Real-Time Surface-to-Air Missile Engagement Zone Prediction Using Simulation and Machine Learning

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Agenda

- Introduction
- Related Work
- Simulation and Analysis Tools
- Methodology
- Results
- Conclusion and Future Work

Introduction

- Surface-to-Air Missile in Modern (SAM) Air Defense
  - Essential component of modern air defense systems
  - Main function: Defend against airborne threats
- Engagement Zone (EZ)
  - Definition: Region where SAM can engage and eliminate a target
  - Importance: Crucial for military strategies
  - Influencing factors
    - Missile systems (propulsion and guidance)
    - Target characteristics (speed, altitude, evasive maneuvers)

Introduction

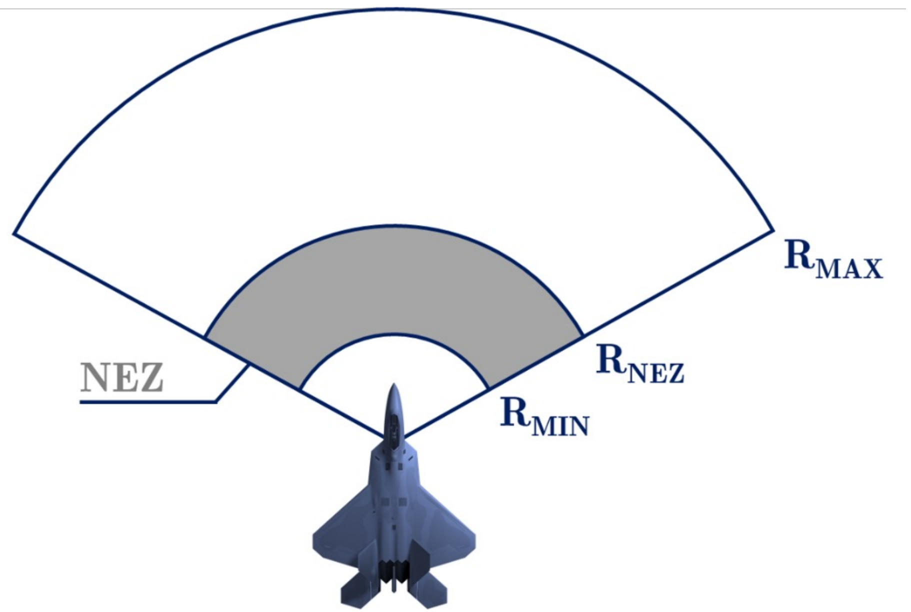
- Traditional Simulation Challenges
  - **High** computational costs
  - **Long** processing times
  - Affects speed and effectiveness of defense strategies
- Machine Learning (ML) as a Solution
  - Optimizes complex computational processes
  - Address computational limitations in SAM EZ simulations
  - Integrates ML with custom simulation tools
  - Trains supervised algorithms for predictions

Introduction

- Main Contributions of this work
  - Demonstrates how machine learning can accelerate SAM EZ simulations
  - Enhances air defense strategies and SAM system performance with **real-time** insights
  - Merges simulation with machine learning for a dynamic military strategy, promoting informed decisions
  - Provides a comparative study of machine learning algorithms, focusing on performance, training, and inference times
  - Identifies strengths and areas for improvement in these algorithms

