Evolutionary Computation on Complex Spatially-Distributed Networks

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ABSTRACT

In this paper, we describe a new computational approach to optimize the architecture of complex spatially-distributed networks. The proposed approach is based on an evolutionary search of "what-if" networks generated from a seed network. A genetic algorithm optimizes the network toward certain objective measures. The utility of the proposed method is illustrated on an example using the Canadian Search and Rescue capability for the High North region.

Categories and Subject Descriptors

J.7 [**Computer Applications**]: Computers in Other—*Military*

General Terms

Algorithms

Keywords

Socio-technical networks, performance measures, optimization, genetic algorithms

1. INTRODUCTION

Networks are useful and versatile tools for modelling complex systems. Of particular significance to defence are complex socio-technical systems [4]. These are the systems that involve large numbers of interconnected heterogeneous components (people, teams, organizations, equipment, and physical assets) that can be distributed over vast geographic space. Examples include military capabilities, critical infrastructure systems, and adversarial systems and networks.

Network models are well suited to represent such systems: the nodes model system components and the links represent relationships among those components. The nodes can be geo-referenced to reflect the spatial components of the system. Combined with evolutionary computation, network models become well suited for modelling system evolution.

2. NETWORK OPTIMIZATION

We propose a network optimization method by an evolutionary search of "what-if" networks generated from a seed network. This method streamlines the generation of such scenarios by applying evolutionary computation to optimize the network toward certain objective measures (e.g., [1]). Spatial networks lack explicit edge weights since the distances between connected nodes can be computed through a distance measure. The optimization of such networks relies on the modification of the network structure (equivalent to the Structural Optimization for Dynamics problem [2]).

We consider networks of spatially-distributed nodes with the connectivity implied from the distance measure d such that nodes u and v are connected if $d(u, v) \leq r$, for a connectivity range $r \geq 0$. The nodes are disconnected otherwise. For a seed network N_s of size n, we define a *deletion set* D and an *addition set* A. D stores up to d nodes removed from N_s and A stores up to a new nodes added to N_s. This representation allows us to construct a perturbed network $N = (N_s \setminus D) \cup A$ of size $n - d + a$ from N_s by applying the deletions found in D and additions found in A.

The optimization method is a standard genetic algorithm with a population of perturbed networks where each network N_I is represented as a pair of deletion and addition sets $I = (A, D)$ with respect to a seed network N_s. The evaluation of an individual I is performed by constructing the perturbed network N_I and applying suitable objective measure calculations on the resulting network.

Reproduction is performed using fitness proportional selection and the genetic operators of mutation and crossover as illustrated in Figure 1. Mutations modify the sets A and D by the addition or removal of nodes based on respective probabilities p_{add} and p_{rem}. Only the nodes of the seed network N_s can be added to the deletion set D. The addition set A can be augmented by new nodes at locations that are either randomly selected from a discrete spatial region or selected based on a geometric assessment.

Crossover on two individuals $I_1 = (A_1, D_1)$ and $I_2 = (A_2, D_2)$ produces a child $I_c = (A_1 \times A_2, D_1 \times D_2)$. For each indexed set position, the crossover operator $\times$ randomly, based on a probability $p_c = 0.5$, selects an element of either set at that position ($\forall i\ A_c[i] = A_1[i]$ or $A_2[i]$ and the equivalent on set D). One of the parent sets might be padded with null elements in order to keep the set sizes equal. The null elements are removed from the resulting sets.

3. SAR EXAMPLE

To show the utility of the proposed optimization method, we present an example using the Search and Rescue (SAR) capability for Canada's Arctic. The Canadian SAR system is represented as a complex socio-technical network, SAR-

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a) Mutation

$A = \{a, c, d, \underline{e}\}$	before mutation
$A' = \{a, c, d, \}$	after removal of e
$A'' = \{a, c, d, \underline{z}\}$	after addition of z

b) Crossover

$A_1 = \{\underline{a}, b, \underline{c}, d, \underline{e}\}$	crossover parent 1
$A_2 = \{z, \underline{a}, u, \underline{*}, *\}$	crossover parent 2
$A_c = \{a, a, c, *, e\} = \{a, c, e\}$	crossover child

Figure 1: Examples of the (a) mutation and (b) crossover operators on the set A. Nulls are represented as $*$ and selected elements are underlined.

