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Using a genetic programming–based hyper-heuristic strategy, we automatically build evolutionary algorithm operators to solve the bi-objective water distribution network design issue.

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ABSTRACT

Finding the appropriate pipe diameters that give the greatest service at the lowest cost is at the heart of the water distribution network (WDN) design challenge, which is of ongoing relevance in the UK and across the world. As a result, a plethora of solutions to this issue have been presented in the literature, with many of them taking a more bespoke, artisanal approach. In this research, we look into a new hyper-heuristic technique that use genetic programming (GP) to develop mutation operators for evolutionary algorithms (EAs) tailored to a dual-goal formulation of the WDN design issue (minimizing WDN cost and head deficit). The evolved operators, once developed, may be employed indefinitely across all EAs on all WDNs to boost performance. We show that it is possible to develop a set of mutation operators for a single training WDN using a unique multi-objective approach. The top operators are rigorously tested on three different, more difficult test networks. In this experiment, we develop a set of 83 operators. Ten that made the cut are dissected here. While GP5 exhibits the method's capacity to locate well-known operators like a Gaussian, GP1 is proven to be very successful and adds important domain-specific learning (pipe smoothing).

Key words

Water distribution network, genetic algorithm, hyper-heuristic, mutation, optimization.

INTRODUCTION

Optimising pipe sizes in a water distribution network to meet customer demand under operational hydraulic restrictions like head and velocity requirements is at the heart of the water distribution network design challenge. Changing the diameters of pipes has an effect on the network's hydraulic conditions and, by extension, the network's quality as measured by its capacity to meet varying demand points. Because each pipe has an impact on the overall hydraulic conditions, alterations to a single pipe will have varying impacts on the conditions throughout the network due to the interdependencies between the relative sizes of the various pipes. Therefore, the size of each pipe in the network must be considered in conjunction with the other pipes. Due to this combinatorial impact, it is hard to enumerate all conceivable designs in an acceptable amount of time, even for relatively small networks. WDN design is considered an NP-hard task because there are an enormous number of possible solutions—for instance, if there were six alternative sizes for each pipe in a network of only 30 pipes, there would be 2.21 1023 possible combi nations—far more than can be evaluated in a practical amount of time.By creating computational models of these networks in software like EPANET (Rossman), the quality of possible WDN designs (candidate solutions) may be assessed against a variety of criteria, such as the capacity to supply demand. Such models allow for the automated evaluation of possible network architectures, paving the way for the adoption of optimisation methods such genetic algor items (GAs) (Goldberg; Simpson et al.; Savic' & Walters 1997). Evolutionary algorithms (EAs), of which GAs are a subset, are inspired by nature and seek optimal network designs by iteratively mutating and proposing new designs across a large number of generations.

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This process is meant to resemble Darwinian evolution. Although it has been shown repeatedly in the literature that these conventional optimization techniques are effective at solving the WDN design problem, a new methodology known as hyper heuristics has emerged in recent years that is more effective at solving a broad class of optimization problems, including the WDN design problem. Hyper-heuristics use machine learning techniques to tailor the optimiser (e.g., EA) to each problem, such as the WDN design problem, through automated learning methods or, as is the case in this paper, the construction of optimised heuristics (like a GA's mutation operator), resulting in improved performance over traditional optimisers like EAs. It is possible to optimize large-scale problems in a reasonable amount of time with the help of meta-optimisation techniques like hyper-heuristics, which allow for more efficient solution of optimisation problems by optimising the optimiser and tailoring them to the problem.

The water supply network design conundrum

Historically, the WDN design problem has been formulated as a single-objective problem where the quality of the network is based solely on the economic impact of the design; that is, for a given layout, the best network design is the one that satisfies the hydraulic requirements at the lowest possible cost. A range of allowable node pressures or pipe velocities is often provided as the hydraulic restrictions. The literature is full of several approaches to the WDN issue and their respective merits. The usage of GAs (Goldberg &; Simpson &; Savic & Walters) and other meta-heuristic EAs (Laumanns et al.) is widespread. These approaches model the evolutionary process by searching for optimal network architectures across several generations using 'populations' of individual designs. It is widely accepted that EA approaches need a significant number of evaluations of prospective networks in order to discover suitable network designs, despite the fact that these techniques have been proved to be successful in solving a range of single-objective and multi-objective variations of the WDN. However, exploring bigger network designs might be prohibitive due to the costly nature of EA search (in terms of time and computer resources) and the complexity and sluggish run durations of many networks' simulation tools.

