Data Farming and Analytics for Air Defence

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***Abstract*—The proliferation of air-based threats, largely due to technological advancements in propulsion, coupled with global instability, warrants research into air-defence capabilities. In this exploratory project, various air-defence scenarios were used to determine the optimal parameters to protect high-value targets from incoming threats. Datasets were generated and farmed through MANA (Map Aware Non-Uniform Automata), an agent-based modelling software. Subsequently, machine learning techniques and statistical analysis were applied to identify salient parameters, as determined by two measures of performance: Asset Survival Rate and Proportion of Missiles Intercepted. For both measures of performance, interceptor sensor range was determined to be the parameter of importance.**

***Keywords*—Air defence, military, simulation, agent-based modelling, machine learning, data farming, decision tree, random forest**

I. Introduction

Bolstering air defence capabilities is a vital consideration for state militaries as it is an essential component of national security. As highlighted in current events, this importance is demonstrated daily in the Ukraine due to its conflict with Russia. While defensive capabilities have progressed in this era of great technological advancement, so too have offensive capabilities, specifically in the number, speed, and maneuverability of air threats, which test the limits of current defence mechanisms. Take the example of Israel's Iron Dome*,* the crux of its air defence strategy. While Israel claims mission success based on the number of missiles the dome has intercepted, so too has Hamas with the number of missiles that penetrated the dome. This suggests that there is room for continued research to enhance defence mechanisms against instruments with nuclear payloads.

In its simplest form, air-defence scenarios can involve missiles, interceptors, and sensors. An air threat is launched, and is detected by a sensor, which then passes the information to the response capability. This could be missile launchers, countermeasures, or machine guns, which then fires a response, such as triggering an interceptor to eliminate a threat. For this research, variations of this scenario were simulated in a computer-based modelling software, from which datasets were generated (farmed) and analyzed. For these simulations, an inexhaustive list of manipulated parameters include missile and interceptor quantities, missile and interceptor speeds, lethality, and sensor detection ranges. From here, statistical analysis and machine learning processes were applied to the datasets to determine the most salient parameters for air defence.

II. Related Works

While much of the national defence literature is confidential, there have been several public studies released by Defence Research and Development Canada (DRDC) which involve the use of machine learning to predict scenario outcomes using pre-existing databases, and data farmed from MANA (Map Aware Non-Uniform Automata)[1] simulations [1].

A DRDC study (2020) titled, *Forecasting the Casualty Rate of Future Terrorist Attacks* [2]*,* reported the occurrence of 96,570 terrorist attacks between 2010 and 2018. These attacks pose major challenges to law enforcement and medical personnel, and as a result there is high value in being able to predict their occurrence and the expected casualties based on various factors. Using data from the Study of Terrorism and Responses to Terrorism (START) database, the DRDC implemented random forest models to predict causality rates based on the region of attack, target type, attack type and weapon type.

Additionally, Amyot-Bourgeois et al. (2021) [3] employ data farming via MANA coupled with machine

[1] MANA will be further discussed under the *Methodology* section.

learning to analyze conflict between two neighbouring countries. The study focuses on defence strategies utilized by one NATO country against a hostile neighbouring country practicing expansionist policies in the form of invasion. Random forest and k-nearest neighbours was used to evaluate how the deployment of unmanned aerial vehicles, tanks, and the implementation of various sensor ranges could impact successful defence for the NATO nation.

III. Methodology

The project consists of five main stages: design & simulation, data farming, processing of farmed data, implementation of machine learning, and exploratory data analysis and visualization (Fig. 1).

