Modelling Search and Rescue Systems with Dynamical Networks

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***Abstract*—This paper explores the application of network technologies to modelling the Search and Rescue (SAR) capability for the Canadian Arctic. Under the proposed approach, the SAR capability is viewed as a complex socio-technical system that comprises social and technological components from different environmental domains. The system is modelled as a set of inter-linked networks with embedded heterogeneous agents. Evolutionary computation is used to optimize the architecture of the network of Northern airports - one of the networks included in the SAR model. The proposed methodology is applicable to a variety of defence systems that involve large numbers of heterogeneous components.**

I. Introduction

When we think complex systems, we think networks. The concept of a network, as understood in the rapidly developing field of network science [1], provides a natural way to represent systems of many interacting components. A network is defined as a set of items, called nodes, with connections between them, called links [2]. In this manner, networks can efficiently represent system components and relationships among those components in high-level mathematical models.

As pointed out by Pestov in [3], there are considerable advantages in using network models for complex system representation. Firstly, networks can be visualized as graphs with network nodes and links represented by graph vertices and edges, respectively. In this way, one can depict and then visually examine interactions within a system. Furthermore, network measures and performance metrics are readily available for system analysis, both at the level of individual components (e.g. centrality measures) and at the system level (e.g. performance measures) [4]. Finally and most importantly, networks are dynamic constructs, as they can change their state and structure in time, providing means for modelling system evolution.

Depending on the nature of dynamics, all network models can be subdivided into three broad categories:

1) Networks with rich functional/state dynamics, but fixed structure. In these network models, the nodes have mathematical functions assigned to them (e.g. Boolean functions in Random Boolean Networks [5]). The function assignment allows to dynamically change the state of the network without changing the number of nodes and connections between them.
2) Networks with varying topology, but no functions assigned to the nodes. These network models can modify their structure according to the rules of attachment, when new nodes and links are added with some assigned probability. Well-studied examples include small-world and scale-free networks [1].
3) Networks with coupled structural and functional dynamics, or as referred to in [6] – adaptive networks. In these network models, structural changes cause changes in functional/state dynamics and vice versa. Most real networks show such adaptive behaviour [6].

Agent-based approaches and evolutionary computation provide powerful tools for modelling network dynamics. Defence and security applications of agent-based networked technologies are explored by Pestov and Verga in [7]. The application of evolutionary computation for optimizing network architecture is considered in this paper.

Many complex systems take the form of networks and show the network-like dynamical behaviour. In this paper, we are concerned with socio-technical systems – a special type of complex systems of particular significance to defence. The specifics of socio-technical systems are discussed below.

A. There Is More in a Name

Socio-technical systems combine components of social and technological nature such as people, teams, physical assets, equipment, and devices. They may also include knowledge, protocols, resources, and locations. A military capability can be viewed as a complex socio-technical system, as it comprises integrated project teams, real property, utilities, equipment, and processes [8].

Carley [9] argues that such systems are better represented by sets of inter-linked networks between different types of node: e.g. agents, organizations, resources, knowledge or areas of expertise, geographic locations, tasks, and events. Pestov [10] applies this approach to socio-technical systems of interest to defence. For instance, the Capability Engineering (CE) process is represented in [10] by 3 different node classes: agents, areas of expertise, and tasks; and 4 inter-linked networks: workflow, expertise, team, and task assignment (see [10] for details). This representation allows for automated identification of capability gaps in terms of people's expertise in large CE projects, using straightforward matrix algebra operations on networks.

Although the approach by Carley [9] provides an efficient framework for representing heterogeneity between different node classes, it does not accommodate heterogeneity within the agent class. In many real systems, however, agents could differ in a variety of ways: by the role they play in a network, by the environmental domain in which they operate, and by degree of their mobility. This heterogeneity is important and should be reflected in network models.

A joint capability is an example of a socio-technical system with embedded heterogeneous agents. In the defence context, jointness means interoperability across different environmental domains. Therefore, the operational network of a joint capability (which is, in this context, the network between agents) may include components from different environmental domains (e.g. aircraft, ships, ground teams, etc.). In this paper, we will take the Carley's approach further to accommodate the agent heterogeneity in network models of joint capabilities.

B. *Where to Look for Inspirations*

The development of a joint capability is a complex CE process. The goal of this process is to deliver an inherently joint capability with acceptable performance over extended time frames. Acceptable performance normally means strategic readiness, agility, resilience, robustness, and responsiveness to rapidly changing external conditions.

