Using Fuzzy Cognitive Maps for Knowledge Management in a Conflict Environment

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Abstract—In modern military battlefield environments, the availability of data and information has increased exponentially. Through information and communications technology, individuals and teams can access real-time data about almost any aspect of their current conflict situation, but this instantaneous availability of information to individuals and teams in these conflict situations does not always result in better or faster decisions. Instead, the speed and volume of data made available through surveillance, monitoring, analysis, computer, and communications technology can quickly overwhelm decision makers. Worse, different decision makers that need to coordinate their actions as part of a team effort might use different filters to reduce their data to something more manageable, or what they perceive as more relevant, to their emerging situation. To better manage the information in real time, a mediator is necessary. Fuzzy cognitive maps are proposed as one possible technique for mediating the information made available to decision makers. Such maps were used as part of a research project that used novice teams to simulate an Airborne Warning and Control System (AWACS) crew managing air assets in a conflict situation. The process of constructing the maps, their role in the simulation, and preliminary results of the test runs of the AWACS simulation are presented.

Index Terms—Cognitive systems, command and control, fuzzy cognitive maps, information mediator, situated cognition.

I. INTRODUCTION

CONTEMPORARY patterns of battle management and military decision making require reassessment of traditional perspectives (e.g., [1] and [2]) to enable cognitive readiness and agile, fluid operations that correspond to dynamic, constantly changing, threat situations. Young and McNeese [3] have outlined salient problem characteristics that are entwined and cooccurring in complex unfolding situations, involving information, technology, and people constraints, and that are useful to consider for battle management activities of the 21st century. These characteristics are portrayed in Figs. 1 and 2.

A. Contemporary Information Warfare

As an example of the way battle management has evolved (and is evolving), take the continuing military operations in the ongoing Iraqi war. Certainly, the presence of multiple teams encountering unexpected situations of violence and uncertainty, coupled with technologies that promote any-time, any-place mobile teamwork, couples high response capabilities with highly vulnerable—even volatile—environments. These encounters are often unexpected, require joint constructions of knowledge among distributed forces, and require perception of an amorphous and equally distributed threat force. Strangely enough, though, individual war fighters and tactical units (i.e., teams) have never had the broad bandwidth, information retrieval-search capabilities that digitally can bring large quantities of intelligence to bear upon a source problem immediately. This high information profile for a situation—at first pause—may seem to provide a significant advantage for victory. However, upon closer reflection, what often occurs is that individual warfighters may be overwhelmed with a great deal of information that causes a person to engage in multiple cognitive processes to search and cycle through what is relevant based on what they are experiencing.

B. Information Overload Environments

In modern battlespace operations, the profusion of information technology has created a situation where the pace of data generation can overwhelm operators [4]. In dynamic, emerging situations, the volume of data and the speed at which operations...
occur give an operator or a team of operators little time to assimilate the data, evaluate it, plan a course of action, and implement that plan. Operators may not have the time and resources to properly attend to the battlespace dynamics, producing at best a suboptimal decision that wastes resources or, at worst, a plan of action that results in a disaster.

Within the naturalistic decision making community [5], the type of phenomenon described above is referred to as information overload [6] and is often prevalent in complex socio-technical systems. Information overload can have scatological effects and cause dire circumstances for individuals and teams trying to maintain cognitive readiness. Sources and levels of information that an individual (or team) have to interpret and understand may be interrelated, but often in unknown, improbable, or uncertain ways. Teamwork that transpires in situated cognitive settings often has a number of transactive, criss-crossing paths that involve individual-to-group and group-to-individual knowledge transfer [7]. For practical work this means that individual workers are often tied to their teamwork by the levels of information they process, and concomitantly, how these levels are interrelated to the group process or product. Because these transactive, emergent elements of teamwork are often mediated by information and communication technologies (e.g., computer supported collaboration protocols, see [8]), it is critical that the human-computer interfaces that bring teams together in work: 1) produce high situation awareness; 2) reduce information overload; and 3) entwine individuals with team work in effective patterns, all while accomplishing their intended purpose.

C. Operator and Team Process Problems

Information overload in situated cognitive environments is not the only problem operators face. Compounding the uncertainty created by data-generation and synthesis technology are operator-related and team-related problems. A good example of an operator-related problem is mental stress, possibly created by the overwhelming nature of the current problem being managed [9]. Causes of stress might be the critical nature of the task or it might be caused by an overwhelming number of tasks that need to be addressed. Under such circumstances, the volume of data available and its dynamic nature can conspire to confuse or distract the operator. In such a situation, data may be assimilated but not properly synthesized, resulting in the loss of situation awareness. Such an operator may focus on a task that requires minimal intervention while neglecting another task or situation that is critical. This phenomenon may be similar to what has been referred to as channelized attention in aviation/human factors literature [10].

These types of problems are further exasperated given team-work demands where members coordinate their own area of focus in a joint operation with other team members who are attending to their own specialty. Working together is often accomplished through technological means. Remotely distributed team members have the capability today to do any-time, any-place activities via electronic, digital connectivity. This situation represents what others have referred to as distributed cognition [11], [12] or situated cognition [13], and highlights the potential benefits as well as difficulties of mobile transactions. This individual-to-group activity cycle with a high intake from varied information sources creates opportunities for information saturation, pockets of misunderstanding or uncertainty at the group level, degrees of conflict involving problem misperception, and an inability to make a decision in a timely fashion (based on what another team member needs). Furthermore, these situations may require teams to be on the same page (i.e., establish common ground) very quickly. Typically, teams can form fairly reliable team mental models [14], [15] when they are articulating in face-to-face interaction [7]. However, our research shows that the metacognitive processes inherent in teamwork can begin to breakdown in distributed cognitive settings where distance is a factor [16]. Taken together, these team impediments form a state which McNeese and Vidulich [17] term cogminutia fragmentosa. Additional problem characteristics, if addressed properly, can help avoid cogminutia fragmentosa and are shown in Fig. 2.

