DEVELOPING A METHODOLOGY FOR THE DESIGN OF WATER DISTRIBUTION NETWORKS USING GENETIC ALGORITM

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ABSTRACT

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The realization of planning, design, construction, operation and maintenance of water supply systems pictures one of the largest infrastructure projects of municipalities; water distribution networks should be designed very meticulously. Genetic algorithm is an optimization method that is based on natural evolution and is used for the optimization of water distribution networks.

Genetic algorithm is comprised of operators and the operators affect the performance of the algorithm. Although these operators are related with parameters, not much attention has been given for the determination of these parameters for this specific field of water distribution networks.

This study represents a novel methodology, which investigates the parameters of the algorithm for different networks. The developed computer program is applied to three networks. Two of these networks are well known examples from the literature; the third network is a pressure zone of Ankara water distribution network.

It is found out that, the parameters of the algorithm are related with the network, the case to be optimized and the developed computer program. The pressure penalty constant value varied depending on the pipe costs and the network characteristics. The mutation rate is found to vary in a range of [0.0075 – 0.0675] for three networks. Elitism rate is determined as the minimum value for the corresponding population size. Crossover probability is found to vary in a range of [0.5 – 0.9]. The methodology should be applied to determine the appropriate parameter set of genetic algorithm for each optimization study. Using the method described, fairly well results are obtained.

Keywords: Genetic algorithm, optimization, water distribution network, design, Ankara

ÖZ

SU DAĞITIM ŞEBEKELERİNİN GENETİK ALGORİTMA KULLANILARAK OPTİMİZASYONUNA YÖNELİK BİR YÖNTEM GELİŞTİRİLMESİ

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Su kaynakları sistemlerinin planlanması, tasarımı, inşası, işletmesi ve bakımı belediyelerin en büyük altyapı projelerini oluşturmaktadır. Bu nedenle, su dağıtım şebekeleri son derece titiz bir şekilde tasarlanmalıdır. Evrimsel tabanlı bir optimizasyon yöntemi olan genetik algoritma, su dağıtım şebekelerinin optimizasyonunda kullanılmaktadır.

Birçok operatörden oluşan genetik algoritmanın performansı içindeki operatörlerden etkilenmektedir. Bu operatörler parametrelere bağlı olmalarına rağmen, su dağıtım şebekeleri ile ilgili çalışmalarda parametrelerin bulunmasına gereken önem verilmemiştir.

Bu çalışma, farklı şebekeler üzerinde genetik algoritmanın parametrelerini inceleyen yeni bir yöntem sunmaktadır. Geliştirilmiş olan bilgisayar programı üç farklı şebeke üzerinde uygulanmıştır. Bu şebekelerin ikisi literatürdeki iyi bilinen örneklerden olup, üçüncüsü ise Ankara su dağıtım şebekesinin bir basınç bölgesidir.

Sonuç olarak; algoritma içindeki parametrelerin optimizasyon yapılmak istenen şebeke, optimizasyonun hedefi ve geliştirilen bilgisayar programı ile ilişkili olduğu bulunmuştur. Birim basınç cezası değeri şebekenin özelliklerine ve boruların maliyetlerine göre değişmektedir. Mutasyon oranının üç farklı şebeke için [0.0075 – 0.0675] aralığında değiştiği bulunmuştur. Elitizm oranı, popülasyon büyüklüğüne karşılık gelen en düşük değer olarak belirlenmiştir. Çaprazlama olasılığının ise [0.5 – 0.9] aralığında değiştiği bulunmuştur. Yöntem, genetik algoritmanın uygun parametrelerinin belirlenebilmesi için her optimizasyon çalışmasına uygulanmalıdır. Tarif edilen yöntem kullanılarak, iyi sonuçlar elde edilmiştir.

Anahtar Kelimeler: Genetik algoritma, optimizasyon, su dağıtım şebekesi, tasarım, Ankara

To my Family

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1

INTRODUCTION

1.1 General

All living organisms need water. Water is the most important resource on this planet for the continuation of life. Since ancient times, people have tried to manage fresh water to be able to survive. Today, in modern cities people use water supply systems to have potable water.

A water supply system is a collection of elements such as reservoir(s), pump(s), pipes, different kinds of valves, storage tank(s), having the purpose of providing required amount of potable water at sufficient pressure to the consumers.

The realization of planning, design, construction, operation and maintenance of water supply systems pictures one of the largest infrastructure projects of municipalities; the cost of water supply projects may reach values at the order of million dollars for Greater Cities. Ankara municipality has reserved 55,000,000 YTL (42,000,000 US$) for construction and maintenance of total 641,000 meters of pipelines for 2006 (Keleş, 2005). According to Environmental Protection Agency (EPA, USA) total infrastructure investment of United States for the next twenty years in order to supply potable water to consumers is about 150.9 billion US$ (EPA, 2001). Because of these high amounts of money, water supply system projects should be designed very meticulously.

Traditionally, the design of water distribution networks (WDNs) has been based on the experience of the designer; the designer establishes the network design regarding the street plan and the topography. In fact, there is no unique design for any distribution project; there may have been various solutions each satisfying the desired hydraulic conformity for the same street plan and the same demand pattern; but, the cost of each solution may be different. Thus, the problem becomes the determination of the least cost design satisfying the hydraulic conformity criteria. However, a network containing only about twenty-five pipes will require solutions of millions of different combinations in order to identify which one is the least cost design.

There is a significant body of literature reserved for optimization of distribution networks. Linear programming, dynamic programming, nonlinear programming techniques were applied to the problems of network design. New techniques such as stochastic optimization including Genetic Algorithm (GA) have been started to be employed for designing water distribution networks.

1.2 The aim of this study

In this study, genetic algorithm is applied to the problem of optimal design of water distribution networks since GA is able to search complex solution spaces efficiently. A computer program using a modified GA will be developed. As an objective, the parameters of the modified GA will be discussed on two well known networks from the literature and a methodology for the use of the program will be proposed. Supplementary comments on the methodology will be made by examining another network, which is relatively larger. Two of the networks are well known examples in the literature and the third network, N8-1, is an existing pressure zone part of the water distribution system of Ankara. All these networks differentiate from each other by means of some characteristics, basically pipe sizes. Regarding the results of investigations, the appropriate parameter values for specific networks are determined. By evaluating the results, uniqueness of each optimization program concerning GA, each network and each case will be shown. To be more comprehensible, claiming that the parameters of GA such as mutation rate, crossover probability, penalty constant etc. can not have ideal values for all cases; these parameters should be adjusted for each network and each case to be optimized.

In Chapter 2, the past studies related with the optimization of the capital cost of the WDNs will be summarized. In Chapter 3, a detailed explanation of genetic algorithm will be made and the parameters of the algorithm will be explained. In Chapter 4, the structure of the developed computer program will be discussed. After giving the information about the algorithm and the developed program, utilization of the program for two well known networks will be presented in Chapter 5. Moreover, a methodology for applying GA on the WDN's will be developed. Using this methodology, the parameters of GA will be found for these networks. In Chapter 6, the computer program will be applied on an existing WDN, N8-1. In the last chapter conclusions and suggested further studies will be presented.

CHAPTER 2

LITERATURE REVIEW

2.1 Earlier optimization studies

As an essential part of modern cities, water distribution networks are one of the largest infrastructures. Due to high capital costs and difficult maintenance opportunities, researchers try to design the WDNs in an optimal way for four decades. Because of nonlinear relationships between the parameters of WDNs, optimization of sizing of pipes becomes quite hard. Until now significant amount of researchers studied on the optimization of WDNs by computerized techniques.

Being the pioneers of this field, Alperovits and Shamir (1977) proposed to use linear programming gradient method to obtain the optimal design of water distribution networks. Earlier works has been made by Watanatada (1973), Hamberg (1974) and Rasmusen (1976) by using a network solver inside their methodology. In order to accomplish the same aim, Lai and Schaake (1969) and Kohlhaas and Mattern (1971) did not prefer to use a network solver but they treated the case in which head distribution in the network is fixed. Alperovits and Shamir's principal approach that aims to reduce the complexity of the original nonlinear nature; which is a result of head loss formula, is followed and improved by many researchers in the following years (Quindry et al. 1981; Goulter and Morgan 1985; and Fujiwara and Khang 1990).

Since water distribution networks behave nonlinearly due to the Hazen-Williams or Darcy-Weisbach head loss formula, linear programming techniques become quite poor to reach the optimal solution. For this reason, researchers applied nonlinear optimization techniques to pipe network problems (El-Bahrawy and Smith 1985, 1987; Su et al. 1987; Lansey and Mays 1989a; Lansey et al. 1989; Duan et al. 1990). The problem of nonlinear techniques is that, the rounding of pipe diameters does not guarantee the solution found to be optimal or even feasible. The other approach, that should include a network solver inside is based on enumeration of a limited number of alternatives, with the name partial enumeration (Gessler 1985). However it was found that this approach may fail to find the optimum result even for a moderate sized network (Murphy and Simpson 1992).

All the approaches discussed above, i.e., linear, nonlinear, and enumeration techniques require simplifications on the general problem; as a result, they do not guarantee to find the global optimal in the search space. Being unimodal functions their solutions are strictly dependent on the initial population and they are all prone to fall into the local optimums instead of finding the global optimum. To reach the global optimum, recently a new heuristic technique developed that is based on the evolution theory of Darwin, genetic algorithm (GA). GA does not need simplifications and it is capable to be applied on discrete optimization problems like sizing of pipes of a water distribution network. Being a multi-modal function, GA does not depend on the initial population in the complex solution space. Although GA is the most promising optimization method when compared to the traditional methods, it still does not guarantee to find the global optimum.

2.2 Overview of Genetic Algorithms and their application to WDNs

Genetic algorithm (GA) was first proposed by Holland (1975) and further developed by Goldberg (1989) and others. This algorithm is based on the population dynamics in nature such as, natural selection and natural genetics. Algorithm combines the survival of the fittest among string structures to form a search algorithm (Goldberg, 1989). The idea behind the algorithm is to explain the adaptive processes of natural systems and adapt them to artificial systems using software. GA optimization, being a computerized algorithm, uses binary strings and using some operators tries to reach the global optimum. Basically, the algorithm is based on the principle of the survival of the fittest from generation to generation. As generations continue, the fittest of the population approaches to either local or global optimum for the function.

As GA demonstrated their capabilities to achieve better results in complicated cases, it was also used in WDNs by many researchers. Simpson et al. (1994) introduced GA to the optimization problem of WDNs. They investigated a three-operator GA comprising reproduction, crossover, and mutation. Throughout their study, they compared the performance of GA with other deterministic optimization techniques such as enumeration and nonlinear programming. After applying complete enumeration, nonlinear programming, and GA to pipe network optimization, they concluded that; GA technique is very effective in finding the near-optimal or optimal solutions for a case study network in relatively few evaluations. While applying GA, they used different parameter sets and by investigating the results on their networks, they interpreted that; the results were not highly sensitive to the parameters of GA for their case study. Dandy et al. (1996) developed an improved GA for pipe network optimization. They introduced a variable power scaling fitness function, adjacency mutation operator and using of Gray codes rather than binary coding. The power of fitness function increases as program proceeds. The value of power increases from 1 to 4 to augment the performance of the algorithm. Adjacency mutation operator and Gray coding scheme are used to avoid from Hamming cliff. After comparing the result of simple GA and improved GA, they concluded that improved GA produces significantly lower cost solutions than the simple genetic algorithm. Savic and Walters (1997) applied their program (GANET) that uses standard GA to three pipe network optimization problems using the recommended values for parameters from the literature. They preferred to use Gray coding and elitist strategy throughout their runs. After the runs, they concluded that the comparison of solutions obtained by GANET and other optimization techniques shows that GA produced good designs even without unnecessary restrictions imposed by split-pipe or linearizing assumptions. Abebe and Solomatine (1998) introduced a global optimization tool that incorporates EPANET as the hydraulic network solver. They implemented GA, Adaptive Cluster Covering with Local Search (ACCOL) and Controlled Random Search (CRS) to their global optimization tool. After testing these methods on two test networks, they compared the results of previous studies and the methods of their global optimization. Finally they concluded that, GA shows more efficient and effective performance compared to other methods. A modified GA was proposed by Montesinos et al. (1999). They made several changes in the selection and mutation processes of the simple GA in order to optimize the convergence of the algorithm. While selecting the chromosomes for crossover, the least fit strings are eliminated and they are replaced by the duplicates of the fittest individuals. The mutation operation is applied while not disturbing the fittest chromosome. These two modifications give elitist character to the algorithm. The effectiveness of modified GA is tested on a network and it is shown that, modified GA achieved the known optimal solution in fewer evaluations than previous GA formulations. Gupta et al. (1999) applied GA for optimization of water distribution systems and compared the results with the nonlinear optimization technique through the application to several case studies. They indicated that GA results in lower cost solution.

Using one of the global search algorithms, Loganathan et al. (1995) and Cunha and Sousa (1999) used annealing algorithm for optimal design of WDNs. Eusuff and Lansey (2003) proposed shuffled frog leaping algorithm for water distribution optimization. Keedwell and Khu (2004) used hybrid genetic algorithm for the design of WDNs, by seeding local representative cellular automata approach into genetic algorithm to provide a good initial population. Similarly, Zyl et al. (2004) used hybrid genetic algorithm for operational optimization of WNDs. They combined two hillclimber strategies Hooke and Jeeves and Fibonacci methods with GA.

Recently, Neelakantan and Suribabu (2005) proposed a modified genetic algorithm to improve the convergence of the algorithm. The modification is applied by dividing the algorithm into two. The first part comprised of simple GA and the second part starts with the results of simple GA and the program continues. With the new parameter, pre-mutation, they achieved faster convergence to optimum in their modified GA. Güç (2006) applied genetic algorithm for the optimization of water distribution systems by using three basic operators and testes his algorithm on Ankara N8-3 network. Şen (2004) explained the operators of the GA in details.

CHAPTER 3

GENETIC ALGORITHM

3.1 Introduction to Genetic Algorithm

Genetic algorithm is one of the global optimization and stochastic search techniques that is based on the mechanism of natural evolution. The idea behind genetic algorithm is the Darwin's evolution theory and the survival of the fittest. Genetic algorithm has been developed by John Holland (1975), his colleagues and his students at the University of Michigan. The goals of their research were to explain the adaptive processes of natural systems and to design artificial systems software that retains the important mechanisms of natural systems (Goldberg 1989).

When compared to traditional optimization techniques, GA differs from these techniques in four ways:

- GA works with coding of the parameters set, not the parameters themselves.
- GA searches from a population of points, not a single point.
- GA uses objective function, not the derivatives.
- GA uses probabilistic transition rules, not deterministic rules (Goldberg 1989).

Genetic algorithm is acting on the chromosomes of the population in order to accomplish basic genetic operations such as selection, crossover, mutation; genetic operators do not concern network hydraulics. Hydraulic conformities of the network are checked on the basis of a hydraulic network solver. Essential parameters describing hydraulic conformity of a water distribution network are nodal pressures and flow velocities. As each chromosome in the population is a candidate network, the performance of that chromosome (candidate network) is measured by means of specific penalty functions; one is portraying basically the adequacy of the pressure field, the other one is picturing essentially sufficiency of the velocity field in order not to cause any settlement of minerals on the pipe walls.

3.2 Structure of Genetic Algorithm

Genetic algorithm initiates with randomly generated initial set of chromosomes. These chromosomes form a population. The size of the population, in other words, the number of chromosomes should be defined previously. The chromosomes are strings of binary bits and their size depends on the characteristics of the network. With predefined number of chromosomes, evolution begins with first iteration and it continues till the last iteration. Throughout iterations new chromosomes are obtained, called offspring. These iterations, which lead to obtain offspring, are called generations. In every generation the chromosomes evolve to reach the global optimum; then, the best chromosome is stored. This loop of generating offspring continues until reaching a predefined generation number. After that, the best solution found among all generations is displayed as the optimum or a good enough solution of the problem. The general structure of genetic algorithm is described in Figure 3.1.

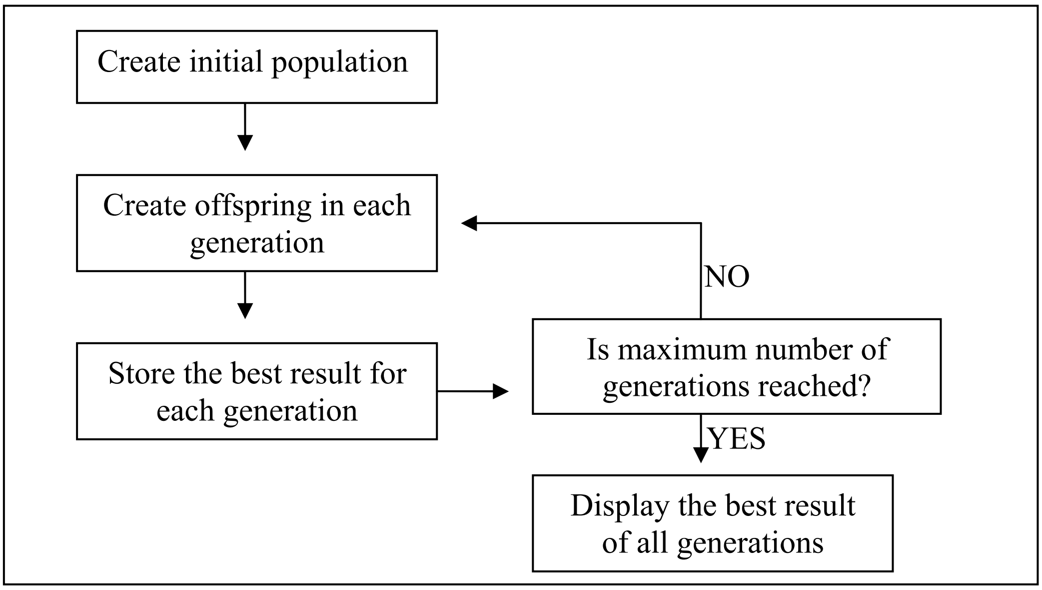

Figure 3.1. General Structure of Genetic Algorithm

During the evolution of the population, operators of genetic algorithm play significant role. These operators are selection, crossover, and mutation. These operators will be explained in details in the following sections.

3.3 Chromosome Concept

In the previous section, it is stated that all elements of genetic algorithm consist of binary elements. This means that, a conversion of water distribution network elements into binary code is necessary. The pipes are entitled as genes in the code. The length of genes depends on the number of candidate pipe diameters. For less than 5 pipes 2 bits binary elements are enough. If more than 4, less than 9 pipes are available, user need 3 bits binary elements. The length of gene should be the powers of 2 (2^2, 2^3, 2^4 etc.). In Table 3.1 the relationship between the gene size and the available pipe diameters is tabulated. As an example, the binary elements for eight different pipe diameters are shown in Table 3.2.