There is no better example of a system, which displays the above performance characteristics, than a biological system. During millions of years of evolution, biological systems have developed viable solutions to such 'engineering' challenges as achieving the balance between effectiveness and cost efficiency, maintaining integrity in the face of predation or random damage, redundancy handling, error handling, and the ability to refine and evolve the structure of the entire network through local interactions (adaptiveness) [11].

As pointed out in [11], structural organization of biological systems, which 'has been honed by evolution', can provide potential solutions to real-world problems in other domains. The CE is an engineering domains that could truly benefit from bio-inspired solutions derived from such biological examples as mycelial fungi planar networks studied in [11].

Evolutionary Computation (EC) and its sub-class, Genetic Algorithms (GA), are techniques that mimic natural evolutionary processes. EC combines iterative randomized search and optimization algorithms to solve combinatorial problems with large search spaces [12]. GA are a type of evolutionary algorithms that implement natural mechanisms inspired by biological evolution (namely: natural selection, inheritance, crossover, and mutation) to the population of the optimization problem (e.g. binary strings, trees, or graphs) [13]. Network optimization can also be performed with GA [13].

Conventional approaches in complex network analysis rely on the computation of measures of network performance without modifying the structure of a network [2], [4]. Perturbations of a network allow for generation and optimization of "what-if" networks. Such functionality is included in some network analysis software (e.g., Near-term analysis in ORA [14]), but still requires manual selection of the network entities to perturb. Whereas GA allow for automated optimization of networks by applying bio-inspired reproduction mechanisms to the population of "what-if" networks [13]. In the process of repeated application of the reproduction mechanisms, evolution of the population takes place. The standard GA use a single objective function that evaluates each individual to a numerical fitness value. For an optimization task with GA, the algorithm tries to minimize or maximize the fitness of the individuals in the population.

The application of GA to the optimization of network paths and to the routing in networks is discussed in [15], [16], [17]. An overview of network optimization problems is given in [18].

In this paper, we are concerned with the identification of network structure for which a predefined function of network performance is optimized (i.e. a Type III optimization problem, according to the classification of network optimization problems suggested by Motter and Toroczkai in [18]).

C. *Outline of the Paper*

In Section II, we lay out a modelling framework that extends the approach by Carley [9] to socio-technical networks with embedded heterogeneous agents. The application of the proposed modelling framework is illustrated in this section on the Search and Rescue (SAR) capability for the Canadian Arctic.

In Section III, we show how evolutionary algorithms can be used to optimize the architecture of the network of Northern airports – one of the networks included in the SAR model.

In Section IV, we give our conclusions and point to some potential avenues for future research.

II. Network Representation

Let us consider the Canadian SAR system, as a use case for the application of network technologies. We proceed with the construction of a network model of this socio-technical system, which we call the SARnet. Our goal will be to put together a modelling framework that can adequately represent the system heterogeneity and interplay between structural and functional dynamics.

The Canadian SAR system is an inherently joint capability, as it involves operations across several environmental domains and coordination between different government departments, the private sector, local communities, and, in some cases, international bodies. The involved government departments are the Department of National Defence (DND) and Canadian Forces (CF), Canadian Coast Guard (CCG), Royal Canadian Mounted Police (RCMP), Environment Canada, Parks Canada, Transport Canada, and Natural Resources Canada (NRC).

The system is administered by the National Search and Rescue Secretariat (NSS). The land and sea area under Canadian jurisdiction is divided into 3 SAR regions. A designated Joint Rescue Coordination Centre (JRCC) oversees SAR operations in each region.

In this study, we are concerned with the Arctic region, the main part of which falls under jurisdiction of JRCC Trenton located on the CF air base in Trenton, Ontario. The lower half of Baffin island and eastern part of the Labrador Peninsula fall under JRCC Halifax located in Halifax, Nova Scotia. JRCC Halifax also serves as a back-up facility for JRCC Trenton.

As noted in recent publications (cf. [19]), the opening of the Arctic has led to significant increase of shipping activities, as well as continuing increase of air traffic over the region. In particular, the rapid expansion of maritime transit through the Northwest Passage and the emergence of Arctic cruises make the assessment of current and required SAR capabilities important. The modelling framework, which we propose below, will facilitate such assessments.

A. Node Classes and Networks

Here, we follow Carley [9] in representing the SAR system by a set of interlinked networks between different node classes. Note that the choice of node classes and networks between those nodes is problem specific and should be carefully tailored to project needs [10].

