MULTI-DIMENSIONAL DATA FARMING: EXTENDING DATA FARMING FOR MULTI-SCALE DECISION SUPPORT BY INTEGRATING NOVEL AI TECHNIQUES

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ABSTRACT

Traditional Data Farming (DF) consists of a toolbox of established analysis techniques that are available for an analyst-led study of a particular military operation in support of a single decision-maker. Multi-Dimensional Data Farming (MDDF) is a new and automated analytical process that provides accelerated support to military decision-making at multiple scales. At the strategic level, MDDF can inform decision-makers in planning long timescale campaigns, while at the tactical level, MDDF allows investigation of emerging technologies in shorter timescale operations. More importantly, MDDF explicitly addresses the interplay between a long timescale campaign and embedded short timescale operations, which is rarely tackled in the literature. MDDF extends DF by integrating novel AI techniques (Automated Machine Learning, eXplainable AI) and eXtended Reality visualization in an AI agent which automatically investigates the multi-dimensional parameter landscape and efficiently provides decision-makers with insight into the best, worst and most promising Courses of Action. We illustrate our new MDDF approach through a hybrid warfare scenario consisting of a Border Operation (interdiction of illegal migrants) embedded within a multi-faction (Blue, Red and Green forces) hybrid war campaign. Combining AI techniques exploring operations at multiple scales (domain, level, time) and boosting strategic and tactical understanding, MDDF innovates multi-scale decision-making.

1.0 INTRODUCTION

Data Farming (DF) is the analytical process of exploring a simulation of a real dynamical system in operation to infer properties of that system which may inform decisions about its efficient and effective management. DF first creates the scenario to investigate and leverages experimental designs, high performance computing, analysis, and visualization techniques in pursuit of that goal. Previous research conducted by MSG-088, MSG-124 and MSG-155 has provided the theoretical underpinnings, proof of concept and software tools to enable analysts to conduct DF studies on their system of interest. NMSG Scientific Achievement Award winning MSG-088 [1] codified the DF concept for NATO based on the DF Loop-of-Loops (see Figure 1-1).

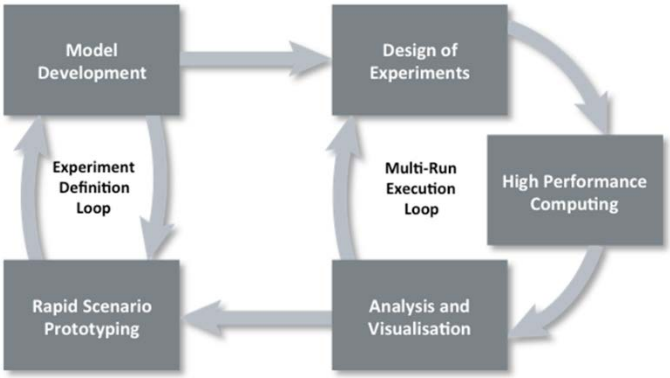

Figure 1-1: Data Farming Loop-of-Loops.

DF typically pursues one of two broad goals, either characterization or optimization. Characterization seeks to replace the black-box simulator of the system in operation with a white-box emulator whereby the input-output relationship is made transparent. This emulator, or meta-model, provides insight to the analyst regarding causal linkages in the system and allows the relative trade-off between varying each input factor to be quantified. Optimization, on the other hand, seeks not to understand the functional form of the input-output relationship, but to use the meta-model to determine the input factors best settings (i.e., courses of action (COAs)) that drive the system's response to a desired target value.

In the military context DF allows decision-makers to obtain improved situational awareness and to make more informed and robust decisions. Traditional DF is an interactive man-in-the-loop process, in NATO primarily to support military decision-making throughout the development, analysis and refinement of COAs, as illustrated in Figure 1-2.

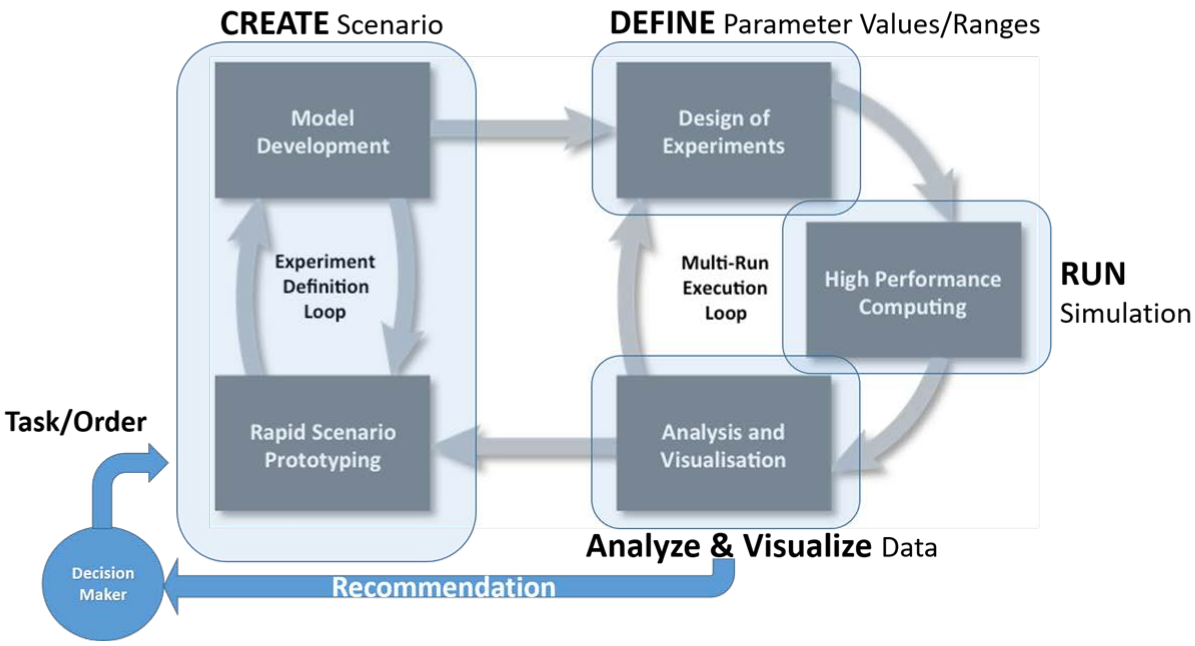

Figure 1-2: Data Farming Decision Process.

