GENETIC ALGORITHM TECHNIQUES FOR CALIBRATING NETWORK MODELS

Dragan A. Savic and Godfrey A. Walters

D.Savic@exeter.ac.uk
G.A.Walters@exeter.ac.uk

Report Number:95/12

1995

Centre for Systems and Control Engineering,
University of Exeter,
North Park Road,
Exeter, EX4 4QF,
Devon,
United Kingdom.

This work was funded by SERC Grant GR/J09796

Abstract

Computer models for analysing pipe flows and pressures in water distribution networks are in widespread use throughout the world as essential tools for the efficient operation and improvement of very complex systems. Models invariably incorporate a number of unknown parameters, the values of which must be chosen so that the modelled performance matches as closely as possible that of the real network. The process of calibration involves both expensive data collection and a complex parameter optimisation problem.

This report presents novel Genetic Algorithm based parameter calibration procedures developed to match hydraulic model output with observed data sets.

(Key words: Networks, Calibration, Modelling, Optimization)

TABLE OF CONTENTS

ABSTRACT .... **I**

TABLE OF CONTENTS .... **II**

LIST OF TABLES .... **II**

LIST OF FIGURES .... **II**

INTRODUCTION **1**

MATHEMATICAL FORMULATION **3**

STANDARD CALIBRATION PROCEDURES **5**

GENETIC ALGORITHMS AND OPTIMIZATION **7**

Genetic Algorithms and Calibration 8
GA for Continuous Parameter Optimization 9

CASE STUDY **11**

CONCLUSIONS **17**

ACKNOWLEDGEMENT **18**

REFERENCES **18**

Appendix A 22
Appendix B 35

LIST OF TABLES

Table 1. Initial Estimates of Pipe Roughness Coefficients 13

LIST OF FIGURES

Figure 1. Supply and distribution arrangements for Danes Castle 11
Figure 2. Node pressure error for the three demand conditions 13
Figure 3. Pipe flow errors for the three demand conditions 14
Figure 4. Comparison of different solutions 15

Introduction

The ability to model larger water distribution systems (WDS) has improved considerably during the past decade[3,16]. Nowadays, it is widely acknowledged that design and operation of such systems depend critically on the efficiency and accuracy of mathematical models utilised to model the systems' behaviour under a variety of conditions. Before a model is used, it must be adjusted to ensure that it will predict, with reasonable accuracy, the behaviour of the system it models, i.e., it must be calibrated. This is widely acknowledged by the research community and several studies on WDS calibration have been published in the past two decades[4,13,19,30].

The problem of WDS model calibration, even if only for water quantity, (pressures and flows) is highly complex due to the large number of parameters examined and non-linear due to the flow equations. Several researchers have addressed this problem developing methods to minimise the difference between the values of the observed data and those computed by the network simulation model. These methods are based on the use of analytical equations[30], simulation models[19], or optimisation techniques[13]. Techniques based on analytical models may be applied to very small networks or may alternatively require large network to be simplified by considering only the skeleton network. Simulation techniques can handle larger networks but are generally restricted to a single loading condition. The most promising calibration procedures are based on optimisation. However, the success of current methods usually depends on linearizing assumptions or the unrealistic calculation of partial derivatives. In addition, they are generally local optimisation procedures which tend to become entrapped in local minima or suffer from numerical instabilities associated with matrix inversion.

Since models capable of simulating the hydraulic behaviour of pipe networks are complex in terms of size, non-linearity, and discrete nature, the use of analytical methods or classical optimization techniques requires many simplifications. These in turn may cause unsatisfactory or unrealistic results. On the other hand, Genetic Algorithms, which belong to a class of stochastic optimisation techniques capable of dealing with complex, multi-modal and discontinuous functions, have the required robustness and efficiency as well as conceptual simplicity to handle the aforementioned problems. Over the course of the last two decades these computer algorithms have proved their usefulness in various domains of application[29]. Recently, they have been applied to a broad spectrum of water resources problems[1,2,14,17,21,23,31,33].

The research described in this report combines theoretical and practical work in modelling (simulation) and Genetic Algorithms (optimisation) to develop novel, efficient and robust calibration procedures and tools. It is believed that the availability of these tools and an increased understanding of the data requirements for reliable model construction has great potential benefits. These include improved operation and more purposeful monitoring of water supply systems, increased quality of supply and ultimately lower costs to water companies and consumers.

Mathematical Formulation

A distribution network may be viewed as a connected graph with arcs representing pipes and nodes representing network elements like valves, pumps, reservoirs, demand points, etc. Two hydraulic variables are associated with network elements, namely flows and heads. The following mathematical statement of the problem is presented for a general water distribution network. The equations of the network express flow conservation at nodes and relations between head losses and heads for arcs:

$$\sum_{j \in J(i)} q_{ji} = c_i \tag{1}$$

$$\Delta h_{ij} = h_i - h_j \tag{2}$$

where $J(i)$ is a set of nodes adjacent to node i, c_i is the consumption at node i, q_{ji} is the flow from node j to node i, Δh_{ij} is the head loss in the pipe connecting i and j and h_i is the head at node i. The head loss Δh_{ij} to friction associated with flow through a pipe can be expressed in a general form as:

$$\Delta h_{ij} = R_{ij} q_{ij} \left| q_{ij} \right|^{n-1} \tag{3}$$

where R_{ij} and n ($n > 1$) depend on the flow resistance law selected. In this work the Colebrook-White formula is used to calculate resistance coefficient R_{ij} as a function of the friction factor f_{ij}, the diameter d_{ij} of the pipe connecting i and j, flow q_{ij} and the pipe length L_{ij}:

$$R_{ij} = \varphi\left(f_{ij}, d_{ij}, q_{ij}, L_{ij} \right) \tag{4}$$

The friction factor f is a function of the roughness of the pipe k, the diameter d, the flow q through the pipe and the viscosity of the fluid (which is for this work considered constant).

For specified pipe characteristics, demand patterns and reservoir heads the system of non-linear equations (1)-(4) has a unique solution defined by the flows and heads in the whole network. There are several iterative techniques[11] available for solving the above system which are incorporated into modern simulation tools[22, 34, 35]. These tools allow network analysts to concentrate solely on building realistic representation of the water distribution network thus enabling easier development of models. If input data for the model are correct, then predicted pressures and flows will match observed values. However, two main sources of problems are associated with data collection for real networks: (a) not all input parameters are measured directly because of the expense of data collection; (b) even if it is possible to measure all parameters a certain amount of inaccuracy will still be associated with readings in the field.

Standard Calibration Procedures

Techniques and procedures for constructing a WDS model may vary but in the UK they are summarised by the Water Research Centre (WRc plc) into the following activities[35]:

- inspection of supply, distribution and consumer records and maps,
- site inspection of plant and equipment,
- preliminary field measurement,
- field measurement exercise,
- entry of network data for a computer analysis, and
- calibration of the network model.

The basic aim of the inspection of supply, distribution records and maps is to select network data which will justify their inclusion in the model. For example, pipes which are below certain size are either ignored or grouped together and replaced by equivalent pipes. Since the demand for water is modelled to take place at nodes consumer records and maps are inspected in order to enable allocation of the total demand to network demand zones and finally to nodes. The demand allocation is aided by the field measurement exercise which involves flow measurement of significant demands, transfers to and from the network and from source works, pump stations and reservoirs. The key to meaningful calibration is having field measurements corresponding to more than one flow rate. In addition to flows the exercise also entails pressure logging at as many key sites as possible, e.g. at pump stations, in known problem areas, at large diameter pipes, etc.

Calibration performed using modern simulation packages commences when input data including an initial estimate of the roughness values of all pipes is entered into the model. The model is then analysed and the results compared with the field test measurements. Calibrations of this type proceed based on a tedious and time-consuming trial-and-error procedure where the parameter values are adjusted based on the hydraulic results and the hydraulic analysis is repeated. This iterative process continues until some stated operating specifications are satisfied or no viable change in input parameters which improves agreement between observed and predicted values can be found. In the latter case, the possibility of modelling anomalies, such as reduced pipe diameter due to internal corrosion, an incorrectly modelled open/closed valve, etc., should be investigated.

The above presented calibration procedure is extremely tedious and, even assuming enough time and resources are given for model building, depends critically on the analyst's skills and his/her understanding of the WDS being studied. Often this procedure will result in a less than optimum solution and may not be effective when a large number of variables and operating conditions are investigated.

Genetic Algorithms and Optimization

Genetic Algorithms (GAs) are biologically motivated adaptive computer techniques based on natural selection and genetic operators[8,15,20]. These algorithms are often used to solve complex optimization problems[29]. There are many variations of GAs but the following general description encompasses most of the important features.

Consider a GA for a parameter optimization problem where a set of real-valued variables $x=(x_1, x_2,\ldots, x_n)$ is to be found which maximise/minimise some objective function

$$\max_x f(x) \tag{5}$$

The analogy with nature is established by the creation within a computer of a set of solutions called a *population*. Each individual in a population is represented by a set of parameter values which completely describe a solution. These are encoded into *chromosomes*, which are, in essence, sets of character strings analogous to the chromosomes found in DNA. Standard GAs (SGAs) use a binary alphabet (characters may be 0's or 1's) to form chromosomes[9]. For example a two-parameter solution $x = (x_1,x_2)$ may be represented as an 8-bit binary chromosome: 1001 0011 (i.e., 4 bits per parameter, x_1 = 1001, x_2 = 0011). In that particular form the algorithm requires an additional mapping from bitstrings to real-valued parameters.

The initial population of solutions, which is usually chosen at random, is allowed to evolve over a number of *generations*. At each generation, a measure (*fitness*) of how good each chromosome is with respect to the objective function is calculated. This is achieved by simply decoding binary strings into parameter values, substituting them into the objective function and computing the value of the objective function for each of the chromosomes. Next, based on their fitness values individuals are selected from the population and recombined, producing offspring which will comprise the next generation. This is the *recombination* operation, which is generally referred to as *crossover* because of the way that genetic material crosses over from one chromosome to another. For example, if two chromosomes are $x = (x_1,x_2)$ = 1111 1111 and $y = (y_1,y_2)$ = 0000 0000, the two offspring may be z = 1100 0000 and w = 0011 1111.

