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Abstract—Efficient coordination among all assets participating in a response to a search-and-rescue (SAR) incident has long been a focus of many governments and organizations. Finding innovative solutions that guarantee a swift reaction to the distressed entity with a rational use of the available resources is pivotal to the success of the SAR operation. In spite of the plethora of successfully deployed SAR systems, we witness a substantial gap when it comes to the integration of risk-driven analyses into the underlying machinery of any decision support platform that leans upon the in-field SAR assets. This paper extends a recently proposed risk management framework [1] by adding automated modules for risk monitoring and response selection. An evolutionary multi-objective optimization algorithm is used to navigate across the discrete space of all available assets and their set of actions in order to present a limited number of promising responses to a SAR operator, who will ultimately decide what action must be carried out. The proposed methodology was validated in the context of a simulated nautical SAR scenario in the Canadian Atlantic coastline with nine different types of ground, maritime and aerial assets.

I. INTRODUCTION

Canada has been actively looking at the problem of coordinated search-and-rescue (SAR) operations around its large land mass and very long coastlines. At the heart of maritime SAR operations is a vessel in distress (VID). The main goal of a SAR mission is to get to the VID in as quick a time as possible while keeping an eye on system efficiency. In order to do so, one has to take into consideration many factors, which are grouped within the confines of this paper as a VID object profile (VIDOP). These factors may include:

- VID information (e.g., vessel identification, last known position, course, speed, track, distress signal)
- Vessels in vicinity (VIVs) of the VID, and their own object profiles (VIVOPs).
- Other available sensor (e.g., Doppler) information to improve detection accuracy
- SAR resources, and their object profiles (SAROPs), available for the potential rescue mission
- Alerts previously issued regarding the VID
- Risk factors associated with a VIDOP or a VIVOP

Typical challenges in maritime SAR operations include reaching the distressed vessel in a short period of time (given the very large coverage area being monitored with a small number of available assets), handling coastal SAR situations (due to the presence of small unidentified ships such as fishing boats), as well as coordinating SAR operations (due to dissimilar vessel capabilities and limitations on the vessels’ operability due to the sea state and weather conditions). It is important to note that, in SAR missions, all false alarms are treated as true ones until proven otherwise.

The goal of this paper is to assist a user (e.g., a SAR planner) who must decide what the best response is to deal with a particular VID. A response is thought of in terms of a combination of available resources (i.e. assets) and their possible actions. To this end, we have augmented the initial version of a recently proposed risk management framework (RMF) [1] with automated modules for risk monitoring and response selection. The former involves the real-time inspection of the overall system risk and the creation and maintenance of a contingency plan to lower this indicator, whereas the latter is concerned with the presentation to the user of a limited number of promising responses to cope with the perceived threats upon one or more system nodes. The final decision is made by the user on the basis of their domain expertise.

The RMF is applied to a maritime SAR scenario in order to reduce the response time, focalize the response operation and optimize its overall cost. Data from maritime objects are collected from two major data sources: (1) Automatic Identification Systems (AISs), which allows to resolve questions such as what is the position of the VID and who is around it. This is the basis for the generation of the potential responses (i.e. combination of resources and actions) to mitigate the distress situation; and (2) weather/sea state sensor data feeds used to assess the conditions faced by the VID, VIV and SAR assets.

With this information, risk features are automatically extracted from the raw data streams and their overall impact on each vessel is evaluated. Those vessels that exceed a permissible risk threshold become VIDs and thus trigger a need for an adequate response selection. Because the number and types of available assets and their coordinated actions is usually large, finding out what the best response is according to multiple decision criteria is a complex problem. In this paper, we explore the discrete space of potential responses with the aid of an evolutionary multi-objective algorithm.

The rest of the manuscript is structured as follows. Section II is related work. A general description of the risk-
driven framework is offered in Section III. The risk monitoring module is presented in Section IV. Experimental results based on a maritime SAR scenario are described in Section V and conclusions are stated in Section VI. Finally, note that the data used in this paper are provided for illustrative purposes only to explain the presented concepts and do not reflect actual values.

