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Optimal Allocation of Distributed Resources Using Fuzzy Logic and a Genetic Algorithm

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13. ABSTRACT (Maximum 200 words) A fuzzy logic-based resource manager (RM) that will allocate electronic attack (EA) resources distributed across many platforms is under development. The platforms will consist of ships, helicopters, airplanes, land-based facilities, robotic devices, and, potentially, satellites. The RM will allow codification of military expertise in a simple mathematical formalism known as the fuzzy decision tree. The fuzzy decision tree will form what is known as a fuzzy linguistic description, i.e., a formal fuzzy if-then rule-based representation of the system. Since the decision tree is fuzzy, the uncertainty inherent in the root concepts propagates throughout the tree. The functional form of the fuzzy membership functions for the root concepts will be selected heuristically and will generally carry one or more free parameters. The free parameters in the root concepts will be determined by optimization both initially and later at noncritical times. A genetic algorithm will be used for optimization.			
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OPTIMAL ALLOCATION OF DISTRIBUTED RESOURCES USING FUZZY LOGIC AND A GENETIC ALGORITHM

1. INTRODUCTION

Modern naval battle forces generally include many different platforms each with its own sensors, radar, ESM, and communications. The sharing of information measured by local sensors via communication links across the battlegroup should allow for optimal or near-optimal decisions. The survival of the battlegroup or members of the group depends on the automatic real-time allocation of various resources.

A fuzzy logic algorithm has been developed that automatically allocates electronic attack (EA) resources in real-time. The particular approach to fuzzy logic that will be used is the fuzzy decision tree, a generalization of the standard artificial intelligence technique of decision trees [1].

The controller must be able to make decisions based on rules provided by experts. The fuzzy logic approach allows the direct codification of expertise, forming a fuzzy linguistic description [2], i.e., a formal representation of the system in terms of fuzzy if-then rules. This will prove to be a flexible structure that can be extended or otherwise altered as doctrine sets (i.e., the expert rule sets) change.

The fuzzy linguistic description will build composite concepts from simple logical building blocks known as root concepts through various logical connectives such as "not," "and," and "or." Optimization will be conducted to determine the form of the membership functions for the fuzzy root concepts.

Section 2 gives a brief introduction to the ideas of fuzzy set theory, fuzzy logic, decision trees, and root and composite concepts. Section 2 uses these concepts to develop the kinematic-ID subtree, which is an important component of the decision tree. Section 3 describes the root concept elevation. Section 4 gives a brief discussion of genetic algorithms and describes the optimization of the root concepts "close" and "elevation." Section 5 discusses association algorithms and points out the usefulness of a particular fuzzy logic-based association algorithm. Section 6 discusses the multiplatform model, the communication model, and the associated optimization procedures. Section 7 provides examples of the algorithm's allocation of EA resources distributed over three platforms against an airborne targeting radar. Section 8 examines future research topics. Finally, Section 9 provides conclusions.

2. A BRIEF INTRODUCTION TO FUZZY SETS, LOGIC, AND DECISION TREES

The resource manager (RM) must be able to deal with linguistically imprecise information provided by an expert. Also, the RM must control a number of assets and be flexible enough to rapidly adapt to change. The above requirements suggest an approach based on fuzzy logic. Fuzzy logic is a mathematical formalism that attempts to imitate the way humans make decisions. Through the concept of the grade of membership, fuzzy set theory and fuzzy logic allow a simple mathematical expression of uncertainty. The RM will require a mathematical representation of domain expertise. The decision tree of classical artificial intelligence provides a graphical representation of expertise that is easily adapted by adding or

pruning limbs. Finally, the fuzzy decision tree, a fuzzy logic extension of this concept, allows easy incorporation of uncertainty as well as a graphical codification of expertise.

This section develops the basic concepts of fuzzy sets, fuzzy logic, and fuzzy decision trees and provides examples from a primitive military doctrine set.

2.1 Fuzzy Set Theory

This subsection provides a basic introduction to the ideas of fuzzy set theory. Fuzzy set theory allows an object to have partial membership in more than one set. It does this through the introduction of a function known as the membership function, which maps from the complete set of objects X into a set known as membership space. More formally, the definition of a fuzzy set [3] is

If X is a collection of objects denoted generically by x , then a fuzzy set A in X is a set of ordered pairs:

$$A = \{(x, \mu_A(x)) | x \in X\}$$

$\mu_A(x)$ is called the membership function or grade of membership (also degree of compatibility or degree of truth) of x in A which maps X to the membership space M .

The logical connectives "and," "or," and "not" are defined as

$$\text{or} : A \cup B \rightarrow \mu_{A \cup B}(x) = \max[\mu_A(x), \mu_B(x)]$$

$$\text{and} : A \cap B \rightarrow \mu_{A \cap B}(x) = \min[\mu_A(x), \mu_B(x)]$$

$$\text{not } B : \bar{B} \rightarrow \mu_{\bar{B}}(x) = 1 - \mu_B(x)$$

2.2 Fuzzy Decision Trees and Root Concepts

In this section, methods of constructing classical and fuzzy decision trees are discussed. The fuzzy decision tree provides a graphically intuitive way of propagating information from basic to complex concepts.

A classical decision tree is a standard artificial intelligence technique for making decisions. Its graphical nature allows an easy intuitive representation of information. The method of constructing decision trees, both classical and fuzzy, is best illustrated through an example. Consider the following simple military doctrine set, i.e., a set of rules provided by an expert:

- R1: IF target is *Attacking* or *Bearing-in* or *Maneuvering*, THEN the target is *Important*
 R2: IF target is *Close* and not *Friend*, THEN the target is *Attacking*.

These rules can be represented in a tree form as shown in Fig. 1.

In Fig. 1, the root concepts are "close," "friend," "bearing-in," and "maneuvering." The composite concepts are "attacking" and "important." The root and composite concepts are placed in their own boxes. The boxes are connected with lines. Vertices marked with a horizontal line are read as "and," unmarked vertices as "or," and lines marked by a circle indicate negation.

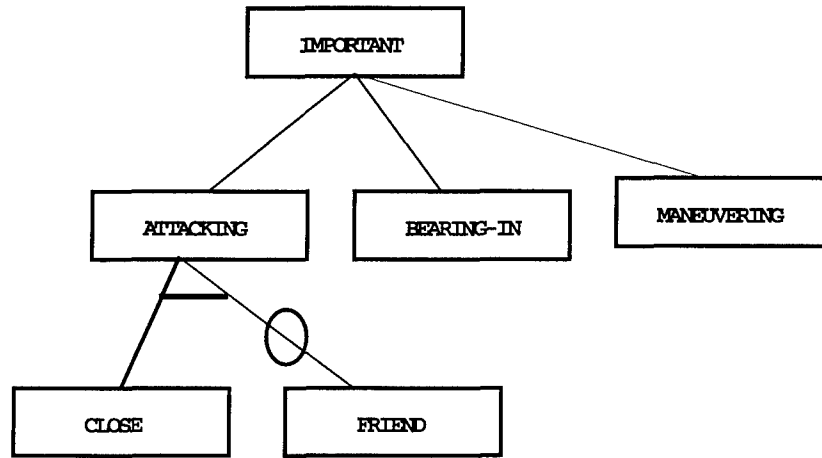


Fig. 1— Decision Tree for rules R1 and R2

The conversion from a classical decision tree to a fuzzy decision tree is carried out by assigning each classical root concept, those boxes at the bottom-most level of the decision tree, membership functions and then converting all classical “or,” “and,” and “not” operations to the analogous fuzzy operations.