A primary purpose for this paper is to propose, build, and test a method of overcoming cogminutia fragmentosa at the team level of operations in order to allow timely execution of battle management missions without further incidents. Enacting this objective will facilitate our goal of enhanced and adaptive team performance. The approach we have taken is presented in the following sections, with the emphasis placed on creating an intelligent group information mediator to assist multiple team members as they recognize and adapt their actions to respond to team interdependencies (where individual tasks must coalesce with higher-level and more abstract group functions).

Because the resources required are too numerous or the environment changes too quickly for a single person to develop adequate situation awareness to properly tend to the tasks at hand, many complex battlespaces are managed by multiperson teams rather than individual operators. Under these circumstances, a team of operators is used whose members have differentiated responsibilities (function allocation [18], [19], role allocation [20]), or use distributed information (distributed cognition [21]), or some combination of these three. But to be effective, the team, in some sense, must behave as a single individual or with a single mindedness. This has often been referred to by others from the perspective that the team has to construct a shared mental model in order to operate with an effective single mindedness [15], [22], [23]. To be effective, team members must mesh properly in their interpretation of the available information and their actions to must develop a complimentary picture of the emerging situation; i.e., team situation awareness. These are prime concepts in theory, but in practice it is often incumbent upon the information and communication technologies (and the resident human–computer interface for teams) to mediate actual single mindedness amongst team members. Frankly, there are numerous examples where interfaces have not been designed to address individual and/or team problems, and where multiple errors and failure occur in complex situations. The purpose of the case study reported in this research is to explore new envisages of human–computer and intelligent interfaces for teamwork, wherein team situational awareness is enhanced and the distribution of work is adaptive to the constraints that emerge in the battlespace environment.
II. INTELLIGENT INTERFACES IN SUPPORT OF TEAMWORK

Modern technology, in some sense, has created a paradox for decision makers. On one hand, it can provide real-time data about almost any aspect of a battlespace. On the other hand, having complete data does not necessarily provide efficient control or understanding. Data can be generated at such a pace that assimilating it to develop situation awareness becomes problematic. This paradox can be compounded when a team or team of teams must use the data to coordinate their actions to achieve a goal [24]. Because of the extensiveness of the data, parsing or filtering it by individual members or teams is required. But individuals or teams may parse or filter it in different ways, resulting in alternate assessments of the situations and different courses of actions.

One possible way to mitigate the information overload problems created by technology is to use intelligent interfaces to filter and control the data made available to the decision makers and, in some instances, to make the decisions. A number of intelligent interfaces/decision aids have already been developed in this capacity [25], [26]. Most were primarily designed as an intelligent tool for managing information, and most were developed to support a single user, not a team. To be effective in a team setting, an intelligent interface must be more than just a data mediator; it must be a team member [27].

As Norman has maintained, systems must be designed in ways that make us smart and overcome errors [28]. Hence, an intelligent interface that bridges individual-to-team work in complex situations must be one that controls information flow and manages knowledge, while making smart decisions to help operators maintain their situation awareness. A truly intelligent interface would also address the emergent qualities of complex problems, and therein elaborate changes in contextual variation to team members that is so important in maintaining situational awareness.

III. INFORMATION MEDIATION

One main concept upon which an intelligent interface could be formulated is that of information mediator. As an information mediator, the intelligent interface could filter the information about the tasks to be controlled as a function of the environment in which the task is embedded, and the capabilities of the likely members of the team that would attend to and process a selected task.

The information mediator function encompasses not only a filtering operation per se, where the actual data presented to the decision makers is reduced, but it also encompasses a synthesis function. For most effective use, the available data needs to be synthesized into a more usable, context-driven format that accommodates the cognitive limitations of the decision makers. In a fast paced, dynamic, emergent environment, raw data are generally not the best way to present information to a decision maker. Better formats can generally be found that provide information about higher level questions a decision maker must address. Higher level questions reflect intelligent interaction among team members.

For example, one question that a decision maker might need to address is whether an aircraft can continue a mission or return to base. In one display scheme, data about the speed, heading, and remaining fuel on an aircraft could be provided, but this then requires that the decision maker be able to recognize certain cues in the data to answer the simple question of whether the aircraft should return to base. In a dynamic situation with many targets and multiple friendly assets, overlooking or failing to recognize when certain aircraft need to return to base will almost certainly occur. To prevent a disaster, such decision makers might use suboptimal tasking rules, such as sending aircraft to refuel early to reduce the chances of a mishap. An alternate display might synthesize the data about fuel, speed, heading, distance to refueling, etc. in some complex way to determine the need to return. To further reduce the data on a screen, and reduce the attendant cognitive overload, the synthesized data could be presented as a visual cue, such as a color spectrum from green to red with different shades indicating different levels of needing to refuel.