II. RELATED WORK

Response to SAR incidents has been a focus of many governments and thus finding innovative solutions to coordinate rescue efforts when an incident occurs is of great importance. One of the main issues is coping with the inherent complexity of monitoring an unpredictable and continuously changing maritime environment in which SAR incidents may occur. Human resource allocation is limited, expensive and insufficient to ensure that the intended area remains distress-free. Operators must ensure that all incidents are responded to in an appropriate manner with as few resources as possible. As a result, SAR response coordination solutions are increasingly relying upon the identification of risk sources that prevail in a given area and their monitoring is thus crucial to guarantee the uninterrupted operation of Decision Support Systems (DSSs) and ultimately, the integrity of the SAR response.

Despite the plethora of successful SAR-deployed systems in the past two decades, there is still a substantial gap, both in theory and practice, when it comes to the integration of risk-driven analyses into the internal machinery of any RMF that leans upon the in-field (i.e. operational) SAR factors. The need for such a framework stems from the fact that risk-driven features are to be extracted from the raw data streams flowing from the environment and subsequently processed. Additionally, any potential response scenario (in the form of an actuation over the environment involving humans, vessels or the sensors themselves) to mitigate the perceived distress situation has to take into account its probability of success and a set of risk-related metrics that would help the decision maker better assess the current situation and favourably respond to it. As the risk perception varies over time, so should its influence over the decision-support process.

A. Risk Management Frameworks

When exploring the current state of the art on risk management frameworks for DSSs, the following related methodologies were encountered. We provide a brief description for each and briefly contrast them with our proposed solution.

Hidden Markov Model (HMM)-based Real-Time Risk Management: The studies in [2] and [3] adopt continuous HMMs to evaluate system risk based on predefined qualitative categories (e.g., assets and their features) and a weighted sum approach. However, they rely to a large extent on a priori system knowledge (e.g., event occurrence probability, impact of the observations, initial state distribution, state transition rate matrix, etc.). Furthermore, a HMM is required for each asset’s feature (i.e. confidentiality, integrity and availability), which makes the system’s representation entangled and sensitive to slight departures from the envisioned initial models.

Risk Modeling in Critical Infrastructures: Aubert et al. [4] and Schabrer et al. [5] are concerned with risk modeling in critical infrastructures. The former aims at modeling the security properties of interdependent systems and measures their risk levels and assurances. The latter envisions a service decomposition graph for risk assessment and an online monitoring tool of three risk parameters.

None of the previous frameworks exploit clustering of the input risk features as a visual aid for the user, which can then manually alter the modeling of the system’s risk factors. Additionally, none provide easily interpretable granules for shaping the input risk features or any adaptation mechanism for their associated weights; they are thus not environment adaptable human-centric platforms.

B. Multi-Criteria Decision Analysis

Multi-Criteria Decision Analysis (MCDA) revolves around structuring or solving decision problems that take multiple criteria into account. Typically, these criteria are conflicting, with cost or price often involved. The general problem solving steps include:

1) Identify the decision context, decision objectives and decision makers (DMs)
2) Identify the alternatives
3) Identify the problem’s criteria
4) Construct a decision table (or evaluation matrix) for each of the alternatives
5) Standardize the raw scores to generate a prioritized decision table (e.g., normalization)
6) Determine a weight assigned to each criterion (direct or indirect methods)
7) Apply decision rules to compute overall assessment for each decision alternative
8) Perform a sensitivity analysis to assess the robustness of the preference ranking

Table I summarizes various state-of-the-art MCDA techniques with comments to their inner-workings as well as any potentially identified drawbacks for simulation and implementation purposes.