But this process is time consuming, even with the software tools developed for the design of experiments, analysis, and visualization. Feedback loops lead to re-adjustments and re-processing. However, military decision-makers want and need to make decisions fast. Traditional DF only allows partial analyses for large multi-scale campaigns with many factions and operations interacting at various levels with each other. An innovative approach is needed. **MSG-186 Multi-Dimensional Data Farming** is extending this research to support a multi-model, multi-operation approach to better understand the immense complexity of future military hybrid challenges in large campaigns.

Multi-Dimensional Data Farming (MDDF) automates simulation decision-making by the integration of innovative artificial intelligence (AI) techniques and allows improved and faster decisions in highly complex multi-scale, multi-domain, and multi-level hybrid war campaigns.

In Section 2, we demonstrate the traditional DF approach to a tactical-level military operation. In Section 3, we illustrate the novel MDDF approach to a multi-scale problem, consisting of a multi-faction, multi-domain campaign in which the tactical-level operation has been embedded. Section 4 then outlines the conceptual and architectural elements that comprise the Design, Analyse and Visualise Experiments (DAVE) agent which underpins MDDF, before providing some summary thoughts in Section 5.

2.0 TRADITIONAL DATA FARMING

NATO defines a hybrid threat as one that combines conventional, irregular, and asymmetric activities in time and space, and methods include disinformation, cyber-attacks, economic pressure, deployment of irregular armed groups and use of regular forces. Horne and Stilwell list a selection of hybrid warfare actions, grouped by intensity level, ranging from legitimate power to acts of war [2]. The migrant crisis on the Belarus-Poland border in 2021 has been regarded by European Union (EU) and United States leaders as a hybrid attack. Belarusian state-run agencies reportedly organized and encouraged travel from the Middle East and Africa for several thousand asylum seekers and migrants, with security forces escorting them to the border [3]. Poland reportedly deployed ten thousand soldiers to assist the border guards. As NATO has an extensive land border to non-NATO and non-EU states, a Border Operation scenario is an interesting case study for a DF experiment.

2.1 Border Operation Scenario

The Border Operation scenario is developed in MANA [4], focusing on a small segment of a fictitious border zone with terrain features including roads, fields, evergreen forests, and frozen bodies of water. Migrant agents cross the border at various times and if not intercepted, they move deep into Green territory towards a safe destination. Green controls its border with a combination of fixed and moving border patrol agents, sensors (small UAVs patrolling the border and mini-UAVs organic to some of the border patrols) and fences. Sensor detections communicate the position to border patrols, which move to intercept and arrest the detected migrant agents. While apprehending migrant agents, they are unable to intercept others, but once completed the patrol returns to its earlier position or patrol route. The simulation ends when all non-intercepted migrant agents reach the safe Green area.

The decision factors for the Border Operation are related to the selected border control assets, and the noise factors pertain to the migrant agents feature as detailed in Table 2-1. The area to patrol is divided into two zones. The measure of effectiveness is the proportion of intercepted migrants.

Table 2-1: The decision and noise factors of the Border Operation.

	Factor	Min	Max	Type
Decision - Green	UAV Quantity	1	2	Binary
	Sensor Range (km)	1	10	Real
	Speed (km/hr)	10	100	Real
	Zone 1 Patrol Quantity	0	2	Discrete
	Visual Range (km)	0.5	2	Real
	Speed (km/hr)	30	100	Real
	Interception Processing Time (sec)	1800	7200	Real
	Detected Location Duration (sec)	900	3600	Real
	Zone 2 Patrol Quantity	0	2	Discrete
	Mini-UAV Sensor Range (km)	1	5	Real
	Speed (km/hr)	30	100	Real
	Interception Processing Time (sec)	1800	7200	Real
	Detected Location Duration (sec)	900	3600	Real
	Southern Border Fence	0	1	Binary
Noise - Migrant	Migrant Groups Quantity	9	36	Discrete
	Speed (km/hr)	3	9	Real
	Visual Range (km)	0.5	2	Real
	Transit by Road? (or Forest)	0	1	Binary
	Degree of Avoidance of Patrols	-100	0	Real
	Intensity of Border Crossing	0	1	Real

2.2 Characterization and Optimization

Typical DF meta-models used for characterization are low-order-polynomials (usually up to second order) within a general linear modelling framework. However, even with only a moderate number of factors, to fit a fully second-order meta-model for the Border Operation DF characterization would lead to an impractically large design of experiments. Thankfully, the Pareto principle (or 80/20 rule) often applies in practice, so that one may initially employ a first-order meta-model (with a more manageable design size) to identify the subset of input factors which critically affect the outcome (both statistically and practically), before fitting a fully second-order linear meta-model involving only these critical factors.

The Orthogonal Latin Hypercube (OLH) and Nearly Orthogonal Latin Hypercube (NOLH) classes of designs developed by the SEED Center at the Naval Postgraduate School [5] are often employed in DF studies. Here, we illustrate their use on the Border Operation characterization task. One issue with these designs is that they are built assuming all the factors are continuous, which necessitates various degrees of rounding to accommodate binary or discrete factors, such those of Table 2-1. Another complication is that from the tabulated designs, we needed to choose the NOLH for up to 22 factors (and remove two arbitrary columns) which yields a design with 129 design points. So, we see that this design selection and generation process is cumbersome and very manual in nature.

Assuming a first-order meta-model, we find that only 5 Green (decision) factors and 2 migrant (noise) factors both statistically and practically affect the mean proportion of migrant interceptions. Using the same design to fit a fully second-order linear meta-model to these factors further identifies 5 two-factor interactions (e.g., the effect of the number of patrols in Zone 2 depends on the value of the interception processing time in Zone 2) and 2 quadratic effects (e.g., the effect of the migrant groups' speed is non-linear), as listed in Table 2-2. The magnitude of the factor effect is represented by its meta-model coefficient, and the statistical significance by its T-statistic.