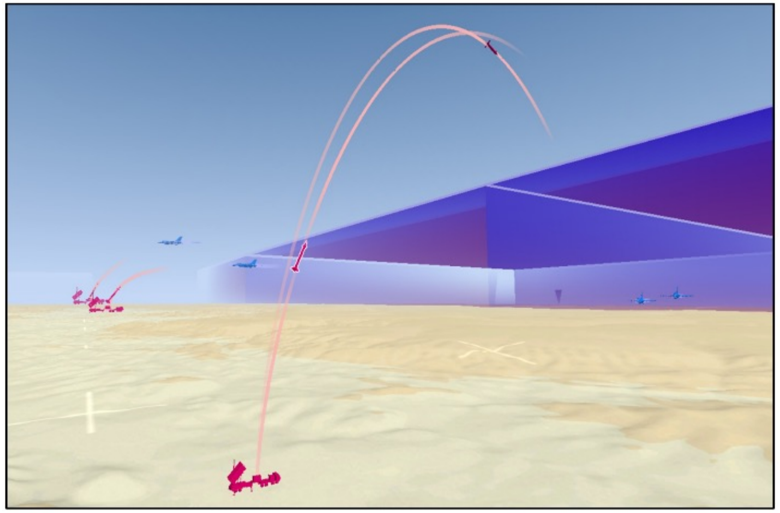
Related Work

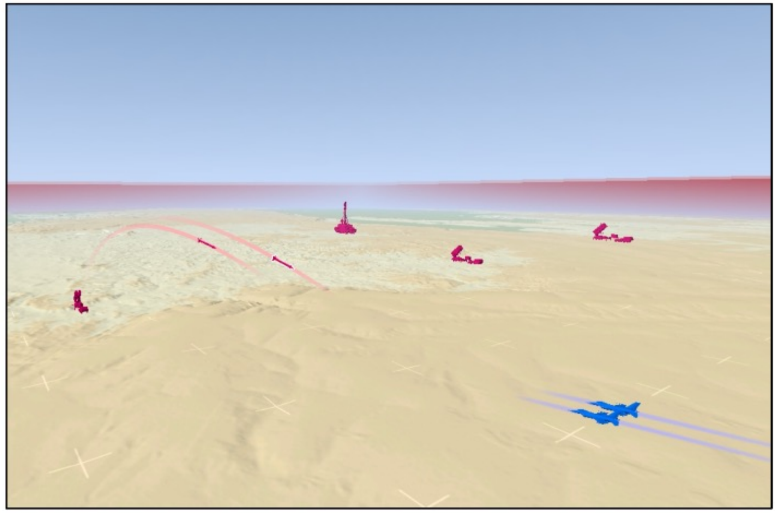
- Traditional Methods
  - Philips (1991): Advocated for Monte-Carlo simulations
  - Farlik et al. (2017): Modeled missile system fire capabilities for military training
  - Li et al. (2020): Refined air-to-air missile attack zones using advanced mathematical methods
- Machine Learning Applications
  - Yoon et al. (2010): Wavelet Neural Network
  - **Birkmire (2011): Multilayer Perceptron**
  - **Dantas et al. (2021): Deep Neural Network**