So for track i , the following grades of membership associated with the corresponding root concepts must be defined:

$$\mu_{\text{friend}}, \mu_{\text{close}}, \mu_{\text{bearing-in}}, \text{ and } \mu_{\text{maneuvering}}$$

Pursuing the second component of the above description, i.e., the conversion of classical “and,” “or,” and “not” into the related fuzzy set-theoretic quantities, gives the following grades of membership for the composite concepts “attacking” and “important”:

$$\begin{aligned} \mu_{\text{attacking}}(i) &= \min[\mu_{\text{close}}(i), 1 - \mu_{\text{friend}}(i)] \\ \mu_{\text{important}}(i) &= \\ &\max[\mu_{\text{attacking}}(i), \mu_{\text{bearing-in}}(i), \mu_{\text{maneuvering}}(i)] \\ \mu_{\text{important}}(i) &= \\ &\max[\min[\mu_{\text{close}}(i), 1 - \mu_{\text{friend}}(i)], \\ &\mu_{\text{bearing-in}}(i), \mu_{\text{maneuvering}}(i)] \end{aligned}$$

The resulting grades of membership for composite concepts are used for establishing priorities for resource allocation.

Figure 1 is referred to as the kinematic-ID subtree. It is a subtree of a larger fuzzy decision tree used by an isolated ship for allocation of its own EA resources. Each ship in the battlegroup has an isolated platform tree that allocates its EA resources. These isolated platform trees, when linked together by information from line-of-sight communication, form a larger tree known as the multiplatform tree. It is this tree together with information sent over communications links that determines allocation of EA

resources over the entire battlegroup. A more detailed account of these concepts will be published in the near future [4].

2.3 Root Concept Membership Functions

The next step required for implementation of the fuzzy linguistic description is defining membership functions for the root concepts. There is not an a priori best membership function so a reasonable mathematical form is selected. This subjective membership function will be given in terms of one or more parameters that must be determined. The parameters may be set initially by an expert or they may be the result of the application of an optimization algorithm. Section 4 discusses the possible use of a stochastic optimization algorithm to determine the unknown parameters in root concept membership functions.

As a first example of a membership function definition consider the root concept "close." The concept "close" refers to how close the target/emitter on track i is to the ship, or more generally, the platform of interest. The universe of discourse will be the set of all possible tracks. Each track i has membership in the fuzzy set "close" based on its range R (nmi) and range rate dR/dt (ft/s). An appropriate membership function might be

$$\mu_{close}(i) = \frac{1}{1 - \alpha |R_i - R_{min}| / \max(-\dot{R}_i, \dot{R}_{min})}$$

The parameters to be determined by optimization are

$$\alpha, R_{min}, \text{ and } \dot{R}_{min}.$$

The root concept "bearing-in" has a membership function with a similar form and optimization requirements. The root concept "friend" is defined in terms of emitter ID. The concept ID employs information theoretic techniques in its application. Finally, the root concept "elevation" illustrates the use of military expertise and is examined in detail in the next section.

3. THE ROOT CONCEPT "ELEVATION"

Before the membership function for the root concept "elevation" can be described, greater insight into the military problem must be given. Many of today's advanced military weapons maintain certain elevation characteristics when attacking, especially antiship missiles, to avoid electronic detection. Most radars can not scan near the zenith. Therefore, threat emitters known as "divers" will try to fly above this scanning height in order to avoid detection, as illustrated in Fig. 2. The other newer threats are known as "skimmers," as depicted in Fig. 3, and they take advantage of the noise clutter on the ocean surface. Detection near the ocean surface is difficult, thus allowing small objects like missiles to approach a ship undetected.

The concepts of "divers" and "skimmers" have been merged into a single concept "elevation." An explicit, but tentative, form for the membership function for "elevation" is explored below.

Figure 4 depicts a coordinate system where the horizontal axis, the x-axis, resides in the plane of the ocean and the vertical axis, the z-axis, is perpendicular to the ocean's plane. The elevation angle ϕ is measured from the z-axis. The five-sided object at the origin of the coordinate system represents a ship and the oval at height h and elevation angle ϕ is an approaching emitter.

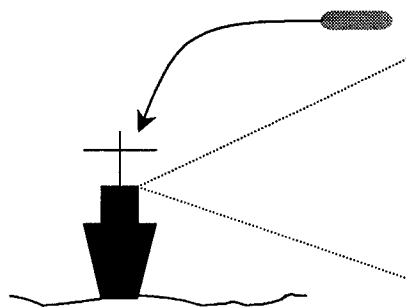


Fig. 2 — A "high diver" type missile

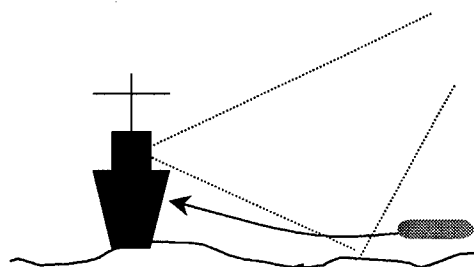


Fig. 3— A "sea-skimmer" type missile

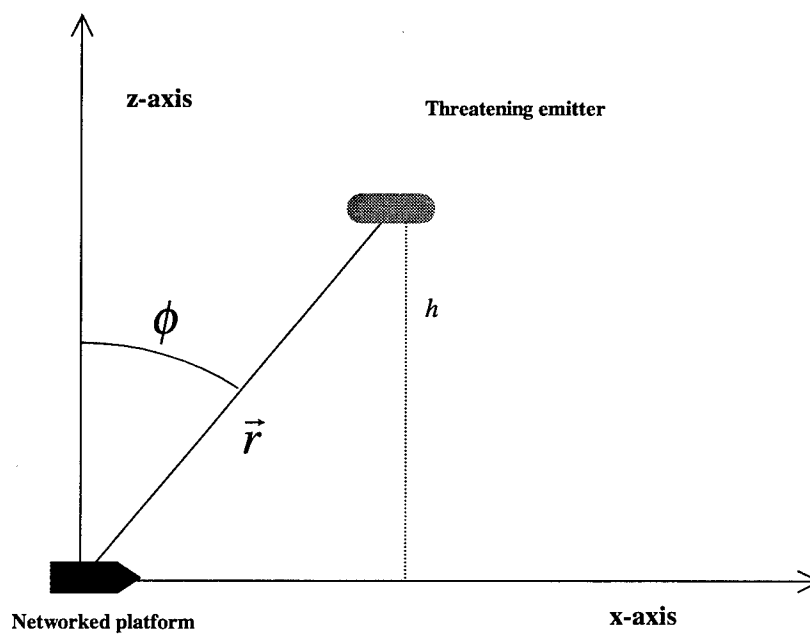


Fig. 4 — The coordinate system defined for the threatening emitter and the ship under attack

The membership function for the root concept "elevation" is designed to return a value of unity whenever an emitter's elevation angle is near those angular bounds consistent with a "diver" or a "skimmer." It will also return a value of unity when the absolute value of the instantaneous time rate of change of the elevation angle, $d\phi/dt$, measured in rad/s is sufficiently large.