Reviewing the algorithms presented in Table I, the most suitable class of methods to apply to the stated problem are the evolutionary multi-objective (EMO)-based algorithms. The reasons are as follows:

- We cannot guarantee crisp input values (thus, TOPSIS is not appropriate)
- We do not necessarily have all of the DM preferences and inputs (thus, goal, fuzzy and MAUT are not suitable)
- We need to determine the best course of action (i.e. alternative) to take (therefore, outranking cannot be used)
- We are dealing with a multi-dimensional problem with multiple objectives (thus, we cannot apply WSM/SAW or WPM)
- We are dealing with a real-time scenario with a low computational requirement (as a consequence, AHP/ANP and Group DM are not feasible)
TABLE I
SUMMARY OF MCDA TECHNIQUES

<table>
<thead>
<tr>
<th>MCDA Technique</th>
<th>Description</th>
<th>Comments</th>
</tr>
</thead>
<tbody>
<tr>
<td>Compromising, (e.g., Technique for Order Preference by Similarity to Ideal Situations (TOPSIS) [7])</td>
<td>Chosen alternative should be the closest to the ideal solution and farthest from the negative-ideal solution</td>
<td>Crisp values are required for the performance ratings and the criteria weights</td>
</tr>
<tr>
<td>Goal programming [8]</td>
<td>Generalization of linear programming to handle multiple conflicting objective measures</td>
<td>Information about decision maker’s preferences is required beforehand for priority levels, weights and goal targets</td>
</tr>
<tr>
<td>Fuzzy [9]</td>
<td>Utilized in most of the MCDA processes, i.e. find a ranking, assess the importance of multiple attributes, select an alternative</td>
<td>Depends on the definition of the decision maker’s goals and their associated membership functions to manage uncertainties</td>
</tr>
<tr>
<td>Multi-Attribute (e.g., Simple Multi-Attribute Rating (SMART) [10])</td>
<td>Use utility functions to transform raw performance of the alternatives to a common dimensionless scale</td>
<td>Requires a decision maker to specify the best and worst case for each criterion in order to generate a utility function</td>
</tr>
<tr>
<td>Outranking (e.g., ELECTRE [11], PROMETHEE [12])</td>
<td>Choose alternatives which are preferred for at least some of the criteria and yet do not cause an unacceptable level of dissatisfaction for one criterion</td>
<td>Produces a family of leading alternatives; hence, it may not be able to identify the best alternative. Difficult to interpret the results</td>
</tr>
<tr>
<td>Evolutionary Multi-Objective Optimization (EMO) (e.g., NSGA-II [13], SPEA-2 [14])</td>
<td>Fast, elitist genetic algorithms that locate a set of Pareto-optimal non-dominated solutions</td>
<td>Sensitive to certain parameters such as the fitness sharing factor between two solutions</td>
</tr>
<tr>
<td>Scoring (e.g., WSM, SAW, WPM [15])</td>
<td>Most commonly used techniques; highest scoring alternative is selected</td>
<td>Difficult to communicate/construct</td>
</tr>
<tr>
<td>Scoring (e.g., Analytic Hierarchical Process (AHP) [16] &amp; Analytic Network Process (ANP) [17])</td>
<td>Converts subjective assessment of relative importance to a set of overall scores and weights through pairwise comparisons</td>
<td>Suffers from comparison inconsistencies and leads to a large number of comparisons</td>
</tr>
<tr>
<td>Group Decision Making (DM)</td>
<td>Produces better decisions than any individual one and reduces the effects of individual bias</td>
<td>Takes a lot of time and resources; may not achieve consensus</td>
</tr>
<tr>
<td>Evidential Reasoning (ER)-based [18]</td>
<td>Uses an extended decision matrix with attribute-to-alternative belief structures</td>
<td>Novel/untested approach for dealing with uncertainties (e.g., subjective judgments or lack of data)</td>
</tr>
</tbody>
</table>

- We have uncertainties in the environment and we have no evidence that ER is better than fuzzy at dealing with those uncertainties.