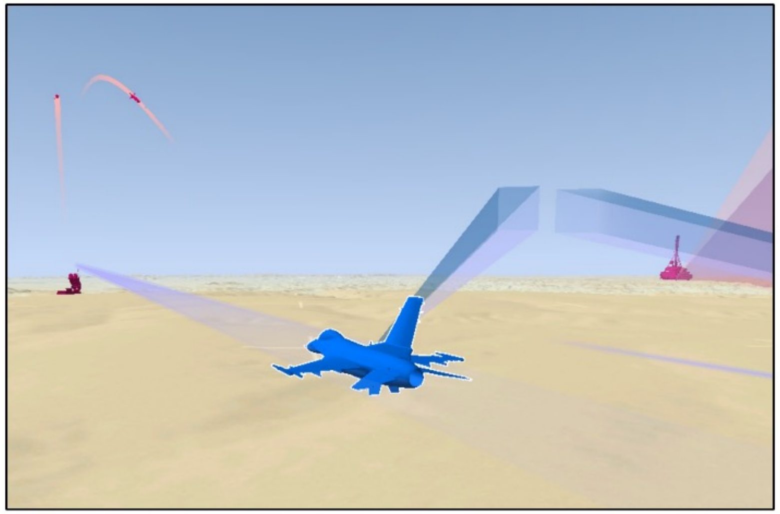


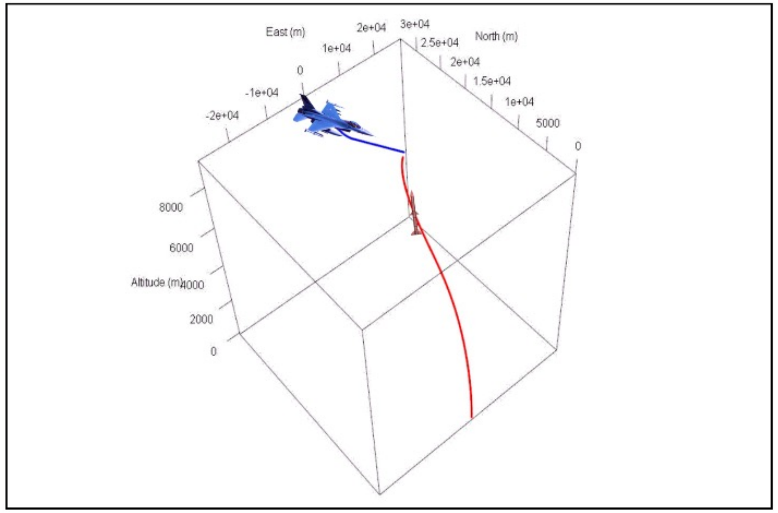
Simplified air-to-air missile's Engagement Zone representation