Table 2-2: The second-order meta-model coefficients relating the influential decision and noise factors to the mean proportion of migrants intercepted in the Border Operation.

Factor	Coefficient	T-Statistic
Constant	0.463	237.1
Zone 1 Patrol Quantity	0.188	118.3
Zone 2 Patrol Quantity	0.186	116.2
Zone 2 Mini-UAV Sensor Range (km)	0.059	30.7
Migrant Groups Quantity	-0.110	-57.3
Zone 1 Interception Processing Time (sec)	-0.077	-39.9
Zone 2 Interception Processing Time (sec)	-0.080	-41.6
Migrant Groups Speed (km/hr)	-0.163	-85.8
Zone 1 Patrol Quantity*Zone 2 Mini-UAV Sensor Range (km)	-0.051	-17.7
Zone 1 Patrol Quantity*Migrant Groups Speed (km/hr)	-0.056	-20.3
Zone 2 Patrol Quantity*Zone 2 Interception Processing Time (sec)	-0.069	-25.1
Zone 2 Mini-UAV Sensor Range (km)*Migrant Groups Quantity	-0.061	-17.2
Migrant Groups Quantity*Zone 2 Interception Processing Time (sec)	-0.052	-12.9
Zone 2 Mini-UAV Sensor Range (km)*Zone 2 Mini-UAV Sensor Range (km)	-0.053	-13.5
Migrant Groups Speed (km/hr)*Migrant Groups Speed (km/hr)	0.087	23.4

The types of causal linkages underpinning the input-output relationship in the Border Operation are now revealed, so that (a) robust optimal capability decisions can be determined - in that two patrols in each zone is the most impactful COA (but where the speed of the patrols is not important) and minimizing the interception processing time in each zone (perhaps by improved procedures) is the second priority; and (b) a contingent optimal capability decision to be identified - in that a larger Zone 2 Mini-UAV sensor range is optimal if there are fewer migrant groups and vice versa. Finally, the number of migrant groups, and their speed, both attenuate

Green's effectiveness significantly – more so with migrant speed, though this effect is subject to diminishing returns.

As this example shows, traditional DF can reveal factors of importance to operational commanders, leading to more informed tactical decisions in the face of uncertainties and complexities.

3.0 MULTI-DIMENSIONAL DATA FARMING

However, the decision problem at the strategic level is the allocation of resources between the Border Operation and an ongoing Campaign (we only consider resources applicable in both, such as logistics, sensors and C4 systems) where the success of the latter depends (in part) on the success of the former.

MSG-186 introduced a multi-faction, multi-domain, campaign-level conflict scenario and associated simulation incorporating Lanchester and epidemic based modelling [6]. Here, we build on that work by addressing the interplay between a long timescale campaign and embedded short timescale operations, and by extending DF with novel AI techniques which automatically investigates the multi-dimensional parameter landscape and efficiently provides decision-makers with faster insight on various COAs.

3.1 Hybrid War Campaign Scenario

In [6] we presented a multi-faction multi-domain combat model called ACE (according to the Attrition, Cyber and Epidemic modelling concepts based upon) which describes two armed allied forces, Blue and Green, fighting a Red force in both the physical and cyber domains. The Campaign starts with classical Lanchester attrition (Blue and Green vs. Red) before Blue suffers a cyber-attack infecting susceptible units and reducing their effectiveness. As a countermeasure, all Blue units upgrade their systems over time and become immune to the cyber-attack.

In this paper, Red launches a hybrid operation on Green, by additionally triggering the Border Operation of Section 2.1, in support of two strategic objectives: to force Green to divert resources away from the Campaign and to lower Green public opinion in support of the Campaign (both thus lowering the chances of Campaign success). We embed the Border Operation in the ACE model and illustrate how tactical operations may influence Campaign outcomes through MDDF, as illustrated in Figure 3-1.

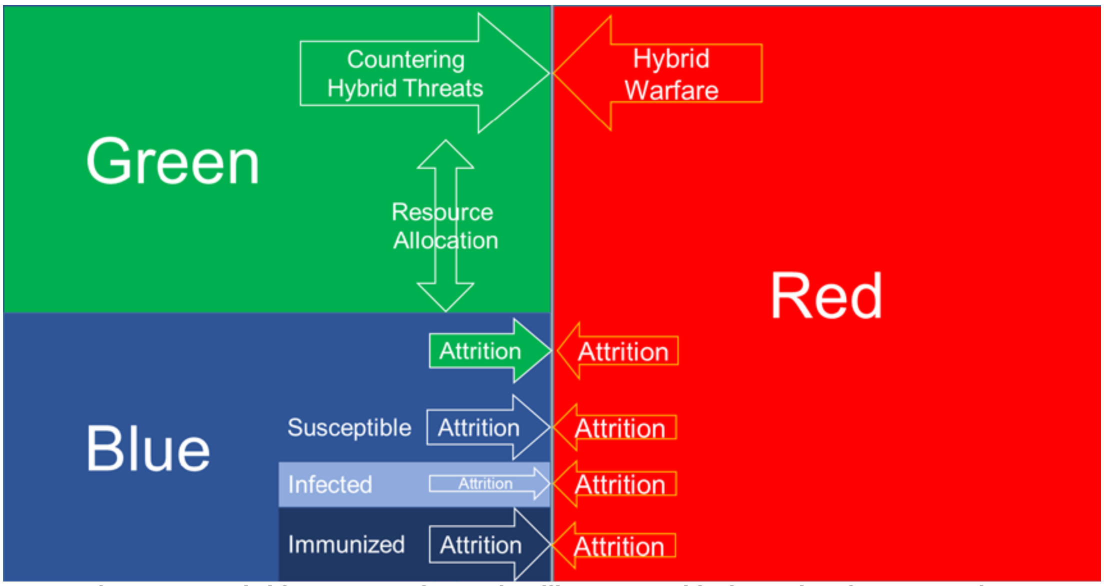

Figure 3-1: Hybrid war scenario used to illustrate Multi-Dimensional Data Farming.