IV. APPROACH

To evaluate whether a software mediator for the synthesis and filtering of available data enhanced the performance of a team a simulation was used. The vehicle chosen was a commercially available software package, distributed dynamic decision-making (DDD), that simulated the workings of an Airborne Warning and Control System (AWACS) crew [29]. The DDD simulation was modified according to our experimental requirements to embed an information mediator within the software. AWACS teams are primarily involved with the tasking and management of assets in an airspace, including fighters, bombers, and tankers. Fuzzy cognitive maps were used as a software mediator to determine when an asset was in a critical state.

A. AWACS Operations

An AWACS crew consists of three Weapons Directors (WDs) and a Senior Director (SD) who manage the assets in a particular region of airspace. It is their responsibility to monitor tracks in the airspace under their control, determine in what ways each asset must be serviced, and manage the completion of any required tasks. The air assets within their responsibility are a combination of friendly aircraft on particular missions and hostile aircraft threatening these and other assets. The AWACS team must monitor these hostile tracks, determine their intent, identify a course of action to respond to each track, and manage the deployment and execution of the response.

As a team model/simulation an AWACS crew was chosen for a number of reasons. It provided a well-documented framework for team definition and a way to develop a realistic environment. Further, using the natural constraints a real crew might encounter allowed the realization of time-critical, emergent situations and matched many of the problem characteristics identified by Young and McNeese [3].
B. DDD Team Simulation

DDD is a commercially available, multiuser simulation package that has been used in a variety of military applications to model and assess various aspects of team work [29]. Although it has several variants, the one used here specifically modeled the management of an airspace that encompassed friendly and hostile air assets that included fighters, bombers, bases, and refueling aircraft. The package was modified, as we will describe, to accommodate the capabilities of the lab that housed it, and to meet the needs of this research. Chief among these were a reduction in size of the AWACS team and the addition of a fuzzy cognitive map as an information mediator. The reduction in the aircrew creates a demanding and time-resource pressured environment, while at the same time providing a realistic basis coincident with a “doing more for less” philosophy that is apparent now in many military operations.

To give the participants uniform capabilities, the AWACS team modeled in this DDD simulation was modified to exclude a senior director. Without this central authority to impose situation awareness when necessary, the team of three WDs needed to rely on each other, hence strengthening requirements for team interdependency, and the available intelligent interface to reach congruent understandings of the changing environment in which their assets were embedded. This gave greater flexibility and control in assessing the efficacy of intelligent displays and information mediators in developing team situation awareness.

C. AWACS Joint Task Requirements

An airspace managed by an AWACS crew can encompass a number of aircraft, both friendly and hostile, with the team organized in a variety of ways to accomplish its mission. In one organization, the airspace under management is divided into lanes, with each WD responsible for any activity within his/her lane. In another method, WDs manage all assets associated with a particular function: check in, aerial refueling, combat air patrol, offensive strikes against enemy bases, etc. Since novice teams were participating in the project for limited periods of time, it was felt that if they were organized by lane they might not have enough time to master all of the features of each of the assets incorporated in the simulation. Instead, the WDs were organized by function with each controlling a subset of the available assets. One director controlled assets for combat air patrol, another aircraft for attacking enemy bases, and the third refueling assets. This also gave each different missions and different capabilities requiring them to develop a common situation awareness to be effective.

Each WD monitored the asset within their mission responsibility to determine if a critical event occurred. When such an event occurred, it was then serviced by the WD. For example, if an aircraft was low on fuel, the WD would provide it with instructions, a course and heading, to either a tanker or base to refuel. The WD needed to analyze the airspace in which the aircraft passed through to determine which of these two options was most appropriate. Table I provides a listing of the critical events that could be encountered in the simulation.

<table>
<thead>
<tr>
<th>Critical Event</th>
<th>Possible Actions</th>
</tr>
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<tbody>
<tr>
<td>Aircraft Low on Fuel</td>
<td>Land Aircraft</td>
</tr>
<tr>
<td>Aircraft Low on Weapons</td>
<td>Land Aircraft</td>
</tr>
<tr>
<td>Threat to High Value Asset</td>
<td>Move Asset</td>
</tr>
<tr>
<td>Aircraft Threatened</td>
<td>Divert Aircraft</td>
</tr>
<tr>
<td>Base Threatened</td>
<td>Launch Interceptors</td>
</tr>
<tr>
<td>Threat</td>
<td>Vector Airborne Aircraft to Intercept</td>
</tr>
</tbody>
</table>

Key to the success of the performance of a WD was the monitoring of all the assets within their responsibility and the timely servicing of critical events. There are a variety of ways in which a WD could accomplish this. One technique used to ensure that all assets within a WD’s control are periodically checked is called walking the clock. A WD will start at one point on the screen and proceed around it a clockwise fashion, examining each asset that they come to that is their responsibility. The asset is examined to determine if it is or is about to become critical. If it is critical, the asset is serviced. They then continue the process with the next asset encountered on the screen for which they have responsibility. This process is continued until the entire screen is covered, and then repeated. This technique of cycling through the assets in a systematic fashion ensures that no asset is neglected.

D. AWACS Human–Computer Interaction

The technology available for the AWACS crew is such that a WD must zoom the screen in on their local console to obtain detailed information about the asset and the region of space in which it is operating. The process of zooming in, though, requires time and also limits the field of view of this WD. While zoomed in, they can no longer see the rest of the screen and, consequently, other assets that may be within their responsibility. This can significantly increase the chances that a critical event will be missed and therefore not serviced. The DDD simulation was modified to incorporate this constraint by requiring the operator to zoom their display in on that asset to service it.

