Case Based Disruption Monitoring

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Abstract. Mine countermeasures (MCM) and Unmanned Combat Logistics (UCL) missions take place in very complex and uncertain environments which poses complexity for planning and explanation algorithms. In order to keep a mission on target, constant monitoring and frequent schedule adjustments are needed. To address this capability gap, we have developed the Case-Based Disruption Monitoring and Analyzing (CDMA) algorithm. The CDMA algorithm automatically detects disruptions within a mission and attempts to determine possible root causes. Once confirmed, our second developed algorithm, CLOSR modifies existing schedules to compensate for these root causes. Evaluation of CDMA on simulated MCM operations demonstrates the effectiveness of case-based strategy.

1 Introduction

Unforeseen disruptions occur when planning in the real world. When monitoring for such disruptions and providing an explanation as to why the disruption occurs, better insight is provided in order to fix the plan. Mine Countermeasure Missions (MCM) for example, uses planning constantly. MCM planning uses a variety of resources and each resource has its own set of capabilities and operational constraints, as well as characteristic failure points.

Mine Countermeasure Missions (MCM) missions must respond to frequent disruptions, and recovering to these disruptions can be complex. MCM missions involve the location, identification, and neutralization of enemy explosive ordnance in a maritime context. This is key to naval power projection and sea control, two core capabilities of U.S. maritime power, as characterized by *A Cooperative Strategy for 21st Century Seapower* [4]. Due to high complexity and uncertainty when scheduling MCM missions, accurate plans must be created and frequently revised once a mission has started. Frequent disruptions in MCM operations can occur due to many types such as: changes in sea state, visibility, weather, equipment failure, etc. Situations like these interfere with resource availability and/or readiness. Therefore, schedules for MCM operations require frequent changes and updates where the disruptions are monitored in order to keep the success of the mission. Current practice calls for manually observing all incoming data for detection of issues that could cause a mission to fail. The manual process prevents thorough exploration of disruptions.

Unmanned Systems have shown their value in combat operations by keeping warfighters from harm's way and delivering unprecedented mission performance [11]. The increase in the volume of their deployments has been exponential. For some unmanned vehicles, 4-8 operators can be required to command a mission [11]. In addition to this scalability problem, complex mission plans need created. These plans require multiple vehicles, crews, and equipment in order to complete the mission. This requires changes throughout the mission and again a manual process to tediously re-align the components of the mission for success.

To meet both needs, we are developing a system for both MCM and UCL operation decision making and planning support called KRePE. KRePE builds upon a foundation of cognitive architecture components and algorithms to perform the real-time monitoring, analysis, and rescheduling tasks that MCM planners and UCL operators perform on a frequent basis. KRePE is the first systems to support interactive rescheduling of entire MCM and UCL operations.

In this paper, we discuss the challenges of continuous situation monitoring, and root cause analysis of mission disruptions through case-based reasoning. We close with an empirical study that demonstrates this effective real-time anomaly detection in order to generate schedule modifications that achieve mission success.

2 Mine Countermeasures Mission Scheduling & Operations

MCM operations involve the location, identification, and neutralization of sea mines [5]. These operations employ surface vehicles, aircraft, divers, and unmanned vehicles, and can take weeks to plan and execute. While the operations are taking place, they are disrupted early and often by events such as unforeseen weather conditions, technological failures, and incorrect enemy course of action estimations. While technology exists to automatically create an initial schedule, distribute tasks, and track task completion, the critical monitoring and rescheduling tasks have been, to date, poorly supported [6].

MCM operations involve a unique set of specialized tasks that must be scheduled to minimize the risk to ships from sea mines. What follows is a brief description of the tasks in an MCM operation and their characteristics. The schedule for an MCM operation tasks multiple vehicles to repeatedly *hunt* and/or *sweep* subsections of a specified *threat area* where mines are expected, slowly transiting back and forth in a lawnmower-like search pattern, until the risk of remaining mines is reduced to an acceptably low level. The paths followed by these search vehicles are referred to as *tracks*.

Hunting is a search and destroy activity that encompasses, use of specialized sensors to find underwater objects that are *mine-like*, identification of mine-like objects as *mines* or *non-mines*, and neutralization of all discovered mines. The *probability of detection* describes the equipment's sensitivity within that range to the size and reflectivity of mine casings. Because mines may be missed, missions are commonly evaluated according to a *percent clearance* objective. Percent clearance is defined as the probability that a mine at any given position in the search area will be detected.