The probability that a chromosome from the original population will be reproduced into the new generation is dependent on its fitness value. Fit individuals will have higher probability of being selected than less fit ones. Hence, the new population will have more of the better solutions. Mutation also plays a role in the reproduction phase, though it is not the dominant role, as is popularly believed, in the process of evolution. In SGAs mutation randomly alters each bit (also called *gene*) with a small probability. For example, if the original chromosome is $x = (x_1, x_2)$ = 1111 1111, the same chromosome after mutation may be x' = 1110 1111.

In essence, Genetic Algorithms rely on the collective learning process within a population of individuals, each of which represents a search point in the space of potential solutions. They draw their power from the theoretical principle of implicit parallelism[9]. This principle enables highly fit solution structures (*schemata*) to receive increased numbers of offspring in successive generations and thus lead to better solutions.

Genetic Algorithms and Calibration

In recent years, many researchers have begun to investigate the use of evolution based computer methods for calibration of various hydraulic/hydrologic models. Wang[33] investigated the use of GAs combined with fine-tuning by a local search method for calibration of a conceptual rainfall-runoff model. Models were calibrated by minimizing the residual variance defined as the sum of square of differences between computed and observed discharges.

Duan et al.[6] introduced the shuffled complex evolution method for a similar problem by hybridising a genetic algorithm with the Simplex search method. The objective function used was the mean daily square root of the difference between the observed flows and simulated flows.

Babovic et al.[1] used GA and the hydrodynamic MOUSE package to fit Manning numbers to pipes while Mohan and Lucks[17] reported on use of GAs for estimating parameter values of some linear and non-linear flow routing and water quality prediction models.

Most of those studies[1,17,33] used the GA formulation with binary representation requiring an additional decoding procedure from bitstrings to real-valued parameters being calibrated. This representation has several advantages over other encodings[5]. It is simple to create and manipulate, it is theoretically tractable, and it is widely applicable since very many problems can be encoded in binary strings. The mapping from a binary string to a parameter can be accomplished in many different ways but the precision of the mapping is limited to

$$\pi = \frac{x_{\max} - x_{\min}}{2^n} \tag{6}$$

where $x_{\min}$ and $x_{\max}$ are the lower and upper bounds on parameter x and n is the length of the bitstring representing parameter x. To construct a multi-parameter coding one can concatenate several bitstrings into a single chromosome representing a set of parameters. However, when dealing with a large number of parameters requiring high accuracy representation, a solution chromosome becomes increasingly long and the power of the GA search diminishes.

GA for Continuous Parameter Optimization

Instead of working with binary coding and applying problem-independent genetic operators, the size of WDS calibration problems dictates direct representation of decision variables. This simply means that bitstrings of SGA are replaced with real numbers. The change simplifies the algorithm in that no additional mapping is necessary since these numbers represent unknown parameters of the WDS model. However, other alterations to the SGA are required. Firstly, random binary initialisation is replaced with random real number initialisation. This is simply achieved by generating lists of real numbers that fall within parameter limits ($x_{\min}$, $x_{\max}$).

The SGA crossover operator may also be used for real number chromosomes since it does not depend on the representation scheme. Similarly to the SGA recombination genetic material crosses over from one chromosome to another. Let $x = (x_1,...,x_n)$ and $y = (y_1,...,y_n)$ be the parent chromosomes. Then the offspring $z= (z_1,...,z_n)$ may be computed by

$$z_i = \{x_i\} \, or \, \{y_i\} \tag{7}$$

where x_i or y_i are chosen with some probability of crossover p_c. In addition to this, an operator suitable for continuous parameter optimization may be used. Namely, *average crossover*[5] takes two chromosomes and produces one offspring that is the result of averaging the corresponding parameters of two parental chromosomes

$$z_i = \frac{x_i + y_i}{2} \tag{8}$$

Other crossover operators like *extended intermediate recombination* and *extended line recombination* [18] can also be used.

The mutation operator has been investigated for binary domains by many authors [8] and there have been many suggestions on how often it should be applied to a chromosome. The authors are of the opinion that that the mutation rate should be inversely proportional to the number of bits in the chromosome as suggested by Mühlenbein and Schlierkamp-Voosen[18]. However, an operator analogous to binary mutation, but suitable for continuous parameter optimization must be used since simple bit inversion is not possible with the floating-point representation.

An obvious way to mutate a real-valued parameter x is to randomly select a number that falls within parameter limits $x_m \in [x_{min}, x_{max}]$. Alternatively, the new parameter may be given by

$$x_m = x + z \tag{9}$$

where z is a number in the mutation range interval. This range can be a constant value throughout the evolution process or it may be a function of the generation number. By exploiting an analogy with annealing processes the range should become smaller with the evolution process approaching final stages.

Case Study

The proposed algorithm is used to provide a calibrated network model for the Danes Castle Zone of Exeter City (Devon, UK). This network was chosen for the study because it provides a complex calibration problem to solve and because the necessary input and output data were readily available. Namely, the network model for this zone was already built in 1991 when South West Water Services Limited (SWW) commissioned Ewan Associates to develop the model [7].

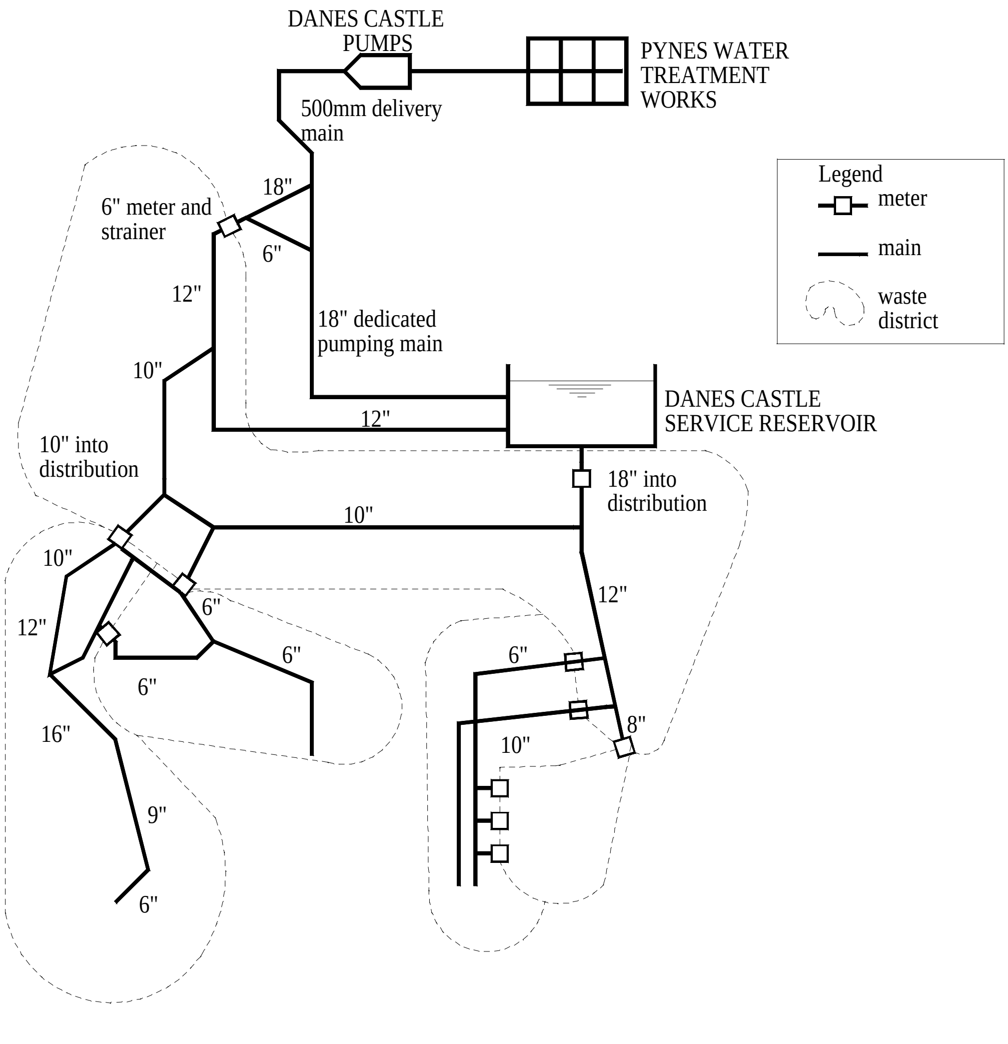

Figure 1. Supply and distribution arrangements for Danes Castle

The Danes Castle zone is supplied from Pynes Water Treatment Works (see Figure 1). Water is drawn from the River Exe and after treatment is pumped via a dedicated 18” main directly to the Danes Castle service reservoir and via a 12” pumping main directly into distribution.

The skeleton of the network is given in Figure 1, while the full network used in the original calibration exercise [7] and subsequently in this study consists of 197 nodes and 242 elements (see Appendix A for the input data). Of the 197 nodes, one is a fixed-head reservoir (at treatment works) and one is the Danes Castle service reservoir. Of the 242 network elements, two are pumps and three are modelled as throttling valves. In 1991, the Danes Castle reservoir was known to be in poor condition and it was reconstructed in 1992/93.

In order to monitor leakage, five waste districts have been set up as shown in Figure 1. These zones were serving between 1559 and 4498 properties each. Information obtained from these zones were used for demand calculations.

A 48 hour field test was undertaken between 13th and 15th August 1991. Flows were monitored into or within the system at 15 locations while pressures were monitored at 23 locations including the water level variation at Danes Castle service reservoir and the pump suction and delivery pressures at Pynes Treatment Works.

