Measuring Team Performance and Coordination in a Mixed Human-Synthetic Team Training Environment

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ABSTRACT

The Air Support Operations Center (ASOC) is a complex sociotechnical system. It manages routine events and crises by processing a massive flow of information that originates from a variety of external agencies via numerous communication channels and procedures and across a variety of classification levels. To address the challenge of training individuals and teams to face the complexities of the ASOC environment and to learn how to effectively coordinate, the Air Force has developed the Joint Air-to-Ground Simulation System (JTAGSS). JTAGSS provides ASOC operators with the opportunity to train as a team and to encounter realistic scenarios presented in operational contexts. To achieve this training opportunity, while maintaining current support of operations, work is currently underway to apply a combination of both human and synthetic agents to fill the variety of ASOC positions (Myers, et. al., 2016). Effective training in any environment, and particularly in an environment that requires close coordination across heterogeneous entities, requires effective measurement. To realize the impact of training on the operational environment, trainers must know what to measure, how to measure it, and how to communicate the results. Currently, there are no reliable measures of performance (MOP) and measures of coordination (MOC) that trainers can utilize to ensure progress in teams within the JTAGSS. The purpose of this research was to develop and validate measures of team coordination for mixed human and synthetic teams. The researchers applied the Rational Approach to Developing Systems-based Measures (RADSM) approach (Orvis, DeCostanza, & Duchon, 2013) to develop and validate the coordination measures. The coordination measures were based on virtual communications data and validation was accomplished through a Monte Carlo simulation which utilized representative training data. This study provides evidence of the use of communications-based data in measuring performance related to team coordination.

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INTRODUCTION

Effective team performance and training in dynamic work environments, from military Command and Control (C2) centers to emergency response teams to corporations, relies on close coordination and collaboration among team members (Entin & Serfaty, 1999; Kozlowski & Ilgen, 2006; Marks, Mathieu, & Zaccaro, 2001). Individuals must not only be experts at their job functions, but they must also be able to effectively communicate critical information and anticipate the needs of their teammates. Achieving high levels of coordination and performance requires explicit communication of information and requirements as well as an implicit understanding of others' needs and states (MacMillan, Entin, & Serfaty, 2004). Training individuals and teams to succeed in these environments is predisposed on the ability to measure the degree to which they are effectively coordinating and performing.

The Air Force's Air Support Operations Center (ASOC) is a complex sociotechnical system. It manages routine events and crises by processing a massive flow of information that originates from a variety of external agencies via numerous communication channels and procedures and across a variety of classification levels. Within the ASOC and other similar dynamic environments, the challenge of successful operation remains the same—knowing what to do with all the information spread across different individuals and how to use that information to collectively make decisions to control the system. Cognitive processes that lead to such decisions at the individual level are influenced by higher-level constructs, such as team cohesion and shared situational awareness, and are inherently shaped by formal and informal coordination and communication processes (Kozlowski & Chao, 2012). Communication and coordination in complex, dynamic environments become even more difficult when the members of the team represent different technical specialties or career fields. The heterogeneous mix of technical specialties in the ASOC and their potentially differing cognitive frames exacerbate the coordination challenges.