Sweeping is an activity that uses specialized apparatus to destroy all mines present in a given area either by cutting the chains that connect them to the ocean floor or employing signal generators which mimic the magnetic and acoustic signatures, of ships, to trigger mines that are activated by those signatures.

The operation schedule, which may consist of hundreds of tasks of heterogeneous types, must be repeatedly adjusted over the course of the operation in response to unexpected events which invalidate it. The task of keeping the schedule up to date despite hundreds of interrelated tasks is complex, difficult, and laborious, particularly given the constant time pressure of typical operations. Modifications to schedules are kept to a minimum, in order to reduce expense and opportunities for error; we refer to this characteristic as *minimal operational disruption*. However, modified schedules must also fulfill operational requirements such as percent clearance, time limits, and risk to equipment. These difficult tasks (i.e., monitoring, response, and rescheduling) can be greatly aided by new computational tools.

3 Unmanned Logistical Combat Systems

Unmanned systems have been frequently demonstrated in combat operations, where they keep warfighter personnel from harm and delivering unprecedented mission performance [11]. Unmanned system applications range from enhanced battlespace awareness, to logistics support. Unmanned Combat Logistics (UCL) missions focus on resource management and delegation among battlefields and stationed posts. While the operations are taking place, disruptions can take place by events such as unexpected fuel loss, technological failures, and unavailable crew members needed for cargo unloading. UCL missions involve tasks that must be scheduled to distribute resources while making sure schedule conflicts between requests do not exist.

4 CDMA

One way to reduce the burden on MCM and UCL operators is to help with constant monitoring of disruptions that will impact the mission. Constant monitoring of a vast array of disruption types can be quite difficult. In addition to detecting the disruption, diagnosing the root cause of the problem can be daunting, or easily overlooked. Case-Based Disruption Monitoring and Analyzing (CDMA) handles both disruption monitoring and providing possible root causes.

Case-based reasoning (CBR) is a problem solving paradigm that relies on general knowledge of a problem domain along with specific knowledge examples, or cases. These cases consist of a mapping between problems and a solution. When a new problem is introduced, generally CBR systems maps this new problem to the most similar problem case already stored in its knowledge base and provides a solution associated with the known problem. We describe the knowledge representation and the CDMA algorithm in detail in the following subsection.

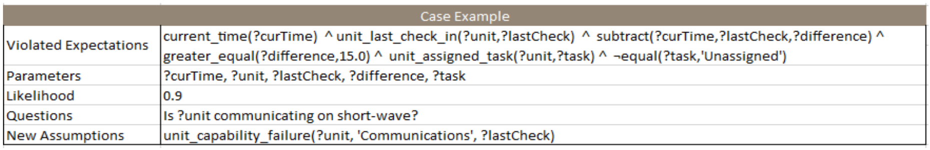
4.1 CDMA Representation

CDMA uses case-based reasoning for monitoring and analysis of disruptions that will impact an ongoing operation. Based on current assumptions and observations of the world, the CDMA algorithm determines if a disruption has occurred. A disruption case in our system consists of three parts: the problem, solution aid, and a solution. The problem consists of two parts: violated expectations and parameters. The solution aid consists of three parts; the root cause likelihood, root cause questions and parameters. And lastly, the solution consists of new assumptions and parameters.

The problem is specified as a list of violated expectations and a list of variable parameters. The case applies when all of the violated expectations are met; and the parameters indicate which variables are applied to a specific problem instance. An example problem representation is shown in Figure 1. In this example, there is disruption where the operator has not heard from unit within the past 15 minutes while it was out in the field performing a task.

The solution aid consists of a likelihood and list of root cause questions. This information can be accessed by an operator through an interactive decision making process. The likelihood provides an apriori probability of how likely a particular root cause is for a given disruption. The root cause questions provide a set questions that can help the operator deduce what is causing the disruption. The parameters that were used in the problem aspect of the case populates the variables within the questions, detailing the questions to a specific unit, piece of equipment, etc. If these questions are answered, the likelihoods for the root causes adjust to this information. Using the example from above, Figure 1 provides the entire case representation.

The solution is specified as a list of new assumptions and a list of variable parameters. The new assumptions are a set of suppositions or beliefs as to which root cause explains the disruption. The parameters are those from the violated expectations instantiating the problem information into these new assumptions.



