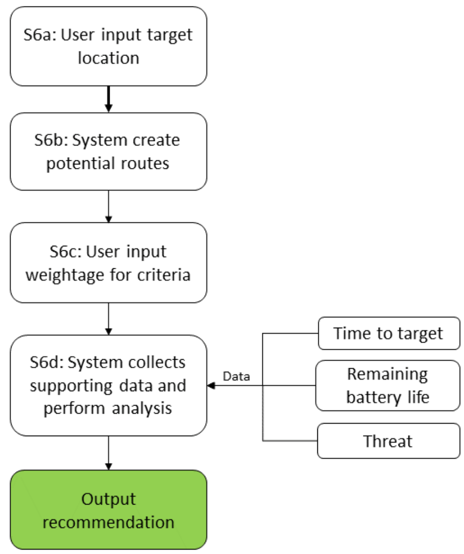


Figure 2.3. Implementing MAUT in the methodology

To demonstrate the methodology, a simplified stakeholder requirement is summarized in Figure 2.4.

2.6.2 Development of UAS DT (Step 2)

The Cameo Enterprise Architecture software and the MagicGrid framework is used to create a simplified architecture of the UAS used for the LMD mission. Similar to [37], detailed modeling is minimized by excluding subsystems that do not directly impact the route selection algorithm. As such, components such as a camera, a central computer, etc., are not included. The block definition diagram in Figure 2.5 shows the UAS solution architecture (in blue) that addresses the problem domain based on the stakeholder requirements. Notably, one may observe that the propulsion subsystem does not have a problem domain abstraction. This is because the stakeholders do not explicitly specify the need for a propulsion system during the development of the solution architecture as they are more concerned with endurance. However, one could have included it as it supports system requirement of endurance and speed as well.

#	Name	Text
1	⊟ SN1 Stakeholder Need	
2	SN1.1 Endurance	UAS shall be able to conduct up to 60 minutes of mission time
3	SN1.2 Speed	UAS shalll be able to fly up to 20m/s
4	SN1.3 Payload	UAS shall be able to carry up to 5 kg payload
5	SN1.4 Range	UAS shall be able to communicate with the GCS up to a max distance of 10km
6	SN1.5 Route Optimization	UAS shall be able to select optimal route autonomously

Figure 2.4. Stakeholder's needs captured in DT software

Two key functions of the UAS (the UAS Motor and the Optimization Module) are further decomposed to identify the system interactions and functions. See Figure 2.6.

The route optimization subsystem's activity diagram is further decomposed as shown in Figure 2.7. The user "Turn[s] On" the system to activate the route optimization module. As part of the "Initialization," if an error is detected the module returns to the "Off Mode." Otherwise it proceeds to "Optimizing Route" which is expanded on in Figure 2.8.

When the route optimization module receives a signal to start route optimization, it triggers the retrieval of threat data which corresponds to the Probability of Hit, and begins calculations for remaining battery life and time to target location. Upon completion of the optimization, the route optimization module outputs the recommended route to the operator in a semi-autonomous system or directly to the UAS in a fully-autonomous system implementation. A similar decomposition of the motor subsystem activity diagram has been conducted but is not shown here as it is not a key function of interest for the route selection.

2.6.3 Development of Parametric Equations (Step 3)

It is important to note that the variable of interest required for the optimization should be defined i n t he s ystem M OEs a s s hown i n F igure 2 .9. T his e nables t he o peration analysis software to identify the parameters of interest when it subsequently integrates with the model. In the case study, the UAS's maximum speed in meters per second is an important variable of interest as it impacts the time to target and remaining battery life criteria. The speed of the UAS can be derived from the speed of the motor.