The ASOC supports critical operational and tactical missions and, therefore, is tightly controlled through the use of operational checklists and formal processes (e.g., Air Tasking Orders (ATO)) to maintain reliability. Air Force Instruction 13-114 Volume 3, ASOC Operations Procedures (AFI 13-114 Vol 3, 2009), frequently mentions the importance of coordination, and how it must occur during all phases, from planning to execution. Furthermore, Section 3.2.1 states, "The ASOC must have and use systems that permit cross component collaboration, that can gain the situational awareness necessary to make well founded recommendations that correctly match air component capabilities to immediate land component air support requests, and systems that automate mission tracking to maintain all affected agencies' SA." Sections 3.2.1.1 and 3.2.1.2 provide a rather extensive list of communication processes and tools: "internet chat rooms, face-to-face meetings/briefings, telephone calls, VTCs (Video Teleconferences), TBMCS (Theater Battle Management Core System) Web applications (WARP (Web Air Request Processor), ESTAT (Execution Status and Monitoring), etc.), SIPRNET, JABBER, Adobe Connect, IRC, …." However, the environment in which the ASOC is most active can be assumed to involve crisis, time-criticality and urgency, uncertainty and ambiguity, and potentially even moments of chaos and confusion, all of which may not conform neatly to preexisting operational checklists. The sheer number of information and communication sources that exist in the ASOC coupled with the extensive list of external agents creates a risky team environment in which coordination is paramount—its absence can be catastrophic. Furthermore, the operational environment will provide a steady stream of interruptions, each of which will impact not only performance on active tasks, but also overall situational awareness necessary to manage emergent crises (Rudolph & Repenning, 2002). Considering this, it is critical that the ASOC be able to efficiently and effectively coordinate the variety of simultaneous and integrated tasks, ensuring that each is properly performed in pursuit of the overall mission.

The Air Force has developed the Joint Air-to-Ground Simulation System (JTAGSS) to address the challenge of training individuals and teams to face the complexities of the ASOC environment and to learn how to effectively coordinate. JTAGSS provides ASOC operators with the opportunity to train as a team and to encounter realistic scenarios presented in operational contexts. Because the ASOC is inherently a team-oriented environment, effective training in JTAGSS requires that all critical positions be filled. When facing the reality of conducting training exercises where individuals have varying levels of experience and expertise, have complicated schedules, often must travel to training sites, and have ongoing duty assignments, the prospects of filling all the seats in the training event are grim. Furthermore, the levels of training required for individuals can vary greatly based on the complexity of the required tasks for the duty position and the experience of the individual. This can lead to wasted time and training costs for other team members. To address this, the Air Force is developing Autonomous Synthetic Teammates (Myers, et. al, 2016) to fill positions within JTAGSS and similar environments. These software agents are intended to act and interact in a human-like manner with humans and other agents (including making mistakes when, for example, their workload is too high). The use of these realistic and cognitively inspired agents enables tailored and more flexible training for individuals and teams while maintaining a realistic training environment.

While the Air Force has taken great steps toward optimizing the training experience, a critical remaining gap exists when it comes to the measurement of the critical skills and performance targeted during training. In order to realize the impact of training on the operational environment, trainers must know what to measure, how to measure it, and how to communicate the results. Currently, there are no reliable measures of performance (MOP) or measures of coordination (MOC) that trainers can utilize to ensure progress in teams within the JTAGSS. Even within the literature, there are a lack of solid coordination measures (Salas, Cooke, & Rosen, 2008). Given the relatively unique context of the ASOC, there is a need for an improved measurement approach capable of handling the data available from the extensive set of communications tools, used across a variety of individuals and teams. In this paper, we describe an approach to measuring coordination among human and synthetic agents in an ASOC. This new measurement approach utilizes communications and other systems-based data to minimize interference during training, while providing trainers with useful insights about the functioning of individuals (human or synthetic agent) and teams (human or human-machine). The authors have developed novel indicators and metrics of coordination tailored specifically for ASOC teams utilizing a previously developed measurement process, as described in the next section. Because the synthetic teammates are designed to behave and act like their human counterparts, the measures of coordination and performance discussed in this paper are the same for all teams, whether purely human or mixed human-synthetic agent teams. This enables effective comparison of mixed human and synthetic agent teams with purely human teams.

DEVELOPMENT OF MEASURES OF PERFORMANCE AND COORDINATION

To develop theoretically grounded, conceptually relevant indicators of coordination within the ASOC environment, the authors utilized the Rational Approach for Developing Systems-based Measures (RADSM; Orvis et al., 2013). The RADSM approach consists of six steps: 1. Identification of context and constructs; 2. Identification of construct indicators (behaviors and attributes) derived from previous theoretical work; 3. Identification of systems-based measures based on available data; 4. Development of measurement indicators which identify theoretical behaviors and attributes in the systems-based data; 5. Instantiation and application of indicators; and, 6. Validation. The remainder of this paper details each step of this process and how it was applied to measurement of ASOC teams.