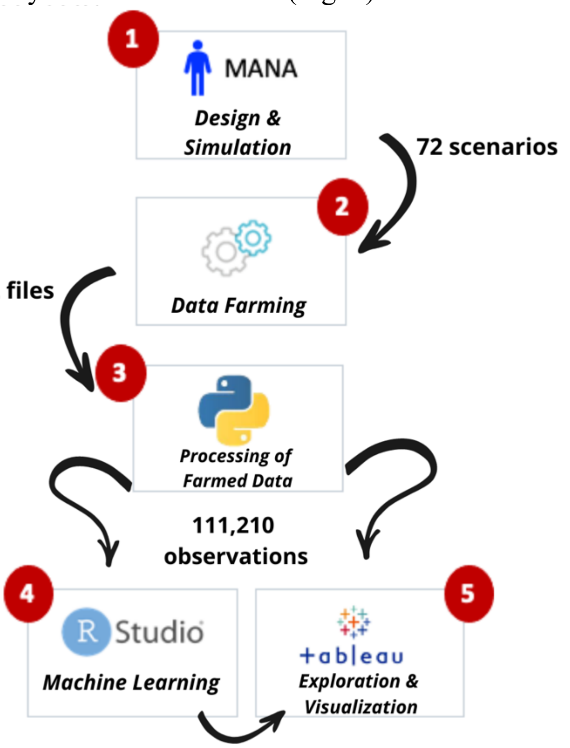

Fig. 1. Project Stages

Design, simulation, and data farming was done in MANA, a computer-based modelling software developed by New Zealand's Defence Technology Agency. It is used to explore intangibles and complexities in warfare. Specifically, it is utilized to provide analytics for, and to forecast outcomes of, military operations. For the project, software version 4.04.3 was used (MANA 4).

A. Design and Simulation

The first stage of the project involved the design and simulation of various air defence scenarios. The map size was set to 500x500, and simulation step count was set to 800. In an effort to keep certain parameters constant and to avoid potential biases, this served as the base scenario for our simulations, from which new scenarios will be modelled upon. This base scenario consisted of three missiles, three interceptor bases, three interceptors, and three asset classes. In the base scenario, each class consisted of a single agent.

New scenarios were developed by changing the total number of agents, varying from three to nine for missile and interceptor classes. From here, four new scenarios were developed by manipulating missile class stealth probability between 0 and 0.3. This parameter provides the relationship between the detection probability of the missiles and the outcomes. From this, 72 new scenarios were created – 18 scenarios (with various agent quantities) in combination with 4 missile class stealth values.

To imitate real-life scenarios, the simulations were designed such that the interceptors and assets were not easily visible to the missiles, unless from a very close range. Fire mode/target for missiles and interceptors were set to "high explosive/sqd SA". Upon reaching their target destinations, the missiles would detonate, effectively killing the assets. To compare vantage points, relative to missiles, the whole field was visible to interceptors within a given detection range.

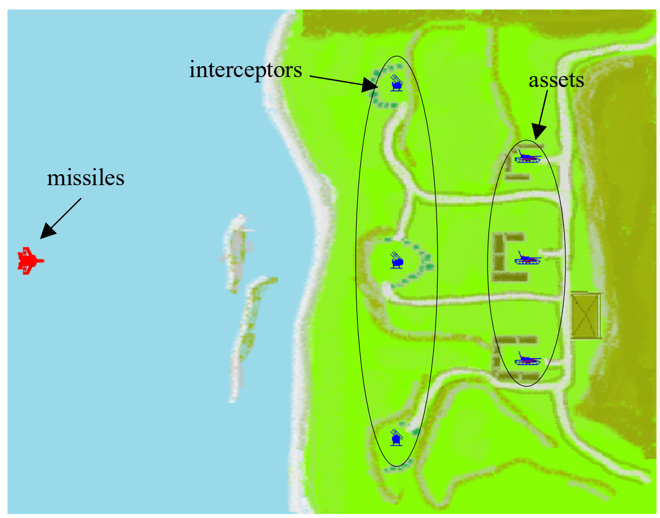

Fig. 2. Map of Air Defence Scenario

Interceptors had an identical blasting radius to the missiles – for both classes, the range to center was set to 10. Given the blasting range, it is possible for a detonation to occur which would only result in an interceptor killing itself. In some cases, the hit probability of interceptors and speed differential would allow missiles to escape the blast radius of the interceptors. Additionally, the speed of the missiles was held constant at 70, and as a result, only the speed of interceptors was changed. Table I highlights the coordinates of each respective class within the 500x500 grid.

TABLE I. CLASS LOCATION COORDINATES ON THE MAP

Classes	Home		Waypoint	
	X	Y	X	Y
Missile Class 1	20	249	400	149
Missile Class 2	20	249	400	249
Missile Class 3	20	249	400	349
Interceptor Class 1	300	74	-	-
Interceptor Class 2	300	249	-	-
Interceptor Class 3	300	424	-	-
Asset Class 1	400	149	-	-
Asset Class 2	400	249	-	-
Asset Class 3	400	349	-	-

B. Data Farming

In this stage data was farmed by applying various parameter ranges to the data farming editor. These parameters can be found in Table II.