	Case Example
Violated Expectations	current_time(?curTime) ^ unit_last_check_in(?unit,?lastCheck) ^ subtract(?curTime,?lastCheck,?difference) ^ greater_equal(?difference,15.0) ^ unit_assigned_task(?unit,?task) ^ ¬equal(?task,'Unassigned')
Parameters	?curTime, ?unit, ?lastCheck, ?difference, ?task
Likelihood	0.9
Questions	Is ?unit communicating on short-wave?
New Assumptions	unit_capability_failure(?unit, 'Communications', ?lastCheck)

Fig. 1. Case Representation for CDMA algorithm.

With the use of a standard relational database called the Integrated Rule Inference System (IRIS)[8], CDMA can reuse case(s) in the problem space without having to generate new cases for each set of parameter values. From the example, we do not need to create new cases for each type of equipment or unit, as it can handle all of the parameters. When monitoring detects a disruption, it alerts operators with a message. After alerting the operator, CDMA adds the confirmed root cause assumptions to the knowledge base. These new assumptions trigger schedule repair to occur because the disruption affects the mission.

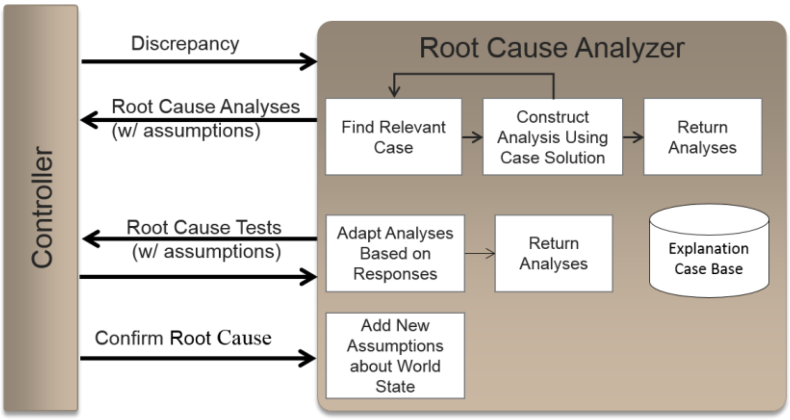

Controller
Discrepancy
Root Cause Analyses (w/ assumptions)
Root Cause Tests (w/ assumptions)
Confirm Root Cause
Root Cause Analyzer
Find Relevant Case
Construct Analysis Using Case Solution
Return Analyses
Adapt Analyses Based on Responses
Return Analyses
Explanation Case Base
Add New Assumptions about World State

Fig. 2. Workflow for CDMA algorithm.

4.2 CDMA Algorithm

CDMA performs the following steps for disruption monitor and analysis as shown in Figure 2:

1. ***Find Relevant Case***: To find a possible disruption, CDMA searches through the list of cases finding a relevant case that matches a violated expectation. Each case that matches provides a possible root cause for the disruption.
2. ***Construct Analysis Using Case Solution***: To analyze a disruption, the parameter values indicated by a specific violated expectation are substituted for the variable parameters specified by an individual case problem.
3. ***Return Analyses***: Each possible disruption is provided on screen for the user to review, detailing the types of root causes for the disruption, along with additional information such as root cause tests and likelihood for each cause.
4. ***Adapt Analyses Based on Responses***: Optional step and can be repeated. Users can answer these root cause test questions in order to better understand the disruption, adjusting the likelihoods of the root causes.
5. ***Return Analyses***: If Step 4 is performed, the system returns updated likelihoods, sorted with highest likelihood first, along with clearing out infeasible causes.
6. ***Add New Assumptions about World State***: After confirming, the selection of a root cause for a disruption creates new assumptions about the world and why the disruption occurred. These new assumptions are added into the knowledge base of the agent, providing new information that can be used to generate schedule repair if necessary.

5 CLOSR

To repair schedules that meet the criterion of minimal operation disruption, we use the Case-Based Local Schedule Repair (CLOSR) algorithm [10]. After CDMA creates new assumptions, the CLOSR algorithm uses a case-based strategy to apply previously generated schedule minimally disruptive schedule repairs. Subsequent to case reuse, an adaptation process examines and resolves conflicts created by the schedule repair procedure. This algorithm is useful for its speed and flexibility. For more detail, please see prior work.

