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DEVELOPING COMPUTATIONAL RESOURCES AND DATA CENTER ALTERNATIVES TO SUPPORT TRAC-MONTEREY MODELING AND SIMULATION

by

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13. ABSTRACT (maximum 200 words)

This capstone project at TRAC-MTRY focuses on developing efficient post-processing and data storage solutions for combat simulations, addressing challenges in data management and access. Employing a systems engineering approach, the study explores a hybrid system combining on-premise high-performance computing (HPC) and cloud-based solutions, aiming for optimal scalability, reliability, and security. Alternatives generated through General Morphological Analysis (GMA) include on-premises HPC, cloud-based solutions, hybrid models, and edge computing. The project features a detailed functional decomposition, examining sub-functions like data preconditioning, compression, storage, verification, and retrieval. Evaluation criteria encompass scalability, accessibility, availability, cost, and security, guiding the assessment of each option's feasibility in alignment with TRAC-MTRY's objectives.

Findings indicate that while each alternative has merits, trade-offs exist in cost-effectiveness, scalability, and integration ease. The project offers insights into system requirements and viable solutions. Future research recommendations involve process accuracy analysis and further evaluation of identified alternatives. The recommended solution is a cloud-based approach, considering stakeholder constraints. Potential cloud options include Microsoft Azure, Amazon Web Services, and the Army Research Laboratory High-Performance Computing Center, all affiliated with the Department of Defense.

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ABSTRACT

This capstone project at TRAC-MTRY focuses on developing efficient post-processing and data storage solutions for combat simulations, addressing challenges in data management and access. Employing a systems engineering approach, the study explores a hybrid system combining on-premise high-performance computing (HPC) and cloud-based solutions, aiming for optimal scalability, reliability, and security. Alternatives generated through General Morphological Analysis (GMA) include on-premises HPC, cloud-based solutions, hybrid models, and edge computing. The project features a detailed functional decomposition, examining sub-functions like data preconditioning, compression, storage, verification, and retrieval. Evaluation criteria encompass scalability, accessibility, availability, cost, and security, guiding the assessment of each option's feasibility in alignment with TRAC-MTRY's objectives.

Findings indicate that while each alternative has merits, trade-offs exist in cost-effectiveness, scalability, and integration ease. The project offers insights into system requirements and viable solutions. Future research recommendations involve process accuracy analysis and further evaluation of identified alternatives. The recommended solution is a cloud-based approach, considering stakeholder constraints. Potential cloud options include Microsoft Azure, Amazon Web Services, and the Army Research Laboratory High-Performance Computing Center, all affiliated with the Department of Defense.

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LIST OF ACRONYMS AND ABBREVIATIONS

ARL	Army Research Lab
ARM	advance RISC machine
ASA (ALT)	Assistant Secretary of the Army (Acquisition, Logistics, and Technology)
CPU	central processing unit
DCAEP	Data Center Analysis and Evaluation Process
DCAEP-M	Data Center Analysis and Evaluation Process Model
DIS	Distributed Interactive Simulation
DISA	Defense Information Systems Agency
DOD	Department of Defense
DoS	denial of service
ECMA	Enterprise Cloud Management Agency
FFBD	Functional Flow Block Diagram
GB	gigabyte
GMA	General Morphological Analysis
GPU	graphical processing unit
HLA	High-Level Architecture
HPC	high-performance computing
HQDA	Headquarters Department of the Army
IaaS	Infrastructure as a Service
ICOM	Input Controls Outputs Mechanism
IISc	Indian Institute of Science
IL	Impact Level
IL6	Impact Level 6
LAMMPS	Large-Scale Atomic/Molecular Massively Parallel Simulator
M&S	modeling and simulation
MTBF	mean time between failure

NIST	U.S. National Institute of Standards and Technology
PaaS	Platform as a Service
RDMA	Remote Direct Memory Access
RTO	recovery time objective
SaaS	Software as a Service
SERC	Supercomputing Education and Research Center
SMART	specific, measurable, achievable, realistic, timely
SOI	System of Interest
STEM	science, technology, engineering, mathematics
SWOT	strength, weakness, opportunities, and threat analysis
TB	terabyte
TENA	Test and Training Enabling Architecture
TRAC-AFC	The Research and Analysis Center – Army Future Command
TRAC-MTRY	The Research and Analysis Center – Monterey
TRADOC	U.S. Army Training and Doctrine Command
VELaSSCo	Visual Analysis for Extremely Large-Scale Scientific Computing
VM	virtual machine

EXECUTIVE SUMMARY

I. Introduction and Background

The Research and Analysis Center – Monterey (TRAC-MTRY) faces a critical challenge in continuing its modeling and simulation activities due to impending data center closure and insufficient computational and database resources. Capability gaps resulting from the closure of TRAC-MTRY's data center will adversely impact significant Army research programs that TRAC-Monterey supports. This capstone project sought to provide a solution to these challenges by developing a set of postprocessing and data storage alternatives for combat simulations in support of TRAC-MTRY, while also analyzing appropriate measures to compare alternatives. This study also sought to address these research questions:

1. How does the computational performance differ across the alternatives for postprocessing, considering Army Research Laboratory high performance computing (ARL HPC) and commercial cloud service providers facilitated by Enterprise Cloud Management Agency (ECMA) or Cloud Army, regarding speed, scalability, and reliability?

2. What are each alternative's capacity limits and scalability for postprocessing and data archiving, and the impact on long-term feasibility?

3. How do the ease of use and accessibility to postprocessing and archive data compare to alternatives?

The study produced an objective hierarchy, functional decomposition, morphological analysis, SMART metric evaluation, and qualitative comparisons to judge alternatives against explicit system requirements rooted in life cycle costs, scalability, availability, and total cost of ownership. The team provided analysis and insights to support informed decision-making regarding postprocessing alternatives for TRAC-MTRY. The project did not aim to address solution implementation or data center management.

II. Literature Review

The team used the review of the literature to examine prior research related to TRAC-Monterey's efforts to determine post-processing and data storage alternatives for its modeling and simulation (M&S) activities. The team conducted a literature review using credible sources from multiple scholarly databases, libraries, and open-source websites using journals, articles, published research, books, Army doctrine, and meeting minutes. The review covers data center requirements for M&S, including hardware, software, infrastructure needs, and personnel considerations.

The review highlights the generation of "big data" from military simulations and the limitations of legacy information technology (IT) systems in managing large, complex datasets. A review of past work has been conducted on cloud computing and high-performance computing (HPC) solutions, which are considered more flexible and lower-cost options for data centers. They offer better scalability and processing speed. However, organizations must balance their processing throughput needs with accessibility, costs, and user requirements. The literature review concluded with an observation of the gaps in the research related to M&S post-processing when using the ARL HPC Center, Cloud-Army, and a hybrid course of action that uses ARL HPC and Cloud-Army.

The team conducted prior research on approaches such as traditional project management, agile development, and lean principles to gain knowledge and understanding of which process to use to develop alternatives. The Systems Engineering Process, which includes methodologies like the Vee model, requirements analysis, functional decomposition, and interface management, was considered a viable process for the capstone. The team determined that systems engineering offered a comprehensive and integrated approach that utilizes specific methodologies to provide a structured and adaptable framework. This approach effectively addresses the technical complexities and aligns with the operational and strategic dimensions of TRAC-MTRY's unique challenges.

III. Methodology

The capstone team used a comprehensive methodology for developing a post-processing and data storage system for TRAC-MTRY, utilizing a system engineering approach with the “Vee” model as the foundation. This approach begins with an in-depth stakeholder analysis to identify and prioritize the needs and requirements of all parties involved. This step is crucial for framing the system’s objectives and ensuring that the development of the system aligns with stakeholder expectations. Following this, the methodology involves defining the system’s functions and boundaries using the Input, Output, Controls, and Mechanisms (ICOM) model, accompanied by context diagrams for clarity. A detailed functional decomposition is then conducted, breaking down the system into manageable parts to ensure comprehensive coverage and clarity in system design and limits. An objectives hierarchy, informed by the stakeholder analysis, is developed next. This hierarchy serves as a guiding framework for establishing both functional and non-functional requirements of the system, ensuring that the final design aligns with the overarching goals.

The conceptual design phase employs Function to Component Tracing to match each system function with an appropriate component, facilitating effective system verification and validation. Additionally, General Morphological Analysis (GMA) is used to generate feasible data storage alternatives, systematically exploring different combinations and approaches. The development of alternatives includes an infeasibility analysis to eliminate impractical options. Finally, the methodology proposes criteria for evaluating the feasibility of the alternatives, focusing on scalability, accessibility, availability, and total cost. This ensures that the selected solution not only meets the stakeholder requirements but also remains practical and cost-effective.

Overall, this methodology emphasizes a structured, stakeholder-focused approach to ensure development of data storage system alternatives that are both efficient and aligned with user needs. This methodology allowed the team to systematically generate metrics, measures, and alternatives that TRAC-MTRY can use to evaluate potential options.

IV. Analysis

To aid TRAC-MTRY in determining an efficient process, the team focused on identifying the system and developing measures that TRAC-MTRY could use to determine viable solutions. Our analysis defines the system and its function and identifies performance measures derived from requirements.

During the identification of system requirements, we conducted stakeholder analysis and system definition to ensure clarity and accuracy. A thorough analysis was conducted to understand stakeholders' needs, requirements, and objectives, leading to a clear understanding of their priorities. The analysis differentiated between internal and external stakeholders, emphasizing TRAC-MTRY, M&S teams, and COMBAT XXI developers as primary stakeholders with high interest and influence on system requirements. The primary requirements focused on a system for evaluating post-processing and data storage alternatives, prioritizing availability, accessibility, and performance.

In congruence with the stakeholder analysis, we defined the post-processing and data storage system as the physical and non-physical infrastructure required to process COMBATXXI modeling and simulation data derived from realistic operational scenarios directed by Army Futures Command. The system, visualized through the ICOM model, must process extensive data, and store it for future use by TRAC-MTRY data analysts. This definition sets the foundation for developing a robust and efficient system tailored to meet specific data management requirements. The system's scope is also defined, including its boundaries, interfaces, and requirements for compliance with broader institutional requirements.

The analysis describes the system's boundaries and interfaces, including its top-level function to process and store modeling and simulation data for TRAC-MTRY. Primary external interfaces include the Headquarters, Department of the Army (HQDA) and the Defense Information Systems Agency (DISA), significantly impacting the system's viability and compliance. This highlights the importance of integrating the system within the existing organizational structure and ensuring adherence to broader institutional requirements.

The functional breakdown of the system is explained using three tools: a decomposition hierarchy diagram, a hierarchy table, and a Functional Flow Block Diagram (FFBD). It covers seven high-level functions and 19 sub-functions, detailing each function's role in the system's operation, specific roles in processing, and storing data.

The objective hierarchy involves organizing objectives, with higher-level objectives representing broader goals and lower-level objectives representing more specific, actionable targets that support achieving the higher-level objectives. The hierarchy covers performance, accessibility, availability, and cost, detailing each objective's subfunctions and their contribution to the system's goals—a direct translation from the stakeholder analysis. Subfunctions under these objectives were specified, highlighting their contribution to achieving the overarching system goals.

After the objective hierarchy was complete, the team developed a Function-to-Component matrix where the team identified the relationship between functions and physical components required for post-processing and storage. The team identified 31 components commonly used to complete the seven functions specified for post-processing and storage. The team condensed the component list down to eight essential components due to the team's capacity (knowledge, time, and resources) to analyze the components for the GMA.

The GMA explores possible configurations for each system component, presenting various subcomponents and their roles. This analysis aids in developing a flexible and adaptable system capable of accommodating various operational scenarios and requirements. The possible configurations include server options, which differ in control and speed, central processing units (CPUs) with unique processing strengths, graphical processing units (GPUs) that vary from high performance to cost-effective, storage options with varying accessibility and security, user interfaces tailored to different interaction styles, and various security levels.

Finally, an analysis of feasible and infeasible components and configurations was conducted. This analysis identified cloud-based and hybrid on-premises/cloud solutions as feasible, considering factors like DOD compliance, scalability, and cost. The analysis concludes by discussing viable alternatives like the Army Research Laboratory High-Performance Computing Center, Amazon Web Services, and Microsoft Azure.

V. Conclusion

The team's use of a tailored systems engineering process led to the identification of two primary solutions: a cloud-based infrastructure capable of handling top-secret material and a hybrid system combining on-premises and cloud technologies. The cloud-based solution is favored for its scalability, availability, and performance flexibility, while the hybrid system, despite its scalability, requires more internal support, affecting long-term viability.

Performance measures initially centered around latency, throughput, and speed were re-evaluated in favor of scalability, accessibility, availability, and costs. This shift aligns better with TRAC-MTRY's operational needs and stakeholder priorities. Comparative analysis revealed that while Army Research Laboratory High-Performance Computing Centers (ARL HPCs) matched current scalability levels, Amazon Web Services (AWS) and Azure showed significant improvements, especially over the hybrid option, which faces feasibility challenges in the long term.

The project encountered limitations in expertise, resource availability, and time, limiting the depth and breadth of analysis. The lack of subject matter knowledge and restricted access to historical data impeded a complete understanding of the existing system. As a result, some conclusions might not fully capture the system's specific challenges, indicating a need for enhanced data access in future projects. The capstone timeline prevented exhaustive exploration and testing of all alternatives to ensure comprehensive evaluations and feasibility assessments. The limitations can be addressed in future work on the capstone project.

The team recommends a cloud solution based on preliminary research of the system and considering the stakeholder constraints and limitations. The potential options identified are Microsoft Azure, AWS, and ARL HPCs. Future work should extend the evaluation of the proposed solutions, utilizing SMART measures, value models, and decision matrices for deeper analysis. Simulating performances of these alternatives and benchmarking them against TRAC-MTRY's current system will provide more comprehensive insights. The team's process, tailored specifically for TRAC-MTRY's challenges, also warrants further assessment for accuracy and efficiency in future projects.

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I. INTRODUCTION AND BACKGROUND

A. BACKGROUND AND PROJECT SCOPE

The Research and Analysis – Monterey (TRAC-MTRY) organization faces a significant challenge in maintaining one of its primary lines of effort: Advance Models and Simulations (Wade and Jablonski 2023). Hindered by insufficient computational and database resources given the impending closure of their data center, their ability to conduct analysis on modeling and simulation (M&S) activities, including processing and postprocessing data, has been severely impacted. On a macro level, the diminished capacity of TRAC-MRY to conduct M&S will critically affect significant Army research and analysis efforts, as their mission is to "conduct novel, relevant and credible applied research to advance military operations analysis" in support of the Assistant Secretary of the Army (Acquisitions, Logistics, and Technology) (ASA [ALT]), and the Department of Defense (DOD) (Wade and Jablonski 2023, 6).

Modeling and Simulation necessitate extensive computational power and robust databases for management and storage (Coll 2016). A typical M&S process involves (1) a user uploading collected data to software for running a simulation or model to understand better the data, usually in a visual format, otherwise known as processing; (2) the software, running on a server, extrapolating results and information from the model or simulation to generate new information, otherwise known as postprocessing (Coll 2016, 4). Although straightforward, these comprehensive processes can take from a few hours to a week, even with modern technology. Moreover, the input data often undergo substantial transformations in data units (e.g., 100 megabits to 1 gigabit). This large data set must be stored for retrieval. Thus, time efficiency, how quickly the data can be processed, and data management, how the user can extract and store the data are two primary concerns that adequate computational and database resources will resolve. The lack of computation and database resources is caused by two main components, resources, and organizational structure.