The following node classes can be included in the network model SARnet:

- *Organizations:* various organizations involved in SAR operations (see above).
- *Locations:* geographic locations relevant to SAR operations (e.g. Northern airport locations).
- *Knowledge:* areas of expertise, protocols, and procedures (jumping on water, paramedic expertise, the Major Air Disaster (MAJAID) and Major Marine Disaster (MAJMAR) protocols [20], etc.).
- *Resources:* resources required for the conduct of SAR operations (e.g. MAJAID kits, fuel cashes, arctic survival caches, airport and heliport facilities, accommodation facilities).
- *Tasks:* various processes, duties, and jobs associated with the conduct of SAR operations.
- *Agents:* active players that perform tasks, possess knowledge, access resources, and process and exchange information. (see Subs. II-B).

It should be noted that the above list of node classes is not inclusive and can be easily expanded, if needs arise.

The following networks can be constructed between the node classes specified above:

- *Organizational net:* links organizations and also links agents with their respective organizations.
- *Capability net:* links resources with resource owners (in this case, with organizations).
- *Support net:* links resources with geographic locations (in this case, with airport locations).
- *Knowledge net:* links agents with their respective areas of expertise.
- *Requirement net:* specifies knowledge (or resources) required to successfully execute a task.
- *Assignment net:* shows tasks assigned to agents.
- *Operational net:* network between agents that represents the operational architecture of a response to a particular SAR incident.
- *Location net:* links various geographic locations (e.g. the network of Northern airports).

The first five nets in the above list are provided as input data, while the remaining three need to be computed. The assignment net can be derived by multiplying the corresponding matrices of the knowledge and requirement nets which are already provided (see Annex B of [10] for details of matrix algebra operations on networks). The operational net cannot be derived from other networks, as it is dynamically created in response to a SAR incident (see Subs. II-C). An efficient way to compute the location net is to use a distance measure defined on the set of nodes representing geographic locations, as we elaborate in Subs. II-D.

B. Agents

Agent nodes represent diverse entities of the SAR system: CCG officers, SAR technicians, Canadian Ranger patrol groups, JRCC Trenton, aircraft and ships equipped with the crew, various information systems, and more. They differ by the role they play in the network, by the environmental domain in which they operate, and also by their mobility.

To accommodate this heterogeneity into the SARnet, we identify 5 types of agents based on their specialization and functionality: sensor, router, actor, database, and controller.

Sensor agents represent entities that detect and report SAR incidents. Sensors gather and then forward information to designated router nodes. The Search and Rescue Satellite Tracking (SARSAT) system, which provides distress alert and location information on SAR incidents to SAR authorities, is an example of a sensor agent. The 911 operators and police are represented in the network model as routers.

Actor agents represent entities that are directly involved in the conduct of SAR operations. These are the teams of SAR technicians, Army jumpers, search aircraft, chartered ships, ground search teams, CCG Auxiliary volunteers, etc. They accomplish the bulk of the SAR duties during an incident. Actors can seek and exchange information, request access to resources, establish new links with neighbouring agents, and create shortcuts to distant agents.

Databases store information and make it available to other agents. Some of these facilities are read only (e.g. telephone directories), whereas others are computer databases. Information System on Marine Navigation (INNAV) and SAR Mission Management System (SMMS) are examples of database agents. Both systems are dynamic information sources that are able to acquire and process new information and exchange that information through knowledge.

The role of a controller agent is to coordinate the SAR incident management and response. These agents have the bird's-eye view of the entire network and the power to modify and to add new nodes and links. They also control the information flow and task assignment. JRCC Trenton and the SAR Master (the CCG officer who oversees a SAR response) are controller agents in the SARnet.

Note that agents could change their role during various phases of a SAR response. For example, an actor could assume the functions of a controller, if required. Similarly, a router may become an actor in a SAR operation. The knowledge net is a key to determining who can do what task in the SARnet. (For a sake of clarity, we assume that an agent cannot hold more than one role simultaneously.)

The environmental or operational domain is an important agent property, especially for the SARnet which represents a joint capability. The SARnet agents operate in 6 environmental domains: maritime, land, air, space, cyber, and cognitive. The meta-network can be partitioned based on those domains to help identify capabilities suitable for specific domains. Some agents could operate in several environmental domains, whereas others cannot change the domain of their operation.