3.2 Enhanced Military Decision Making

We wish to identify COAs that maximize the probability of success of the Campaign, either averaged over the settings of noise factors (*best COA*); given the worst setting of noise factors (*worst COA*); or given the easiest setting of noise factors (*most promising COA*). The probability of success is defined by $P\big(R(t_f) = 0 \big| B(t_f) > 0, G(t_f) > 0\big)$, where t_f is the annihilation time of Red. This probability is to be maximized over all possible COAs (i.e., the decisions factors of Table 2-1), where experiment replications may be generated through the noise factors of Table 2-1. The descriptions of the parameters of the ACE model are given in Table 3-1, along with the simplifying assumptions made for the following illustration.

Table 3-1: Parameters of the ACE model [6] and relative assumptions.

quantity	value	description
B_0		initial size of Blue force
R_0		initial size of Red force
G_0	$R_0/10$	initial size of Green force
$b_{r,A}$	r_g	effectiveness of susceptible resp. immunized Blue units on Red
$b_{r,V}$	r_g	effectiveness of infected Blue units on Red
r_b	r_g	effectiveness of Red force on Blue
r_g		effectiveness of Red force on Green
g_r	$5 \cdot r_b/3$	effectiveness of Green force on Red
α_0		supply rate of Green force
β_A		immunization rate of Blue force against cyber attacks
β_V		infection rate of Blue force to cyber attacks

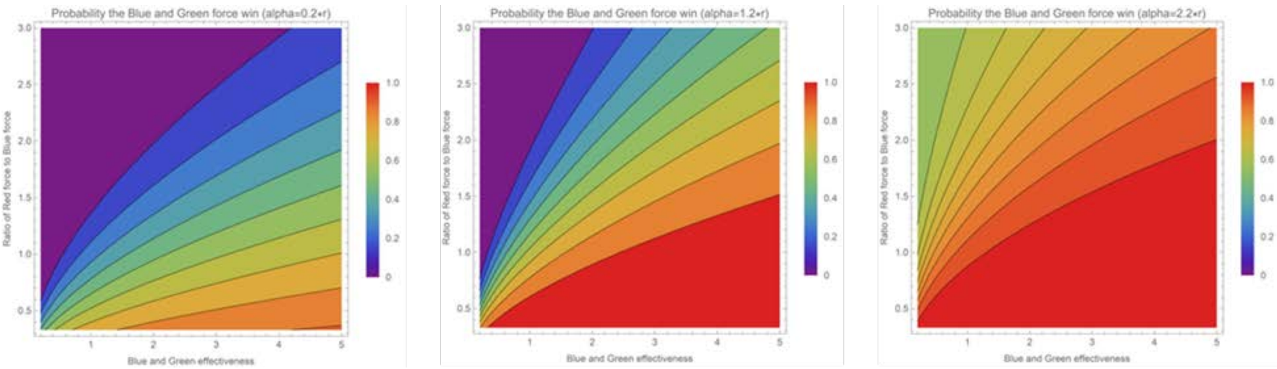

Figure 3-2: Contour plots of the probability of Campaign success (without cyber elements) as a function of the effectiveness of the Blue (Green) force against Red and the ratio of the initial Red to Blue forces for: (a) $\alpha_0 = 0.2 \times r_g$, (b) $\alpha_0 = 1.2 \times r_g$, (c) $\alpha_0 = 2.2 \times r_g$.

Figure 3-2 displays the probability of Campaign success without the cyber elements, for values of $\alpha_0$equal to (a) $0.2 \times r_g$(b) $1.2 \times r_g$and (c) $2.2 \times r_g$ (where we have assumed $r_b = r_g$). The horizontal axis is the effectiveness of the Blue force against Red (assumed equal to that of the Green force against Red), while the vertical axis is the ratio of the initial sizes of the Red and Blue force. We also assume that the initial Green force is one tenth of the Red force as in Table 3-1.

This probability increases along the horizontal axis but decreases along the vertical axis. Generally, as $\alpha_0$increases (from left to right), the probability of success increases. This is consistent since α_0 represents the supply that increases the size of the Green force. In (a), the Green force will decrease with time, while in (b) the Green force will increase with time. In (c) the combined Green and Blue forces will be more effective than the Red force. This case generally ensures Campaign success if the ratio of the Red force to that of the Blue force is less than or equal to three as shown in Figure 3-2(c).

Before we delve into the details of the interplay between the Campaign and the Border Operation, we illustrate how this could be done at a conceptual level. Suppose that part of the Green force is diverted from the Campaign to the Border Operation. This means that the original α_0 allocated to the Green force will decrease by $\delta > 0$ and this amount reallocated to the Border Operation. The greater δ is the more successful the Border Operation will be. We define the compounded probability of success as the probability of Campaign success multiplied by δ/α_{max}. Figure 3-3 shows the compounded probability of success as a function of δ for three cases, $R_0/B_0 = 1,\ 2,\ 3$, all with $\alpha_{max} = 3 \times r_g$. Note that in each scenario there is a δ that maximizes the compounded probability of success (e.g., the middle curve with $R_0/B_0 = 2$ of Figure 3-3 has a maximum for $\delta = 1.25 \times r_g$). In general, the compounded probability of success increases with decreasing R_0/B_0. This means that the Blue and Green forces are more successful when there is less Red force and it would be possible to divert more Green force to the Border Operation.

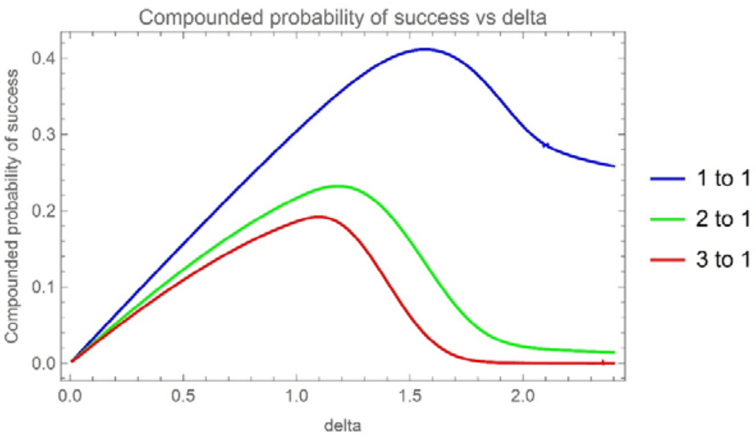

Figure 3-3: Compounded probability of success vs. δ for $\alpha_{max} = 3 \times r_g$ and three values of R_0/B_0.