TABLE II. PARAMETERS OF INTEREST

Parameter	Unit	Range	Incr.
Missile quantity	-	3-9	1
Interceptor quantity	-	3-9	1
Detection range	grid	50-250	25
Interceptor speed	-	50-100	10
Interceptor hit probability	%	0-100	10
Missile stealth	%	0-30	10

The number of simulations for each generated scenario was set to 10, which allowed us to collect 10 samples for each scenario. In addition, the *"Record casualty location data"* option was selected, which would allow us to determine if a missile was eliminated by interceptors based on their termination location, as the main farmed data output does not provide information on this. In total, more than 70,000 files – main output .csv files, .xml files (scenario configuration) and casualty location information .csv – were generated.

C. Processing of Farmed Data

The farmed main output .csv files did not contain all the information required for analysis. It was instead limited to the quantity of destroyed assets and scenario file names. The scenario configuration .xml file contained all the parameter values from which scenarios were generated. Finally, the casualty location information .csv file contained the information on the location of destroyed missiles, from which we would be able to determine successfully intercepted missiles.

As fragments of each scenario were dispersed across different files, a custom Python script had to be developed to effectively process the data. This script enabled us to automate the process of merging the data into a single dataset for analysis, effectively increasing efficiencies by eliminating the need for time-consuming, manual labour.

D. Implementation of Machine Learning

After the data generating process was complete, it was fed into decision tree and random forest machine learning models using RStudio. These helped us gain an understanding of the relationship between parameters and outcomes and determine the parameters which impacted outcomes the most. The implementation of machine learning models will be further discussed in *Analysis*.

E. Exploratory Data Analysis and Visualization

Parallel to the implementation of machine learning processes, Tableau was used to perform preliminary and exploratory data analysis. The result of these will be expanded upon in *Analysis* section. In addition to this, Tableau was also utilized for data visualization.

IV. ANALYSIS

Following the completion of data farming and data processing, it was necessary to determine a metric which would allow our model to classify whether or not the outcome of a scenario was successful. As a result, our analysis evaluates the success of a defence scenario using two Measures of Performance (MOP). Asset Survival Rate (ASR) and the Proportion of Missiles Intercepted (PMI) were used to determine the success of each scenario run. Scenarios which resulted in the survival of at least two of the three assets were classified as a success. Additionally, scenarios which yielded a missile interception rate of 75% or greater were also deemed a success. A breakdown of each MOP and the boundary pertaining to their binary classification for defence success/failure can be seen below.

$$ASR = \begin{cases} Success, & Assets\ Survived\ \geq 2/3 \\ Failure, & Assets\ Survived\ < 2/3 \end{cases}$$

$$PMI = \begin{cases} Success, & Proportion\ of\ Missiles\ Intercepted\ \geq 3/4 \\ Failure, & Proportion\ of\ Missiles\ Intercepted\ < 3/4 \end{cases}$$

Our analysis models the relationships between the established MOPs and the following independent variables: interceptor speed, interceptor hit probability, interceptor quantity, interceptor sensor range, missile detection probability and missile quantity.

A. *Preliminary Analysis*

Preliminary data analysis was conducted following the completion of data farming and data processing to evaluate relationships within the raw cumulative data. Exploratory data analysis allows for the observation of obvious relationships to be quickly verified, while also providing information regarding potential abnormalities within our data. Several preliminary findings will be discussed below.