RADSM 1: Identify Context and Construct of Interest

In this effort, the ASOC environment was identified as the context of interest. The ASOC plays a critical role in managing and effectively coordinating close air support (CAS) missions. The ASOC's main external coordination functions are with Army units – maneuver and/or field artillery (FA) – and with the Air and Space Operations Center (AOC). For CAS execution, the ASOC is the primary control agency of the Theater Air Control System (TACS), which is the Air Force's airspace C2 system. Collocated with the CORPS tactical operation center (TOC), the ASOC is responsible for keeping Tactical Air Control Parties (TAC-P) apprised of current and forecasted operations, updating the Army of the air situation, and employing air support.

The ASOC is comprised of multiple roles who coordinate internally and externally with a number of other roles. The key internal roles of focus in this paper include the Joint Air Request Net (JARN) operator, the Air Tasking Order Manager (ATOM), and the Procedural Controllers (PC). Additionally, the Joint Terminal Attack Controller (JTAC) and aircraft pilots, while external to the ASOC, are highlighted as key roles to consider in their interactions with the ASOC. Subject Matter Experts (SMEs) familiar with the functioning of ASOC teams and Air Force instructional documents (AFI 13-114 Vol 3, 2009) were used by the authors to map out an initial picture of coordination within the ASOC during CAS or XCAS missions (XCAS missions are on-call airborne alert missions as opposed to pre-planned CAS missions). Figure 1 provides an example of the coordination points for the roles of interest as information flows throughout the ASOC and with external actors.

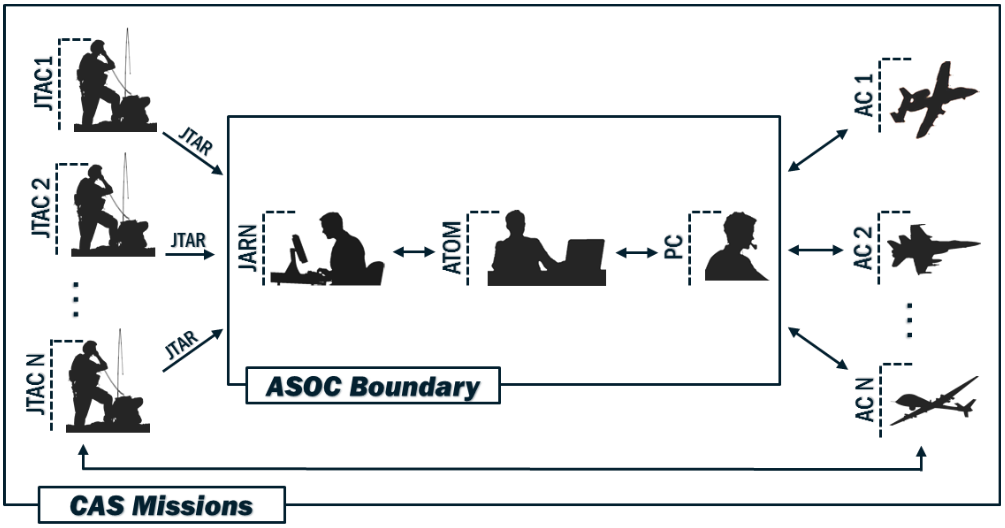

Figure 1: Coordination and information flow among ASOC members and external agents during CAS missions.

Information flows into the ASOC through the JTAC. Specifically, the JTAC sends a Joint Tactical Airstrike Request (JTAR), either voice or digital, which is processed by the JARN operator. The processed JTARs are then sent to the ATOM who pairs each JTAR to an aircraft, if available. Once a JTAR is paired with an aircraft, the PCs are responsible for communicating the mission and route to the aircraft, who then communicates with the JTAC regarding mission execution. After mission execution, the aircraft is responsible for reporting battle damage assessments (BDA) and expenditures back to the PC, who then provides the aircraft with information about transition and exit altitudes and corridors. While this description of the activities and information flow within the ASOC may be simplified, it highlights a number of critical coordination points among these key roles during a CAS or XCAS mission. Coordination breakdowns at any one of these points can cause the disruption of the process, and ultimately, lead to the failure of missions. As such, it is important to be able to develop measures of coordination that can be used to track the communication efforts within the ASOC and identify when coordination is breaking down.