Given previous work by the authors in the utilization of EMO optimization approaches, such as the Non-dominated Sorting Genetic Algorithm (NSGA-II) [6], to map one hundred tasks with passenger/cargo requirements to ten air platform types, and NSGA-II’s efficiency at locating a set of Pareto optimal non-dominated solutions (i.e. not possible to improve any criterion without sacrificing at least another one), we have chosen NSGA-II as the MCDA technique for simulation and implementation. Other more efficient techniques could be used; however, at this time we are concerned with demonstrating a concept and not with algorithm efficiency.

III. RISK MANAGEMENT FRAMEWORK FOR WSNs

The idea of developing an evolving risk management framework has been previously explored by the authors in the form of a multi-modular, multi-source, risk-driven architecture [1] featuring a highly automated design yet preserving a pivotal human-centric nature. Fig. 1 displays its internal structure.

The work on the framework primarily focused on the risk assessment and risk visualization modules. The risk assessment module quantifies the overall risk posed by any system node on the basis of the local risk across all risk features. It is conceived as a rule-based system that uses interpretable information granules like fuzzy sets and shadowed sets for the rules’ antecedents and consequents, as depicted in (1).

\[
\text{IF } \text{RISK}(F_i) \text{ is HIGH OR } \ldots \text{ RISK}(F_n) \text{ is HIGH} \quad (1)
\]

THEN TOTAL_\text{RISK}(S) \text{ is HIGH}

where RISK\((F_i), i = 1..n\) is an information granule (either a fuzzy or a shadowed set) whose membership function \(\mu_{X_{\mu_i}}(\cdot)\) is set by the user according to general expert domain knowledge, and TOTAL_\text{RISK}(S) is the overall risk of a
particular node $S$. The user may specify the initial rule for each risk feature and adjust it afterwards upon observable node failure or an unexpected event occurring in the environment, as shown in Fig. 2.

![User-specified fuzzy/shadowed modeling of the risk features.](image)

The risk visualization module allows the user to watch clusters corresponding to the system nodes in the risk feature space, as portrayed in Fig. 3. The human expert is thereby able to alter the level of the perceived threat for a particular node or group of nodes (i.e. node cluster). This knowledge is immediately incorporated into the system via “Evolving Shadowed Clustering” (ESC) which relies on the shadowed set formalism [19]. The continuous data stream is split into a series of discrete data snapshots and ESC operates on one data snapshot at a time. A snapshot contains the set of risk features $R_1...R_N$ for all system nodes $S_1...S_M$. ESC includes a dynamic cluster formation process in which clusters are merged, split, deleted or created in order to align the state of the current data snapshot with the knowledge structures (i.e. clusters) discovered up to the previous snapshot. It also keeps track of the structural variation across two consecutive snapshots and triggers an alarm whenever a cluster shift (i.e. abrupt translation of a cluster in the risk space) is detected.

Finally, cluster visualization provides a general representation of the system’s prevalent dynamics and thus can be applied to any risk source (e.g., cyber-attack, measurement error, collision likelihood, etc.).

![Cluster-based risk depiction of 8 sensor nodes in the (battery level, intrusion distance) risk space.](image)

### IV. The Risk Monitoring Module

In this paper, we discuss the augmentation of the existing version of the RMF through the incorporation of an appropriate response selection mechanism that can be eventually actuated upon the environment to effectively deal with the perceived distress situation upon a particular system node (e.g. sensor, vessel, moving target) or a group of such nodes. The schematic representation of this extended framework version is offered in Fig. 4. Note that this extension partly implements the response monitoring module of the original framework shown in Fig. 1. The challenge here is designing an efficient technique that allocates and schedules a set of limited available resources to respond to multiple concurrent distress situations on the system’s nodes.

