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Operational Analysis and Logistics Engineering: Simulation

Advanced Defensive Tactics: Integrating Simulation and Machine Learning in Aerial Warfare

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Abstract

The study developed and evaluated the winding maneuver, a new defensive maneuver against threats, threat reaction, aimed at improving aircraft penetration into hostile territories against passive and semi-active surface-to-air missiles. The maneuver, based on navigation principles and evasive maneuvers, was simulated using the Aerospace Simulation Environment (ASA) software in combat scenarios. Data analysis involved experimental design, statistical testing, application of machine learning models, and optimization through metaheuristics. The results indicated that the winding maneuver significantly improves aircraft survival rates and mission success, as demonstrated by the Victory Capability Determinant (VCD) metric developed in the study. The optimized configuration of the maneuver, obtained using the Genetic Algorithm, was verified through new simulations, confirming its operational effectiveness.

I. INTRODUCTION

The evolution of air defense strategies has been marked by increasingly robust measures to prevent the entry and operation of adversarial forces in theaters of operations [1].

Essential for protecting sensitive areas and supporting the security of ground and maritime operations, air defense involves neutralizing enemy missiles and aircraft [2], [3].

In such scenarios, weapon systems play a central role, particularly missiles in the aerial domain. Missiles can be classified into three main categories: active radar homing (ARH) missiles, semi-active radar homing (SARH) missiles both commonly used in beyond visual range (BVR) combat [4] and passive homing (PH) missiles [5], typically guided by infrared and effective in within visual range (WVR) combat [2], [6].

Active-guidance missiles use self-emitted signals, such as active radar, to track and engage targets. In contrast, passive and semi-active missiles rely exclusively on target emissions or external sources for guidance [7]. This study refers to the latter two categories as Externally Guided Missiles (EGM).

Passive and semi-active missiles pose challenges for executing traditional evasive maneuvers due to uncertainty about the presence of a real threat. Passive missiles use the target's emissions for guidance, while semi-active missiles rely on radar signals emitted by an aircraft or ground-based air defense systems (GBAD) [7].

Since these missiles do not emit radar signals themselves, the targeted aircraft lacks precise information about their approach, making timely evasive maneuvers difficult [1]. Anticipating maneuvers without confirmation of a threat does not guarantee effective defense, while evading based solely on radar detection can compromise the success of the entire operation [8].

In this context, GBAD systems represent a greater threat than airborne threats, as their positions remain undetectable by radar and they exploit terrain for concealment [2], [9].

Simulations are widely used to evaluate BVR operations due to the difficulty of direct observation, the scarcity of historical data, and the limitations of real-world tests [1], [10]. Tools like the Aerospace Simulation Environment (from portuguese, *Ambiente de Simulação Aeroespacial* - ASA) [11] offer a practical alternative for assessing new defensive techniques without the high costs associated with real flights. Moreover, computational simulations serve as effective tools for developing doctrines and tactics in controlled aerial warfare scenarios [12].

Data science, particularly machine learning (ML), complements simulations by offering predictive models that create explanatory regressions of observed behaviors [13]. These models predict outcomes without requiring additional simulation runs, reducing computational time and broadening the analysis of possible operational scenarios [12].

Integrating these elements, operations research (OR) aims to optimize complex systems by maximizing or minimizing performance criteria, such as efficiency or cost, in stochastic contexts where traditional mathematical models are insufficient [14]. Metaheuristics effectively explore solution spaces, identifying near-optimal solutions when exact methods are not feasible [15]. Predictive models based on ML are further applied in optimization to identify configurations that enhance operational efficiency while considering system constraints [13].

This study aims to present, based on the authors' best knowledge, an innovative aerial maneuver for defense against surface-to-air threats equipped with passive or semi-active missiles, enhancing penetration capabilities in hostile terrain. The maneuver's initial development involved conceptual design derived from literature and expert consultations, simulations for experimentation, ML and statistical techniques for result analysis, and metaheuristics to achieve efficient configurations.