To develop theoretically grounded and operationally relevant indicators of coordination that can be assessed in this environment, the next two steps of the RADSM process provide a conceptual overview of coordination, and relevant coordination behaviors supported by the literature (Step 2), as well as identify the data available from within the ASOC that can be used to assess coordination (Step 3). In Step 4, the conceptual coordination behaviors are considered in light of the available data from the ASOC context to identify and develop context-specific indicators of coordination.

RADSM 2: Develop Construct Indicators (Behaviors and Attributes)

Before developing a list of coordination indicators that are supported by the literature, it is important to first understand how coordination is defined more broadly. While the importance of coordination for the success of teams and organizations has been well documented (e.g., Marks et al., 2001; Mathieu et al., 2001), the way coordination is conceptualized varies across researchers. For example, various researchers define coordination as "The effective management of dependencies among sub-tasks, resources (e.g., equipment, tools) and people" (Espinosa, et. al., 2001); "Orchestrating the sequence and timing of interdependent actions. Involves pacing activities within determined temporal boundaries" (Marks, Mathieu, & Zaccaro, 2001); "Leveraging team members' familiarity with 'who knows what within the team' and allows teams to work together by directing information to the appropriate person, agreeing upon the way such information should be stored accessed, and by whom" (Mathieu, 2008); "The exchange of information between two or more team members through formal and informal and oral or written transactions in order to integrate their respective contributions" (Rico, et al., 2008); "Sequences of actions that different members perform to overcome a roadblock" (Cooke & Gorman, 2009).

When looking across these definitions, the target of the coordination activities is one high level bifurcation that exists in how researchers talk about coordination – the target may be information sharing or sequencing of actions. Specifically, while some researchers talk about coordination in terms of how information is exchanged among team members to integrate their respective ideas and perspectives (Rico et al., 2008), others focus more broadly on the sequencing of actions that team members perform to accomplish a goal or overcome a challenge (Cooke & Gorman, 2009; Marks, Mathieu & Zaccaro, 2001). While the emphasis on information sharing versus actions may vary across definitions, it is argued that effective coordination requires both. In fact, Rosen and colleagues (2011) discuss a number of general coordination markers that represent both information sharing and action. For example, coordination was suggested to be marked by the sequencing of team task behaviors to minimize downtime, as well as passing information to one another in a timely and efficient manner. Ultimately, at the core of these definitions, it is clear that coordination requires sequencing, timing, and a knowledge of what the right information or actions are, as well as the right person or people who need to be involved.

Beyond the definitions of what coordination is, it is also important to consider how coordination occurs within teams and organizations. The literature describes two ways by which individuals and teams can coordinate – explicitly or implicitly. Explicit coordination requires some form of communication and focuses on information sharing or actions that are taken in response to requests (Butchibabu, 2016; Serfaty, et.al., 1993). In other words, information or actions are pulled from others through prompts, requests, questions, or commands communicated from someone else. Explicit coordination may include activities, such as planning or strategizing, which are undertaken with the specific intention of managing or directing task-directed behavior (Fisher et al., 2012; Rico et al., 2008). Specifically, explicit coordination might include activities such as one or more team members asking questions about what to do next, asking for assistance or backup, negotiating or discussing timelines, or requesting information from others about their individual tasks to be able to sequence actions across team members.