The membership function for "elevation" is defined in two steps. The membership function, $\mu_{tmp-ele}$, defined below approaches unity if the emitter has an elevation angle consistent with a "diver" or a "skimmer." Its value is linear in between these two extremes.

$$\mu_{tmp-ele} = \begin{cases} \frac{2\phi}{\phi_{min} - \phi_{max}} - \frac{\phi_{min} + \phi_{max}}{\phi_{min} - \phi_{max}}, & \phi_{min} < \phi < \frac{\phi_{min} + \phi_{max}}{2} \\ \frac{2\phi}{\phi_{max} - \phi_{min}} - \frac{\phi_{max} + \phi_{min}}{\phi_{max} - \phi_{min}}, & \frac{\phi_{min} + \phi_{max}}{2} \leq \phi < \phi_{max} \\ 1, & \phi \leq \phi_{min} \text{ or } \phi \geq \phi_{max} \end{cases}$$

The second membership function defined below for the concept "diver-ele" will approach unity if the emitter's elevation angle is near the maximum value associated with "divers" or if $|d\phi/dt|$ is changing rapidly, since rapidly changing elevation angle can also be indicative of a diver.

$$\mu_{diver-ele} = \frac{1}{1 + \sigma |\phi - \phi_{max}| \max\left(\left|\frac{d\phi}{dt}\right|, \dot{\phi}_{min}\right)}$$

The concept "elevation" is defined in terms of an "or," i.e., a max operation over the two preliminary concepts of elevation.

$$\mu_{elevation} = \max(\mu_{tmp-ele}, \mu_{diver-ele})$$

The parameters to be determined are

$$\sigma, \dot{\phi}_{min}, \phi_{min} \text{ and } \phi_{max}.$$

4. OPTIMIZATION

Many different types of optimization algorithms are found in the literature. Many of these algorithms are known as greedy algorithms because they will find as a solution the first extremum encountered in a parameter space. Reference 5 provides examples of this kind of algorithm.

An algorithm that has the capability to explore parameter space before settling on a solution intuitively would seem to have greater probability of selecting an optimal or near-optimal solution than a greedy algorithm. Examples of algorithms of this kind are stochastic optimization algorithms, which include simulated annealing [5] and genetic algorithms [6].

A genetic algorithm (GA) is an optimization method that manipulates a string of numbers in a manner similar to how chromosomes are changed in biological evolution. An initial population made up of strings of numbers is chosen at random or is specified by the user. Each string of numbers is called a

“chromosome” or an “individual,” where each number slot is referred to as a “gene.” A set of chromosomes forms a population where each chromosome represents a given number of traits that are the actual parameters being varied to optimize the “fitness function.” The fitness function is a performance index that we seek to maximize.

Operation of the genetic algorithm proceeds in steps. Beginning with the initial population, “selection” is used to choose which chromosomes should survive to form a “mating pool.” Chromosomes are chosen based on how “fit” they are (as computed by the fitness function) relative to the other members of the population. More fit individuals retain more copies of themselves in the mating pool so that they will have greater representation in the next generation. Next, two operations are taken on the mating pool. First, “crossover” (which represents mating, the exchange of genetic material) occurs between parents.

In crossover, a random spot is picked in the chromosome, and the genes after this spot are switched with the corresponding genes of the other parent. Following this, “mutation” occurs. Mutation represents the change of values of randomly selected genes in a chromosome. After the crossover and mutation operations occur, the resulting strings form the next generation and the process is repeated. A termination criterion is used to specify when the genetic algorithm should end (e.g., the maximum number of generations or until the maximum fitness exhibits little or no change over a certain number of generations).

The following characteristics are also considered advantages of the genetic algorithm:

- the genetic algorithm works on a population of points, not a single point,
- they work directly with strings of characters representing the entire parameter set, not the individual parameters,
- the search is guided by probabilistic rules, not deterministic rules. The inherent randomness in this procedure allows the genetic algorithm to escape local maxima,
- genetic algorithms, like simulated annealing represent a form of optimization that does not require derivatives. The genetic algorithm only requires information about how fit a given solution is, i.e., the effect of the solution on the fitness function.

4.1 The Optimization of “Close”

Figure 5 illustrates how the parameters from the membership function for the root concept “close” were converted into chromosome form for the genetic algorithm. The chromosomes are formed in a similar manner for other root concept membership functions.

The construction of good fitness functions for this application requires insight in four areas, with the rules being derived from geometry, physics, engineering, and military doctrine. Several classes of fitness functions are being explored. The fitness functions tend to be highly nonlinear and nondifferentiable at many points. For classical optimization algorithms, the nondifferentiability might have posed a problem, but it offers no difficulty for a genetic algorithm.

The fitness functions currently being explored are expressible mathematically as a linear combination of products of Heaviside step functions [7]. The step function arises from the rule-based origin of the fitness functions. The arguments of the fitness functions are given by the difference of the membership function and a parameter characteristic of expertise. The linear combinations of products of the step functions are typically averaged over an ensemble of kinematic scenarios, where each element of the ensemble differs from the others in terms of initial conditions. For example, the ensemble used to optimize the membership function for the root concept “close” consists of elements with different initial values for range, and its first two derivatives with respect to time. From these initial values, the range and

$$\mu_{close}(i) = \frac{1}{1 + \alpha |R_i - R_{min}| / \max(|\dot{R}_i|, \dot{R}_{min})}$$

Fig. 5 — The membership function for “close” and the method by which chromosomes are formed

range rate are calculated as a function of time, allowing the membership function for “close” to be optimized over many physical scenarios. This is referred to as a geometric-kinematic ensemble. Despite the nonlinearity and nondifferentiability of the fitness function, because of the rules used in its construction, genetic algorithm based optimization has proven to be effective.

The method described above for constructing fitness functions is only a first step. The fitness functions constructed in this manner are most applicable to isolated platforms. The ultimate goal is to construct a resource manager/scheduler that is optimal in its performance when dealing with multiple dissimilar platforms. By pursuing the isolated platform model first, the region of parameter space that must be explored for the multiplatform problem is reduced. It would be expected, on intuitive grounds, that parameters for the multiplatform problems should lie within some neighborhood, of those solutions for the isolated platform model. The motivation for this assumption is that at any given time, each platform may be called upon to defend itself. Once the isolated platform parameters are selected for each root concept membership function, neighborhoods around these parameters can be defined, and a parameter space for the multiplatform problem formed by constructing a product space from the coordinate spaces defined by each isolated platform neighborhood. Therefore, the potentially large parameter space that must be explored for the multiplatform problem is constrained through the use of a priori information, significantly reducing the runtime of the genetic algorithm. This procedure has proven effective in producing very high quality multiplatform performance. The performance of the model and the potential risk of restricting parameter space in this way will be examined in a future paper [4].