Three loading conditions were considered in the analysis:
(a) Peak demand - at 10:00h on the 13th of August.
(b) Average demand - at 16:00h on the 13th of August (see Appendix A).
(c) Minimum (night) demand - at 03:30h on the 13th of August.

The calibration process adopted and carried out by Ewan Associates comprised of the following tasks:

(1) to match the total system flows;
(2) to assess the predicted and observed total pressures for each snapshot and make reasoned adjustments to pipe roughness coefficients; and
(3) to report model anomalies.

Initially theoretical roughness values from standard hydraulic tables [10] were adopted for various materials as in Table 1. Steps (2) and (3) were carried out through a trial-and-error procedure based on the consultant’s experience and knowledge of the system. The results of the calibration[7] in terms of prediction errors, are presented in Figure 2 and Figure 3.

Table 1. Initial Estimates of Pipe Roughness Coefficients

Material Type	k value (mm)	Assumed Pipe Condition
Cast Iron	6.00	80 years of moderate attack
Asbestos Cement	0.15	Good
Ductile Iron	0.15	Good
PVC	0.10	Good
Relined Mains	0.15	Good

It should be noted that the pressure logger at node 5050 failed for the minimum demand loading condition (peak in Figure 2). Resulting pipe roughness coefficients are given in Appendix B (second row, under the heading "Ewan"). There were numerous modelling anomalies reported by Ewan Associates [7] which were not resolved at the time since they warranted additional investigation work. The anomalies were mainly caused by flow restrictions ("throttling") in particular pipes which may have occurred because of pipe tuberculation, internal pipe corrosion or even because the situation in

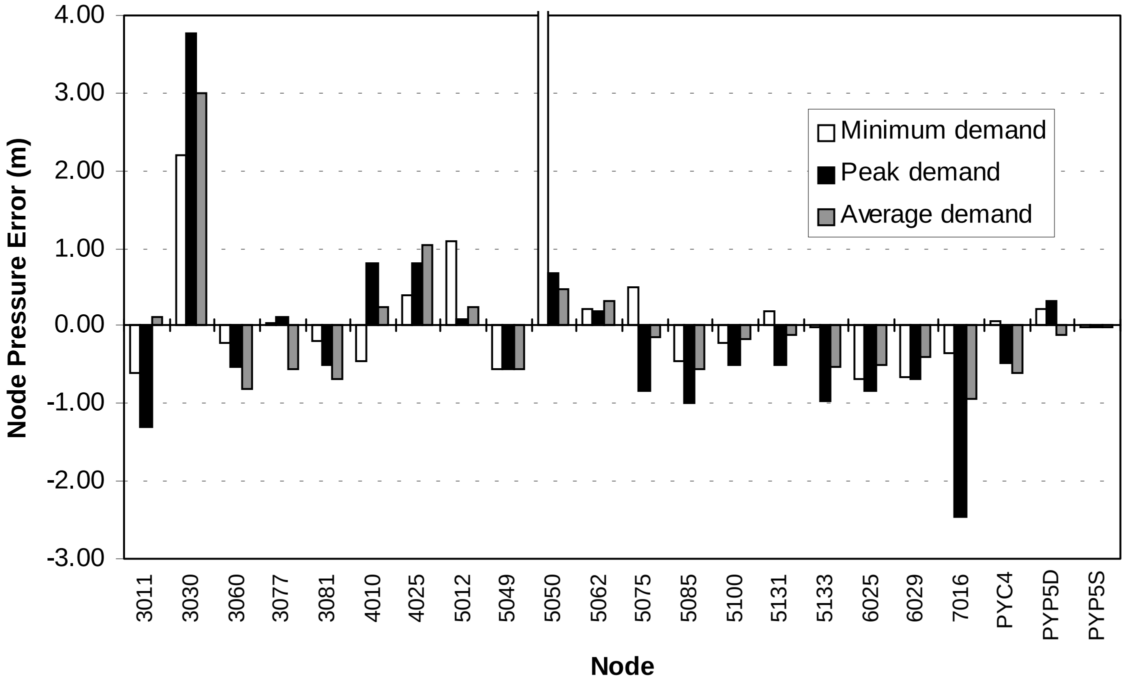

Figure 2. Node pressure error for the three demand conditions [7]

the network had changed since the mains geographic plan was made. Without further investigation these problems were solved by assigning high *k* (roughness) values to those pipes (e.g., pipes 3, 10, 12, 16, etc.).

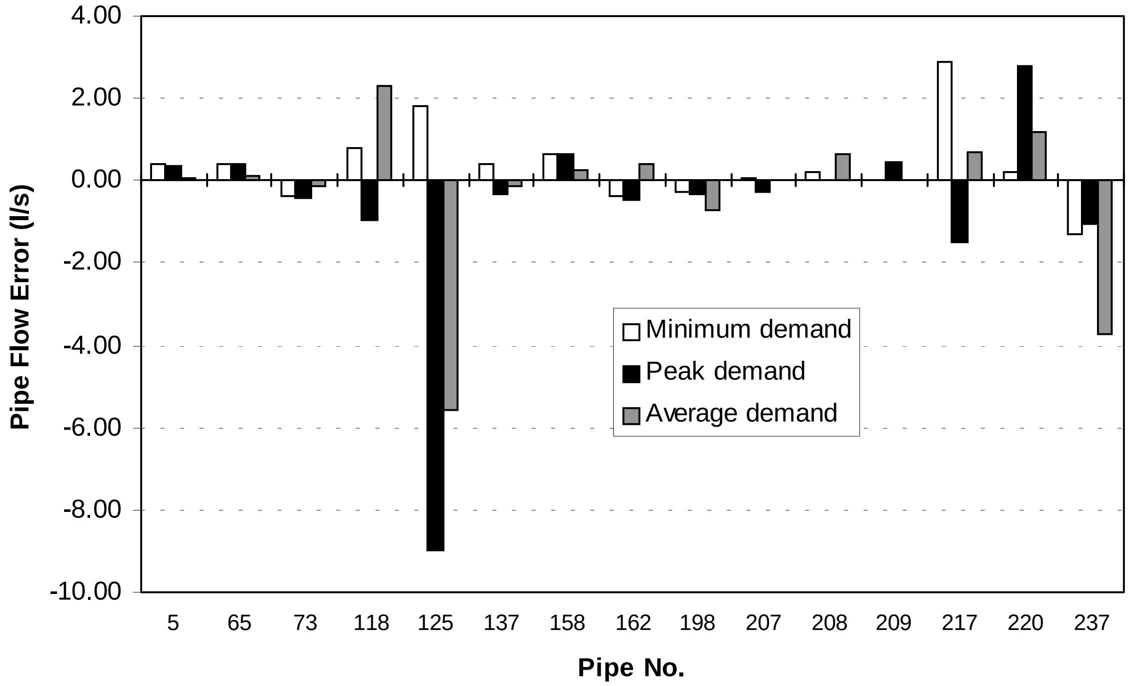

Figure 3. Pipe flow errors for the three demand conditions [7]

Although the number of parameters to be estimated cannot exceed the number of total observations available for all the loading conditions, the solutions obtained using the GA technique are based on fitting friction factor values to each of the pipes. This assumption was used for several reasons:

(a) to demonstrate model capabilities to deal with a large number of variables;

(b) to obtain an initial grouping of pipes in absence of detailed knowledge of the age and the service condition of pipes;

(c) to investigate how different and unrealistic solutions can result from attempting to acquire more information from collected data than is available.

Once consistent results have been obtained, groups of pipe with similar friction values can be identified and the GA can be restarted again. Starting from an initial grouping of pipes based only on nominal pipe diameters may introduce initial bias and prevent realistic solutions from being found.

The objective function used in this work is:

$$f(x) = p_1 \sum_i (H_i^o - H_i^p)^2 + p_2 \sum_j (Q_j^o - Q_j^p)^2 \qquad (10)$$

where, $p_{1,2}$ are normalising coefficients, and H_i^o and H_i^p are the observed and predicted heads at node *i*, respectively, and Q_j^o and Q_j^p are the observed and predicted flows through the pipe *j*.

Since GAs are stochastic-search techniques, solutions obtained running the program with different random seed values used to initialise the evolution process may be different. Therefore, several GA runs were necessary to ensure that the solutions identified were of good quality. Figure 4 shows results, in terms of sums of squared errors for both pressure heads and flows in the network, obtained by the original calibration study [7] and the 10 GA runs.

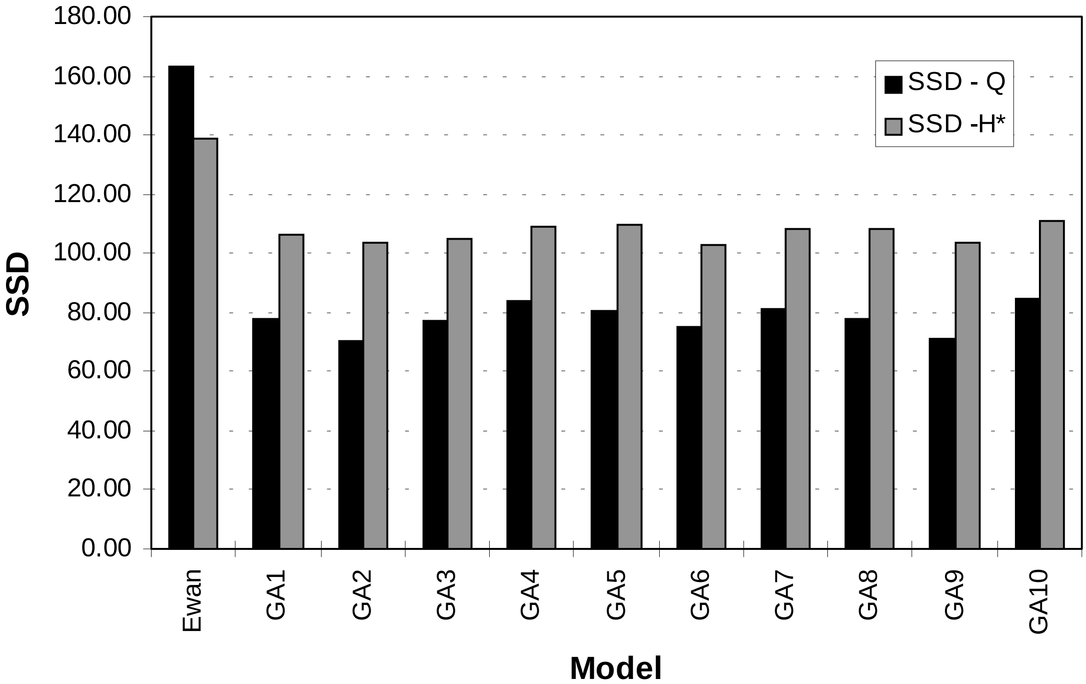

Figure 4. Comparison of different solutions

Since information regarding the internal condition of the mains was not available the initial values for calibration parameters were initially restricted to k_{min} ≤€*k*€≤ k_{max}. Resulting roughness values obtained by the GA are presented in Appendix B (under the heading “k_{max}=20 mm”). However, results obtained in the original study and the GA results indicate that better calibration results may have been obtained if higher roughness values were used. The table in Appendix B shows results obtained for $k_{max} = 60$ mm.