II. THEORETICAL FOUNDATION

A. *Threat Reactions*

Defensive maneuvers in aerial scenarios, known as threat reactions, are critical for aircraft survival in both WVR and BVR combat [1], [5], [9]. These maneuvers fall into two main categories: defensive and preventive. Defensive maneuvers are direct responses to detected threats, while preventive maneuvers are measures taken to avoid initial detection [16].

Various authors [1], [2], [5], [9], [16] describe a range of evasive and preventive maneuvers, such as barrel rolls, F-Pole maneuvers, Immelmann turns, Split-S, low-altitude navigation (LAN), low-contour navigation, cranks, and breaks. While numerous threat reactions are detailed in the literature, none have been specifically developed to ensure a minimum safety margin for mission continuity, particularly against EGM. This gap is evident in both BVR and WVR combat scenarios.

Certain maneuvers, however, present potential applications in the absence of a dedicated EGM defense maneuver, though their use in the intended scenario remains undefined. Low-contour navigation involves planning routes between waypoints along the terrain's lowest elevations, leveraging natural obstacles to avoid detection [17]. Constant-turn-rate curves [16] use steady lateral acceleration to make missile trajectory predictions more difficult. The crank maneuver minimizes exposure to missile engagement zones while supporting missile guidance, positioning the target at the radar's gimbal limits, and emphasizing lateral displacement over range [5]. Finally, the break maneuver involves a high-intensity turn to disrupt a missile's line-of-sight (LOS) tracking, degrading seeker performance and guidance systems [5].

B. *Winding Maneuver*

This study proposes a new threat reaction called the winding maneuver, designed to enhance aircraft survivability in surface-to-air threat environments, specifically against EGM.

Developed based on operational knowledge from Brazilian Air Force pilots, this maneuver addresses the absence of a specific technique to improve mission safety under such threats. The winding maneuver combines elements of low-contour navigation [17], constant-turn-rate curves [16], crank, and break maneuvers [5], tailored for use against surface-to-air EGM.

The maneuver involves low-altitude, serpentine flight paths with alternating right and left turns, interspersed with brief straight segments. This lateral movement reduces the vector speed toward the target. To compensate for this reduction, a multiplier factor is applied to the aircraft's velocity. Figure 1 illustrates the maneuver planning.

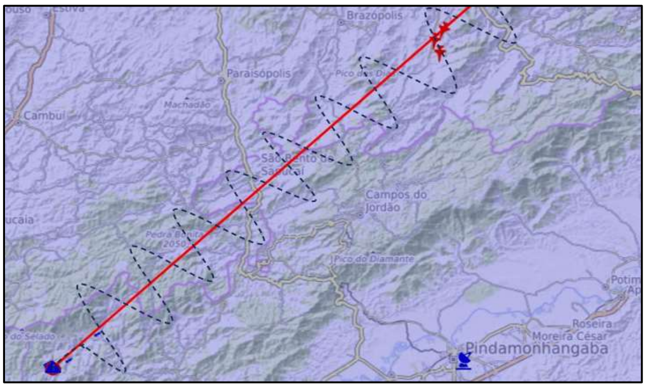

Fig. 1. Planning the winding maneuver.

The planning process requires detailed terrain analysis using topographic maps to define low-contour navigation routes that maximize coverage. Safe starting and ending points must be established. The aircraft adjusts to the terrain at low altitudes, incorporating frequent turns and brief straight segments, with real-time trajectory adjustments to avoid detection. The maneuver concludes at a safe point, allowing a return to normal navigation, making it ideal for high-threat surface-to-air EGM areas with a significant risk of interception by enemy air defenses.

Simulation as an Experimentation Tool

Conducting air defense experiments is highly costly due to the expensive systems involved, such as aircraft and missiles, making it challenging to obtain representative data [2], [18]. Simulations offer a cost-effective alternative, addressing practical difficulties in real-world testing [2], [18]. Using computational resources, simulations replicate real-world operations or processes, proving essential in military contexts for analyzing combat, developing tactics, and assessing equipment and technological advancements [11].