![Response-aware risk management framework.](image)

The risk feature extraction, risk visualization (represented in Fig. 4 by its underlying clustering algorithm) and risk assessment modules of the framework developed by Falcon et al [1] will be reused. By clustering the system nodes (e.g., vessels) in the risk feature space using ESC and assessing the risk level of all cluster prototypes, we should have a better idea of what cluster(s) should contain the riskiest nodes. If the total risk posed by any node exceeds a permissible threshold, an alarm is triggered and a set of potential responses is considered.

A response is envisioned as a combination of available assets and a set of their predefined actions. For instance, in a SAR scenario for a particular VID, there could be coast guard vessels, speedboats, reconnaissance helicopters, evacuation personnel (e.g., divers) and medical teams, as well as other commercial vessels (non-SAR assets) available to address the rescue. In terms of actions, the helicopters could approach the VID to obtain live footage of the situation and the coast guard vessels could come close enough so as to launch a passenger rescue operation by dispatching the medical teams and/or divers to prevent people from drowning.

Decision makers (e.g., SAR planners and operators) take into account different criteria about the decision problem, such as VID location-based degree of distress, sea state, weather conditions, regional hostility metric, operability and safety factors among others, to decide on the group of potential responses to be considered. These make up the decision problem’s criteria (risk features).
Each potential response is evaluated through a set of possibly conflicting optimization objectives (e.g., response latency, response cost, casualty probability) by using an MCDA algorithm (e.g., EMO optimization, rank/score-based schemes, fuzzy methods) and selecting the most promising response, which is then applied to the environment as shown in Fig. 7 in order to mitigate the risk over the system nodes. This leads to another iteration of the closed loop within the response-aware RMF where the values of the risk features for one or more system nodes may change thus affecting the risk picture offered by the framework.

The experimental scenario in Section V is governed by the following configuration:

- **Decision context:** SAR scenario around a VID
- **Decision objectives to minimize:** response latency, response cost and casualty probability
- **Decision makers:** SAR planners and operators
- **Alternatives:** the set of potential responses to cope with the distress situation
- **Decision problem’s criteria:** VID location-based degree of distress, sea state/weather conditions, regional hostility metric and collision factor

### A. Asset Descriptions

There are a number of assets that could be involved in a particular SAR response. Each of those assets has certain characteristics that only allow it to get to within a certain distance from the VID. Once there, the asset may freely move within a response ring (i.e. a concentric donut) around the VID to ensure optimal coverage. There are three response rings defined in this paper:

- **Response Ring 0:** Ring around the VID where critical responders are allowed to operate (e.g., speed boat)
- **Response Ring 1:** Ring around the VID where moderate responders are allowed to operate (e.g., medical vessel)
- **Response Ring 2:** Ring around the VID where support responders are allowed to operate (e.g., oil tanker)

Table II summarizes the maritime, aerial and ground assets considered during the simulations. All assets have a location and a certain number of people on board (except UAV).

#### B. Risk Features (Decision Criteria)

The list of local risk features to be calculated for each asset are summarized in the next four sub-sections.

1) **Collision Factor:** This factor indicates the probability of collision of one maritime asset with another and is calculated on the basis of shared AIS reports from nearby maritime assets and the vessel’s own localization devices. It is modeled after a triangular membership function $\mu_{CF}(x)$ with parameters $A = B = 50m, C = 100m$, where $x$ represents the distance between vessels.

2) **Degree of Distress:** This factor indicates the severity of the potential sinking of the vessel and is proportional to the number of people aboard plus any additional impact on the environment (e.g., an oil spill caused by the sinking of an oil tanker). It is modeled as a weighted sum as follows:

\[
\mu_{DD}(X) = 0.5 \mu_{RP}(X) + 0.3 \mu_{RE}(X) + 0.2 \mu_{RF}(X) \tag{2}
\]

where $X$ is a maritime object, $\mu_{RP}()$, $\mu_{RE}()$ and $\mu_{RF}()$ are fuzzy sets denoting risks associated with people, the environment and the fuel level, respectively. Their underlying membership functions are outlined below.