Agent mobility is another important agent property. We differentiate between mobile, stationary and portable agents. Mobile autonomous agents can change their location, while stationary agents remain at the same location during simulations. Portable agents can be transported to a new location.

The above types of agents should be taken into account when evaluating network resilience to both random and targeted removal of vertices. The related problem for homogeneous networks has been studied by Albert *et. al* in [21]. The effects of agent heterogeneity on network resilience are being investigated in our group.

C. The Operational Network

The operational network is not provided with input, but dynamically created, when a response to a SAR incident is initiated. The following events trigger the creation of the operational network:

1) A sensor agent detects a SAR incident and sends distress alert and location information through an appropriate router to the controller agent JRCC Trenton.
2) JRCC Trenton initiates a SAR response by appointing one of the controller agents representing CCG officers on duty, as the SAR Master.
3) From now on, the SAR Master is responsible for the SAR operation in question until closure of the case.
4) The SAR Master takes necessary steps to conduct the SAR operation, such as
   a) consulting database agents for location of CCG or commercial vessels in the vicinity of the incident;
   b) activation of CCG Auxiliary actor agents in the vicinity of the incident;
   c) engagement of actor agents representing ground search teams;
   d) requesting a dispatch of actor agents representing search aircraft with SAR technicians;
   e) declaration of MAJAID or MAJMAR, depending on the scale and nature of the incident;
   f) establishment of a Forward Operating Base (a new controller agent) to coordinate the SAR response;
   g) coordination of evacuation; etc.

As a result, the operational network between agents actively involved in the SAR response is created: new nodes are added (e.g. commercial ships, near the incident, are chartered to conduct rescue) and new links and shortcuts are created (e.g. between the SAR Master and CCG Auxiliary nearest to the incident location).

The operational network is the most important network in the system, as its measures could serve as performance indicators for the entire SARnet.

D. The Northern Airport Network

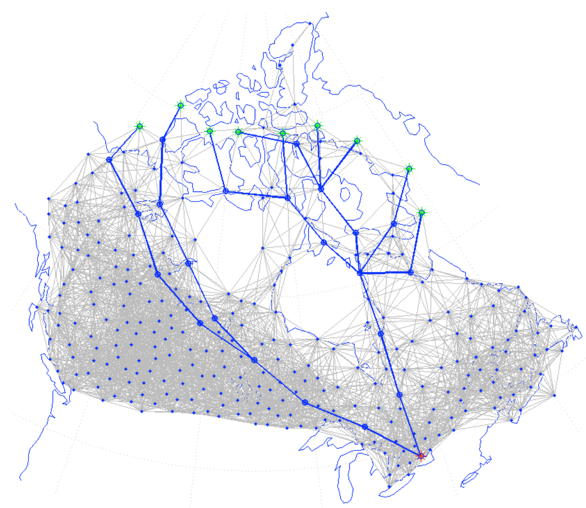

Fig. 1. The network of Northern airports and SAR response paths.

The network of Northern airports is another example of a network that is not provided, but needs to be computed. In this subsection, we show how it could be done using a distance measure defined on a set of location nodes.

Let us consider a set of nodes S, which represent geo-referenced locations of Northern airports. Let $d(u,v) \geq 0$ be a geographic distance between any pair of nodes $(u,v) \in S$. Then, the connectivity function δ on S can be defined, as follows:

$$\delta(u,v,r) = \begin{cases} 1 & : \quad 0 \leq d(u,v) \leq r \\ 0 & : \quad d(u,v) > r \end{cases} \tag{1}$$

In Eq. 1, $r \geq 0$ is connectivity range. We say that two nodes (u,v) are connected, when $\delta(u,v,r) = 1$, and not connected, when $\delta(u,v,r) = 0$. Then, according to Eq. 1, each value of r generates a network on S.

Figure 1 shows the network of Northern airports on the map of Canada, computed with the connectivity range $r = 5.8$ arc degrees (approx. 354 nmi). The distance of 5.8 arc degrees corresponds to the fuel range of the rotary wing aircraft CH-146 Griffon. In Figure 1, the airport location nodes are shown by blue dots and the links are depicted by grey lines. The red star corresponds to the location of CFB Trenton, and the green stars represent possible incident sites on the cruise ships route in the Northwest Passage. SAR response paths are represented as minimum hop shortest paths by blue lines.

The original data set included $1,462$ Canadian airports from the 2008 Canada Flight Supplement [22], which led to $359,022$ links with $r = 5.8$. To decrease the size of the problem, we pruned this data to select representative airports within a radius of 1 arc degree, chosen arbitrarily. This pruning technique decreases the number of airports to 286 and the number of links to $8,208$ in Figure 1.