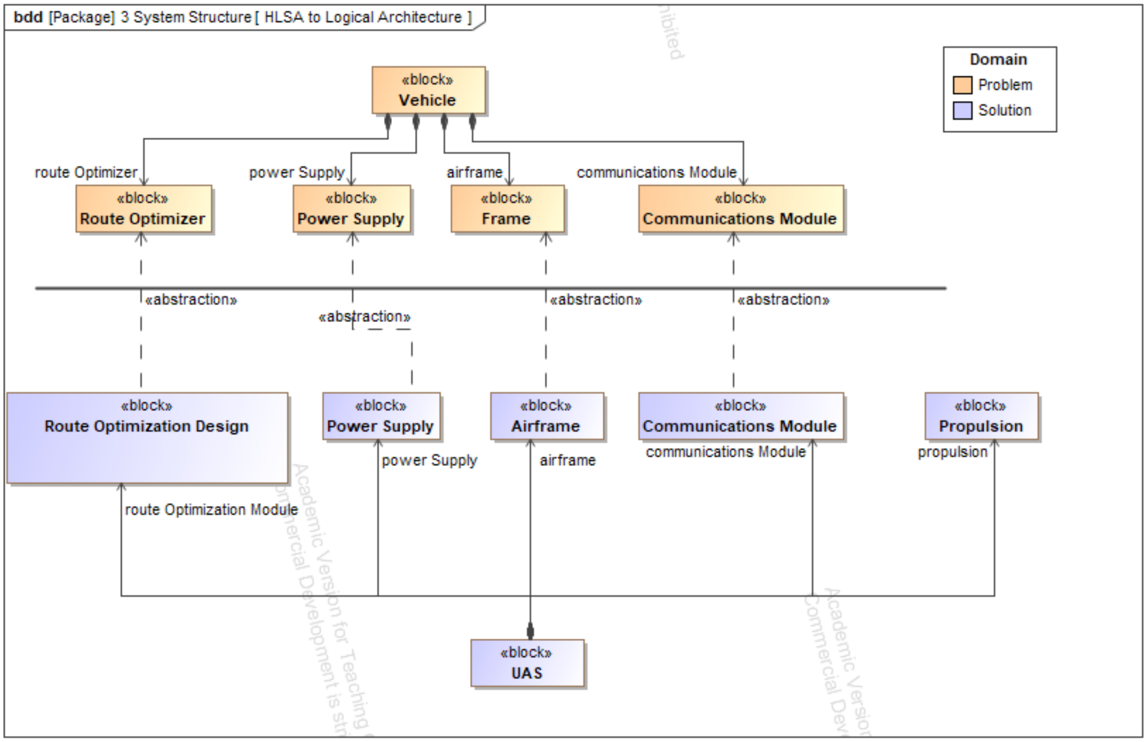


Figure 2.5. UAS block definition diagram

2.6.4 Integration with Operations Analysis software (Step 4)

After building the functional model, the DT can then be integrated with other analytical software to demonstrate the route optimization capability. Notably, we observe that while system architecture software has been enhanced with analytical capabilities to perform system trade-offs and AoA, separate software is still generally required for more elaborate operations analysis and simulations. Beery and Paulo made a similar observation albeit from a different perspective; they mentioned that “utilization of analysis procedure external to SysML modeling process prevents any oversimplication of system performance ... if detailed modeling of mission performance is not conducted” [34]. Bonanne’s report [49] also cites the use of external tools such as Matlab or System Tool Kit for simulation.

For this case study, we use ModelCenter to conduct the simulations by extracting input data from a model – in this case the UAS DT – and then perform the operations analysis, which in this case is route selection based on MAUT. We use ModelCenter due to the nature of the case study simulation which demonstrates a particular function of the UAS