4.2 The Optimization of “Elevation”

From the previous definition of the root concept “elevation,” there are four parameters that need to be determined: ϕ_{min} , ϕ_{max} , σ , and $\dot{\phi}_{min}$. The first two are determined based on typical radar limitations. The second two parameters σ and $\dot{\phi}_{min}$ are determined by genetic optimization with each chromosome taking the form

$$\{\sigma, \dot{\phi}_{min}\}.$$

The genetic algorithm uses operations of crossover and mutation. The crossover and mutation probabilities are 90% and 1%, respectively.

The limits of the parameter space are determined by experimentation. The range of values for σ was 1 to 99/s and that for $\dot{\phi}_{\min}$ was 0.5 to 2.0 radian/s.

The algorithm's stopping criteria is a maximum number of generations or that the maximum fitness fails to change by a certain amount over a prespecified number of generations. The maximum number of generations typically allowed is 1000.

The fitness functions currently being explored are expressible mathematically as a linear combination of products of Heaviside step-functions [7] as for the root concept "close." The step function arises from the rule-based origin of the fitness functions. The fitness functions are highly nonlinear and non-differentiable at many points. The arguments of the fitness functions are given by the difference of the membership function and a parameter characteristic of expertise. The linear combinations of products of the step functions are typically averaged over an ensemble of kinematic scenarios, where each element of the ensemble differs from the others in terms of initial conditions. For example, the ensemble used to optimize the membership function for the root concept "elevation" consists of elements with different initial values for the elevation angle, and its first two derivatives with respect to time. From these initial values, the elevation angle and time rate of change of elevation are calculated as a function of time allowing the membership function for "elevation" to be optimized over many physical scenarios. The ensemble involved can be divided into two subsets. One subset reflects the behavior of divers; the other, skimmers. In conclusion, this approach allows the concepts of "elevation" to be very effective in dealing with a multitude of different threats.

In Fig. 6, the membership function for the root concept "elevation" is displayed. It is plotted as a function of elevation angle ϕ and $d\phi/dt$. Finally, the values of σ and $\dot{\phi}_{\min}$ were those found by genetic algorithm-based optimization.

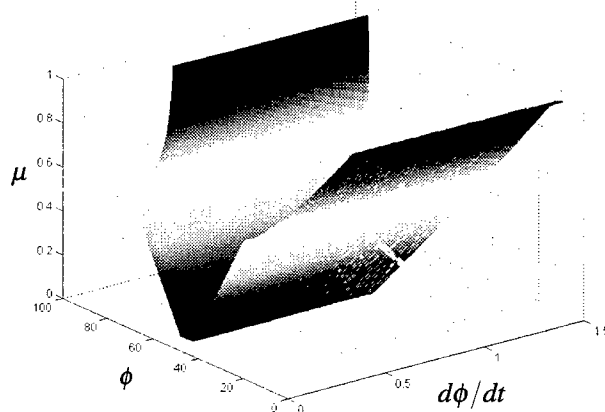


Fig. 6 — The membership function for "elevation"

The behavior of the membership function reflects the military doctrine used in its construction. Its value approaches unity as ϕ approaches 00 or 900. Larger values of ϕ may be indicative of "skimmers" and smaller values "divers." Finally, a large value of $|d\phi/dt|$ can result in a large value of the membership function as this could indicate a "diver."

5. DEALING WITH IMPERFECT ASSOCIATION

It is assumed that the data provided as input to the RM has already been associated, i.e., the appropriate ESM and radar data have already been perfectly assigned to the same emitter. Association of the ESM and radar data is valuable since radar provides range and bearing information for use in the root concept "close" and ESM can provide ID, bearing, RF and PRI of the emitter. Unfortunately, the association of ESM and radar is generally not perfect given the sparse, intermittent and noisy nature of data. The fuzzy association algorithm described below will be used in future simulations to examine the effect of good, but imperfect association on the RM's decisions.

The abilities of two different association algorithms to associate data as a function of the measured ESM points will be compared. These algorithms are the fuzzy association algorithm described in Refs. 8 through 12 and a Bayesian philosophy algorithm described in Ref. 13 and referred to here as the TW-algorithm.

The two association algorithms are compared using the same simulated ESM and radar data. The emitter has a bearing of 0 degrees. This is absolute truth for this simulation. Radar has determined there are objects traveling with bearings of 0, 1, and -1 degrees. For simulation purposes zero mean Gaussian noise with 1 degree standard deviation is added to simulate noise in the ESM measurement process. This is a difficult association problem since there are radar measurements not only at 0 degrees, but also radar measurements within one standard deviation of truth.

Since the radar measurements contain truth it is expected that a good association algorithm will associate the zero degree radar track with the ESM data. A probability of association between each radar track and the ESM data is calculated as in Refs. 8 through 13. Both algorithms give rise to five hypothesis classes describing whether or not the ESM data is associated with a radar track. It is desirable that when radar contains "truth," i.e., in this case the zero degree track, the track corresponding to truth, be firmly correlated with the ESM data. In this way the probability of making an inappropriate assignment of range is minimized. The notion of firm correlation is defined in detail in Refs. 8 through 13. The other hypothesis classes will not be displayed, as they are not interesting for the example that follows and only serve to obscure the results.

Both the fuzzy association and TW-algorithms can be used to associate noisy ESM and noisy radar measurements [8-12]. The radar measurements for radar track j at time t_i will have zero mean Gaussian noise added to them. The variance of the noise will be denoted as σ_{ij}^2 for the j^{th} radar track at the i^{th} time.

Figure 7 presents results for three radar tracks with the following bearings: $\mu = 0^\circ, 1^\circ, -1^\circ$ with $\sigma_{ij} = 0.1^\circ$ for all times t_i and radar tracks j . The radar noise standard deviation is consistent with levels found in modern radar systems. Since the radar results contain truth, i.e., a target moving with constant bearing of 0° a good association algorithm will establish that there is a firm correlation between the ESM data and the 0° bearing track.

Figure 7 plots the probability the association algorithms establish a firm association between ESM data and the radar measurements. The fuzzy association algorithm results are given by the curve marked with o 's and the TW results are indicated by the curve marked with $+$'s. The vertical axis indicates probability of firm correlation (FCT) and the horizontal axis the number of data points necessary to establish that level of probability.