Simulation and Analysis Tools





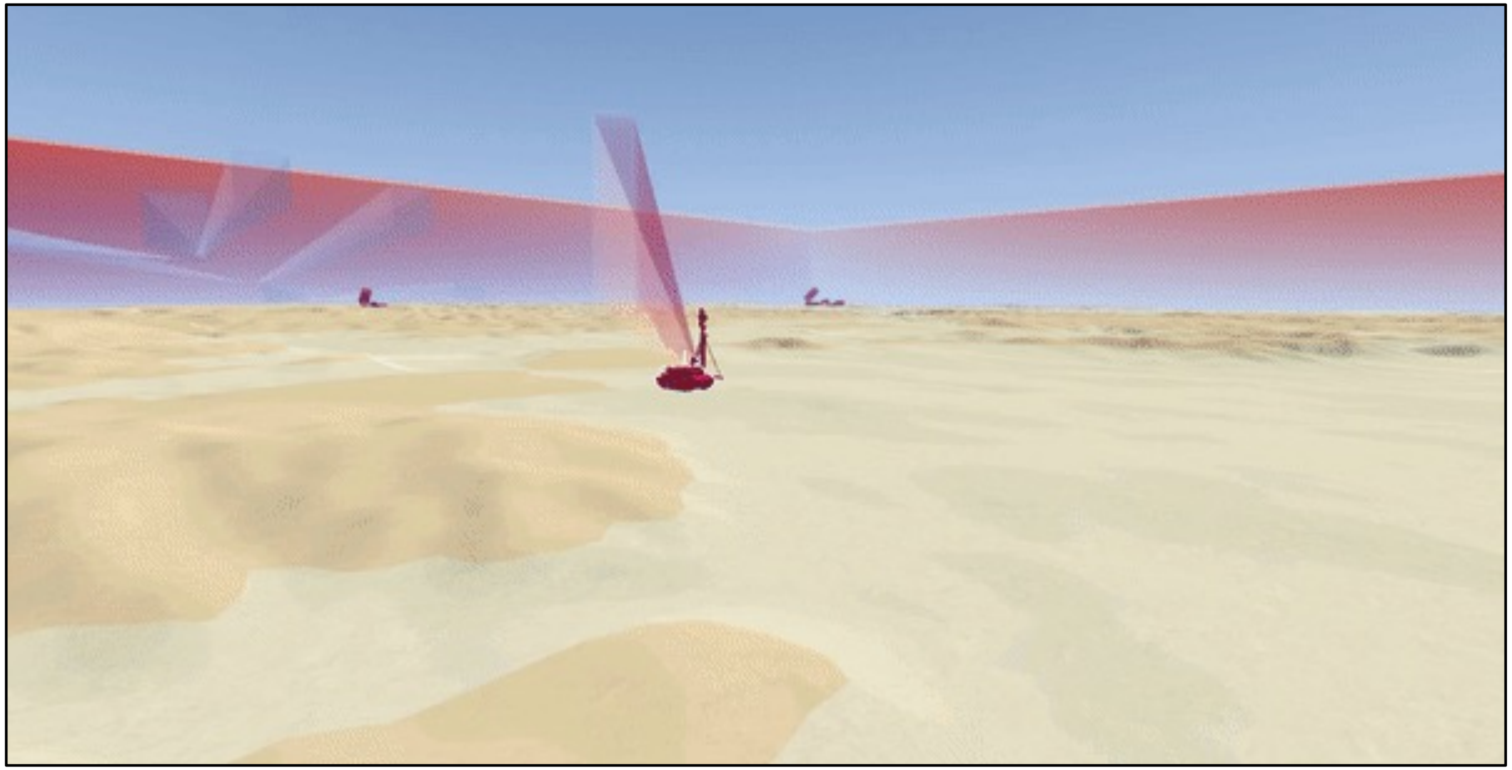




- Constructed using **R** programming language
- Leverages R's statistical and graphical capabilities
- Based on a **5-degree-of-freedom** model for **Fox 3** missile simulation
- Features
  - Proportional navigation
  - Aggressive post-launch climb (loft maneuver)
  - Models both stationary and maneuvering targets

Simulation and Analysis Tools

- Aerospace Simulation Environment – **Ambiente de Simulação Aeroespacial (ASA)** in Portuguese (Dantas et al. 2022)
- Custom-made in **C++** for advanced programming flexibility
- **High-fidelity** representation for accurate scenario reproduction
- Supported by the Brazilian Air Force
- Dedicated to modeling and simulation of military operational scenarios



Methodology

- Used the simulation tool for estimating the maximum range of two SAMs
  - SAM_1 (medium-range engagements)
  - SAM_2 (long-range engagements against ballistic missiles)
- Parameters Considered
  - Target elevation relative to the launcher ($\mathbf{x_1}$): -5,000 ft to 45,000 ft
  - Target speed ($\mathbf{x_2}$): 200 kt to 850 kt
  - Absolute value of target aspect angle relative to the launcher ($\mathbf{x_3}$): 0° to 180°
  - Tool calculates missile's maximum range (**y**) based on these parameters
  - Targets modeled as passive aircraft, maintaining consistent speed and altitude