Conclusions

Various complex problems that arise in hydraulics and water resources in general have been solved using evolution-based programs and their hybrids. The applications of these techniques yield remarkable results with respect to the number of possible solutions an engineer may be faced with when dealing with the design and management of hydraulic systems. This report describes the development of a nonlinear optimization model for pipe network calibration. The model developed is based on GAs but departs from classical GAs in its representation. The use of floating-point representation enables calibration of a large number of unknown parameters without compromising accuracy and precision of the solutions.

The capabilities of the developed model are ascertained using data of an actual water distribution network. The results obtained by applying the developed model to the Danes Castle network (Exeter, Devon) clearly show the advantages over trial-and-error procedures used to match hydraulic model output with observed data sets. The efficiency of the procedure is tested by running the model several times with different seed values for the random number generator. Each GA run produced a solution better (with respect to the objective function used in this work) than the original study. The high level of agreement between the results of different runs also demonstrates the robustness of the procedure.

With respect to other optimization or analytical models, the GA-based calibration tool: (a) is easier to use because it does not need complex mathematical apparatus to evaluate partial derivatives or to invert matrices; (b) can handle larger networks, several loading conditions and a larger number of calibration parameters; and (c) permits easy incorporation of additional parameter types (pipe diameters, demands, etc.) and constraints into the optimization process.

It can be anticipated that the number of applications in this area will steadily grow since GAs are not only effective, they are also easily realisable due to the conceptual simplicity of the basic mechanisms. Their potential is even greater when parallel forms of the algorithms can be developed and executed in low-cost multiprocessor computing systems.

Acknowledgement

This work was supported by the U.K. Engineering and Physical Sciences Research Council, grant GR/J09796. We are also grateful to Ewan Associates for providing us with the report for the original calibration study and to South West Water Ltd. for providing us with the data for the Danes Castle network.

References

1. Babovic, V., Larsen, L.C. and Z. Wu, (1994), Calibrating Hydrodynamic Models by Means of Simulated Evolution, Hydroinformatics 94.

2. Cieniawski, S.E., Eheart, J.W. and Ranjithan, S., (1995), Using Genetic Algorithms to Solve a Multiobjective Groundwater Monitoring Problem, *Water Resources Research*, Vol. 31, No. 2, 399-409.

3. Coulbeck, B. (ed.), (1993), Integrated Computer Applications in Water Supply, Proc. of the *International Conference on Integrated Computer Applications for Water Supply and Distribution*, Research Studies Press, Taunton, UK.

4. Data, R.S.N., and Sridharan, K., (1994), Parameter Estimation in Water-Distribution Systems by Least Squares, *Journal of Water Resources Planning and Management Div.*, ASCE, 120(4), 405-421.

5. Davis, L., (1991), *Handbook of Genetic Algorithms*, Van Nostrand Reinhold, New York.

6. Duan, Q., Sorooshian, S., and Gupta, V.K., (1994), Optimal Use of the SCE-UA Global Optimization Method for Calibrating Watershed Models, *Journal of Hydrology*, 158, 265-284.

7. Ewan Associates, (1991), Network Analysis Report for the Danes Castle Zone of Exeter City, Vol. I, November 1991, p.29.

8. Goldberg, D.E., (1989), Genetic Algorithms in Search, Optimization, and Machine Learning, Addison-Weley, Reading, MA.

9. Holland H. J. , (1975), Adaptation in natural and artificial systems, University of Michigan Press, Ann Arbor.

10. Hydraulic Research Wallingford, (1983), Tables for the hydraulic design of pipes and sewers (fourth edition), Hydraulic Research Station Ltd.

11. Jeppson, R.W., (1983), Analysis of flow in pipe networks, Ann Arbor Science, Michigan.

12. Khomsi, D., G.A. Walters, A.R.D. Thorley and D. Ouazar, (1996), A Reliability Tester for Water Distribution Systems, *Journal Computing in Civil Engineering*, ASCE, 10(1), 10-19.

13. Lansey, K.E., and Basnet, C., (1991), Parameter Estimation for Water Distribution Networks, *Journal of Water Resources Planning and Management Div.*, ASCE, 117(1), 126-144.

14. McKinney, D.C. and Lin, M-D., (1994), Genetic Algorithm Solution of Ground-water Management Models, *Water Resources Research*, Vol. 30, No. 6, 1897-1906.

15. Michalewicz, Z. , (1992), Genetic Algorithms + Data Structures = Evolutionary Programs, Springer-Verlag.

16. Miller, D. (edt.), Water Pipeline Systems, Proc. of the *2nd International Conference on Water Pipeline Systems*, Mechanical Engineering Publications, London, UK, 1994.

17. Mohan, S. and Loucks, D.P., (1995), Genetic Algorithms for Estimating Model Parameters, in M.F. Domenica (ed.) *Integrated Water Resources Planning for the 21st Century*, ASCE, New York, pp.460-463.

18. Mühlenbein, H. and D. Schlierkamp-Voosen, (1993), Predictive Models for the Breeder Genetic Algorithm, I. Continuous Parameter Optimization, *Evolutionary Computation*, Vol. 1, No. 1, 25-49.

19. Rahal, C.M., Sterling, M.J.H., and Coulbeck, B., (1980), Parameter Tuning for Simulation Models of Water Distribution Networks, *Proc. Instn Civ. Engrs*, Part 2, 69, pp. 751-762.

20. Rechenberg, I., (1973), Evolutionsstrategie, Frommann-Holzboog, Problemata 15.

21. Ritzel, B.J., Eheart, J.W. and Ranjithan, S., (1994), Using Genetic Algorithms to Solve a Multiple Objective Groundwater Pollution Containment Problem, *Water Resources Research*, Vol. 30, No. 5, 1589-1603.

22. Rossman, L.A., (1993), The EPANET water quality model, in Coulbeck, B. (ed.), *Integrated Computer Applications in Water Supply*, Vol. 2, Research Studies Press, Taunton, Somerset, pp. 79-93.

23. Savic, D.A. and G.A. Walters, (1995), An Evolution Program for Optimal Pressure Regulation in Water Distribution Networks, *Engineering Optimization*, Vol. 24, No. 3, pp. 197-219.

24. Savic, D.A. and G.A. Walters, (1995), Genetic Operators and Constraint Handling for Pipe Network Optimization, *Lecture Notes in Computer Science 993, Evolutionary Computing*, Fogarty,T.C. (ed.), Springer-Verlag, pp. 154-165.

25. Savic, D.A., G.A. Walters and J. Knezevic, (1995), Optimal Opportunistic Maintenance Policy Using Genetic Algorithms, 1: Formulation, *Journal of Quality in Maintenance Engineering*, Vol. 1, No. 2, pp. 34-49.

26. Savic, D.A., G.A. Walters and J. Knezevic, (1995), Optimal Opportunistic-Maintenance Policy Using Genetic Algorithms, 2: Analysis, *Journal of Quality in Maintenance Engineering*, Vol. 1, No. 3, pp. 25-34.

27. Savic, D.A. and G.A. Walters, (1995), Place of Evolution Programs in Pipe Network Optimization, *Integrated Water Resources Planning for the 21st Century*, M.F. Domenica (ed.), American Society of Civil Engineers, New York, USA, pp. 592-595.

28. Savic, D.A. and G.A. Walters, (1994), Evolution Programs in Optimal Design of Hydraulic Networks, in *Adaptive Computing in Engineering Design and Control '94*, edited by I.C. Parmee, University of Plymouth, Plymouth, UK, pp. 146-150.

29. Savic, D.A. and G.A. Walters, (1994), Genetic Algorithms and Evolution Programs for Decision Support, Proceedings of an *International Symposium on Advances in Logistics*, edited by J. Knezevic, University of Exeter, United Kingdom, pp. 72-80.

30. Walski, T.M., (1983), Technique for Calibrating Network Models, *Journal of Water Resources Planning and Management Div.*, ASCE, 109(4), 360-372.

31. Walters, G.A. and Lohbeck, T.K., (1993), *Optimal layout of tree networks using genetic algorithms, Engineering Optimization*, 22, pp.27-48.

32. Walters, G.A. and D.A. Savic, (1994), Optimal Design of Water Systems Using Genetic Algorithms and Other Evolution Programs, Keynote paper in Hydraulic Engineering Software V Vol. 1: Water Resources and Distribution, edited by W.R. Blain and K.L. Katsifarakis, Computational Mechanics Publications, pp.19-26.

33. Wang, Q.J., (1991), The Genetic Algorithm and its Application to Calibrating Conceptual Rainfall-Runoff Models, *Water Resources Research*, Vol. 27, No. 9, 2467-2471.

34. Wood, D.J., (1980), Computer Analysis of Flow in Pipe Networks Including Extended Period Simulations, University of Kentucky, Lexington, Kentucky (Revised 1986).