Conversely, implicit coordination represents the ability of team members to act in concert without the need for overt communication (MacMillan, Entin, & Serfaty, 2004; Rico et.al., 2008). When individuals coordinate implicitly, they are able to anticipate what is needed by other team members and proactively act or push information to others without being asked (Serfaty, et.al., 1993; Entin et.al., 1999). To do this effectively, team members have to have a shared mental model of the task and role responsibilities to be able to operate based on unspoken assumptions about what others on the team are likely to do or need (Espinosa, et.al., 2001). For example, team members might proactively provide status updates to other team members who need that information to effectively move forward with their own tasks (Entin & Serfaty, 1999). While implicit coordination does not preclude communication, it does lend itself to team members being able to more dynamically adapt, adjust, and synchronize their actions during a task without the need for explicit communication. Butchibabu (2016) broke down implicit coordination further based on the type of information that is being shared. Specifically, Butchibabu noted that deliberative-implicit coordination is focused on the anticipatory action and communication of goal-related information among teammates, while reactive-implicit coordination is focused on proactively acting on and relaying updates on the current state when triggered by changes in the environment.

While both explicit and implicit coordination can be effective, explicit coordination requires more cognitive resources than implicit coordination due to the need for individuals to pull information from others (MacMillan, Entin, & Serfaty, 2004). As such, implicit coordination has been shown to be more beneficial for performance when teams are under greater time pressure or operating in highly demanding environments, like the ASOC. However, implicit coordination requires a level of familiarity and shared understanding that is likely to be limited in newly formed teams, in teams containing newly integrated synthetic agents, or in teams where members are frequently replaced. As such, it is important to consider the types of conceptually-relevant behaviors that would represent either aspect of coordination.

Additionally, when considering the behaviors or attributes that best represent coordination, it is also important to consider that coordination can be viewed and assessed as either a process – that is, acts of coordination – or as an outcome – that is, the effectiveness, or success, of coordination (Espinosa, et.al., 2001). When coming from a team process perspective (e.g., Marks et al., 2001), coordination is a process that should be measured by assessing the behavioral acts of coordination, rather than focusing on the evaluative component of success. Ultimately, however, both elements are important for the overall success of the mission. As such, in addition to identifying the process-focused behaviors and attributes of coordination, the authors have also provided a list of more evaluative, outcome-focused attributes that might be considered when developing a coordination measure.

Based on the conceptual work reviewed above, the authors have identified a set of construct behaviors and attributes relevant to the construct of coordination. Examples of these behaviors and attributes, listed in Table 2 below, have been organized into the four categories described above: explicit coordination, deliberative-implicit coordination, reactive-implicit coordination, and coordination success (outcomes). These conceptually-driven behaviors and attributes are used as the basis for identifying context-specific indicators of coordination that are relevant to, and feasible to assess within, the ASOC environment.

Table 1. Example coordination behaviors and attributes from the literature

Construct	Example Attributes/ Behaviors
Explicit Coordination	Requesting or prompting team members for information or actions. Asking questions about what to do next, what information is needed, etc. Providing direction on what team members need to do next. Commanding other teammates to perform actions. Transferring information and resources in response to an explicit request.
Implicit – Deliberative Coordination	Providing task-relevant information to other team members without an explicit request. Proactive communication of intentions related to goals. Proactive communication about upcoming goals or steps in a process. Taking the next step/action without being prompted, told, or asked. Appropriately prioritizing actions and information based on understanding of situation/goals.
Implicit – Reactive Coordination	Sending status updates (about where you are, what is going on, etc.) to team members. Re-syncing behaviors in the face of a change without need for explicit communication. Using existing knowledge of protocols or processes to know when a status update should be sent out (based on timelines, priorities, etc.).
Coordination Success (Outcome)	Team members get the information they need from other members in a timely fashion. Implicit communication is greater (increases) under high complexity situations. Explicit communication is less (decreases) under high complexity situations. Ratio of implicit to explicit coordination increases under high complexity. Deadlines are met.

RADSM 3: Identify System-based Information

The third step of the RADSM process involves assessing what systems-based data is available within the context of interest. In this case, the goal is to compile a list of the types of data that can be captured and used within the ASOC environment to assess coordination. The data types described in Table 3, below, were identified through discussions with SMEs familiar with the ASOC environment and from Air Force instructional manuals (e.g., AFI 13-114 Vol 3, 2009). For each data type listed, the source of that data is identified as well as a description of the nature of the data and data features that can be extracted to be useful for measurement development. The goal is to use the different data features to develop a range of coordination indicators that can be assessed within the ASOC. The Sociometric Badges, mentioned in the table, are wearable sensor packages that provide a range of information regarding social interactions, such as proximity to other individuals, time spent talking, and movement (See Olguin & Pentland, 2008 for more information).