This analysis illustrates the type of interplay between the Campaign and the Border Operation. However, the actual situation would be more complex as it depends on many factors, such as the time when the Border Operation is initiated by Red and its duration, and the number and type of assets allocated to the Border Operation.

To conduct the experiments, we link the inputs and outputs between the Campaign and the Border Operation, as follows. Table 3-2 describes a notional cost for each unit increase in an attribute of an asset employed in the Border Operation above its minimum value (see Table 2-1), along with a unit cost for each asset. Choosing a setting for each of these decision factors within their minimum and maximum values allows a total cost for that COA to be determined. For example, the sensor range of the two UAVs is 4km larger than its minimum value (of 1km), so the sensor cost for each UAV is 4 times 1, or 4. Similarly, its speed is 20 km/hr larger than its minimum value (of 10 km/hr), so the speed cost for each UAV is 20 times 0.05, or 1. Thus each UAV has a total cost of 15 (5 for its attributes and 10 for the asset) and since there were 2 UAVs in this COA, the total cost for the UAV component is 2 times 15, or 30. Finally, to link the different scales of the Campaign and Border Operation, we determine the maximum cost COA (by setting all factors to their maximum values in Table 2-1, here totalling 662.8) and specify what fraction of G_0 that is equivalent to (e.g., 662.8 might be viewed as equivalent to one-tenth of the initial starting force of Green).

Table 3-2: Mapping of the cost of each unit for the 14 decision factors of the Border Operation.

Factor	Cost_Unit	Setting	Cost_Total
UAV Quantity	10	2	30
Sensor Range (km)	1	5	
Speed (km/hr)	0.05	30	
Zone 1 Patrol Quantity	50	1	85.1
Visual Range (km)	1	1	
Speed (km/hr)	0.5	80	
Interception Processing Time (sec)	0.001	3000	
Detected Location Duration (sec)	0.004	3000	
Zone 2 Patrol Quantity	50	2	121.2
Mini-UAV Sensor Range (km)	1	4	
Speed (km/hr)	0.5	40	
Interception Processing Time (sec)	0.001	2000	
Detected Location Duration (sec)	0.004	1500	
Southern Border Fence	200	1	200
			436.3

When the Border Operation begins at $t = t^*$ the Green force in the Campaign $G(t) = G_{UC}(t) + G_{BO}(t)$ is partitioned into that force prosecuting the Campaign $G_{UC}(t)$ and the resources allocated to the Border Operation $G_{BO}(t)$. At time $t = t^* + dt$, the Border Operation concludes, and those resources $G_{BO}(t)$ allocated to the Border Operation return to the Campaign. The final linkage from the Border Operation to the Campaign is the function $\alpha = \alpha(t, p_N)$ entering the Green equation of the ACE model [6]:

$$\alpha(t, p_N) = \begin{cases} \alpha_0 \quad , & t_0 \le t < t^* + dt \\ \dfrac{\alpha_0}{1 + \gamma \cdot p_N^4}, & t \ge t^* + dt \end{cases} \tag{1}$$

Here, p_N is the percentage of non-intercepted migrants at the end of the Border Operation, α_0 is the parameter of Table 3-1 and $\gamma = 1.2$. This function encodes the Green public opinion which decreases as the percentage of non-intercepted migrants increases indicating that the supply rate of Green to the Campaign diminishes if the Border Operation is getting unsuccessful.

3.3 Accelerating Automation

While Latin Hypercube designs have grown in popularity for DF studies, a newer class of design – specifically suited for the two-stage meta-modelling process illustrated above – has been developed. Definitive Screening Designs (DSDs) [7] only require three levels at most for each factor and are more efficient than competing Latin Hypercube designs. For the Border Operation, it suffices a DSD with only 50 design points rather than the NOLH with 129 design points. Also as indicated in Section 2.2, low-order polynomial linear meta-models have been common in DF due to their ease of interpretation. Machine Learning (ML) models, such as Random Forests and Neural Networks, are often considered black-box models because it is not easy to understand how they map inputs to outputs. Still, black-box models have been shown to be powerful predictors, creating a trade-off between interpretability and performance. Now, advances in eXplanable AI (XAI) allow a broader range of DF meta-models to be considered without sacrificing interpretability [8]. When additionally coupled with automated ML (autoML), it is possible to increase the level of automation in building meta-models within a DF process [9]. These newer designs, more sophisticated meta-models, and increased automation underpin the science of MDDF, and will enhance the analyses that will be possible.

To illustrate, we use autoML to train, tune, and test four different families of models for predicting the mean proportion of migrant interceptions in the Border Operation using the DSD data. Figure 3-4 summarizes the predictive performance using two metrics, mean absolute error (MAE) and root mean squared error (RMSE), and the variable importance for each model. Here, the variable importance is an example of XAI and indicates which decision factors (df1-df14) and noise factors (nf1-nf6) have the greatest influence on the proportion of migrant interceptions. The models tended to identify the same top 7 factors, of which 6 are as in Table 2-2. A Gradient Boosting Machine (GBM) had the best performance (lowest error) followed by a Generalized Linear Model (GLM). Therefore, autoML does not necessarily exclude interpretable models (e.g., GLM) from consideration. Instead, autoML is introduced within DF to efficiently consider multiple types of models and automatically select the highest performing model. Additionally, black-box models do not require that a functional form be known or specified, which is advantageous in scenarios where there is limited intuition about the nature of the input-output relationship.