35. WRc Engineering, (1989), *WATNET, Analysis and Simulation of Water Networks and a Guide to the WATNET3 Computer Program*, Swindon, UK.

Appendix A

Nodes		
ID	Elevation (m)	Demand (l/s)
3000	10.4	0.438211
3001	8.38	0
3002	7.92	0
3003	10.06	1.704568
3004	8.7	1.842017
3010	8	1.267655
3011	18.99	0.641376
3015	8.23	0
3020	12.8	1.154087
3025	22	0.428796
3026	23.7	1.154466
3027	24.49	0
3030	24.49	0
3035	23	0.125274
3040	12.19	2.166761
3041	20.97	0
3045	12.19	0
3050	12.19	0.122498
3051	6	0.419707
3052	6	0.082232
3053	6	0.079397
3054	6	0.028356
3060	6.07	0.532309
3061	6	0.04537
3062	6.4	0.079397
3063	6.4	0.053876
3064	6.4	0
3070	9.67	0.325956
3071	9.67	0.098264
3072	9.5	0.102082
3073	6.4	0.039698
3074	9.5	0
3075	6.4	0.04537

Nodes		
ID	Elevation (m)	Demand (l/s)
3076	5.7	0.065219
3077	5.25	0.412519
3080	10.5	0.318678
3081	9.08	0.324231
3082	9	0
3083	19.81	0.290322
3084	19.81	0.706857
3085	11.89	0.276816
3090	9	0.393162
3095	6.68	0
4000	7.5	1.932201
4010	6.89	1.334978
4015	7.32	0.686687
4016	7	0.50752
4020	7.62	0.732494
4021	8	0.548623
4022	8	0.443823
4023	8	0
4025	6.83	0.395239
4030	6.53	0.457622
5000	21	0.399252
5005	22.19	0.345727
5010	15.5	0.10029
5012	14.19	0.166443
5015	14.63	0.258059
5020	16.15	0.334326
5021	26	0.254054
5025	14.33	0.305591
5030	14.33	0
5035	12.19	0.431554
5040	32.31	0.702543
5045	40	0
5049	43.79	0
5050	43.68	0
5060	39.5	0.532204
5062	39.586	0.508377

Nodes		
ID	Elevation (m)	Demand (l/s)
5065	36.25	0.86899
5070	9.8	0.857269
5075	8.41	0
5080	10.36	0.288257
5085	12.93	0
5090	39.56	1.148491
5095	38.5	0
5100	27.43	0.502038
5105	28	1.447096
5110	28	0
5115	18	1.574201
5120	26	0.697161
5125	13.41	0.767554
5130	9.14	0.220817
5131	29.78	0
5133	33.08	0
5135	8.53	0
5140	7.92	0.766705
5200	54.89	0
5205	55.21	0
5210	46	0
5215	43	0
5216	43	0
5220	43	0
5225	44.5	0
5226	44.5	0
5230	33.4	0.331111
5235	38	0.256451
5240	37	0.862208
5241	37	0
5245	34.5	0
5246	34.5	0
5247	34.5	0
5300	54.89	0
5301	54.89	0
5303	55.21	0

Nodes		
ID	Elevation (m)	Demand (l/s)
5305	34.7	0
5310	34.7	0
5315	41	0.295332
5320	41	0
5325	41	0.099179
5326	34.16	0.102082
6000	24.5	0.250994
6005	24.3	0.108573
6010	21.79	1.408546
6015	19.5	0.340329
6016	19.5	0
6020	15	0
6025	19.86	1.228856
6024	19.86	0
6026	28	0.163063
6027	28	0.146429
6028	21.3	0.303642
6029	28.35	0.072383
6030	21.3	0.170721
6035	21	0.098955
6040	21	0.056042
6041	20.42	0.764201
6042	8.84	0.530838
6043	21.03	0.238455
6045	16.03	1.318714
6050	10.03	0.078609
6054	10	0
6055	10	1.069331
6060	9.5	0
6061	9	0
7000	19.51	-0.35878
7005	19.2	0.380454
7010	19.2	0.568682
7009	19.2	0
7011	17.1	0.81789
7015	19.2	0.068484

Nodes		
ID	Elevation (m)	Demand (l/s)
7014	19.2	0
7016	21.74	0.800935
7017	25	1.021349
7018	25	0.461837
7020	18.38	0
7021	18.38	0.22786
8000	10.4	0
8002	15	0.02
8004	15.24	0
8006	15.24	0
8008	34.444	0
8100	7	0
8104	61.3	0
8106	61.3	0
8110	61.3	0
8112	61.3	0
8114	7.5	1.93
8116	7.5	1.93
8118	60.01	0
8122	60.01	0
8124	34.44	0
8130	15	0
8140	6.72	4.15
8150	16	0
8160	36	0
8200	16	0
8202	16	0
8204	16	0
8206	16	0
8208	15.8	0
8210	27.1	0.103681
8212	20	0
8214	18.26	0
8216	15.8	0
8218	17.18	0
8220	17	0

Nodes		
ID	Elevation (m)	Demand (l/s)
8222	17.17	0
8224	17.19	0
8226	17	0
8228	17.17	0
8230	16	0
8232	16	0
8234	16	0
8236	16.5	0
8238	13.78	0
8240	13.93	0
8300	34.44	1.79
8310	12	1.87
8312	8.53	0
8314	7.5	0
8316	17.5	0.28
8318	9.75	0
8320	6	2.27

Pipes					
ID	Head Node	Tail Node	Length (m)	Diameter (mm)	*k* (mm)
1	3000	3001	110	203	1.5
2	3000	3002	100	300	0.5
3	3000	3010	290	254	70
4	3000	3010	290	102	10
5	3000	8000	10	254	10
6	3002	8314	315	300	0.5
7	3003	3004	410	100	1
8	3003	3020	130	300	0.5
9	3003	8314	420	300	0.5
10	3010	3011	590	102	80
11	3010	3015	500	152	20
12	3010	3020	760	305	70
13	3015	8314	10	152	20
14	3020	3025	300	152	1.5

Pipes					
ID	Head Node	Tail Node	Length (m)	Diameter (mm)	*k* (mm)
15	3020	3030	360	305	60
16	3020	3035	420	229	100
17	3025	3026	180	152	1.5
18	3025	3027	190	152	1.5
19	3030	3035	75	305	30
20	3030	3040	1170	406	20
21	3040	3041	200	229	1.5
22	3040	3045	200	229	35
23	3045	3050	30	152	35
24	3045	3060	520	229	45
25	3050	3051	720	152	35
26	3050	3070	440	152	40
27	3051	3052	190	152	10
28	3051	3052	190	102	10
29	3052	3053	105	102	10
30	3052	3063	330	152	10
31	3053	3054	200	150	10
32	3053	3064	315	152	10
33	3060	3061	50	152	10
34	3060	3063	405	152	10
35	3061	3062	315	152	10
36	3061	3073	320	152	30
37	3062	3063	200	152	10
38	3062	3076	405	152	10
39	3063	3064	150	102	10
40	3070	3080	110	152	30
41	3070	8318	100	152	10
42	3071	3072	295	152	10
43	3071	3072	305	152	10
44	3071	8318	10	152	10
45	3072	3073	185	152	35
46	3072	3074	190	152	35
47	3072	3077	300	152	40
48	3073	3075	100	152	10
49	3074	3075	185	152	10
50	3074	3076	150	152	10

Pipes					
ID	Head Node	Tail Node	Length (m)	Diameter (mm)	*k* (mm)
51	3075	3076	295	152	10
52	3076	8114	95	152	90
53	3077	8100	1250	180	0.05
54	3077	8100	1210	180	0.05
55	3077	8116	490	152	40
56	3080	3081	295	102	10
57	3080	3085	105	152	25
58	3081	3082	85	76	1
59	3082	3083	405	150	0.1
60	3083	3084	100	76	1
61	3084	3085	250	102	1
62	3085	3090	375	152	20
63	3090	3095	1015	152	20
64	4000	4010	300	152	1.5
65	4000	8314	50	102	30
66	4010	4015	160	152	1
67	4015	4016	505	102	1
68	4015	4020	105	152	1
69	4020	4021	185	152	1.2
70	4020	4025	310	152	1.2
71	4021	4022	40	152	1.2
72	4021	4023	40	152	1.2
73	4023	8312	100	150	1.2
74	4025	4030	370	152	1.2
75	4030	8140	300	152	1.2
76	5000	5005	385	305	40
77	5000	8216	190	305	40
78	5005	5010	400	305	40
79	5010	5012	95	305	40
80	5010	8150	20	152	1
81	5012	5015	395	305	40
82	5015	5020	100	305	650
83	5015	5025	695	254	55
84	5020	5021	205	305	650
85	5020	8002	5	152	1.5
86	5021	8104	1090	305	650

Pipes					
ID	Head Node	Tail Node	Length (m)	Diameter (mm)	*k* (mm)
87	5025	5030	40	150	25
88	5025	5050	505	254	60
89	5025	5070	950	254	40
90	5030	5035	100	150	20
91	5035	5040	300	150	0.1
92	5035	8310	50	152	0.1
93	5040	5045	315	150	0.1
94	5040	5065	360	150	0.1
95	5045	5050	150	457	12
96	5045	5060	30	254	13
97	5045	5226	500	305	2
98	5049	8110	270	457	1
99	5049	8206	3000	457	0.75
100	5050	5200	125	457	5
101	5060	5062	245	254	13
102	5062	5095	400	254	4
103	5070	5075	180	254	40
104	5075	5080	200	254	5
105	5075	5125	380	150	10
106	5080	5085	45	254	1
107	5080	5130	195	300	0.5
108	5080	8000	100	381	10
109	5085	5090	400	152	0.5
110	5090	5095	110	178	1
111	5090	5100	240	152	4
112	5095	5100	200	102	4
113	5100	5105	170	150	1
114	5105	5110	50	150	1
115	5110	5115	90	150	3
116	5110	5125	305	152	0.5
117	5110	5125	265	254	0.3
118	5110	5131	650	254	0.1
119	5115	5120	705	102	4
120	5120	5241	400	102	4
121	5125	5130	125	254	0.1
122	5130	5135	100	300	0.5