Table 3.1. Available Pipe Diameters and the Gene Size

Number of available pipe diameter (n)	Gene size (#)
1<n≤4	2^2
4<n≤8	2^3
8<n≤16	2^4
16<n≤32	2^5
32<n≤64	2^6

Table 3.2. Chromosomes for Eight Different Pipes

Binary elements	Pipe diameters (mm)
000	80
001	100
010	120
011	200
100	250
101	300
110	350
111	400

3.4 Parameters of Genetic Algorithm

3.4.1 Selection

During the evolutionary process, at the beginning of each generation all chromosomes should be evaluated. This evaluation is made by converting the binary chromosomes of the population, to real networks and solving all these networks by a network solver one by one. This network solver may be an internal program or external software that is integrated into the main algorithm. By solving each network, the associated nodal pressures and flow velocities can be found. To rank the chromosomes according to their total costs, the hydraulic conditions of the networks should be converted to cost values using penalty functions. The detailed explanation of penalty functions will be given in Section 3.4.4. Beside the hydraulic conditions, the capital cost of the networks should be calculated. The capital cost of the network can be calculated by multiplying the unit prices of each pipe with corresponding pipe lengths. After evaluating the penalty costs and the capital costs, these values are summed up and the chromosomes are ranked according to their total cost values. After that, the fitness values of all chromosomes (candidate networks) are calculated.

The fitness value (eqn. 3.1) is equal to one over the summation of the capital cost and the penalty cost for each chromosome. After computing the fitness values of all chromosomes, the probabilities of selection of each chromosome can be calculated. The probability of selection for each chromosome (eqn. 3.2) is the division of chromosome's fitness value by the summation of all fitness values throughout the population.

$$f_i = 1 / (C_c + P_c)_i \qquad (3.1)$$

C_c: capital cost of i_{th} chromosome
P_c: penalty cost of i_{th} chromosome

$$p_i = f_i / \sum_{i}^{n} f_i \qquad (3.2)$$

p_i : probability of selection of i_{th} chromosome
f_i : fitness of i_{th} chromosome
n : number of chromosome in the population

Table 3.3 shows an example of calculating the probability of selection for a population consisting of 4 chromosomes. The chromosomes are 15 bits long so that they are composed of 5 pipes each may have 8 different available diameters and the cost values are unreal numbers.

Table 3.3. Sample Calculation for a Population of Four Chromosomes

No.	Chromosomes	Pipe cost	Penalty cost	Total cost	Fitness	Prob. of selection
1	010011001010101	140	70	210	0.00476	36%
2	101001100101100	166	273	439	0.00228	17%
3	110101100101001	181	250	431	0.00232	18%
4	001010001001110	108	160	268	0.00373	29%
Total		595	753	1,348	0.01309	100

After computing the fitness values for each chromosome, the selection process begins. During this selection process the roulette wheel method is used. The mate chromosomes are selected according to their probability values on the roulette wheel. The chromosomes have their portions on the wheel equivalent to their fitness values (see Figure 3.2). Then a random number is generated (wheel is turned) and selection is made according to this number. So, more fit chromosomes are more willing to be selected with respect to its slot size on the wheel. The roulette wheel selection method is advised by Goldberg (1989). This method helps preferential selection of more fit parents with the expectation of producing more fit offspring for next generation. After mating the chromosomes according to their fitness values, the crossover process begins.

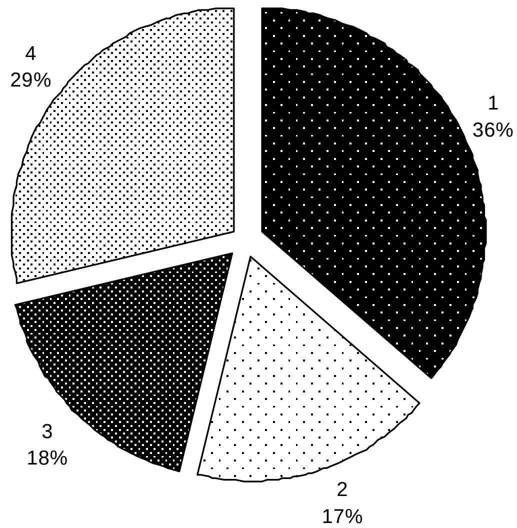

Figure 3.2. Chromosomes with Portions According to Their Fitness Values

3.4.2 Crossover

Crossover is the key parameter to reproduce new chromosomes. After the mating of selected chromosomes, the parents may crossover some of their bits with each other. The occurrence of crossover is controlled by a random number and a predefined crossover probability. Using the selection process, when the mating of chromosomes is completed, a random number is generated. If this number is less than the predefined crossover probability the crossover is applied to the selected mates, otherwise these parents are passed to next generation as offspring and the algorithm moves to the next couple. This looped process repeats for all mates throughout the population.

Crossover can be explained basically as the exchange of bits (genetic information) between the parents. The occurrence of exchange creates offspring different than both parents. The exchange of bits among the parents can be made using one point, two points or multi point crossover. The points indicate the bits that will transfer to the other parent. For example; if two point crossover is made, two random numbers (one greater than the other) are generated. The bits between these two numbers are exchanged. For more detailed explanation see Figure 3.3.

Parents before crossover	Parents after crossover points are determined	Offspring
010011001010101	010***011001010***10101	101***011001010***01100
101001100101100	101***001100101***01100	010***001100101***10101

Figure 3.3. Two Point Crossover

Multi point crossover follows almost the same method as two point crossover. Again random numbers are generated that are not equal to each other; the bits between these numbers are exchanged among the parent chromosomes (see Figure 3.4). Among crossover types one point crossover is the most conservative one. One point crossover exchanges bits only from the end point of the chromosome. For this method only one random number is generated and the bits between this number and the last bit are exchanged. In the following chapters, the strategy behind the crossover type will be discussed on different networks. Also the effects of this parameter while searching for the optimum will be discussed.

	Before crossover	The selection of bits	Bits exchanged
Single point crossover	XXXXXXXXX	XXXXX***XXXX***	XXXXX***YYYY***
	YYYYYYYYY	YYYYY***YYYY***	YYYYY***XXXX***
Three point crossover	XXXXXXXXX	X***XX***XXX***XXX***	X***YY***XXX***YYY***
	YYYYYYYYY	Y***YY***YYY***YYY***	Y***XX***YYY***XXX***
Four point crossover	XXXXXXXXX	X***XXX***XX***X***XX	X***YYY***XX***Y***XX
	YYYYYYYYY	Y***YYY***YY***Y***YY	Y***XXX***YY***X***YY

Figure 3.4. Crossover for Multi Point Cases

During crossover, the exchange rules between parents sometimes may be confusing. One method of crossover deals with the genes and the other deals with the bits. Since there is no rule for this method, it is preferred to use bit by bit crossover in this study which is not utilizing the genes. Also in Figure 3.3 it can be seen that 7 bits are crossed over although this example population has 5 pipes and each pipe is 3 bits. If crossover is realized by the genes, multiples of 3 bits should be exchanged.

3.4.3 Mutation

Mutation is another operator of genetic algorithm and maybe the most effective one that affects the performance of the algorithm in searching the global optimum. Mutation is the exchange of bits from 1 to 0 or reverse (Figure 3.5). After crossing over of selected chromosomes is completed, mutation operator is applied to the population. During mutation operation, all the population is considered bit by bit. From the beginning of the population till the end, for each bit a random number is generated. If this number is less than the mutation probability that is predefined, mutation occurs on this bit. If the random number is greater or equal to the predefined mutation probability, mutation operator moves to the next bit and another random number is generated for that bit. This process continues till the end of the chromosome at the same manner.

Before mutation	01001100101010101011010001101100101001001
	↓ ↓
After mutation	01001101101010101011010001100000101001001

Figure 3.5. Mutation

The chromosome can be exposed to mutation several times according to its length and the predefined mutation probability. Concerning this operator, mutation rate is one of the parameters that affect the algorithm. There is not a commonly accepted value for this rate in the literature. In the following chapters, this rate and its effect on the algorithm will be discussed.

The operators described above are the general steps that are all discussed and delineated in the literature. While the meta-heuristic is preserved, the solutions that are formed are still dependent on the values of parameters.

3.4.4 Penalty function

Before the selection of mates, the members of the population (chromosomes) are ranked according to their fitness values. The fitness values are calculated by equation 3.1. To form this formulation there is a need for penalty costs. Penalty costs show the hydraulic performance of each candidate network (chromosome) in the search space. The hydraulic performance of each network is converted into costs using the penalty function. Penalty function both portrays the adequacy of pressure field and the sufficiency of the velocity field in order not to cause any settlement of minerals on the pipe walls. So; the penalty function is the most important parameter of the genetic algorithm.

Throughout this study; for the optimization of WDNs, the objective is to minimize the capital cost of the network while providing the hydraulic conformities. In other words, the objective is to minimize the summation of the capital cost and the penalty cost for the network. The fundamentals of optimization imply that more complex objection function you have, more difficulty you will face to reach the optimum. So, the objective function's simplicity is very important to find the global optimum. The simplicity of the objective function can be achieved by ignoring the effects of some hydraulic constraints. As low pressure problems may result in lack of water in those junctions, low pressure constraint is more important than any other constraints. Also high pressures in junctions may result in leakage problems and this is another important constraint. Similar to pressure heads, the flow velocities affect the networks. High flow velocities may damage the pipes while very low flow velocity may increase the aging of pipes. Also low flow velocities affect the quality of potable water due to the some inorganic reactions. However, in some networks, especially in large ones, the velocity problems may sometimes be inevitable. Due to these characteristics of velocity problems, in the literature some researchers (Simpson et al., 1994; Savic and Walters, 1997; Vairavamoorthy and Ali, 2000) did not considered velocity constraints in the optimization of WDNs. Similarly, in this study it is preferred to consider only the pressure constraint during the optimization problem for the sake of simplicity. Another disadvantage of considering the velocity constraint is the increased evaluation time of the program.

Penalty functions are not widely described in the literature research, studied. In this study, a penalty function considering only the pressure violation is used. The penalty function (eqn. 3.3) penalizes the network, both by investigating the degree of violation at the nodes and the generation number. This heuristic approach pushes the penalized networks to vanish as the generations reach to the limit generation number by using a power (k) in the penalty function. Another addition to penalty function is the degree of violation. As pressure value diverge from a pressure range, the penalty of the chromosome increases. Moreover, the penalty function penalizes the upper limit pressure violations and lower limit pressure violations in different manner. As lower pressure limit is more important than upper limit violation, the penalty of lower pressure limit violation is greater.

$$P_j = \left(\sum_i^n \begin{pmatrix} \left| \sqrt{(pl_l+1)}^k - p_i \right|^2 * u; & \Leftrightarrow p_i \le 0 \\ \left| (pl_l+1) - p_i \right|^k * u; & \Leftrightarrow 0 < p_i < 30 \\ 0; & \Leftrightarrow 30 \le p_i \le 80 \\ \left| (pl_u) - p_i \right| * u; & \Leftrightarrow 80 < p_i \end{pmatrix} \right) \quad (3.3)$$

$$k = \left({G_c}/{G_l} \right) + 1; \longrightarrow k : [1;2] \quad (3.4)$$

u: unit pressure penalty constant, predefined

k: power for the penalty function

n: number of nodes in the network

pl_l: lower pressure limit, predefined

pl_u: upper pressure limit, predefined

p_i: pressure of each node, i=1,2, … ,n.

P_j: pressure penalty of j^{th} chromosome, j=1,2, … ,J.

J: total number of chromosomes in the population

The power, k is a value depending on the current generation number (G_c) and generation number limit (G_l). It is defined in equation 3.4.

Penalty function is plotted for pressures -10 to 90 in Figure 3.5. For more detailed description, in Figure 3.6 the pressure interval is chosen as [21:90]. The lower pressure limit and upper pressure limit is chosen as 30 m and 80 m respectively for both figures. In both figures, it is obvious that as the degree of violation for the pressure limits increase, the pressure penalty increases. In addition, as generations go on, k value goes from 1 to 2 stepwise and penalty increases.

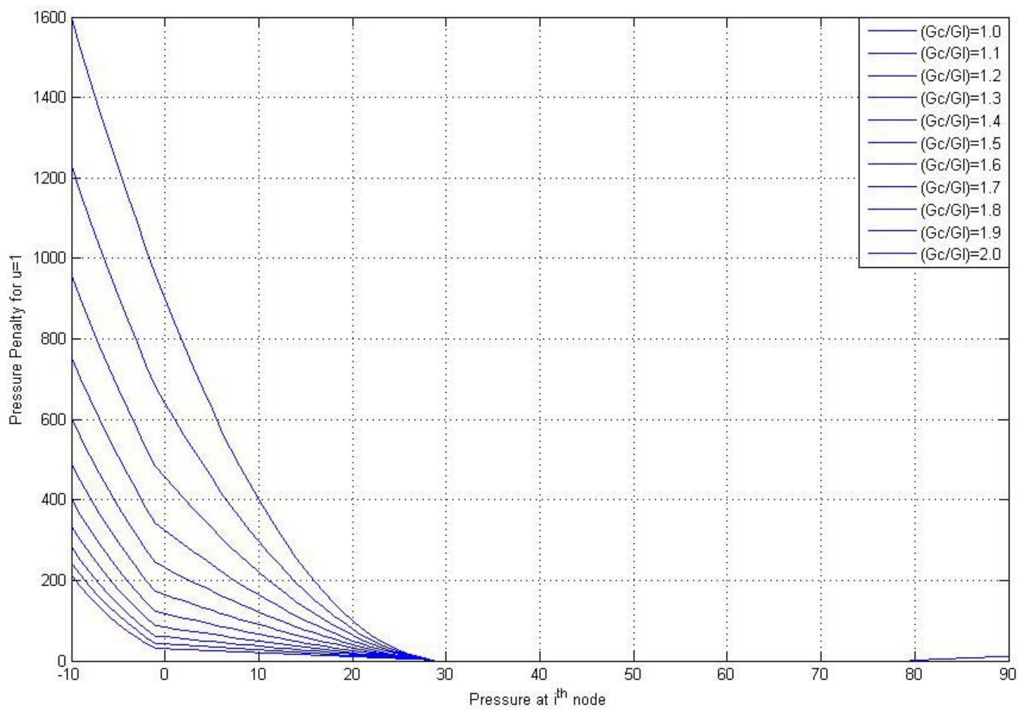

Figure 3.6. Penalty Function for Pressures: [-10:90]

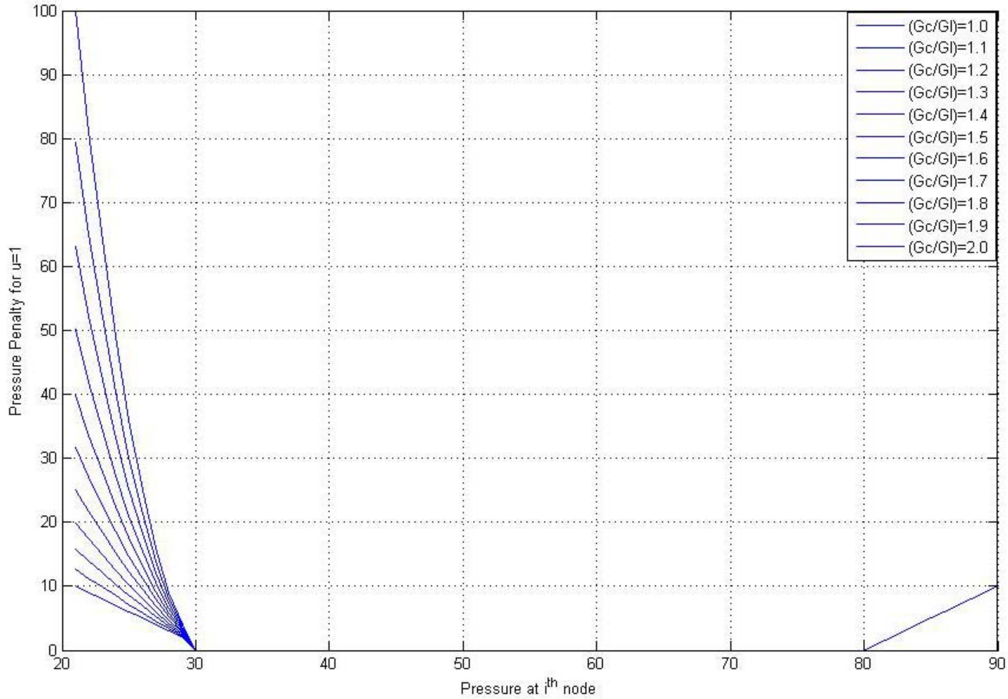

Figure 3.7. Penalty Function for Pressures: [21:90]

As penalty function play an important role in the optimization problem in this study, the effect of this function is discussed. To investigate the penalty function's role, the elements (i.e., n, pl_l, pl_u) of the equation (eqn. 3.3) stabilized but the unit pressure penalty constant (u) varied. In the following chapters, with this methodology the pressure penalty constant will be tried to be found for each network and additional comments will be made.

3.4.5 Elitism concept

Another modification that applied to the genetic algorithm is the elitism parameter. As the name implies, elitism means the protection of some promising chromosomes throughout the crossover and mutation operators. During crossover and mutation, the selected chromosomes are modified. Crossover and mutation are conducted to improve fitness. However, it may be possible that they can lead to less fit individuals.

Elitism is the protection against destructive changes in the population. It is first introduced by Kenneth De Jong (1975). Tolson et al. (2004) used this operator during their optimization study on the water distribution networks. Montesinos et al. (1999) applied some modifications that is similar to the elitism but did not clearly emphasize this parameter.

When elitist method is used, before the selection of chromosomes for crossover and mutation, predefined number of the best chromosomes are selected and protected against crossover and mutation. They move directly as offspring for that generation too the next. There is not a certain rule to determine the number of selected chromosomes. The number of these chromosomes is defined by an elitism rate before initiating the program. In the following chapters, the effects of elitism rate on the algorithm will be discussed using different networks.

3.4.6 Consequent runs

As mentioned previously, GA is one of the stochastic optimization methods. The randomized operators inside the algorithm affect the performance throughout the generations. Although, having better performance compared to traditional optimization techniques (Simpson et al., 1994), GA may converge to local optimums in the search space of the network.