Real-world scenarios introduce uncertainties from uncontrollable factors like environmental variations and human performance. In response, computational simulations incorporate stochasticity to simulate variability and unpredictability in real conditions [10]. A single scenario analysis may not adequately represent expected behaviors, necessitating robust responses to achieve reliable expected outcomes [14].

Simulation robustness is ensured through techniques that establish statistical representativeness in the data. By leveraging the law of large numbers, simulation averages converge to expected values as observations increase, provided specific conditions are met. Determining the minimum number of executions to ensure reliable results is an iterative process of repetition and data analysis [19]. This rigorous control of experimental conditions and repeatability provides significant advantages in reducing costs and ensuring quality data collection [20].

C. *Experiment Design*

Design of Experiments (DoE) is employed to plan and analyze simulations, efficiently extracting information and ensuring statistically valid conclusions [21],[22]. It begins with screening influential factors and optimizing them to maximize performance. By integrating stochastic data and uncertainty modeling, DoE enhances simulations with confidence intervals that better reflect real-world conditions, capturing the diversity of pilot capabilities and operational doctrines [22], [23].

DoE methods, such as Latin Hypercube Design (LHD), divide the sample space into smaller regions for internal sampling, ensuring homogeneous coverage and reducing estimator variance. This approach accelerates convergence, minimizes required iterations, reduces spurious correlations, and improves space-filling properties [24], [25].

D. *Exploratory Data Analysis*

Exploratory data analysis uses statistical and probabilistic methods to identify patterns, and trends, and quantify uncertainties, supporting informed decision-making [26]. When analyzing simulation data, excluding outliers is critical to avoid distortions in explanatory models like those used in ML [27], [28].

Statistical tests such as Kolmogorov-Smirnov (K-S) and Welch's t-test are applied for sample comparisons. The K-S test assesses whether two samples follow the same distribution without assuming normality [29], while Welch's t-test compares the means of two independent samples with differing variances [26].

Confidence intervals (CI) provide uncertainty estimates for simulation measurements, offering a range within which the true population parameter is expected with a given confidence level [26].

E. *Prediction and Optimization Techniques*

Supervised learning, a subset of ML, is applied in predictive modeling to forecast continuous variables based on observed data [30]. Regression techniques in supervised learning, such as neural networks, random forests, and support vector machines (SVM), are particularly effective for analyzing and predicting simulation outcomes [30], [31].

Model quality is evaluated using metrics like mean squared error (MSE), root mean squared error (RMSE), and the coefficient of determination (R^2), which measure prediction accuracy and the proportion of variability explained by the model [30].

By integrating ML with simulations, outcomes can be predicted without re-execution, saving computational resources and time [32]. When combined with OR, ML extends optimization capabilities, exploring vast solution spaces to identify near-optimal configurations. Metaheuristics, such as Genetic Algorithms (GA), paired with ML, assist in identifying configurations that enhance operational efficiency [33].

III. METHODOLOGY

A. *Experiment Scenario*

The experiment was structured with two sides: the attacking force and the defensive force. The attacking force, evaluated for its use of the winding maneuver to penetrate enemy territory, comprised three squadrons of four General Dynamics F-16 Fighting Falcons [34]. Each aircraft was equipped with two general-purpose bombs to strike a designated ground target.

The DoE methodology was employed to plan the experiment, identifying and screening factors with the greatest system impact. These factors were adjusted within the ranges outlined in

TABLE I. EXPERIMENTAL VARIABLE RANGES

Variable	***Minimum***	***Maximum***
Execution of the Winding Maneuver	0 (No)	1 (Yes)
Turn Rate	0°	90°
Speed Multiplier Factor	1.0	2.0
Straight Line Time After Each Turn	0 sec	60 sec

The scenario focused on surface-to-air defense by GBADs, consisting of three batteries positioned along the attacking squadrons' navigation path. GBADs were configured as short- to medium-range systems, with four launchers each equipped with eight externally guided missiles (EGM), specifically semi-active missiles, totaling 24 missiles [35], [36], [37]. Reload time was set at six minutes [16], and the effective engagement zone (WEZ) was randomized between 5 and 50 nautical miles (NM) [16]. The WEZ variability reflected the battlefield's dynamic nature and its influence on defense system effectiveness [5], [16].