6 Evaluation

We hypothesize that the discrepancy monitoring and analysis capabilities of CDMA are both necessary and sufficient to achieve stated objectives despite the occurrence of disruptive events. To demonstrate this, we ran the CDMA algorithm in an automated manner on a series of simulated MCM and UCL operations. For each, we measured and compared the performances of three decision makers: (1) a decision maker that ignores all alerts and keeps the original schedule, (2) a decision maker that acknowledges disruptions and chooses a random root cause from those suggested and (3) a decision maker that acknowledges the disruptions and chooses the root cause with the highest likelihood. The contrast indicates the performance improvement that can be achieved by adopting the recommendations made by the CDMA algorithm.

Our study examines an MCM mission with a mine clearing objective. As it is impossible to ensure that 100% of mines are removed in the real world, missions are planned to achieve a high level of percent clearance. This means that there is a high chance that a mine at any given point in the search area would be observed if it existed. The operations conducted in our study are intended to achieve a 95% clearance level; in other words, we would expect 95% of the mines present to be removed. We hypothesize that the decision maker using KRePE case-base will achieve these performance objectives, and that the decision maker that ignores the disruptions will not. This will demonstrate both that monitoring and analyzing disruptions is necessary to achieve an acceptable level of performance under simulated conditions, and that the system is sufficient to achieve that performance.

For a UCL mission for unmanned aircraft with resource management objectives, we hypothesize that the decision maker using KRePE's CDMA algorithm will achieve mission objectives, and that the decision maker that does not reschedule will not. This will demonstrate both that monitoring and analyzing disruptions is necessary to achieve an acceptable level of performance under simulated conditions, and that the system is sufficient to achieve that performance.

6.1 Experimental Framework

A simulator for MCM operations, Search and Coverage Simulator (SCSim), was developed at Knexus Research Corporation to support rapid and repeated evaluation and testing of MCM decision support systems and component algorithms. SCSim simulates search missions involving multiple heterogeneous search units, including ships and helicopters, each with different available equipment configurations. Mines and mine-like objects are distributed randomly by SCSim in fields and lines according to pre-set distributions with variable density and object counts. This facilitates evaluation of algorithm performance under varying operating conditions. As a benchmark, automated testing of a two month operation takes less than one minute.

SCSim simulates the assignment of parameterized tasks to units according to a schedule, including transit, sweep, and hunt tasks. Task parameters include, for example, the equipment to use for sweeping, and sensor depth for hunting. To simulate a mission, SCSim automatically generates appropriate tracks for each task and simultaneously changes the position of each vehicle along its assigned tracks. Observations (e.g., contacts) are generated based on vehicle's positions and the sensor equipment in use. Interactions of deployed sweeping equipment is also simulated, and changes the internally represented status of mines. In addition to the scheduled tasks, SCSim is responsible for simulating random events, the unexpected difficulties that invalidate an existing schedule. Examples of such events include equipment failure, bad weather, and operator errors.

An individual mission test using SCSim is controlled by a scenario description. Scenario descriptions include, at a minimum, the vehicles and equipment available for use, threat areas to be cleared of sea mines, and task areas where vehicles will operate. Other elements of the scenario specify random distributions for mine like objects, mine line placements, and events that may occur. To mimic the real world as closely as possible, SCSim provides only partial observations for the purposes of rescheduling. For example, when a helicopter's communications system fails, its position is no longer reported to the system. As a result, the helicopter appears not to move.

Experiments in KRePE are driven by a test harness that integrates with SCSim as shown in Figure 3. The test harness takes scenario parameters as input, which specify the area of operations, available assets, and the ranges of random experimental variables, such as what mine types will be deployed and when events will trigger. The Test Generator uses these parameters to generate a set of random scenarios. The Test Runner enacts each scenario by initializing SCSim and an appropriate Decision Maker that acts as a user of the system. Each decision maker encodes different responses to situations, such as alerts, that arise during the mission simulation. To compare the performance of different decision makers, every decision maker is run through the same pool of randomly generated scenarios. As each simulated mission completes, metrics are collected and recorded. After all simulated missions are complete, the Performance Evaluator tabulates and summarizes these results in a human readable form.

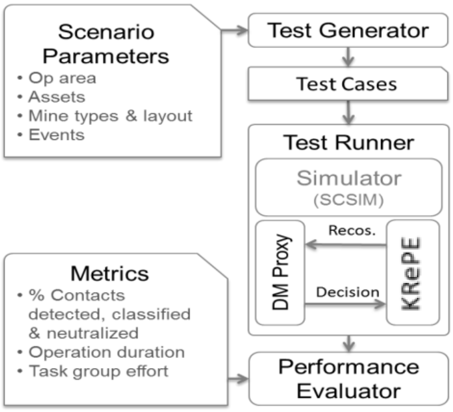


Fig. 3. KRePE simulation driven evaluation

6.2 KRePE UCL Setup and Results

A simulator for UCL operations, Anomaly Detection and Recovery for Unmanned Systems Simulator (ADRUSSim), was developed at Knexus Research Corporation to support rapid and repeated evaluation and testing of UCL decision support systems and component algorithms. ADRUSSim simulates combat logistics missions involving multiple heterogeneous Unmanned Aerial System (UAS) units, each with different available equipment configurations.