As previously described, the task for WDs in an AWACS crew is the timely management of critical events. Each critical event must be identified and serviced appropriately. Loss of situation awareness occurs when the WD becomes distracted or inattentive to important details about an asset, and the critical event it is undergoing is missed. In certain situations, another WD can assume control over an asset and service the critical event, and thus restore situation awareness to the team. This is
not always possible, though. As a WD monitors an asset they accumulate a variety of knowledge about it from which they can make informed decisions about its status. When another WD assumes responsibility for an asset, this history is lost and, with it, immediate and detailed knowledge about its status.

E. Overall Modeling Methodology

For the research conducted in this study, time and resource limits precluded a full development of decision aids or display changes that would alter the way the information is formatted and displayed. Instead, intelligent agents and display changes were proposed that would enhance the capabilities of the team to identify and deal with critical events as they occurred. The key constraint in this identification process was the limitations of the simulation to be used. The ability to reprogram the display or incorporate extensive artificial intelligence was limited, so only those changes that could be made with limited reprogramming were considered. Even with this constraint, several viable interventions were possible.

F. Intelligent Information Visualization

To enhance the ability to develop situation awareness, the display needed to be altered in two ways. In the first, critical events were tagged so that any WD could easily identify it without the need for the accumulated knowledge acquired by monitoring an asset for a period of time. In the second, information needed to be available on a screen so that any WD could identify when another WD might miss or be unable to see that an event is critical that is their responsibility.

The chief time that a WD would be unable to identify when an event is critical is when he has zoomed in on another asset to service it. In this case, the rest of the battlespace is absent from his screen. A simple modification that modeled this was to provide an outline on every screen showing the field of view for each WD. Thus, one WD could quickly ascertain what part of the airspace that another WD was viewing. To accomplish this visual aid, the simulation display was modified to draw a box on each screen indicating the current field of view of each WD. The boxes were colored coded to match the scheme used in identifying the control of various assets used in the simulation. When one WD was zoomed in on a particular part of the screen, other WDs knew this through a square on their screen indicating their limited field of view.

By itself, the addition of the outline of the field of view of each WD on a screen could not necessarily increase the situation awareness of the team. As each WD worked with an asset, they accumulated knowledge about that asset—its mission, speed, remaining fuel, etc. This accumulated knowledge helped a WD determine when an asset was undergoing a critical event. Without additional aids, another WD would know only when an asset could not be seen by another WD, not when it was entering a critical event.

G. Information Mediation Aiding

The second intervention needed was a decision aid that assessed when an asset was at a critical juncture and required servicing. This decision aid provided an appropriate visual cue, in this case, having the icon representing the asset blink. This second intervention would improve the ability of a WD to identify when an asset was critical without having worked with it. In the simulation used here, fuzzy cognitive maps were implemented as such mediators.

V. BUILDING AND IMPLEMENTING AN INFORMATION MEDIATOR-FUZZY COGNITIVE MAPS

Fuzzy cognitive maps are a qualitative method to model the intricate interactions that might take place in a complex situation [30]–[32]. The maps themselves are digraphs with nodes and edges connecting the nodes. Nodes represent variable concepts associated with some attribute of the problem. An edge connecting two nodes indicates the presence of a cause-effect relationship with the direction of the edge indicating which node is the cause and which is the effect. Because only changes in states are captured in the map (i.e., whether the underlying concept increases, decreases, or there is no change), a common metric is not needed to measure changes in the various nodes. Thus, apples can be compared to oranges in the context of the map.

Because of the variety of information that can be modeled in it, a fuzzy cognitive map is an ideal platform for an information mediator that controls an intelligent display. An information mediator takes raw data and formats into a form most appropriate for the context in which it is embedded to aid the decision maker. The format of the same data can change as the context changes. Because of this, information mediators can be essential in the development of situation awareness, both individual and team, in time-critical situations. Since the same data can indicate different situations depending on the overall context in which it is generated, different team members can easily develop different interpretations of what is going on and respond in different ways.

Using an information mediator can overcome some of this difficulty. With an information mediator controlling an intelligent display, the data would be presented in the most appropriate manner for developing a common situation awareness among the team members. The map would incorporate not only quantitative attributes such as aircraft speed and remaining fuel, but many qualitative aspects of the environment and context such as enemy threats, pilot quality, etc. The map can then be used to assess and to determine the situation the assets are in and not just the status of the assets. All team members can then act on this common assessment of the situation and coordinate their actions accordingly.

To implement this decision aid, fuzzy cognitive maps were constructed for each critical event that an asset in the simulation could undergo. Each map incorporated relevant information about the conditions creating the critical event. For example, the map for determining if an aircraft needed to refill used information about the fuel status of the aircraft, its distance to a
refueling asset, and the distance that the aircraft could fly on the remaining fuel (see Fig. 3). Increasing the remaining fuel on the aircraft increased the range that it could fly. Decreasing the remaining range of the aircraft or increasing the distance to the nearest refueling asset each tended to increase the chances that the asset would run out of fuel [33]. Each of these attributes contributed, directly or indirectly, to the chances that the aircraft would run out of fuel—a critical event.