Net, consisting of various heterogeneous nodes (e.g., agents, knowledge, resources, tasks, locations).

We consider the scenario of a Major Air Disaster (MAJAID) in the High North region. The disaster response teams must travel from their base of operation to the disaster site to deliver equipment and aid. The reach of large SAR aircraft (e.g., C-130 Hercules) is limited due to specific airport requirements. Thus, the primary SAR role of large aircraft is to carry and drop-off supplies and to carry large numbers of survivors between suitable airports.

To reach the disaster site and carry survivors back to the nearest airport or hospital, smaller aircraft (usually rotary wing aircraft such as the CH-146 Griffon) must be used. However, these smaller aircraft have very limited range (at least 6 hops of a Griffon helicopter are required to reach the most remote areas of the High North from the Great Lakes).

We consider a sub-network of SARNet composed of georeferenced location nodes representing airports. The connectivity is calculated by a distance measure connecting nodes with a great-circle distance of at most a given threshold radius r. Figure 2 shows a sample network connecting Canadian airports with $r = 354$ nautical miles (corresponding to the fuel range of the Griffon aircraft).

The genetic algorithm optimizes this spatially-distributed location network based on several objective measures: connectivity, cost, and robustness. The network is either optimized in the number of nodes (or correspondingly the values of d and a) or optimized with respect to certain measures and fixed values of d and a.

The connectivity of the network (i.e., ability to reach nodes) is measured with respect to a response path network (blue in Figure 2) from a source location (representing a SAR base of operations) and destination locations (representing possible SAR disaster sites in Canada's North). Optimizing this objective is related to finding a minimal subnetwork (equivalent to a minimal subset of spatially-distributed nodes) that preserves the connectivity of the response paths.

The cost measure augments the connectivity measure with an additional cost metric. The costs are derived from a risk analysis of the system and disaster scenarios. Optimizing the cost measure is related to finding minimal subnetworks such that costs of response paths are minimized or finding subnetworks with fixed values of d and a such that the costs are minimized.

The third objective uses network analysis measures of betweenness centrality, degree, and biconnected components to assess the robustness of the network to loss of network

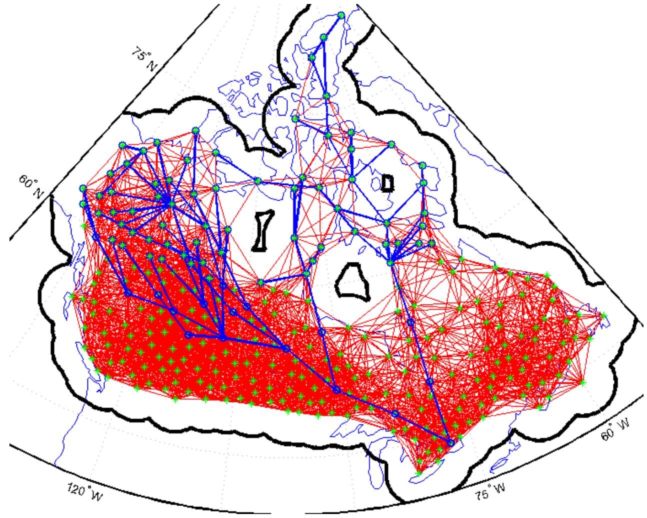

Figure 2: A network (red) of selected Canadian airports (green), displayed on the map of Canada, computed with distance threshold radius $r = 354$ nmi and showing shortest paths from Trenton, ON to airports in Canada's North (blue). Data from [3].

nodes. Optimization of this objective finds subnetworks that optimize the network measures (e.g., minimizing the number of biconnected components or minimizing betweenness centrality of nodes) while still preserving the connectivity of the response paths.

Node deletion in this network corresponds to the inability to land on the corresponding airport (represented as probability p_{rem}). Note that, p_{rem} can differ for each location node. Node addition corresponds to the identification of new possible airport locations. Thus, experiments with $a > 0$ can be used to identify the possible improvement to the capability and performance of the modelled SAR network through the proposed building of new airports.

4. CONCLUSION

In this paper, we presented a new computational approach for optimising network architecture of spatially-distributed complex socio-technical systems. The proposed approach is based on a standard genetic algorithm searching through networks by removal and addition of network nodes. The utility of the proposed method is illustrated on an example using the Canadian Search and Rescue capability for the High North region.

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