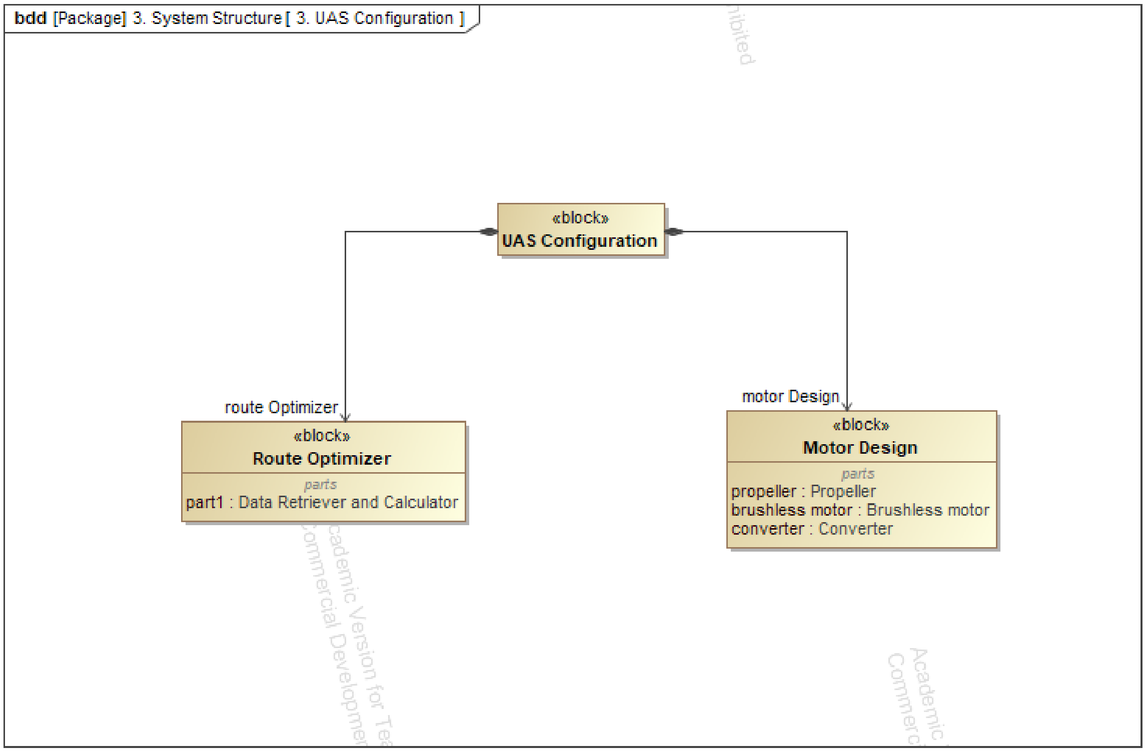


Figure 2.6. UAS component requirement

and performs what-if analysis based on a variety of scenarios. In addition, ModelCenter has the capability to integrate with several modeling software packages including Cameo Enterprise Architecture, Excel, Matlab and many others. We chose to not use the Cameo Enterprise Architecture program with the Simulink add-ins but this approach would be useful if one is interested in performing trade-studies on the UAS architecture. An example is discussed in Willemsen et al. [50], where different brake components are compared for a vehicle brake system.

2.6.5 Operator Define Risk-attitude Weightage (Steps 5)

In this step, the operator defines their weightage for each of the criteria. As the weightage sums up to 1, the operator is forced to prioritize between the criteria. Refer to Table 2.2 for the weightage defined for the case study. In this case, the operator is assume to take a balanced approach where there is equal emphasis between Time to Target and Probability of Hit. There is lower priority for the Remaining battery power criteria as there is lower

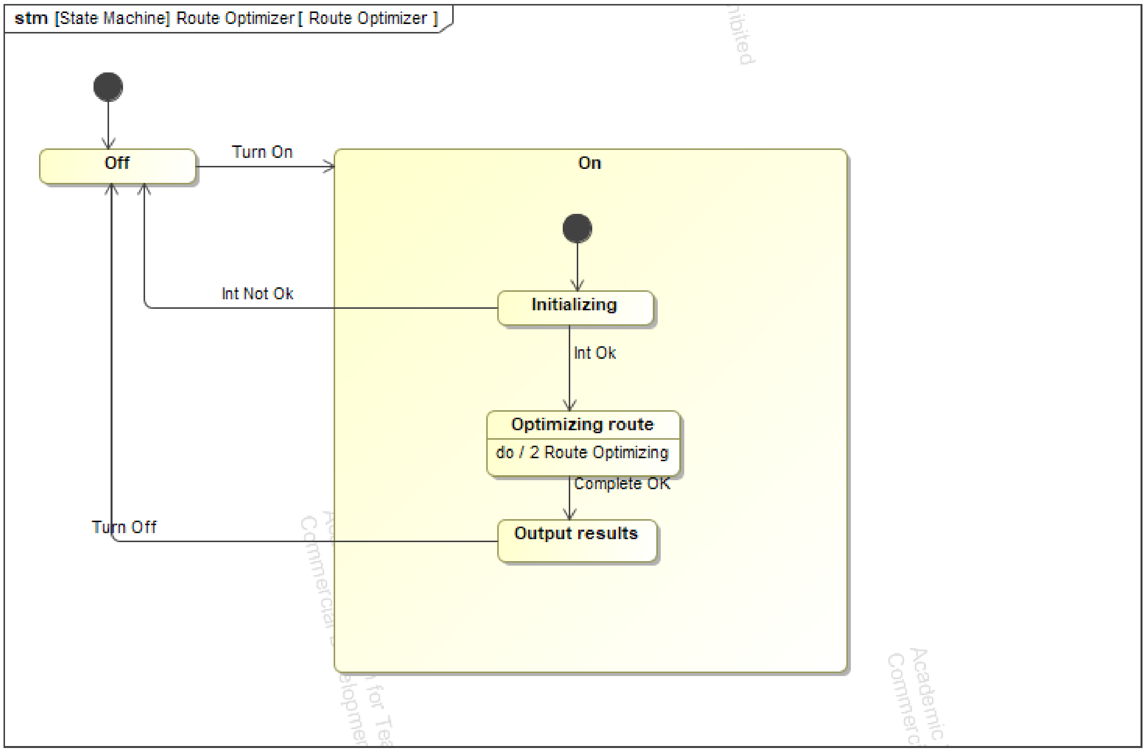


Figure 2.7. UAS route optimization module activity diagram (a)

Table 2.2. User-defined weightage for each of the criteria

Criteria	Risk-attitude weightage
Time to Target	0.4
Remaining battery power	0.2
Probability of Hit	0.4
Sum	1.0

probability for an extended mission.