ADRUSSim simulates the assignment of parameterized mission requests to units according to a schedule, including retrieving cargo and delivering cargo and returning. Task parameters include, for example, the destination and resources used in a mission. To simulate a mission, ADRUSSim automatically generates appropriate schedules for each mission request. Observations about the world are generated based on vehicles' positions and the sensor equipment in use. In addition to simulating scheduled tasks, ADRUSSim is responsible for simulating random events, the unexpected difficulties that invalidate existing schedules, such as equipment failure, fuel loss, and unavailable crew for unloading cargo.

The KRePE system thus far demonstrates that having the CDMA algorithm in place monitors and detects disruptions along with providing schedule fixes for these disruptions. Preliminary test runs indicate that missions are more often successful when these schedule repairs are conducted. However, we have yet to run experiments to confirm this hypothesis statistically.

6.3 KRePE Experiment Setup

Our KRePE experiments used three decision makers and ten randomly generated test scenarios. The first decision maker, “KRePE DM”, confirms the correct root cause with the highest disruption likelihood and selects a new schedule from those generated to activate. The second decision maker, “Random DM”, randomly chooses a root cause and selects a new schedule from that root cause. The third decision maker, our baseline, “Ignore DM”, ignores KRePE’s recommendations, never changing its schedule when prompted. Comparing performance of these three decision makers allows us to measure the efficacy and correctness of schedules generated by case-base disruption monitoring system.

The performance of each decision maker was evaluated in each of the ten randomly generated scenarios, generated as summarized in Table 1. Scenarios differ primarily in the thirty random events that occur, and the positions of mines and mine-like objects. Each event was additionally parameterized with a trigger time (chosen randomly over the first six-hundred hours of the mission) and target unit (chosen randomly among the six tasked assets). The times were chosen in this fashion because events that occur when a unit has already performed all its tasks cause no problems, and therefore are uninteresting to our study. Four mine lines at various depths and mine types were placed randomly in each scenario, each with a length (i.e., mine count) between ten and thirty.

The fixed parameters used in all scenarios included the area searched, and seven assets, consisting of four helicopters, two MCM ships, and one support ship that performs no tasks itself. Each ship and helicopter has available equipment for hunting mines, contact sweeping, detection, and mine neutralization.

6.4 KRePE Metrics

We evaluated KRePE DM, Random DM, and Ignore DM using the following three metrics: (1) *Percent contacts detected:* This measures the percentage of mines detected by a unit; (2) *Percent mines neutralized:* Percentage all mines are neutralized by a unit; (3) *Operation duration:* Total simulation time required to complete the operation.

The first two metrics are calculated based on the true number of mines and mine-like objects generated in the scenario. These summarize the plan's effectiveness in terms of how well the MCM mission goal of searching for and eliminating mines was achieved. Each scenario generated includes a large number of non-mine mine-like objects uniformly spread throughout the threat area, so the percent contacts detected value is an approximation of the percent clearance, or probability that a mine would be detected at any given location. The third metric, operation duration, illustrates a plan's efficiency by measuring the total simulation time required to complete all tasks.

6.5 KRePE Results

Experiments were run on an i7 processor laptop, taking one hour to complete. The results of our experiments are summarized below. Figure 4 shows a scatter plot that displays the percentage of existing contacts that were detected and duration of each mission operation. It is clear that the duration of an operation performed by Ignore DM varies little, as the original schedule is never updated, whereas the duration of KRePE DM and Random DM missions may vary greatly. A schedule can be lengthened dramatically when new mine types have been discovered; to ensure safety, many new hunt and/or sweep tasks must be introduced to clear the additional mines. Similarly, if vehicles are damaged beyond repair, the diminished resources can greatly increase mission length. The increased time and repaired schedules allow KRePE DM to outperform Ignore DM by classifying between 95 and 100% of the mine like objects in every mission. Random DM, like KRePE DM, responds to disruptions, but because it does not choose the most likely cause, its task performance is not as high as KRePE DM's. Note that neither Ignore DM nor Random DM represents any real human decision maker; rather these results should be interpreted to show the difficulty of the task and that CDMA's suggestions are benefitting mission performance.