Simulations were conducted using the ASA, an advanced platform capable of modeling complex scenarios and performing multiple iterations to collect robust data [11]. Variance stability analysis determined the point at which simulation results stabilized, measuring the coefficient of variation (CV) for each batch of simulations [18]. This approach ensured the sample's representativeness, establishing the minimum number of iterations required for statistically significant results [20].

B. *Attack Effectiveness Metric*

Evaluating air defense systems' effectiveness requires a combination of scientific and analytical approaches, involving the creation of comprehensive indices that incorporate variables relevant to specific objectives [21]. Guo et al. [23], for instance, used metrics like damage rate, target destruction rate, and mission success rate to assess drones and fighter aircraft effectiveness in air-to-ground attack missions.

In this study, a metric called Victory Capability Determinant (VCD) was developed, integrating concepts from previous studies [1], [23], [38]. VCD evaluates effectiveness based on the ability to achieve offensive objectives and survival rates.

$$\mathrm{VCD} = \frac{1}{10}(2 \times p_a + 2 \times p_m + 6 \times p_b) \qquad (1)$$

Where:

- p_a: Proportion of operational attacking aircraft remaining after the simulation.
- p_m: Proportion of missiles evaded relative to total missiles fired.
- p_b: Proportion of bombs delivered on target relative to a total allocated.

The weighted sum of these proportions is normalized by dividing by 10. This metric evaluates various aspects of military operations, reflecting the efficiency and effectiveness of the attack.

C. Statistical Hypotheses

To analyze the effectiveness of the winding maneuver, outliers were excluded from the dataset. Simulations with and without the maneuver were then compared using statistical tests appropriate for sample conditions, whether or not the data followed a normal distribution.

Welch's t-test was used to compare mean values between the two samples, and the Kolmogorov-Smirnov (K-S) test was applied to compare their distributions. Additionally, CI provided precision estimates for simulation results, supporting data-driven conclusions.

D. Machine Learning Models

Regression models enable the prediction of dependent variables based on independent variables, avoiding repeated simulation executions and conserving resources [39].

The ML models applied in this study included linear, quadratic, and cubic regression, with and without factor interaction [26], [30]; decision trees using Boosting and Bagging techniques [39]; Random Forest models; Splines; Generalized Additive Models (GAM); Support Vector Machines (SVM) [30]; as well as Artificial Neural Networks, Gaussian Process Regression (GPR).

The data was split into training (70%) and testing (30%) sets, following common ML practices [32], [44]. Hyperparameter tuning for the ML models was performed using a GA, chosen for its effectiveness in optimizing model performance [42].

The model selected for prediction and optimization was the one with the highest R^2 value and the lowest RMSE, as evaluated on the test set [21].

E. Optimization

The representative model allowed for exploring various configurations to identify the highest VCD value in the scenario. To optimize this search, a GA was employed, leveraging its ability to explore the solution space and identify configurations meeting system constraints [43].

IV. RESULTS

To evaluate the winding maneuver's effectiveness, 1,000 simulations were conducted, with results converging after approximately 800 iterations. Convergence criteria were established based on a CV threshold of 0.01.

Statistical analysis using Welch's t-test and the K-S test indicated that the winding maneuver significantly improved air attack operations' effectiveness. With a significance level of 0.01% and a p-value below $2{,}2 \times 10^{-16}$ for both tests, a significant difference was confirmed between simulations with and without the maneuver.

The average VCD values were 0.50 for the group using the maneuver and 0.10 for the group without it. Figure 2 illustrates data dispersion and mean results.

For a 99% confidence level (corresponding to a 1% significance level), the CI for VCD means ranged from 0.46 to 0.55 with the winding maneuver and from 0.09 to 0.11 without it. These findings indicate that the true population mean lies within these intervals in 99% of possible samples.