Hyper-heuristics

In recent years, a novel approach known as hyper-heuristics has arisen in the area of optimization (Cowling et al., Burke et al.). Using highly specialized domain-specific knowledge, this new paradigm is committed to extracting essential optimisation mechanisms and making them more generic across many diverse sets of optimisation issues. Selective hyper-heuristics and generative hyper-heuristics have been found in the literature (Burke et al.,). In order to improve search time and accuracy, selective hyper-heuristics are developed to optimize the selection and sequencing of existing "low-level heuristics," such the mutation operators in an EA. The MCHH (McClymond et al. b) is an online selective hyper-heuristic for embedding in meta-heuristics; the AMALGAM (Read et al.) is a multi-method online selective hyper-heuristic that controls population assign mint for multiple meta-heuristics; both are examples of selective hyper-heuristics used in hydro-informatics.

METHOD

Keed well and Khu () point out some aspects of the WDN design challenge that might be used to speed up and refine the search. To begin, the network topology is unchangeable, and every connection between pipes (the optimization parameters) is also set in stone. In addition, simulation allows us to link unique conditions to each pipe. The upstream node's head, for instance, may be linked to each pipe that feeds it while we evaluate the network as a whole to establish the design's viability. If the head pressure at a node is too high, for instance, it's fair to presume that the diameter of the pipes serving that node is too great and may benefit from being lowered. In a similar vein, if a node has a head deficit, it's likely because the pipe feeding it is too narrow. By using these guidelines, one may construct knowledgeable mutation operators that care for these hydraulic considerations while designing new networks. This section explains how to create innovative mutation operators for the WDN design problem using a multi-objective generative hyper-heuristic framework. A hyper-heuristic framework for generating solutions the overall generative hyper-heuristic framework for this investigation is shown in Figure 1. 'Optimal' mutation operators that can be applied to any WDN are evolved with the help of a training network, in this case a basic WDN. The generative framework comprises three distinct steps: initialization, generation, and evaluation. The initial population of mutation operators used in the optimization process is generated at random during the initialisation phase. The sample network designs to the underlying WDN that are used to test the evolved mutation operators are also generated during the initialise phase. To provide as much of a

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Volume 9, Issue 1, Jan 2022

level playing field as possible, we have locked in the sample solutions (potential WDN designs).

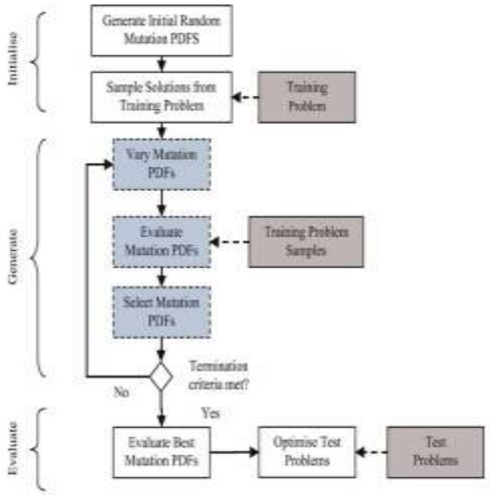

Figure 1 | General generative framework. Elements with dashed, shaded boxes indicate generative optimisation actions and grey shaded elements indicate interaction underlying problem class. The framework shows how a probability distribution function (PDF), in this case a specialised GP tree, can be evolved using samples from a training network in using the generative hyper-heuristic approach.

contrasting how different mutation operators are changing throughout time.

The create phase is an optimization loop in which a subset of the current population of mutation operators is subjected to variation, evaluation, and selection based on how well it matches designs taken from the underlying training network. This optimization cycle is iterated until a cut-off is reached, such as a certain number of generations. The best evolved mutation operators are then further assessed by being inserted into identical EAs and being applied to a set of test networks (in this instance, the Anytown benchmark and two real-world WDNs) once the generative optimisation phase has concluded. In the assessment step, we test how effectively the developed mutation operators work throughout the whole search process and how applicable they are. Over-fit mutation operators are removed from the training network during the assessment phase.

LABORATORY SETUP

In this part, we present an experiment that demonstrates how the aforementioned hyper-heuristic approach may be used to optimize EA mutation operators for the WDN design issue. The experiment was designed to prove the viability of the suggested approach in general, rather than in reference to any particular EA technique. Instead, the suggested method is intended to be EA-agnostic so that it may be used with any specialized EA or an EA that is more complex than the ES used here. Due to the potential for complex characteristics of more complex EAs to muddy the data and obscure the aspects of interest in this experiment, we opted for a basic EA, in this instance an ES. The experiment is carried out so that specialized mutation operators that have developed to solve the WDN design issue may be compared to one another and to a standard operator from the literature, such as a Gaussian mutation, for purposes of evaluation. Other, more complex optimization methods are not compared to the evolved operators since they are outside the scope of this research and cannot be compared fairly due to the presence of numerous additional variables that would considerably skew the findings, such as the selection strategy. Since evolved operators are not complete stand-alone optimization strategies, there is no need for a comparative examination of them with other optimisers.