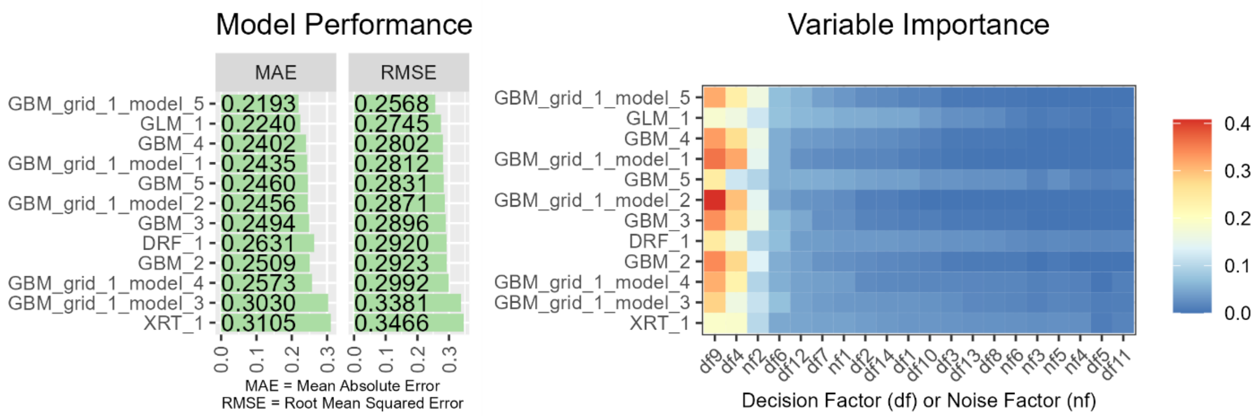

Figure 3-4: Summary of autoML results for the Border Operation based on a DSD. Four families of meta-models were considered - fixed grid of Generalized Linear Models (GLMs), fixed and random grid search of Gradient Boosting Machines (GBMs), Default Random Forest (DRF), and Extremely Randomized Trees (XRT).

Another approach to employ ML models in DF is the application of Bayesian optimization techniques [10] as a sequential design strategy. While the DSD design uses substantially fewer design points than the NOLH design, conducting further experiments on demand might be desirable, which are likely to improve the quality of the meta-models. Bayesian optimization offers a framework to find optima of black-box functions (such as response functions from DF experiments) that are difficult to evaluate due to their computational costs. The objective function is assumed to be unknown, while enough information is available to place a prior distribution over it. Experiment points or function evaluations are treated as data points, which are used to generate the posterior distribution of the objective function. Further, an acquisition is introduced, which is used to determine the next experimental points. The most common method to define the prior/posterior pairs are Gaussian Processes (GPs) [11].

Since the methodology's core is comprised of a GP fitted to the experimental data, we illustrate the results of fitting a GP to the available DSD dataset, below. The factors used were obtained by an initial sensitivity analysis, and 4 of 7 are the same as in Table 2-2. The hyperparameter tuning was carried out using cross-validation and choosing the best-performing combination. Figure 3-5 shows the model's overall performance, which received an R^2 of 0.99 on the training data and an R^2 of 0.63 on the test data, while Figure 3-6 displays what are known as partial dependence plots (another example of XAI) associated with each factor, which can be used to compare and contrast with the second-order meta-modelling results in Table 2-2.

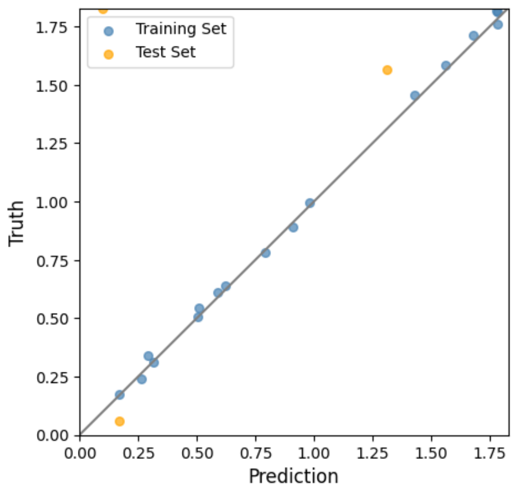

Figure 3-5: Performance plot of the GP fitted to the DSD experiments.