Note that the network-generation technique, which we describe above, can be applied to any set of nodes equipped with a distance measure. For instance, a kinship measure can be used to create a social network between nodes representing individuals. Similarly, the Hamming distance can be used to create a network between nodes representing binary strings.

III. Network Optimization

We will use the network of Northern airports developed in the previous section to illustrate the utility of the network-optimization method introduced by us in [23]. This problem falls into a widely studied class of technological networks such as power grids, airline routes, the Internet, and other communication networks [2]. The method that we propose here is based on an evolutionary search of 'what-if' networks generated from a given seed network by node deletion and addition. Subs. III-A describes the proposed method, and Subs. III-B provides an example of its application.

A. Method Description

Consider a network generated by a specified connectivity range r, such as that shown in Figure 1. We proceed with optimizing this network toward a certain objective measure. Each problem instance $P = (\delta, N_s, D_s, A_s)$ of this optimization problem consists of the connectivity function δ, as defined by Eq. 1, and three sets: the seed set N_s of size n, the seed deletion set D_s, and the seed addition set A_s. The seed network is created by applying the connectivity function δ to N_s to generate network links.

The seed deletion set D_s of size $d_s^* \leq n$ denotes the nodes of N_s that can be removed from the seed network. The largest deletion set is the set N_s itself. The seed addition set A_s stores a_s^* nodes that can be added to the seed network. The spatial locations of these new nodes are computed randomly, heuristically or hand-picked, depending on the specific problem instance. Note that $N_s \cap A_s = \emptyset$.

The optimization task $T = (P, d^*, a^*, O)$ consists of the problem instance P, maximum size of the working deletion set $d^* \leq d_s^*$, maximum size of the working addition set $a^* \leq a_s^*$, and objective measure O. The working deletion set $D_i \subseteq D_s$ stores $d_i^* \leq d^*$ randomly chosen nodes from the seed deletion set whereas the working addition set $A_i \subseteq A_s$ stores $a_i^* \leq a^*$ random nodes from the seed addition set. The genotype of each individual stores two vectors of sizes d^* and a^* which store the working deletion set and the working addition set, respectively. The unused elements of the genotype vectors (if $d_i^* < d^*$ or $a_i^* < a^*$) are stored as null nodes.

A perturbed network is formed by applying the connectivity function δ to a perturbed node set $N_i = (N_s \setminus D_i) \cup A_i$ of size $n - d_i^* + a_i^*$. The evolutionary algorithm is a genetic algorithm working on a population of perturbed seed networks, where each network individual I_i is represented as a pair of working deletion and addition sets $I_i = (D_i, A_i)$. The evolutionary algorithm searches for an optimal perturbed network with respect to the specified objective measure O. This optimization corresponds to the problem of finding subsets of the seed node sets (D_i and/or A_i) that create perturbed networks which optimize (typically minimize or maximize) the objective.

The evaluation of each individual I_i is performed by constructing the perturbed network and applying the objective measure calculations on the resulting network. To speed up the computation, the distances between the nodes in $N_s \cup A_s$ are precomputed using the distance d and stored in matrix E_s. Each individual perturbed network is a subnetwork of a highly connected extended seed network stored in E_s.

A perturbed network is represented by the adjacency matrix E_i formed from E_s by removing the nodes in D_i and removing the nodes that are not in A_i (or equivalently, that are in $A_s \setminus A_i$). Node removal is accomplished by zeroing the corresponding rows and columns. The connectivity function δ is applied to E_i to create the perturbed network. The resulting network is subjected to a fitness calculation based on the specified objective measure O.

In this paper, we use objective measure calculations based on connectivity and cost (see Subs. III-B). Network analysis measures, such as betweenness, are used for optimization of transport on complex networks in [15].

a) Mutation:		
A	$= [a, c, d, \underline{e}]$	before mutation
A'	$= [a, c, d, \underline{*}]$	after removal at index 4
A''	$= [a, c, d, \underline{z}]$	after addition at index 4
A'''	$= [a, \underline{w}, d, z]$	after modification at index 2
b) Index Crossover:		
A_1	$= [\underline{a}, b, \underline{c}, d, \underline{e}]$	crossover parent 1
A_2	$= [z, \underline{a}, u, \underline{*}, *]$	crossover parent 2
A_c	$= [a, a, c, *, e]$	crossover child
c) Single Point Crossover:		
A_1	$= [\underline{a, b, c}, *, d]$	crossover parent 1
A_2	$= [z, u, *, \underline{w, *}]$	crossover parent 2
A_c	$= [a, b, c, w, *]$	crossover child; crossover point at index 3

TABLE I
Examples of genetic operators.