TRAC-MTRY is in the early stages of planning for the termination of its data center. The challenge is exacerbated by the need for more resources to execute M&S instead of the TRAC-funded on-premises (on-prem) data center on the Naval Postgraduate School campus. TRAC-MTRY does not have the financial means to upgrade and sustain an on-prem data center for M&S activities, the personnel or capacity to operate and maintain an on-prem data center, cutting-edge technology for enhanced M&S efficiency, and faces competition for computational and database resources from other organizations, effectively undermining time, and data management optimization.

To investigate potential root causes, the team developed Figure 1, an Ishikawa diagram. This diagram allows the team to break down the various elements of an organization, including its technology, resources, and infrastructure, to identify key areas of concern.

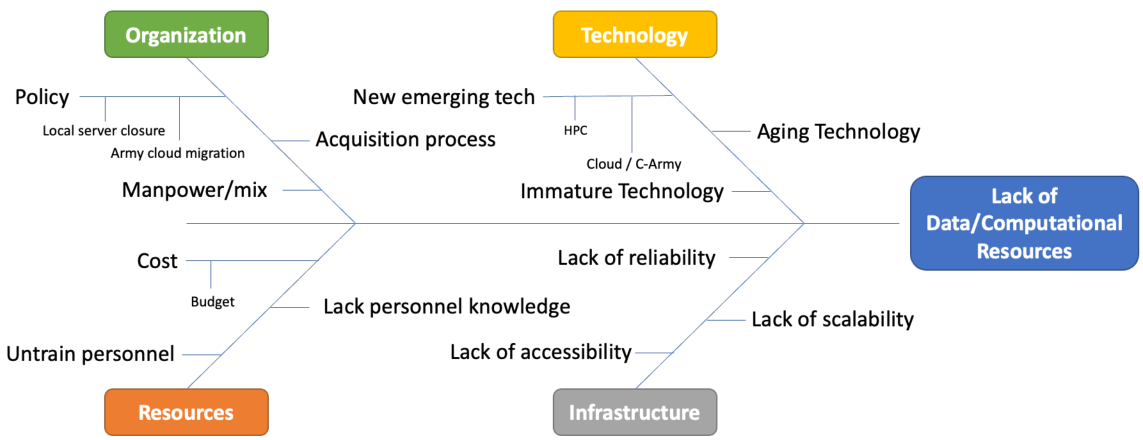

Figure 1. Ishikawa (Fishbone) Diagram

During the initial meetings with stakeholders, we made a point of focusing on these four key areas, recognizing their importance in determining the root causes of any issues we may encounter. As we moved forward with the analysis in Chapter III we utilized the Ishikawa diagram once again to illustrate how these various factors interacted with one another in the TRAC-MTRY system. Through this approach, the team were able to gain a more detailed understanding of the underlying factors impacting the performance of the system and develop a comprehensive plan for addressing them moving forward.

B. PROJECT OBJECTIVE

This project aims to develop a set of postprocessing and data storage alternatives for combat simulations in support of TRAC-MTRY. Considering both cloud environments' computational performance and feasibility, the aim is to evaluate the following alternatives: the Army Research Lab (ARL) High-Performance Computing (HPC) Centers or commercial cloud environments. This study will address the main question, what are the appropriate measures to compare alternatives and the following sub-questions:

1. How does the computational performance differ across the alternatives for postprocessing, considering ARL HPC and Commercial Cloud Service Providers facilitated by Enterprise Cloud Management Agency (ECMA) or Cloud Army, regarding speed, scalability, and reliability?
2. What are each alternative's capacity limits and scalability for postprocessing and data archiving, and the impact on long-term feasibility?
3. How do the ease of use and accessibility to postprocessing and archive data compare to alternatives?

The initial hypothesis, drawing from the literature review and multiple stakeholder meetings, is that postprocessing and data archiving on ARL HPCs will provide a more efficient computational performance and cost efficiency but will have limitations regarding accessibility and user-friendliness. This hypothesis will transform into quantifiable metrics as our research unfolds.

The final deliverable is an analysis methodology recommendation for TRAC-MTRY to assess the best postprocessing and data storage system. This provides TRAC-MTRY with the relevant insight needed to decide which data center alternative to transition to. This will be based on which option meets their requirements, providing better performance and a granular cost-benefit analysis to support the decision.

1. Scope

The project entails identifying the requirements necessary to address the capability gap due to the imminent closure of TRAC-MTRY's data center. This will involve analyzing the M&S process, establishing the lack of computation and database resources, and evaluating the financial and personnel resources required to upgrade and maintain a migration (Analysis of Alternatives) to the Cloud (cArmy), utilization of Army Research Lab HPC center, or a hybrid solution where the M&S occur on HPC and postprocessing and storage of data on the cArmy. It is important to note that the project does not encompass implementing the recommended solutions or managing the on-premises data center.

2. Risks and Limitations

The experimental research method has several risks and limitations. The project team does not have a background in modeling and simulation. TRAC-MTRY was the facilitator for combat simulations relevant data for the project team to analyze. This is a risk because we need to rely on subject matter experts with full-time duties. Another potential risk is the availability and accessibility of the required computational and database resources for conducting the experiments. Limited resources may affect the scalability and generalizability of the findings. Another limitation is the potential bias introduced by the sample size and selection of participants for the qualitative data collection. The project team is also limited by time and funding if resources are unavailable locally and travel is needed. Moreover, the experimental scenarios may not fully capture all real-world complexities, which could impact the generalizability of the results. By employing an experimental research method, this study aims to provide empirical evidence and insights to guide the decision-making process regarding the future computational and database resources for TRAC-MTRY's modeling and simulation activities.

3. Benefit of Study

The stakeholders can expect analysis and insights to enable informed decision making regarding post-processing alternatives for TRAC-MTRY. The stakeholders can expect a comprehensive comparison of the alternatives with respect to performance optimization, cost reduction, and resource allocation. TRAC-MTRY, Army Futures Command, COMBATXXI, and NPS faculty and students are expected users of the project results.

The expected formal products include an objective hierarchy, functional requirements decomposition, morphological box and analysis, SMART Analysis, infeasibility diagram, and a initial set of alternatives for TRAC-MTRY to consider. It also contains a detailed comparison of post-processing data storage alternatives with determined metrics, and a final capstone report, presenting arrived conclusions and recommendations. The stakeholders are expected to review the analysis and leverage the results/findings to implement a feasible post-processing process for TRAC-MTRY modeling and simulations data. The stakeholders are expected to use the findings in future related research efforts for TRAC post-processing processes.

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II. REVIEW OF PRIOR WORK

The team conducted a literature review using credible sources from multiple scholarly databases, libraries, and open-source websites using journals, articles, published research, books, Army doctrine, and meeting minutes. At the conclusion of the literature review the team discovered gaps in the research related to M&S post processing when using the ARL HPC Center, the Army's ECMA, and a hybrid course of action that uses ARL HPC and Army's ECMA. The team's research will aim to fill those gaps and assist with developing a process to analyze data center alternatives. The review of the literature is divided in three sections: TRAC- MTRY M&S, Computational and data infrastructure requirements, and M&S tools.

A. TRAC-MRY M&S

1. Data Center Requirements for M&S

The hardware, software, data, infrastructure, and other resource requirements for M&S are important to understand when comparing options to enable TRAC-MTRY to accomplish its mission. Understanding data center requirements for modeling and simulations is important not only for TRAC-MTRY but also for the other DOD organizations.

Kerravala's (2020) article, "What are Data Centers," defines the composition, architecture, and standards for data centers. The author defines a data center "as a physical facility that enterprises use to house their business-critical applications and information" (Kerravala 2020, 1). The article is valuable to this research efforts as it defines the core functions of the data center into three categories "compute, storage, and networking" (Kerravala 2020, 1). Identifying the core functions is vital to determining the measures to examine and compare the post-processing alternatives against.

The Army Science Board (2021) conducted a study on Modeling and Simulations (M&S) to assess and determine M&S "capability needs, gaps, state-of-the-art capabilities external to the Army that can be leveraged to close the gaps, and how the Army is organized and manages talent to meet its M&S needs in support of support of strategic decision making, acquisition, training, and test and evaluation" (Army Science Board 2021, 1). The study highlighted that many M&S tools were outdated and designed up to three decades ago for a different threat environment. It also highlights the consequences of the inability to model future threats, including "being unprepared, systems failing due to inadequate development, and losing DOD and Congressional leadership confidence in Army assessments and capabilities" (Army Science Board 2021, 2), as well as references the Army cloud strategy that shifts from traditional data centers to cloud alternatives and provides context to M&S development needs ranging from modeling, data management, talent management, resources, and policy. The article illustrates the need to leverage technological advancements to progress M&S capabilities to take advantage of the commercially available technology to avoid obsolescence. Figure 2 depicts modeling and simulation capabilities from the 20th through 21st century and the lack of modern technology for the force of the future. According to the report, "the future operating environments that address peer military capability are not reflected in Army simulators" (Army Science Board 2021, 12). According to the report, "the future operating environments that address peer military capability are not reflected in Army simulators" (12).

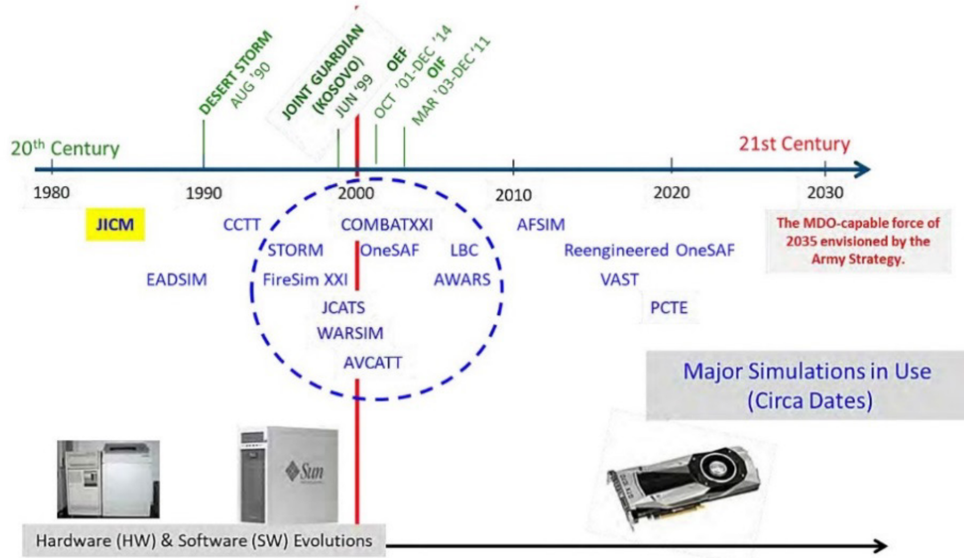

Figure 2. Overview of M&S Technology from 20th Century to 21st Century
Source: Army Science Board (2021).

The Army Science Board report identifies talent management as a need. Personnel are required to conduct M&S and maintain data centers. Clearance, training, and educational requirements are associated with the operations at a data center. The report identifies a potential shortage in Army's "STEM expertise to model multi-domain operations," there is no mandated quota for the larger officer commissioning sources (Army Science Board 2021, 6). Personnel training, clearance, and educational requirements are important to analyze and understand as it has implications for the available pool of applicants, the time required for training, and the cost. In addition to the personnel required to manage the IT infrastructure, personnel are required to maintain and secure the facilities.

Enterprise Cloud Management Agency (2022) published the cloud plan strategy that describes the efforts of the Army to modernize and leverage cloud technology to reach the Army objectives. The strategy outlines the plan to reduce data centers with planned closures of seven, bringing the remaining data centers to five (Enterprise Cloud Management Agency 2022, 3). The strategy outlines the intent for "data centers to migrate an on-premise data center to cArmy and on certain instances allowing applications to remain on-premises in a private cloud" (Enterprise Cloud Management Agency 2022, 4). This strategy is relevant to our research efforts as it provides potential constraints to the post-processing alternative when comparing on-premise, HPC, and cloud solutions.

The demand for digital data affects the data centers through increased demands. Rădulescu, Rădulescu, and Lazaroiu (2018) outline metrics in the article that can be used to measure the efficiency of data centers. The article is relevant to research efforts as it identifies the hardware, infrastructure, and environmental requirement consideration for a data center. The article identifies the growing energy consumption due to constant energy-intensive data center operations. This is an important metric and requirement related to other factors, such as cost and environmental impacts. The metrics identified can be used to "measure and compare performance and energy efficiency of data centers" to the alternatives of cloud solutions, on-premises, and hybrid solutions (Rădulescu, Rădulescu, and Lazaroiu 2018, 609).

2. Military M&S Big Data

Modeling and Simulation is a field utilized by private-sector businesses, enterprises, healthcare sectors, and the military to study and analyze complex problems and situations. M&S typically generates large amounts of data due to the number of replications or complexities of the simulation model, mostly known as "big data." Military simulations generate large amounts of data mainly because of the complexity of the scenarios and the large-scale simulations; the big data that emerge from these simulations are extensive. M&S big data can have a variety of usages, but in the Military, "It is used to study complicated problems such as weapon systems acquisition, combat analysis, and military training" (Song et al. 2015, 1). Combat simulations are utilized for planning purposes giving the Combatant Commander different scenarios and enough data to make informed decisions. The data can contain information about units and weapon systems' performance during operations and missions in different environments, according to Guo et al. (2016).

Song et al. (2015) and Guo et al. (2016) agree that the characteristics of the big data generated by combat simulations are extensive and continually increasing. They recognize the high amount, fast development, and variety of formats of files that military M&S produce and that traditional parallel computing cannot facilitate data management (processing and storage) of the datasets. They both recognize the limitations on performance and scalability that traditional IT infrastructures possess in managing big data and being unable to grow with the velocity of combat military M&S. Even when this is a constraint and a limitation to the performance of military simulations on local data centers, TRAC-MTRY has an internal process that has been working for them for years. The Army has decided to migrate to the cloud (cArmy). Given the requirements of running complex, high-resolution simulations with many replications that generate a large amount of data that needs to be processed and stored for military M&S. TRAC-MRY is in a position to find the best solution for their military M&S section migration from the legacy system (local servers).

TRAC-MTRY has different options, (1) to utilize ARMY HPCs where they have already seen a performance increase (develop faster simulations runs), (2) use the Army HPCs to run the simulations and utilize the cloud for post-processing and storage of data, or (3) migrate entirely to the cloud where they do not have any experience on how the simulations will run. One thing we know that is constant, mainly with military simulations on HPCs, is that higher resolution and simulation speed can generate even larger datasets faster. According to Song et al. (2015), the amount of data or volume that creates an HPCs being more efficient in running the replications of military simulations creates challenges for data management and data processing. He mentioned two challenges that are an area of concern; one is the effort that has been put into the requirements for the performance of this simulation and little to none to the processing of the simulations; second, he focuses on the requirements emergence for the military simulations big data and the limitations of legacy systems and traditional technologies or data centers.