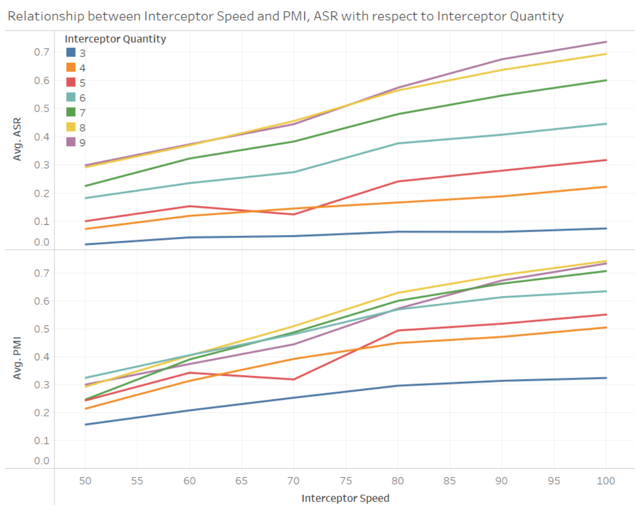

Fig. 3. Interceptor Speed vs. Measures of Performance

Our analysis highlights a strong positive relationship between interceptor speed and mission success rates, measured in terms of ASR and PMI. Figure 3 depicts this relationship, while using a color gradient to differentiate between various interceptor quantities. While increasing interceptor speed benefits both MOPs for all interceptor quantities, it is worth noting that the magnitude of this increase varies across interceptor quantities. As seen in Figure 3, gains in successful outcomes differ across interceptor quantities particularly when interceptor speeds are between 60-80. As noted previously, all scenarios fixed missile speed at 70, and as a result, this likely attributed to the fluctuation in the mentioned interceptor speed range. As the speed of the interceptor approaches the missiles speed (70), outcomes become more heavily influenced by interceptor quantity.

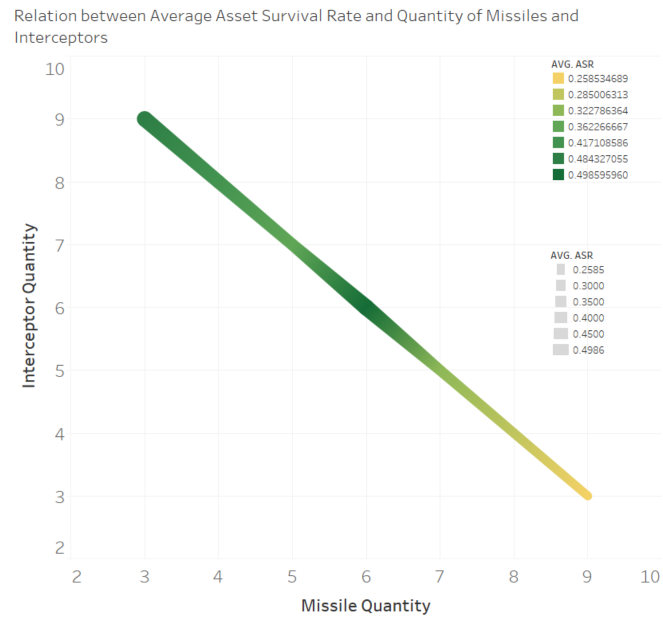

Fig. 4. Interceptor & Missile Quantity vs. Asset Survival Rate

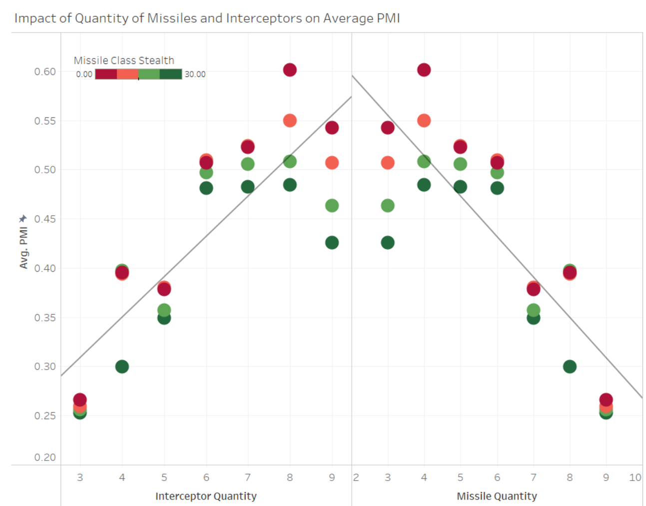

Fig. 5. Missile and Interceptor Quantity vs. PMI[2]

Moreover, Figure 4 highlights the relationship between missile quantity, interceptor quantity and the ASR measure of performance. Overall, ASR increases as missile quantity decreases and interceptor quantity rises. Additionally, it is worth noting that when the quantity of missiles and interceptors are breaking-even, ASR also yields a high average. This may imply that when the number of missiles and interceptors are equal, ASR is directly influenced by other parameters such as speed, detection range and hit probability, which in this case, plays in the favour of successful defence.