2.6.6 Conduct of Operations analysis (Step 6)

Figure 2.10 shows the input and output variables from ModelCenter. The green arrows refer to the inputs that ModelCenter requires from the DT, while the red arrows represent the outputs which are calculated. Using the Design-of-Experiment tool embedded within ModelCenter, one can simulate a variety of route distances and threat levels, and validate

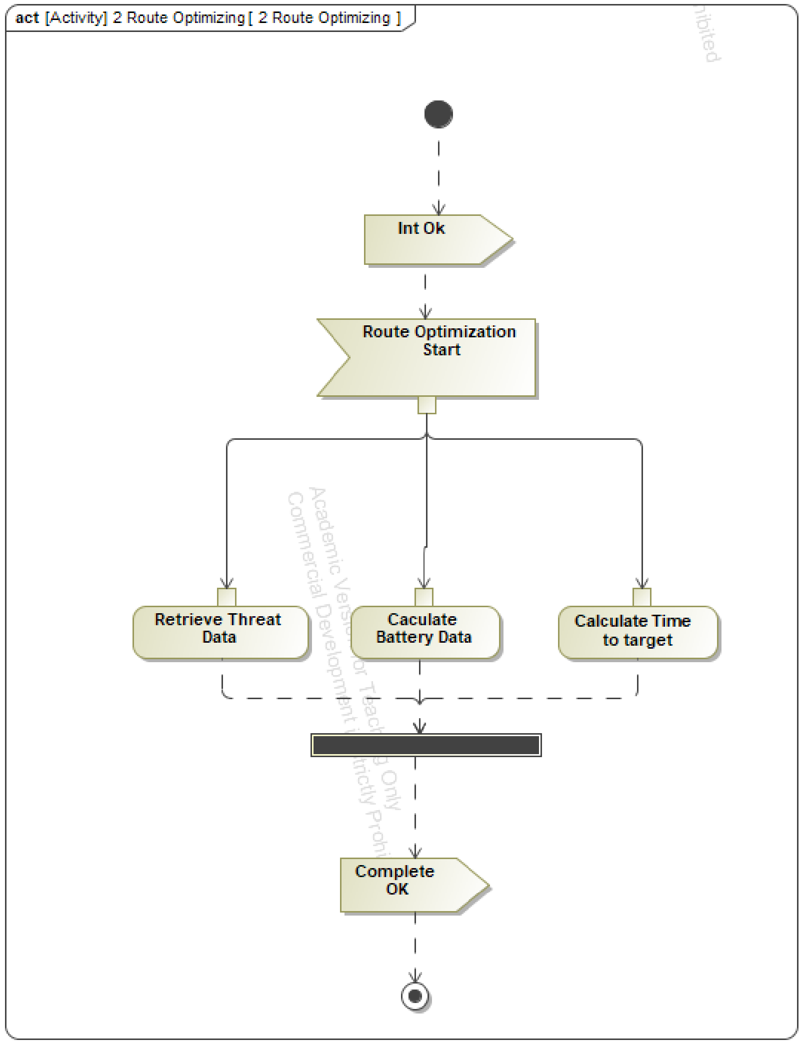


Figure 2.8. UAS route optimization module activity diagram(b)

that the most optimal route with the highest objective value is selected. Figure 2.11 shows an extract of the simulation result. A total of 720 runs are simulated based on a 6 factorial design-of-experiments of the variables. The variables are Route distance A, B, and C, and the Probability of Hit for each route.

To validate the fidelity of the simulation result, we conduct further analysis on of the simulation outcome. Run 417 from Figure 2.11 is selected. We selected Run 417 as it showcases one of the operator's dilemmas in decision-making. That is, the operator's decision between a short and risky route compared to a longer but safer route. The simulation

