Chapter 1

COOPERATIVE BEHAVIOR SCHEMES FOR IMPROVING THE EFFECTIVENESS OF AUTONOMOUS WIDE AREA SEARCH MUNITIONS*

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Abstract

The problem being addressed is how to best find and engage an unknown number of targets in unknown locations (some moving) using multiple autonomous wide area search munitions. In this research cooperative behavior is being investigated to improve the overall mission effectiveness. A computer simulation was used to emulate the behavior of autonomous wide area search munitions and measure their overall expected performance. This code was modified to incorporate the capability for cooperative engagement based on a parameterized decision rule. Using Design of Experiments (DOE) and Response Surface Methodologies (RSM), the simulation was run to achieve optimal decision rule parameters for given scenarios and to determine the sensitivities of those parameters to the precision of the Autonomous Target Recognition (ATR) algorithm, lethality and guidance precision of the warhead, and the characteristics of the battlefield.

Keywords: Cooperative engagement, cooperative behavior, autonomous munitions, wide area search munitions.

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1. Introduction

1.1. General

The problem being addressed is how to best find and engage an unknown number of targets in unknown locations (some moving) using multiple cooperating autonomous wide area search munitions. The problem is exacerbated by the fact that not all target priorities are the same, the munition target discrimination capability is never perfect, and target destruction is never a certainty even once engaged. Further, factors such as clutter density throughout the battlefield and ratio of targets to civilian or military non-targets create even more complications for these smart, yet simple-minded, munitions.

This research does not necessarily provide the precise solution to this rather complex problem; rather, this research provides a possible methodology for how to attack this problem using different optimization methodologies and shows some sample results.

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1.2. Background

The United States Air Force has significantly reduced the size of its military forces as a response to changing national military objectives and diminishing budgets. This reality has forced the Air Force to look for more cost effective ways of achieving its extremely crucial mission. One development has been the creation of small, lightweight, low-cost, autonomous munitions fully equipped with INS/GPS navigation and seekers capable of Autonomous Target Recognition (ATR). The intent in using these autonomous munitions is to employ larger numbers of cheaper, less sophisticated munitions as opposed to fewer numbers of expensive, complex munitions. However, in order to realize the full capabilities of a system composed of large numbers of smaller subsystems (or agents), the individual agents must behave cooperatively. Methods of evaluating mission effectiveness of these munitions have previously been developed for the case of non-cooperating munitions [7]. In this research cooperative behavior is being investigated to improve the overall mission effectiveness.

In a study provided by RAND [6], the rationale was developed for investigating cooperative behavior between Proliferated Autonomous Weapons (PRAWNs). They showed by implementing a cooperative weapon behavior logic into a computer simulation that there was a definite added potential when cooperation was incorporated into the logic of PRAWNs. This study supported the hypothesis that while the individual munitions may be less capable than conventional munitions under development today, through communication across the swarm of weapons, the group exhibits behaviors and capabilities that can exceed those of more conventional systems that do not employ communication between weapons. The potential benefits which come about through shared knowledge include relaxed sensor performance requirements, robustness to increases in target location errors, and adaptivity to attrition and poor target characterization.

In this study, however, a fixed decision rule (called "swarming algorithm") was used. This algorithm was based on the foundations of two areas of study: ethology (the science of animal behavior) and robotics developed in the civil sector. The collective intelligence that seems to emerge from what are often large groups of relatively simple agents is what the engineers of the RAND study tried to capture in their swarming algorithm. While this algorithm worked for what they were doing, the research did not show how this decision algorithm compared to other possible decision algorithms. Also, the RAND study concentrated on a very specific battlefield layout that was composed of large clusters of targets and no possibility of encounters with non-targets or clutter. By not taking into account non-targets or clutter, the munitions had no false target attacks. According to Jacques [7], methods and models for evaluating the effectiveness of wide area search munitions must take into account the degradation due to false target attacks.

Scientists studying animal behavior have identified and analytically modeled many behaviors of natural organisms that have parallels to the tasks that weapons must achieve in order to search for, acquire, and attack targets. Some of these studies include Reynolds' considerations for the formation of flocks, herds, and schools in simulations in which multiple autonomous agents were repulsed by one another (and other foreign objects) by inverse square law forces [12] and Dorigo's studies of ant colony optimizations [5]. Scientists in the field of robotics have developed architectures for the controlling of individual robots or agents, which allow groups of individuals to experience the benefits of group or swarm behaviors. These include the studies by Arkin, Kube and Zhang, Asama, and Kwok. Arkin demonstrated an approach to cooperation among multiple mobile robots without communications [1], and Kube and Zhang also researched the use of decentralized robots performing various tasks without explicit communication [8]. Asama sums up the challenge in choosing the right behaviors for your agents by saying that "an autonomous and decentralized system has two essentially contradictory characteristics, autonomy and cooperativeness, and the biggest problem in the study of distibuted autonomous robotic systems is how to reconcile these two features" [2]. Kwok considered the problem of causing multiple (100's) of autonomous mobile robots to converge to a target using an on-board, limited range sensor for sensing the target and a larger but also limited-range robot-to-robot communication capability [9].