[2] Also known as Defence Success Rate.

B. *Machine Learning Implementation*

Following the preliminary analysis, data was split into a training and test set using a random stratified split, where 80% of data was allocated to the training set and the remaining 20% was allocated to the test set. Machine learning algorithms (decision trees and random forests) were used to determine variables of the greatest importance for predicting successful missile defence.

Decision trees act as a valuable tool in the machine learning community which enable the visual mapping of parameter relationships, while detailing the impact that nodes have on predicted outcomes. At each node within the tree, we predict the model outcome, using the most frequent value at the node. The primary objective of the decision tree is to find a tree which minimizes nodal "impurity", or the likelihood of incorrect predictions. Mathematically, this can be represented below, where T denotes the tree, and $Q_m(T)$ represents the node "impurity".

$$Q(T) := \sum_{m=1}^{M} Q_m(T)$$

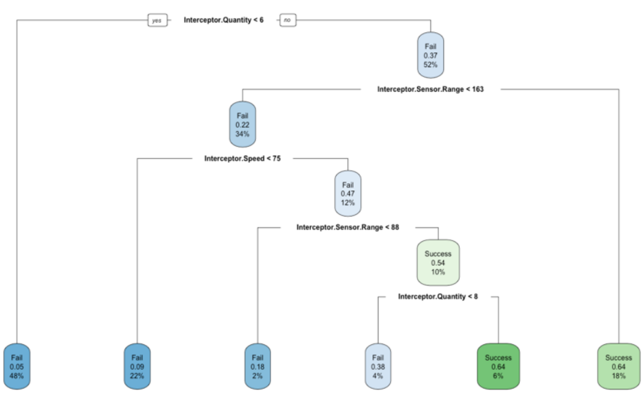

Fig. 6. ASR Decision Tree

More specifically, Gini indexing was used to determine the optimal split, which can be denoted using the equation below. Nodes are split at the point in which node impurity is minimized.

$$Q_m^{GI}(T) := \sum_{k=1}^{K} p_{mk}(1 - p_{mk})$$

A decision tree for ASR can be seen in Figure 6 which highlights the role various features play in model prediction for ASR. The decision tree can be viewed as a roadmap for success in determining favorable model outcomes. Beginning at the apex of the tree, the initial node is split using interceptor quantity and a threshold value of 6. Scenarios run which involve less than 6 interceptors have a 48% probability of failing. Proceeding down the right branch of the tree, the decision tree model's next node is split using interceptor sensor range and a threshold value of 163. Scenarios have an 18% chance of succeeding given that interceptor range is greater than 163. Predicted outcomes based on various other parameter combinations can be found using the decision tree.

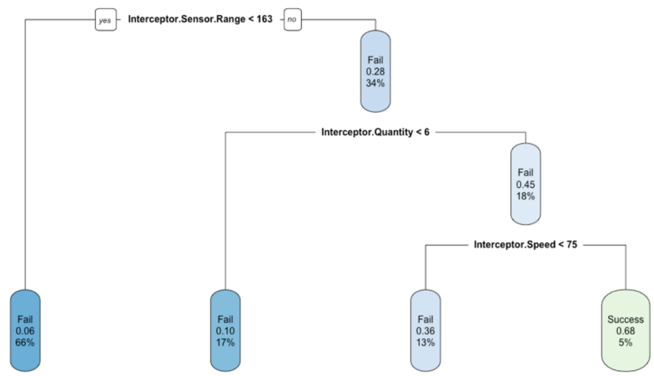

Fig. 7. PMI Decision Tree

Figure 7 highlights similar relationships found between the independent variables and their predictive power using PMI as the model's measure of performance. A threshold value of 163 was determined again by the model as an optimal splitting point. Scenarios involving interceptor sensor ranges of less than 163 are predicted to fail 66% of the time.

Due to the tendency for decision tree models to overfit in their predictions, our analysis also included the utilization of a random forest model which modeled its predictions using 140 decision trees. Random forests allow for bootstrapping with replacement, in which a decision tree is fit per generated bootstrap sample. Results will then be averaged across all trees. The results of this model will be further discussed under *Results*.