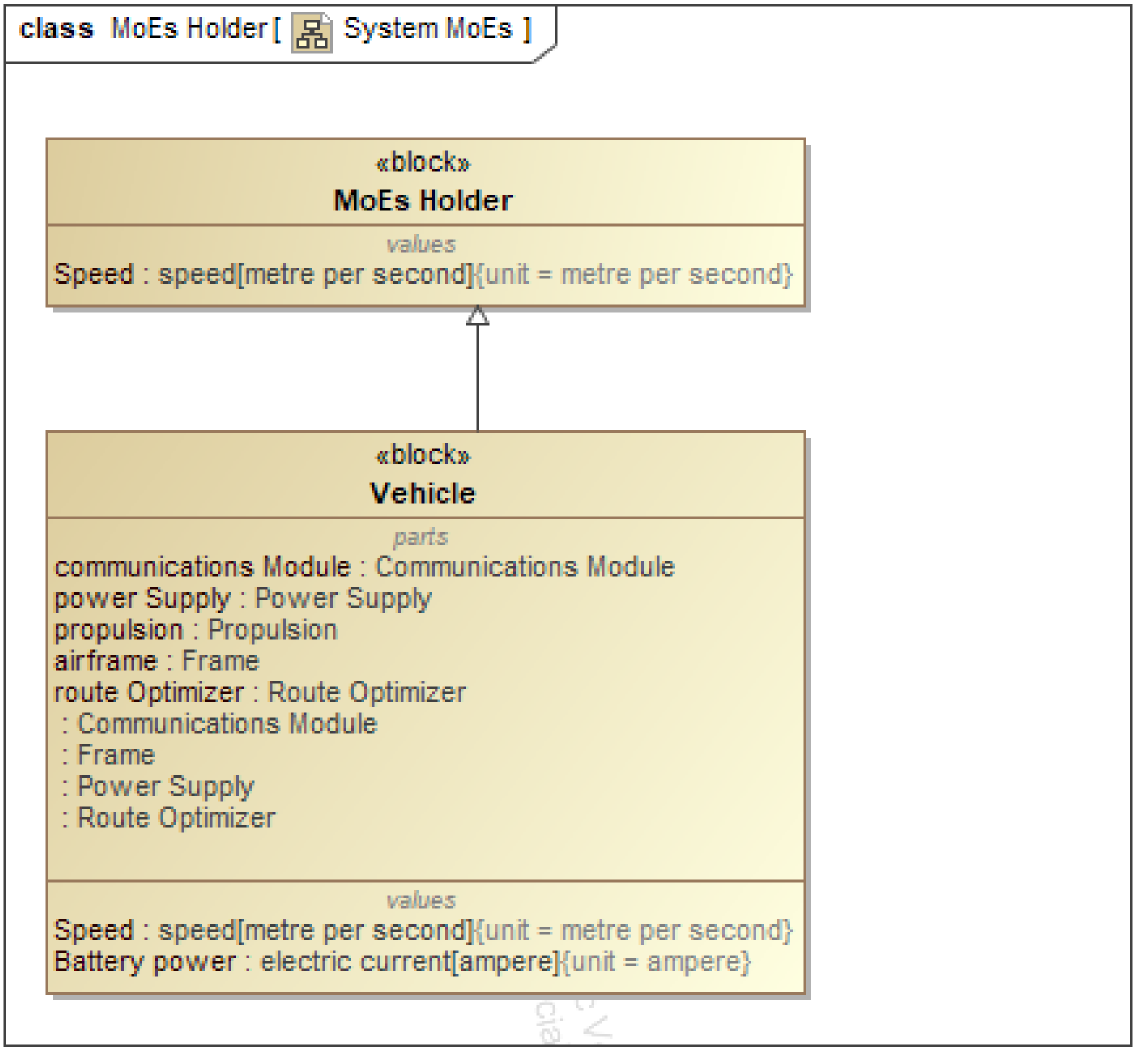


Figure 2.9. Defining MOEs for the UAS

determines Route A to be the shortest at 1000 m, yet with the highest threat probability of 0.4 due to exposure to the adversary's air defense assets. The remaining battery life is a function of the route distance; hence, it is not simulated as unique variable. Route B, on the other hand, is the longest route at 15000 m but has the lowest threat probability at 0.001. Refer to Figure 2.12 for details. The simulation recommends Route B as it has the highest objective function of 0.79569. In this case, Route B is selected despite the UAS having to travel a significantly longer distance and with 1500 percent longer duration compared to Route A. Refer to Figure 2.13 for a validation of ModelCenter's output in excel. If the