\[
\mu_{RP}(X) = \begin{cases} 
0.5 & \text{if } 0 < x < 200 \\
1 & \text{otherwise}
\end{cases}
\]

\[
\mu_{RE}(X) = \begin{cases} 
0.20 & \text{if } X \text{ is an aerial asset} \\
0.10 & \text{if } X \text{ is a speedboat} \\
0.20 & \text{if } X \text{ is a CCG, tugboat or medical vessel} \\
0.50 & \text{if } X \text{ is a cruise} \\
0.4+ & \text{if } X \text{ is an oil tanker} \\
0.6\mu_{OST}(X, \text{dwt}) & \text{otherwise}
\end{cases}
\]
where $\mu_{OSI}(dwt)$ is the potential impact of the oil spill on the environment and is quantified as follows:

$$
\mu_{OSI}(DWT) = \begin{cases} 
0.10 & \text{if } DWT \leq 20K \\
0.20 & \text{if } 20K < DWT \leq 50K \\
0.40 & \text{if } 50K < DWT \leq 100K \\
0.60 & \text{if } 100K < DWT \leq 200K \\
0.80 & \text{if } 200K < DWT \leq 300K \\
1.00 & \text{otherwise}
\end{cases}
$$

where $DWT$ stands for deadweight tons. Finally, $\mu_{RF}(X_{fuel})$ is modeled as a triangular shadowed set with parameters $A = B = 0, C = 100$ and $\lambda = 0.10$.

The overall risk computation for an asset proceeds as outlined in (1), where the local risk perceptions $\mu_{F_i}(\cdot)$ are calculated as indicated in Section IV-B2 and their amalgamation is computed by applying the T-conorm shown in (3).

$$
\tau = \max_{i=1}^{n} \{w_i \cdot \phi(\mu_{F_i}(x_i))\} \quad (3)
$$

where $w_i$ is the user-specified weight of the $i$-th risk feature and $\phi(\cdot)$ is a mapping to the fuzzy/shadowed space.

3) Sea State: This risk feature indicates the threat posed by the prevalent sea conditions and is randomly generated according to the Douglas Sea Scale [20] based on the vessel location as follows: Calm: Risk = 0, Smooth: Risk = 0.1, Slight: Risk = 0.2, Moderate: Risk = 0.4, Rough: Risk = 0.6, Very Rough: Risk = 0.8, High: Risk = 0.9 and Very High: Risk = 1.0

4) Regional Hostility Metric: This risk feature indicates how hostile the region where the vessel navigates is. As our simulations are mostly concerned with Canadian coastlines, the regional hostility metric is low and hence modeled as a random number $r \sim U(0, 0.2)$.

C. Decision Objectives

A potential solution (set of responding assets) is encoded as a binary NSGA-II chromosome and will be evaluated according to the decision objectives listed in the next three sub-sections.

1) Response Latency: This decision objective represents the total time required by all actively responding assets to arrive at their ring-specific target location. It is computed as follows:

$$
\text{TotalLatency} = \sum_{i=1}^{n} \text{Latency}(A_i) \quad (4)
$$

For simplicity, the time each asset $A_i$ needs to move from its current location to its target coordinates is a function of the distance from the VID. It is assumed the asset can travel at a fixed velocity depending on its type as follows: CCG: 120 km/h, Medical vessel: 40 km/h, Tugboat: 60 km/h, Oil tanker: 40 km/h, Speed boat: 200 km/h, Cruise: 100 km/h, Helicopter: 250 km/h, Light aircraft: 200 km/h, UAV: 250 km/h.