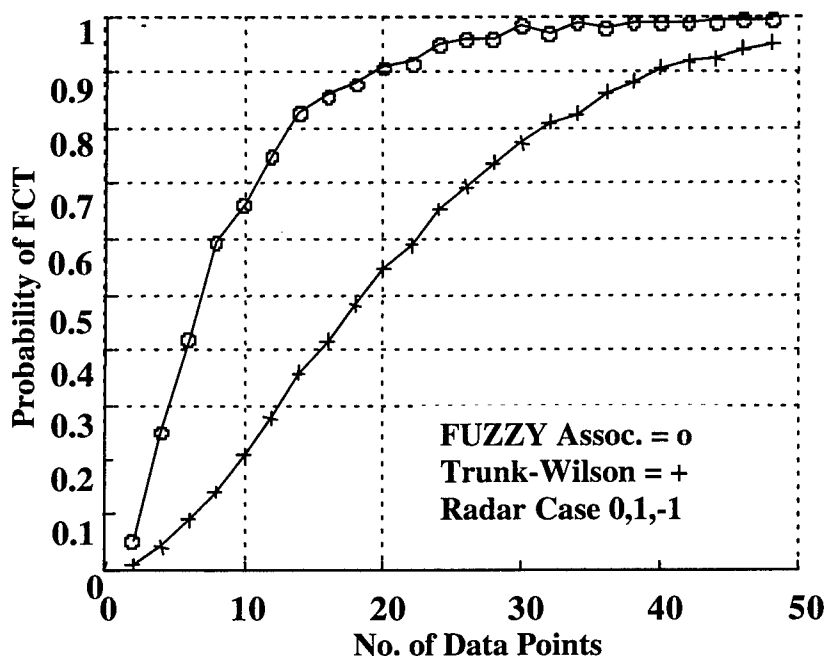


Fig. 7 — Fuzzy and Bayesian association

The fuzzy association algorithm results are always superior to the TW algorithm. At 10 data points, the fuzzy algorithm has established a 65% probability of FCT, between the ESM data and the 0-degree radar track. The TW algorithm requires about 24 points to establish the same level of probability of FCT. The fuzzy algorithm establishes an 80% probability of FCT by the 12th data point, whereas the TW algorithm requires about 30 points to reach the same level of success. The fuzzy algorithm reaches 90% probability of FCT at 20 data points and the TW algorithm at about the 38th point. Therefore, the fuzzy algorithm establishes high probabilities of firm correlation with between a third to half the data required by the TW algorithm. In this sense, the fuzzy algorithm is two to three times faster than the TW algorithm. Also, this is a difficult example for any association algorithm since there are two additional radar measurements within one noise standard deviation. The results are only slightly inferior to the case where radar is simulated as noiseless as found in Ref. 11. The ability of the fuzzy algorithm to make high quality decisions with much less data than the TW algorithm is significant since real data is frequently sparse and intermittent.

The above examples are for the case where there is 100% detection of ESM and radar data. In Ref. 11, it is shown with a detection rate as low as 70% of the ESM points, the fuzzy association algorithm experiences little deterioration, whereas the TW algorithm's performance is greatly degraded.

The example in Fig. 7 is for the case of a single emitter. Reference 11 shows that the fuzzy association algorithm gives a similar level of performance if there are one, four, or 10 emitters, even when ESM detection rates drop down to 70%. In particular, for 10 emitters closely spaced in the RF-PRI plane, the fuzzy association algorithm displays results like those found in Fig. 7, but the TW algorithm deteriorates more than 40% by the 48th data point.

The use of the fuzzy association algorithm will allow association decisions to be made with a sixth to half the data required by the Bayesian association algorithm. Faster association of ESM and radar tracks means better assignment of range and ID's to potential threats. As a final observation, the use of both a fuzzy RM and a fuzzy association algorithm would allow linguistic data to be shared between the two

rules and other linguistic data is not an option, if a non-fuzzy association algorithm like the TW algorithm were to be used for association.

6. THE MULTIPLATFORM MODEL: ITS COMMUNICATION INTERACTION AND OPTIMIZATION

The resource manager is made up of three parts, the isolated platform model, the multiplatform model, and the communication model. As previously discussed the isolated platform model provides a fuzzy decision tree that allows an individual platform to respond to a threat. The multiplatform model allows a group of platforms to respond to a threat in a collaborative fashion. The communication model describes the means of communication or interaction between the platforms.

6.1 The Communication Model

The communication model used in conjunction with the multiplatform model is similar to a real military fleet communication system. Each platform has a predetermined number of messages that it can send. As in real communication systems, due to network resource limitations, there must be a prioritization of which message each platform is to send across the network. The message priorities are high, medium and low.

The messages also consist of three types. The message types refer to different "events." Typically in the simulations that have been conducted to date the three types considered were "threat," "engagement," and "position." There can be incoming "threats," platforms can be "engaging" and existing threats, or there can be information about platform's "position" being communicated.

6.2 Co-evolutionary Evolution

In nature, a system never evolves separately from the environment that contains it. Both biological system and environment simultaneously evolve. This is referred to as co-evolutionary evolution [14]. In a similar matter, the fuzzy resource manager should not evolve separately from its environment, i.e., enemy tactics should be allowed to simultaneously evolve. Certainly, in real-world situations, if the enemy sees the resource manager employ a certain range of techniques, they will evolve a collection of counter techniques to deal with the resource manager.

The current approach to isolated and multiplatform optimization uses ensembles of military scenarios. Each ensemble has a certain collection of enemy responses. So effectively during optimization, the resource manager is exposed to many different enemy responses, thus in a deterministic way the enemy simultaneously evolves. So the current approach to optimization could be considered a rudimentary form of co-evolutionary optimization.

7. AN EXAMPLE OF MULTIPLATFORM RESPONSE

In this section, a specific example of the fuzzy RM's ability to optimally allocate electronic attack resources is examined. Input requirements and output characteristics are considered, and illustrated through the actual output of the current implementation of the RM.

7.1 Input Scenario and Output of the Fuzzy RM

The fuzzy RM requires as input, the position and number of ally platforms, e.g., ships, planes, etc., also emitter range, bearing, heading, elevation, and the emitter ID, with the associated uncertainty for the ID. The effect of the data is to stimulate the various fuzzy logic concepts like “close” resulting in different “actions” by the algorithm. The emitter ID is used to determine the technique or techniques (for ID’s with uncertainty) that the ally platform or platforms can execute against the emitter.

Figure 8 shows a battleforce of three ships and also an incoming aircraft with targeting radar. In this scenario, the ID of the threat radar is known with 100% certainty. The fuzzy RM determines, for this emitter that the carrier can effectively deal with it, while the other two ships continue to monitor for other threats.