Reproduction is performed using fitness proportional selection and the genetic operators of mutation and crossover, as illustrated in Table I.

Table I gives examples of the following genetic operators on networks: (a) network mutation, (b) index crossover, and (c) single point crossover applied to an arbitrary set A. In the table, nulls are represented as $*$ and selected elements are underlined.

The ratio of crossover vs. mutation is highly dependent on the specifics of the problem, but it is typically kept in the range $[0.6, 0.8]$. The mutation rate is typically very low (less than 0.1 per gene) and specified on the level of genes (in this case, individual nodes in the deletion or addition sets).

Mutations modify the sets A_i and D_i by the modification, addition or removal of nodes. Mutation is applied per index location of each set. If a node at index j is a null node, it is replaced, with probability p_{add}, by a randomly chosen node from the corresponding seed set. If a node is a non-null node, the node is modified, with probability p_{mod}, by selecting a random node or heuristically chosen node (e.g., a neighbour node). Alternatively, the non-null node is removed (i.e., replaced with a null node), with probability p_{rem}.

Crossover on two individuals $I_1 = (D_1, A_1)$ and $I_2 = (D_2, A_2)$ produces a child $I_c = (D_1 \times D_2, A_1 \times A_2)$. The crossover operator $\times$ is applied independently on the deletion sets and on the addition sets of both parents. Using indexed crossover, the crossover operator $\times$ randomly (with probability 0.5) selects an element of one parent set for each indexed set position (i.e., $\forall i \; A_c[j] = A_1[j]$ or $A_2[j]$ and the equivalent on set D).

Single point crossover randomly chooses a crossover point in range $[0, a^*]$ and range $[0, d^*]$ for the addition and deletion vectors, respectively. The child is created by copying the content of each set from parent 1 up to the crossover point, then from parent 2 up to the end of the vectors. Thus, for a crossover point p, $A_c[1:p] = A_1[1:p]$ and $A_c[p+1:a^*] = A_2[p+1:a^*]$. Note that for $p = 0$, $A_c = A_2$ and for $p = a^*$, $A_c = A_1$. The same applies to the deletion set D_c.

B. High North MAJMAR Scenario

To illustrate the utility of the network-optimization method, we consider a hypothetical MAJMAR incident along the cruise ships route in the Northwest Passage. The SAR response is handled by the CH-146 Griffon aircraft through a series of airport fuel stops (network hops). At least 6 hops are required for these aircraft to reach the remote areas of the High North from the Great Lakes [24]). But their operation is not constrained by specific landing and take-off requirements such as that of the C-130 Hercules.

The SAR response teams are dispatched from the source node, representing CFB Trenton (red star in Figure 1), to the target nodes (green stars in Figure 1) to deliver equipment and aid. The source node, airport locations, and target nodes are connected using the connectivity function δ, defined in Eq. 1, with connectivity range $r = 5.8$ arc degrees, corresponding to the fuel range of the CH-146 Griffon aircraft. A SAR response path to a target node is defined as a shortest path between the source node and target node.

The seed deletion set is composed of 69 nodes (a subset of the pruned airport location nodes). The seed addition set is composed of 200 nodes that are randomly located within the area bound by [60,83] degrees North latitude and [-60,-135] degrees longitude. No effort is made to eliminate invalid or unwanted (e.g., an airport on a body of water) locations in this work because of an illustrative nature of this example.

The genetic algorithm optimizes the airport network based on several objective measures, including connectivity and cost, searching for well performing solutions (local optima but often not global optima). This analysis allows the identification of capability gaps in the network, and correspondingly in the modelled system.

Node deletion optimization finds groups of airports that can cause a significant impact on the network connectivity or time of the SAR response, if they were to be disabled, either through weather or other means. Node addition optimization corresponds to the identification of new possible airport locations to improve the performance of the SARnet.

For the experiments presented below, we used a custom genetic algorithm from the MATLAB Optimization Toolkit. We ran the genetic algorithm with a population of 200 individuals for 50 generations with 2 elite individuals. Crossover and mutation were performed with probability 0.8 and 0.2, respectively. Both genetic operations were self-fixing to eliminate invalid solutions or duplicate nodes.