This map and others constructed for the remaining critical events were used to develop a set of If/Then rules for determining if an asset or event was critical which were incorporated into the simulation as a mediator for tagging such assets. The icon for the asset was then made to blink on the monitor to provide a visual cue that a critical event was occurring.

To review, two major modifications were made to the DDD simulation to support this research. In one, outlines were displayed on each operator’s screen to indicate the field of view of the other WDs. In this way, any participant could quickly judge when an asset of another WD was outside their field of view. The other major modification was the use of fuzzy cognitive maps as information mediators. Maps were constructed for the conditions that led to each critical event for an asset from which If/Then rules were implemented in the simulation that identified when an asset was undergoing one. The icons for such assets were then made to blink to provide a visual cue to the operators that it needed servicing.

Another key feature of the DDD simulation was the ability to log a variety of data in real time about the assets, tasks, and other environmental parameters associated with the battlespace. The time that an asset was critical, the decision maker that originally controlled the asset, the type of event that caused it to be critical, when the asset was serviced, and who the decision maker was that serviced it were all logged from the simulation. Additionally, to provide a way to generate a test group, the two decision aids—the field of view outlines and the fuzzy cognitive map software mediator—were made switchable. Some teams had the benefit of the decision aids while others did not.

VI. Extracting If/Then Rules From a Fuzzy Cognitive Map

A. If/Then Rule for Asset Needs to Refuel

The process used to extract if/then rules for the critical event of an asset needing to refuel will be now described. This event occurred whenever an asset began to run low on fuel and risked the possibility of running out and crashing. Not only was the determination of this event a function of the fuel on board the asset, it was also a function of the distance to the nearest refueling asset. For example, the fuel available on an aircraft could be low, but it might still be able to continue its mission if the nearest refueling asset were close enough. The basic structure of the fuzzy cognitive map used for this situation was given in Fig. 3.

The key determinate of this critical event was whether the remaining distance the aircraft could fly was sufficient to reach the nearest refueling asset, either a tanker aircraft or a friendly base in the simulation. Increasing the remaining fuel on the aircraft increased the range that it could fly. Decreasing the remaining range of the aircraft or increasing the distance to the nearest refueling asset both tended to increase the chances that the asset would run out of fuel.

In the simulation, the remaining range that the aircraft could fly was a function of its fuel consumption, the fuel available on board, and its velocity. The fuel consumption (FC) was linearly proportional to the aircraft’s velocity, $V$

$$FC = kV$$

where $k$ was $FC_{\text{max}}/V_{\text{max}}$, $FC_{\text{max}}$ is the fuel consumption of the asset, and $V_{\text{max}}$ is the maximum velocity possible. The remaining range that the aircraft could fly was the product of its velocity and the remaining time it could fly, $t$. This variable was ultimately a function of the fuel consumption rate and the remaining fuel on the aircraft.

The time the aircraft could travel, $t$, was related to the fuel consumption by

$$t = \frac{FR}{FC}$$

where fuel remaining (FR) was the remaining fuel on the asset and FC was the current fuel consumption rate of the aircraft. In the DDD simulation, FC was given in pounds per second and FR was given in pounds. By definition, the range the asset could fly, $R$, at a constant velocity, $V$, was $Vt$. Using (1) and (2), the range, $R$, was a function of only a single variable, FR, the fuel remaining, with $k$ as defined previously

$$R = \frac{FR}{k}.$$

Thus, the determination of the refueling critical event depended on only three parameters: $R$, the remaining range that the aircraft could fly, FR, the fuel remaining, and $D$, the distance to the nearest refueling asset.

To provide enough coverage of the measurable values for the determining parameters, each was divided into five fuzzy levels, given in Table II.
TABLE II
DEFINITION OF FUZZY LINGUISTIC VALUES FOR PARAMETERS IN ASSET NEEDS TO REFUEL CRITICAL EVENT

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Fuzzy Value</th>
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<tbody>
<tr>
<td>Fuel Remaining</td>
<td></td>
</tr>
<tr>
<td>FR:</td>
<td>VHF R</td>
</tr>
<tr>
<td></td>
<td>HFR</td>
</tr>
<tr>
<td></td>
<td>MFR</td>
</tr>
<tr>
<td></td>
<td>LFR</td>
</tr>
<tr>
<td></td>
<td>VLFR</td>
</tr>
<tr>
<td>Range an Asset Could Fly R:</td>
<td></td>
</tr>
<tr>
<td>VLR</td>
<td>Very long distance that aircraft can fly</td>
</tr>
<tr>
<td>LR</td>
<td>Long distance that aircraft can fly</td>
</tr>
<tr>
<td>MR</td>
<td>Medium distance that aircraft can fly</td>
</tr>
<tr>
<td>SR</td>
<td>Short distance that aircraft can fly</td>
</tr>
<tr>
<td>VSR</td>
<td>Very short distance that aircraft can fly</td>
</tr>
<tr>
<td>Distance to Nearest Refueling Asset D:</td>
<td></td>
</tr>
<tr>
<td>VLD</td>
<td>Very long distance to nearest refueling asset</td>
</tr>
<tr>
<td>LD</td>
<td>Long distance to nearest refueling asset</td>
</tr>
<tr>
<td>MD</td>
<td>Medium distance to nearest refueling asset</td>
</tr>
<tr>
<td>SD</td>
<td>Short distance to nearest refueling asset</td>
</tr>
<tr>
<td>VSD</td>
<td>Very short distance to nearest refueling asset</td>
</tr>
</tbody>
</table>

In general, the nodes defined in the composite fuzzy cognitive map were of a binary nature. A value of 1 indicated that the fuzzified concept was present, a 0 that it was absent. As such, the differentiated fuzzy levels for each of the basic concepts defining the model were mutually exclusive. Only one fuzzy state was present (had a state value of 1) at any time.

