The Influence of Uncertainties on Optimization of Vaccinations on a Network of Animal Movements

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ABSTRACT

This summary presents the results reported in the article Krzysztof Michalak and Mario Giacobini, "The influence of uncertainties on optimization of vaccinations on a network of animal movements" which studies the influence of uncertainties on the effectiveness of vaccination schemes obtained by using evolutionary algorithms and vaccination strategies. In this work the uncertainties are represented as unknown disease cases and changes introduced to the network of contacts by a rewiring mechanism. The experiments show that evolutionary algorithms outperform vaccination strategies when provided information is accurate, that is, when most disease cases are known and the intensity of rewiring is low. With higher level of uncertainty the strategies produce better results. Results presented in the article motivate further work in several areas: modelling and prediction of changes in the contacts network, development of computational methods for estimating the number of initial disease cases, and hybridization of evolutionary optimizers with vaccination strategies and other knowledge-based approaches.

CCS CONCEPTS

• **Mathematics of computing → Evolutionary algorithms**; **Combinatorial optimization**; • **Applied computing → Multi-criterion optimization and decision-making**;

KEYWORDS

Disease prevention, Epidemics control, DPEC, Graph-based problems, Combinatorial optimization, Multiobjective optimization

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1 INTRODUCTION

This article addresses the problem of optimizing a vaccination scheme intended to stop an epidemic that spreads among animal farms and pastures through animal movements. The decisions to vaccinate or not are taken at the farms level, so the decision space in the considered optimization problem is $\Omega = \{0, 1\}^{N_{farms}}$. The optimization problem is biobjective: f_1 is the number of animals in the vaccinated farms and f_2 is the number of animals infected in a simulation starting with an outbreak of the disease at α_{inf} = 1% of the farms. Both objectives are to be minimized.

The calculation of the objective f_2 is done by simulating an epidemic which propagates from the initially infected farms over a dynamic network of animal movements. In the article, a real-life dataset is used describing animal transports in the Piedmont region of Italy in 2017 as a network (graph) in which nodes are 9313 farms housing 560812 animals and 573 pastures, and edges are animal transports. There are 36293 farm-to-farm movements, 1998 farm-to-pasture movements and 2037 pasture-to-farm movements.

Two approaches to this optimization problem are studied: optimization using evolutionary algorithms and selection of farms to vaccinate using strategies based on the number of farms a given farm trades with, the number of transports of animals sent or received by the farm, the farm size, etc. Evolutionary optimization is performed using three state-of-the-art multiobjective optimization algorithms: the Multiobjective Evolutionary Algorithm Based on Decomposition, MOEA/D [2], the Non-dominated Sorting Genetic Algorithm, NSGA-II [1] and the Strength Pareto Evolutionary Algorithm, SPEA2 [3], all combined with a dedicated local search procedure proposed in this article.

2 UNCERTAINTIES

The focus of the article is the influence of uncertainties on the quality of solutions to the optimization problem obtained by evolutionary algorithms and vaccination strategies. In the article, the uncertainties are represented as random changes to the network of animal transports and to the disease outbreak. Two kinds of uncertainties studied in the article are:

(1) **Unknown disease cases**. The decisions which farms to vaccinate are made with a fraction α_{known} of the actual disease cases known to the method which selects farms for vaccination. In the experiments α_{known} = 0.1, 0.2, 0.5, 0.8, 0.9 and 1.0 was tested. To compensate this lack of information, additional disease cases were randomly generated with the R_a parameter, used as a multiplier for determining how many cases to add, ranging from 0 (no artificially generated cases) to 2 (twice as many artificial cases as the known ones).
(2) **Changes in the contacts network**. The network of contacts used when decisions about vaccinations are made is

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different than the network of contacts used to simulate the epidemic when solutions are evaluated. The changes are introduced via pairwise rewiring of the original graph in which pairs of movements of the same type (farm-to-farm, farm-to-pasture, or pasture-to-farm) are randomly selected and their destinations are swapped, keeping the number of moved animals unchanged. The intensity of the rewiring is controlled by the parameter α_{rewire} = 0.00, 0.02, 0.04, 0.06, 0.08, 0.10, 0.20, 0.30, 0.40 and 0.50. The number of rewired pairs is $\alpha_{rewire} \cdot |E|/2$, where $|E|$ is the number animal movements.