While much of the research in the field of cooperative control of robotics has been able to apply some of the basic principals learned from ethology, the application to cooperative engagement of autonomous weapons is rather limited. Since each of the munitions has a specific Field of View (FOV) on the order of a half mile in width, the munitions are normally programmed to fly a half mile from each other in order to limit the FOV overlap. Scenarios exist where large FOV overlap is desired in the interest of redundant coverage and higher probabilities of success, but the study of these scenarios is more applicable to the cooperative search problem than the cooperative engagement problem. Therefore, the protection and drag efficiencies gained by flocking, schooling or herding are not applicable to this study. However, the concept of ant foraging does have application to the problem at hand. Moreover, what if the ants had the ability to *choose* to follow the pheromone deposits to the known source of food or to *choose* to seek out a different area for a possible larger, better, or closer food source? By what criteria could this decision be made? Is the decision criteria the same for all situations? Taking this analogy one step further (and maybe a little beyond reality), what happens when an ant falsely identifies a poisonous food source as a good food source and causes the colony to subsist off of this unknown danger? These questions have not been answered in the applied research of robotics but are extremely important questions for the application of cooperative control of autonomous wide area search munitions.

1.3. Objectives

The primary objective of this study was to investigate the use of cooperative behavior to improve the overall mission effectiveness of autonomous wide area search munitions. The specific objectives were to:

1. Establish a methodology for measuring the expected effectiveness of a cooperative system of wide area search munitions

2. Develop optimal cooperative engagement decision rules for a variety of realistic scenarios

3. Qualitatively analyze the sensitivities of the decision rule parameters to the precision of the submunition's ATR algorithm, the lethality and guidance precision of the warhead, and the characteristics of the battlefield (clutter density, target layout, etc.)

2. Baseline Computer Simulation

This Monte Carlo based Fortran program was originally developed by Lockheed Martin Vought Systems [10] as an effectiveness model for the Low Cost Autonomous Attack System (LOCAAS). However, it is versatile enough to be used for any generic wide area search munition. The simulation makes no attempt to model the aerodynamics, guidance, etc. of the submunitions, however, it does model multiple submunitions in a coordinated search for multiple targets. Prior to the modifications made through this research, this program had the capability to simulate the following events of the submunition "life cycle":

- Round dispense (any number of rounds)
- Submunition dispense (any number of submunitions per round)
- Submunition flies a user supplied pattern by following predetermined waypoints and looks for targets on the ground
- If a target enters a submunition's FOV, the submunition may acquire it based on the probabilities associated with the ATR algorithm
- Once acquired, the submunition can select that target to engage
- Once engaged, the submunition attempts to hit the target
- Once the target is hit, an assessment is made as to whether the target has been completely destroyed (dead) or is still in working condition (alive)

The simulation allows for any number of targets with varying priority levels, the addition of non-targets (military or civilian), and a user supplied clutter density per square kilometer of battlefield. The simulation is extremely flexible in its capabilities to handle a multitude of input parameters and supplies all sorts of results as output files at the conclusion of each run.

2.1. Inputs to the Simulation

To run the simulation, two separate input files are required. The first contains the information concerning the user supplied flight paths for the submunitions once dispensed from the rounds including waypoints, altitude and velocity, and the second contains all the parameters characterizing the submunitions and the parameters required to run the simulation. Table 1.1 shows a summary of some of the input parameters that must be entered regarding the characteristics of the submunitions and targets.

Since the munition effectiveness is determined by the outcome of Monte Carlo runs, the user also has the ability to pick a baseline seed (which is modified for every repetition in a series) and the number of Monte Carlo trials.

2.2. Outputs of the Simulation

The main output file for the simulation lists all of the input parameters used to run the simulation for tracking purposes. Then for each Monte Carlo repetition,

Table 1.1. Input Parameters to Baseline Simulation

Parameter	*Description*
Numbers:	
Rounds	Total number of rounds dispensed
Submunitions	Total number of submunitions (and submunitions per round)
Target Types	Priority 1, priority 2, non-targets, etc.
Targets	Total number of targets and how many of each type
Discrete:	
Random Targets	Either targets are placed in specific locations or random within a specified area $\leq$ total battlefield area
Blind in Turns	Submunition's target detection is turned off when turning
Reliabilities:	
Round	Probability that round will not fail
Submunition	Probability that submunition will not fail
Probabilities:	(Input for each target type)
Acquisition	Submunition will acquire the target when it enters its FOV
Hit	Submunition will hit the target once its acquired
Kill	Submunition will kill the target once its hit
Correct Identification	Submunition will identify the target correctly or incorrectly (incorrect identifications are distributed among all target types as desired)
Seeker Data:	
Foot Print Width	Width of the FOV on the ground
Beam Width	Beam width in degrees used for vertical FOV
Boresight Angle	Angle at which the LADAR points down from the horizon
Scan Time	Time for the FOV to sweep the entire foot print width
Flyback Time	Time for the FOV to return at the completion of each sweep
Submunition Data:	
Min Turn Radius	Minimum turn radius the submunition can fly
Time of Flight	Total Time of flight from submunition dispense time to expiration
Target Data:	
Locations	Specific locations of all targets if using non-random target layout
Mobility Data	If mobile: start time, heading, speed, acceleration time

a brief history of what each submunition did during that repetition is displayed. Finally, at the end of the main output file, all Monte Carlo repetitions are summarized showing a breakdown, per target type and per individual target, of the number of acquisitions, selections, hits, and kills, as well as the total number of kills and unique kills for that simulation run.