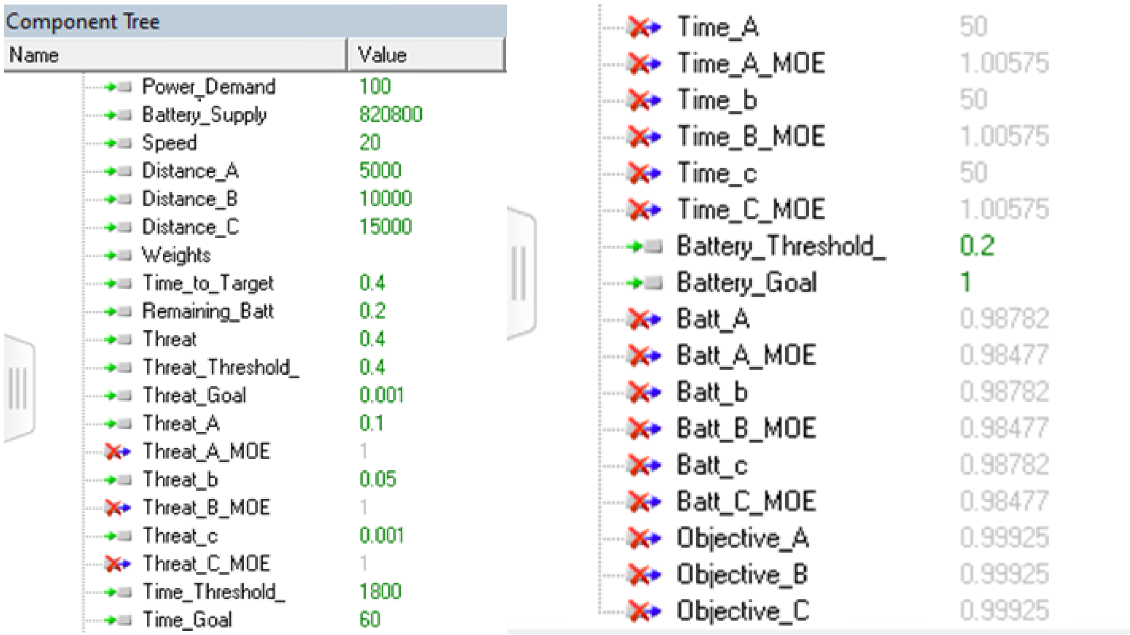
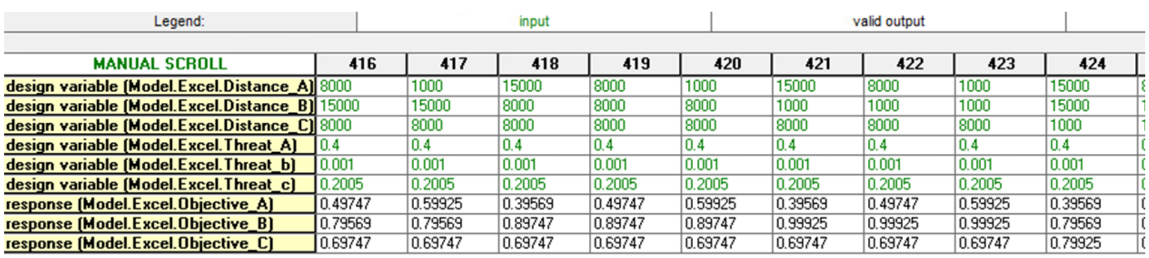


Figure 2.10. Input and output variables in ModelCenter



Legend:	input				valid output				
MANUAL SCROLL	416	417	418	419	420	421	422	423	424
design variable (Model.Excel.Distance_A)	8000	1000	15000	8000	1000	15000	8000	1000	15000
design variable (Model.Excel.Distance_B)	15000	15000	8000	8000	8000	1000	1000	1000	15000
design variable (Model.Excel.Distance_C)	8000	8000	8000	8000	8000	8000	8000	8000	1000
design variable (Model.Excel.Threat_A)	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4
design variable (Model.Excel.Threat_b)	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
design variable (Model.Excel.Threat_c)	0.2005	0.2005	0.2005	0.2005	0.2005	0.2005	0.2005	0.2005	0.2005
response (Model.Excel.Objective_A)	0.49747	0.59925	0.39569	0.49747	0.59925	0.39569	0.49747	0.59925	0.39569
response (Model.Excel.Objective_B)	0.79569	0.79569	0.89747	0.89747	0.89747	0.99925	0.99925	0.99925	0.79569
response (Model.Excel.Objective_C)	0.69747	0.69747	0.69747	0.69747	0.69747	0.69747	0.69747	0.69747	0.79925

Figure 2.11. Extract of ModelCenter simulations

decision is left up to an operator without access to the proposed methodology described in this thesis, one would not be surprised if the decision would have selected Route A or C, which will take a shorter period of time to complete the mission. However, as a result of pre-defined thresholds and the fact that the same risk-attitude weightage is assigned to both Time to Target and Probability of Hit criteria, the recommendation is different.