V. RESULTS

A summary of our model results for their respective measures of performance can be seen below in Table III.

TABLE III. MACHINE LEARNING MODEL PERFORMANCE

Measure of Performance	Metric	Decision Tree	Random Forest
Asset Survival Rate (>65%)	Accuracy	85.1%	85.8%
	Balanced Accuracy	80.1%	70.0%
	Cohen's Kappa	0.58	0.49
Proportion of Missiles Intercepted (>75%)	Accuracy	88.6%	89.7%
	Balanced Accuracy	62.5%	70.6%
	Cohen's Kappa	0.34	0.48

Model accuracy was determined using accuracy, balanced accuracy[3] and Cohen's kappa value. Model accuracy is determined by taking the number of correct predictions divided by all model predictions made. Balanced accuracy is determined by taking an equally weighted combination of sensitivity and specificity. Lastly, the Cohen's kappa statistic is a value between -1 and 1 which represents the correctness of model classification predictions. Values below 0 are representative of no agreement, meaning that values are random, or worse than random [2]. Cohen's kappa can help account for result imbalances (i.e. results which yield high success rates and low failure rates). For all measures of accuracy, a greater value is indicative of a better performing model within our context.

VI. DISCUSSION

A. Key Findings

By using Gini indexing, we can rank feature importance based on how much they influence accurate model predictions. This is done by calculating and ranking the Gini importance. While the actual values of these calculations are not relevant, a parameter's ranking amongst its peers are. Gini importance quantifies the significance that a parameter plays in determining a successful prediction and assigns a greater value to variables which have more influence on model outcomes. Our findings are captured in the Figure 8 and Figure 9 below, where the size of the bubble corresponds to the importance of the parameter in predicting its indicated MOP. When predicting defence scenario outcomes based on ASR, interceptor quantity, missile quantity and interceptor sensor range were identified as the 3 most important parameters. Moreover, when predicting defence scenario outcomes based on PMI, interceptor sensor range, interceptor speed and interceptor hit probability were identified as the parameters of greatest importance.

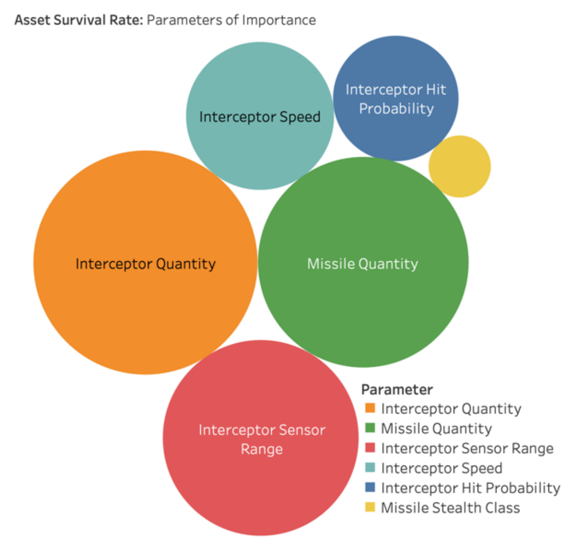

Fig. 8 Asset Survival Rate, Gini Importance Ranking

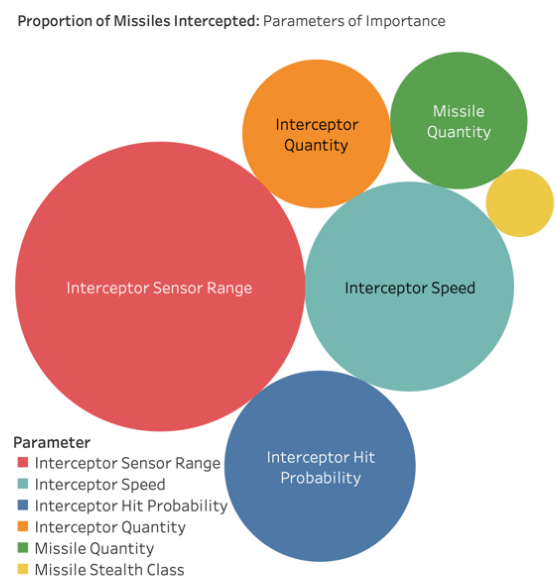

Fig. 9 Proportion of Missiles Intercepted, Gini Importance Ranking

B. Limitations and Challenges

One of the major limitations of MANA is that it is not publicly available, and that it is not an open-source software. Apart from our supervisor and the software

[3] (Sensitivity + Specificity)/2

manual, we had limited information sources from which to refer to throughout. This resulted in a steep learning curve of the software and the development of the design and simulation, which was a major component of the project.