3. Simulation Modifications

The baseline simulation has some capacity for cooperative engagement, but it was insufficient for purposes of this research. Specifically, cooperative attack decisions have to be made immediately upon target declaration, the number of submunitions to be redirected is set a priori, and there is no provision for expanded search if the target is not found by the submunition being redirected. For these reasons, significant modifications were made to the simulation.

3.1. Redirecting Submunitions

The first step in the modification process was to be able to redirect any number of submunitions at any time toward any found targets. The way this was accomplished was using a structured array to store all target information on the targets found. This structured array stored the x, y and z coordinates of the target (if the target was a moving target, these coordinates would be those corresponding to the position of the target at the time it was acquired and selected), and the type of target found. A very important distinction which needs to be made at this point is that the target type stored is not necessarily the correct identification of the target found; it is the identification of the target type determined by the munition that identified that target. Therefore, the type of target found which is stored in this target array may not be the true type of target located at the stored coordinates.

Once the target information was stored, a method for distributing that information had to be determined. Obviously, since this was just a simulation, it would be easy to just provide all submunitions access to all entries in the aforementioned structured array. But is this feasible, realistic or even advantageous? Since this study hoped to gain some insight into the trade-offs between local and global communication, a mechanism for determining whether a submunition received the communicated information had to be implemented. First of all, in this study incomplete communications were not considered, i.e., either a submunition receives all the information about the target or none. However, communications reliability based solely on whether or not the submunition was within a certain maximum communications range didn't seem too realistic either. Therefore, a communications reliability function was developed. In order to keep it relatively simple, this function was solely based on the probability of communication failures increasing as maximum communications range was approached. Maximum communication is not set a priori; rather it is one of the variables to be determined by the design optimization process. The reliability function used is shown in equation (1).

$$\text{Comm Rel} = \begin{cases} 1 & \text{if range} \leq \frac{\text{max comm range}}{2} \\ \left(\frac{\text{max comm range} - \text{range}}{\frac{\text{max comm range}}{2}} \right)^{0.1} & \text{if range} > \frac{\text{max comm range}}{2} \end{cases} \tag{1}$$

Figure 1.1 illustrates an example of this communications reliability function for a maximum communications range of 10,000 meters.

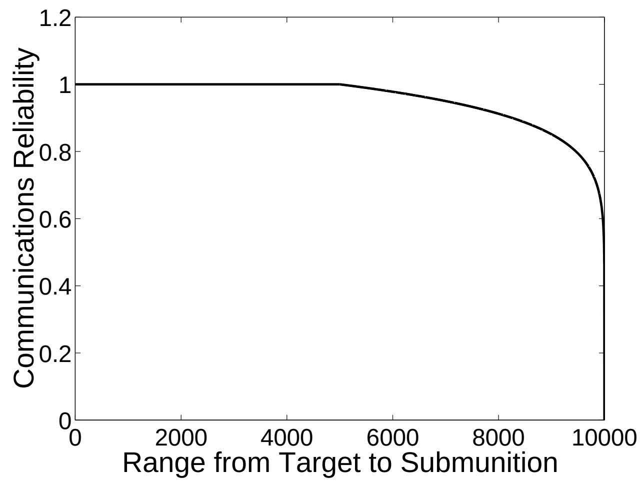

Figure 1.1. Communications Reliability Function

In order to implement the decision algorithm described in the following section, the amount of information that had to be shared among the submunitions had to be determined. For practical implementation concerns, there was a desire to limit the amount of communication required and to limit all communication to words or numbers as opposed to images. This low bandwidth communication seemed most feasible for this application. For this study, the following three pieces of information were communicated for each target found:

- Location of the target
- Type of target
- Specific target to be engaged

The location of the target was communicated as the precise x and y coordinates of the target. The type of target was communicated as either a high priority (priority 1) or a low priority (priority 2). The specific target to be engaged is, in reality, a very difficult piece of information to communicate and keep track of reliably, especially with non-global and non-perfect communications. However, in this study, the target registration problem was not considered.