Table 1 shows the average and standard deviation for each metric and decision maker, along with a confidence value. These confidence values are obtained from a one-tailed t-test with paired examples, and indicate the (small) likelihood that Ignore DM might on average achieve higher values than KRePE DM if many more experiments were undertaken.

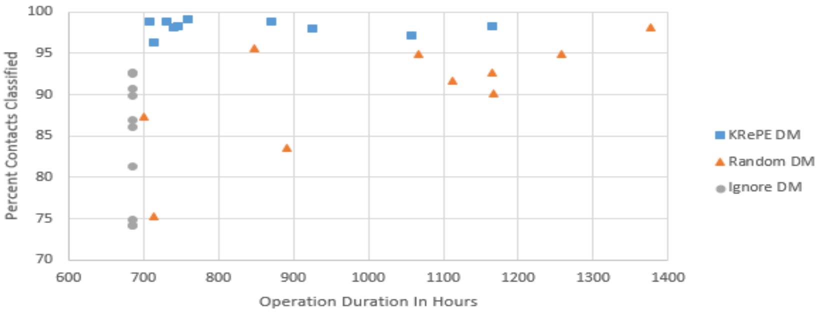
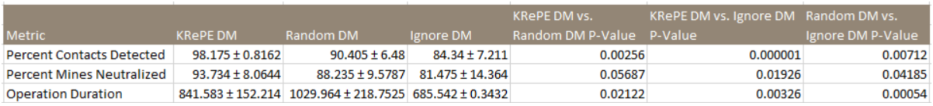


Fig. 4. Scatter Plot of Operation Duration to Percent Contacts Detected

Table 1. KRePE Results



Metric	KRePE DM	Random DM	Ignore DM	KRePE DM vs. Random DM P-Value	KRePE DM vs. Ignore DM P-Value	Random DM vs. Ignore DM P-Value
Percent Contacts Detected	98.175 ± 0.8162	90.405 ± 6.48	84.34 ± 7.211	0.00256	0.000001	0.00712
Percent Mines Neutralized	93.734 ± 8.0644	88.235 ± 9.5787	81.475 ± 14.364	0.05687	0.01926	0.04185
Operation Duration	841.583 ± 152.214	1029.964 ± 218.7525	685.542 ± 0.3432	0.02122	0.00326	0.00054

7 Related Work

Case-based reasoning [1] is a family of intelligent algorithms based on the adaptation and application of known solutions to new problems. It has been applied to many different domains and problems besides real-time discrepancy detection.

DISCOVERHISTORY [9] looks for explanations of observations through abductive reasoning, where it goes from an observation to a hypothesis that accounts for the observation. DISCOVERHISTORY has shown to be effective over a large problem space, it is however slow. Its speed is likely not sufficient for real-time detection of immediate issues required by Unmanned Combat Logistics missions.

A case-based reasoning system, CHEF [7] creates food recipes and explains its own failures. The system tries strategies to see which one can be used to fix the recipe plan. CHEF uses causal rules to explain why its own plan fails. However, the system does not handle constrained resources present in a typical scheduling problem.

The system described in [3] is a CBR system that focuses on wartime equipment maintenance by analyzing feature sets of equipment for maintenance. The system removes a user input for deciding the quality of the equipment. CDMA, in contrast, supports a “man-in-the-loop” in order to allow operators to have control over what should be done about disruptions.

8 Conclusion

We presented the CDMA algorithm that supports real-time monitoring for disruptions, disruption analysis, and rescheduling of tasks in both mine countermeasures and unmanned combat logistics operations. Scheduling in these domains is challenging due to the complexities resulting from a large number of tasks that must be allocated over numerous resources. CDMA includes components that assist operation planners by constantly monitoring the environment for changes, providing analysis of discrepancies, and recommending alternative repaired schedules. We introduced the requirement of minimally disruptive repair as a key operational requirement for automatic schedule repair algorithms in MCM applications.

Our results indicate the efficacy of a case-based strategy; schedule repair was rapid, and created new schedules on demand that ensured the elimination of all mines and increased clearance to a reasonable level. This presents a novel and measurable increase in automated MCM and UCL rescheduling capabilities. In the future, we want to further our UCL domain in order to demonstrate effective case-base disruption monitoring with Unmanned Combat Logistics missions.

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