Therefore, when the optimization algorithms and vaccination strategies make decisions which farms to vaccinate they work with the outbreak and the network that differ from the epidemic simulated when solutions are evaluated.

3 THE INFLUENCE OF UNCERTAINTIES ON OPTIMIZATION RESULTS

In order to assess the influence of uncertainties on optimization results the evolutionary algorithms and vaccination strategies were used to decide which farms to vaccinate in scenarios in which the values of α_{known}, α_{rewire} and R_a parameters were set to the values listed in Section 2. The Pareto front produced by each method was evaluated using the hypervolume indicator. Figure 1 presents the *difference* Δ between the hypervolume attained by the best-performing EA (the MOEA/D algorithm) and the best result attained using the vaccination strategies.

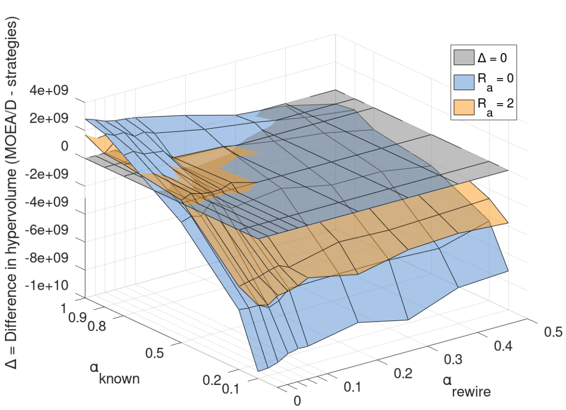

Figure 1: The difference Δ between the hypervolume attained by MOEA/D and the best of the vaccination strategies depending on the value of rewired movements fraction α_{rewire} and known disease cases fraction α_{known}. Surfaces plotted for R_a = 0 (blue) and R_a = 2 (orange). The gray surface shows the reference level Δ = 0.

Clearly, if enough information is given (α_{known} > 0.5, α_{rewire} $\leq$ 0.3) the evolutionary algorithm is able to find better solutions than the vaccination strategies as evidenced by the fact that the blue surface is above the reference level of Δ = 0 (gray). Unfortunately when a half or fewer of the disease cases are known the effectiveness of the EA quickly deteriorates. A deterioration of the optimization results quality, albeit less severe, can also be observed for α_{rewire} > 0.3. A mechanism proposed in the article to counteract the negative influence of the unknown disease cases was to randomly generate additional cases, with the R_a parameter serving as a multiplier determining how many cases to add. The change in the shape of the surface representing the difference between the EA and the strategies for R_a = 2 shows, that additional disease cases, even though they are placed randomly, improve the optimization results when many real cases are unknown. Unfortunately, this improvement comes at a price of deteriorating the results when most of the disease cases are known.

4 FURTHER WORK

Evolutionary optimizers can produce good optimization results, but they require possibly accurate knowledge of the initial cases of the disease as well as the network structure. In the article it was shown that the lack of knowledge of the disease cases can be compensated by randomly adding artificial cases of the disease, but adding too many artificial cases degrades the optimization quality. These observations motivate further work in several areas:

- Modelling and prediction of future contacts in the dynamic network (e.g. of animal movements) with the aim to provide a better approximation of the true network of contacts for the optimization algorithms to work with.
- Development of computational methods for estimating the number of initial disease cases. This direction of research is motivated by the observation made in the article, that the location of randomly added artificial cases of the disease does not have to be known exactly, but adding too few or too many may negatively impact the optimization results.
- Hybridization of evolutionary optimizers with vaccination strategies and other knowledge-based approaches. Because vaccination strategies were less impacted by the lack of information, this line of research seems promising especially for real-life application where uncertainties are usually present.

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