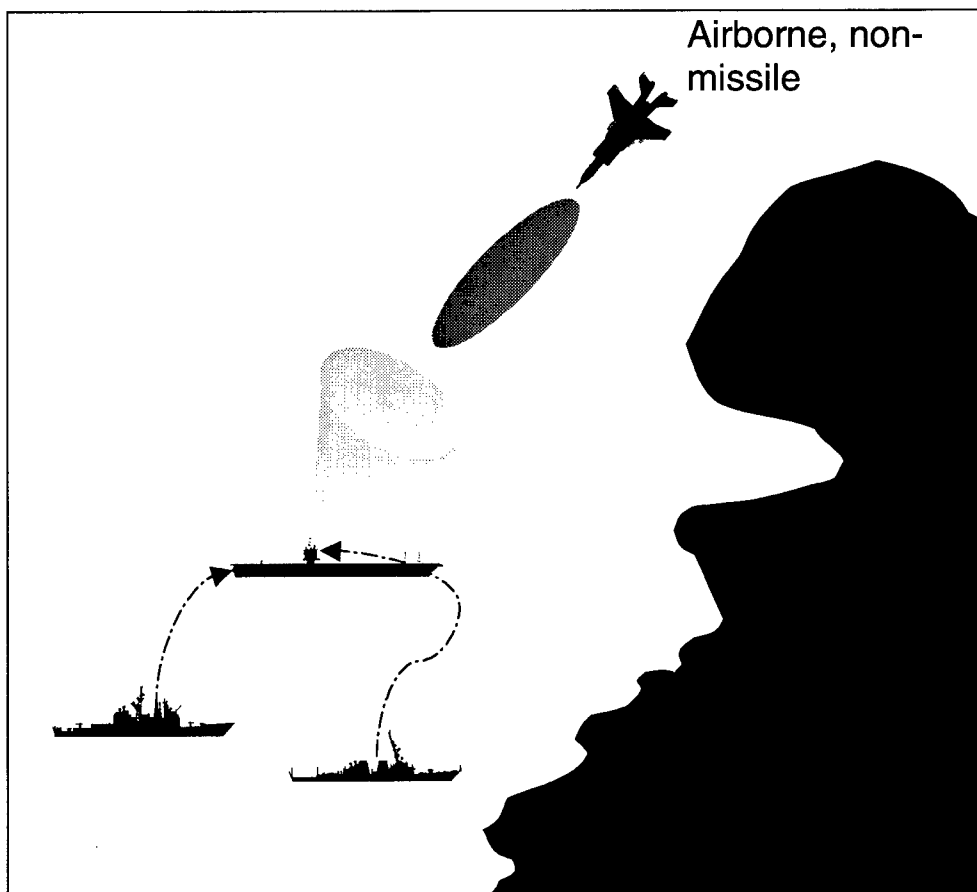


Fig. 8 — Input scenario from radar threat with certain radar ID

Figure 9 shows the algorithm’s output for the scenario in Fig. 8. A polar plot with origin at the centroid of battlegroup is used to display the positions of the three ships (diamonds), the incoming emitter (triangle marked with designation “foe type”), and friendly aircraft (triangles marked with the designation “friend type”). Communications and electronic attack techniques used by each ship are listed to the side. The arrows running from the ships to the foe-type emitter indicate electronic attack.

The algorithm, during its real-time run, displays an image of this type every second. As indicated in the box in the right-hand corner of Fig. 9, the algorithm selects the appropriate techniques for the attacking ship. Finally, it should be noted there are two friendly aircraft in the scenario. The algorithm will not attack an emitter based on kinematic properties if the emitter has been clearly identified as a friend.

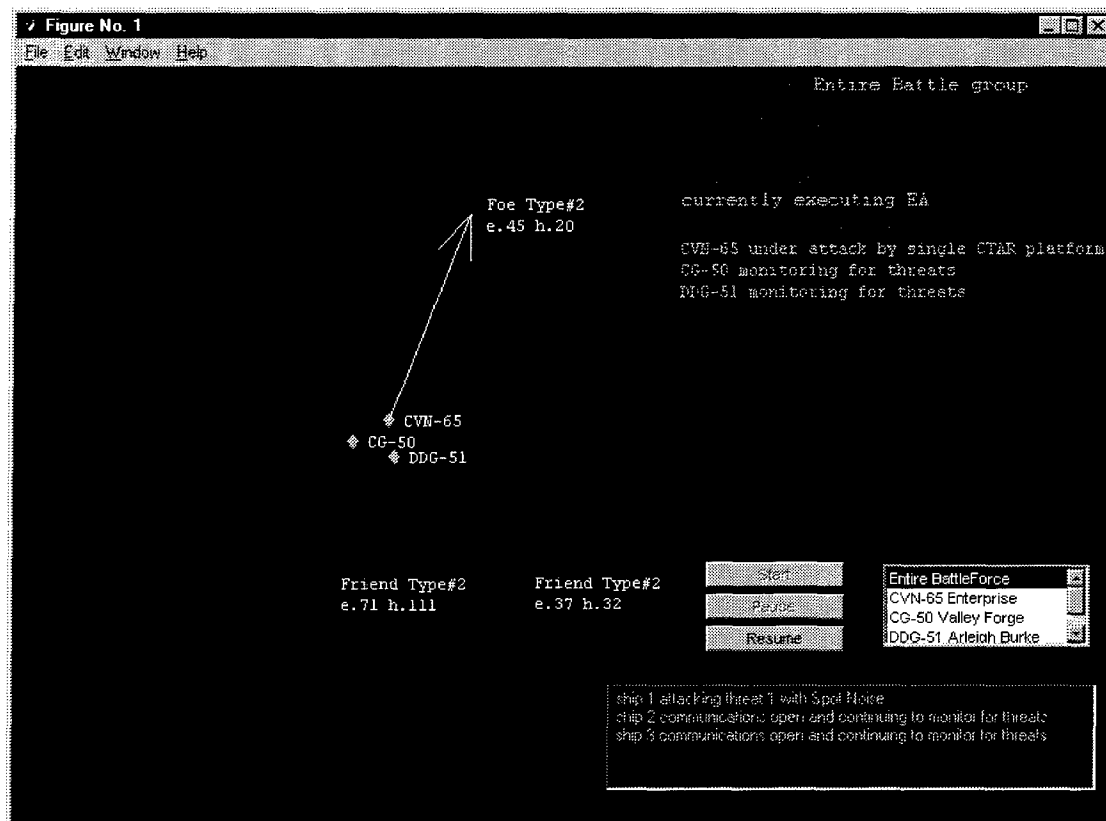


Fig. 9 — RM output during each second of run-time for threat with certain radar ID

In Fig. 10, there is a battleforce of three ships and also an incoming aircraft with targeting radar. However, in this scenario, the type of the threat emitter is not well known. With the threat's classification not being well known, and because the uncertainties indicate a foe of some type, all three ships conduct joint EA against the threat emitter.

The ship acting as a command ship sends communication over the network to other adjacent ships asking for joint EA and selects the electronic counter measures (ECM) technique most likely to be effective against this type of threat. The adjacent ships choose two other ECM techniques based on the emitter's ID and its uncertainty.

It should be noted, each ship has the same software aboard, and can act as a command ship. This significantly reduces the likelihood of the battlegroup being rendered ineffective by the loss of a single platform.