In addition, as solution space is large – as in WDNs – many local optimums may exist instead of only one global optimum. If the search space of the algorithm is described as a terrain with many valleys inside, local optimums can be any valley. Among those valleys, the deepest one is the global optimum and sometimes, especially in large search spaces, genetic algorithm may not find the deepest one. Although modifications on the operators, functions etc. may increase the performance of genetic algorithm, the convergence to a local optimum is inevitable.
When the convergence to local optimums is considered, GA is not to be blamed for not finding the global optimum in every trial. Although there is not a commonly

accepted approach to this characteristic of GA, in this study it is assumed that convergences to local optimums are inevitable and to reach to the global optimum consequent runs are necessary. The consequent runs mean that, running the program with the same parameter set for several times. At the end of each run, save the best result for that run and after the completion of all runs, present the best of best results as the global optimum. Making consequent runs for the network increases the evaluation time. There is not an accepted rule about the run time because it depends on the size of network, the processor of the computer, and the skill of the architect of the code.

Savic and Walters (1997) mentioned that, twenty runs were necessary using different seed number for Hanoi network. Additionally, Neelakantan and Suribabu (2005) used hundreds of trials for Shamir's network to compare their two different genetic algorithm optimization techniques. Simpson et al. (1994) employed ten runs for their optimization study. Dandy et al. (1996) accomplished five runs both for simple GA and improved GA in their study and compared only the best of these runs.

Throughout this study, several runs were made while for each network and for each set of parameter. Although there is not an accepted number for consequent runs throughout this study; the numbers are varied according to the aim of the runs and the characteristics of the network. The runs were held on until the results are interpretable.

CHAPTER 4

RUNNING THE PROGRAM – NOGA

4.1 Overview

The description of genetic algorithm was already made in the previous chapters; its role in the optimization history and water distribution networks was mentioned also. GA is preferably a computer based algorithm and it runs by means of a computer program. It is preferred to design a computer program that uses GA for the optimization of water distribution networks for this study.

Throughout this chapter the structure of the created program, NOGA (Network Optimization using Genetic Algorithm) will be presented. After a brief explanation of NOGA, some details concerning the running process, the computer environment and its components will be presented.

A general overview of NOGA can be displayed using a flowchart (Figure 4.1). NOGA needs the layout of the network before starting the computations. This layout can be drawn using EPANET (U.S. Environmental Protection Agency, 2007) or can be created using any text editor. NOGA is not capable of modifying the layout of the network. NOGA is only responsible for sizing the diameters of pipes and computes the parameters representing hydraulic conformity. Using the provided layout, NOGA runs the genetic algorithm and gives the results.

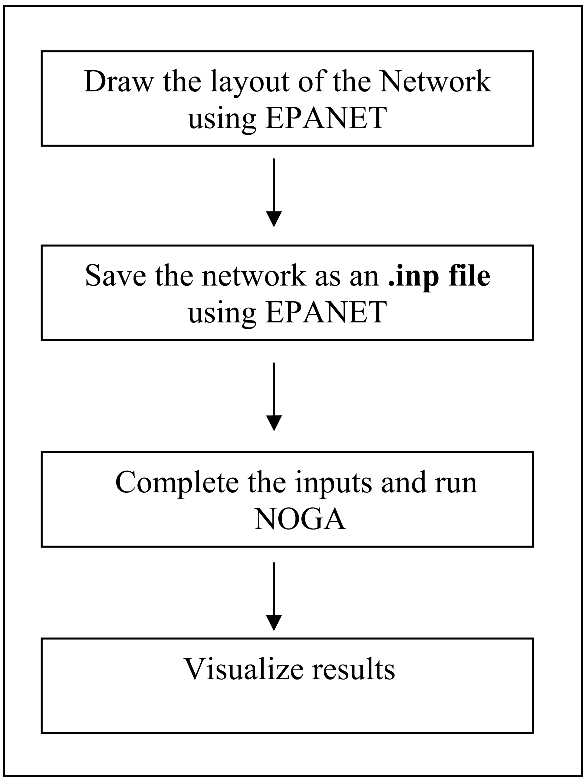

Figure 4.1. General Flowchart of Optimization Process

4.2 NOGA

The name NOGA is comprised of the capital letters of network optimization using genetic algorithm. Although being constructed on the basis of genetic algorithm, structural design of NOGA is unique to its author.

The code of NOGA is written using the MATLAB language which is similar to C, C++, and FORTRAN. MATLAB code can be written using MATLAB's own editor and evaluated using MATLAB's command window. The main code consists of many **.m files** and these files can be executed using commands from the MATLAB command window. These **.m files** work inside the kernel of MATLAB and they can be connected to each other. The main code can be divided into various .m files and this phenomenon gives many advantages to the developer while debugging. After having divided the main code into **.m files**, the computer application performance of all **.m files** can be investigated individually. Although MATLAB applications take more computer time compared to other programming languages, there are other advantages of MATLAB in regard to its user interface. Complicated visualization options, user friendly warnings and convenience in debugging are the major advantages of MATLAB. For these reasons it is preferred to use MATLAB language to design NOGA.

To run NOGA, MATLAB main software is necessary. For visualization support MATLAB 7.0 or higher versions will be helpful. Operating system may be Windows XP which is compatible with MATLAB 7.0. The computer should be at least Intel Pentium Celeron 1.7 GHz or further and RAM should be at least 512 MB. The processor of the computer directly affects the run time of program. So with new technology processors, evaluation times can be reduced. Also the model of the processor affects the performance of the program under some other applications, for example visualizations.

4.3 The structure of NOGA

Genetic algorithm is acting on the chromosomes of the population in order to accomplish basic genetic operations such as selection, crossover, mutation; genetic operators do not deal with network hydraulics. Hydraulic conformities of the network are checked on the basis of a hydraulic network solver. Essential parameters describing hydraulic conformity of a water distribution network are nodal pressures and flow velocities. As each chromosome in the population is a candidate network, the performance of that chromosome (candidate network) is measured by means of a specific penalty function; portraying basically the adequacy of the pressure field. The penalty function converts the performance of the network considering only pressures into cost values using unit penalty costs.

4.3.1 Hydraulic Network Solver – EPANET

Working with GA for design of WDNs, necessitates utilization of a hydraulic network solver - for example, EPANET - very frequently throughout the whole process. To compute the penalty costs, it is required to compute hydraulic conditions of each network for all of the generations. This means that, to find the optimal solution many evaluations need to be realized, i.e. solving the network many times. To achieve this, a hydraulic network solver inside the algorithm is needed. This solver can be a code written by the researcher or an external program that can be compatible with the genetic algorithm environment. Many researchers (Liong and Atiquzzaman, 2004; Abebe and Solomatine, 1998; Keedwell and Khu, 2004; Neelakantan and Suribabu, 2005) in the literature used EPANET as the hydraulic network solver inside their optimization algorithms. In this study, similar to those researchers, it is preferred to use EPANET as the network solver inside the computer program code.

EPANET is a hydraulic network solver program that performs extended period simulation (EPS) of hydraulic and water-quality behavior within pressurized pipe networks. EPANET tracks the flow of water in each pipe, the pressure at each node, the height of water in each tank and the concentration of chemical species throughout the network during a simulation period which is comprised of multiple time steps. In addition to chemical species, water age and source tracing can also be simulated.

EPANET was developed by the Water Supply and Water Resources Division (formerly the Drinking Water Research Division) of the U.S. Environmental Protection Agency's National Risk Management Research Laboratory. It is public domain software that may be freely copied and distributed (U.S. Environmental Protection Agency, 2007).

For NOGA to operate appropriately, a solvable WDN under static loading condition is required. EPANET is a user friendly program with a user interface (Figure 4.2) It also has a toolkit. The EPANET Programmer's Toolkit is a dynamic link library (DLL) of functions that are allowed to be modified to customize EPANET's computational engine for specific needs. The functions can be incorporated into 32-bit Windows applications written in C/C++, Delphi Pascal, Visual Basic, or any other language that can call functions within a Windows DLL (U.S. Environmental Protection Agency, 2007). It is preferred to use EPANET Programmer's toolkit that employed as the hydraulic network solver for convenience.

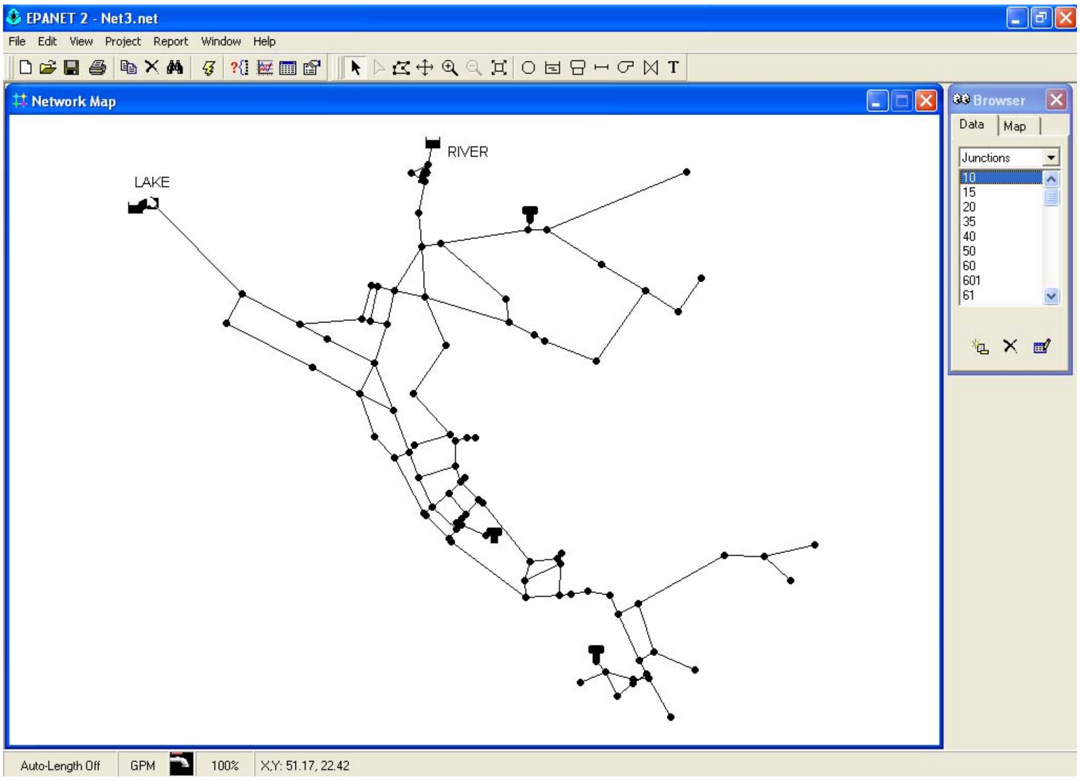

Figure 4.2. EPANET's User Interface

4.3.2 Mechanism of NOGA

In the previous section, the computer environment and the components of the NOGA tried to be explained. In this section, the interaction of EPANET and MATLAB computer environments will be presented.

As already mentioned, the layout of the network should be drawn by EPANET before running NOGA. This layout should contain the lengths of all pipes, elevation and demands of all nodes and all the necessary information of pumps, tanks and reservoirs if they exist. All the pipes should have a diameter. These diameters could be unreal numbers but the network should be executable. If not, the EPANET toolkit can not solve the network and nothing can be done to the network. After completing the layout, the network should be saved as an **.inp file**.

This can be done as follows by clicking in the menu bar: file >> export >> network. Using the popup window, the **.inp file** can be saved by giving a name into the root directory of NOGA on the hard disk (Figure 4.3). This **.inp file** is the input file that is compatible to NOGA. The **.inp file** should contain all the information that the network contains. Another way to create the **.inp file** is to write it using any text editor - for example, Microsoft Notepad - and changing the extension of saved file to **inp**. The difficulty of this way is that, all the network elements should be written in the accurate format. In Figure 4.4 an example format of an **.inp file** is given.

Before running NOGA, the gene size and chromosome length should be defined by looking at the pipe numbers and diameter diversity and these numbers should be entered to the program as input. The detailed information related with the chromosome concept was given in Section 3.3. For example, if the network consists of 10 pipes each may have 12 different diameters, gene size must be 4 bits and chromosome length must be 40 bits. Unit prices of pipes per 1 meter length for each diameter should be given as input as well; these unit prices will be used to calculate the capital cost of the network while computing the costs throughout the process.

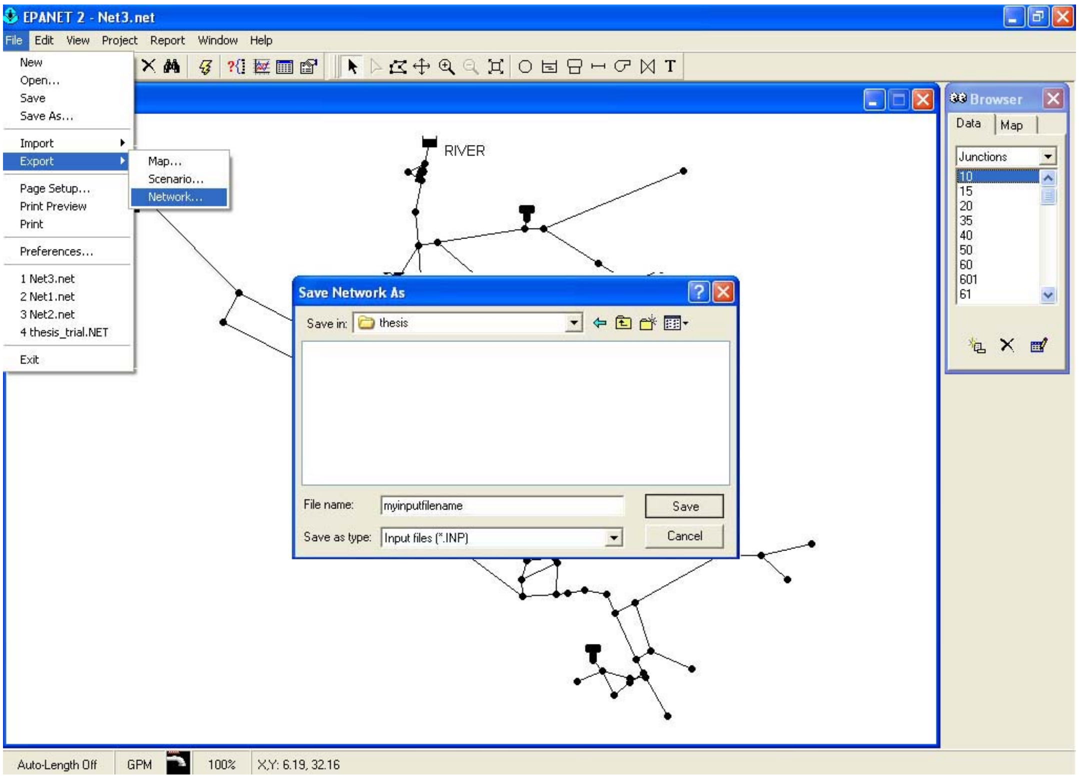

Figure 4.3. Steps to Save a Network as .inp File

```
Net1.inp - Notepad
File  Edit  Format  View  Help
[TITLE]
 EPANET Example Network 1
A simple example of modeling chlorine decay. Both bulk and
wall reactions are included.

[JUNCTIONS]
;ID                   Elev            Demand          Pattern
 10                   710             0                                ;
 11                   710             150                              ;
 12                   700             150                              ;
 13                   695             100                              ;
 21                   700             150                              ;
 22                   695             200                              ;
 23                   690             150                              ;
 31                   700             100                              ;
 32                   710             100                              ;

[RESERVOIRS]
;ID                   Head            Pattern
 9                    800                             ;

[TANKS]
;ID                   Elevation       InitLevel       MinLevel        MaxLevel        Diameter
        MinVol        VolCurve
 2                    850             120             100             150             50.5
        0                                     ;

[PIPES]
;ID                   Node1                  Node2                    Length          Diameter
        Roughness     MinorLoss       Status
 10                   10                     11                       10530           18
        100           0               Open   ;
 11                   11                     12                       5280            14
        100           0               Open   ;
 12                   12                     13                       5280            10
```

Figure 4.4. An Example .inp File

After having declared the input information, NOGA can be run in MATLAB environment. NOGA starts with initial random population consisting of predefined number of chromosomes. These chromosomes denote candidate network configurations. Since all networks are composed of pipes, all chromosomes are composed of genes. Genes are a group of binary bits each corresponding to one pipe diameter only. After having formed the initial population randomly, all the genes are converted to corresponding diameters. This process can be mentioned as converting the binary bits into real network elements. Afterwards, the network with real pipes is obtained. By multiplying the unit prices of pipes with corresponding pipe lengths, the network's capital costs can be found. In this step the lengths of all pipes should be known and this information is handled using EPANET toolkit. To find the penalty cost for each chromosome, - all the networks (chromosomes) - are solved individually using EPANET toolkit in each generation. After solving all the networks of this generation, the nodal pressures are stored and all the networks are penalized according to the penalty function which was defined in the previous chapter. Total cost of each chromosome is the summation of corresponding capital cost and the penalty cost. After sorting the total costs of the networks, NOGA saves the capital cost of the chromosome with the lowest total cost for the first generation. To clarify the last step; for the best chromosome, the capital cost is not the least among the population; the total cost (capital cost + penalty cost) is minimum cost among all chromosomes.

Then NOGA calculates the fitness values of the networks and all these chromosomes are moved to the selection operator. The chromosomes are sorted according to their fitness values; then predefined number of chromosomes are selected for crossover and mutation by the selection operator. As explained in the previous chapter, before crossover and mutation some of the best chromosomes are chosen as elite and they move directly to next generation without any crossover or mutation. Crossover and mutation process is realized as defined in the previous chapter and the new generation is born. Then, children of previous generation become parents of the next generation. Again the chromosomes are converted into networks and all the population is solved using EPANET toolkit. With the same process, the best chromosome for the second generation is saved and the loop continues till the limiting generation number is reached.

As NOGA reaches to the limiting generation number, it finds the lowest total cost among the generations and displays the lowest capital cost and corresponding diameters for the network. The mechanism of NOGA is shown with a flowchart below (Figure 4.5).