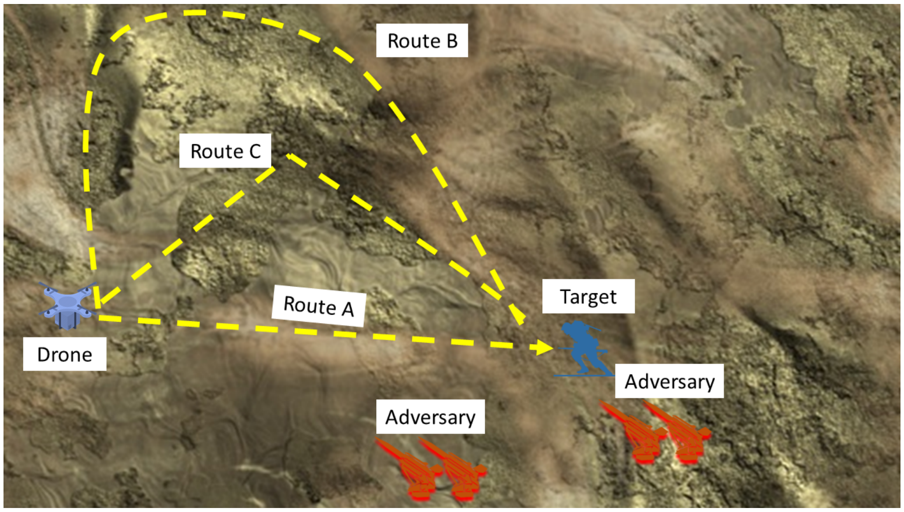


Figure 2.12. Potential routes A/B/C for the UAS to reach the frontline soldiers

2.7 Discussion

We shall now touch on some of the key observations from the development of the DT based on the methodology described in section 2.4 and the results obtained in section 2.6. There are three key observations: (a) Enhance consistency in decision-making, (b) Utility of MBSE software for operations analysis and (c) Importance of data quality. These are explained in the following paragraphs.

First, on enhancing consistency in decision-making, the simulation not only validates the capability of selecting the most optimal route; it also demonstrates an interesting result from the case study. An operator may intuitively select Route A due to its short time to target when under pressure to complete the mission in a dynamic military scenario. However, that may not have been the most optimal decision when evaluated over multiple criteria. Through the definition of risk-attitude weightage prior to operations, the DT and MAUT enhance the quality of decision-making by making them more consistent and traceable. This is especially important if we consider the nature of threat the military faces today with unconventional warfare which involves multiple and ever-changing targets that can be unpredictable. As Figueira and et al. state, decision support tools, such as the one described in this research, contributes to solving conflicts and transforming contradictions [41]. The case study demonstrates the strength and utility of a decision support algorithm.

Raw Data						
		Criteria				
		Time to target	Remaining Battery power	Probability of Hit	Speed	Distance
		Parametric Equation: Distance/ Speed = Time	UAS internal status	External input		
Weight		0.4	0.2	0.4		
Alternatives	Route_A (UAS_1)	50	0.9878	0.4	20	1000
	Route_B (UAS_2)	750	0.8173	0.001	20	15000
	Route_C (UAS_3)	400	0.9025	0.2005	20	8000

Decision Matrix						
		Attributes				
		Time to target	Battery power	Probability of Threat		
		Parametric Equation: Distance/ Speed = Time	UAS internal status	External input	Total Score	Remarks
Weight		0.4	0.2	0.4	1	
Alternatives	Route_A (UAS_1)	1.0057	0.9848	0.0000	0.599253	
	Route_B (UAS_2)	0.6034	0.7716	1.0000	0.795692	Selected Route
	Route_C (UAS_3)	0.8046	0.8782	0.5000	0.6975	

Figure 2.13. Detailed analysis on Run 417 in Excel

Second, while MBSE tools today are capable of performing trade-studies within their software environments, most users still rely on other analytical software to conduct operations analysis on their models. We chose ModelCenter to conduct the design-of-experiment simulations which was not available in the Cameo Enterprise Architecture software. While it is not a limitation in the context of modeling the system, we opine that it would make the process more efficient with the modeling and simulation all done in one environment.

Finally, we assess that decision support algorithms will continue to play an important role in today's context with the proliferation of 4th IR technology such as AI and autonomous systems. However, we note that the quality of data is fundamental to the success of these capabilities. As seen in the case study, the algorithm would recommend the most optimal route based on the data received. And if the data is erroneous, it would impact the decision and thereby impact the mission outcome. As Kunath and Winkler also highlight for the manufacturing industry (an area of study with many similarities to the military), the data quality is low and can rarely be used for simulation-based analysis, which affects the realization of DT. To enable successful implementation of DT in the military context, we should also focus on ensuring the quality of our data.

2.7.1 Future Work

As shown in this thesis, we have demonstrated that the proposed methodology for developing a DT based on MAUT is feasible. Using ModelCenter software as an external toolkit, one is able to conduct simulations to validate the route selection capability of the UAS. Building on this, more complex systems can be developed using the architecture software. This is useful as capabilities are increasingly being fielded as SoS. Thus, we suggest developing DT with more sub and peer systems. Being able to integrate with external analysis software is also beneficial as one would be able to perform more elaborate analysis beyond system architecture issues. This would be useful as one is interested in ME studies which may involve studying system behavior as a function of threat outlook and mission progress. Having said that, system architecting software such as Cameo Enterprise Architecture have also become more capable over the years as they can be integrated with add-in software packages to perform more elaborate studies. Hence system architecting software could also have the potential for detailed simulation capabilities in the future.