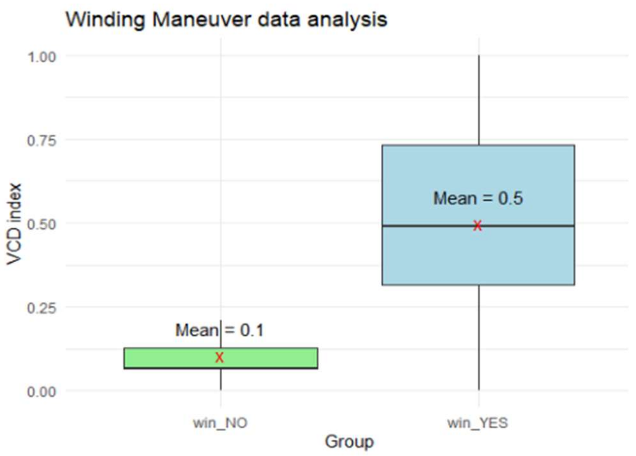

Fig. 2. Comparison of simulation results.

A comparative analysis of ML models identified Random Forest as the best explanatory model, with R^2 and RMSE values of 0.95 and 0.07 for the training set, and 0.64 and 0.16 for the test set, respectively.

Optimization using the GA produced optimal parameters: a turn rate of 80°, 25 seconds of straight-line flight time, and a speed multiplier of 1.5, resulting in a predicted VCD of 0.98. New simulations using this configuration yielded an average VCD of 0.83 for the maneuver group and 0.09 for the non-maneuver group. At the same confidence level, the CI for the VCD of the optimized maneuver ranged from 0.81 to 0.84, while the CI for the non-maneuver group remained unchanged. Figure 3 illustrates the results of the new simulations under the optimized conditions.

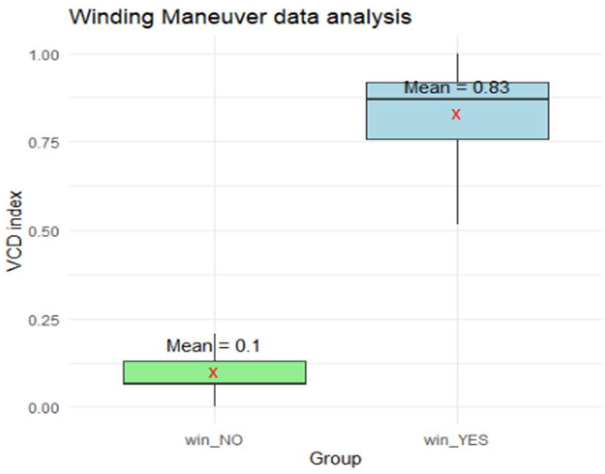

Fig. 3. Comparison of new simulations with the optimized winding maneuver configuration.

V. CONCLUSION

This study developed and evaluated a new threat reaction, the winding maneuver, designed to enhance aircraft penetration in hostile territories, particularly in high surface-to-air threat environments involving passive and semi-active missiles (EGM).

Conceived based on Brazilian Air Force pilots' operational expertise, the winding maneuver integrates principles of Low-Contour Navigation, Constant Turn Rate Curves, and crank, and break maneuvers to reduce detection and engagement by enemy GBAD systems.

Simulations conducted using the ASA software validated the maneuver's effectiveness across configurations. Statistical analysis confirmed significant improvements in mission success rates and aircraft survival, reflected in higher VCD values when employing the maneuver.

The VCD metric, developed specifically for this study, quantified attack operation effectiveness by considering aircraft survival, missile evasion, and bomb delivery rates. The maneuver's effectiveness was further supported by ML techniques, with Random Forest identified as the best predictive model. GA optimization produced an optimized configuration that substantially increased the average VCD value, as confirmed by additional simulations.

Findings suggest the winding maneuver has the potential to significantly alter operational dynamics in combat scenarios involving surface-to-air EGM, enhancing aircraft survival and offensive mission success rates while reducing enemy air defense system effectiveness.

Future research should evaluate the maneuver's performance in air-to-air EGM scenarios, explore additional supervised ML algorithms, and develop new metrics to further validate its effectiveness, contributing to the evolution of more efficient air defense tactics.

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