In Table 1, we can appreciate that most simulations generate data in GB and TB. And in some cases, the velocity is only 1 second to generate extensive large amounts of data files. This creates data collection and processing issues because of the number of resources consumed to provide the processing and analytics of the data.

Table 1. Military Big Data Simulations Data Generation Adapted from Song et al. (2015).

Overview of military big simulations

(a) Simulation related properties

Cases	Simulation Level C	M	E	G	The number of entities	The number of simulation replictions	Model resolution	Time advancing	Simulation execution time
Joint forces experiments	✓	✓	✓		Millions	Several	High	Real-time	weeks
Data farming projects	✓	✓	✓		Dozens~hundreds	Thounsands~millions	Low	Faster-than-real-time	Hours
COA analysis	✓	✓	✓		Thousands	Hundreds~thounsands	Low medium	Faster-than-real-time	Minutes hours
Acquisitions of new military system			✓	✓	A few	Tens~ of thousands	High	Faster-than-real-time 0n real-time	Days or weeks
SSN analysis				✓	Tens of thousands	Several	High	Faster-than-real-time	Days
Test and Evaluation of the THAAD system			✓	✓	A few	Several	High	Real-time	Months

Simulation level: **C, campaign** **M, mission** **E, engagement** **G, engineering**

(b) Data-related properties

Cases	Data contents	Data generation period	Data scale per experiment	Typical analytical application
Joint forces experiments	Sensor data, entity status (take Urban resolve e.g.)	1 ms	TB	Effectiveness of ISR sensor. Statistical result of mission execution
Data faming projects	Depend on specific problem and can involve all kinds of physiscal and behavioral data of simulated entities and battlefield events, such as damage and survival	< 1ms	GB~TB	Correlation, trend, and outlier analysis related to command and control, peacekeeping operation, combat, and so forth
COA analysis	Civil behavior, culture, weapon, terrain, killing, victims and so forth	< 1 sec	GB~TB	Task execution analysis, operational effectiveness analysis
Acquisition of new military system	Communication, sensor, command, and control, weapo, and so forth	N/A	TB	Identify the key performance parameter, system level trade-off analysis, and MOE about raid, protect, detect, reaction, tracking, engagement, and soforth
SSN analysis	Sensor, data and special events such as launch, breakup, abd in-orbit	< 1 sec	TB	MOP of sensor device
Test and evaluation of the THAAD system	Maneuver, sustainment, command and control, communication, radar track data, and so forth	N/A	TB	MOE, MOP of defense system

B. COMPUTATIONAL AND DATA INFRASTRUCTURES

1. Cloud Computing for M&S

A possible alternative to these issues can be cloud computing. Cloud computing is an emerging technology that provides many benefits, such as flexibility in performance and scalability, that can help or solve the issue of different organizations or the government, in this case, TRAC-MTRY, with big data management generated by combat simulations. Cloud computing is a service that is usually provided to customers through internet browsing or an application, “the concept of cloud computing is defined by the U.S. National Institute of Standards and Technology (NIST): as a model that can achieve convenience for obtaining the required resources (including networks, servers, storage, applications, and services) through network access on demand, and the required resources can be quickly provided or released, with little management effort or little interaction with service providers interaction” (Badger et al. 2012, 2–1). They also describe the characteristics of the cloud. These essential characteristics are On-demand self-service, Broad network access, Resource pooling, Rapid elasticity, and Measured Service. All these provide over-the-network capabilities, typically through a website that can optimize the need of the consumer based on their demand. For example, the cloud will move resources like storage space, processing, and network bandwidth to satisfy multiple customers in different locations, making these transactions seamless for the consumer.

Cloud elasticity and scalability allow the cloud service provider to claim unused resources to support high-demand users with data processing and storage. When users require more storage or computing capacity, it allows the cloud infrastructure (network) to assign the available resources to the user that will need the most. Reliability on the cloud creates redundancy in the system by creating multiple copies on different databases to allow the continuation of services, while virtualization hides this process from the customer. The advanced self-configuration technology allows the cloud to auto-assign the resources within customers and decide which data will be stored and where it will be stored.

There have been studies that show the advantage of cloud computing vs. legacy systems. And how cloud computing can process large amounts of data faster than traditional solutions. The following table (Table 2) shows the details and the advantage of cloud computing over traditional solutions.

Table 2. Comparison between Traditional Solutions and Cloud Computing Solutions. Source: Rossetti and Chen (2012).

	Traditional Solution	**Cloud Computing Solution**
Operating System	Window 7 Enterprise	Linux
Number of Cores	2	1 for each VM; 15 in total
RAM	2 GB	1251 MB for each VM
Simulation time for 1 replication	2 minutes and 41 seconds	Around 2 minutes and 35 seconds on a VM
Total time spent on the simulation for 30 replications	75 minutes and 52 seconds	49 minutes and 20 seconds

Table 2 shows the benefits of cloud computing against traditional or legacy systems. It demonstrates the capability of processing large datasets and more replications in the least time. As the number of replications increases, "the total time spent on the cloud computing solution for 30 replications is 35% less than the time spent on the traditional solution" (Rossetti and Chen 2012, 11). This confirms the claims that the cloud has been able to rapid scalability and elasticity or resource pooling to meet customer demands. This relevant study measures the efficiency of a large-scale simulation of an entire complex supply chain network that will generate a large amount of data. That can be comparable or a guide for the data collection and processing of military big data from complex simulations on the cloud. This research simulates a large-scale multi-echelon supply chain distribution network from top to button.

Kadhim et al. (2018) describe cloud computing as the "most promising networking infrastructure" because of the different benefits that the technology provides to customers. Not only can it manage large amounts of data for storage and processing, but it also can launch large-scale applications at a lower cost. Kadhim et al. (2018) and Cayirci (2013) describe that cloud computing is rooted in essential characteristics: (1) virtualization allows the customer to connect to the cloud via the web through various devices; (2) Service-oriented that provides three types: Infrastructure as a Service (IaaS), Platform as a Service (PaaS), and Software as a Service (SaaS). The most common is SaaS, where everything happening in the infrastructure is hidden from the customer, and he uses the cloud software and applications without the need to install any software on his device locally. As well as the ability to access programs, platforms, and applications from different locations and devices without any upfront cost of licensing or infrastructure. There are four general cloud modes known, (1) Private cloud: where the service is provided to a single organization, (2) Community cloud: where the service is provided to a specific community, (3) Public cloud: where services are open source, and the public can access, (4) hybrid cloud: where a combination of any of two or more of the architectures are utilized.

The cloud typically provides services at a lower cost due to fewer facilities that require fewer personnel and maintenance. In addition, multiple resources (software, hardware, licenses, and applications) are shared among customers, lowering the utilization cost. TRAC-MRY will not have to invest in high-end computers or software because the cloud will provide the software and applications needed. The same with licensing for different products for multiple computers because by utilizing the cloud, the same license is utilized for all the machines connected to the cloud. And lastly, and probably the higher cost, the Army will not have to invest in computer infrastructure (servers), maintenance, and maintainers. As well as all the other costs of the physical infrastructure to secure the local servers and the utilities cost that all these servers will consume.

When delving into cloud-based storage for data derived from modeling and simulation, it is essential to consider specific requirements that differ from those of on-premises storage. In this regard, Miao et al. (2016) article on secure private cloud storage offers valuable insights into the matter, which is highly relevant to our current research exploring cArmy as a cloud-based solution. The article meticulously compares public and private cloud construction methodologies and identifies the necessary measures for public cloud storage, such as encrypted access control methods, data storage, encryption, decryption, and access control. The authors propose a highly secure storage system worth exploring and comparing with other cloud storage processes, highlighting the critical importance of reliability, scalability, and security. The paper comprehensively explains the process architecture and system techniques, an indispensable resource for researchers and practitioners in the field.

While Johnson and Tolk (2013) recognize the benefits that cloud computing brings to M&S, they discuss another issue, the need for standard architecture. They raise the issue of developers needing a standard architecture process for creating simulations. Traditional computer programs and interactions are based on client/server relations, where the customer requests information on a local computer with all programs and applications already installed, and the server response completes the transaction. Therefore, "consequently, most current simulations are designed for client-server systems" (Johnson and Tolk 2013, 1), creating problems with other systems' interoperability.

There are several architectures to deal with this interoperability issue; Distributed Interactive Simulation (DIS), the Test and Training Enabling Architecture (TENA), and High-Level Architecture (HLA). Nevertheless, there is a need for a new standard architecture because of the high demand of requirements that is asked for the cloud to provide to the new emergences of M&S. The new architecture developed to try to solve this challenge "is called the Distributed Simulation Engineering and Execution Process (DSEEP), is intended as a high-level process framework into which lower-level systems engineering practices native to any distributed simulation user can be easily integrated." (Johnson and Tolk 2013, 5). Incorporating concepts from all previous architectures (DIS, TENA, HLA) supports the interoperability within different systems and M&S architectures.

Some other issues need to be considered, as addressed by Kadhim et al. (2018). Security issues can happen by an inside job (employee) and external threat (hacker). As explained before, the cloud has the characteristic of virtualization or virtual machine (VM), where multiple users can access the cloud on the same computer. This can allow or open an opportunity for a person to access another user's virtual machine. Also, a customer with malware on his computer, without knowing, can inject a virus into the cloud. Therefore, on military accounts, the level of authentication for a user is able only to access the authorized data and not classified data on different levels. A hacker can access the cloud through third-party software or application bugs. Hacker malware can compromise this transaction when a company submits a new software update. As well as a hacker can emplace bugs on many individuals' computers unnoticed and utilize the many to create a denial of service (DoS) consisting of multiple users consuming resources simultaneously to degrade the service.

Even when, in the case of TRAC-MRY, the ideal cloud service is the private cloud, most big companies' cloud providers have other customers utilizing the same servers or data centers to store their data. This means that if any of the situations discussed above happen can affect any other customer (individual or organization) data stored on that network or data centers. While all these issues should be considered, the cloud also has the security advantage of creating multiple copies of data for redundancy. The data centers at one geographic location provide easy management and more affordable security monitoring by more skilled cybersecurity experts.

2. Benefits of Using High-Performance Computing Centers for M&S

High-performance computing, modeling, and simulation are interrelated technologies that offer various benefits in various fields. They both allow for the rapid and accurate simulation of complex systems that would be impossible to model using traditional stand-alone computers. For TRAC-Monterey to migrate to this technology, it is vital to analyze the benefits of using this data processing and storage method. This is relevant to research efforts as TRAC-MRY has an HPC system and is exploring options to use the system for processing simulations.

Ezell and Atkinson (2016) define HPC and provides insights into the systems' benefits, challenges, and use cases. Their article defines high-performance computers as systems that use "processing capability and storage capacity to rapidly solve complex computational problems across a diverse range of scientific, engineering, and industrial fields." The authors provided case studies in the article that demonstrate the benefits of HPC in modeling and simulation, which led to cost savings and research and design acceleration. An additional HPC benefit identified by the authors is that the system allows for "highly precise simulations" of numerous phenomena previously unanalyzed due to exorbitant cost and inadequate speeds in comprehending component interactions.

This applies to our research efforts as TRAC-MRY's mission and lines of effort are linked to the execution of M&S and data analysis.

HPC has become an essential component research and innovation. It has replaced traditional core stand-alone modems for most high-tech companies and is highly considered for military use due to its diverse benefits. "Engineering, data science, process design, and research use it to solve complex problems and manipulate large chunks of data quickly and cost-effectively" (NISP n.d.). weblink further explains the benefits of HPC, which include improved speed, reduced costs, and support for research and innovation. HPCs have replaced traditional supercomputers due to their ability to handle complex computational problems. Netto et al. (2019) describes the HPCs as "clusters of computers that can handle complex computational problems in aerospace, life sciences, finance, and energy industries. They are managed by batch schedulers that receive user requests to run jobs queued whenever resources are under heavy use" (1).

Adapting HPC use for the military also improves data processing speed and interconnection between systems. According to Ping-Jing and Jun-Sheng (2022), four main benefits are currently driving the development of high-performance interconnection networks: "(1) aiming at 100 Gbps line speed to increase interconnection communication bandwidth, (2) merging and deepening cooperation between interconnection and computing to reduce transmission delay, (3) adopting a multiprotocol network convergence architecture to reduce costs, and (4) improving system density through chipset-based optoelectronic common-mode integrated packaging." NISP (n.d.) also describes HPCs as a "technology that improves data processing speed. A typical stand-alone computer system has a relatively low central processing unit (CPU) capacity. Generally, this allows a computer to run only one model at a time, slowing down the whole process as a result." NISD (n.d.) explains that "using advanced technology with recent CPUs, GPUs, and Remote Direct Memory Access (RDMA), HPC enables you to run multiple models or simulations simultaneously and performs calculations much more efficiently than before."

Cost is a significant factor when transitioning from a 120-core server to HPCs. Indeed, any organization or the Military's decision will largely depend on the difference in the cost of running HPC compared to operating on a 120-core server. In a study conducted at the Supercomputing Education and Research Centre (SERC) at the Indian Institute of Science (IISc), on “Cost-Benefit Analysis of Public Clouds for Offloading In-House HPC Jobs,” Prabhakaran and Lakshmi (2018) analyzed the cost benefits for an organization to operate using HPC. Their study explains that “the best cost of computing on the public cloud is around three times as expensive as the in-house compute cost of HPC.” The primary factor contributing to the reduced expenses was the great accessibility and effective use of the cutting-edge system at SERC, the favorable academic pricing, and the economic support manpower expenditure. However, the same conclusion would hold for similar large organizations with similar structures and data processing and storage. This study also realized a significant economic benefit of HPC over the cloud. In this specific case of SERC, the authors also observed that “if all the small jobs that the company processed until December 2017 were run on the cloud, these jobs would cost around $13.5 million. Based on this, it is currently established that the commercial cloud platforms are not performance or price-competitive in comparison to the in-house HPC” (Prabhakaran and Lakshmi 2018).

Bostanci, Shareef, and Tuma (2020) conducted an experimental comparison of using high-performance computers vs. using single-board ARM-processor-based computers such as Raspberry Pi and Parallella. The experimental study aims to demonstrate the potential benefits of immersion cooling over air-based natural and forced convection approaches. And both HPC and using single-board ARM-processor-based computers were used, and the cost was compared. According to (Bostanci, Shareef, and Tuma 2020), the potential benefits of immersion cooling over air-based cooling methods are temperature control, frequency maintenance, execution time, and energy consumption. The results indicate that immersion cooling with dielectric fluids can effectively cool ARM-based clusters and enable them to perform at maximum capacity. This research contributes to developing low-cost, high-performance computing clusters that can be utilized in various applications such as education, military use, smart buildings, and transportation systems. This study by (Bostanci, Shareef, and Tuma 2020) demonstrates the significant benefit of using HPCs. The fact that it is less costly will provide cost savings for TRAC-Monterrey should they choose to use HPC for post-processing data storage.