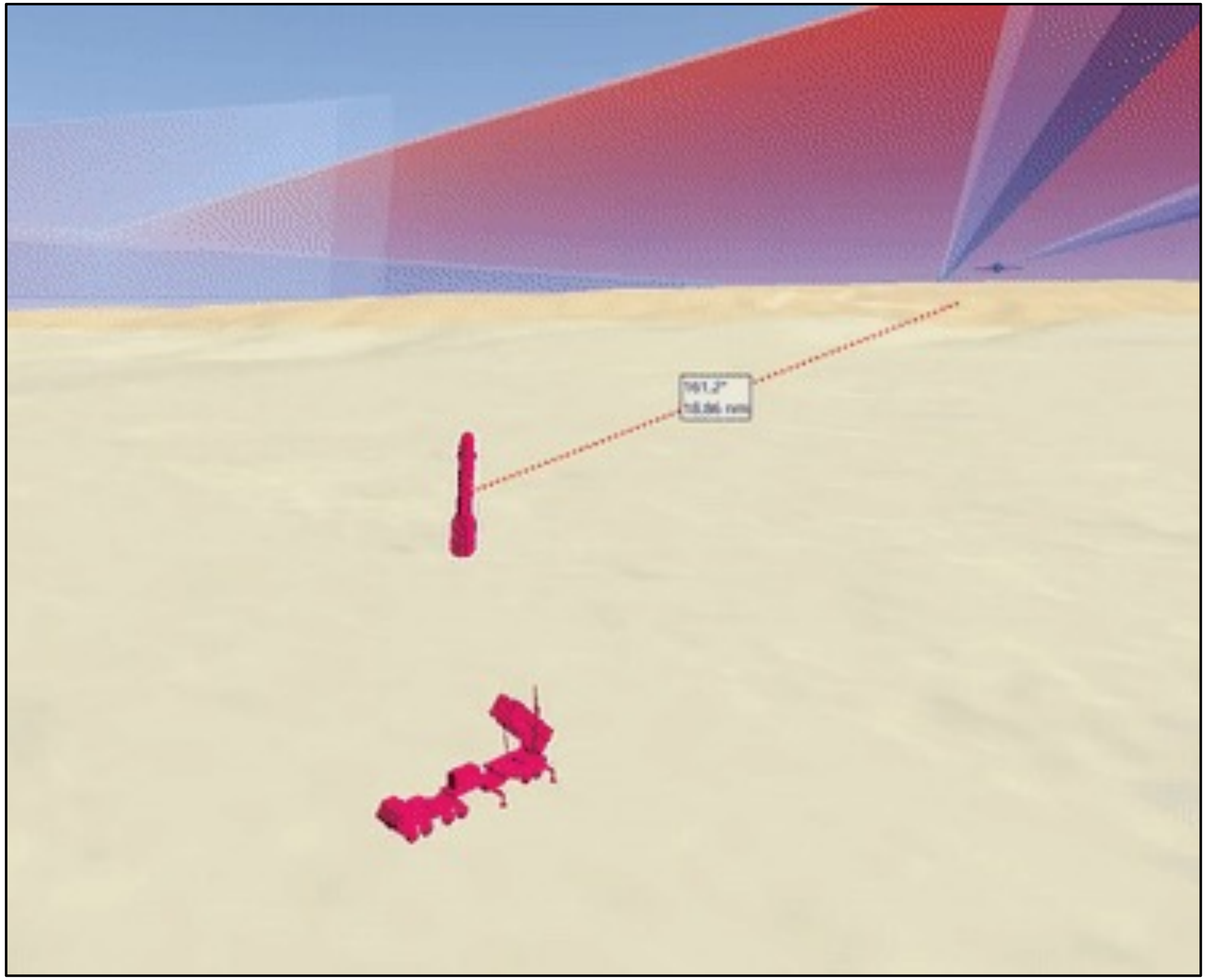
Methodology

- Data Sampling
  - Generated **5,000** maximum range samples for each SAM: Latin Hypercube Sampling
  - Each sample included values for: $\mathbf{x_1}$, $\mathbf{x_2}$, $\mathbf{x_3}$, and a corresponding $\mathbf{y}$ value
  - Experiments run on Intel Xeon Gold 6230R CPU (2.10GHz, 64 GB RAM)
  - Split aspect angle range into five intervals: [0°, 144°), [144°, 153°), [153°, 162°), [162°, 171°), [171°, 180°)

	Target elevation relative to the launcher (x1) in ft	Target speed (x2) in kt	Absolute value of target aspect angle relative to the launcher (x3) in degrees
1	23993.2581011245	419.844499827809	109.627997544374
2	35699.9004737164	692.667248013255	4.02976322527975
3	24230.6916546814	353.870903029134	87.2440944781601
4	4273.33746293637	245.15537008238	123.093129392143
5	-1627.42513800816	554.487796150901	129.260288483854