A challenge in the completion of this research was that the data farming editor of MANA allowed us to generate scenario files (for later farming) by changing only two parameter combinations at a time. Our designs required the manipulation of three parameters for each scenario type, and as a result, we had to proceed in combinations of two, which resulted in the process being semi-manual.

Designing scenarios was an additional challenge, as there were numerous ways to approach the simulation of real-life scenarios, especially in consideration of the number of parameters that could be manipulated. However, because the process was semi-manual, and in order to mitigate biases and avoid the creation of too complex scenarios, for the purposes of this research, the simulation design had to be simple.

In addition, because the generated files were of different types, and output .csv files had non-standard table formats, it was challenging to retrieve and combine the required information into a single table format with easily accessible tools.

VII. Conclusion

In the analysis of simulated scenarios, interceptor sensor range was determined to have the highest ranking of Gini importance, as determined when using PMI as our measure of performance. Moreover, interceptor sensor range had the highest average importance ranking across both random forest models. This is rather intuitive, as it can be assumed that early detection provides an extended opportunity window to neutralize the threat. Additionally, an equally important observation was that the most salient parameter for success, as determined by ASR, was interceptor quantity, and this was further reinforced by its dependence on the number of threats, which was the third most important parameter. These results reveal that it is vital to consider air defence saturation as a key requirement for air defence system acquisition. Even the most robust and effective systems can be overwhelmed by a large number of relatively cheap threats.

However, this result needs to be considered with caution, as the limitations imposed by the curvature of the Earth and missile manoeuverability were not considered. Thus, it is only applicable in the context of short-range air defence engagements, for instance, for tactical air defence during army operations.

While some observations made in this paper could be generalized to be applicable to continental defence, further research would be required to fully substantiate this. A consequential consideration would be the relative speeds of incoming threats, which prompt questions such as: at what point is the threat too fast to be intercepted mid-flight, and thus, at which point would other means of defence need to be sought?

Despite the generalization, and while only an exploratory project, this research is significant as it confirms preliminary assumptions in air defence, and subsequently contributes to the modernization of defence mechanisms in an era of great technological advancements. Moreover, it can be used to preliminary inform the direction of the Department of National Defence's air defence strategy.

Canada's defence policy, *Strong, Secure, Engaged,* links the Department of National Defence to the North American Defence Command (NORAD), a binational military unit between the United States and Canada in the realms of aerospace and maritime warning and defence [4]. Within the purview of NORAD is the North Warning System, a series of sensor systems purposed to protect the North American airspace by detecting airborne threats. As adversaries continue to expand their nuclear arsenal, and with the increased threat of hypersonic missiles, pressure on the Canadian federal government to invest in updating these defence infrastructures has also increased. This research reaffirms the salience of sensor range in air defence. While nuclear warfare is destructive and costly, the proliferation of air-based threats and the expansion of capabilities warrant strategic investments to ensure continental defence and national security.

VIII. Team Member Contributions

A divergence in educational backgrounds, and consequently, skillsets, was the foundation of this class from the beginning, with the formation of groups with *technical* and *domain* experts. We found that it is this divergence that has been the greatest asset for our team, as it enabled us to apply our strengths to the different components of the project to eventually produce a unitary report that is reflective of our multidisciplinary background and varied skillset. Contributing to a fruitful learning experience for all involved, there were opportunities for us to learn from each other's strengths throughout.

In the completion of the project, we regularly consulted with our supervisor for direction and guidance. Joseph and Arshad led the design of scenario simulations using MANA, as well as the data farming process. Arshad consolidated this data using a customized Python script. Joseph was then able to apply machine learning techniques and statistical analysis using RStudio. Following this, both Joseph and Arshad used Tableau to create informative visuals to support our research. Petruska took charge of the writing and visual design components of the project, such as report and presentation, and related this to international affairs to provide relevance and practical application to our research.

ACKNOWLEDGMENT

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