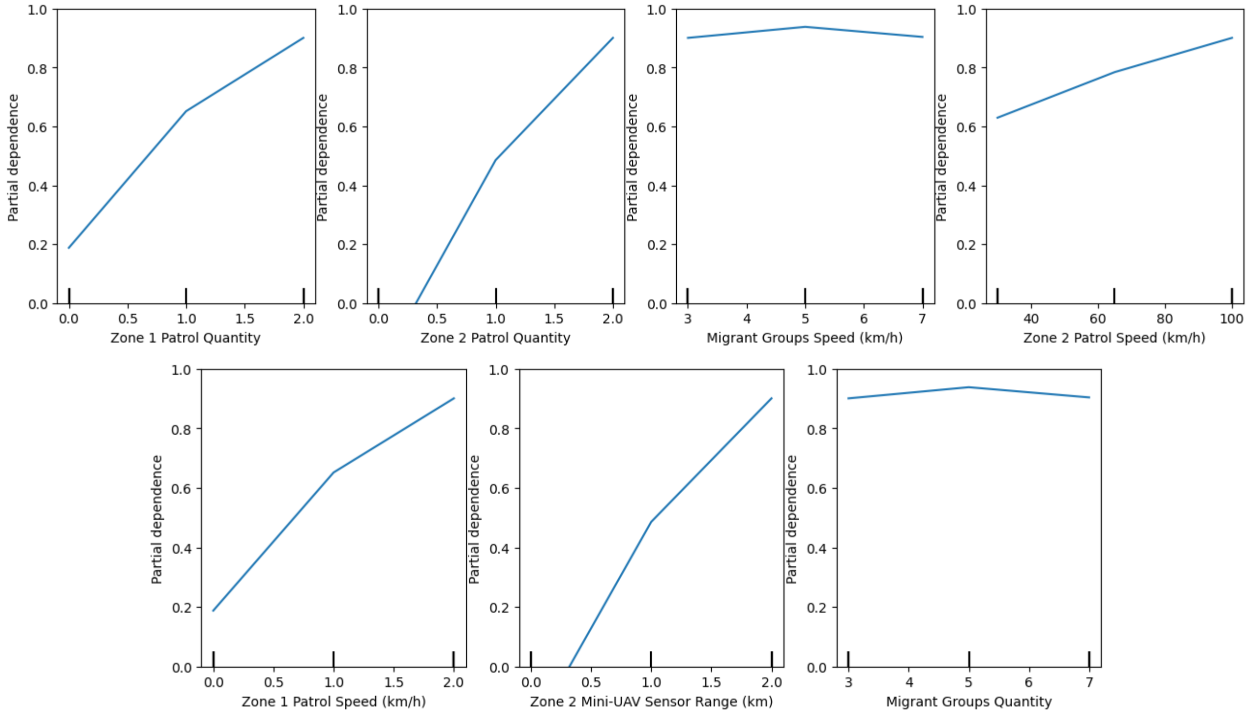

Figure 3-6: Partial dependence plots for the factors used in the GP meta-model.

4.0 DESIGN, ANALYZE, AND VISUALIZE EXPERIMENTS (DAVE)

The multi-run execution loop of DF comprises the design of experiments, high performance computing, analysis and visualization. The exploitation of newer autoML and Bayesian optimization techniques allows one to accelerate the building of meta-models within the loop-of-loops DF process, and hence, to identify faster the best, worst and most promising COAs in multi-faceted scenarios. Figure 4-1 depicts the overall concept of the Design, Analyze and Visualize Experiments (DAVE) agent, in the context of the hybrid warfare scenario used in this paper. This AI agent will automatically investigate the multi-dimensional parameter landscape and optimize the probability of success of the Campaign while being cognisant of both the resource tension and negative consequences of a poorly managed Border Operation. DAVE is an AI agent which will efficiently provide decision-makers with actionable insight.

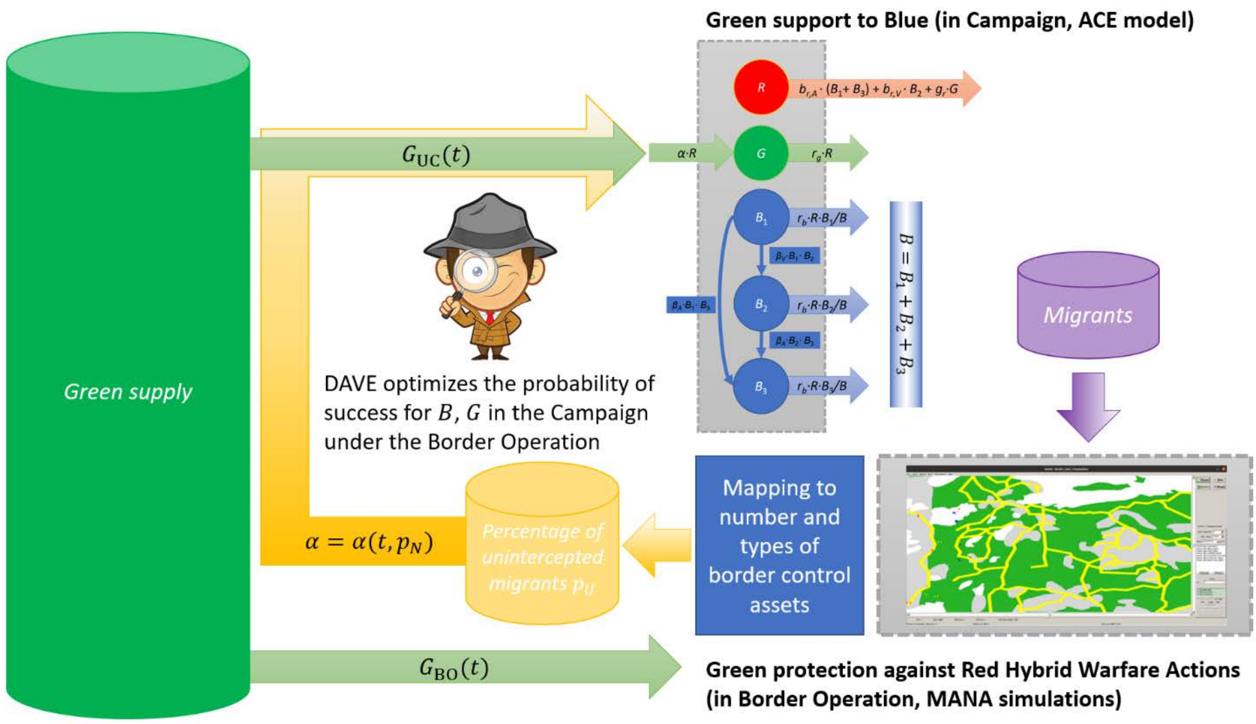

Figure 4-1: High-level illustration of the concept for the Design, Analyze and Visualize Experiments agent.

4.1 Architectural Overview

The technical implementation aims to develop a Demonstrator for the AI-based methodologies described above, reaching Proof-of-Concept (PoC) status in 2023 and extended and examined in detail during the CWIX Exercise in 2024. As during the PoC, the goal is more on creating a robust system and working processes, during CWIX in 2024 also the possibilities of an extended explainability of DAVE using eXplainable AI and eXtended Reality technologies as usability testing will be more in focus. The analytical objective is to develop an AI-based assistant able to conduct DF experiments and optimization tasks on an automized basis. As shown in Figure 4-2 DAVE is intended to act in the user environment of a DF Analyst and support them in their analysis tasks.