3.2. Decision Algorithm

The purpose of the decision algorithm was to provide a criteria by which the submunitions could "decide" whether or not to participate in a cooperative engagement. In developing the algorithm, the goals were to incorporate all important factors that should be taken into account for making a cooperative engagement decision and to keep it simple since the available computing power aboard these submunitions is minimal. After several iterations, the following (in no particular order) were determined to be the most important factors that needed to be included in the decision algorithm:

- Fuel remaining
- Target priority
- Range rate from submunition to target
- Range from submunition to target
- Number of submunitions that have already engaged a particular target

To keep the decision algorithm simple, the basic first order expression shown in equation (2) was used.

$$\text{Threshold} = \alpha_1 * x_1 + \alpha_2 * x_2 + \alpha_3 * x_3 - \alpha_4 * x_4. \tag{2}$$

where

x_1 = Normalized Fuel Remaining
x_2 = Normalized Target Priority
x_3 = Normalized Range Rate
x_4 = Normalized Number of Engaged Submunitions on a particular target
α_i = Weighting Parameters

Normalizing the fuel remaining in the simulation was easily accomplished by normalizing time of flight or search time. Since each submunition had a twenty minute total search time, the normalized time of flight was the current time divided by 1200 seconds. Target priority was normalized by assigning a value of one to a priority one target, one-half to a priority 2 target and zero for anything else.

The purpose of incorporating a range rate parameter in the decision rule was to apply little influence on the decision (or even discourage a cooperative engagement) when the range rate was negative (the submunition is moving towards the target) and to encourage a cooperative engagement when the range rate is positive (the submunition is moving away from the target). This provided a means for allowing the submunition to continue its predetermined search pattern if it was flying in the general direction toward a known target location.

The expression used to normalize range rate is shown in equation (3) with $\dot{r}$ defined by a backward difference.

$$\text{normalized range rate} = \left| \frac{\dot{r} - \text{vel}}{2 * \text{vel}} \right| \tag{3}$$

where

$$\dot{r} \quad = \quad \frac{\text{range}_i - \text{range}_{i-1}}{\text{time}_i - \text{time}_{i-1}}$$

Figure 1.2 illustrates the function for normalized range rate shown in equation (3).

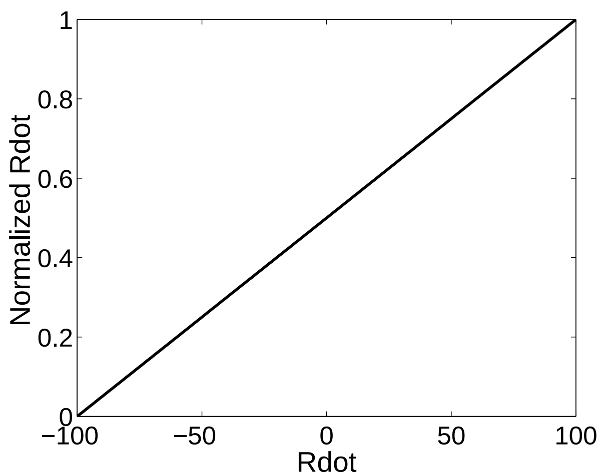

Figure 1.2. Normalized Range Rate

The actual range from the submunition to a specific target is not explicitly used in this decision algorithm, however, a range check was added to the simulation to ensure that a submunition is not redirected toward a target that cannot be reached based on insufficient fuel remaining.

The last parameter in the decision algorithm is the normalized number of engaged submunitions on a specific target. The purpose of this parameter is to discourage multiple cooperative engagements on a single target in an attempt to spread out the total hits and not send all submunitions after the same target. When a target has been engaged by only a single submunition, then this parameter should not be discouraging a cooperative engagament on that target. However, once one submunition has cooperatively engaged a target (resulting in a total of two munitions attempting to hit that specific target), this parameter should be invoked to discourage any additional submunitions from choosing to cooperatively engage that target. Equation (4) was used to normalize this parameter.

$$\text{Normalized Parameter} = \text{Number of engaged submunitions} - 1 \qquad (4)$$

Note that in equation (2) a "-" sign is implemented in front of this parameter in order to *discourage* a cooperative engagement as this parameter increases. As desired, this parameter equals zero when only one submunition has engaged a specific target but then increases in value as more submunitions cooperatively engage that target.

The implementation of the decision rule in equation (2) was rather simple. Once a target is found, the information about that target is communicated by the submunition that identified the target. Then at all subsequent time steps, every submunition that received the communication and is not in an engaged status will calculate all of the normalized parameters and the decision algorithm, equation (2). When multiple targets are found and communicated, then at all subsequent time steps the normalized parameters and the decision algorithm are calculated by each submunition for each target individually. If the total for the decision algorithm exceeds the decision threshold, then a cooperative engagement on that target by that submunition occurs. That submunition then communicates globally with 100% reliability that it has engaged that specific target (ignores all target registration issues). Relaxing this assumption would require revisiting the target registration problem which is beyond the scope of this study.

3.3. Additional Modifications

In order to best achieve the objectives of this study, a few additional changes needed to be made to the simulation. The first was a simple modification to the main output file to include the values of each normalized parameter as well as the weights on the parameters every time a cooperative engagement was invoked. This provided a means to track all cooperative engagements, and ensure the decision algorithm was being implemented properly.