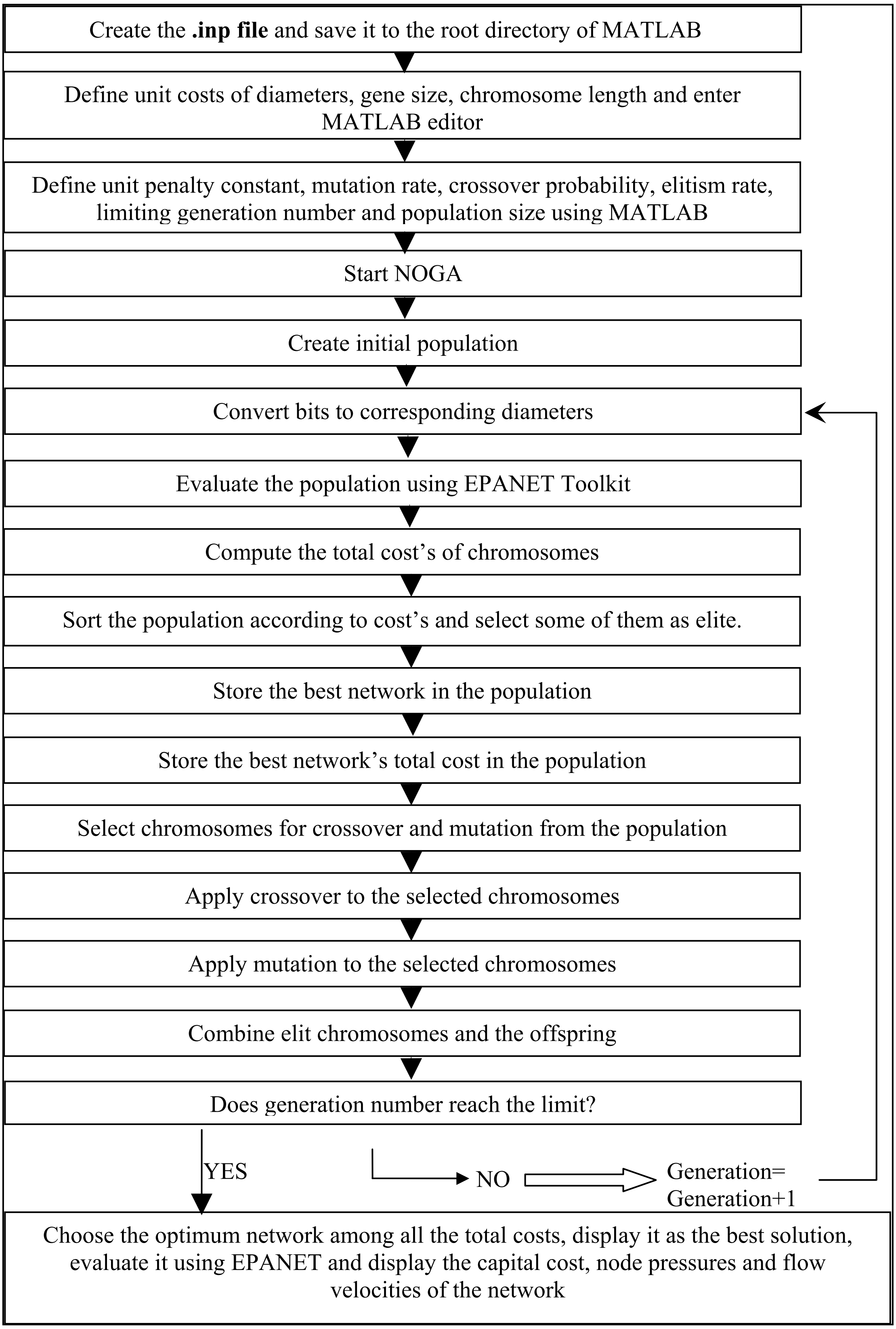

Figure 4.5. Detailed Flowchart of Optimization Process

4.3.3 Displaying the results of NOGA

When the allowed number of generations is reached, the program displays the optimum network configuration (chromosome) among all generations as the result and terminates. The diameters of the pipes of the final network can be seen in the MATLAB command window or it is also possible to visualize the diameters in Microsoft Excel program if it is loaded in the computer. Or the results can be exported in Microsoft Notepad format and can be opened using that program. Also the optimum network can be analyzed and the pressure heads at the nodes and velocities in the pipes can be visualized in the MATLAB command window. This information also can be exported to Microsoft Notepad or Microsoft Excel as well. Additionally, if EPANET is loaded to the computer the final network can be opened, visualized and analyzed using EPANET with typing related commands to the NOGA environment.

Beside NOGA's strong analytic capabilities, its visualization methods are very powerful. By saving the appropriate results of each generation, the variation in the system capital costs, penalty costs or total costs can be visualized using related commands. Using MATLAB environment many types of plots can be realized. These plots can be saved in **.jpg file** format and can be visualized using any picture viewing program such as Windows' default Photo Viewer program. After saving these plots with **.jpg file** format, these plots will also be compatible with Microsoft Office programs such as Word, PowerPoint etc.

By saving the appropriate data for each generation, any type of information is ready to be visualized after NOGA has terminated. Also these information and results can be exported to well known file formats and can be visualized in other computers. In addition, using related MATLAB functions, many types of plots can be drawn and exported to common file formats.

CHAPTER 5

THE METHODOLOGY

As previously described, Genetic Algorithm is composed of many operations. Throughout these operations - mutation, selection - randomized operators take role. These operators, depending on the parameters of the algorithm - mutation rate, elitism rate - may affect the performance of the algorithm. The effects of these parameters may vary depending on the gene size, chromosome length that is characteristic of the network or may vary depending on the structure of the computer program.

As described in the fourth chapter, the objective function to be minimized is the total cost of the network. Pressure penalty constant is a parameter that is involved while calculating the total cost of the network. With varying cost values for each specific network, the pressure penalty constant values should also differ. The pressure penalty constant may also differ depending on the penalty function that is specific to the computer program.

So, these parameters which are specific to the network, specific to the computer program and the case to be optimized, affect the main algorithm. Beside the critical role these parameters have taken, not much attention has been given for determination of them in the field of water distribution network optimization studies. Since, GA has a wide usage for the optimization of WDNs, these parameters should be determined in a case specific manner for the networks to be optimized.

In this study, a heuristic methodology is developed to determine the important parameters for specific cases. This novel methodology basically investigates some of the parameters and offers an approach how to reach a final parameter set for each network. While developing the methodology, NOGA was run for two well known networks. These networks are Shamir's (Alperovits and Shamir, 1977) and Hanoi (Fujiwara and Khang, 1990) networks. These two networks are well known examples from the literature and many researchers tried to obtain the optimal designs of them. The network characteristics are different in that; it allows making interpretations relating the characteristic of the network and the parameter set.

5.1 Searching the global optimum

As mentioned, it is a common view that genetic algorithm is one of the advisable methods of searching the global optimum in a search space. Since water distribution networks have a big space of solutions, genetic algorithm is one of the most effective optimization methods (Simpson et al., 1994). Although genetic algorithm is described more or less the same, the parameters of the algorithm may strictly affect the way of searching the global optimum. Since these parameters are specified by the developer and no commonly accepted rules or formulas exist, all programs are unique and structural details depend on the author, although the main algorithm is more or less the same.

It is obvious that, the parameters such as mutation rate, crossover probability etc. are strictly related with the characteristic of the network. Mutation rate is directly affected by the number of bits; that is related with the chromosome length, which is depending on the size of the network. Savic and Walters (1997) proposed a relationship between the mutation rate and the chromosome length.

Elitism rate and crossover probability are affected by the size of the search space which is depending on the size of the network. Pressure penalty constant depends on the pressure constraints for each network to be optimized and the cost of the members of the network. Pressure penalty constant value also depends on the penalty function. So, as the network differs, the parameters of the algorithm should also differ.

To be more comprehensible, it is claimed that, the parameters of genetic algorithms such as, mutation rate, crossover probability, penalty constant etc. can not have ideal values. The values of these parameters should be defined for the each case to be optimized. To select these parameters, water distribution networks should be run with varying parameters. Next, these parameters and the system's optimum costs should be analyzed together. Since these parameters are all related with each other, for each set of runs, only one parameter should be varied while the others are kept constant. A novel methodology is developed to explore this character of the algorithm.

The steps of this methodology are given below. These steps will be described and discussed in details while investigating the related networks.

1) First, decide on the initial mutation rate, elitism rate, crossover probability, crossover type, population size and allowed number of generations using own experience or searching literature.

2) With the decided values, NOGA is run several times with varying pressure penalty constant. The appropriate pressure penalty constant value varies in a predefined interval. While varying the pressure penalty constant value, NOGA should be run for several times for each pressure penalty constant value. This is a set of runs for investigating the pressure penalty constant value investigation. Note that NOGA considers only pressure constraint while penalizing the networks.

3) After having completed the set of run for determining the pressure penalty constant value, decide on the final pressure penalty constant for that network by examining the results. While examining the results, the capital cost of the network and its hydraulic conformity should be taken into account.

4) After determining the appropriate value of pressure penalty constant, similar procedure is applied to determine the mutation rate. Again an appropriate

interval is chosen for varying mutation rate and NOGA is run several times for each mutation rate.

5) Similar to the third step, decide on a value of mutation rate by examining the results.

6) Apply similar processes for elitism rate, crossover probability and crossover type sequentially.

This sequence is preferred with respect to the importance of parameters for the route to the global optimum. Pressure penalty function is the most important criterion since it is a parameter of the objective function. The second and the third important parameters are decided as the mutation and elitism rates. The other parameters are thought to be relatively less important compared to the first three; they are investigated after deciding the first three parameters. Different sequences may also be investigated. Although different orders concerning GA parameters may give different results, this sequence of parameters is preferred within this study. After sets of successful runs, the values of these parameters are determined and these values reflect the final set of parameters for that network for NOGA.

The described methodology will be applied to two well known networks that are Shamir's network and Fujiwara's Hanoi network throughout this chapter.

5.2 Shamir's Network

5.2.1 Overview of Shamir's network

Alperovits and Shamir (1977) introduced a network into literature to test their method called linear programming gradient. They presented a network operating under gravity for one loading. After Alperovits and Shamir, their simple network was studied by many researchers (Savic and Walters, 1997; Neelakantan and Suribabu, 2005; Gupta et al. 1998; Keedwell and Khu, 2004).

This network consists of 8 pipes each may have 14 different diameters, 6 nodes, 1 reservoir and 2 loops. The pipe lengths are all 1000 m, and assumed Hazen-Williams coefficients are all 130. Solution space contains $14^8 = 1.48*10^9$ different possibilities. The layout of Shamir's network is given in Figure 5.1. The node demands and elevations are given in Table 5.1. The unit prices for each pipe diameter for one meter length are given in Table 5.2.

Since there are 14 available pipe sizes, each pipe diameter is defined in 4-bits genes. One chromosome consists of 32 bits. 4-bits gene composition allows 16 available pipe sizes but in this network only 14 pipes exist. For 15^{th} and 16^{th} genes unreal diameters and unreal cost values are used (Table 5.2). The minimum pressure requirement for all nodes is 30 m. No velocity constraint is taken into account for this network.

Table 5.1. Nodal Demands for Shamir's Network

Node	Nodal Demands (m^3/hr)	Node Elevations (m)
1 (reservoir)	-1120	210
2	100	150
3	100	160
4	120	155
5	270	150
6	330	165
7	200	160

Table 5.2. Unit Prices and Binary Codes for Each Pipe Diameter

Diameter (inch)	Diameter (mm)	Binary Code	Unit Price ($/m)
1	25,4	[0000]	2
2	50,8	[0001]	5
3	76,2	[0010]	8
4	101,6	[0011]	11
6	152,4	[0100]	16
8	203,2	[0101]	23
10	254,0	[0110]	32
12	304,8	[0111]	50
14	355,6	[1000]	60
16	406,4	[1001]	90
18	457,2	[1010]	130
20	508,0	[1011]	170
22	558,8	[1100]	300
24	609,6	[1101]	550
39.4	1000	[1110]	1000
39.4	1000	[1111]	1000

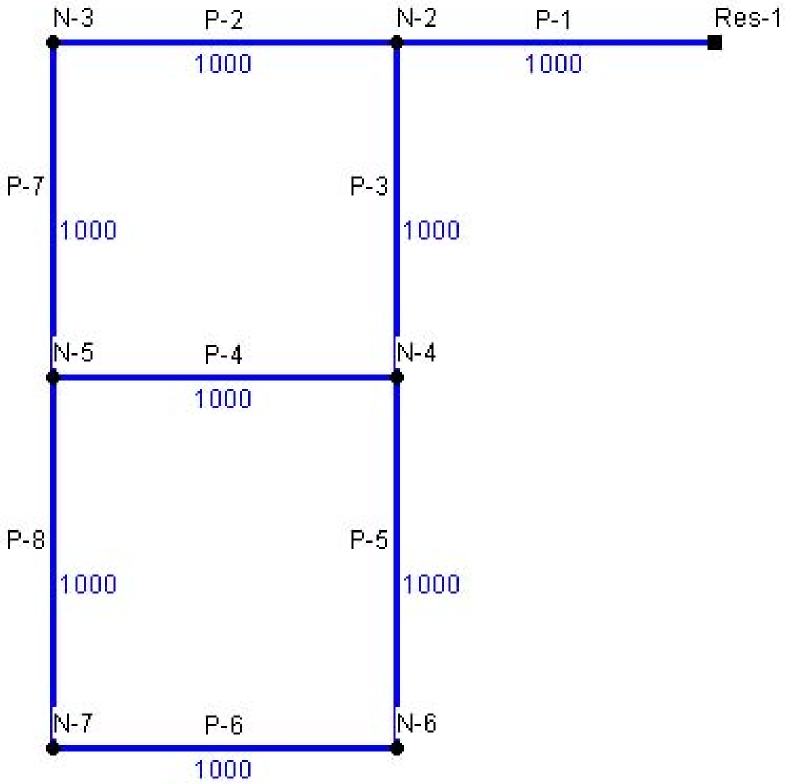

Figure 5.1. Layout of Shamir's Network with Pipe Lengths

5.2.2 Applying the methodology on Shamir's network

To find the optimum parameters for Shamir's network, the sequential methodology is applied exactly as outlined in Section 5.2. After deciding on an initial set of parameters, firstly, pressure penalty constant is investigated. After fixing the pressure penalty constant, mutation rate is found. After fixing two of them, elitism rate is found. After these three main parameters, crossover probability and crossover type are also investigated.

5.2.2.1 Investigating the pressure penalty constant

To find the suitable pressure penalty constant value, all other parameters are initially set to constant values using own experience. The set of all parameters are given in Table 5.3. The values of the parameters are chosen from the literature and by own experience. The pressure penalty constant (PPC) takes the value from the interval of [500, 10000]$ with steps of 500$. That means PPC = {500, 1000, 1500, 2000, … , 9500, 10000}$. NOGA was run 5 times for each pressure penalty constant and the system pipe costs and system pressure penalties are calculated for each pressure penalty constant value (see Figure 5.2). As can be seen from the figure after pressure penalty constant is equal to 5500$, system is not penalized. There is an exception at pressure penalty constant is equal to 7500$ but it is negligible in the whole domain. After this founding, all runs will be made with pressure penalty constant equal to 6000$.

Choosing low pressure penalty constant means not penalizing the promising individuals destructively. If individuals were strictly penalized because of the pressure violation, they may be destroyed and some useful genes may be lost just from the beginning. This may lead gene pool, to get narrower. On the other hand, using low pressure penalty constant value, the individuals are penalized but never destroyed. This is the reason why 6000$ is chosen as pressure penalty constant instead of any greater value. However 5500$ pressure penalty constant value can be chosen instead of 6000$ but 6000$ is preferred to be on the safe side since only 500$ units is not though to change many in the search space for this specific example.

Table 5.3. Parameter Set for Pressure Penalty Constant Investigation

Parameter	Value
Pressure penalty constant	[500, 10000]$
Mutation rate	3 %
Elitism rate	4 %
Crossover probability	90 %
Crossover type	2 points
Population size	50 chromosomes
Number of allowed generations	5000
NOGA trial number	5
Tolerable pressure interval	[30, 80] m

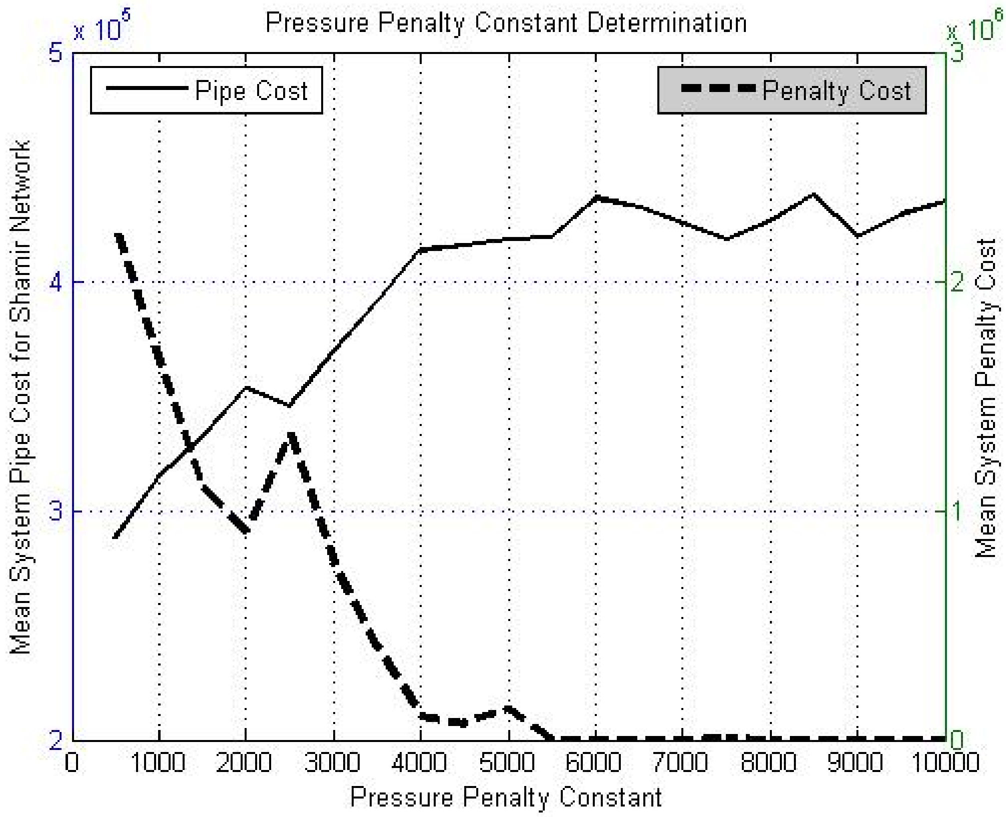

Figure 5.2. Pressure Penalty Constant vs. System Costs

5.2.2.2 Investigating the mutation rate

Similar to the investigation of pressure penalty constant, to find the optimum mutation rate all other parameters are fixed and only mutation rate is varied. The mutation rate takes the value from an interval of [0.0025, 0.1000] with steps of 0.0025. That means mutation rate = {0.0025, 0.0050, 0.0075, … , 0.0975, 0.1000}. The set of all parameters are given below in Table 5.4. NOGA was run 5 times for each mutation rate and the system pipe costs and system pressure penalties are calculated (see Figure 5.3).