2.8 Conclusions

This thesis introduces a proposed methodology to model a system using a DT that is able to enhance mission engineering through a route selection algorithm. The DT model leverages SysML as SysML is assessed to be more suited for the development of system architect and it is widely used in the system engineering field, which supports traceability of system requirements and provides continuity if the model is used for other studies. We also demonstrate that the use of a MAUT algorithm to support operators' decision-making processes enhances the consistency of the decision. This is valuable in dynamic military scenarios when one may have to manage several concurrent LMD missions with an ever-changing threat situation. The DT can be used for mission engineering studies by integrating it with other simulation and analytical software packages. This can support the war-gaming and strategic studies as system behaviors can be simulated based on the user's inputs. As systems become more complex and interconnected in the 4th IR, the ability for humans to match the speed and capability of computers and machines is being stretched. Thus, the concept of DT and decision support algorithms to assist humans in conducting his mission is one that is valuable and should be further explored.

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CHAPTER 3:
Conclusion

This chapter summarizes the key observations and findings from the research conducted for this thesis. In addition, it highlights the potential applications for MBSE and DT in the military context. Lastly, it describes other areas of future work that can build on the research conducted in this thesis beyond what was discussed in Chapter 2.

3.1 Conclusion

With increasingly complex combat environments, the use of multiple drones in operations, and the rise of unconventional warfare, it is increasingly challenging for operators who are required to conduct multiple mission and operate multiple assets simultaneously [51]. The employment of models and DT to enhance operators' decision support processes serves to ease the load and help operators to focus on mission planning, which can have a positive impact on mission success. The results obtained from the this research has demonstrated that the methodology is able to (1) create a workable DT that is a suitably accurate reflection of the system of interest and (2) support the operator's decision-making process and enhance the quality of the decision.

Beyond verifying the methodology, the results of the case study also highlight three key observations.

3.1.1 The model enhances consistency in decision-making

Through the definition of risk-attitude weightage prior to operations, the DT and MAUT enable the decision to be more consistent and traceable. We are able to prevent human-factors such as having "missionitis" – which refers to an operator being overly fixated on accomplishing the mission [52]. With a quantifiable method of decision-making, it also supports traceability and allows for further optimization in subsequent operations to enhance mission outcomes.

3.1.2 There is utility in MBSE software for operations analysis

I observe that while MBSE software has expanded its capability to be able to conduct trade-studies, many users continue to rely on other external software to conduct operations analysis and simulations. Coincidentally, Cloutier and Obiako report in their survey that while MBSE has recorded an increasing influence in various industries, the perceived value of MBSE by software engineers declined from 2012-2018 [53]. In this regard, I assess that MBSE software should continue to improve its user-friendliness and capabilities if it is to serve as a end-to-end solution for a system's cradle to grave life cycle.

3.1.3 Importance of data quality

It is important to note that that minute differences from risk-attitude weightage to data inputs for each criteria can have a significant impact in the final decision recommendation. Hence there is a need to ensure the data input into the models are accurate and clean.

To this end, the thesis has demonstrated the benefits of using MBSE methodology to develop a DT that can support route selection for a UAS conducting LMD mission. The same methodology can be applied to other similar military operations, for instance for Unmanned Ground Vehicless (UGVs) and Unmanned Underwater Vehicless (UUVs). The idea is to support asset route selection which may enhance the probability of mission success based on the user's risk-attitude. With increased interest in the use of autonomous systems for military operations, the development of DT will be be useful for the system during the various phases of its life-cycle. During the system development phase, the model can be used for developmental test and evaluation. During operations and support phase, an engineer or operator can continue to use the model for warfare simulation and operational decision support. Additionally, the use of a multi-criteria based decision analysis for route selection can also be employed on other military missions such as for Humanitarian Assistance and Disaster Relief (HADR) missions. In a HADR mission area where a system is often exposed to environmental threats with limited resources, the use of MAUT to support route selection decisions may enhance the consistency in decision-making. These benefits are likely to be compounded if engineers and operators do deploy autonomous systems for HADR missions in the future.

3.2 Future Work

As discussed earlier, applications of MBSE and DT is likely going to proliferate further in military organisations as the push for digital transformation efforts continues. For the purpose of this study, the Cameo Enterprise Architecture software was used to develop the UAS model but the same process can be explored using other software packages such as Core or Capella. From the systems perspective, engineers can continue to build more a elaborate UAS DT which encompass more sub-systems. This would allow systems engineers to conduct a wider variety of simulation and design-of-experiments to evaluate the performance of each sub-system and how it impacts route-selection. In relation to the other potential applications mentioned in the previous section (Section 3.1), other UGV or UUV models can be built for a slightly varied mission and operating environment while following the methodology described in this thesis. It may also be useful to explore integrating system models with more complex programs such as Matlab or Java, which has the capability for visualizing the routes and over-laying actual maps.

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