A second change was an attempt to answer the following question: what should happen to a submunition that is sent off its original search pattern to cooperatively engage a target that it cannot find? This situation could result from a failure of the ATR algorithm on either the original munition that identified the "target", or the munition searching for the previously found target. In order to accomodate this, an attempt was made to create a new search pattern for the redirected submunition that focused on the location of the target that was cooperatively engaged. The new pattern used was a growing figure-8 centered on the communicated target location. This pattern would initially turn the submunition around after it crossed the expected target location to fly right back over it as an attempt to acquire and classify the target if it simply "missed" it the first time. If the target was still not selected on this second pass, then the submunition would continue flying past the target, but this time farther past the target, in the opposite direction in which the submunition first approached the target area. It would then turn around and fly back toward the target until the submunition engages a target or expires (search time depletes)–the submunition cannot participate in a second cooperative engagement on a different target.

The behavior chosen to handle this situation is not necessarily that which would be implemented operationally, nor was any research completed that showed this behavior would produce optimal results. This situation was deemed outside the scope of the research and could better be addressed by a study in cooperative search.

4. Applied Response Surface Methodologies

Response surface methodology is a collection of statistical and mathematical techniques useful for developing, improving, and optimizing processes. Most applications include situations where several input variables potentially influence some performance measure or quality characteristic of the system. The purpose of RSM is to approximate the measures of performance, referred to as response functions, in terms of the most critical factors (or independent variables) that influence those responses. In doing this, a response surface can then be mapped out showing how variations in the independent variables affect the responses.

A typical RSM according to Myers and Montgomery [11] is broken into phases. The first experiment is usually designed to investigate which factors are most influential to the responses with the intent of eliminating the unimportant ones. This type of experiment is usually called a screening experiment and is typically referred to as phase zero of a response surface study. Once the important independent variables are identified, phase one begins with the intent of determining if the current levels or settings of the independent variables result in values of the responses near optimum. If the current settings or levels of the independent variables are not consistent with optimum performance, then adjustments to the input variables that will move the responses toward the optimum must be made. To do this a first order model and the optimization technique called the method of steepest ascent are employed. Phase two of the response surface study begins when the process is near the optimum. At this point models that will accurately approximate the true response functions are desired. Because the true response surfaces usually exhibits curvature near the optimum, models of at least second order must be used. Then, finally, the models of the various responses must be analyzed to determine the settings for the independent variables that provide the optimal expected performance over all responses.

For this study, RSM was used to determine the optimal settings for the α_i's in the cooperative engagement decision algorithm shown in equation (2) as well as the maximum communications range. The optimal α_i's were simply the weights on the parameters used in the decision rules. A high weight on a parameter means that that parameter is of high importance in making the decision to cooperatively engage, whereas a low weight on a parameter can be interpreted to mean that that parameter is less important (or even insignificant) in making the decision to cooperatively engage. A low maximum communications range implies that local communications are employed, whereas a high maximum communications range implies global communications.

4.1. Independent Variables

Because of the relatively small number of input variables, the phase zero screening experiments were not necessary for this study. Therefore, the first step was to choose the ranges of the independent variables to begin the RSM. A decision threshold for equation (2) was, without loss of generality, chosen equal to one (the α_i's could be scaled to accommodate a non-unity threshold value). In picking the ranges for the independent variables, careful consideration was made to ensure the RSM studies would be investigating the effects of different cooperative engagement decision rules. Therefore, the values for the independent variables when chosen at their extremes had to be able to result in the possible triggering of the decision algorithm. Since the first three parameters in the decision rule (as described on page 9) were normalized to have maximum values of one, the weights on these parameters could not be all less than one-third or else a cooperative engagament would be impossible. This would, therefore, result in an RSM study investigating the effects of different cooperative engagament decision rules *and* no cooperation at all. Since this was not the goal, minimum values for the first three parameters had to be chosen greater than one third. Table 1.2 shows the values used for each independent variable.

The values chosen in Table 1.2 ensure that even when the independent variables are chosen at their extremes, cooperative engagements are still possible. The maximum communications range values were chosen based on a battlefield that was approximately 300 square kilometers in size.

Table 1.2. Independent Variable Ranges for RSM

Variable	*Weight on*	*Minimum*	*Maximum*
α_1	Time of Flight	0.4	0.8
α_2	Target Priority	0.4	0.8
α_3	Range Rate	0.4	0.8
α_4	Number of Munitions	0.4	0.8
Maximum Communications Range		5 km	15 km

4.2. Responses

The responses had to be chosen to somehow accurately measure the expected mission effectiveness for wide area search munitions. Four responses were chosen:

- Unique Kills
- Total Kills
- Total Hits
- Target Formula

Unique kills was defined as the expected number of unique, real targets killed (each target can only be killed once). Total kills was defined as the expected number of submunitions to put lethal hits on a real target. Total hits was defined as the expected number of real target hits. Finally, the target formula response was used as a means of measuring the hits on high priority targets (priority one) versus hits on low priority targets (priority two) and incorporating a penalty for any hits on non-targets. This target formula is shown in equation (5) where "# prior 1 hits" means the number of hits on priority one targets, "# prior 2 hits" means the number of hits on priority two targets, and "# non-target hits" means the number of hits on any non-targets.

$$\text{Tgt Formula} = 2 * (\text{\# prior 1 hits}) + (\text{\# prior 2 hits}) - (\text{\# non-target hits}) \quad (5)$$

A simple example can be used to distinguish and better understand these responses. This example has five submunitions, 2 real targets (one high priority and one low priority) and one non-target. Submunition #1 hits target #1, a high priority target, but does not kill it. Submunition #2 hits that same target (target #1) but kills it. Submunition #3 hits and kills target #2, a low priority target. Then submunition #4 also hits target #2, and this engagement is also deemed a kill (even though the target was already dead) . Finally, submunition #5 hits the non-target. The responses for this example are shown in Table 1.3.