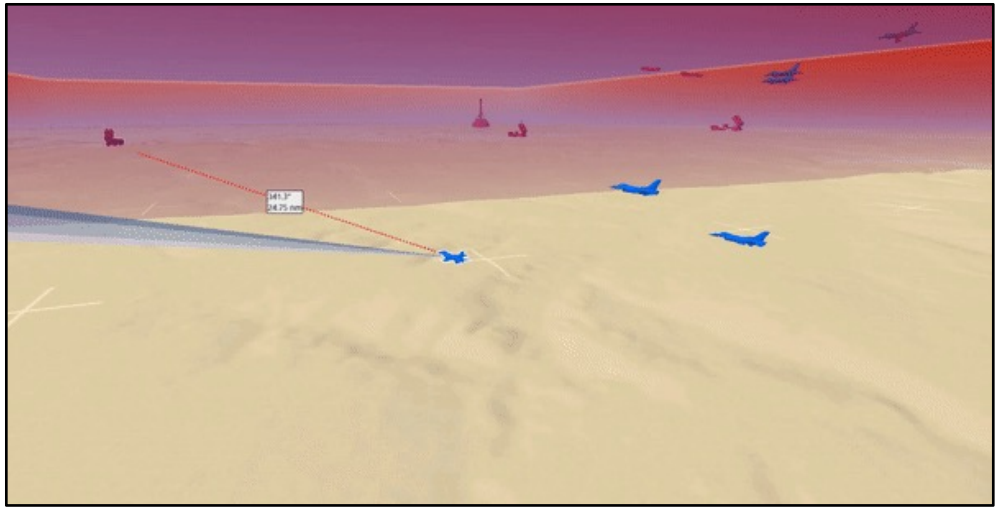
Methodology

- Development of New EZ Models
  - **Artificial Neural Network (ANN)**, **Random Forest Regressor (RFR)**, and **Polynomial Regression (PR)**
  - Allocated **80%** of samples for model training and validation
  - Used **5-fold cross-validation** for training and validation
  - Reserved **20%** samples for model testing



Methodology

- Model Assessment
  - Primary objective: Identify model with the low prediction errors and processing time
  - Employed various metrics for in-depth model comparison
  - Evaluated benefits of a singular EZ model versus separate models for five distinct aspect angle sectors – [0°, 180°) vs [0°, 144°), [144°, 153°), [153°, 162°), [162°, 171°), [171°, 180°)
  - Compared models derived from ANN , RFR, and PR



Results

- SAM System Overview
  - Utilized two SAM systems, SAM_1 and SAM_2
  - Integrated **5** distinct sample sets for each SAM system
  - Introduced a sixth sample set, combining the original five, spanning from 0° to 180°
  - **3** different machine learning methods
  - Generated a total of **36** predictive models, with **18** models for each SAM type
- Performance Metrics
  - Coefficient of Determination (R^2)
  - Root Mean Squared Error (RMSE) in nautical miles (nm)
  - Mean Absolute Percentage Error (MAPE)
  - Processing Time (PT) in seconds

Results

- Testing Phase Highlights
  - Performance metrics compared using the remaining **20%** of the sample sets
  - Among models, **ANN and RFR often outperform PR** in R^2 across most sectors
  - For RMSE, **ANN excels in SAM_1,** whereas **PR and RFR are superior in SAM_2**
  - MAPE metrics display varied results, with **PR often having the highest error in SAM_1 but excelling in SAM_2**
  - In terms of processing time (PT), **RFR demonstrates consistent speed across all sectors** in both SAM_1 and SAM_2, highlighting its computational efficiency
  - Estimation times of all models are below the **0.01 seconds** threshold
  - The simulation tool takes considerably longer (around **34 seconds**) for similar estimations

Conclusion and Future Work

- Key Findings
  - Machine learning boosts efficiency & speed of SAM EZ simulations
  - Overcomes traditional computational limitations in defense strategy planning
  - Successful integration of ML with custom simulation tools: Precise & efficient SAM EZ predictions
- Analysis Highlights
  - PR: Low prediction error, room to improve processing speed
  - RFR: Best processing time efficiency with strong error reduction
  - ANN: Good error reduction, slower than RFR

Conclusion and Future Work

- Challenges
  - Need for vast training data & risk of model overfitting
  - Emphasis on constant evaluation & refinement
- Future Directions:
  - Optimize ML models for faster processing & better accuracy
  - Integrate newer ML models for potential improvements
  - Address challenges: Efficient data augmentation & model regularization