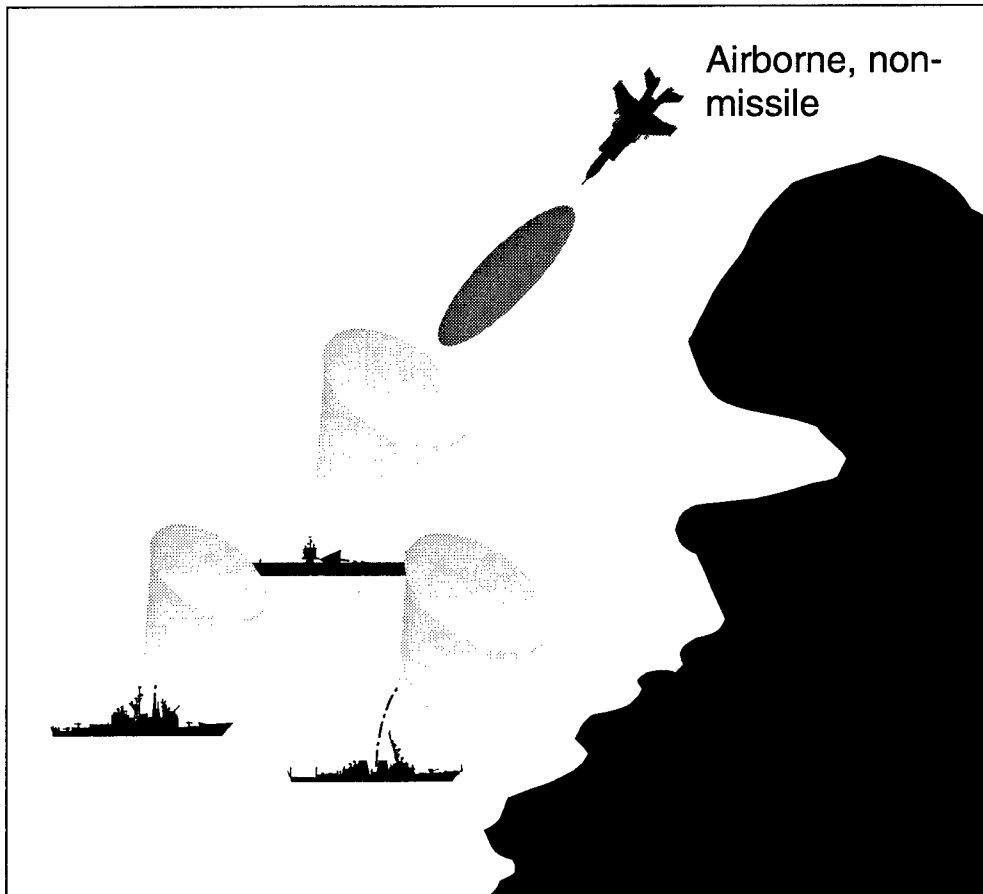


Fig. 10 — Input scenario for aircraft threat with uncertain ID

Figure 11 shows the algorithm's output for the scenario depicted in Fig. 10. A polar plot with origin at the centroid of battlegroup is used to display the positions of the three ships (diamonds), the incoming emitter (triangle marked with designation "foe type"), and friendly aircraft (triangles marked with the designation "friend type"). Communications and electronic attack techniques used by each ship are listed to the side. The arrows running from the ships to the foe-type emitter indicate electronic attack.

The algorithm, during its real-time run, displays an image of this type every second. As indicated in the box in the right-hand corner of Fig. 11, the algorithm chooses the appropriate techniques for all three attacking ships. As consistent with military doctrine, all three ships are conducting joint EA. Finally, it should be noted, as above, there are two friendly aircraft in the scenario. The algorithm will not attack an emitter based on kinematic properties if the emitter has been clearly identified as a friend.

Figure 12 shows a battleforce of three ships and also an incoming aircraft with targeting radar. However, in this scenario, the type of the threat emitter is not well known. With the threat's classification not being well known, and because the uncertainties indicate a foe of some type, all three ships conduct joint EA against the threat emitter.

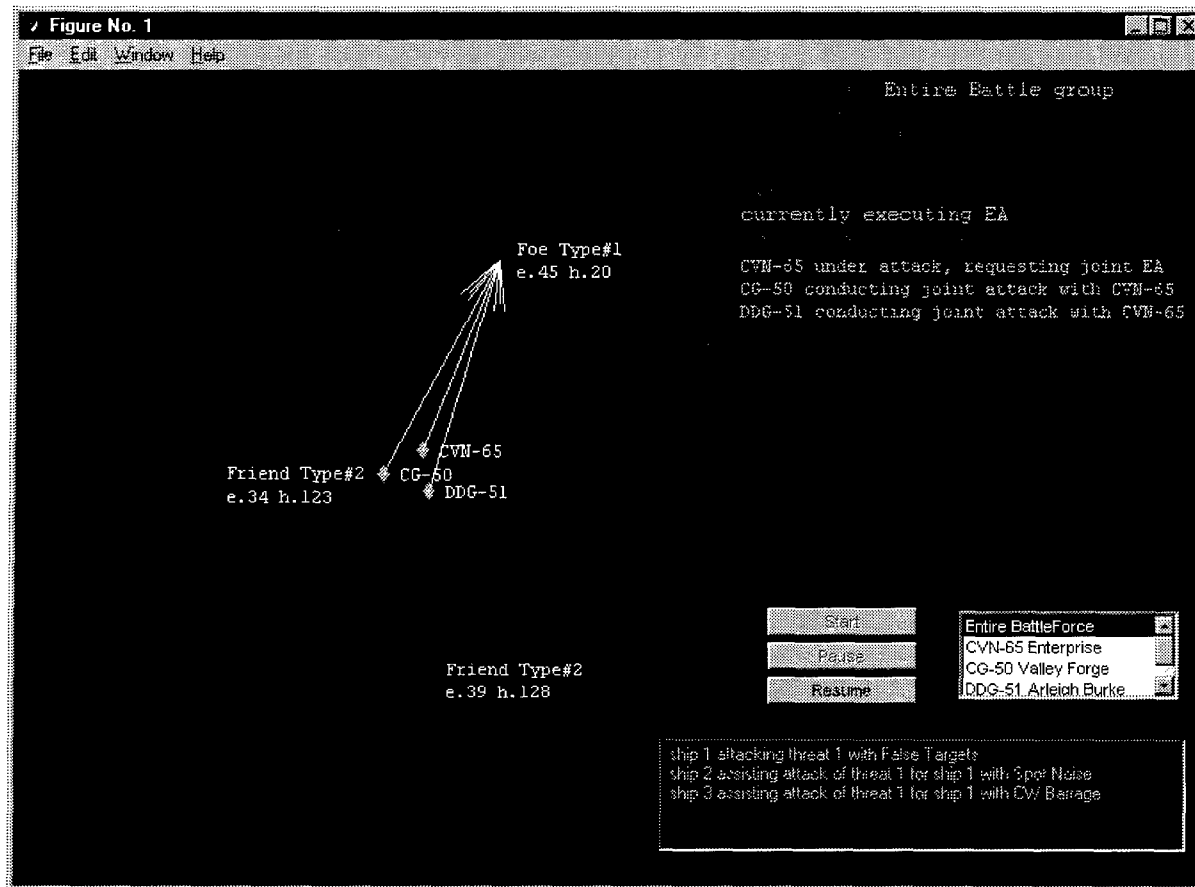


Fig. 11 — RM output during each second of run-time for radar threat with uncertain ID

Unlike the case in Fig. 10, a helicopter arrives after the beginning of the battle. It is determined to be a foe with uncertain radar ID. The fuzzy RM determines joint EA is called for and directs the three ships to split their beams and simultaneously conduct joint EA against the incoming airplane and helicopter. During its run, the algorithm produces output similar to Figs. 9 and 11.

The algorithm has been determined to be effective by comparing its output to the judgment of human experts. Statistical evaluation of the algorithm's effectiveness will be published in the near future [4].

7.1 Sparse Data

A RM designed to function in the real world must be able to deal with partial data. To test the algorithm, the input data was rendered sparse by random deletion. Even with a loss of up to 50% of the original data, the algorithm still determined the optimal EA techniques for each platform.