2) Response Cost: This decision objective represents the total cost of the response operation. For simplicity, this is the sum of the cost of moving each responding asset to its target location. It is computed as follows:

$$
\text{TotalCost} = \sum_{i=1}^{n} \text{Cost}(A_i) \quad (5)
$$

where individual assets have the following costs:

$$
\text{Cost}(A_i) = \text{DistanceToVID}(A_i) \times \text{MovingCost}(A_i) \quad (6)
$$

and MovingCost($A_i$) is as follows: CCG: $\$100/km$, Medical: $\$250/km$, Tugboat: $\$175/km$, Oil tanker: $\$300/km$, Speed boat: $\$80/km$, Cruise: $\$125/km$, Helicopter: $\$75/km$, Light aircraft: $\$80/km$ and UAV: $\$70/km$

3) Casualty Probability: The Casualty Probability decision objective represents the probability that casualties will occur in the set of responding assets when assisting the VID. This is a function of the number of people aboard each asset and the casualty probability of the asset itself. It is computed as follows:

$$
\text{OverallCasualtyProbability} = \max(\text{CasualtyProb}(A_i) \times \text{CasualtyProbPeople} (#\text{PeopleAboard})) \quad (7)
$$

where, CasualtyProb($A_i$) reads as: CCG: 3%, Medical: 5%, Tugboat: 7%, Oil tanker: 6%, Speed boat: 9%, Cruise: 10%, Helicopter: 4%, Light aircraft: 5%, UAV: 0%

D. Potential Response Consideration

Crucial to the response-aware risk framework are the potential response consideration and the alternative response selection modules.

For the former, NSGA-II [6], a fast and elitist EMO approach, was chosen due to its ability to concurrently explore multiple potential responses (i.e. chromosomes) in a combinatorial fashion guided by the demonstrated efficiency of genetic operators like crossover, mutation and recombination, together with a distance-aware ranking of the population.

1) Response Strategies: The response strategies for a particular VID are formalized in the form of a change of location of some of the assets. The response selection module will lean on a NSGA-II implementation in which a potential response is encoded as a binary vector of $N$ elements, where $N$ is the total number of assets available to respond to the situation regardless of their geographical proximity to the VID. Once a set of assets is encoded in a chromosome (those bits are set to 1), determining their end locations is a function of reaching the VID as close as possible without provoking unnecessary collisions while attempting to form a combination of links across response rings, a concept better known as a response chain which starts with the VID’s location and ends with the destination endpoint (e.g. triage station). The end location for each asset involved in the simulated response must lie within the response ring and along the response chain for that particular asset, as depicted in Table II.

E. Alternative Response Selection

In the current implementation, the decision maker will pick an alternative response out of the set of non-dominated solutions in the first Pareto front yielded by NSGA-II. The decision maker’s selection could change in the future for another SAR scenario with identical configuration. This could be simulated, for instance, by adding weights to the different
decision objectives and letting the decision maker adjust those weights over time based on his/her own perception of the effectiveness of the previously conducted SAR operations.

The alternative response selection module also requires an efficient method that quickly sweeps through the set of potential responses and, with or without human intervention, selects the most appropriate response (or a limited number of them) that will be presented to the decision maker, who ultimately chooses what actions are to be carried out.

V. EXPERIMENTAL RESULTS

A maritime SAR scenario along the Canadian Atlantic coastline has been simulated to validate the feasibility of the response-augmented RMF. Fig. 5 portrays the locations of the nine types of assets involved in the empirical study, 80 in total (including 77 maritime/aerial assets and the three triage stations for injured personnel treatment).

The AIS-based and weather-related data feeds reported by all maritime assets have been transformed by the automatic risk feature extraction module in Fig. 4 into the four risk features described in Section IV-B. Subsequently, the risk assessment module takes over and provides local risk values for each risk feature attached to each maritime/aerial asset.

FIG. 5. The simulated SAR scenario includes 77 maritime/aerial assets and three ground assets (triage stations). © Google Earth 2012

In order to determine the presence of VIDs in the region, a simple inspection of the overall risk for each asset will suffice. Those nodes that crossed the risk threshold \( \rho = 0.9 \) were flagged as VIDs in our study. In practice, however, this real-time linear exploration of the nodes’ risk assessment could be rendered infeasible if the number of assets involved in the SAR operation is extremely large.