As can be seen from Figure 5.3, system average pipe cost has three bottom points among non-penalized solutions. These minimum points are indicated with star signs. On these points 4 of 5 trials found the result with lowest cost among the feasible solutions that is incredible. Also the thicker line that indicates the system penalty cost shows that in many mutation rates, system has penalized. But in the interval of 0.0550 to 0.0675 system is not penalized and two of three stars fall into that interval.

It can be said that, as mutation rate increases, genetic search becomes a random walk. With high mutation rates, the mutation operator destroys the population although some individuals are protected by the elitism operator. This obstruct the algorithm to converge to the optimum result. Due to these reasons it is preferred to use 0.0675 as mutation rate for next investigations.

Table 5.4. Parameter Set for Mutation Rate Investigation

Parameter	Value
Pressure penalty constant	6000$
Mutation rate	[0.0025, 0.1000]
Elitism rate	4 %
Crossover probability	90 %
Crossover type	2 points
Population size	50 chromosomes
Number of allowed generations	5000
NOGA trial number	5
Tolerable pressure interval	[30, 80] m

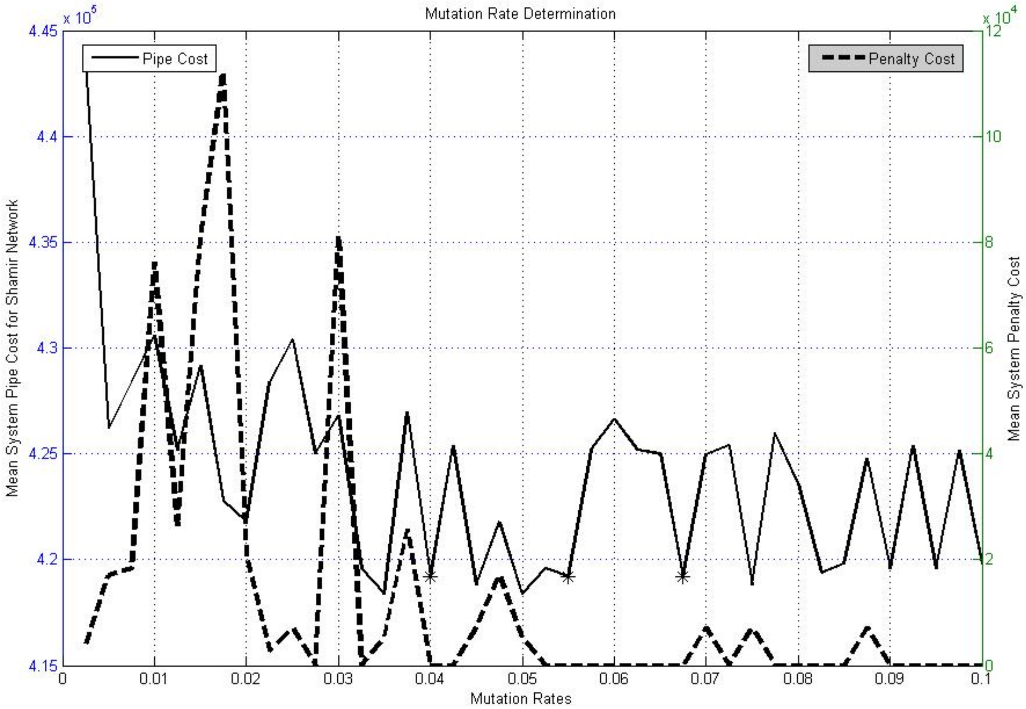

Figure 5.3. Mutation Rates vs. System Costs

Mutation also affects the convergence speed of the optimization process. In the search space, the optimization algorithm converges to a solution, which means the optimum solution. Since mutation directly affects the optimization process, it also affects the convergence speed. In Figure 5.4 the result generation numbers are plotted with respect to the mutation rates. Result generation number means the number of generation in which the best result is found. As can be seen from Figure 5.4, as mutation rate increases, algorithm faces with difficulties to find the optimum solution. But if referred to Figure 5.3 with small mutation rates, algorithm may find solutions far away from optimum. If two figures are compared (Figure 5.3 and 5.4) it can be concluded that as mutation rate increases, algorithm finds a better result in higher generations. Moreover with high mutation rates the final networks found, are hydraulically well conditioned; in other words, system is not penalized (Figure 5.3). Again, when referred to Figure 5.3 and 5.4 if number of allowed generations is large enough, high mutation rate does not destroy the result. Additionally, increasing the allowed number of generations helps the program to find better results by enlarging the search space. Note that, while investigating the Shamir's network the number of allowed generation is chosen moderately high (5000). As a conclusion; it can be clarified that, while using high mutation rates, algorithm needs moderately high generation numbers to converge since high mutation rate slow down the convergence. On the other hand, using low mutation rates increase the convergence but can not guarantee the solution found to be global optimum.

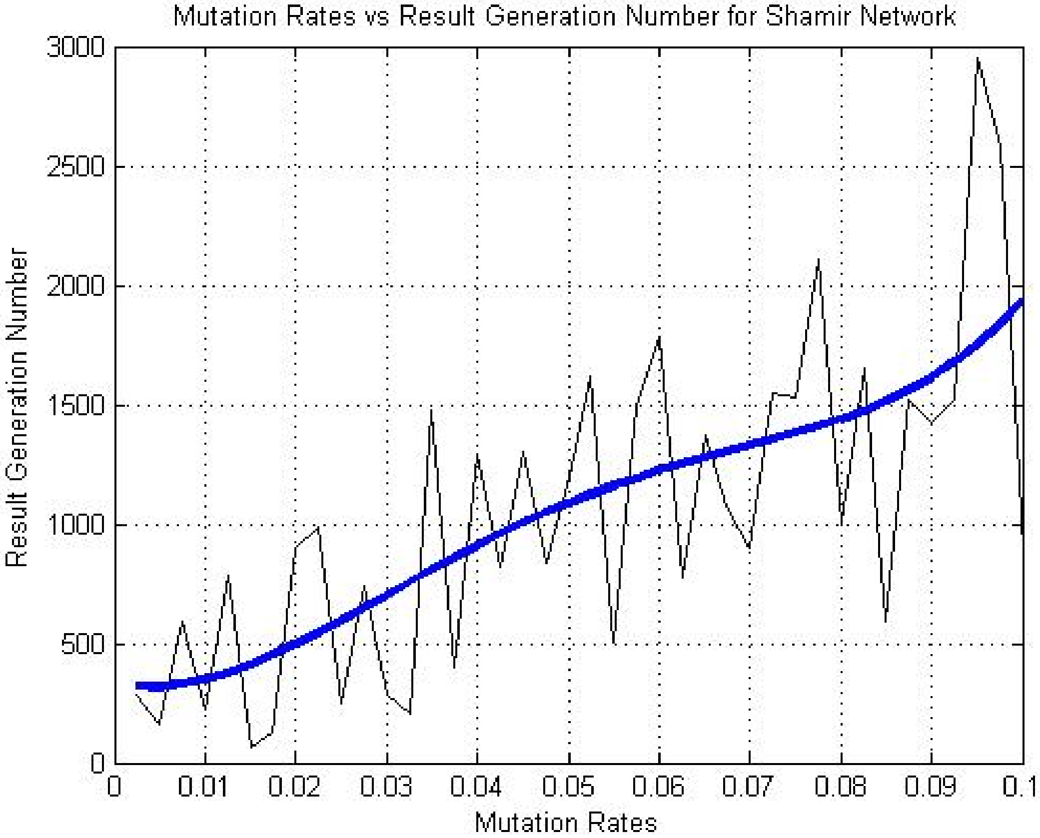

Figure 5.4. Mutation Rates vs. Result Generations

Another way to investigate the results is, looking at the minimum values over five trials. Figure 5.5 indicates the minimum values for each run. The star signs show the best result for the Shamir's network which is 419000$. The values lower than the 419000$ refers to hydraulically bad conditioned networks. As can be seen from the figure, with high mutation rates, algorithm's optimal solution possibly becomes global optimum for that system. With low mutation rates, system may converge to a cheaper solution but it may possibly be hydraulically bad conditioned. This fact indicates the advantage of high mutation rates for Shamir's network.

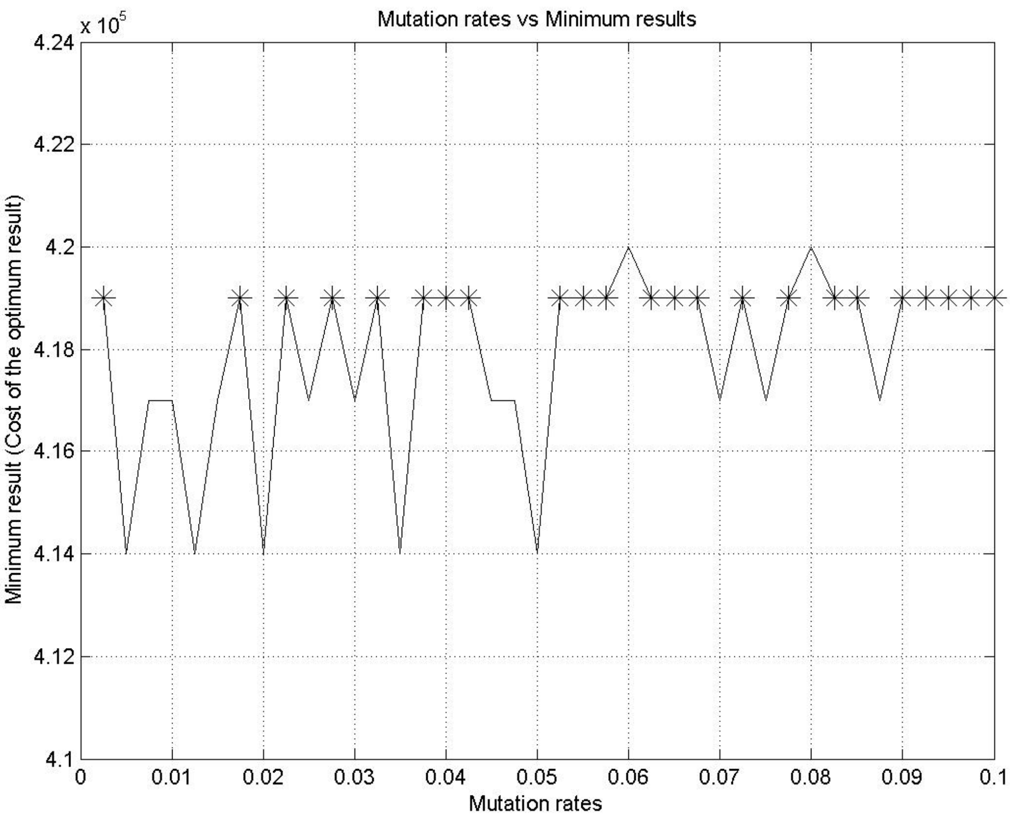

Figure 5.5. Mutation Rates vs. Minimum Results

5.2.2.3 Investigating the elitism rate

Similar to the investigation of previous two parameters, to find optimum elitism rate all other parameters are fixed and only elitism rate varied. The elitism rate takes its value from an interval of [0, 0.32] with steps of 0.04. Since elite members should be even numbers, and the population size is 50; minimum step size for elitism rate becomes 0.04. Tested elitism rates are: {0, 0.04, 0.08, ... , 0.28, 0.32}. The set of all parameters are given in Table 5.5. To investigate the elitism rate NOGA was run 10 times for each elitism rate, and the system pipe costs and system pressure penalties are calculated (see Figure 5.6).

Table 5.5. Parameter Set for Elitism Rate Investigation

Parameter	Value
Pressure penalty constant	6000$
Mutation rate	0.0675
Elitism rate	[0, 0.32]
Crossover probability	90 %
Crossover type	2 points
Population size	50 chromosomes
Number of allowed generations	5000
NOGA trial number	10
Tolerable pressure interval	[30, 80] m

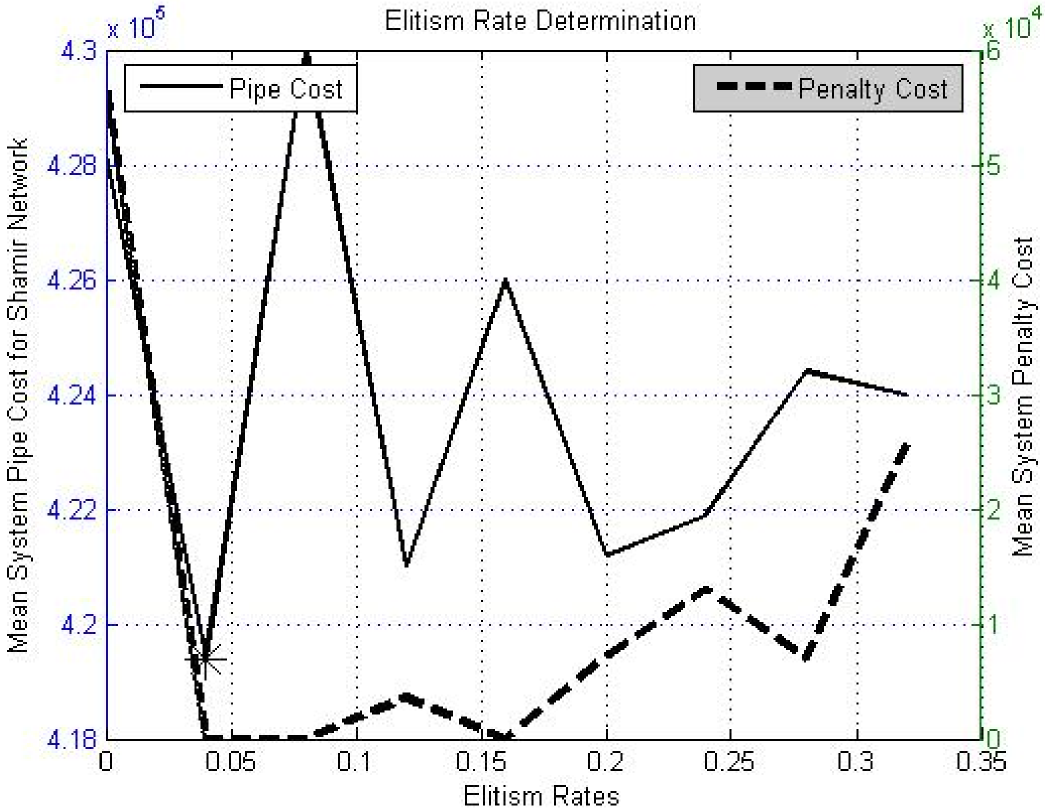

Figure 5.6. Elitism Rates vs. System Costs

As indicated in Figure 5.6, system is not penalized only with three elitism rate values among 10 trials. They are 4%, 8% and 16%. Among these three, the lowest average cost corresponds to 4% elitism rate. Considering minimum values versus elitism rates among 10 trials (Figure 5.7), with three elitism rates NOGA found the lowest cost solution. These elitism rates are again 4%, 8% and 16%. Evaluating these two figures (Figure 5.6 and Figure 5.7), the most suitable value or elitism rate is selected as 4%.

In addition to the proper elitism value for Shamir's network, the role of elitism operator can be discussed by looking at Figure 5.6 and 5.7. In both figures, the necessity of elitism operator is obvious. The worst results are handled with 0% elitism rate in terms of both system cost and penalty cost. This means that, choosing some individuals as elite members, helps the optimization program to converge and it is a necessity. However, choosing many members as elite may force the program converge to local optimums instead of global optimum. So, choosing the lowest elitism rate (4% for this case) will help the program converge to the best result.

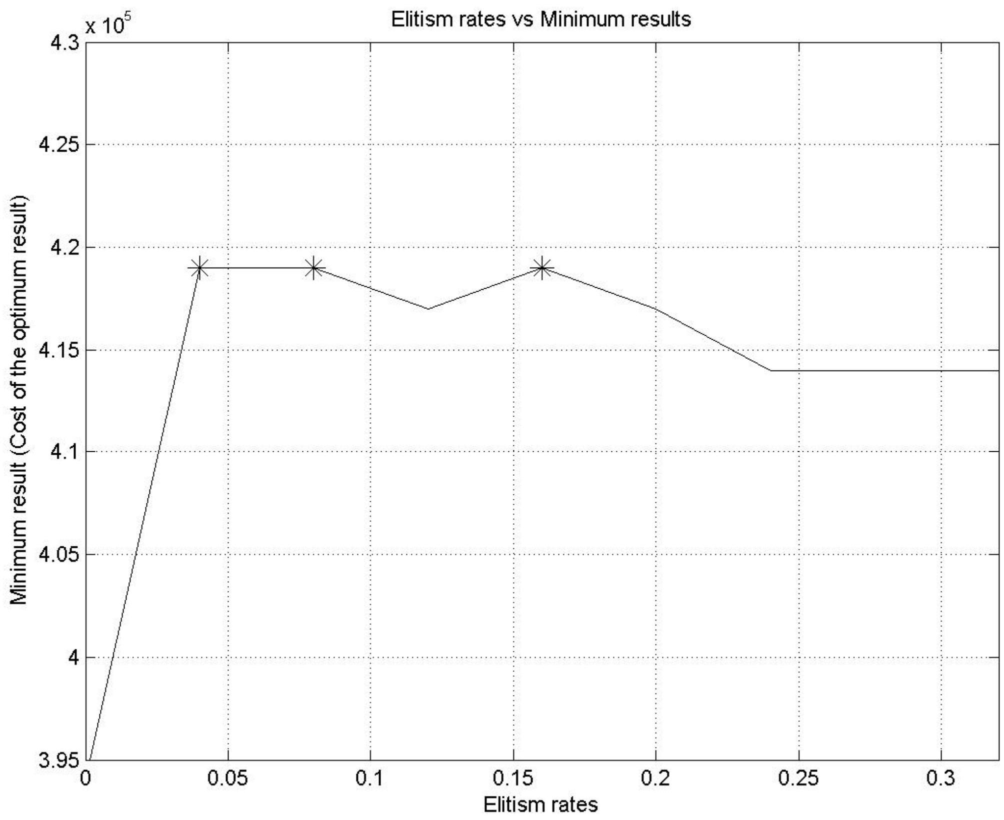

Figure 5.7. Elitism Rates vs. Minimum Results

5.2.2.4 Investigating the crossover probability

To find the optimum crossover probability value, a similar process to the determination of previous parameters has taken. While keeping all other parameters constant, the crossover probability parameter varied in a range and NOGA was run 20 times for each set. The crossover probability takes its value from an interval of [0.3, 1.0] with steps of 0.05 that means crossover probability = {0.30, 0.35, ... , 0.95, 1.0}. The set of all parameters are given below in Table 5.6. After the sets of trials the mean system costs and system penalty costs are plotted (see Figure 5.8).