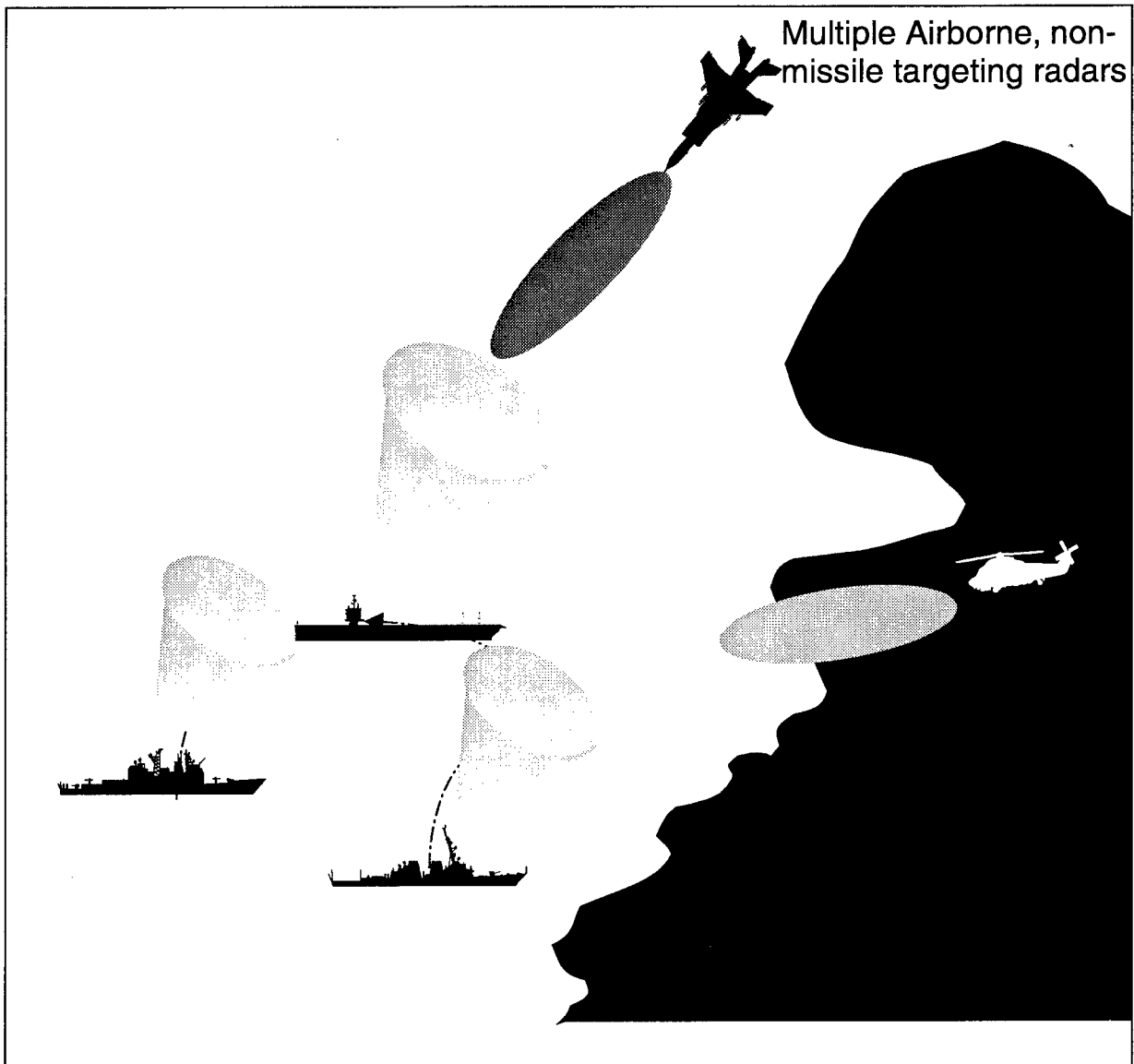


Fig. 12 — Input scenario for airplane threat with uncertain radar ID, late arriving helicopter threat with uncertain radar ID to the right

8. FUTURE DEVELOPMENTS

There are several activities that will be conducted in the near future. These include: expansion of the rule set, research related to improved optimization, expansion of the technique library, the invention of new multiplatform electronic attack techniques that make good use of the resources distributed over multiple platforms, and validation of the multiplatform resource manager. Other research topics that may be pursued are listed below.

8.1 Platform – Environment Interactions

As previously stated, a system does not exist independent of its environment. When defining the doctrine for the concept “elevation,” one of the types of threats mentioned was the “skimmer.” A skimmer deliberately flies near the ocean surface to hide in radar clutter resulting from electromagnetic

scattering from the ocean. This is one example of an environmental effect on sensor input data and hence the decisions of the RM. Other potential environmental effects that can be significant are those due to weather, e.g., visibility limitations, limitations of radar, etc.; and space based effects, such as solar flares occurring and effecting communications.

The RM must have decision logic built into it to deal with these environmentally based events. Therefore, rules must be defined that will take into account the effects of weather, scattering due to the ocean surface or cloud cover, and space-based events. Future work on the algorithm will include defining these rules, quantifying related uncertainty, and determining relevant parameters through optimization.

In the future, more sophisticated, and likely more computationally complex, forms of co-evolutionary optimization will be explored with hope of providing a better optimized and, hence, more adaptive RM. The new form of co-evolutionary optimization being explored involves giving the enemy a fuzzy rule set that is not unlike the fuzzy decision tree of the RM. Parameters are selected by genetic optimization for the RM fuzzy decision tree and simultaneously the fuzzy decision tree for the enemy. Both the allied and enemy groups are multiplatform systems. Both friendly and enemy multiplatform systems internally interact through their own communication models and "perceive" environment through their own sensor sets (e.g., radar, ESM, IFF, and IR).

Essential to this process is the construction of good fitness functions and measures of effectiveness. The fitness functions are, of course, used for the genetic optimization; the measures of effectiveness, for establishing the validity of the algorithm's response.

8.2 Geopolitics

The geopolitical structure of an environment relates to the terrain as well as the political beliefs of the inhabitants of that particular area. For example, tactics used against the advanced Russian Navy in an open blue water engagement will not be the same as the tactics used against the Iraqi Navy in the Persian Gulf. Future work will include rules and parameters that are selected with geopolitics in mind.

9. CONCLUSIONS

A fuzzy logic-based algorithm for optimal allocation and scheduling of electronic attack resources distributed over many platforms is under development. The kinematic-ID subtree that forms the core of the isolated ship model has been discussed and used to illustrate the mathematical concepts involved. Root concept membership function construction has been discussed. Optimal performance for the algorithm is obtained by selecting values of the free parameters in the root concept membership function using a genetic algorithm. The use of a genetic algorithm requires the construction of a fitness function. The fitness functions constructed for this task are based on insights obtained from geometry, physics, engineering, and military doctrine. The fitness functions are in general nondifferentiable at many points and highly nonlinear, neither property providing an obstacle for a genetic algorithm. The fuzzy RM has been shown to be effective for a number of demanding scenarios and will be tested further in the future.

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