As given in (3), the remaining range that an aircraft could fly, \( R \), was determined by only the FR. A one-to-one correspondence was assumed between the two fuzzy levels for these parameters. A fuzzy value of very high for the fuel remaining implied a fuzzy level of very high for the remaining range. A fuzzy value of low for fuel remaining implied a fuzzy level of low remaining range. This gave the relationships for determining the fuzzy value of \( R \) given the fuzzy value of FR, as shown in Table III.

DEP, the chances that the aircraft ran out of fuel, was defined using two fuzzy states, HDEP, a high chance that the aircraft ran out of fuel, and LDEP, a low chance that the aircraft ran out of fuel. An asset was tagged critical for this event when its fuzzy value for DEP was HDEP. That is, it was a critical event for the asset whenever there was a high chance of it running out of fuel.

HDEP occurred when the remaining range of the aircraft was less than the distance to the nearest refueling asset, plus some safety margin

\[
R < D + \text{Safety Margin}. \quad (4)
\]

This condition was implemented by setting HDEP equal to 1 whenever the cardinal rank of the fuzzy level for \( R \) was less than the cardinal rank of the fuzzy level for \( D \), yielding VeryShort < Short < Medium < Long < VeryLong. So, for example, HDEP was 1 whenever \( D \) was long (LD) or very long (VLD) and \( R \) was medium (MR).

Using this relation, the following rule was derived for HDEP:

\[
\text{HDEP} = \text{VSR} + \text{SR} \cdot (\text{SD} + \text{MD} + \text{LD} + \text{VLD}) + \text{MR} \cdot (\text{MD} + \text{LD} + \text{VLD}) + \text{LR} \cdot (\text{LD} + \text{VLD}) + \text{VLR} \cdot \text{VLD}. \quad (5)
\]

In (5) the addition symbol (+) represents the Boolean operator OR, and the multiplication symbol (·) the Boolean AND operator.

Since DEP and LDEP were mutually exclusive, whenever HDEP was 1, LDEP was 0, and vice versa. Thus, an additional rule defining LDEP was not necessary.

Since a one-to-one relationship was assumed between fuzzy levels for \( R \), the range to the nearest refueling asset, and FR, the remaining fuel on board, the fuzzy levels for FR can be substituted for their corresponding fuzzy levels for \( R \) into (5), giving (6). The final form for the rule for assessing HDEP is only a function of the distance to the nearest refueling asset and the remaining fuel on board.

\[
\text{HDEP} = \text{VSR} + \text{SR} \cdot (\text{SD} + \text{MD} + \text{LD} + \text{VLD}) + \text{MR} \cdot (\text{MD} + \text{LD} + \text{VLD}) + \text{LR} \cdot (\text{LD} + \text{VLD}) + \text{VLR} \cdot \text{VLD}. \quad (6)
\]

B. Determining the Fuzzy Values for the Measurable Parameters for Refueling Cases

In a fuzzy cognitive map, conditions or states of the system are presented as nodes that are restricted to the integer values −1, 0, 1. A value of 1 represents an increase in the underlying concept represented by the node, 0, no change and −1, a decrease. The inputs were measurable parameters in the sense that their values were determined in the simulation by a continuously varying function that yields a specific numerical quantity. Before the fuzzy rule embodied in (6) can be implemented, a method was needed to map the crisp values from the simulation to the fuzzy values in the equation.

To make the fuzzy sets somewhat independent of platform, the fuzzy values and their corresponding ranges were assessed as percentages of maximum available values for the platform.
TABLE IV
KEY ATTRIBUTES OF ASSETS IN DDD SIMULATION

<table>
<thead>
<tr>
<th>ID</th>
<th>Asset</th>
<th>Maximum Fuel (pounds)</th>
<th>Fuel Consumption (pounds/s)</th>
<th>Maximum Velocity (units/s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>AWACS</td>
<td>60000</td>
<td>3.333</td>
<td>0.1667</td>
</tr>
<tr>
<td>2</td>
<td>Tanker</td>
<td>60000</td>
<td>3.333</td>
<td>0.0556</td>
</tr>
<tr>
<td>6</td>
<td>F-16</td>
<td>6972</td>
<td>1.867</td>
<td>0.1667</td>
</tr>
</tbody>
</table>

TABLE V
NUMERICAL RANGES FOR $\alpha$ FOR FUZZY VALUES FOR FR, REMAINING FUEL

<table>
<thead>
<tr>
<th>Type</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>VLFR</td>
<td>$0 \leq \alpha &lt; 0.125$</td>
</tr>
<tr>
<td>LFR</td>
<td>$0.125 \leq \alpha &lt; 0.375$</td>
</tr>
<tr>
<td>MFR</td>
<td>$0.375 \leq \alpha &lt; 0.625$</td>
</tr>
<tr>
<td>HFR</td>
<td>$0.625 \leq \alpha &lt; 0.875$</td>
</tr>
<tr>
<td>VHFR</td>
<td>$0.875 \leq \alpha \leq 1.0$</td>
</tr>
</tbody>
</table>

Key values for each of the platforms used in the simulation are given in Table IV.

