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GENERALISING HUMAN HEURISTICS IN AUGMENTED EVOLUTIONARY WATER DISTRIBUTION NETWORK DESIGN OPTIMIZATION

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Introduction

The use of evolutionary algorithms (EAs) for finding near optimal water distribution network (WDN) designs is well-established in the literature. Even though these methods have the ability to generate mathematically promising solutions based on defined objective function(s), the resulting solutions are not necessarily suitable for real-world application. This is because of the size, complex and non-linear nature of WDNs, which make it difficult to define important factors that a water engineer or an expert needs to consider during the design process in an objective function. Incorporating an expert in the optimization process has been used to deal with this problem and to guide an EA's search toward obtaining more practical solutions[1]. Accordingly, this study proposes a methodology for capturing and generalizing engineering expertise in optimizing small/medium WDNs through machine learning techniques, and integrating the resultant heuristic into an EA through its mutation operator to find the optimum design for larger WDNs. The methodology is examined on the Modena WDN design problem and the results demonstrate better performance in comparison with a standard EA approach.

Methodology

The methodology involves the following three interconnecting elements:

1. <u>Engineering interaction capture system</u>

The HOWS framework is used for the interactive optimization process of WDN design[2] using a server-client architecture. The server is responsible for configuring and automatic optimization of the WDN problem, whilst the client is responsible for network visualisation and recording user interaction. In this paper, the user is provided with a randomly generated solution to the WDN problem and asked to manually optimize a small/ medium WDN by reducing design cost whilst satisfying the minimum pressure head constraint. The user interacts with the network by selecting the components (i.e. nodes, pipes) of the network. Basic hydraulic information such as pressure will display when selecting a node in the network. In addition, a dialog displaying a list including available commercial diameters associated with their cost and hydraulic information will appear when selecting a pipe. Also, the influence of selecting a diameter for a pipe is provided to the user via a look-head feature that computes the objective function, in this paper minimizing network cost, aiding the user select a more suitable new diameter when making a decision. After the user changes the diameter of a pipe, the change is sent to the server which logs the change and runs a hydraulic simulation on the new network configuration and computes the new objective function and constraint values. This information is then sent to the client which updates the hydraulic state of the network to consider the updated intervention.

2. <u>Human derived heuristics model</u>

This model builds upon recent works[2], [3] that used decision trees to capture expert knowledge and used it in an EA's mutation operator for a WDN optimization design problem. The results of those studies demonstrated that integrating expert water systems knowledge into an EA increases the overall performance. However, in both studies the interaction from a user(s) on a WDN are recorded and then applied into the same network which is impractical in case of large WDNs. This is because it is almost impossible for a user to make a large WDN optimum through manual intervention, a process that is likely to lead to user fatigue [3]. The methodology presented in this paper was developed with the aim to generalize model features to enable the user to create generalizable heuristics on small/medium networks, and apply them automatically to larger networks. The purpose of the decision tree model used in this paper is to predict, given a randomly chosen pipe and the current network hydraulic state, whether the diameter of the selected pipe would be increased or decreased. A decision tree-classifier based learning approach[4] is employed which requires a fixed input schema. In this methodology the following seven normalized features, local to the selected pipe, are considered; the current diameter, velocity, upstream head deficit, downstream head deficit, influence, flow and length. The decision trees are trained on small/medium WDNs using the normalized input features and then applied to a larger WDN design problem. Each input feature is normalized based on the following equation, $f_{nor} = (f - f_{min})/ (f_{max} - f_{min})$. Where, f_{nor} = normalized value for desire input feature; f = input feature value in the selected pipe; f_{min} and f_{max} = minimum and maximum values for the desire input feature detected in all used networks in the HOWS framework. For example for diameter f_{min} and f_{max}= smallest and largest available diameter in all used networks. The overall model accuracy is assessed using explained variance and the leave- one-out cross validation method. Also the impact of each input feature is assessed using principal component analysis (PCA)[4].

3. Integrating heuristics into EA

The trained decision tree model in the second step is integrated into an EA through the mutation operator. The Human Derived Heuristic (HDH) mutation operator is designed to replace the standard mutation in an EA. The HDH mutation decodes the chromosome and randomly selects a pipe in the network, then the selected pipe's normalised input features are applied to the HDH model which predicts whether to increase or decrease the diameter and the next larger or smaller value is applied to the selected pipe. The EA employed in this paper is a Single Objective GA (SOGA) [5].

Results

The combined interaction from four users on four small/medium benchmark WDNs from the literature were collected and used to train the decision tree model. The resultant model is then applied to a larger network namely Modena to assess the ability of the HDH method. The detail of these network are summarised in Table (1). The population size, crossover, and a bit mutation probability are fixed at 100, single-point and 1/n respectively, where n represents the number of bits in the chromosome. The experiment involved standard SOGA and SOGA with HDH mutation probability of 0.5. Each algorithm was run 30 times over 500,000 fitness evaluations each. Leave-one-out cross validation found the decision tree model achieves an accuracy of 0.95 in predicting a new diameter for a selected pipe. PCA shows that current diameter for a pipe, followed by flow velocity and upstream head deficient are the most effected parameters in picking a new diameter for the pipe, which makes sense from an engineering point of view. Figure 1 shows the average network cost of the algorithms over 500,000 evaluations. As observed from the figure, in the case of standard SOGA, the addition of the human trained model increases performance as the search progresses.

Table 1. Networks detail

Network Id.	No. of Junctions	No. of pipes	No. of available diameter	No. of reservoir
Hanoi	31	34	6	1
Blacksburg	30	35	14	1
Fosspoly	36	58	22	1
Pescara	68	99	13	3
Modena	268	317	13	4

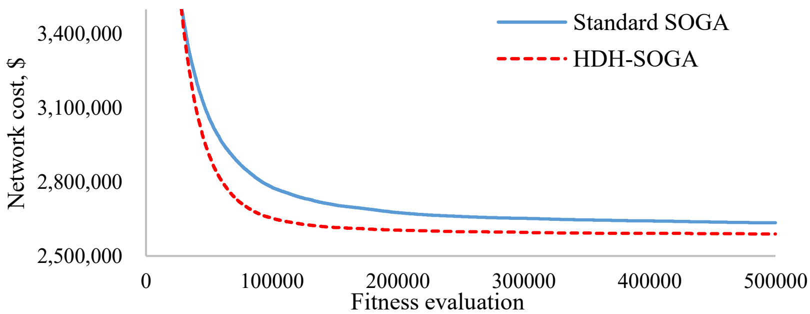

Figure 1. Average network cost results vs fitness evaluation for Modena network.

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