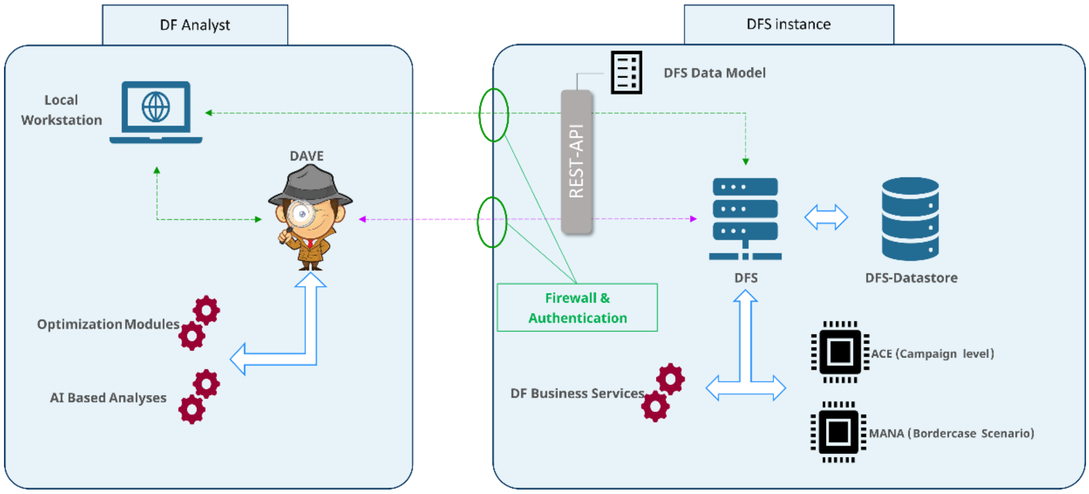

Figure 4-2: Architectural Overview of the MSG-186 Demonstrator of DAVE connected to a DFS-instance.

The technical implementation of DAVE is based on the Data Farming Services (DFS) architecture developed by MSG-155 [12]. DFS acts as a DF engine for the overlying elements and supports the AI-based methodologies implemented in DAVE. Figure 4-2 illustrates the Demonstrator as a DFS-instance, containing all business services needed to conduct standard DF experiments, as well as the simulation MANA (operational level) and ACE (campaign level). The DFS-instance is accessible via REST-API based on a data model for all business objects agreed by MSG-155. DAVE implementation, based on this data model, can now execute single simulation runs up to complete automized DF experiments. This supports AI-based methodologies like screening or Bayesian optimization.

4.2 Analysis Workflow

As DAVE is intended to automatically perform analyzation and optimization tasks, we propose an architecture which consists of a classical layered software design (see Figure 4-3).

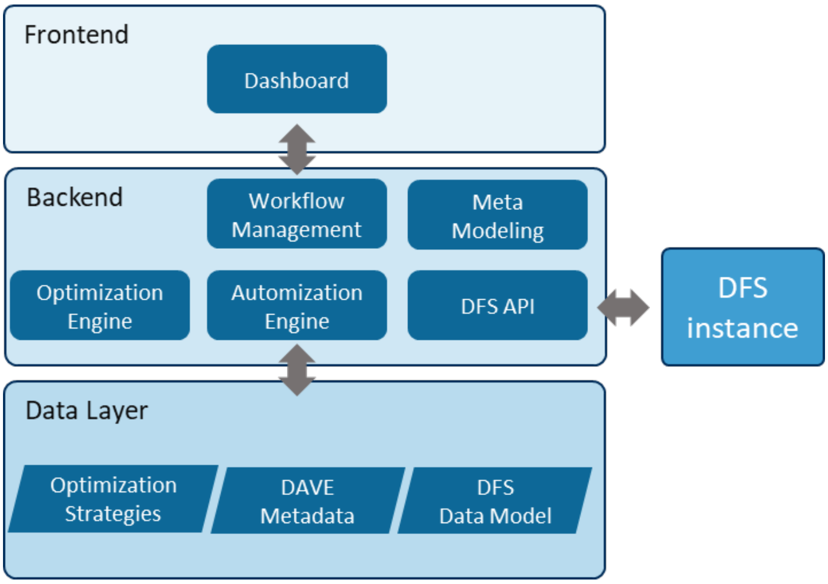

Figure 4-3: DAVE software architecture with functional element blocks and connection to the DFS-instance.

Important is the dashboard functionality in the frontend, which enables the user to monitor the automized process of DAVE. The backend uses AI-based meta-modelling techniques to automatically perform DF experiments in a sequential manner. Furthermore, the optimization engine will be backed by configurable and exchangeable optimization strategies, to adapt DAVE on different use cases. DAVE itself will work internally based on the DFS data model extending it by metadata needed for the internal optimization and modelling elements.

The Demonstrator Use-Case will use DAVE for the following analysis workflow: (1) Execute single ACE simulation runs at campaign level. (2) Identify decisive point(s) in simulation results and derive optimization goal with relevant parameters. (3) Map parameters from campaign to operational level, configure optimization strategy and start DF experiment. (4) Automatically conduct iterative DF experiment with optimization strategy and derive optimal parameter setting using AI-based meta-modelling. (5) Map optimal parameter setting back to campaign level, adapt ACE simulation and analyse/visualize result changes.

5.0 SUMMARY

Our work serves as a proof of concept of the ACE framework. That is, we describe for the first time the interplay of a long-time scale campaign and a short-time scale operation. We show the complexity that arises in terms of time, sharing of resources and domains involved. This is a first attempt to understand how one can win a battle (operation) but lose a war (campaign) if we divert too many resources to the operation. We illustrate through MDDF how it is possible to combine AI techniques exploring operations at multiple scales (domain, level, time) and optimize the probability of winning the campaign, even with the burden of a border operation, by selecting the correct resource allocation scheme. From the modelling perspective, we introduce a new multi-model approach to couple simulation models of different aggregations that allow more comprehensive multi-level military planning and decision-making.

In reality, a campaign is coupled with not one operation but many of them and of many types. The sheer complexity of such a prospect is an interesting one. There are two general directions for future work. The first is the further development of tools and techniques underpinning MDDF to boost strategic and tactical understanding, The development of MDDF allows us to accelerate the automation process making it efficient and effective in analysing large and complex multi-dimensional data spaces. Our AI driven automation may extend the application of MDDF to wargaming as a resource and time efficient simulation support in wargaming in domains like mission support or training and education.

The second is to understand the nature of war: when we fail why we fail. This will make our world a better and safer place.

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