Minimal Connectivity (node deletion): The optimization problem with respect to minimal connectivity identifies the extent of disruption on the SAR response due to perturbations caused by node deletion. Node deletions represent the inability to land on the corresponding airports, because of bad weather or other disruption. The objective function counts the number of target nodes reachable from the source node. The optimization algorithm minimizes this number via deletion of nodes from the network.

We conducted experiments using deletion sets of size $d = 5, 10, 15, 20, 25$ (10 trials each). Experiments with $d = 5$ were only able to isolate 1 target node, whereas experiments with $d = 10$ could isolate 2 target nodes. Experiments with $d = 15$ and 20 were able to isolate more nodes.

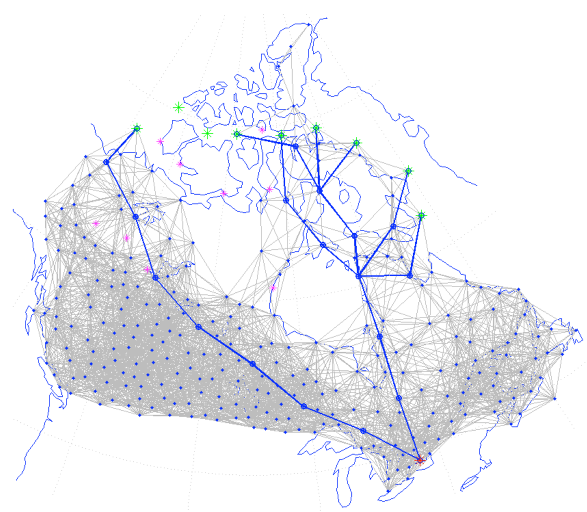

Fig. 2. Results of minimal connectivity experiments for $d = 10$.

Figure 2 shows SAR response paths for $d = 10$. Deleted airport nodes are represented by magenta stars. As can be seen from the figure, a significant segment of the cruise ships route becomes unreachable, when 10 airports are deleted from the network.

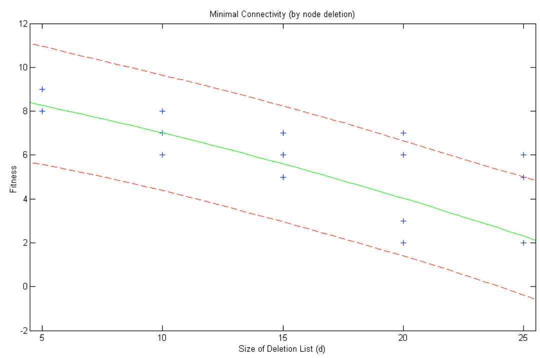

Fig. 3. Fitness results of minimal connectivity experiments.

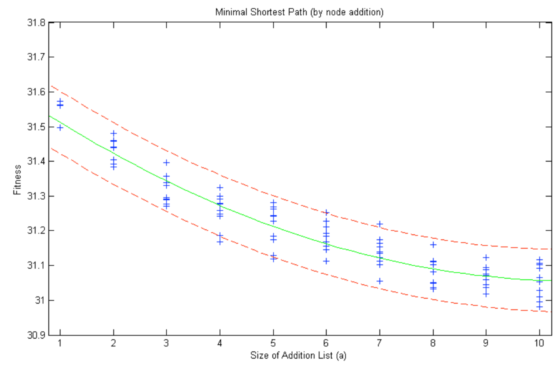

Fig. 4. Fitness results of minimal shortest path experiments.

Figure 3 shows the impact of the size of the working deletion set on the fitness of the best solution. In the figure, points are fitted using a quadratic curve with a 95% confidence interval. The fitness values range from 0 to 9. There was no noticeable difference in fitness values between the results using 20 and 25 deletion nodes.

Minimal Shortest Paths (node addition): The cost measure augments the connectivity measure with an additional cost metric. The simplest cost metric for spatially-distributed networks is the distance between any two nodes. It can be calculated using geographic distance or hop distance. The geographic distance between any two points is represented as the weight of the edge between them. The cost of a SAR response path is then measured as geographic distance (e.g., using arc degrees).

The hop distance simplifies the costs by assigning a weight of 1 to each network edge. Then the cost of a path represents the number of refuelling stops that an aircraft needs to make along the path.

The minimal shortest path experiments demonstrate a simple path distance cost measure with an enforced connectivity restriction. The costs are minimized by the addition of nodes. The optimization problem searches for an optimal working addition set of up to the specified a nodes such that the costs are minimized.