RESULTS

Agents of mutation that have evolved

Figure 3 shows a scatter plot of the hyper-heuristic objective values for all 20 of the evolved mutation operators (including the 10 chosen mutation operators) that were evolved on the Hanoi training problem using SPEA2. You may find the full set of findings for all 83 Pareto optimum evolved operators in Table 3 of Appendix 1 (visitable at http://www. iwaponline.com/jh/016/226.pdf). As described in the Method section, three different sets of sample network designs were used to assess the efficacy of each of the evolved mutation operators. In this example, the training network was Hanoi. Overall, the results from theValues for 20 of the 83 most effective evolved mutation operators are listed in Table 1. For the 10 emphasized mutation operators shown in Figure 3 and discussed in further depth below, the objectives are indicated. Each GP operator's 'close','mid', and 'far' objective values are shown in their respective columns. Newly added columns provide the standard deviation of values acquired across the training set to demonstrate the degree of variation in the performance of the mutation operators across each target.

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[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
GP1	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
GP2	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
GP3	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
GP4	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
GP5	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
GP6	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
GP7	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
GP8	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
GP9	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
GP10	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
GP11	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
GP12	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
GP13	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
GP14	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
GP15	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
GP16	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
GP17	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
GP18	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
GP19	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
GP20	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

operator on sample network designs from each sample set in order to establish its fitness, or objective quality. The 'close' metric was judged based on how well it performed on a set of optimal network configurations. Themed' goals were evaluated using the 'average' quality network design set, while the 'far' goals were evaluated using the 'worst' quality set. The quality of the mutation operator for the 'near' and'mid' range set of network designs is presented along the (x, y) axes. The size of the points indicates the relative importance of the third goal, which is to evaluate mutation operators on network topologies that are "far" from the Pareto front. In most cases, mutation operators that do well in the 'near' range network design’s goal tend to do poorly in the 'far' objective, and vice versa for those that are strong in the'mid' objective. The general rise in point sizes ('far' objective) as the'mid' objective values rise demonstrates the poor relationship between the two metrics.

Two of the objectives are shown on the (x, y) axes for the mutation operator quality on the ‘close’ and ‘mid’ range set of network designs used for training. The third objective, assessing mutation operators on network designs ‘far’ from the Pareto front, is indicated by the size of the points; where smaller point sizes are given for smaller, better objective values on that set of points. Generally, the mutation operators which perform well on the ‘close’ range network design’s objective do not perform well on the ‘far’ objective, while those that are good in the ‘mid’ objective tend to perform well on the ‘far’ objective. The weak correlation between the ‘mid’ and ‘far’ objectives can be seen by the general increase in point sizes (‘far’ objective) as the ‘mid’ objective values increase. The evolved mutation operators produce an interesting Pareto front where the GP evolved mutation operators are most commonly specialised for one of the three different objective values. This produces a higher density of evolved solutions at the extremities of the Pareto front with fewer mutation operators producing a good trade-off between all three objectives. Ten GP evolved mutation operators are highlighted on the plot (Figure 3) which represent a range of GP trees and objective values. Of specific interest are GP1, GP5 and GP10, which are shown later in the test WDN optimisation results to produce very different convertgene behaviours. Of note are objective values of the GP1 and GP5 mutation operators which are both shown below o perform well on the test WDN problems as well as obtaining potentially the most favourable trade-off between the three objectives on the training Hanoi problem. The GP1, 5 and 10 mutation operators are shown in Figure 4. Each of the three mutation operators represent a different class of evolved mutation operator and were selected to illustrate the variety of mutation operators that can be constructed using the multi-objective generative hyper-heuristic method proposed in the Method section. The mutation operators range from entirely deterministic operations in GP10 through to the entirely random GP5. GP1 provides a mix of these two types of operation through a combination of random mutation and deterministic, domain-specific operations.

CONCLUSION

In order to solve the bi-objective WDN design issue, this work introduces a unique GP evolved decision tree generative hyper-heuristic approach. Domain information, in the form of attributes like downstream node head conditions, is used by many of the GP decision tree-based mutation operators to choose the sort of mutation to apply to each chosen pipe. The Hanoi benchmark issue is used to train the technique and its GP evolving mutation operators, which were developed using SPEA2. On the Anytown benchmark and on two real-world networks, we evaluated 10 different GP evolved mutation operators from the top evolved mutation operators. The results revealed the varying behaviours and resulting convergence features of the mutation operators. Some of the improved mutation operators were also shown to be more stable on the bigger test networks. While the GP10 mutation operator does well on the smaller networks, it struggles to scale to the bigger 81-pipe industrial network, demonstrating how evolved mutation operaactors may 'over-fit' to training difficulties. One mutation operator (GP1) consistently performed the best, achieving the best final generation outcome across all the test networks, demonstrating the method's promise. Interestingly, the examination of the GP tree shows that GP1 converges more slowly than many of the GP developed mutation operators, suggesting it has a greater exploration capability and, thus, better outcomes.

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