Tomich, Grazulius, and Grant (1987) state that the primary benefit of procuring a commercial data acquisition and control system (HPC) is the quick deployment time. They assessed and demonstrated how HPCs are superior for performing the interface for data gathering in surface analysis. Their article centers on a micro-computer-based system for data collection, data manipulation, and control intended for Perkin-Elmer Physical Electronics model 550 SAM/XPS system. It discusses the system requirements, design considerations, hardware selection, and software design. Regarding systems requirement and design, Tomich, Grazulius, and Grant (1987) explain that the design of a data acquisition system must consider factors such as the number and type of signals, data acquisition rate, and signal/data processing requirements. The SAM/XPS system utilizes digital and analog signals for input and output operations. Analog signals are used for collecting Auger data, while digital signals are employed for pulse counting in XPS data collection. The system should efficiently handle the data acquisition rate and support various signal/data processing needs. Their article describes a versatile computer interface for data acquisition in surface analysis, specifically designed for the Perkin-Elmer Physical Electronics model 550 SAM/XPS system. The interface design incorporates hardware components for system control and data input, while the software provides menu-driven control programs and data manipulation routines. The system offers flexibility, high resolution, and efficient data acquisition capabilities. This proves that HPCs can process larger complex data even faster. This will enable TRAC-Monterey to process and store data at a faster time rate.

Banerjee, Prasanna, and Sinha (1999) analyzed researchers' findings during the 1999 6th International Conference (HiPC'99), addressing some advantages of high-performance computers. They discussed speed, solving complex data problems, and performance, as well as advancements in network protocols and interconnects for HPC systems showcased at the conference. Researchers presented novel approaches for improving network performance, reducing latency, and increasing bandwidth in high-speed networks. The papers discussed switch designs, routing algorithms, network topologies, and communication protocols optimized for HPC applications—these contributions aimed to facilitate faster and more reliable communication among nodes in HPC clusters. Banerjee, Prasanna, and Sinha (1999) state that HiPC'99 also addresses algorithms and applications. HiPC'99 featured papers focusing on algorithmic developments and their applications in various domains. Researchers presented novel algorithms for solving complex computational problems efficiently on parallel architectures using HPC. Additionally, the conference showcased the application of HPC in diverse areas, including computational biology, data mining, weather modeling, and scientific simulations. These papers demonstrated the real-world impact of HPC and highlighted its potential for advancing research and innovation. Another aspect addressed during HiPC'99 was Performance Evaluation and Benchmarking. Banerjee, Prasanna, and Sinha (1999) described that a significant aspect of HPC is evaluating system performance and benchmarking methodologies. HiPC'99 included papers that addressed performance evaluation techniques, metrics, and tools for HPC systems. Researchers presented novel approaches to assess the efficiency and scalability of parallel algorithms and methodologies for benchmarking HPC systems. These contributions aimed to provide insights into system performance and facilitate comparisons among different HPC platforms. Studies like this emphasize the advantages of HPC over other data storage and processing methods as early as 1999.

The article "Why High-Performance Modelling and Simulation for Big Data Applications Matters" by Grelck et al. (2019) provides a comprehensive exploration of the importance of employing advanced modeling and simulation techniques in the context of big data applications. The authors underscore the significance of high-performance computing (HPC) methods in addressing the challenges posed by big data applications. They highlight the exponential growth in data volume and complexity and the consequent need for efficient modeling and simulation approaches. The article discusses how conventional computational methods struggle to handle big data's immense scale and speed, resulting in suboptimal performance and scalability issues. Various high-performance modeling and simulation aspects are examined, including parallel algorithms, distributed systems, data partitioning, load balancing, and resource management. Grelck et al. (2019) demonstrate the practical relevance of high-performance modeling and simulation through multiple case studies and real-world applications. These examples illustrate how the proposed techniques can enhance the performance and scalability of big data applications, facilitating more accurate analysis, prediction, and decision-making. The authors provide a solid theoretical foundation while offering practical insights into implementing and deploying high-performance modeling and simulation techniques. Based on the case studies presented in the article, high-performance modeling and simulation offer tangible benefits, showcasing improved performance, scalability, and efficiency in various domains, including scientific research, industrial applications, and data-driven decision-making. The authors make a valuable contribution to big data analytics, emphasizing the significance of high-performance computing techniques in overcoming the challenges associated with data's ever-expanding volume and complexity. This is particularly relevant to TRAC-MRY, as they are grappling with a similar issue concerning the proper storage of post-processing big data.

The rapid advancement of high-performance computer systems has necessitated efficient interconnection networks to meet the growing demand for data transfer and communication among various components. In this article, Ping-Jing, Lai, and Jun-Sheng (2022) critically examine the survey titled high-performance interconnection networks in high-performance computer Systems. Their survey provides a comprehensive overview of high-performance computer systems' state-of-the-art interconnection network technologies. The survey conducted by Lu et al. aims to provide a comprehensive understanding of high-performance interconnection networks by analyzing various architectural designs, routing algorithms, and flow control mechanisms. The authors emphasize the importance of interconnection networks in achieving high performance and scalability in modern computer systems. They highlight the challenges in designing efficient interconnection networks and present various solutions proposed in the article. Ping-Jing, Lai, and Jun-Sheng (2022) focus on traditional interconnection network technologies and highlight emerging technologies such as photonic interconnects, optical circuit switching, and hybrid interconnects. It discusses their potential to address conventional electrical interconnects' limitations and improve high-performance computer systems' performance.

Ping-Jing, Lai, and Jun-Sheng (2022) survey is well-structured and comprehensively analyzes the state-of-the-art interconnection network technologies. It offers valuable insights into design considerations, performance trade-offs, and future trends in this field. However, a few areas could have been further elaborated or addressed, such as evaluation metrics used to compare and assess the performance of different approaches, recent advancements and practical implementations, and case studies of these networks in real-world high-performance computer systems. The rapid advancement of high-performance computer systems has necessitated efficient interconnection networks to meet the growing demand for data transfer and communication among various components. In this article, Ping-Jing, Lai, and Jun-Sheng (2022) critically examine the survey titled high-performance interconnection networks in high-performance computer Systems. Their survey provides a comprehensive overview of high-performance computer systems' state-of-the-art interconnection network technologies. The survey conducted by Lu et al. (2022) aims to provide a comprehensive understanding of high-performance interconnection networks by analyzing various architectural designs, routing algorithms, and flow control mechanisms. The authors emphasize the importance of interconnection networks in achieving high performance and scalability in modern computer systems. They highlight the challenges in designing efficient interconnection networks and present various solutions proposed in the article. Ping-Jing, Lai, and Jun-Sheng (2022) focus on traditional interconnection network technologies and highlight emerging technologies such as photonic interconnects, optical circuit switching, and hybrid interconnects. The article discusses their potential to address conventional electrical interconnects' limitations and improve high-performance computer systems' performance.

HPCs allow TRAC-MRY to continue modeling and simulation activities while mitigating financial overhead by leveraging shared computational and data infrastructure. This infrastructure solution requires continued exploration to ensure that performance measures required to process M&S events are met.

C. M&S TOOLS

1. M&S Post-Processing Significance and Optimization

One of the key issues at hand for TRAC-MTRY is optimizing the process for post-processing simulations and storing simulation data. Understanding the significance of post-processing is important to analyze necessary data center resources to align against these activities. Post-processing results in the transformation of relatively small data into big data, which presents the concerns mentioned previously in the literature review. Tovey et al. (2023) and Coll (2016) stressed the critical role post-processing plays concerning large data sets of the key issues at hand for TRAC-MTRY is optimizing the process for post-processing simulations and storing simulation data. More specifically, post-processing is the analysis of simulations of unstructured data, as covered in the project "Visual Analysis for Extremely Large-Scale Scientific Computing" (VELaSSCo) (Coll 2016). Coll informs us that post-processing "extracts information from the meshes using a variety of techniques that allow a better understanding of the results" (4). VELaSSCo discusses the importance of improving the management of a rising big data challenge and its use in simulations. VELaSSCo points out that one of the key difficulties in simulations, especially with remote high-performance computer infrastructures, is the ability to analyze output data dispersed over multiple servers.

As we evaluate the TRAC-MRY transition from on-premises services to remote service either through the ARL HPC Centers or a Cloud services provider, the ability to execute and maintain organized M&S data over remote servers requires examination. The VELaSSCo project worked to solve this by generating real-time visuals to analyze modeling and simulation output data and improving the management (storage and access) by efficiently isolating pertinent information while processing simulations generated from large amounts of data with multiple parameters. As TRAC-MRY continues experimenting with HPCs, this project recognizes that HPCs alone are not a solution to optimizing post-processing; modern computational power, data, and simulation tools should accent HPCs. Post-processing reduces the human computational load required to generate insightful inferences to verify or validate the analysis (Tovey et al. 2023). While post-processing reduces human computational load, it places the computational burden on the hardware. When analyzing alternatives for TRAC-MTRY, it is critical to determine which solution uses its hardware resources in the most logical and efficient method.

Post-processing activity resource requirements depend on many variables, such as the data size, number of simulations, duration of simulations, and tools and software used. The larger the data set, the more time and resource usage are needed for post-processing, as Wolter et al. (2007) put it in "Markov Prefetching in Multi-Block Particle Tracing": "Post-processing of large-scale data sets is time-consuming" (27). Wolter et al. (2007) argue for paralleling or maintaining data that isn't needed on a separate memory core while an additional memory core processes the currently needed data. Ideally, this speeds up the post-processing and uses computational resources efficiently. Two additional articles, "Performance Benefits of Heterogenous Computing in HPC Workloads and Scheduling Batch" (Lee, Grochowski, and Geva 2012) and "Heterogenous Jobs with Runtime Elasticity in a Parallel Processing Environment" (Kumar, Shae, and Jamjoom 2012) provide insight as to the computational and resource requirements for post-processing data concerning modeling and simulations. In the former article, Lee, Grochowski, and Geva (2012) discuss the growing number of processing cores required to process simulations and that the capability and limitations of the chip multi-processor constrain the benefits of multiple cores. This is an important concept to understand when servers are running parallel jobs for simulations and determining how to optimize processing simulation jobs. Lee, Grochowski, and Geva evaluated homogenous and heterogenous chip-multiprocessors and found that heterogenous chip-multiprocessors have a 1.35x faster computational time. The improved performance is backed up by Nik Jedrzejewski (2016), who highlights that heterogenous is better at optimization, power usage, and reliability due to the heterogenous chip-multiprocessors having two or more cores with different architectures, while homogenous cores share the same architecture. This is relevant as TRAC-MTRY is weighing the possibility of using the Army Research Lab HPC infrastructure, which will have less hardware modification flexibility than a cloud service provider. When analyzing alternatives, our research must determine multi-chip processor performance and whether a potential solution requires an abundance of heterogenous chips.

The time it takes to execute post-processing activities is an additional resource burden. Kumar, Shae, and Jamjoom (2012) analyzed alternatives to reduce the job-wait time for post-processing. Job-wait time is a considerable factor when using the ARL HPC center; as mentioned before, this center is used by multiple Army entities that compete for jobs. Kumar, Shae, and Jamjoom focused on an adaptive resource job execution time framework for processing jobs, or runtime elasticity, rather than one-time identification of required resources and established time for processing jobs. Simplifying this even more, they analyzed the ability to execute jobs simultaneously rather than in sequence, which maximizes resources to run multiple post-processing jobs. Kumar, Shae, and Jamjoom's scope included HPCs, as HPCs are built around submit-time elasticity. Job-wait time and submit-time elasticity is a considerable factor when using the ARL HPC center; as mentioned before, the ARL HPC is used by multiple Army entities who compete for jobs. Submit-time elasticity results in processing bottlenecks due to computational resources not being ready for post-processing before submission. HPCs are known to have a high utilization rate, which increases competition for jobs, increases processing times, and is associated with processing delays. Kumar, Shae, and Jamjoom (2012) propose that HPCs should transition to a runtime elasticity concept to efficiently use computational resources by "mixing and blending of batch and dedicated (reservation-based) jobs, and (2) extensions and reductions in the time dimension" (75). This is supplemented by using post-processing tools such as programming languages to optimize computational resources, decreasing run time, and maximizing the runtime elasticity (Corral-García, Lemus-Prieto, and Pérez-Toledano 2021).

2. Potential M&S Post-Processing Tools

Optimizing post-processing activities requires tool analysis (software, programs, applications) just as much as hardware analysis, as introduced in the previous section. This tool analysis informs research on the capabilities and allows for measurements when comparing data center alternatives taking into consideration flexibility to implement helpful tools. Whether it's ARL, a cloud service provider, or another alternative, the ability to apply post-processing tools to that environment is critical as it adds flexibility in conducting modeling and simulation to get the desired results. The focus of this research isn't on one specific tool but rather on a comprehensive review that demonstrates the potential opportunity to implement post-processing tools to supplement hardware limitations.

As TRAC-MTRY experiments with ARL-shared HPCs, they must find ways to reduce reliance on those data center resources to execute more simulations faster. This will allow TRAC-MTRY to run more M&S jobs in less time, ultimately influencing the efficiency at which they can perform analysis. Post-processing tools are advantageous for big data jobs when running multiple jobs simultaneously, in parallel, or when large statistical outputs are preferred—often the case with TRAC-MRY M&S jobs. Perez and Windham (2011) used programming languages like C++ and tools incorporated into MATLAB to automate post-processing, relieving the human work hour burden from hours to minutes. Lagares, Rivera, and Araya (2022) also used a C++ post-processing tool, Aquila, to improve scalability and efficiencies using out-of-core, or externally stored data. Lagares, Rivera, and Araya state, "modern times have brought application developers and scientists the advent of increasingly more diversified and heterogeneous computing hardware, which significantly complicates the development of performance-portable applications" (1), which increases the post-processing load. C++ allowed the research team to demonstrate scalability while improving post-processing performance, using memory and bandwidth resources increasingly efficiently, and decreasing latency. This data was not stored internally on HPC resources but on external hard drives, so it freed up HPC computational processing power to execute jobs faster. The Aquila library, hosted by C++, stores post-processing computational code that focuses on improving CPU and GPU performance and optimizing file formats, minimizing data on memory, structuring the underlying network meshes, and "provide [s] as much information as possible at 'compiling time'" (Lagares, Rivera, and Araya 2022). The Aquila library, hosted by C++, stores post-processing computational code that focuses on improving CPU and GPU performance and optimizing file formats, minimizing data on memory,

structuring the underlying network meshes, and "provide [s] as much information as possible at 'compiling time'" (Lagares, Rivera, and Araya 2022, 5). This is relevant to TRAC-MRY as they currently have archived data on-premises, and while ARL HPC is using the R programming language as opposed to C++, a cloud environment will allow for either programming language providing more flexibility to further optimize post-processing.

Relevant to Army modeling and simulation, Fortunato et al. (2017) discusses alternative tools for modeling and simulation to improve pre-and post-processing in "Pre- and Post-Processing Tools to Create and Characterize Particle-Based Composite Model Structures." Fortunato identifies tools associated with the software Large-scale Atomic/ Molecular Massively Parallel Simulator (LAMMPS) to simplify composite model processing. The inference is that the physical resources for post-processing (processors, cores, memory) aren't the only components requiring analysis, but a software approach using programming languages could provide valuable insight to improve or optimize post-processing activities.