Table 1.3. Responses for Example

Response	*Explanation*	*Value*
Unique Kills	targets #1 and #2	2
Total Kills	submunitions #2, #3, and #4	3
Total Hits	submunitions #1, #2, #3, and #4	4
Target Formula	2 hits on target #1 (high priority target)	
	2 hits on target #2 (low priority target)	
	1 hit on a non-target	5

4.3. Phase 1

The purpose of phase one is to determine if the current ranges for the independent variables shown in Table 1.2 result in responses that are near optimal. To accomplish this a 2^{5-1} fractional factorial design was used. This orthogonal resolution V design required a total of 16 runs to complete. Each design was augmented with four center runs resulting in a total of 20 runs. For each run the values for each of the four responses were recorded. Using an analysis of variance (ANOVA) for each response, an attempt to fit first order models to each response was made. Whenever a first order model was appropriate, the method of steepest ascent was used to traverse the response surface to a new operating region that was closer to the optimal design point. The method of steepest ascent is summarized by the following few steps.

1 Fit a planar (first-order) model using an orthogonal design

2 Compute a path of steepest ascent where the movement in each design variable direction is proportional to the magnitude of the regression coefficient corresponding to that design variable with the direction taken being the sign of the coefficient

3 Conduct experimental runs along the path

4 Choose a new design location where an approximation of the maximum response is located on the path

5 Conduct a second fractional factorial experiment and attempt to fit another first order model

If a second first order model is accurately fit, then a second path of steepest ascent can be computed and traversed until a region is reached where a higher-order model is required to accurately predict system behavior.

In this study, after the initial fractional factorial design was completed, a first order model was never adequate. Therefore, the method of steepest ascent was never required because the starting region of design seemed to always be close enough to the optimal point over all responses.

4.4. Phase 2

The purpose of this phase is to build second (or higher) order models to accurately predict all responses and choose the settings for the independent variables that will result in the optimal expected performance over all responses. Since the resolution V fractional factorial was already completed at the appropriate design point, the ideal second order design would be able to simply augment the first design to decrease the total number of runs, thereby saving time and money. Therefore, the Central Composite Design (CCD) was used. This design requires three parts:

- Two-level factorial design or resolution V fraction
- 2k axial or star runs (k = # of independent variables)
- Center runs

The resolution V fraction contributes to the estimation of the linear terms and two-factor interactions. It is variance-optimal for these terms. The axial points contribute to the estimation of the quadratic terms. The center runs provide an internal estimate of error (pure error) and contribute toward the estimation of quadratic terms. Since the phase one experiments required the fractional factorial design and the center runs, to complete the CCD the axial runs were all that was required.

The areas of flexibility in the use of the CCD resides in the selection of α, the axial distance, and the number of center runs. According to Myers and Montgomery [11] and Box and Draper [3], the CCD that is most effective from a variance point of view is to use $\alpha = \sqrt{k}$ and three to five center runs. This design is not necessarily rotatable but is near-rotatable. Therefore, the four center runs completed in the initial augmented fractional factorial design were sufficient for the CCD, and the 10 additional axial runs at $\alpha = \sqrt{5} = 2.236$ were all that were required to complete the CCD.

Once all runs were complete, a mechanism for choosing the values of the indendent variables that would result in the most-optimal mission effectiveness for all responses had to be determined. Because of the complexity and multi-dimensionality of the response surfaces, a simple overlaying of contour plots to graphically choose the point which appeared to be optimal over all responses was not applicable. Therefore, the Derringer and Suich [4] desirability function for optimizing over multiple responses was employed. This method allows for the creation of desirability functions (d_1, d_2, d_3, d_4) for each response where the desirability function can target a specific value, minimize or maximize a response. Since all the responses in this study were measures of mission effectiveness, the desirability functions used were all maximizing. Then a single composite response (D) is developed which is a weighted mean of the desirabilities of the individual responses. The weights in the composite response allow more emphasis on specific individual responses when computing the single composite response. In this study, extra emphasis was placed on two of the responses: the number of unique kills and the number of hits on priority one targets (target formula).

In order to find the optimal conditions using this method, each of the individual desirability functions (d_1, d_2, d_3, d_4) and the composite desirability function (D) must be computed at each design point according to the individual responses. Then a response surface must be built with the computed response D, and appropriate methodology must be applied for finding the conditions that maximize $\hat{D}$ (the model that provides the expected values of D). Since this method will result in many possible combinations of independent variables that will "optimize" the overall mission effectiveness, many of the various combinations must be applied and compared in order to choose the "optimal" settings.