Table 5.6. Parameter Set for Crossover Probability Investigation

Parameter	Value
Pressure penalty constant	6000$
Mutation rate	0.0675
Elitism rate	0.04
Crossover probability	[0.3, 1.0]
Crossover type	2 points
Population size	50 chromosomes
Number of allowed generations	5000
NOGA trial number	20
Tolerable pressure interval	[30, 80] m

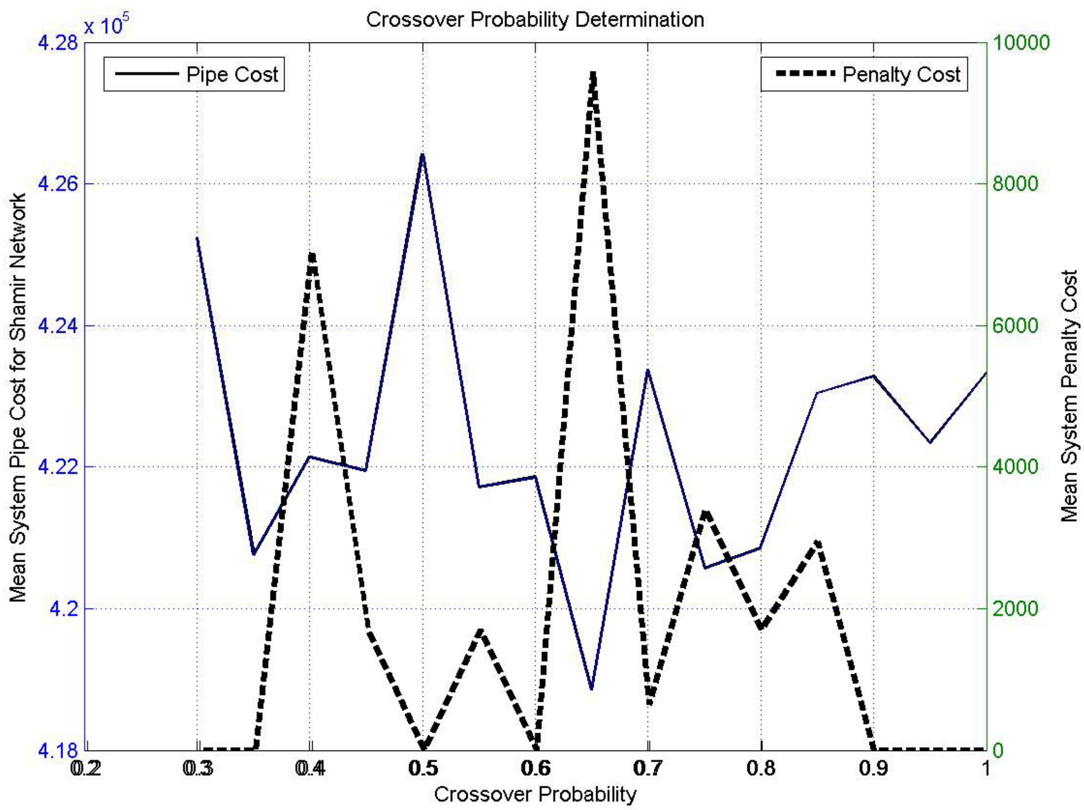

Figure 5.8. Crossover Probabilities vs. System Costs

In Figure 5.8, it is obvious that in many crossover probabilities the system is penalized. There is not an obvious interval of non-penalized result except the [0.9, 1.0] interval. Among 20 trials, the solutions corresponding to 0.9, 0.95 and 1.0 crossover probabilities are non-penalized ones. Similarly, in Figure 5.9, after crossover probability is equal to 0.90, the results have lowest costs. Since there is no strict violation between the results of 0.90 ~ 1.0 making the decision is difficult.

It is preferred to choose 0.90 crossover probability to protect some of the parents from breeding compared to 1.0 crossover probability. When 1.0 crossover probability is chosen, all the parents will be crossed over and their genotype will be changed. On the other hand, by choosing the crossover probability lower than 1.0, some of the parents become the offspring of the next generation. Similar to elitism concept, they are protected for one generation only and randomly it increases the search space. In addition Goldberg (1989) offers the crossover probability in the interval of [0.6, 1.0].

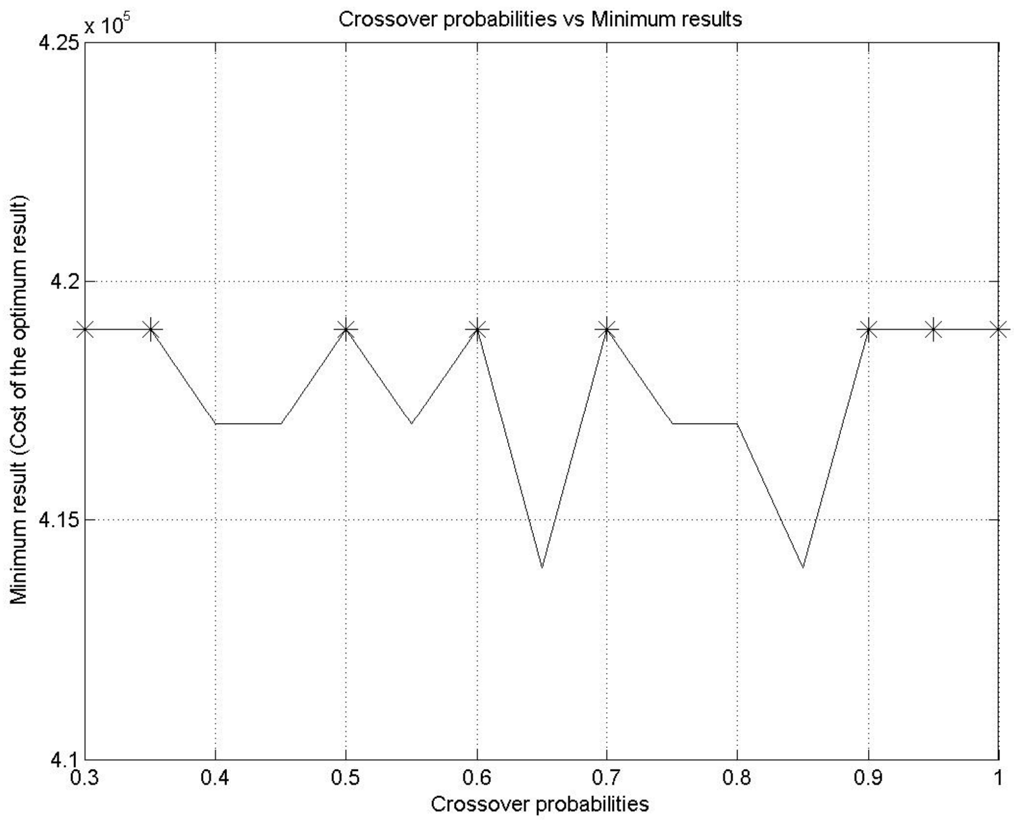

Figure 5.9. Crossover Probabilities vs. Minimum Results

5.2.2.5 Investigating the crossover type

To find the optimum crossover type value, a similar process to the determination of previous parameters has taken. While keeping all other parameters constant, the crossover type varied in a range and NOGA was run 20 times for each set. The crossover type means the crossover process that is defined in previous chapters. The crossover type value changes from 1 to 4 with steps of 1. If second type of crossover is chosen; it means that the parents will exchange their genes from two points on the chromosome. The set of all parameters are given below in Table 5.7. After the sets of trials; the system costs, system penalty costs and minimum costs are plotted (see Figure 5.10).

Table 5.7. Parameter Set for Crossover Type Investigation

Parameter	Value
Pressure penalty constant	6000$
Mutation rate	0.0675
Elitism rate	0.04
Crossover probability	0.90
Crossover type	[1, 4] points
Population size	50 chromosomes
Number of allowed generations	5000
NOGA trial number	20
Tolerable pressure interval	[30, 80] m

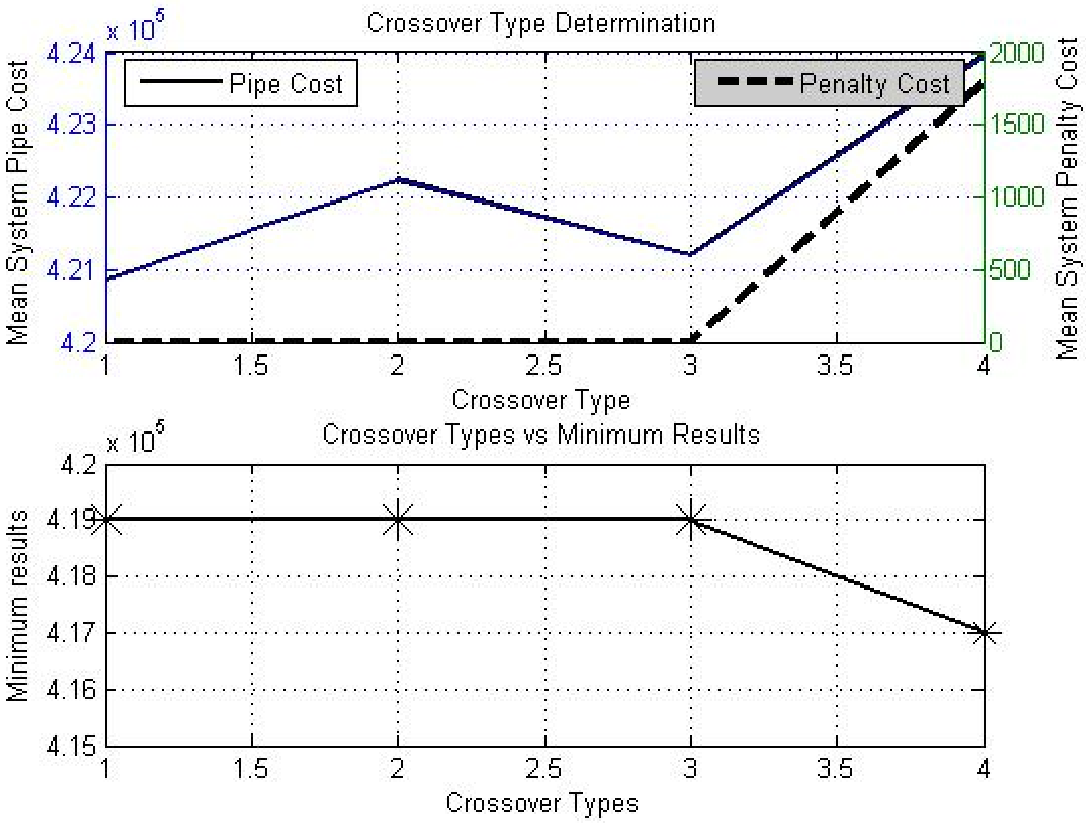

Figure 5.10. Crossover Types vs. System Costs and Minimum Results

As mentioned before, crossover type only affects the gene exchange between the mates. Since there is not a significant variation between the processes of different crossover types, the results are close to each other. By looking at Figure 5.10, it can be mentioned that, the mean system pipe costs are very close to each other in first three crossover types. Similarly through these types no system is penalized. Among these close results, it is hard to choose a crossover type but it is preferred to choose one point type crossover that corresponds the minimum mean system pipe cost. Also in the above figure, it can be seen that in the first three crossover types, the algorithm found the best result.

5.2.3 Final set of parameters for Shamir's network

In Section 5.2.2, the parameters for Shamir's network for NOGA tried to be found. By fixing all the parameters except one and varying that last parameter, a methodology is tried to be developed. As parameter values are decided throughout the methodology the performance of the algorithm improved. The major sign of this alteration is emphasized in Figure 5.10. In that figure, the results of first three crossover type consist of 60 trials. Among 60 trials any solution is not penalized. This shows the strength of the parameters chosen with the methodology and also shows the strength of the methodology. As a result of this solid methodology the final parameter set is given below in Table 5.8.

Table 5.8. Final Parameter Set for Shamir's Network for NOGA

Parameter	Value
Pressure penalty constant	6000$
Mutation rate	0.0675
Elitism rate	0.04
Crossover probability	0.90
Crossover type	1 point

After gathering this parameter set, the effects of allowed generation number on the results of algorithm can be tested. Although Shamir's network seem to be easily solved it is almost inevitable to abandon pressure penalties due to the character of the network. In the network's solution space there are some local optimum valleys that are so close to best result obtained in term of the capital cost. While searching for the global optimum, NOGA can fall into one of these valleys and the program will give this solution as the optimum. Moreover, some of these valleys may result in pressure penalties. Since this event is inevitable, the necessity of conducting several runs emerges.

Although there are local optimums (i.e., valleys) in the search space, to avoid the program get stuck in one of these local optimums, allowed generation number can be increased. To investigate the effects of the number of allowed generations on solutions, one last investigation is completed on the Shamir's network. Using the final parameter set, NOGA was run 100 times for 3000, 5000 and 8000 generations. The results of these investigations are tabulated below (Table 5.9).

Table 5.9. Number of Allowed Generations vs. Performance of NOGA

Number of allowed generations	Number of penalized solutions	Cap. Cost = 419000$	Cap. Cost = 420000$	Cap. Cost > 420000$	Total	Average Result Generation Number
3000	7	45	34	14	100	896
5000	0	43	46	11	100	1295
8000	2	46	47	5	100	1544

In the above table, number of penalized solutions, number of solutions with 419000$ capital cost (best result), number of solutions with 420000$ capital cost and number of solutions greater than 420000$ are summarized. In the solution space of Shamir's network there are three solutions with lower capital costs than other solutions. These three solutions also supply the pressure requirements for [30, 80] interval. Two of them are local optimum results with 420000$ capital cost and the other is the best result with 419000$ capital cost. These solutions are very close – or same – with respect to the capital cost. On the other hand, they are different from one another with respect to the diameter sequence. The pipe diameters of these solutions are listed in Table 5.10. This table also shows how difficult to step out to global optimum when the program faces with the local optimum among the generations. So, while measuring the performance of the algorithm, the solutions with 420000$ capital cost should be considered. In Table 5.9 the performance of allowed generation number is tried to be measured. Comparing the first and the second column, for 3000 generations, NOGA resulted with 7 penalized solutions out of 100 trials. On the contrary, with greater generation numbers, pressure penalties are almost abandoned. Number of results with 419000$ and 420000$ are very close to each other for all allowed generation numbers but a small increase at the performance is visible if 420000$ results are considered. Additionally, number of results with greater than 420000$ capital costs behave like the penalized solutions. When the number of allowed generations increases, NOGA finds cheaper results. The last column indicates that, when the allowed generation number increases, the results may be found in further generations. This also means that the program does not converge fast. One disadvantage of increasing the allowed generation number is the run time of the program. As generation numbers increases, the time spent for computation also increases.

Table 5.10. Pipe Diameters of Some Optimal Results for Shamir's Network

Pipe No.	Pipe Diameters (mm)		
1	508.0	457.2	457.2
2	254.0	355.6	254.0
3	406.4	355.6	406.4
4	25.4	25.4	101.6
5	355.6	355.6	406.4
6	254.0	152.4	254.0
7	254.0	355.6	254.0
8	25.4	254.0	254.0
Total Cost	**420000$**	**420000$**	**419000$ Best Result**

5.3 Fujiwara and Khang's Hanoi Network

5.3.1 Overview of Hanoi network

Fujiwara and Khang (1990) applied two-phase decomposition method on the planned water distribution trunk network in Hanoi, Vietnam. Hanoi network consists of 32 nodes, 34 pipes each may have 6 different diameters and 1 reservoir. The network is composed of 3 loops; assumed Hazen-Williams coefficients are all 130. The layout of Hanoi network is given in Figure 5.11. The elevation of all nodes is 0 m except that the reservoir elevation which is 100m. The nodal demands and pipe lengths are given in Table 5.11. The unit prices for each pipe diameter for one meter length are listed in Table 5.12. Unit cost of a pipe (C) can be found by the formula; $C = 1.1 * L * D^{1.5}$ where L (m.) and D (in.) are pipe length and diameter, respectively. Please note that, for NOGA that kind of pipe diameter - cost function is not necessary. Similar to Shamir's network, Hanoi network does not contain any pumping facility.

With its relatively large solution space ($6^{34} = 2.87*10^{26}$), many researchers (Fujiwara and Khang, (1990); Savic and Walters, (1997); Vairavamoorthy and Ali, (2000); Neelakantan and Suribabu, (2005); Cunha and Sousa, (1999); Abebe and Solomatine, (1998); Liong and Atiquzzaman, (2004)) tried their methods and algorithms on

Hanoi network. The comparison of some of these researchers' and the author's results will be provided in Section 5.3.4.

Since there are 6 available pipe sizes, each pipe diameter is defined in 3-bits genes. One chromosome consists of 102 bits. 3-bits gene composition allows 8 available pipe sizes but in this network only 6 pipes exist. It is preferred to use middle sized pipe diameters for 5th and 6th genes instead of using unreal numbers (Table 5.12). Using middle sized diameters saves time during computation since all individuals among the population have real pipe diameters. If unreal pipe diameters are replaced instead; the program would have spent more time to converge and this will decrease the performance of the algorithm. The minimum pressure requirement for all nodes is 30 m. No velocity constraint is taken into account for this network.