The optimization of post-processing for M&S is a valuable concept that can save resources and time while producing better results. Optimization works with post-processing tools and how hardware for computation power is utilized. Data centers provide the foundation for enabling optimization, and thus Army modeling and simulation must consider data center requirements to execute sustained and efficient M&S activities.

D. NAVIGATING METHODOLOGIES: THE CASE FOR SYSTEM ENGINEERING

During the beginning of the capstone project, our team faced the complex challenge of enhancing TRAC-MTRY's data storage and post-processing system. We considered approaches such as traditional project management, agile development, and lean principles to tackle this challenge. We acknowledged the difficulty of this task and explored various methodologies.

It was clear that the systems engineering process, which includes methodologies like the Vee model, requirements analysis, functional decomposition, and interface management, was highly effective. The Vee model placed great importance on validation and verification, meaning testing and feedback were conducted rigorously at every stage. Requirements analysis enabled us to gather stakeholder requirements meticulously, while functional decomposition helped to break down the system into smaller, more manageable components.

Systems engineering offers a comprehensive and integrated approach that utilizes specific methodologies to provide a structured and adaptable framework. This approach effectively addressed the technical complexities and aligned with the operational and strategic dimensions of TRAC-MTRY's unique challenges. The capstone team laid a strong foundation for the project's future phases by grounding our research in the systems engineering process.

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III. METHODOLOGY

A. METHODOLOGY BACKGROUND

To answer the three primary research questions, the team took a system engineering approach to determine modeling and simulation (M&S) post-processing and storage system alternatives for TRAC-MTRY. Fig 3 illustrates the foundation of the research methodology for developing the system of interest (SOI) post-processing and data storage system and potential alternatives. The team followed the left side of the Vee model as the blueprint to define and decompose the system and verify the system through conceptual design and performance measures. The Vee model helped to create a plan for breaking down the necessary work to develop a data and storage system and a process for evaluating potential storage solutions that TRAC could use.

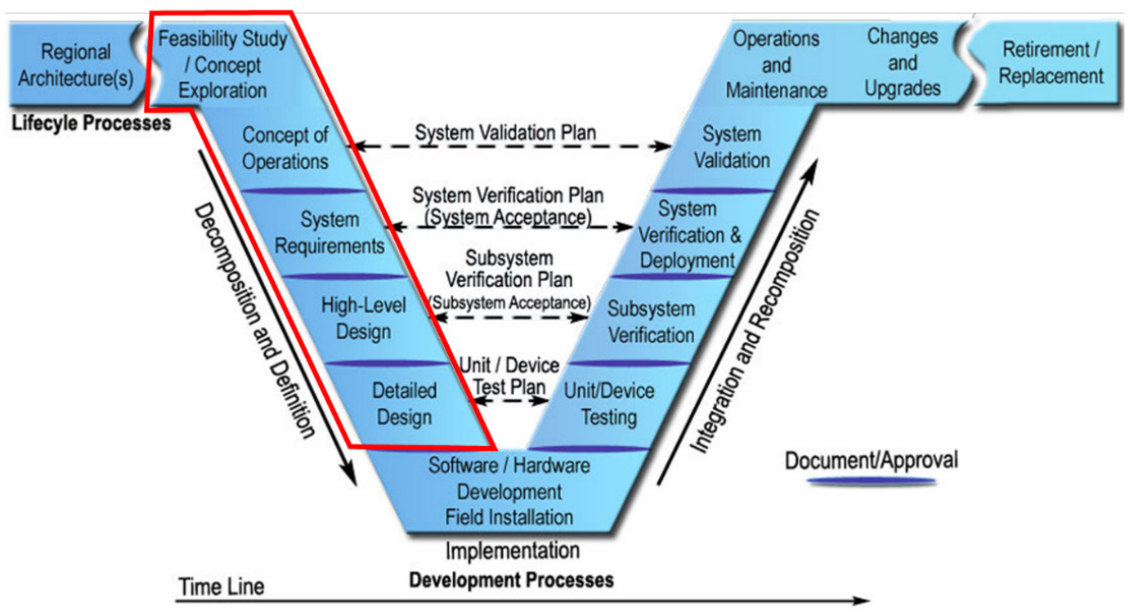

Figure 3. System Engineering "Vee" Model

A tailored systems engineering methodology is applied in this research to derive a constructive analysis that ultimately aided in developing suitable and feasible post-processing and storage system alternatives. The following sections describe process used to create storage system alternatives.

Identify System Requirements: System requirements were created by first identifying all stakeholders and conducting stakeholder analysis. The team further defined the storage system and developed a functional decomposition and objective hierarchy, which ensured detailed and traceable system requirements.

Creating a Conceptual Design: The system's conceptual design was created by defining all system functions necessary and affixing a component to every function. The team created a general morphological analysis (GMA) within the conceptual design process. The GMA explored and generated feasible M&S data storage alternatives.

Developing Alternatives: Alternatives were developed by conducting an infeasibility analysis. The infeasibility analysis focused on options (aligned with attributes) generated from the GMA. The infeasibility analysis helped blacklist infeasible alternatives and whitelist feasible alternatives that addressed stakeholder requirements.

Performance Measures: The team verified the system and derived alternatives using performance measures to meet stakeholder requirements. Performance measures were derived from results of functional analysis and objectives hierarchy.

B. DEFINING SYSTEM REQUIREMENTS

The capstone team completed a detailed requirements analysis to facilitate the development of performance measures. The analysis provides an understanding of the stakeholder's objectives and requirements, and the system's functions, requirements, constraints, and essential inputs needed to aid TRAC-MTRY in selecting an alternative for their M&S post-processing. Defining system requirements included stakeholder analysis, storage system definition, functional decomposition of the storage system, and creation of an objectives hierarchy.

1. Stakeholder Analysis

The capstone team conducted a stakeholder analysis to determine the needs and expectations of the stakeholders for the post-processing and data storage system. The team performed stakeholder analysis using four steps: 1) stakeholder identification, 2) elicitation of stakeholder needs and requirements, 3) prioritization of stakeholders based on influence and impact, and 4) establishment of engagement methods. This process identified the top-level decision-makers and acknowledged external organizations' influence. The team used various tools to comprehensively understand and prioritize stakeholder needs.

2. System Definition Storage System

The team defined system activities that described the post-processing and data storage system which would satisfy the stakeholder needs. The expectations and requirements identified during the stakeholder analysis were the foundation for this phase. The team used the Input, Output, Controls and Mechanisms (ICOM) model and context diagram tools to aid in defining the system. The team then identified the high-level functions necessary for the storage system. The critical function of this phase for the team was to ensure that the system design aligned with the stakeholders' needs and objectives.

3. Functional Decomposition

Blanchard and Farbycky note that "a critical step in implementing the systems engineering process is the accomplishment of the functional analysis and the definition of the system in functional terms" (2011, 773). The capstone team used structured analysis and design techniques for the functional decomposition of the post-processing and data storage system. The Ishikawa diagram, mentioned in Chapter 1, identified the core elements of the system: organization, technology, resources, and infrastructure. Stakeholder requirements refined these aspects, which scoped and bound the system appropriately. Scoping ensured comprehensive coverage while bounding defined system limits. The team developed a functional hierarchy, functional flow block diagram, and a functional decomposition hierarchy table aid the process design.

4. Objectives Hierarchy

The team developed an objective hierarchy to provide a framework for capturing and communicating the system's overarching goals and priorities. The objective hierarchy was created using stakeholder analysis. The objectives hierarchy captured how the stakeholder expects the system to behave. Additionally, the objectives hierarchy informs the development of non-functional requirements for the storage system. The functional requirements are developed from the functional hierarchy. Non-functional requirements focus on the behavior, attributes, and characteristics that the system should have.

C. CONCEPTUAL DESIGN

After identifying functional and non-functional requirements, the team initiated the development of the conceptual design. In the system engineering process, engineers ideate during the conceptual design phase to envision solutions to a particular problem or meet specific requirements. The process is a high-level approach focusing on understanding the problem and generating solutions without delving into detailed design or implementation. Blanchard and Fabrycky (2011) define conceptual design as "the first and most important phase of the system design and development process" (56). The team used the conceptual design to support the generation of alternatives for post-processing and data storage systems.

1. Function to Component Tracing

Functional description was the foundation for identifying the components required to accomplish the system's mission. The team drafted a function-to-component trace to ensure that the components account for every function the system should perform. A function-to-component trace also helped with (1) verification—the system performs the functions that it was designed to do, and (2) validation—the functions that the system performs are what the user needs. The component tracing provided the framework for the GMA to identify alternatives.

2. General Morphological Analysis

The team utilized GMA to explore and generate feasible alternative solutions. GMA is a structured way to break down a problem and consider all potential solutions systematically. The primary tool the team used for GMA is the **Morphological Box**. The box is a matrix where each row represents a specific aspect or attribute of the problem, and each entry in a column represents a potential option or approach for that attribute. By considering all combinations for the storage system, the team identified numerous potential alternatives.

D. ALTERNATIVES

Exploration of alternatives is a pivotal step that ensures the chosen solution is robust. This phase involved examining different approaches, methodologies, or designs that can fulfill the system's requirements and objectives. The GMA was the means to generate post-processing data storage alternatives. The team conducted an infeasibility analysis in the form of an infeasibility diagram to eliminate alternatives or component combinations that would not meet stakeholder requirements.

An infeasibility analysis is an evaluation process to identify alternatives that might not have been feasible due to various constraints or limitations. Alternatives may not be viable due to technical challenges, financial implications, operational inefficiencies, or other factors -based on requirements- that render a solution impractical. By conducting an infeasibility analysis, the team filtered out alternatives that, despite their apparent benefits, were not implementable by TRAC-MTRY. The infeasibility analysis ensured that the remaining alternatives were theoretically sound and practically feasible, in terms of stakeholder requirements and the system's overarching goals. The team narrowed the alternatives through this meticulous process, ensuring that the selected post-processing data storage solution was feasible and implementable.

E. POTENTIAL MEASURES FOR EVALUATING ALTERNATIVES

Developing potential measures for evaluating alternatives was vital as it established whether each selected M&S post-processing and data storage system alternative satisfied stakeholder requirements. The evaluation measures are an aspect of validation in which the measures capture the stakeholders' needs and specifications. Additionally, the performance measures were in line with what the users required from the system. The component tracing provided the framework for the GMA to identify alternatives. The team developed three measures for evaluating alternatives. These measures were further decomposed into specific, measurable, achievable, relevant, and time-bound metrics. Functional decomposition and objective hierarchy resulted in the following high-level measures.

Scalability: The team defined scalability as the ability to easily expand the capacity and performance of the storage system as demand increases. Two aspects of scalability were identified as horizontal scalability (ability to add more nodes/servers as needed to scale out capacity and performance), and vertical scalability (ability to scale up capacity and performance on a single node/server by adding resources such as drivers, memory, and CPUs).

Accessibility: Accessibility was a direct requirement from the TRAC stakeholders. The team defined accessibility as the ease and speed with which stored data could be retrieved, accessed, and utilized by authorized users or applications. As a measure of evaluation for alternative M&S storage systems, the team examined and compared how data is stored, organized, and made available for use.

Availability: The team determined that availability is the percentage of time the data storage system is operational and accessible. The system availability was also used as a measure of reliability and uptime for the data storage system.

Total Cost: The team determined that the cost of infrastructure, which includes system hardware, software, all supporting elements such as office buildings and lab space, and personnel cost, constituted the total cost. The team performed a detailed analysis of this total cost on all M&S storage alternative systems to determine the cost of each system alternative.

IV. ANALYSIS

In this chapter, the team conducts an analysis of the system of interest, associated measures, and potential alternatives that can satisfy the stakeholders' requirements for the post-processing system. The team employs system engineering methodologies and a general morphological analysis and an infeasibility analysis to decompose the system and evaluate options, respectively. Our analysis defines the system and its function and identifies performance measures based on the requirements.

A. IDENTIFYING SYSTEM REQUIREMENTS

1. Stakeholder Analysis

The stakeholder analysis conducted for the TRAC-MRY project, as detailed in Table 3, reveals a complex interplay of priorities, needs, and concerns, underscoring the importance of balancing diverse interests in the system's development.

The stakeholder analysis highlighted the key priorities and system attributes, forming the basis for setting objectives and requirements. Table 3 distinguishes between internal stakeholders (directly impacting system requirements) and external stakeholders (indirectly influencing decision-making). The primary stakeholders for this project are TRAC-MTRY, M&S teams, and COMBAT XXI developers. These stakeholders have a high level of interest and influence the system's requirements The project sponsor, TRAC-MTRY, is interested in a process for evaluating alternatives for post-processing and data storage and has identified availability and affordability as two of the critical attributes of the system. The M&S team prioritizes the post-processing system's availability, accessibility, and performance. The primary stakeholders were routinely engaged to ensure that the resultant system design met stakeholder needs and expectations.

Table 3. Stakeholder Analysis

Priority	Stakeholders	Type	Needs	Goals
Internal				
1	TRAC-MTRY	Sponsor	Requires an analysis to evaluate alternatives for post-processing and data storage	Effective methodology and tools for evaluation alternatives for post processing and data storage
2	COMBAT XXI Devs	Facilitator	Software meets needs of TRAC M&S data performance measure requirements	System Architecture that effectively support M&S software and applications
3	M&S Team	End-Users/ Analysts	Require system availability, accessible real-time, and performs quickly	Accuracy and reliability of simulation results for decision-making
4	TRAC – AFC	Sponsor/ Analyst/User	Require data center alternatives for post-processing and data storage	Identification of best solution for postprocessing and storage of M&S data
5	AFC	Decision-maker	Cost-effective solution for M&S data postprocessing and storage	Efficient use of resources and budget allocation for data processing and storage
External				
6	ARL	Enabler	Optimizing resource allocation to support users	Meeting requirements by providing an effective and suitable system
7	Cloud Army	Enabler	Enable full cloud capacity to leverage Army M&S needs – Adhere to DISA Impact Level security standards	To provide a cost-effective service that meets M&S data postprocessing and storage requirements
8	TRADOC	Bystander	Effective and efficient solution that support M&S data processing and storage	M&S postprocessing and storage system that support decision making and training

The team reviewed the insights from the stakeholder analysis to determine the priorities. The top two priorities identified are to provide a process to evaluate post-processing and data storage alternatives and to provide alternatives that meet the stakeholders' availability needs. The stakeholder priorities are the foundation for objectives and requirements. The stakeholder's analysis identified the system's key attributes: performance, availability, accessibility, security, cost, and scalability.

2. System Definition

In congruence with the stakeholder analysis, we defined the post-processing and data storage system as the physical and non-physical infrastructure required to process COMBATXXI modeling and simulation data derived from realistic operational scenarios directed by Army Futures Command. The system must be able to process extensive data at scale and store the data for future use by TRAC-MTRY data analysts upon request. Figure 4, the Input, Control, Output, and Mechanism (ICOM) model, comprehensively represents the system's makeup.