Table 2. Example Systems-based Data Available within the ASOC Environment

Data Type	Data Source	Data Feature(s)	Information Extracted from Data
Face-to-face interaction	Sociometric Badge: Infrared (IR) sensor	• IDs of people interacting face-to-face • Time stamp (and duration) of interaction	Who is interacting face-to-face; when an interaction occurred; how long the interaction lasted

Data Type	Data Source	Data Feature(s)	Information Extracted from Data
Physical proximity	Sociometric Badge: Bluetooth (BT) sensor	• IDs of people within close proximity of each other • Time stamp (and duration) of when they were in close proximity	Who is near whom; when two or more people were in close proximity; how long they were in close proximity
Face-to-face vocal communication	Sociometric Badge: Audio sensor	• IDs of people talking • Time stamp of when they were talking • Vocal characteristics (tone, pitch)	Who is speaking to whom; when they are speaking; what tone they were speaking in; how long they were speaking
Individual physical movement	Sociometric Badge: Accelerometer	• IDs of people • 3-axis accelerometer readings • Time stamps	Who is moving or active; when they are moving or active; how long they are moving or active; whether two people are moving or active at the same time; possibly mimicry (one person moves after another person moves)
Email	Microsoft Outlook (or other email client)	• Sender/receiver of an email • Time stamp (when sent) • Subject content • Body content • Attachments	Who sent messages to whom; who received messages from whom; how many people the same messages were sent to; when messages were sent; what (the content) of the message title and body included; how the message was communicated
Text Chat	IRC (or other chat client)	• Sender/receiver of a chat • Chat room • Time stamp (when sent) • Message content	Who was present in a chat room when a message was sent; who sent messages to a specific person or a chat room (and which room); when chat messages were sent; what (the content) of the chat message included; how the message was communicated
VoIP call logs	Cisco Call Manager	• Names of people on call • Time stamps (start/end) of call	Who was participating in the call; when the call occurred; how long the call lasted

RADSM 4: Develop Measures and Measure Components

The fourth step of the RADSM process consists of matching the construct indicators identified in Step 2 to the data sources identified in Step 3 for the purpose of creating objective “indicators” or “metrics” that can be used to assess coordination within this environment. Similar to a survey measure of a construct that contains multiple items, the goal is to create multiple indicators or metrics of coordination using the available systems-based data. When developing these metrics, the authors focused specifically on identifying indicators that could assess the coordination happening between each pair of key roles (e.g., coordination between ATOM and PC) whether they are human or synthetic agent. By identifying indicators that can be assessed at the dyadic level, it will provide the opportunity to aggregate the coordination indicators up to the team or system level to provide a more global assessment of coordination within the ASOC. The goal was to develop a small set of possible coordination indicators for each type of coordination identified in Step 2 above.

To do this, the authors observed ASOC training in the JTAGSS and discussed the ASOC environment, CAS, and XCAS mission processes with SMEs to determine typical behaviors and systems used by the ASOC team in the completion of their tasks. The initial focus is on indicators of explicit coordination, as they are more easily observable in the ASOC environment, though development of implicit coordination indicators proceeds in a similar manner. Through dissecting the processes performed by the individuals depicted in Figure 1, the team developed a series of elements for consideration. The first is the sequence of activities, specifically targeting the flow of communication across individuals within the ASOC. The second element is the timing of behaviors, targeting whether they were provided at the appropriate time given the part of the mission. The third element refers to the steps and actions preformed with regard to a specific mission request and whether the roles are performing the tasks that should be done at that moment. The final element is prioritization, which aims to capture whether coordination activities are taking into account the multiple simultaneous demands on the ASOC and responding appropriately. Additionally, the team also considered the impact of the time of the mission in when this behavioral indicator would occur given that there may be differences in the correctness of behaviors based on when an action occurred. For example, it would be beneficial for the PC to communicate with the ATOM regarding upcoming missions post-mission, not during a mission. Table 4 provides the cursory indicator list for explicit coordination behaviors within the ASOC. For each of these indicators there will be an associated rating scale. For example, at the low end it would be that the individual, dyad or team failed to complete the behavior, in the middle of the spectrum would be an indication of the behavior being completed but slowly or not to the fullest extent, and at the high end of the spectrum would be the effective completion of the behavior.