Pipes					
ID	Head Node	Tail Node	Length (m)	Diameter (mm)	*k* (mm)
123	5131	5133	20	305	0.1
124	5131	5226	820	305	1.5
125	5133	5235	350	305	0.1
126	5135	5140	215	150	1
127	5135	8312	105	300	0.5
128	5200	5205	490	254	1
129	5200	5300	7	457	2
130	5205	5210	190	254	2
131	5210	5215	40	254	2
132	5215	5216	290	150	2
133	5215	5220	40	254	2
134	5220	5225	340	203	2
135	5220	5320	15	203	2
136	5225	5226	10	152	2
137	5225	5230	290	203	55
138	5225	5325	100	203	1
139	5230	5235	350	203	55
140	5235	5240	350	305	1
141	5235	5241	400	203	5
142	5240	5245	600	305	0.5
143	5241	8160	150	203	5
144	5245	5246	10	203	0.5
145	5245	8008	10	254	1
146	5245	8300	185	305	0.5
147	5247	8124	10	203	0.5
148	5300	5301	10	457	2
149	5300	5305	610	254	1
150	5301	5303	405	152	1
151	5301	8118	5	457	1
152	5305	5310	100	254	1
153	5310	5315	40	254	1
154	5315	5320	25	203	1
155	5320	5325	100	203	120
156	5325	5326	300	152	1
157	6000	6005	300	152	3
158	6000	8160	395	152	3

Pipes					
ID	Head Node	Tail Node	Length (m)	Diameter (mm)	*k* (mm)
159	6005	6010	535	152	3
160	6010	6015	480	152	10
161	6010	6016	400	254	40
162	6010	8008	525	254	1.5
163	6015	6016	5	152	1.5
164	6015	8004	5	102	25
165	6015	8006	5	102	1
166	6015	8130	315	102	10
167	6015	8316	55	102	10
168	6016	6020	400	254	40
169	6020	6025	320	203	40
170	6025	6024	5	152	10
171	6025	6026	300	150	60
172	6025	6035	605	203	10
173	6024	6030	45	102	10
174	6024	8130	500	102	10
175	6026	6027	70	102	60
176	6027	6028	255	102	60
177	6027	6029	200	102	60
178	6028	6029	300	102	60
179	6028	6030	80	102	60
180	6030	6035	485	102	1.5
181	6035	6040	90	203	1.5
182	6035	6043	125	102	1.5
183	6040	6041	45	102	1.5
184	6040	6045	420	152	1.5
185	6041	6042	495	102	1.5
186	6041	6045	400	102	1.5
187	6042	8320	300	102	1.5
188	6043	6054	1000	102	1.5
189	6045	6050	300	102	1.5
190	6045	6050	320	152	1.5
191	6050	6054	110	152	1.5
192	6050	6055	215	102	1.5
193	6054	6055	100	152	1.5
194	6055	6060	575	150	1.5

Pipes					
ID	Head Node	Tail Node	Length (m)	Diameter (mm)	*k* (mm)
195	6060	6061	150	150	1.5
196	7000	7005	420	152	1
197	7000	7014	130	152	1
198	7000	8124	450	203	1
199	7005	7010	60	102	1
200	7010	7011	605	102	1
201	7010	7016	275	102	3
202	7009	7014	245	102	1
203	7015	7016	100	102	10
204	7015	7017	385	102	10
205	7016	7018	300	102	1
206	7016	7021	500	80	1
207	7017	8004	300	102	15
208	7018	8006	300	102	1
209	7020	8130	360	80	80
210	8000	8312	125	300	0.1
211	9000	8106	5	305	1
212	8104	8106	1	305	1
213	9000	8112	5	457	1
214	8110	8112	1	457	1
215	8114	8116	2	102	1.5
216	8118	8122	2	457	4
217	8120	8122	5	457	4
218	8200	8204	1	152	0.1
219	8200	8238	500	457	1
220	8202	8216	1	305	1
221	8204	8240	500	457	5.5
222	8208	8210	410	102	1
223	8208	8216	10	102	1
224	8210	8212	195	102	1
225	8210	8214	830	102	1
226	8218	8220	5	500	1
227	8220	8226	5	500	1
228	8220	8236	5	500	1
229	8222	8242	5	500	1
230	8224	8226	5	500	1

Pipes					
ID	Head Node	Tail Node	Length (m)	Diameter (mm)	*k* (mm)
231	8228	8242	5	500	1
232	8230	8232	5	450	1
233	8230	8234	5	450	1
234	8230	8236	130	500	1
235	8232	8234	5	450	1
236	8234	8238	25	457	1
237	8234	8240	25	457	5
243	8102	8120	1	500	1E-07
244	8108	8120	1	500	1E-07

Appendix B

Pipe No.	Roughness Values (mm)										
	Ewan	k_{max} = 20 mm					k_{max} = 60 mm				
		GA Run 1	GA Run 2	GA Run 3	GA Run 4	GA Run 5	GA Run 1	GA Run 2	GA Run 3	GA Run 4	GA Run 5
1	1.5	12.1	14.9	12.8	3.1	14.0	42.8	39.0	34.5	12.7	42.6
2	0.5	20.0	19.9	20.0	20.0	20.0	41.5	59.9	8.9	13.9	59.5
3	70.0	20.0	20.0	20.0	20.0	20.0	60.0	60.0	60.0	59.9	59.9
4	10.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
5	10.0	20.0	20.0	20.0	19.9	20.0	59.9	59.8	55.9	59.3	59.8
6	0.5	20.0	20.0	20.0	20.0	20.0	15.7	6.3	36.4	32.6	14.0
7	1.0	7.6	15.6	7.0	14.7	12.5	14.8	42.3	46.2	25.9	57.7
8	0.5	19.8	19.9	19.8	19.9	19.7	59.7	59.7	59.3	59.7	60.0
9	0.5	20.0	20.0	20.0	20.0	20.0	60.0	60.0	59.9	59.9	60.0
10	80.0	20.0	20.0	20.0	20.0	20.0	23.7	23.9	25.0	23.9	24.9
11	20.0	19.6	18.8	19.9	18.3	18.6	56.2	59.7	59.6	58.5	49.9
12	70.0	20.0	20.0	20.0	20.0	20.0	59.9	59.9	59.8	59.9	59.9
13	20.0	7.9	13.8	11.2	13.2	6.4	31.4	49.4	38.8	43.3	41.3
14	1.5	5.4	4.7	11.6	11.0	8.7	17.7	30.3	33.9	26.4	36.4
15	60.0	20.0	20.0	20.0	20.0	20.0	60.0	59.9	59.9	59.9	60.0
16	100.0	19.9	19.9	19.8	19.9	19.8	59.7	59.9	59.7	60.0	59.8
17	1.5	7.2	5.1	3.9	15.5	11.9	29.8	43.8	31.7	11.2	25.2
18	1.5	6.3	6.2	9.0	4.8	11.9	30.4	22.0	34.7	25.1	29.7
19	30.0	17.6	17.7	18.3	16.0	10.9	50.8	57.8	47.6	52.6	52.8
20	20.0	19.1	18.1	20.0	19.3	19.0	0.5	0.5	0.1	0.2	0.5
21	1.5	3.9	6.5	6.6	10.7	5.7	39.7	28.4	27.5	26.7	20.7
22	35.0	19.6	20.0	19.9	19.3	19.8	0.5	0.9	0.6	0.1	0.8
23	35.0	19.8	19.8	19.6	19.7	19.8	21.5	23.3	8.0	5.6	30.4
24	45.0	7.9	8.3	5.7	8.9	5.9	0.1	0.1	0.0	0.0	0.0
25	35.0	18.1	18.4	18.8	19.0	17.3	46.0	47.9	15.5	30.6	42.9
26	40.0	19.9	19.9	19.9	20.0	19.9	6.2	4.1	23.7	31.9	8.2
27	10.0	14.7	10.6	12.2	12.7	8.3	35.4	11.0	31.7	24.8	38.2
28	10.0	8.8	11.7	2.6	9.3	19.4	40.6	42.5	27.7	45.9	34.7