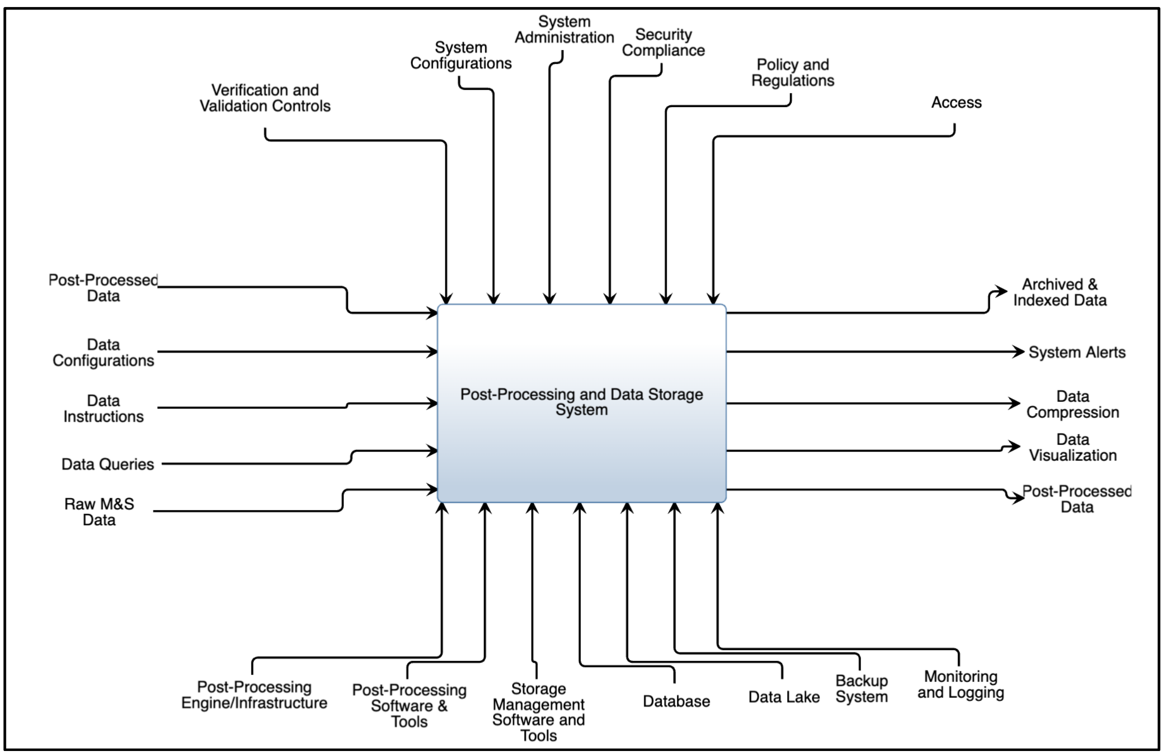

Figure 4. Post-Processing and Data Storage System ICOM

Figure 4 aids in the visualization of the storage system's flow and transformation of data, the parameters for the system, and the mechanisms that facilitate the execution of the system. The primary inputs are Post-Processed Data, Data Configurations, Data Instructions, Data Queries, and Raw M&S Data. Post-Processed Data is data that has been processed by the system which loops back as an input for archiving. Data Configuration is the framework that signals how the system should interpret and manage the data. Data Instructions are the commands the system executes. Data Queries are requests sent within the system to access, retrieve, or manage stored data—both an input and an interaction with outputs. The last input is raw M&S data, the primary source of data the system uses for processing.

Next are the controls, also known as the parameters, that dictate the system's behaviors. Verification and Validation Controls guarantee that there is data integrity and that the processed data is accurate. System Administration, Security Compliance, and Policy and Regulations are the operational governance of the system. The operational governance ensures the system adheres to external and organizational rules, directives, security standards, and internal settings.

The outputs are what the system produces—the deliverables of the system and the manifestation of whether the system has met the needs of stakeholder through measures. They end products of the system inherently rely on the transformation of the inputs discussed earlier. The outputs will manifest the measures of whether the system has met the needs of the stakeholders. Some inputs will coincide with multiple outputs when transforming. Archived and Indexed data depends upon the input of Post-Processed Data, Data Instructions, and Data Queries. This output is the systems' archival repository. System alerts rely on the Data Configurations and Data Instructions. Data Compression, Data Visualization, and Post-Processed Data (output) are direct outputs of transformed Raw M&S Data.

The last feet of the ICOM is the mechanisms of the system. The mechanisms consist of processes, tools, and components the system uses to enable transformations. The Post-Processing Engine and Infrastructure mechanism includes data centers or warehouses encompassing physical and non-physical networks and data architecture. The other mechanisms are the Post-Processing Software & Tools and the Storage Management Software and Tools. The distinction between the two is necessary to understand that storing and post-processing are separate phases in the system's life cycle and require different tools to execute. Database and Data Lake are the non-physical repositories of the system's data—in contrast to the Post-Processing Engine and Infrastructure. The Backup System is a standby system that includes all components discussed in the ICOM. Lastly, monitoring and logging ensure operational governance is adhered to and the system operates as designed.

3. System Boundaries and Interfaces

The Post-Processing and Storage system is the System of Interest. Figure 5 depicts the system, the system's environment, influences, boundaries, and interfaces. The system's top-level function is to process and store modeling and simulation data for TRAC-MTRY.

The primary external interfaces are the Headquarters Department of the Army (HQDA) and the Defense Information Systems Agency (DISA). HQDA sets policies and regulations for the Army, which impacts simulation scenario directives and development, funding, manning, and training. Those factors influence the viability of the system. DISA is the proponent for the Department of Defense network and information infrastructure and thus sets the networking standards for information systems—the Post-Processing & Storage System is an information system. DISA impacts the suitability of providers and data center infrastructure as both must comply with DISA standards.

The system's boundaries are physical, functional, and behavioral. The physical boundaries identified in the Post-Processing & Storage system include the data center infrastructure. The data center infrastructure encompasses the facilities, hardware, devices, and security posture. The functional boundaries include data inputs, retrieval, system responses, processing, and storing. The system requires valid input from users to produce a sound output—whether processing the data or storing it for future use. The behavioral boundaries are the user (M&S Analysts) interactions with the system and the system's response to user interactions and data. M&S Analysts must have the requisite knowledge to operate the system. However, even that knowledge won't mitigate all user-based errors or sabotage. The system's response depends on the system and infrastructure working as intended with the required technical and operational support to enable system functionality, prevent erratic system behavior, and invalid input.

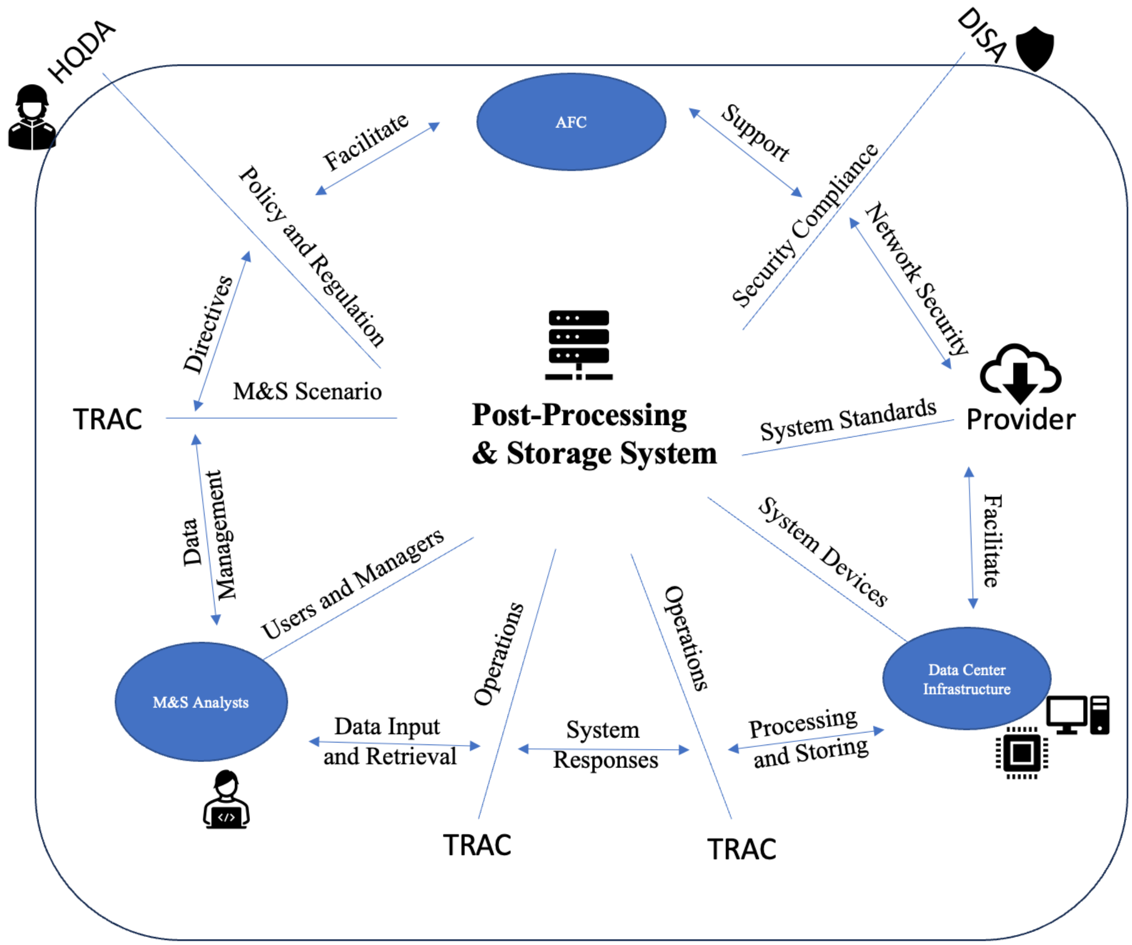

Figure 5. Post-Processing and Storage Context Diagram

4. Functional Decomposition

The team uses three tools to explain the system's functional breakdown. The system has seven high-level functions and 19 sub-functions.

Figure 6, the Functional Decomposition Hierarchy Diagram, illustrates how each function and sub-function relate. Table 4, the Functional Decomposition Hierarchy Table, provides a breakdown and description of each primary function and its underlying sub-functions. Finally, Figure 7, the Functional Flow Block Diagram (FFBD), captures the system's functions from the when data enters the system to retrieval from storage.

Starting with Initiate Postprocessing (1.1), the system signals the execution of the necessary tools and parameters to ensure the environment is ready to process data. Initiation of post-processing has two sub-functions, set up necessary tools and parameters (1.1.1) and prepare the environment for data processing (1.1.2). Set up necessary tools and parameters function loads the required software and adjusts configurations to align with the data type and processing needs. Prepare the environment for data processing ensures the system is ready to receive and continue processing the data.

Transitioning from initiation, the second high-level function of the system is Data Preconditioning (1.2), where raw data is acquired, metadata is collected, and the data undergoes validation, cleaning, and transformation to prepare it for post-processing. The subfunctions of preconditioning are raw data acquisition, metadata collection, data validation and cleaning, and data transformation. Raw data acquisition (1.1.2) involves collecting unprocessed data from various sources. It works in concert with metadata collection (1.2.2), which gathers additional information about the data, such as the date, time, and location. However, raw data can contain inconsistencies or errors addressed in data validation and cleaning (1.2.3). Once cleaned, the function data transformation for processing (1.2.4) ensures the data is in a format optimized for post-processing.

With the data preconditioned, the following high-level function is to execute post-processing (1.3). Post-processing involves analyzing and interpreting the data, followed by data visualization. Data visualization ensures that the data is processed and presented in an easily understandable and actionable manner. Data analysis and interpretation (1.3.1) extract meaningful insights, patterns, or trends. Data visualization (1.3.2) employs techniques to represent the data in intuitive graphical formats to make these insights palpable.

Given the voluminous nature of data, Data Compression becomes pivotal (1.4). Applying specific algorithms reduces the data size, making it more manageable for storage. Apply compression algorithms (1.4.1) reduce the data's size without compromising its essence. Optimize data for storage (1.4.2) ensures the data is ready for efficient storage.

Data storage (1.5) consists of short-term and long-term needs and ensures backup and recovery mechanisms are in place. Short-term storage (1.5.1) provides quick accessibility for frequently accessed data, while Long-term storage (1.5.2) archives data for future utility. Recognizing data's significance, data backup and recovery (1.5.3), safeguards against potential data loss.

Data verification ensures the integrity and completeness of the stored data (1.6). Data Verification uses checksums and integrity (1.6.1), which checks to ensure data integrity. Validate storage completeness (1.6.2) ensures data accountability.

Finally, data retrieval (1.7) provides functionalities for users to access, extract, update, or modify the data as required. Search functions (1.7.1) allow users to pinpoint specific data, while data extraction (1.7.2) facilitates data download as needed. Recognizing that data might need updates, data update and modification capabilities (1.7.3) ensure the data remains current and relevant.

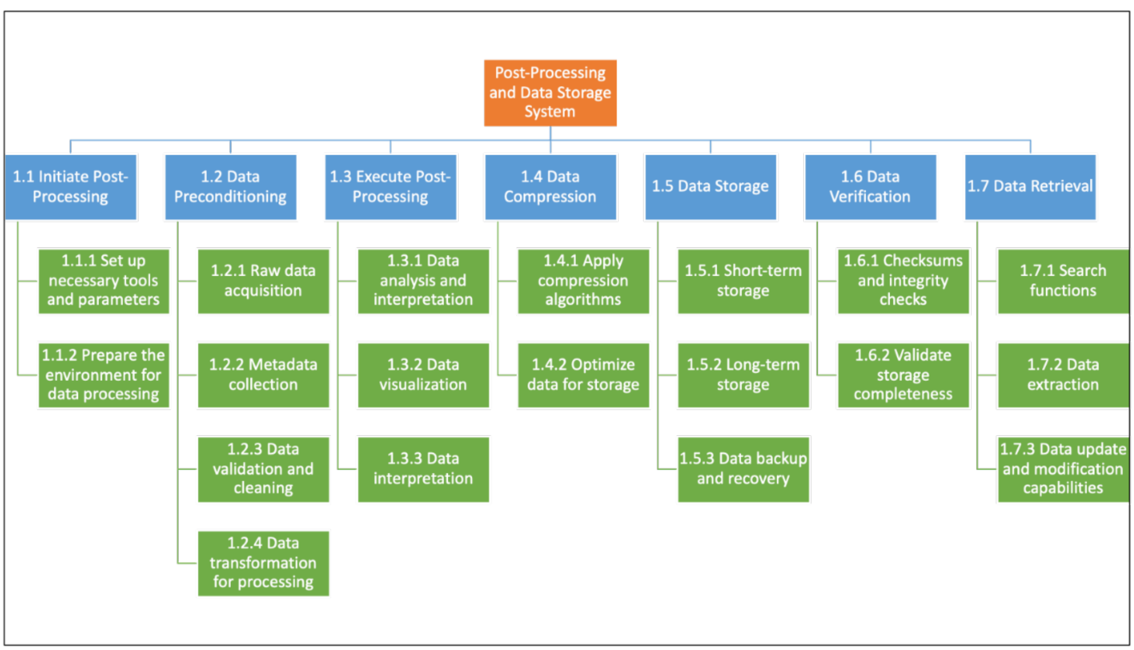

Figure 6. Functional Decomposition Hierarchy Diagram

Table 4 displays an alternative visual representation of the functional decomposition. Table 4 provides descriptions of the sub-functions. This table breaks down the system into its primary functions and its underlying sub-functions description.