The objective function measures the mean response path cost over all of the 9 response paths from the source node to the target nodes (see Figure 1). Since no nodes are deleted, the node additions preserve the response connectivity of the original seed network. Instead of the mean response path cost, one can also use the maximum, minimum, or sum of the response path costs.

Figure 4 shows fitness results for shortest-path experiments with maximum size of the addition set $a = 1$–10 and connectivity range $r = 5.8$ (10 trials per each a value). Points are fitted using a quadratic curve with a 95% confidence interval. The fitness values range from 31 to 31.6 (the mean response path cost over the 9 paths). As can be seen from the figure, the fitness benefit slightly tapers off as the number of added nodes is increased due to higher connectivity in the network.

Figure 5 shows a sample solution with a working addition set of size $a = 10$ for the connectivity range $r = 5.8$. The added points that influence the fitness are shown as red on the blue shortest paths. Added airport nodes are represented by magenta stars. Real distance values were used in the link and path calculations.

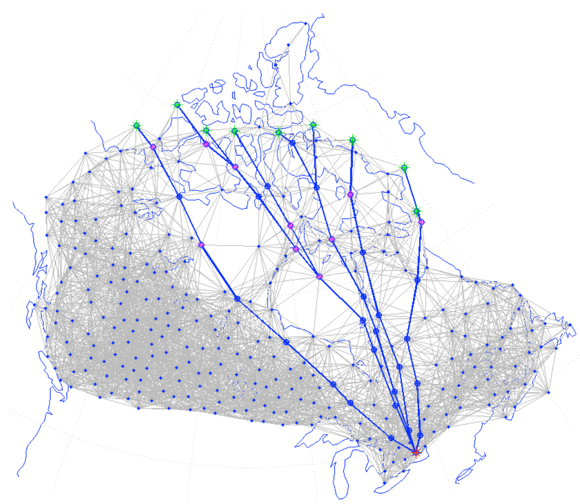

Fig. 5. Results of minimal shortest path experiments for $a = 10$.

The presented method can also be used to identify groups of critical nodes that can cause a large disruption of the SARnet. This could be achieved in the maximal shortest path experiments that search for a working deletion set to maximize the mean hop-based distance cost of the response paths by minimizing the negation of the value.

IV. Conclusions

We have presented a *modelling framework* that extends the network-based approach [9] to socio-technical systems with embedded heterogeneous agents. We have developed this framework with a particular purpose in mind: to provide an adequate model of a joint capability – a special case of socio-technical systems of significant interest to defence. The representation of a joint capability in computer models has until now remained a challenge for researchers.

We have illustrated the application of the proposed framework on the Canadian Arctic SAR system – a joint capability that comprises technological and social components from different environmental domains (Section II). This heterogeneity has been reflected in the presented network model, SARnet, through different agent types and properties, the choice of which depends on agent roles and environmental domains of their operation (Subs. II-B). In Subs. II-C, we have shown how the agent heterogeneity gives rise to the operational net – the most important network in the SARnet.

The network of Northern airports is another important network of the SARnet. Similarly to the operational net, the airport net is not provided with input data, but needs to be computed. We have shown how it can be done in Subs. II-D, using a specified distance measure and connectivity function. The presented *network-generation technique* can be applied to any set of nodes equipped with a distance measure.

In Section III, we have put forward a *computational approach* to optimize the architectures of networks. The method is based on an evolutionary search of "what-if" networks generated from a given seed network by node deletion and addition. A genetic algorithm optimizes the possible perturbed networks toward certain objective measures. In Subs. III-B, we have illustrated the proposed method on the network of Northern airports.

We have shown on this example how small structural changes at the local level can affect dynamics of the entire network. For example, removal of an airport node can cause the creation of several new links between the neighbouring nodes to compensate for the loss of connections through the removed airport. Similarly, the addition of a new airport node can cause the removal of links between neighbouring nodes (and, hence, cost reduction) due to the availability of routes through the new airport.

The study of adaptive networks is a new rapidly developing area with significant potential for defence applications. The synergistic approaches that combine network technologies with bio-inspired computational algorithms are promising for future research. Such network models as the presented SARnet model provide useful insight into complex system behaviour. In addition to the network-generation techniques explored in this paper, the Generative Network Automata (GNA) [25], [26] is worth looking at, as a modelling tool for studying adaptive network dynamics.

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