29	10.0	12.1	17.9	12.8	9.1	13.1	46.5	45.7	54.6	7.5	19.5
30	10.0	3.6	4.0	16.6	6.0	17.2	2.5	25.3	52.8	8.1	14.9
31	10.0	8.1	12.7	15.9	7.8	7.3	37.9	9.0	30.1	35.1	31.5
32	10.0	11.5	15.2	16.4	10.6	13.2	37.5	19.0	32.9	41.6	28.0
33	10.0	19.9	19.6	19.9	19.8	20.0	59.8	56.9	46.8	7.6	54.6
34	10.0	19.7	19.8	19.8	19.5	18.9	56.7	59.2	53.8	55.4	52.5
35	10.0	17.4	16.7	18.6	17.6	18.3	57.2	57.2	36.1	56.1	52.6
36	30.0	19.9	19.9	20.0	20.0	19.7	55.6	58.8	31.5	24.1	29.7
37	10.0	19.1	20.0	16.8	18.9	17.4	8.4	27.7	21.7	4.4	3.9
38	10.0	19.8	19.8	19.8	20.0	19.8	29.1	52.1	9.5	22.3	43.9
39	10.0	9.2	10.3	8.6	12.8	11.6	43.5	36.3	34.0	13.5	31.7
40	30.0	6.2	6.0	2.5	6.0	14.2	0.6	1.5	0.2	1.2	1.7
41	10.0	12.5	13.1	19.6	11.5	18.9	2.3	10.9	57.7	46.9	9.3
42	10.0	0.9	8.5	4.5	1.0	1.1	32.4	11.6	4.9	5.9	26.7
43	10.0	2.6	0.7	0.9	3.4	7.8	32.1	31.4	5.1	4.1	12.8
44	10.0	3.0	5.3	5.1	7.7	3.9	37.0	12.1	22.5	19.4	46.1
45	35.0	19.7	19.2	19.4	18.9	19.3	44.7	42.2	42.1	47.9	57.1
46	35.0	14.6	15.8	17.6	17.9	15.2	37.4	45.7	53.3	46.8	51.9
47	40.0	19.7	19.3	19.7	18.8	19.9	47.0	35.0	48.7	35.1	35.1
48	10.0	19.0	19.7	15.6	18.5	16.3	41.8	40.5	27.3	24.2	56.3
49	10.0	18.3	19.5	7.4	9.7	9.5	35.9	21.9	21.9	7.4	49.9
50	10.0	11.0	6.0	11.4	18.4	12.3	17.2	46.9	52.6	20.6	47.9
51	10.0	8.8	16.1	13.6	13.2	10.1	30.6	42.9	44.0	35.3	37.1
52	90.0	19.6	19.3	19.2	19.7	19.2	10.6	16.7	8.1	46.1	15.2
53	0.1	6.3	10.3	3.1	4.9	9.7	40.6	50.8	57.2	21.9	32.1
54	0.1	14.3	8.4	4.4	15.1	12.8	28.7	36.6	48.7	45.8	16.0
55	40.0	18.1	19.1	18.8	18.8	19.6	57.8	53.3	54.8	58.3	58.6
56	10.0	14.0	5.9	11.7	10.3	6.6	6.8	3.4	0.5	0.7	1.0
57	25.0	7.7	10.3	11.6	10.1	8.9	0.7	42.0	23.9	24.4	16.8
58	1.0	6.4	5.2	4.3	4.1	7.6	50.2	31.7	51.0	51.9	42.1
59	0.1	6.4	12.8	10.7	13.5	6.1	21.3	44.3	51.9	26.8	17.3
60	1.0	8.5	5.4	7.1	9.7	12.1	50.4	40.8	18.4	33.0	23.6
61	1.0	6.9	14.6	13.5	6.0	6.8	3.0	15.1	17.8	2.9	13.8
62	20.0	10.6	18.1	9.3	3.7	6.8	24.6	24.4	8.7	30.4	41.2
63	20.0	7.9	13.8	4.5	9.6	12.6	30.1	48.6	39.8	34.7	8.5
64	1.5	19.5	19.6	19.4	19.2	19.7	59.8	59.5	59.2	60.0	59.7
65	30.0	6.8	3.5	4.5	5.2	4.0	0.0	0.0	0.0	0.0	0.0

66	1.0	18.7	18.1	19.5	16.5	15.3	59.8	59.2	59.1	59.8	59.4
67	1.0	2.8	10.5	8.4	11.6	7.6	51.9	12.8	10.0	47.9	23.4
68	1.0	19.4	19.1	19.7	19.5	19.8	59.8	59.7	59.8	60.0	60.0
69	1.2	1.4	0.0	1.2	1.1	1.6	0.3	0.5	0.2	0.2	0.5
70	1.2	2.7	4.3	3.5	3.4	4.0	3.3	4.4	3.5	3.0	4.0
71	1.2	6.0	10.8	7.1	8.6	15.9	31.6	12.0	10.6	36.7	27.1
72	1.2	1.1	5.8	3.8	2.0	0.4	2.6	1.8	5.2	8.0	2.2
73	1.2	0.5	0.3	0.0	0.3	0.2	0.7	0.3	0.7	0.4	0.7
74	1.2	6.5	12.0	11.8	10.4	5.0	17.1	46.9	14.8	43.0	12.8
75	1.2	14.2	13.7	5.4	15.6	8.6	23.3	33.1	28.5	30.1	26.7
76	40.0	20.0	20.0	20.0	20.0	20.0	59.9	60.0	60.0	60.0	60.0
77	40.0	20.0	20.0	20.0	20.0	20.0	60.0	60.0	60.0	60.0	60.0
78	40.0	20.0	20.0	20.0	20.0	20.0	60.0	60.0	60.0	60.0	60.0
79	40.0	19.9	20.0	19.9	19.9	19.9	59.6	59.9	60.0	59.8	59.9
80	1.0	9.4	7.3	4.8	12.7	12.0	25.0	33.4	17.5	31.5	21.7
81	40.0	20.0	20.0	20.0	20.0	20.0	60.0	60.0	60.0	60.0	60.0
82	650.0	19.7	19.7	19.5	19.9	19.7	59.6	59.8	59.8	59.2	59.9
83	55.0	18.5	18.6	18.3	18.7	18.9	16.3	16.8	16.5	16.5	16.3
84	650.0	19.9	19.8	19.9	19.9	19.9	59.9	59.9	59.8	59.9	59.9
85	1.5	15.0	12.0	11.2	13.0	5.0	8.5	40.0	39.0	34.1	21.9
86	650.0	20.0	20.0	20.0	20.0	20.0	60.0	60.0	60.0	60.0	60.0
87	25.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
88	60.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
89	40.0	20.0	20.0	20.0	20.0	20.0	54.7	43.0	58.4	59.1	48.5
90	20.0	11.5	2.8	12.0	11.5	5.0	21.8	35.9	25.2	38.8	23.9
91	0.1	12.8	9.1	6.0	13.8	14.9	31.4	19.3	40.5	32.7	28.6
92	0.1	4.7	8.0	13.1	6.8	15.0	19.0	29.7	14.6	19.9	53.3
93	0.1	13.1	4.5	6.2	6.3	15.4	41.7	26.7	45.1	45.3	18.9
94	0.1	13.1	13.6	10.9	8.5	3.0	42.3	40.1	10.0	34.5	37.8
95	12.0	20.0	20.0	19.9	20.0	20.0	38.5	0.4	14.1	19.7	31.0
96	13.0	20.0	20.0	20.0	19.9	19.9	0.1	0.0	16.7	0.1	30.2
97	2.0	7.9	8.1	8.5	8.1	8.6	8.6	11.0	16.9	4.8	25.8
98	1.0	19.3	18.2	16.0	19.9	19.1	42.6	21.3	28.4	16.6	43.2
99	0.8	3.5	0.2	0.0	2.2	0.1	0.6	0.2	0.1	0.0	0.4
100	5.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
101	13.0	20.0	20.0	20.0	20.0	20.0	31.1	45.6	28.2	28.7	28.1
102	4.0	20.0	20.0	20.0	20.0	20.0	0.0	6.1	12.1	2.4	6.5

103	40.0	20.0	20.0	20.0	20.0	20.0	60.0	59.9	59.7	59.9	59.7
104	5.0	20.0	20.0	20.0	20.0	20.0	60.0	59.9	60.0	59.9	60.0
105	10.0	20.0	20.0	19.9	19.9	19.8	59.7	59.6	59.7	59.4	59.9
106	1.0	18.8	19.5	19.9	19.6	19.5	60.0	60.0	59.9	60.0	59.7
107	0.5	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
108	10.0	20.0	20.0	19.9	20.0	20.0	59.9	59.8	58.1	59.0	59.8
109	0.5	20.0	20.0	20.0	20.0	20.0	0.0	0.0	0.0	0.0	1.7
110	1.0	20.0	20.0	20.0	20.0	20.0	20.2	17.2	0.0	11.1	0.0
111	4.0	19.9	19.9	19.9	19.9	20.0	50.7	30.0	38.0	56.0	59.5
112	4.0	20.0	20.0	20.0	20.0	20.0	0.4	0.0	2.2	0.0	0.1
113	1.0	20.0	20.0	20.0	20.0	20.0	60.0	60.0	59.9	59.8	5.8
114	1.0	19.9	20.0	19.8	19.9	19.8	59.8	59.9	59.0	59.7	59.9
115	3.0	0.0	2.0	4.0	0.7	3.7	0.4	0.5	2.2	3.0	1.7
116	0.5	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
117	0.3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
118	0.1	13.1	13.3	13.0	12.8	12.9	9.7	9.5	8.6	8.1	6.7
119	4.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
120	4.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
121	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
122	0.5	17.1	17.7	16.3	17.9	19.3	59.5	59.8	59.6	57.4	59.7
123	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
124	1.5	0.0	0.0	0.0	0.0	0.0	0.1	0.0	0.0	0.0	0.0
125	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
126	1.0	16.9	13.5	13.8	7.7	6.4	43.7	34.0	28.4	34.9	14.4
127	0.5	8.4	14.8	14.7	8.7	18.6	58.4	58.9	56.1	56.5	57.8
128	1.0	18.9	18.4	19.4	19.0	18.8	7.9	20.1	10.8	47.0	5.4
129	2.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
130	2.0	19.7	16.4	17.6	14.6	18.2	38.8	38.3	25.6	29.0	21.4
131	2.0	15.0	13.5	18.1	8.4	16.6	38.0	54.4	31.5	49.8	22.6
132	2.0	11.9	5.5	19.8	7.7	11.4	52.2	21.9	15.5	23.4	50.4
133	2.0	11.2	9.5	16.3	15.3	13.2	54.3	23.2	19.6	32.4	56.6
134	2.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
135	2.0	14.7	13.4	11.3	15.3	12.9	32.4	11.1	9.4	22.9	19.5
136	2.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
137	55.0	20.0	20.0	20.0	20.0	20.0	40.1	30.5	22.6	24.1	37.0
138	1.0	19.8	19.4	19.7	19.6	19.7	0.6	7.6	0.1	40.4	4.5
139	55.0	20.0	20.0	20.0	20.0	20.0	57.0	47.7	57.0	53.8	48.6