In those cases, we can use the evolving shadowed clustering algorithm that underlies the risk visualization module in Fig. 4. By having ESC group the system’s nodes in a multi-dimensional risk space defined by the risk features, the inspection is reduced to all cluster prototypes and, subsequently, to all members of the cluster whose prototype exhibited the highest overall risk. Fig. 6 displays a 3D representation of the clustered risk feature space corresponding to the simulated SAR scenario.

FIG. 6. ESC processing the first risk snapshot for the SAR scenario. The 77 maritime/aerial assets were grouped into six clusters.

At this point, the oil tanker #5 (located in the south-east corner of Fig. 5) is identified as a VID since its overall risk level is 92%. The extended framework then triggers a NSGA-II-based search across the combinatorial (binary) space of all candidate responding assets to figure out a reasonable number of non-dominated responses according to the three optimization objectives defined in Sect. IV-C. After 1,000 generations running with a crossover rate of 0.9, a mutation rate of 1/77 and a population size of 30, NSGA-II outputs the highest-ranked individuals in the first non-dominated front. Each response encodes which available assets are to participate in the maritime SAR mission.

Although the number of solutions returned by the EMO approach is manageable, one response must still be chosen by the decision maker (SAR operator). Any alternative selection algorithm could be applied here. For simplicity, a Weighted Sum Model (WSM) was used in our example\(^1\). The user-defined weights for the decision objectives are as follows:

\[ w_1 = 0.3, w_2 = 0.4, w_3 = 0.3 \]

Each Pareto front member yielded by NSGA-II was ranked according to WSM and the highest ranked individual became the selected response to be actuated upon the environment in order to assist the distressed oil tanker. Fig. 7 represents how seven available assets (five maritime, two aerial) coordinate among themselves and change their location along the straight line that connects them with the VID, in an attempt to approach the VID as much as possible within their predefined response rings while forming a response chain to the nearest triage station.

FIG. 7. Seven assets coordinating their actions to assist the VID. (Arlin Inc.)

FIG. 8 portrays an alternative response to the same SAR incident returned by NSGA-II as well. Two maritime assets (CCG and medical vessel) and two aerial assets (UA V and light aircraft) promptly coordinate their actions to assist the

\(^1\) Notice that WSM is used as a straightforward manner to select the final response, but this does not justify the exploitation of a single-objective genetic algorithm to aggregate all objectives into one. We do want to generate multiple non-dominated solutions and WSM is just one way of discriminating among them. Any other MCDA technique in Table I could also be applied.
Casualty probability and hence chose the scenario in Fig. 7. Fig. 8. Another possible response to the oil tanker SAR incident. c

Oil tanker in question. From an optimization perspective, this response is non-dominated with respect to the one in Fig. 7 because the casualty probability of its responder assets does not exceed 5% compared to the 10% contributed by the cruise intervention in the response chain of Fig. 7. However, the SAR operator favored a low-latency, low-cost response with a higher casualty probability and hence chose the scenario in Fig. 7.

VI. CONCLUSIONS AND FUTURE WORK

In this paper, we have presented an extension to the original RMF [1] that includes automated modules for risk monitoring and response selection. We have successfully applied the extended framework to maritime SAR scenarios centered around a VID and proceeded to assist the DM in selecting an optimal response involving various maritime, aerial and ground assets while considering three conflicting objectives, viz response latency, response cost and casualty probability.

Future work includes the completion of the risk monitoring module to create and maintain a contingency plan to lower the overall system risk, as well as the interfacing to the security manager module to effectuate the changes described in the selected response upon the environment. The realization of the risk forecasting module in Fig. 1 completes the closed loop of the RMF, thus enabling its integration into a real-time DSS.

REFERENCES