As described previously, the fuel remaining (FR) was differentiated into five fuzzy sets: very low fuel remaining (VLFR), low fuel remaining (LFR), medium fuel remaining (MFR), high fuel remaining (HFR), and very high fuel remaining (VHFR). It was assumed that these fuzzy values were mutually exclusive; the remaining fuel could be in only one of these fuzzy states at a time. The values for determining membership in which fuzzy value was assessed as a function of the percent of total fuel possible on the aircraft. The fuel remaining was assessed as a function of the parameter $\alpha$, the fraction of total fuel possible on an asset that remained.

$$\alpha = \frac{\text{Fuel remaining}}{\text{Fuel max}}. \quad (7)$$

Given its definition, $\alpha$ was defined only on the interval $0 \leq \alpha \leq 1.0$.

This interval for $\alpha$ was partitioned into five equal increments and the fuzzy values for the remaining fuel assigned to these in their rank order. $\alpha$ Table V shows the ranges for $\alpha$ for each of the fuzzy values.

The distance to a refueling asset was independent of the characteristics of the asset being examined. The remaining distance that an asset could travel, though, was a strong function of certain parameters specific to an asset. As was shown previously, the remaining range an asset could travel, $R$, was determined from the remaining fuel available on the asset, FR. Using the previous definition of $\alpha$, (3) can be rewritten as

$$R = \frac{\alpha \text{Fuel max}}{k}. \quad (8)$$

The constant, $K$, was defined as $\text{Fuel max}/k$, with units of meters, and could be roughly interpreted as the maximum range possible for the asset with a full load of fuel. Using this definition we have

$$R = \alpha K. \quad (9)$$

By transforming to this form, the remaining range was normalized with respect to $K$. Just as with the FR, fuzzy values for $R$ were defined for fractional values of the maximum range possible, $K$. In general, this fraction was defined as $\beta$. If used in defining fuzzy values for the remaining range a subscript of $R$ was added, $\beta_R$. If used for the distance to the nearest refueling asset a subscript of $D$ was added, $\beta_D$. For a given asset with a specific value of $K$, the following definitions of $\beta$ were made:

$$\beta_R = \frac{R}{K} \quad (10)$$

$$\beta_D = \frac{D}{K} \quad (11)$$

where $R$ was the remaining range the asset could fly and $D$ was the distance to the nearest refueling asset. For $\beta_R$, the permissible range of values was 0 to 1.0, while $\beta_D$ could have any value greater than or equal to 0 since, in theory, the distance to a refueling asset could be longer than the distance an asset could fly even with a full load of fuel.

The ranges of $\beta$ for both $R$ and $D$ were the same for the different fuzzy levels, so only one set was constructed. As before, the defining interval for $\beta$ (0 to 1) was partitioned into five symmetric ranges with fuzzy values assigned to each in their rank order. This yielded the definitions shown in Table VI.

Since $D$ was also defined by $\beta$, a similar development was used to give the same intervals for the fuzzy states defined for $D$, except that the final range was open ended.

In the simulation, assets were evaluated about every second to determine if they were undergoing one of several critical events. For this critical event, the distance to the nearest refueling asset, $D$, the remaining range the asset could fly, $R$, and the remaining fuel, FR, were calculated numerically for each assets from information in the simulation. From this information, the parameters $\alpha$, $\beta_R$, and $\beta_D$ were assessed. These numerical values were then converted to fuzzy values using the ranges defined in Tables V–VII. With these values, (6) could be evaluated to determine if the asset was undergoing this critical event.

VII. ANALYSIS AND RESULTS

Several training scenarios and three experimental scenarios were used with each team that participated with only data...
collected from the experimental scenarios used for this analysis. Each of the three experimental scenarios was designed to emphasize a different combat mission. One emphasized refueling assets, another an attack of enemy bases, and the third a defense of friendly airspace. Teams were composed of three people. A total of three test and 18 experimental teams participated with the team pool roughly divided in three groups: a test group with no fuzzy cognitive maps, zoom squares, or pop-up messages (the control group); a second group with just pop-up messages; and a final group with the fuzzy cognitive maps and zoom squares.

It was postulated that using the fuzzy cognitive maps should improve the situation awareness of the teams by allowing them to identify more quickly when assets are critical and, consequently, need servicing. This should reduce the time taken to service the asset and also reduce the number of mishaps; i.e., the number of instances when the asset is lost. Knowing when an asset first reaches a critical state should improve the chances that it can be serviced and is serviced before a mishap occurs. Additionally, since all WDs are provided with the critical state information, it would be expected that a WD with little activity under their control would assume control of some of the assets of a WD that might be overloaded.

To assess the effectiveness of fuzzy cognitive maps as decision aids, two measures were calculated from the data: the average latency for a critical event, and the number of mishaps. The latency is the time between when an asset is initially critical when it is no longer critical, or when a mishap had to occur. To leave a critical state, intervention by a WD was required. Not all critical events were serviced, and not all of these resulted in a mishap. In some cases, the asset became critical near the end of the simulation; for example, beginning to run low on fuel, so there was insufficient time or need to service it. So, in addition to the measures just given, the average number of unserviced critical events was determined from the data. These measures are given for each team (the fuzzy cognitive maps group and the control group) used here by experiment. Each different experiment represents a different scenario used, but each different scenario was the same for all teams.