Table 4. Functional Decomposition Hierarchy Table

Post-Processing and Data Storage System functional decomposition	
1.1 Initiate Post-Processing	
1.1.1 Set up necessary tools and parameters	Prepare the software, tools, and any required configurations to ensure the system is ready for post-processing tasks.
1.1.2 Prepare the environment for data processing	Ensure that the system environment, including hardware and software, is optimized and ready for the data processing phase.
1.2 Data Preconditioning	
1.2.1 Raw data acquisition	Collect the initial, unprocessed data from various sources.
1.2.2 Metadata collection	Gather additional information about the raw data, such as source, timestamp, and any other relevant attributes.
1.2.3 Data validation and cleaning	Check the data for inconsistencies, errors, or missing values and rectify them.
1.3.4 Data transformation for processing	Convert the data into a format or structure suitable for post-processing tasks.
1.3 Execute Post-Processing	
1.3.1 Data analysis and interpretation	Examine the data to derive meaningful insights, patterns, or trends.
1.3.2 Data visualization	Represent the data in graphical or visual formats like charts, graphs, or plots for easier interpretation.
1.4 Data Compression	
1.4.1 Apply compression algorithms	Use specific algorithms to reduce the size of the data without significant loss of information.
1.4.2 Optimize data for storage	Ensure that the compressed data is in a format that's efficient for storage purposes.
1.5 Data Storage	
1.5.1 Short-term storage	Store data that's frequently accessed or needed for immediate tasks.
1.5.2 Long-term storage	Archive data that's not immediately required but might be needed in the future.
1.5.3 Data backup and recovery	Create backup copies of the data to prevent data loss and have mechanisms in place to restore data if needed.
1.6 Data Verification	
1.6.1 Checksums and integrity checks	Use algorithms to verify that the data hasn't been tampered with during storage or transmission.
1.6.2 Validate storage completeness	Ensure that all data meant for storage has been stored correctly and completely.
1.7 Data Retrieval	
1.7.1 Search functions	Provide tools or features that allow users to search for specific data within the storage system.
1.7.2 Data extraction	Allow users to extract or download data from the storage system.
1.7.3 Data update and modification capabilities	Provide functionalities for users to update or modify stored data as required.

Figure 7 displays the system's functional flow to illustrate the sequential process of the system's functions. This Functional Flow Block Diagram (FFBD) serves as a roadmap, offering a clear view of the system's workflow and the order of operations. The system's FFBD captures its functions from when users interact to send data to its storage and eventual retrieval. It represents the system's workflow, making it a valuable tool for system designers and users.

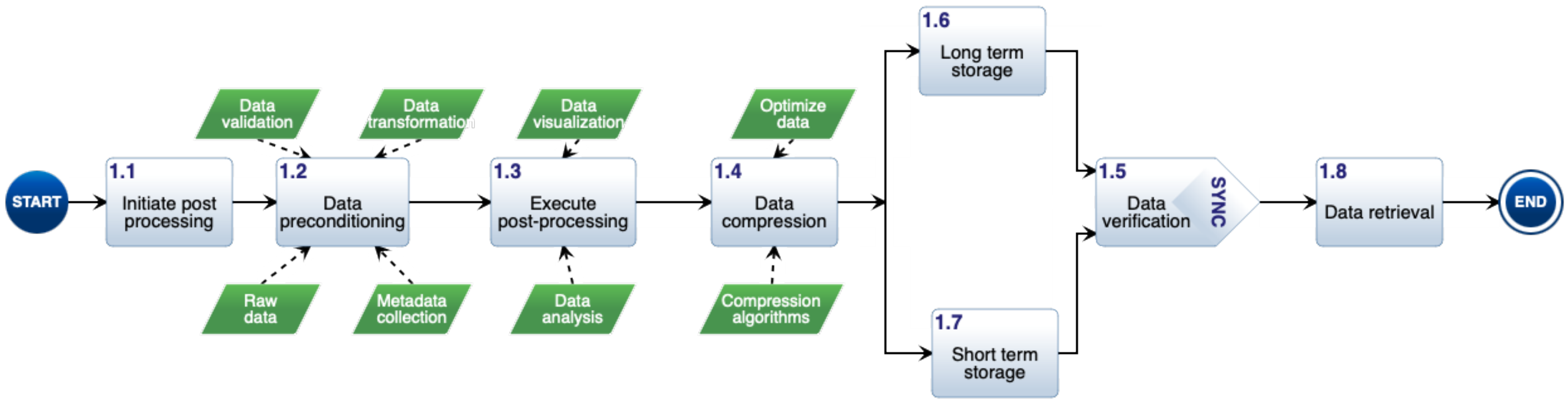

Figure 7. Function Flow Block Diagram

It is essential to align the Post-Processing and Data Storage System functions with the system's goals. Although the functional decomposition provides a roadmap of the system's operations, understanding its objectives clarifies the desired outcomes and the reasons behind each function. This alignment ensures that every operation within the system serves a specific purpose and contributes to the broader goals.

5. Objectives Hierarchy

The team uses an objectives hierarchy to illustrate the stakeholders' goals for the system's behavior. The objective hierarchy involves organizing objectives, with higher-level objectives representing broader goals and lower-level objectives representing more specific, actionable targets that support achieving the higher-level objectives. As shown in Figure 8, the system has four high-level and eleven lower-level objectives.

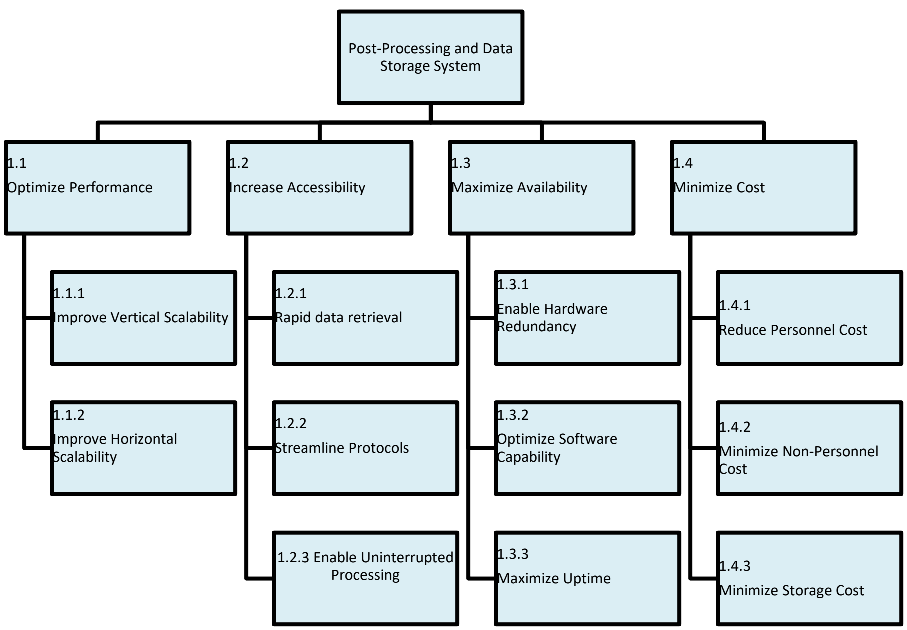

Figure 8. Objectives Hierarchy Diagram

Performance (1.1) refers to the system's ability to provide data rapidly and efficiently to meet the needs of its users. Optimizing performance improves the storage system's ability to ingest, process, store, and deliver data. Vertical scalability (1.1.1) is the system's ability to increase the capacity and performance of the data storage system by adding resources to a single node. Horizontal scalability (1.1.2) increases the data storage system's capacity and performance by adding more servers or nodes to existing infrastructure. When scalable, the system supports concurrent requests and users while maintaining or even improving its performance. Scalability enhances the system's availability by distributing data and workloads across multiple components or locations.

Accessibility (1.2) is the ability for users to access and retrieve data from the data storage system when needed. Here, Rapid data retrieval (1.2.1) is the system's ability to enable user requests for data access and retrieval. Streamline Protocols (1.2.2) are required for users to access the data storage system without unnecessary obstacles. Streamlining these protocols ensures that users can access the data when needed, mitigating constraints such as competing for resources, processes, and procedures. Uninterrupted processing (1.2.3) is the ability of the data storage system to continuously perform input/output operations without any disruption or downtime.

Availability (1.3) is the readiness of the entire data storage system to always respond to user interaction without interruption. Hardware redundancy (1.3.1) focuses on the system's availability. It ensures that even if one storage disk fails, the system can continue providing data access without noticeable downtime due to redundancy and failover mechanisms. Software capability (1.3.2) refers to the functionality, features, and overall intelligence enabled in the data storage system via software programming. This subfunction elevates the essential hardware appliance of the system into an intelligent, high-valued platform tailored to the needs of applications. Uptime (1.3.3) is the amount of time the data storage system is operational and accessible to serve input/output requests.

Cost (1.4) is the total cost, which includes system hardware, software, all supporting elements such as office buildings and lab space, and personnel costs. The data storage system aims to provide efficient data storage and retrieval capabilities while minimizing the total cost of ownership (TCO) over the system's life cycle. Personnel cost (1.4.1) is the expenditures associated with workers required to manage, operate, maintain, and support the data storage system. Personnel cost is dependent on the complexity of the system's technology and is a significant component of the total cost of running and maintaining the data storage system. All other costs (1.4.2 and 1.4.3) are the additional costs of running and maintaining the storage system, such as software and hardware costs, the cost of technological advancements, the cost of building infrastructure and lab space, and equipment costs.

The objectives hierarchy is the strategic tool that illustrates the stakeholders' goals and enables them to allocate resources effectively, monitor performance, manage risks, and ensure that the data storage system aligns with the organization's objectives. It enhances transparency, accountability, and the overall success of data storage-related initiatives.

To effectively evaluate the performance of the data storage system, the team translated the objectives into measures. The scalability objective aims to measure the maximum storage capacity of the data storage system before performance degrades, the number of concurrent users the system can support without a significant decrease in response time, and the cost-effectiveness of scaling the system. The accessibility objective measures the response time for data retrieval, uptime percentage, or the number of successful data access requests from the data storage system. The availability objective measures the uptime percentage of the system, the mean time between failures (MTBF), and the recovery time objective (RTO) in the event of an outage. The cost-effective objective measures the capital costs of storage hardware and software purchases, ongoing support and maintenance fees, facilities and infrastructure costs for storage equipment, and personnel costs for the admin team. It monitors dollar-per-terabyte storage for the data storage system. The objectives are translated into specific measurable, achievable, relevant, and time-bound (SMART) metrics. As illustrated in Table 5, turning objectives into SMART metrics is done by breaking down the broad objectives of the system, which is improving system scalability, improving data accessibility, improving system availability, and reducing total operational cost, into components and assigning measurable criteria or metrics with a numerical term or a clearly defined evaluation criterion.

Table 5. SMART Metrics Table

#	ID	Measure/Metric	Requirement
1	**1.0**	**Scalability**	
2	1.1.1/1.1.2	Horizontal/Vertical Scalability	The system shall provide a 50% (T) up to 100% (O) improvement in processing high-volume jobs during peak usage throughout the system's operational lifespan.
3	**1.2**	**Accessibility**	
4	1.2.2	Rapid Data Retreival	The system shall ensure that 99% (T) and up to 100(%) of data retrieval requests are completed within 24hrs (T) or 12hrs (O) throughout the system's operational lifespan.
5	1.2.3	Streamline Protocols	The system's steps in the data processing and retrieval process shall be equal to (T) the current system or reduced by 50% (O) throughout the system's operational lifespan.
6	1.2.4	Uninterrupted Processing	The system shall perform continues input/output operations with <= 1% downtime during peak operational period, and shall provide uninterupte access to 100% of stored data.
7	**1.3**	**Availibility**	
8	1.3.1	Hardware Redundancy	The system shall ensure continued operation and provide uninterupte access to 100% of stored data, with a 99% reliability and fault tolerence, and a <=1% risk of data loss and downtime due to hardware issues.
9	1.3.2	Software Compatibility	The system shall support 95% of the key software and tools currently used by analysts or introduce improved software and tools with full functionality and no performance degradation. The system shall enable flexibility of future software integration comparative to the current system (T) or more flexible than the current system (O) throughout the system's operational lifespan.
10	1.3.3	Uptime	The system shall achieve 99.99% system uptime (T=O) throughout the system's operational lifespan.
11	**1.4**	**Cost**	
12	1.4.1	Personnel Cost	The system shall incur less than 10% additional personnel cost and less than 10% operational costs (temporary or permanent) or no additional personnel or operational costs (O) throughout the system's operational lifespan.
13	**1.4.2**	**Non-Personnel Cost**	
14	1.4.3	Cost-Effective Storage	The system shall have a lifecycle cost no more than 10% (T) or => (O) than the current system while maintaining (T) or improving (O) current storage capacity and performance throughout the system's operational lifespan.

B. CONCEPTUAL DESIGN

1. Function-to-Component Tracing

The team imitates conceptual design by conducting a function-to-component tracing to elucidate the relationship between the functions for post-processing and storage and the physical components to perform those functions. Table 6 provides an overview of the essential components required for each functional requirement.

Table 6. Function-to-Component Matrix

	Servers	Graphic Processing Unit	Central Processing Unit	Storage Type	User Interface Type	User Input Device	Data Processing Algorithms	Security	User Interface Devices
F1 Initiate Post-Processing	X	X	X		X	X		X	X
F2 Data Preconditioning	X	X	X				X	X	X
F3 Execute Post-Processing	X	X	X				X	X	
F4 Data Compression	X		X				X	X	
F5 Data Storage	X		X	X				X	
F6 Data Verification	X	X	X				X	X	X
F7 Data Retrieval	X		X	X	X	X		X	X

The team identified 31 components commonly used to complete the seven functions specified for post-processing and storage (see Appendix A). The team condensed the component list down to nine essential components. The team reduced the component list due to the team's capacity (knowledge, time, and resources) to analyze the components for the GMA. The Servers, GPUs, and CPUs are necessary for initiating post-processing. They load software and prepare the system for data handling. Data preconditioning relies on servers to gather data and CPUs to run algorithms, which validate data and transform it into the required format. The execution of post-processing depends on the combined efforts of servers for management, CPUs for computation, and GPUs for data visualization. CPUs are primarily responsible for data compression activities, applying algorithms to efficiently compact data for storage. Storage functions use a mix of storage types, ensuring data is accessible for immediate use and securely archived. Backup and recovery systems safeguard against data loss. The security protocols of the system's servers and CPUs ensure data integrity during data verification. Finally, storage types and user interfaces facilitate data retrieval. Storage type and user interface allow quick data search, extraction, and updates, keeping user interaction seamless and data current. These interconnected components form a framework for data processing and storage operations.

2. General Morphological Analysis

The General Morphological Analysis uses the components identified in the function for component analysis. Table 7 provides a matrix of subcomponents to explore the range of possible configurations for each system component.