Table 5.11. Nodal Demands and Pipe Lengths for Hanoi Network

Node	Nodal Demands (m^3/hr)	Pipe	Length (m)
1 (reservoir)	-19940	1	100.00
2	890	2	1,350.00
3	850	3	900.00
4	130	4	1,150.00
5	725	5	1,450.00
6	1005	6	450.00
7	1350	7	850.00
8	550	8	850.00
9	525	9	800.00
10	525	10	950.00
11	500	11	1,200.00
12	560	12	3,500.00
13	940	13	800.00
14	615	14	500.00
15	280	15	550.00
16	310	16	2,730.00
17	865	17	1,750.00
18	1345	18	800.00
19	60	19	400.00
20	1275	20	2,200.00
21	930	21	1,500.00
22	485	22	500.00
23	1045	23	2,650.00
24	820	24	1,230.00
25	170	25	1,300.00
26	900	26	850.00
27	370	27	300.00
28	290	28	750.00
29	360	29	1,500.00
30	360	30	2,000.00
31	105	31	1,600.00
32	805	32	150.00
		33	860.00
		34	950.00

Table 5.12. Unit Prices and Binary Codes for Each Pipe Diameter

Diameter (inch)	Diameter (mm)	Binary Code	Unit Price ($/m)
12	304,80	[000]	45,73
16	406,40	[001]	70,40
20	508,00	[010]	98,38
24	609,60	[011]	129,33
30	762,00	[100]	180,75
40	1016,00	[101]	278,28
20	*508,00*	*[110]*	*98,38*
24	*609,60*	*[111]*	*129,33*

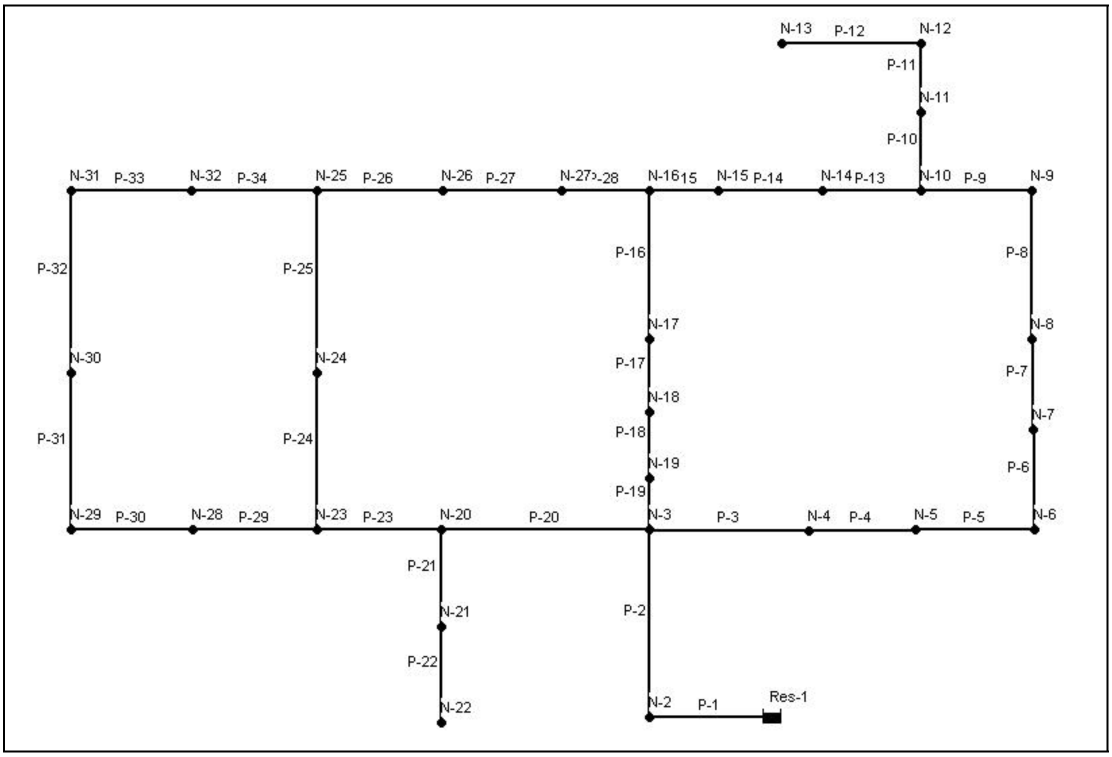

Figure 5.11. Hanoi Network Layout

5.3.2 Developing the methodology on Hanoi network

To find the optimum parameters for Hanoi network almost the same steps of previous work are followed. Firstly, pressure penalty constant is investigated, after deciding the pressure penalty constant; mutation rate, elitism rate, crossover probability and crossover type are investigated sequentially.

Compared to Shamir's network, Hanoi has a greater solution space. This means that, for all of the analysis, more trials were necessary. Although no previously defined trial number is given, the runs were held until the results are interpretable.

5.3.2.1 Investigating the pressure penalty constant

To find the suitable pressure penalty constant, all other parameters are fixed. The set of all parameters are given in Table 5.13. The values of the parameters are chosen from the literature and by own experience.

The pressure penalty constant (PPC) takes the value from the interval of [5000, 100000]\$ with steps of 5000\$. That means PPC = {5000, 10000, 15000, … , 95000, 100000}\$. NOGA was run 10 times for each pressure penalty constant and the system pipe costs and system pressure penalties are calculated. These calculations are shown in Figure 5.12.

Table 5.13. Parameter Set for Pressure Penalty Constant Investigation

Parameter	Value
Pressure penalty constant	[5000, 100000]$
Mutation rate	1 %
Elitism rate	4 %
Crossover probability	90 %
Crossover type	2 points
Population size	50 chromosomes
Number of allowed generations	5000
NOGA trial number	10
Tolerable pressure interval	[30, 80] m

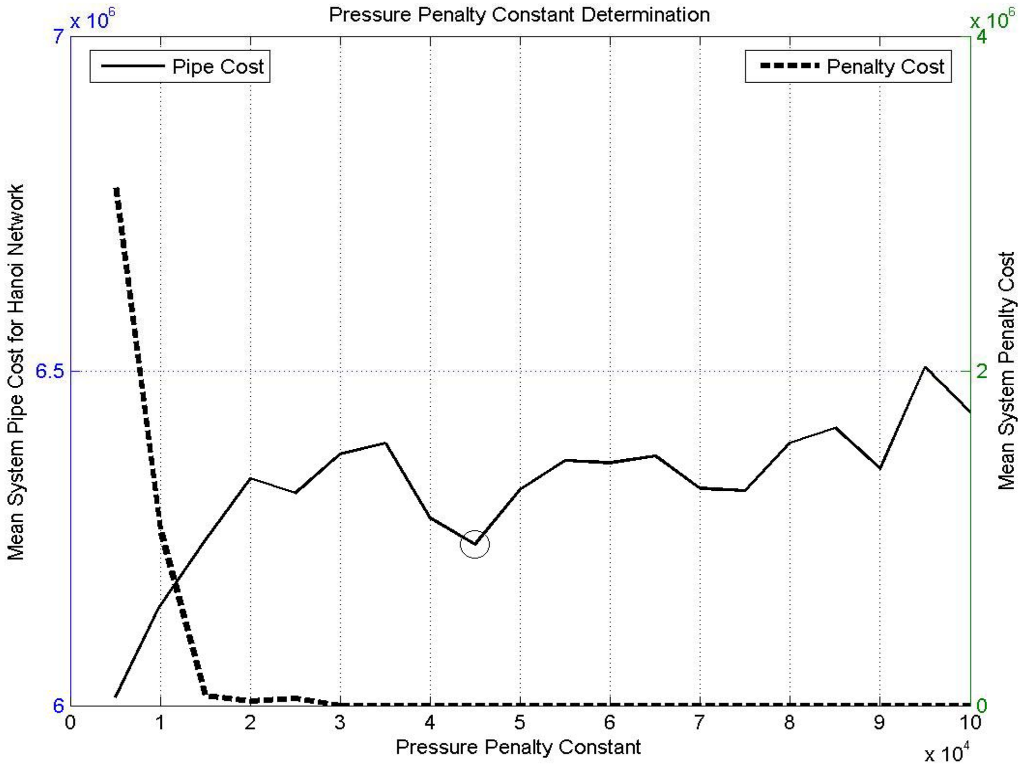

Figure 5.12. Pressure Penalty Constants vs. Mean System Costs

As can be seen from the figure above (Figure 5.12), after pressure penalty constant is equal to 30000$, system is not penalized. This shows the effectiveness of the penalty function of NOGA on Hanoi network. Additionally when the whole figure is considered, minimum mean system cost is found where pressure penalty constant is equal to 45000$. After 45000$, as pressure penalty constant increases, mean system cost also increases.

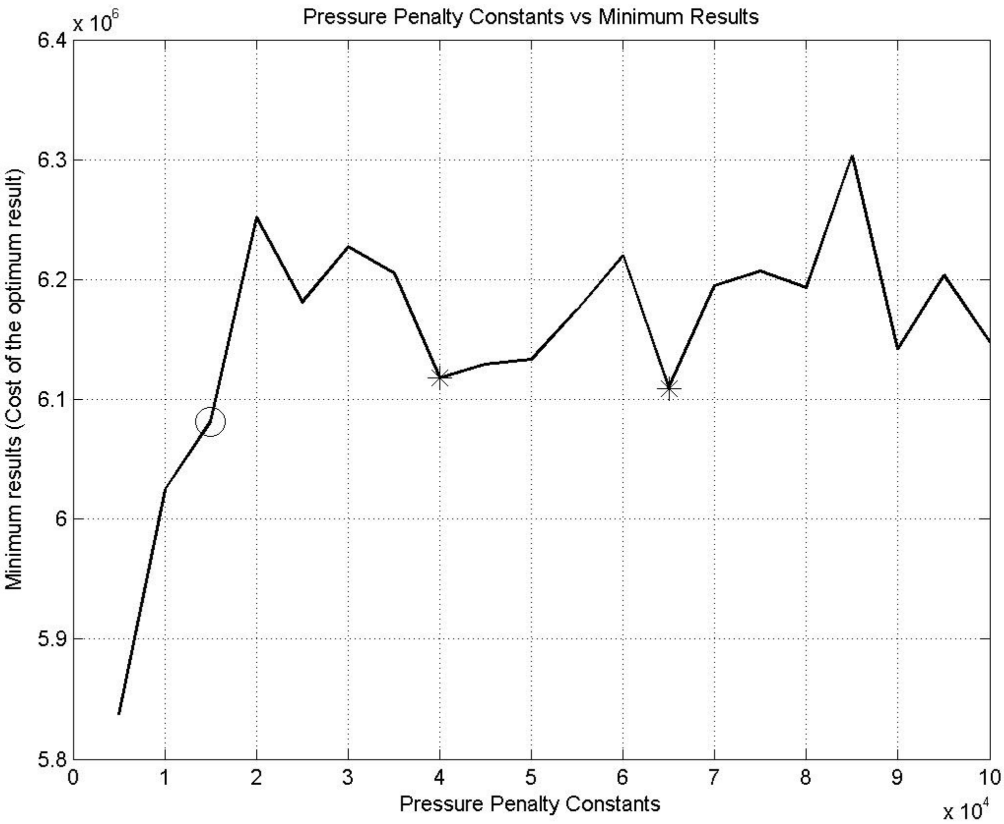

Figure 5.13. Pressure Penalty Constants vs. Minimum System Costs

In Figure 5.13 there are three additional signs that are the first three best results among the minimum results. The “O” sign shows the cheaper cost but this result is in the penalized region; it corresponds the 15000$ pressure penalty constant value. While running NOGA using pressure penalty constant is equal to 15000$, among 10 trials, 5 of them are penalized. One of the non-penalized populations is the least cost solution for the whole set. This interesting event supports the idea that is not to penalize individuals severely since there may be disturbance of promising ones.

The “*” signs indicate the second and the third best result among the trials. One corresponds to 40000$, the other one 65000$. Also the corresponding cost for 45000$ pressure penalty constant is the fourth among the minimums.

By looking at these two figures, it is preferred to use 45000$ as pressure penalty constant for the next investigations. Although 40000$ ~ 65000$ interval is also acceptable, it is preferred to choose the lower boundary side of the interval. Instead of choosing 40000$, 45000$ is preferred to be on the safe side due to the stochastic characteristic of the GA. It should be remembered that the mean system cost corresponding the 45000$ is least of the whole set. Although the best result of these 81 runs corresponds to 15000$ pressure penalty constant, this pressure penalty constant value can not be acceptable since it is in the penalized region.

5.3.2.2 Investigating the mutation rate

Similar to the investigation of pressure penalty constant, to find the optimum mutation rate, all other parameters are fixed and only mutation rates are varied. The mutation rate takes the value from an interval of [0.0025, 0.0500] with steps of 0.0025. That means mutation rate = {0.0025, 0.0050, 0.0075, … , 0.0475, 0.0500}. The set of all parameters are given below in Table 5.14. NOGA was run 11 times for each mutation rate and the system costs and penalty costs are calculated. The results of the runs are shown in two figures of which indicates the penalty costs, mean system costs and minimum costs. These two figures are shown below (Figure 5.14 and Figure 5.15).

Table 5.14. Parameter Set for Mutation Rate Investigation

Parameter	**Value**
Pressure penalty constant	45000$
Mutation rate	[0.0025, 0.0500]
Elitism rate	4 %
Crossover probability	90 %
Crossover type	2 points
Population size	50 chromosomes
Number of allowed generations	5000
NOGA trial number	11
Tolerable pressure interval	[30, 80] m

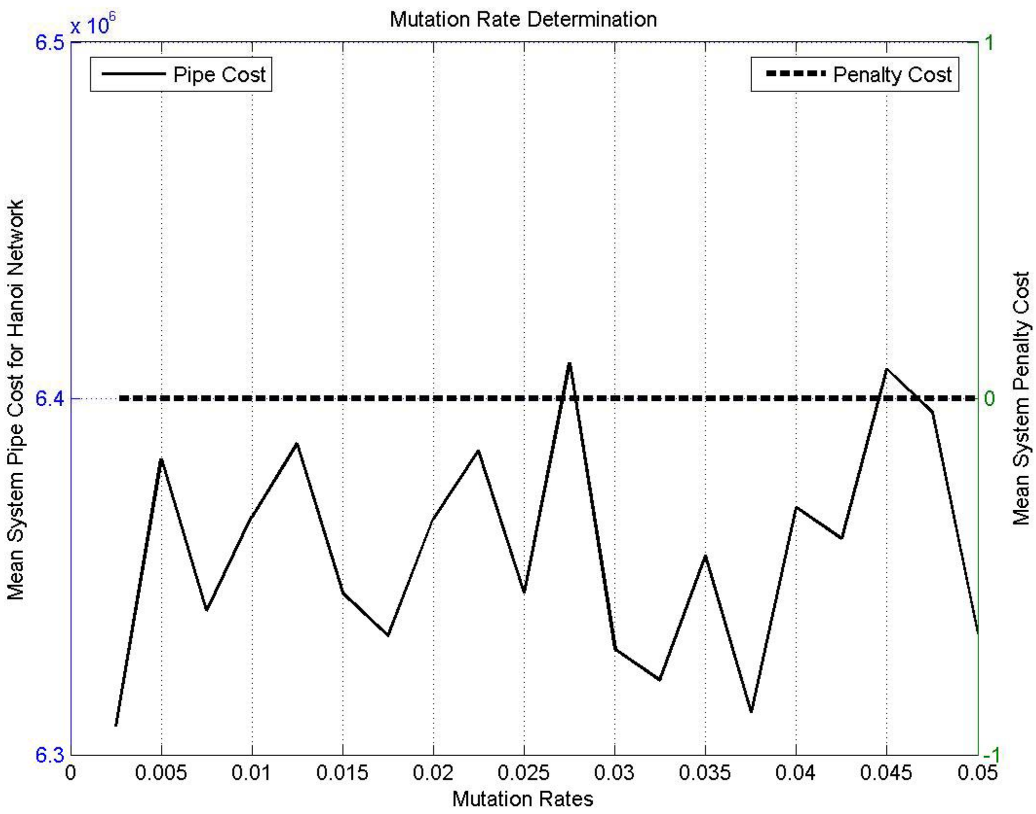

Figure 5.14. Mutation Rates vs. System Costs

In Figure 5.14 the system penalty costs and system pipe costs are shown. Different from Shamir's network, system is not penalized in any occasion. This shows the strength of pressure penalty constant and pressure penalty function in greater search spaces. Additionally, in Figure 5.15, the minimum results and the best three results are shown.

When the upper drawing at Figure 5.15 is considered, after 0.02; as mutation rate increases there is a trend of increase at the minimum values among several trials. Where mutation rate is about 0.0175 and 0.0200 the results are better than the others. When the lower plot at Figure 5.15 is considered, 0.0175 mutation rate gives lower value than 0.0200 among the best three results of 11 trials. Similarly, in Figure 5.14, the mean system pipe cost corresponding to 0.0175 mutation rate is lower than the value corresponding to 0.0200 mutation rate. Although these values are very close to each other and results are not sharply differentiated, it is preferred to use 0.0175 mutation rate for the next investigations.

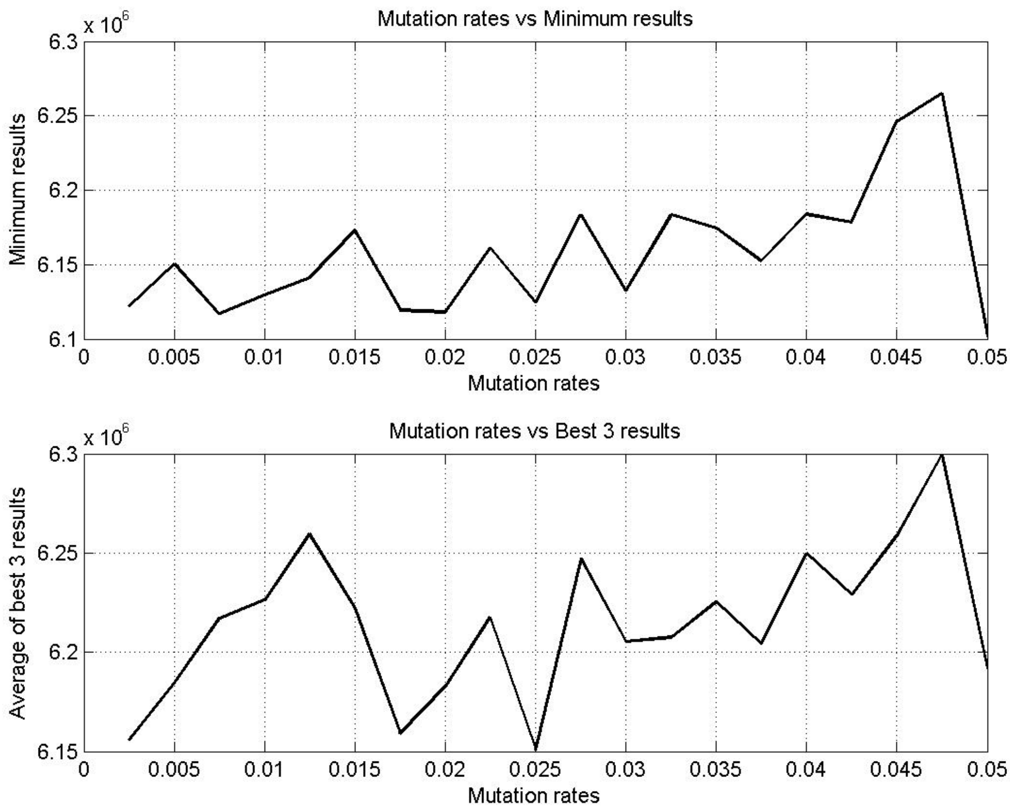

Figure 5.15. Mutation Rates vs. Minimum System Costs

In Section 5.2.2.2, the result generations versus minimum results were analyzed on Shamir's network. When Figure 5.16 is considered, the result generation number starts to increase after about, 0.035. Before that value any differentiation is not obvious. After 0.035, similar to Shamir's network, NOGA faces with difficulties to find the optimum since increasing mutation rate decreases the convergence performance of the program.