5. Results and Analysis

5.1. Quantitative Results and Analysis

Specific numerical results are shown for four scenarios where a cooperative engagement decision algorithm employing the optimal settings resulted in overall improvement over baseline (non-cooperative) performance. Each scenario was defined by three general characteristics:

1 Warhead lethality/guidance precision

2 ATR precision

3 Battlefield characteristics

The specific parameters that were varied in the simulation to define the three general characteristics above were:

1 Probability of Kill (P_k)

2 False target attack rate (α) and probability of target report (P_{TR})

3 Clutter density (η) and whether the targets were clustered or widely dispersed

The battlefield used for all simulations was approximately 300 square kilometers in size. Two groups of four submunitions each (totaling eight submunitions) where employed in all scenarios. Each of the groups flew a serpentine pattern that covered the entire battlefield in approximately 20 minutes. Each scenario had a total of eight real targets (three high priority and five low priority). Also, two non-targets were employed in the vicinity of the real targets and a battlefield η of 0.05 per square kilometer were randomly placed throughout the battlefield in all scenarios.

Table 1.4 shows the parameters defining scenario 1. This submunition has a relatively non-lethal warhead and is searching for targets clustered in a four square kilometer region of the battlefield.

Table 1.4. Scenario 1 Defining Parameters

Parameter	*Value*
P_k	0.5
α	0.0053 per square km
P_{TR}	0.95
Target Layout	Cluster

The RSM described in section 4 was performed on this scenario to determine the ideal weighting parameters for the decision rule (equation (2)). When performing the RSM, each simulation run required was reported as a summary of 200 Monte Carlo runs. Each repetition was completed using a different baseline seed for the Monte Carlo simulation. The resulting parameters are shown in Table 1.5.

Table 1.5. Ideal Parameters for Scenario 1 Decision Algorithm

Variable	*Weight on*	*Ideal Value*
α_1	Time of Flight	0.77
α_2	Target Priority	0.14
α_3	Range Rate	0.35
α_4	Number of Munitions	0.0
Maximum Communications Range		9.8 km

The expected performance of the wide area search munitions employing the decision algorithm with the ideal weighting parameters and ideal maximum communications range was then compared to their baseline performance (no cooperation). Table 1.6 shows these results for each of the responses. The overall percent improvement is simply an average of the percent improvements corresponding to each of the four responses.

Table 1.6. Scenario 1 Results

Response	*No Cooperation*	*Ideal Cooperation*	*Improvement*
Unique Kills	2.7	2.81	4.07%
Total Kills	3.06	3.37	10.13%
Total Hits	6.08	6.515	7.15%
Formula	8.04	8.72	8.46%
Overall			7.45%

Table 1.7 shows the parameters defining scenario 2. This submunition has a *lethal* warhead and is searching for targets clustered in a four square kilometer region of the battlefield (same battlefield as scenario 1).

Table 1.7. Scenario 2 Defining Parameters

Parameter	*Value*
P_k	0.8
α	0.0053 per square km
P_{TR}	0.95
Target Layout	Cluster

The RSM described in section 4 was performed on this scenario to determine the ideal weighting parameters for the decision rule (equation 2) in a similar manner to that for scenario 1. The resulting parameters are shown in Table 1.8.

Table 1.8. Ideal Parameters for Scenario 2 Decision Algorithm

Variable	*Weight on*	*Ideal Value*
α_1	Time of Flight	0.30
α_2	Target Priority	0.36
α_3	Range Rate	0.42
α_4	Number of Munitions	0.0
Maximum Communications Range		20.3 km

The same performance measurements as in scenario 1 were analyzed for this scenario. Table 1.9 shows these results for each of the responses.

Table 1.9. Scenario 2 Results

Response	*No Cooperation*	*Ideal Cooperation*	*Improvement*
Unique Kills	4.13	4.18	1.21%
Total Kills	4.95	5.25	6.06%
Total Hits	6.145	6.53	6.27%
Formula	8.11	8.77	8.11%
Overall			5.42%

Table 1.10 shows the parameters defining scenario 3. This submunition has a relatively non-lethal warhead and is searching for targets widely dispersed throughout the entire battlefield.

Table 1.10. Scenario 3 Defining Parameters

Parameter	*Value*
P_k	0.5
α	0.0053 per square km
P_{TR}	0.95
Target Layout	Widely Dispersed

The same RSM as the previous scenarios was performed on this scenario. The resulting parameters are shown in Table 1.11.

Table 1.11. Ideal Parameters for Scenario 3 Decision Algorithm

Variable	*Weight on*	*Ideal Value*
α_1	Time of Flight	0.71
α_2	Target Priority	0.48
α_3	Range Rate	0.1
α_4	Number of Munitions	0.1
Maximum Communications Range		13.3 km

Table 1.12 shows the results for each of the responses.

Table 1.13 shows the parameters defining scenario 4. This submunition has a *lethal* warhead and is searching for targets that are widely dispersed throughout the entire battlefield (same battlefield as scenario 3).