The lack of data for team T10 in the fuzzy cognitive map group for experiment 3 (Table VII) represents a case where the DDD simulation prematurely terminated. For the other simulations, few assets were lost, and those that were generally were concentrated in a few teams only. This is most likely the result of an insufficient understanding by one or more members of these teams of the mechanics of using the DDD simulation, or in the strategies needed for servicing the assets. Although not explicitly shown in the table, not one of the assets logged as critical in any of the experiments by any of the teams in either of the control groups was transferred to another WD for serving. All assets were serviced by the original owner of the asset.

For experiments 1 and 2 (Tables VIII–XI) there is a definite improvement in performance for the team pool that used fuzzy cognitive maps over the control pool. The average latency time for experiment 1 is higher for the control group (99.38) than the fuzzy cognitive map group (77.99), as is the average latency times for experiment 2 (84.28 versus 73.02). It should also be noted that in both cases the standard deviations of these measures are lower for the fuzzy cognitive map teams. This is consistent with the improvement expected from using fuzzy cognitive maps. Because WDs will know immediately when an asset is critical with fuzzy cognitive maps, they can immediately begin to service the asset to prevent a mishap. Thus, one would expect that the delay time from when an asset goes critical to when the WD realizes it has would be shorter, or much shorter, for the teams using fuzzy cognitive maps than for the control teams. Without this delay time, both the latency time should decrease, as should the standard deviation. The standard deviation should decrease because if one can assume the time to service the same type asset is roughly constant, then much of the variation should be due to the delay in recognizing that the asset is critical and needs to be serviced.

In experiment 1 (Tables VIII and IX), the fuzzy cognitive map pool had an average of 28 critical events, with about half being serviced. The control group averaged about 21 critical events per team for this experiment, with about half being serviced. In experiment 2 (Tables IV and V), the fuzzy cognitive map teams averaged roughly 28 critical events, with the control teams about the same number. The complexity of the task (number of hostiles, more initial constraints on friendly assets, etc.) does...
One might expect that the fuzzy cognitive maps would improve the number or percentage of serviced events over the control group, and this is clearly lacking in the data. One possible reason is that many of the unserviced events occurred near the end of the simulation where there is neither time nor interest in doing something about them. In future studies it will be important to incorporate some way to judge whether an asset left unserviced near the end of the simulation would ultimately result in the destruction of the asset. For assets low on fuel, a determination could be made if the asset has sufficient fuel remaining to reach a refueling asset. For assets threatened by hostile tasks, a determination could be made whether the asset could flee or defend itself from the attack. The number of assets lost is about the same for each group. As stated previously, lost assets are concentrated in only a few teams in each team pool. Although one interpretation for this is that one or more members in each of these teams had trouble with the mechanics of the simulation, the number of teams in each pool is too low to allow more than speculation about any cause/effect relationships that may be present.

Experiment 3 (Tables XII and XIII) presents a departure from the previous two experiments. Of the three, it was the most complex and challenging. For this experiment the opposite of what is expected occurs. The control group has a better performance than the fuzzy cognitive map group. The average latency time of the control group is 64.9 while for the fuzzy cognitive map group it is 106.7. Additionally, the control group services fewer average events than the fuzzy cognitive map group; 33 versus 40. The control pool teams looses only two assets total for the group while the fuzzy cognitive map pool looses ten assets total. One would have expected the opposite to have happened. The fuzzy cognitive map group of teams should have had shorter latency times and lost fewer assets than the control group. The small number of experiments may be the largest contributing factor to this unexpected result. A larger pool of participants...
may produce a result more in line with expectations. Also, experiment 3 was the most challenging of the three, requiring the most sophisticated strategies to complete effectively. It may be the case that the teams without the fuzzy cognitive map aid had a better ability to quickly develop the necessary strategies to execute the missions through personal histories; e.g., they frequently played a strategy game such as chess, or had a previous military background. The fuzzy cognitive map aid was meant to facilitate interteam communication and cooperation, not to enhance the strategic capabilities of the participants.

### VIII. Conclusion

Our objective in this modeling project was to create an intelligent information mediator that could address some of the adaptive responses needed when team members interact in a complex military environment, in this case AWACS operations. Adaptive and timely responses were needed as we specifically “downsized” the AWACS team from three to four members (eliminating the senior WD). As a team of WDs experience the situation of information overload, it is certainly possible that *cogminutia fragmentosa* may arise and continue to break down team performance. We felt that if we could design an intelligent mediator to signal to teams (through decision aid and information display)—areas where their work together could improve performance—then there would be a good chance to demonstrate the worth of intelligent assisted teamwork. Further, we felt that team performance could improve through the use of the mediator by enhancing a team’s mental model by improving their levels of interdependency, given a task that demanded time pressure and working joint assets together. Although our results are decidedly preliminary (and, in turn, subject to all the cautions necessitated by having a smaller than desired subject pool), they show in experiment 1 and 2 that fuzzy cognitive maps can provide the basis for an effective intelligent information mediator.

In summary, we conclude that it is possible to change team performance in a highly complex domain that contains many of the hard aspects of problems through the use of an intelligent mediator. Future work must replicate these findings (given the limits we have stated), but also extend some of the information visualization functions to portray new intelligence in ways that indicate adaptive change in the context or with the teams’ actions as they are parlayed through a group interface.

### REFERENCES


