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Leakage Localization with Differential Evolution: A Closer Look on Distance Metrics

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Abstract

In this paper the impact of different distance metrics as well as different sortings of the parameter space on the shape of the objective function for model-based leakage localization is investigated. Leakage localization is formulated as an optimization problem solved with a differential evolution algorithm. Distance metrics and sortings are evaluated through the convergence speed of the algorithm and the quality of the results in terms of a topological distance from the leak found by the algorithm to the real leak. The algorithm is tested on a hydraulic model of a real-world network and has shown that a Cuthill-McKee ordering of the search space together with correlation distance metric performs the best.

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Keywords: Model-based; genetic algorithm; minkowski metric, correlation, graph ordering

1. Introduction

Finding the approximate area where a leak occurred is possible with model-based leakage localization. Leakage localization is formulated as an optimization problem solved with heuristic algorithms, since the fitness landscape of the problem may contain many local optima, where e.g. gradient based algorithms fail. In this paper we make use of the DE/rand/1 differential evolution (DE) algorithm, which was introduced by [1]. Candidate solutions are expressed

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in a similar way as in [2]. The objective function represents the difference between hydraulic simulations and real-world measurements. For this study they were derived from leakage simulations as well. To obtain the location of the leak, the objective function is minimized. Actually, there are different ways to formulate the objective. One of the most well-known is Euclidean distance, which is a special case of the Minkowski metric of order $p = 2$. Other special cases are Manhattan ($p = 1$) and Maximum metric ($p = \infty$). Additional metrics different to the Minkowski family are Canberra and Sorensen distance or Cosine and Pearson correlation measures. But not only different metrics, also the way the parameter space is sorted has an influence on the optimization problem. Therefore, different orderings of the parameter space are also evaluated. The purpose of this paper is to compare these different metrics and orderings of the parameter space for model-based leakage localization and to determine which metric and ordering performs the best. The comparison is made in form of precise leakage localization as well as computation time in terms of objective function evaluations. For that reason, all these metrics were tested on a real-world hydraulic model located near the city of Graz in Austria, although this paper only deals with simulated and not measured values. A specific leakage scenario was generated at a hydrant in the hydraulic system, which also corresponds to the position where we performed real world leakage localization measurements. The localization problem was then solved with differential evolution for the leakage scenario by applying the above-described metrics and different orderings of the parameter space and evaluated to find the best metric and ordering for the model-based leakage localization problem.

2. Methodology

2.1. Leakage localization with differential evolution

Model-based leakage localization is based on minimizing the discrepancy between real-world measurements m and the corresponding values from hydraulic simulations $\hat{\mathrm{m}}(\mathrm{x})$ to find the approximate location of a leak. Mathematically, an arbitrary metric can be used to describe this discrepancy $\mathrm{d}(\mathrm{m}, \hat{\mathrm{m}}(\mathrm{x}))$.

The problem can be formulated in the following way

$$f(\boldsymbol{x}) = d(\boldsymbol{m}, \hat{\boldsymbol{m}}(\boldsymbol{x})) \longrightarrow \min_{x} f(\boldsymbol{x}) \quad , \tag{1}$$

where f(x) a scalar, one-dimensional function, called the fitness or objective function, which defines an abstract fitness landscape. x is a vector in the parameter space of the function.

For the hydraulic simulations, we make use of EPANET [3] together with OOPNET [4]. In EPANET leaks can be described as pressure dependent demands with the leakage outflow power law equation

$$\mathrm{Q} = \mathrm{c_e} \cdot \mathrm{p}^{\mathrm{e_e}} \quad . \tag{2}$$

Q is the leakage outflow, c_e the emitter coefficient, e_e is the emitter exponent and p is the calculated pressure at the node where the leak occurs. Since we make use of steady state simulations, e_e can be set to a fixed value of e_e = 0.5. Then Q is just dependent on c_e and p. p is calculated by the hydraulic solver, but c_e can be chosen to get the desired Q. Therefore, c_e describes the size of the leak.

The other parameter for finding a leakage is its location L_P where it occurs. Its location is given by the node in the hydraulic system. Hence, the parameter vector $\boldsymbol{x}$ consists of

$$\mathrm{x} = \begin{pmatrix} \mathrm{c_e} \\ \mathrm{L_P} \end{pmatrix} \quad . \tag{3}$$

Finding the right location and size of a leak equals finding the location of the minimum of the fitness landscape in the c_e - L_P space in an arbitrary distance metric. We assume that this optimization problem in most of the cases has to be solved with stochastic algorithms, since the fitness landscape most likely will have many local minima where gradient based algorithms may fail. Thus, we make use of the differential evolution (DE) algorithm in its standard DE/rand/1 implementation [1] throughout this paper. The mutation factor F and the crossover ratio c_r are set to the same value for every simulation ($F = 0.5, c_r = 0.7$) to make a comparison in terms of convergence speed to the right solution between the different distance metrics and different orderings of the parameter space.