The resulting parameters after completing the RSM are shown in Table 1.14.

Table 1.15 shows the results for each of the responses.

Table 1.12. Scenario 3 Results

Response	*No Cooperation*	*Ideal Cooperation*	*Improvement*
Unique Kills	2.72	2.70	-0.74%
Total Kills	3.07	3.35	9.12%
Total Hits	6.295	6.52	3.57%
Formula	8.56	9.245	8.00%
Overall			4.99%

Table 1.13. Scenario 4 Defining Parameters

Parameter	*Value*
P_k	0.8
α	0.0053 per square km
P_{TR}	0.95
Target Layout	Widely Dispersed

Table 1.14. Ideal Parameters for Scenario 4 Decision Algorithm

Variable	*Weight on*	*Ideal Value*
α_1	Time of Flight	0.31
α_2	Target Priority	0.35
α_3	Range Rate	0.40
α_4	Number of Munitions	0.15
Maximum Communications Range		19.7 km

5.2. Qualitative Results and Analysis

As the precision of the ATR is degraded and/or the clutter density increases, this form of cooperative engagement does not offer any advantages and often deteriorates the overall performance of the wide area search munitions. This is because of the hyper-sensitivity to α, the false target attack rate. By degrading the ATR precision and/or increasing the clutter density, α increases. Therefore, what often occurs is that a submunition falsely identifies a clutter or non-target as a real target and then communicates to some of the other munitions the existence of a *real*-target that doesn't actually exist. Then one or more of the other submunitions will decide to cooperatively engage that false target. Now the best event that could occur for that redirected submunition is that it just happens to encounter a real target on its flight path to the false target (the chances of that event occurring being no better than if the submunition

Table 1.15. Scenario 4 Results

Response	*No Cooperation*	*Ideal Cooperation*	*Improvement*
Unique Kills	3.93	3.99	1.53%
Total Kills	4.97	5.3	6.64%
Total Hits	6.225	6.555	5.30%
Formula	8.38	9.03	7.76%
Overall			5.31%

would have just stayed on its original search pattern). However, if that does not happen, the submunition is guaranteed to encounter that false target that it thinks is a real target. Upon encountering the false target, the submunition may correctly identify it and not engage it, but as α increases, this is less and less likely. Therefore, cooperative engagement alone cannot overcome the hyper-sensitivity in wide area search munition effectiveness to increasing α.

What happens when α remains low, but P_{TR} decreases? This means that given real target encounters, the probability that the ATR is correctly identifying the real targets is decreasing, i.e., there is an increase in submunitions not engaging real targets because they are falsely identifying them as non-targets. In this situation, as long as α remains low, cooperation can still improve overall effectiveness. This is because a submunition may later encounter and correctly identify (and therefore communicate and engage) a real target that another submunition may have previously incorrectly identified as a false target. Then through cooperation, the submunition that originally made the incorrect identification could go back and get a second look at that target and possibly correctly identify and engage it. A scenario such as this will also benefit from redundant area coverage with the initial search patterns at the expense of reduced total area coverage rate.

5.3. Robustness and Sensitivity Analysis

To test the robustness of the optimal decision parameters determined for each scenario, the optimal decision rule for one scenario was run on a different scenario and then compared to the baseline performance. For example, the optimal decision parameters for scenario 1 (as defined in Table 1.5) were implemented in the simulation setup to run scenario 2 (as defined by the parameters listed in Table 1.7). This was done for all combinations of the four scenarios described in the quantitative results section (section 5.1). The results proved very little robustness to the selection of the optimal decision parameters. In most cases, the performance with the sub-optimal decision parameters resulted in a zero to two percent overall improvement over baseline performance, but sometimes resulted in deteriorated performance when compared to the baseline.

With these results an attempt was then made to correlate the values of the optimal weighting parameters to the parameters used to define the different scenarios. However, due to the diversity in the optimal weighting parameters across all four scenarios, very little correlation was recognized. The only parameter that displayed some sort of consistency was that associated with the fuel remaining or time of flight–there appears to be some value in waiting until the latter part of the search pattern to choose to cooperatively engage a known target. This, of course, makes sense and allows for the greatest exploration of the entire battlefield.

6. Conclusions and Recommendations

The methods used in this research are not limited to any particular type of wide area search munition and were consciously completed using parameters that describe a very generic wide area search munition. This research, therefore, applies to all wide area search munitions and other cooperative vehicles, and more specific results can be achieved for any specific system by simply modifying the parameters in the effectiveness simulation. Further, the methods developed as part of this research have applications in the more general area of cooperative behavior and control.

The form of cooperative engagement used in this study is most useful in overcoming the limitations on warhead lethality and, to a lesser degree, P_{TR}. However, cooperative engagement alone is not able to compensate for higher false target attack rates. Also, the selection of the optimal weights in the decision algorithm are very sensitive to all battlefield characteristics.

To improve these results, research on cooperative search and cooperative discrimination must be included with the cooperative engagement algorithm to better achieve the full synergistic value of cooperative wide area search munitions.

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