Table 3. Example Indicators of Explicit Coordination

Mission Elements	Mission Timing	Example Behavioral Indicator
Correct Sequence	Pre-mission	JARN confirms JTAR received from JTAC JARN lets the ATOM know when a new JTAR is in the system ATOM informs PC that an aircraft is paired with a JTAR
	During mission	PC reports back to ATOM after communicating mission to aircraft PC hands over communications with aircraft to JTAC during mission
	Post-mission	PC communicates BDA to ATOM
Correct Timing	Pre-mission	PC reviews the ATO at the beginning of a day
	During mission	PC manages aircraft until it gets to where it needs to go for handoff to JTAC
	Post-mission	JTAC checks out with aircraft after mission is completed
Correct Steps/ Actions	Pre-mission	JTAC sends JTAR or information to create JTAR to JARN JARN processes each JTAR JARN completes or finalize JTAR in TBMCS ATOM assigns aircrafts to JTARs
	During mission	PC tracks aircraft in the airspace PC checks that the call signs match for the aircraft that should be in a particular space PC communicate information to aircraft about the mission Aircraft checks in with JTAC for mission execution
	Post-mission	Aircraft reports mission results (mission BDA, expenditures, etc.) back to PC PC provides transition and exit altitudes to aircraft after mission
Correct Prioritization	Pre-mission	JARN prioritizes multiple JTARs that come in "simultaneously" from the JTACs ATOM prioritizes multiple JTARs that come in "simultaneously" from the JARN ATOM assigns aircrafts given prioritization of missions
	During mission	PC manages mission while preparing for next mission PC manages re-tasking mission request
	Post-mission	PC communicates BDA to ATOM while prioritizing upcoming mission

While ratings on each of these indicators could be performed and aggregated by an expert observer or through surveys, one of the goals of this study is to utilize virtual and face-to-face communications to unobtrusively assess these items. To that end, the next step of the process utilizes software and algorithmic approaches to identify occurrences and rate these indicators within the communications data.

RADSM 5: Instantiate Measures

The fifth step of the RADSM process involves the specific instantiation of the systems-based metrics in algorithmic form and in software using the data collected from the environment. In general, instantiation of these indicators can utilize a variety of analysis techniques, from network analysis, to natural language processing, to time series analysis. For example, using natural language processing, one may identify if the correct dialog is used when the PC conveys transition and exit altitudes to the aircraft. Through time series analysis, one can identify the timing of communications to determine if proper doctrine was followed. For example, after the PC receiver BDA from an aircraft, does the PC convey that information back to the ATOM within the correct timeframe? Finally, through social network analysis one can provide a variety of methods for identifying coordination processes and breakdowns. For example, one may see that the network distance (in the graph theoretical sense) between the PC and the JARN is lower than expected, which may indicate a breakdown in the communication chain with the ATOM (who should ideally mediate communications between those two positions). Note that the inherent "messiness" in data, and especially, communications data, can make instantiation of measures using these approaches non-trivial. It may be the case with indicators utilizing natural language processing, for example, that one must consider a tradeoff between true positive and false positive probabilities of detection.