Table 7. General Morphological Box

Subcomponents	Option 1	Option 2	Option 3	Option 4
Servers	On-premises HPC	Cloud-Based	Hybrid	Edge Computing
CPUs	Intel Xeon	AMD	ARM	Quantum Processors
GPUs	NVIDIA	AMD Radeon	Integrated GPUs	AI Optimized GPUs
Storage Type	Local (HDD, SSD)	Cloud Storage	Hybrid Storage	Decentralized Storage
User Input Type	Graphical (GUI)	Command-Line (CLI)	Web-Based	Mobile App
Security	DoD Compliant	IL1-4	IL1-6	Non-DoD Compliant
User interface Devices	Standard Issue/Government Furnished	BYOD	Open-Source Hardware	Custom-Built
Data Processing Algorithms	Batch Processing	Stream Processing	Parallel Processing	Quantum Algorithms
User Interface Devices	Desktop	Tablet	Mobile Device	Laptop

The General Morphological Analysis (GMA) uses the identified components to explore various subcomponents to build system options. The server options are on-premises HPC, cloud, hybrid, and edge computing, which differ in control and speed. The CPUs are Intel Xeon, AMD, ARM, and quantum processors, each with unique processing strengths, with the former being the most common. GPUs vary from high-performance units by NVIDIA to cost-effective integrated GPUs by AMD Radeon and AI-optimized options. Storage options include local HDDs/SSDs, cloud, hybrid, and decentralized storage, each with varying accessibility and security. The User input type offer GUIs, CLIs, web-based, or mobile app access tailored to different interaction styles. Security levels range from DOD compliance to various Impact Levels (IL) and more open non-DOD options. Interface devices vary from standard government-issued to BYOD and custom-built hardware. Data processing algorithms cover batch, stream, parallel, and quantum processing and are adaptable to current and future needs. The red and blue shaded boxes in Table 7 represent two distinct configurations derived from the GMA.

The theoretical designs created in the GMA are further analyzed in the alternative analysis to discern options not viable for post-processing and storage based on stakeholder objectives and requirements.

C. INFEASIBILITY ANALYSIS

The team began the preliminary stages of analyzing alternatives by conducting an infeasibility analysis via the infeasibility diagram, using the insights from the function to component analysis and the GMA. An infeasibility diagram is a visual tool used to evaluate and illustrate the practicality and viability of a project, system, or solution. It typically encompasses various dimensions such as technical feasibility, economic viability, operational practicality, and legal or regulatory compliance. This diagram aids decision-makers in understanding the strengths and weaknesses of different options, highlighting potential risks and benefits, and guiding them towards making informed choices that align with project goals and constraints. By mapping out these aspects, a feasibility diagram serves as a crucial step in project planning and development, ensuring that the proposed solutions are not only theoretically sound but also realistically implementable.

1. Infeasible Solutions

Figure 9 displays the infeasible connections. The team identified that any component that involves a solely on-prem option is not feasible due to DOD directives and budget constraints.

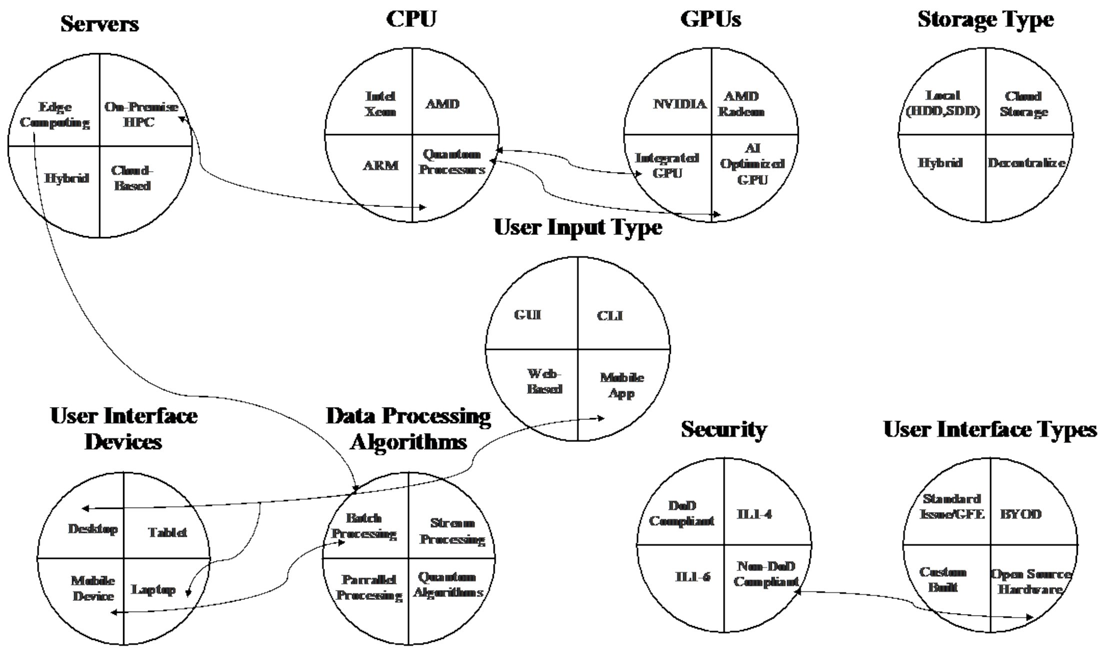

Figure 9. Infeasibility Analysis

The edge computing option for the server component is infeasible as it needs the required processing power to facilitate TRAC-MTRY postprocessing jobs, and its inability to scale increases the current job wait time for analysts during peak hours. The hybrid option requires support for on-premises infrastructure. The stakeholders need more resources (budget, maintenance, personnel) to support a hybrid infrastructure. The quantum processors in the CPU component are not feasible because quantum processing technology is still in its infancy. At the same time stakeholders' timelines and requirements require a technically mature solution to mitigate operational pauses. The justification for the AI-Optimized GPU being infeasible is like that of the quantum processors. The integrated GPU is infeasible due to an integrated GPU/CPU not having the performance and efficiency to process routine M&S jobs. Mobile devices are not feasible with robust data processing algorithms. Using mobile devices would slow down user input and visualization, reducing the number of tasks analysts can complete. User interface type components laptops and desktops are infeasible with user input type mobile app due to mobile applications' optimization for mobile devices such as smart phones and tablets, not laptops and personal computers. Lastly, non-DOD compliant (any component) is not a feasible component with any other component; this includes open-source hardware from the user interface type component.

2. Candidate Solutions

The team identified two of many feasible solutions shown on Table 8. The first feasible solution is a cloud-based infrastructure that can use Intel or AMD CPUs, NVIDIA or AMD GPUs, with scalable cloud storage while operating with all user interface devices and types and supporting all data processing types. The solution can be DOD compliant and has the flexibility to support up to DOD Impact Level 6 (IL6) security standards, which means the infrastructure can host classified material up to Top Secret. This option potentially provides the best scalability, availability, and performance flexibility and can range in technical and financial costs.

The second feasible solution is a hybrid on-premises and cloud solution. This solution is like the first feasible solution regarding feasibility with multiple components. Trade-offs in cost and scale underscore the nuanced differences. The Department of Defense clearly defined its objective of transitioning all local data farms, so TRAC-MTRY would require internal resources to support any potential hybrid solution, which adds additional complexity to a trade-off analysis.

Table 8. Feasible Solutions

Subcomponents	Solution 1	Solution 2
Servers	Cloud-Based	Hybrid on premises
CPUs	AMD/Intel Xeon	AMD/Intel Xeon
GPUs	NVIDIA	NVIDIA
Storage Type	Cloud Storage	Hybrid Storage
User Interface Type	Command-Line (CLI)	Web-Based
Security	IL1-6	IL1-6
User interface Devices	Standard Issue/Government Furnished	Standard Issue/Government Furnished
Data Processing Algorithms	Stream Processing	Parallel Processing

Understanding that the infeasibility analysis produced two similar feasible solutions, we decompose the comprehensive similarities (cloud) into potential alternatives. These alternatives capture all discussed feasible concepts and are realistic options for the stakeholder to consider. The Army Research Laboratory High Performance Computing Center, Amazon Web Services, and Microsoft Azure are viable alternatives. While TRAC is already considering this solution, our analysis also resulted in these alternatives based on technological maturity, including the feasible components, DOD compliance, and current DOD facilitation of similar systems that address the stakeholders' needs.

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V. CONCLUSION

A. PURPOSE

The team conducted the capstone with the primary objective to develop a set of postprocessing and data storage alternatives for combat simulations in support of TRAC-MTRY, while also analyzing appropriate measures to compare alternatives. Additional sub-questions that drove the research include:

1. How does the computational performance differ across the alternatives for post-processing, considering ARL HPC and Commercial Cloud Service Providers facilitated by Enterprise Cloud Management Agency (ECMA) or Cloud Army, regarding speed, scalability, and reliability?
2. What is each alternative's capacity limits and scalability for postprocessing and data archiving, and what is the impact on long-term feasibility?
3. How do the ease of use and accessibility to postprocessing and archive data compare to alternatives?

These questions helped the team systematically approach the system analysis using the methodology discussed in Chapter 3. The team recognizes that each question is nuanced and is only partially answered due to constraints and limitations such as time, expertise, and priorities. The team attempted to solve each question comprehensively within the framework of our analysis.

To answer the research questions, the team followed a methodical approach, which began with assessing the capabilities, identifying system requirements, and breaking down the required system into components. We used GMA to identify potential alternatives and then rigorously evaluated these alternatives based on key performance indicators and infeasibility analysis. Based on the analysis, the team developed potential performance measures for TRAC-MTRY to use for the evaluation of alternatives.

B. RESULTS AND ANALYSIS

The team concluded that applying a tailored systems engineering approach focusing on requirements, conceptual design, and alternative analysis provided an effective process to generate a post-processing and storage system for TRAC-MTRY. The team determined two viable solutions for the Department of Defense's transition from local data centers. The first solution recommends a flexible, cloud-based infrastructure hosting classified material up to the Top-Secret level. This solution offers robust scalability, availability, performance flexibility, and various technical and financial costs. The second solution suggests using a hybrid of on-premises and cloud systems. This solution has nuanced differences in cost and scale but requires additional internal resources for support. The proposed solutions require further analysis by TRAC-MRTY to determine system effectiveness when applied to operation requirements.

To address the analysis of appropriate measures for the system, the team rated specific performance measures such as latency, throughput, and speed as appropriate measures to compare alternatives. Those performance measures are not as relevant as those established in Chapter 4, which deal with scalability, accessibility, availability, and costs. The revelation that latency, throughput, and speed were not appropriate came about through the stakeholders' priorities during stakeholder analysis and analysis of TRAC MTRY's current data processing system and viable alternatives—an increase in the performance measures provides little return on value for TRAC MTRY. Due to the low value placed upon computational performance by stakeholders, sub-question (1) is not thoroughly answered in this capstone.

In reference to sub-question (2) and (3), based on the standard TRAC-MTRY workloads, the research indicates that the ARL HPCs would have similar scalability to TRAC-MTRY's current system. At the same time, AWS and Azure can provide noticeable improvement to scalability. The hybrid option can also offer noticeable improvements in terms of scalability. We assess that the hybrid option is the least viable in terms of long-term feasibility due to the requirement of internal resources to support the on-premises portion of the hybrid option. Next, ARL HPCs would be a long-term risk as the current dedicated modeling and simulation data center will end in 2025. The dedicated ARL will refresh the dedicated M&S HPC center, but scalability challenges remain compared to flexible options with Azure and AWS.

The team focused on developing a process to evaluate alternatives. Still, it became clear that the absence of a process unique to the TRAC-MTRY problem set required the team to execute a process to develop alternatives. Thus, this capstone is a process that generated feasible alternatives for TRAC-MTRY. Each facet of the capstone, integrating the systems engineering framework, was a deliberate step in the process that is replicable. The team decomposed the problem, conducted research through a literature review, conducted a stakeholder analysis, defined the system, decomposed the system, developed measures, and generated alternatives. A critique of the process is that more quantitative analysis is needed to evaluate alternatives and benchmark TRAC-MTRY's current system.

Finally, based on the options the team assessed (Hybrid, Cloud, On-Premises, Edge Compute), the two feasible options are Hybrid and Cloud solutions. Our recommendation is a Cloud solution based on stakeholder constraints and limitations. The potential alternative cloud solutions are Microsoft Azure, Amazon Web Services, and the Army Research Laboratory High-Performance Computing Center—all three have affiliations with the Department of Defense.

C. LIMITATIONS

The team identified knowledge (subject matter expertise), resources, and time resources as the most notable limitations. The limitations impacted the scope and depth of the project. The lack of subject matter expertise and access to historical system data and logs hindered the team's ability to analyze the existing system's performance and capabilities comprehensively. As a result, some recommendations and conclusions may not fully account for the intricacies and unique challenges inherent in the current system. This limitation highlights the need for more in-depth data access in future projects to enable a more thorough and accurate assessment. The capstone's timeline limited the team's ability to analyze and test all potential alternatives to evaluate the effectiveness of the system and the engineering process. The limited timeframe for the capstone project prohibited the team from exploring all potential alternatives in depth or conducting extensive feasibility studies. These limitations can be addressed and rectified in future post-processing and storage project work.

D. FUTURE WORK

Future work should focus on further analysis of the team's proposed alternatives. The SMART measures and metrics proposed in the capstone report can serve as a starting point for TRAC-MTRY to evaluate alternatives. The team recommends tools such as a value model and decision matrix to compare the alternatives to aid in the decision-making process for selecting a post-processing and storage system. We recommend a deeper analysis of the alternatives that incorporates benchmarking TRAC-MTRY's current system's measures and running simulations with the alternatives against the proposed metrics to assess the relevant performance of each alternative. The insight gained from simulating performance will aid in generating an accurate decision matrix.

Additionally, future work should evaluate the team's process to generate feasible alternatives. The tailored process used within the capstone is unique to TRAC-MTRY's data center challenge. An analysis should be done by future capstone or thesis students to evaluate the process's accuracy and succinctness regarding the methodology and steps taken to determine alternatives.

APPENDIX. FUNCTION-TO-COMPONENT MATRIX

	Servers	Graphic Processing Unit	Central Processing Unit	Storage Type	User Interface Type	Data Processing Algorithms	Security	User Interface Devices	Access Control Systems	Performance Optimization	Resource Allocation Algorithms	Memory	Storage System	Operating System	File Systems	File Transfer Tools	User Directories	Shells	Program Model	Compilers	Libraries	Debuggers	Code Profiling and Optimization	Network and Connectivity Devices	Power Management System	Data Management System	Scheduler
F1 Initiate Post-Processing	X	X	X		X		X	X		X	X	X		X				X						X	X	X	X
F2 Data Preconditioning	X	X	X			X	X	X		X	X	X												X	X	X	
F3 Execute Post-Processing	X	X	X			X	X			X	X								X		X	X	X	X	X	X	
F4 Data Compression	X		X			X	X			X	X	X								X	X			X	X	X	
F5 Data Storage	X		X	X			X		X				X		X		X							X	X	X	
F6 Data Verification	X	X	X			X	X	X				X										X		X	X	X	
F7 Data Retrieval	X		X	X	X		X	X					X		X	X	X	X						X	X	X	

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