140	1.0	17.6	8.5	5.1	4.8	7.6	1.0	10.9	0.2	0.0	5.2
141	5.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
142	0.5	7.8	17.4	12.3	14.6	14.0	15.9	4.9	16.1	25.2	17.4
143	5.0	19.0	14.2	16.1	17.0	18.7	44.0	59.9	58.3	59.4	59.5
144	0.5	9.8	18.7	7.7	11.0	11.7	6.0	43.6	28.2	10.5	15.5
145	1.0	10.0	10.9	13.7	12.8	15.0	58.7	56.3	59.4	51.5	58.6
146	0.5	6.1	10.2	8.7	10.8	14.4	35.4	43.0	13.8	29.8	20.0
147	0.5	9.7	7.6	6.7	12.6	11.8	38.4	40.8	20.8	34.9	7.1
148	2.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
149	1.0	18.6	19.9	18.7	19.8	18.5	4.5	3.6	0.2	6.6	0.7
150	1.0	6.9	2.5	8.0	4.6	6.0	36.0	30.9	44.8	17.0	24.3
151	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
152	1.0	16.4	14.8	14.4	18.1	14.4	39.5	50.0	21.6	35.1	1.9
153	1.0	10.0	9.6	2.5	13.6	14.3	13.4	52.3	11.2	37.7	3.3
154	1.0	18.4	15.0	9.4	17.2	10.3	47.8	32.4	34.9	34.6	11.0
155	120.0	19.2	19.7	19.4	20.0	19.8	2.6	14.2	9.4	42.4	0.1
156	1.0	5.8	10.0	5.5	14.3	15.9	6.2	44.8	29.9	8.5	37.4
157	3.0	2.4	2.9	11.1	8.1	15.2	0.0	32.4	0.0	0.4	2.9
158	3.0	20.0	17.7	16.4	15.6	12.0	13.1	1.2	11.2	18.5	13.9
159	3.0	0.1	0.0	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0
160	10.0	11.4	11.2	9.1	14.8	7.4	55.1	51.8	57.7	50.4	59.8
161	40.0	7.1	14.5	6.0	11.9	14.7	8.5	1.4	18.5	1.7	2.9
162	1.5	2.7	0.2	5.0	2.0	1.1	0.3	1.2	0.3	1.8	0.4
163	1.5	1.3	1.8	2.6	2.4	5.0	1.9	13.0	5.0	14.4	1.1
164	25.0	12.4	6.4	13.0	7.3	7.8	29.9	30.1	42.6	53.5	41.2
165	1.0	0.3	0.6	0.3	0.2	0.2	7.3	2.8	2.8	0.8	3.5
166	10.0	18.8	19.4	18.8	19.1	18.0	10.9	38.4	21.7	30.5	58.6
167	10.0	5.8	15.7	7.2	1.2	10.4	45.5	23.6	34.4	32.1	41.4
168	40.0	19.5	18.9	18.8	19.8	19.0	24.8	55.5	31.5	1.1	35.9
169	40.0	19.8	19.9	19.9	19.9	19.7	37.0	33.8	20.6	33.5	16.5
170	10.0	2.5	9.6	7.0	13.0	4.1	39.3	37.8	26.3	28.1	11.9
171	60.0	19.5	17.3	17.0	15.7	17.3	46.9	54.7	52.5	54.0	13.2
172	10.0	17.4	18.8	16.8	16.3	18.4	23.5	23.4	48.4	46.1	37.5
173	10.0	19.1	19.1	17.9	18.8	17.5	56.9	56.0	46.1	22.9	48.3
174	10.0	15.6	15.8	18.1	13.5	16.2	8.1	5.9	23.2	7.9	17.5
175	60.0	16.7	17.5	15.9	19.2	15.6	49.9	44.1	51.9	53.9	43.6
176	60.0	10.9	10.8	9.1	7.7	15.2	53.4	51.5	6.6	21.5	2.5

177	60.0	13.0	12.7	17.4	15.8	8.8	54.8	47.2	40.5	53.1	52.5
178	60.0	6.3	0.2	5.8	2.2	0.9	7.0	5.9	2.3	20.1	3.3
179	60.0	6.4	6.3	5.1	3.2	2.6	1.7	22.9	6.4	32.2	8.3
180	1.5	0.0	0.1	0.0	0.0	0.1	44.9	43.1	43.6	17.7	20.9
181	1.5	2.3	7.1	13.6	9.3	13.9	33.6	32.9	28.1	29.8	15.8
182	1.5	12.0	10.3	6.4	13.0	10.8	36.0	34.5	40.7	38.7	8.1
183	1.5	7.4	4.4	6.5	10.8	9.8	42.2	42.6	17.1	40.8	7.8
184	1.5	14.6	7.9	14.5	12.7	7.5	32.2	34.6	22.2	13.7	27.6
185	1.5	9.7	3.4	15.5	14.7	12.7	29.5	23.8	48.9	48.9	31.0
186	1.5	11.5	3.7	16.2	14.0	10.7	53.2	24.8	33.4	50.3	25.4
187	1.5	6.0	1.6	5.0	8.5	6.5	38.5	18.1	30.9	16.0	15.0
188	1.5	5.5	8.3	15.5	15.2	10.0	32.9	27.9	14.8	19.5	39.9
189	1.5	7.4	7.8	10.5	5.5	5.9	28.6	28.2	5.3	46.1	28.0
190	1.5	3.5	12.2	4.2	6.6	5.9	46.0	12.7	21.4	26.9	30.8
191	1.5	7.9	11.2	13.6	4.4	3.8	38.9	35.5	35.6	46.1	28.2
192	1.5	3.5	13.1	9.7	4.0	10.9	18.3	28.3	42.0	14.1	59.2
193	1.5	14.3	14.9	13.9	7.2	9.1	38.0	54.9	25.3	28.1	44.6
194	1.5	10.1	9.6	8.1	18.1	17.8	13.7	36.9	9.2	41.5	30.7
195	1.5	9.7	4.8	7.4	6.7	8.2	27.5	49.2	17.6	17.1	28.7
196	1.0	15.8	8.6	11.2	17.2	17.0	28.9	4.1	19.2	29.4	2.1
197	1.0	14.4	8.9	13.8	12.3	10.9	26.3	28.9	43.3	19.0	54.8
198	1.0	7.5	2.0	11.0	7.6	9.9	38.1	45.9	16.9	14.6	43.1
199	1.0	18.7	18.3	19.2	5.8	8.1	20.3	13.8	16.2	2.2	2.9
200	1.0	1.2	6.9	15.9	5.2	5.6	4.5	32.4	37.7	48.2	12.3
201	3.0	19.6	19.2	18.3	19.2	19.1	31.8	44.4	57.7	58.2	59.5
202	1.0	8.6	12.4	9.2	11.7	9.2	23.2	34.4	34.4	30.4	26.3
203	10.0	3.6	14.4	10.5	3.1	6.1	6.5	8.5	12.6	27.9	6.9
204	10.0	4.4	12.9	9.4	4.9	9.2	6.1	2.8	8.0	5.1	3.1
205	1.0	0.0	0.0	0.0	0.0	0.0	0.2	0.0	0.0	0.0	0.0
206	1.0	6.7	14.9	9.4	8.8	8.5	12.7	19.6	20.2	37.8	31.4
207	15.0	4.9	4.9	5.2	5.1	4.8	7.7	8.7	5.3	4.8	5.1
208	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.2	0.0	0.0	0.0
209	80.0	4.2	16.5	7.4	5.8	2.6	35.1	29.4	37.0	33.5	26.4
210	0.1	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
211	1.0	14.8	17.2	11.8	19.3	16.6	49.7	58.2	56.4	57.7	57.4
212	1.0	8.2	6.9	16.0	15.9	17.9	34.7	18.9	30.3	58.2	55.7
213	1.0	8.1	6.3	4.8	13.5	13.8	0.5	0.2	5.1	30.8	4.9

214	1.0	6.7	5.5	17.2	19.1	11.3	14.8	7.6	34.3	43.1	41.2
215	1.5	18.6	15.8	13.2	17.3	10.6	48.6	50.7	3.3	29.6	52.0
216	4.0	0.0	0.1	0.0	0.1	0.2	0.0	0.0	0.0	0.0	0.0
217	4.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.0	0.0
218	0.1	0.4	0.3	0.1	0.0	0.0	0.1	0.0	0.3	0.0	0.1
219	1.0	0.2	0.3	0.4	0.3	0.0	0.1	0.4	0.0	0.2	0.0
220	1.0	8.7	6.3	10.5	12.6	15.6	13.3	16.2	49.9	20.0	58.6
221	5.5	2.5	0.6	0.6	1.8	0.6	0.9	0.4	0.6	0.5	0.9
222	1.0	13.3	8.9	8.4	4.3	11.2	14.5	22.9	42.5	19.8	21.7
223	1.0	10.6	11.1	12.3	2.9	12.2	36.1	33.1	48.3	22.3	48.5
224	1.0	11.4	9.4	10.6	6.3	2.0	35.9	41.6	30.2	35.6	37.9
225	1.0	11.8	16.9	5.4	7.5	5.8	36.4	8.9	39.5	36.9	18.8
226	1.0	10.0	3.5	3.0	17.4	18.7	0.3	0.2	59.4	0.9	59.4
227	1.0	12.6	8.7	17.4	8.2	9.9	49.5	16.3	25.8	24.5	29.1
228	1.0	12.6	0.2	4.3	19.2	18.7	36.3	0.3	59.3	2.5	59.6
229	1.0	12.7	16.1	18.6	9.6	11.1	19.2	59.7	11.1	55.0	9.5
230	1.0	8.5	10.3	11.0	8.8	7.1	29.8	45.4	50.9	39.5	27.7
231	1.0	5.0	8.9	13.6	9.9	5.7	47.4	26.3	17.0	22.5	2.8
232	1.0	7.5	2.4	3.6	19.6	19.7	39.2	0.0	59.8	1.7	59.9
233	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
234	1.0	18.0	2.9	0.0	20.0	20.0	35.6	0.0	60.0	0.0	60.0
235	1.0	7.8	4.6	2.4	19.2	19.3	39.6	0.3	59.6	0.2	59.6
236	1.0	8.4	0.0	0.0	0.3	0.2	3.3	0.3	0.2	0.0	0.2
237	5.0	1.0	5.6	18.6	8.7	17.1	57.2	20.9	51.1	0.0	9.7