As an example measure, consider one behavioral indicator in Table 4, "JARN lets the ATOM know when a new JTAR is in the system." One can instantiate this within the data by first considering the set of chat (for example) communications from the JARN to the ATOM. Let's denote this set of communications as $C^{J \to A}$. Next, the goal is to identify the subset of these communications that contain mention of a JTAR. Denote this subset as $C^{J \to A}_{JTAR}$. These messages could be identified by use of the word "JTAR" or by mention of an id for a specific JTAR. The next step is to compare the number of these messages to the actual number of JTARs processed by the ATOM. Denote this number as $|JTAR|$. Then, a measure of the percent of JTARs processed of which the JARN informs the ATOM can be written as:

$$M_1 = \frac{C^{J \to A}_{JTAR}}{|JTAR|}$$

This example is a fairly simple measure that could be refined by additional analysis. For example, one could only look at communications that occur within a short time frame after the JARN has finished processing a JTAR. Or, one could apply more sophisticated natural language processing techniques to identify when the JARN is declaring that a JTAR is ready versus asking a question about a previous JTAR.

RADSM 6: Validate Measures

The final step in the RADSM process is to validate the data and systems-based metrics developed in the preceding steps of the process. Validation of these sort of measures necessarily requires large sets of data that can provide both sufficient examples of the observed behavior as well as ground-truth on the outcomes or processes of interest. In this effort, real data from the JTAGSS environment was not available at the time to effectively validate the measurement indicators. As such, the team developed a process, based on Monte Carlo methodologies, to generate sample communication data between roles within the ASOC.

Monte Carlo simulations (see Mooney, 1997 for further background reading) of a system utilizes random sampling (of the input data, of the simulation parameter space, or both) to repeatedly generate simulation results. While each simulation run may be deterministic in nature, the resulting ensemble of results can provide insight into the dynamics of the system (such as the sensitivity of parameters or initial conditions). In this work, the goal was to utilize a Monte Carlo inspired approach to generate sample communication data sets of roles within the ASOC. These data are then used to test the behavioral items instantiated in Step 5 of RADSM to determine their feasibility as indicators of coordination. While this does not provide validation against real-world data, it does provide some degree of confidence in the sensitivity and robustness of the indicators (e.g., an indicator that varies little across Monte Carlo simulation drawn from both "good" and "bad" scenarios is not likely to be a useful indicator in real-world settings).

This approach begins by first identifying a set of high-level scenarios that represent both "good" and "bad" coordination (as determined by an SME). For example, a "good" scenario might assume that all roles can complete their tasks quickly, hand off information to the appropriate roles, fulfill requests in a timely manner, etc. A "bad" scenario may center on an ATOM who is able to complete his or her tasks quickly, but does not pass that information on to the PC. Rather, he or she waits until the PC prompts him or her for the aircraft information. Using these scenarios, a simulation of communications was developed with parameter distributions representing critical actions and behaviors, such as time spent on task, communications with other members, passing of critical information, etc. The particular distributions vary based on the scenario (for example, in a scenario where the JARN fails to pass information quickly to the ATOM, the parameter distribution representing communications between those individuals would be skewed to the lower end). Monte Carlo simulations are then used to generate a number of data sets for each scenario, against which the behavioral indicators can be tested. One such simulated network is presented in Figure 2.

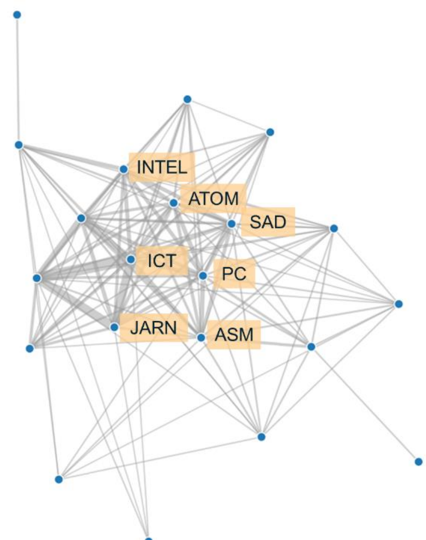

Figure 2. Network of communications produced from a Monte Carlo simulation.

Further work is required to fully process the results of the simulations, but initial results indicate that this is an effective method to simulate data for preliminary validation. Inevitably, real data will be needed to effectively validate the measures with a high-degree of confidence. In subsequent efforts, the authors plan to collect data from several JTAGSS training events for just this purpose.

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