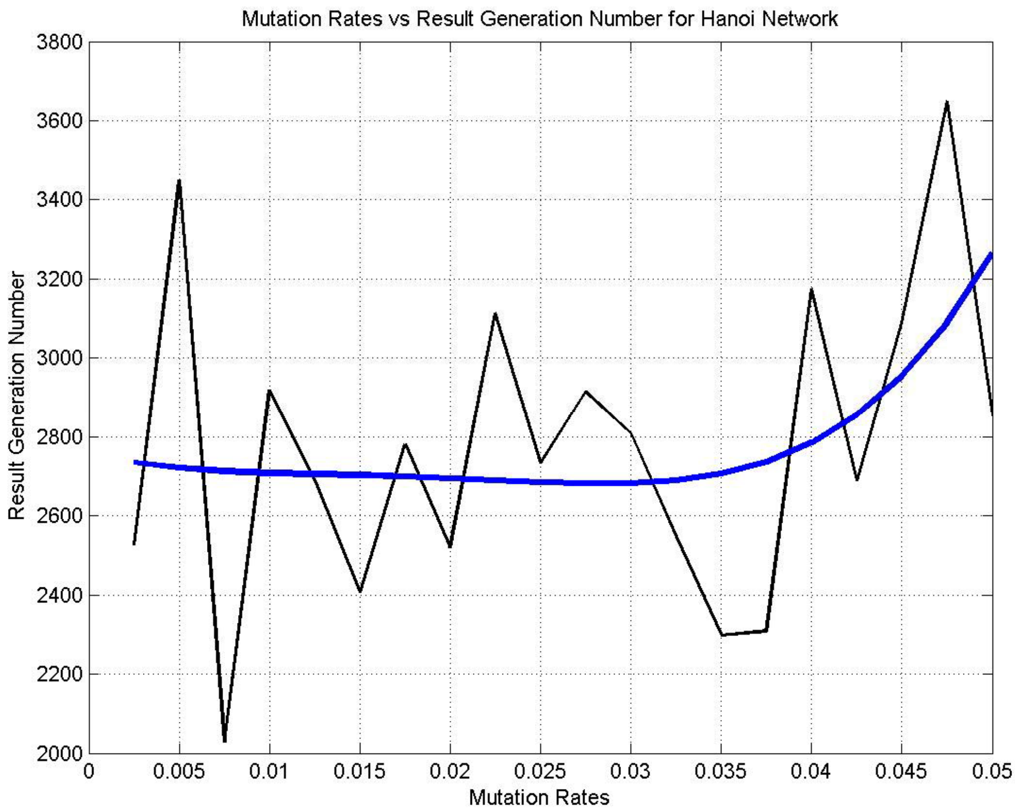

Figure 5.16. Mutation Rates vs. Result Generations

5.3.2.3 Investigating the elitism rate

Similar to the investigation of previous two parameters, to find the optimum elitism rate all other parameters are fixed and only elitism rates are varied. Similar to the investigation in Shamir's network, the elitism rate takes its value from an interval of [0, 0.32] with steps of 0.04. Since elite members should be even numbers, and the population size is 50; minimum step size and also the minimum value for elitism rate becomes 0.04. Tested elitism rates are: {0, 0.04, 0.08, ... , 0.28, 0.32}. The set of all parameters are given below in Table 5.15. For the investigation NOGA was run 20 times for each elitism rate and the results are examined.

Table 5.15. Parameter Set for Elitism Rate Investigation

Parameter	Value
Pressure penalty constant	45000$
Mutation rate	0.0175
Elitism rate	[0, 0.32]
Crossover probability	90 %
Crossover type	2 points
Population size	50 chromosomes
Number of allowed generations	5000
NOGA trial number	20
Tolerable pressure interval	[30, 80] m

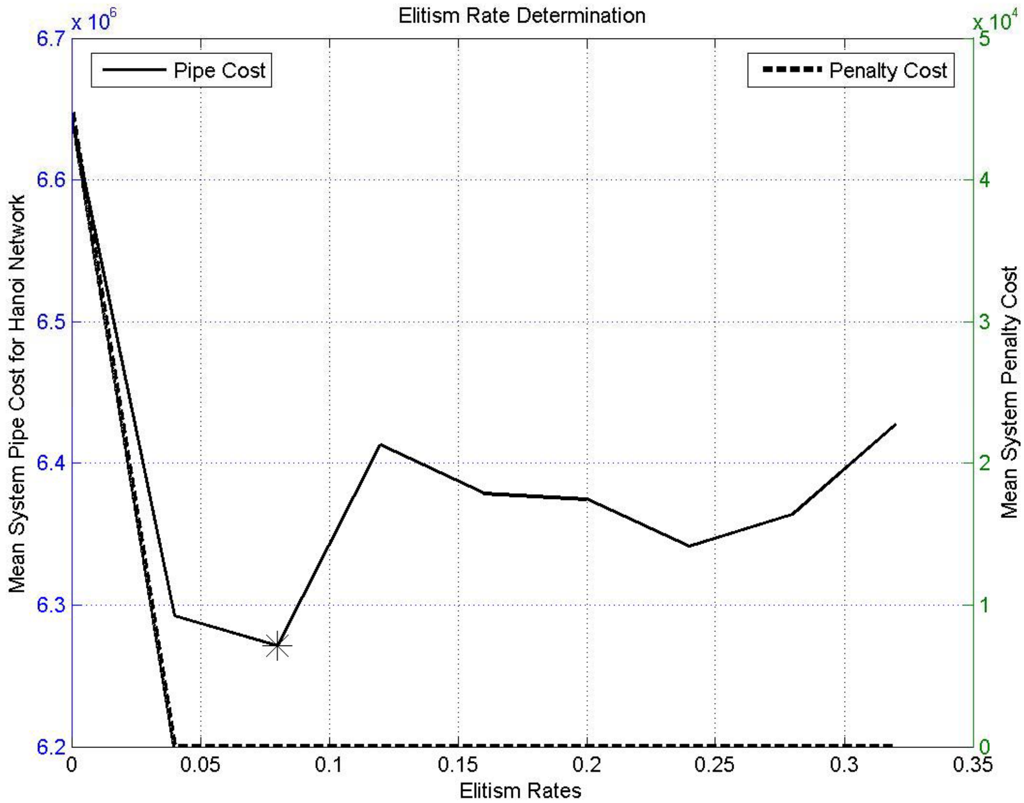

Figure 5.17. Elitism Rates vs. Mean System Costs

Figure 5.17 reflects the mean system pipe costs and the mean system penalty costs for each elitism rate. By looking at the figure it can be said that; similar to the trials of Shamir's network; while using 0% elitism rate system pipe costs and penalty costs are very high. This implies the necessity of the elitism operator in genetic algorithm for Hanoi network also. Other than 0% elitism rate, NOGA found good results especially with low elitism rates. The star sign reflects the minimum mean system cost among 9 elitism rates. Although the star sign corresponds to 0.08 elitism rate, 0.04 elitism rate also gave good results. After 0.08, the mean system cost increased and never drew back. As the mean results corresponding the 0.08 and 0.04 elitism rates are close to each other, investigating the minimum results for each 20 trials become necessary (see Figure 5.18).

Considering Figure 5.18, it is obvious that there is a trend of increase at the minimum costs after elitism rate is equal to 0.04. As elitism rate increased, the minimum costs for each 20 trials were also increased. By looking at these two figures (Figures 5.17 and 5.18) it is preferred to choose 0.04 elitism rate for Hanoi network.

Similar to the investigation of Shamir's network, again the elitism rate is chosen as 4% that means the minimum elitism rate for the defined population size. Both network investigations indicate the necessity of elitism operator but at the minimum level.

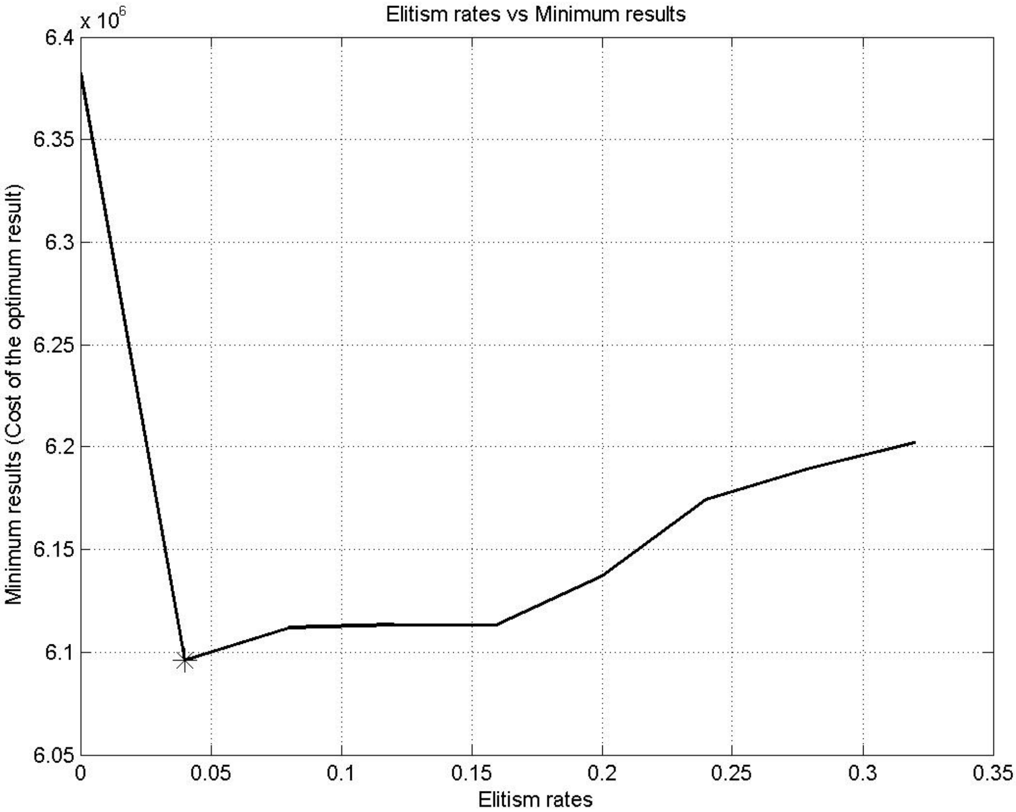

Figure 5.18. Elitism Rates vs. Minimum System Costs

In addition to the previous figures; Figure 5.19 clearly reflects the effect of elitism rate on the convergence of the algorithm. In Figure 5.19, result generation numbers are drawn with respect to the elitism rates. As the elitism rate increases, the result generation number decreases that means the algorithm converges to the optimum fast, which have higher system costs compared to lower elitism rates. In other words; as elitism rate increases, the tendency of converging to a local optimum also increases. On the contrary, with lower elitism rates NOGA finds the results in higher generations but the system costs are lower (Figure 5.17). The reason behind this event is basically the relationship between the search space and the searching action. When the algorithm searches smaller space, it finds the optimum in lower generations (converges fast) however; when it searches larger space, it finds the optimum in higher generations and the results are tend to be cheaper. Finally it can be emphasized that, lower elitism rates helps the program to find the global optimum. This fact is a plus sign to choose the lowest elitism rate for Hanoi network.

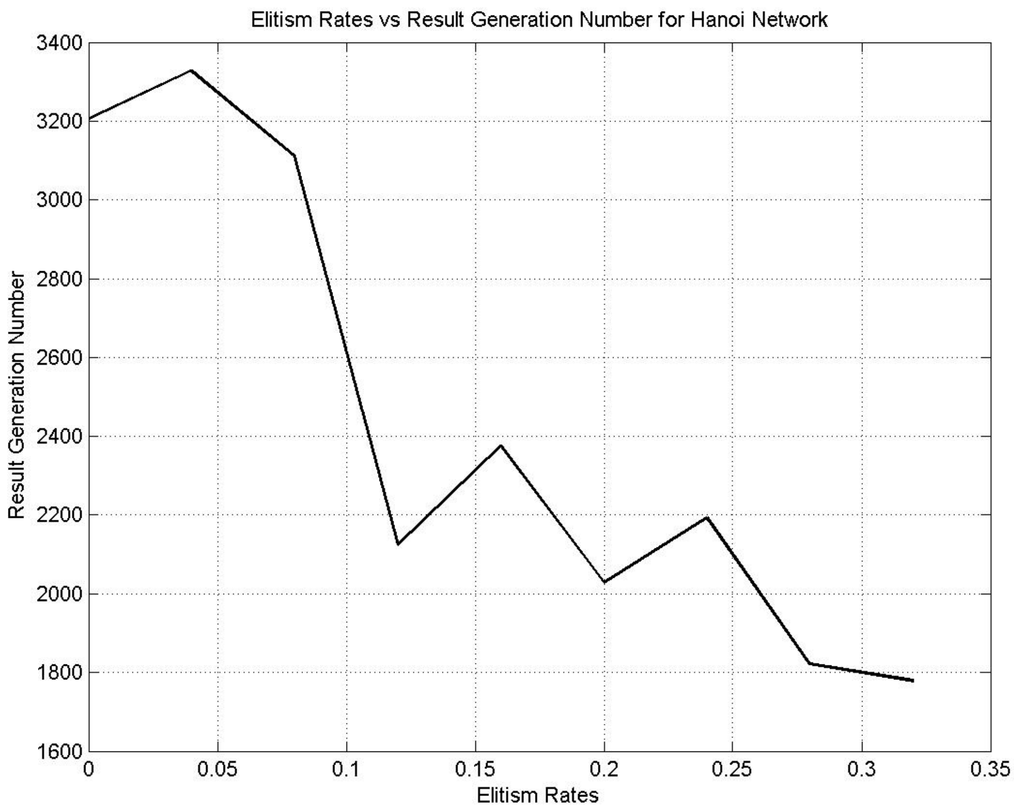

Figure 5.19. Elitism Rates vs. Result Generations

5.3.2.4 Investigating the crossover probability

Similar to the investigation of previous parameters, to find the optimum crossover probability all other parameters are fixed and only crossover probability values are varied. The crossover probability takes its value from an interval of [0.3, 1.0] with steps of 0.05 that means crossover probability = {0.30, 0.35, ... , 0.95, 1.0}. NOGA was run 21 times for each set. The set of all parameters are given below in Table

5.16. After the completion of the sets of trials, the mean system costs and system penalty costs are plotted with respect to crossover probabilities (see Figure 5.20).

Table 5.16. Parameter Set for Crossover Probability Investigation

Parameter	Value
Pressure penalty constant	45000$
Mutation rate	0.0175
Elitism rate	0.04
Crossover probability	[0.3, 1.0]
Crossover type	2 points
Population size	50 chromosomes
Number of allowed generations	5000
NOGA trial number	21
Tolerable pressure interval	[30, 80] m

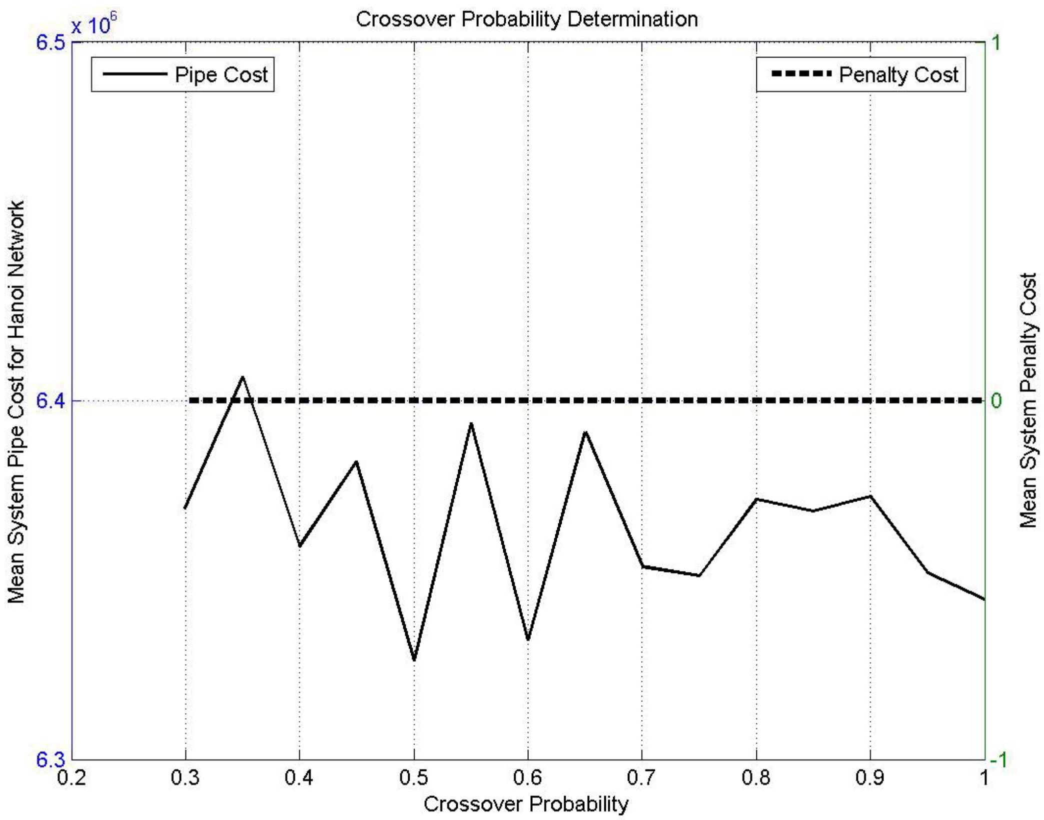

Figure 5.20. Crossover Probabilities vs. Mean System Costs

Figure 5.20 reflects the results of each set of trial that corresponding to a crossover probability value. Similar to the previous investigations in Hanoi network, again none of the individuals are penalized. Considering the mean system costs, at the values 0.5 and 0.6 the values are smaller. Before and after those values, there may be a trend of increase at the mean capital costs. When the minimum costs are considered among these trials (see Figure 5.21), it can be seen that, at 0.5 and 0.6 crossover probability values the NOGA reached the lowest costs. Goldberg, (1989) defined the recommended range for probability of crossover is [0.6, 1.0]. Both considering the mean costs and minimum costs, it is preferred to choose 0.6 crossover probability value. This means that some of the mates are protected from crossing over other than elite members. Changing the genes between the parents with 60 % means about half of the parents are not breeding. This is a type of protection and means that the search space is reduced. However, results show that NOGA reaches the best results using low crossover probability values. This may be a result of large search space of the problem and moderately long chromosome length. To conclude, it can be said that, for the networks with large spaces, not choosing a high crossover probability value increases the performance of the program.

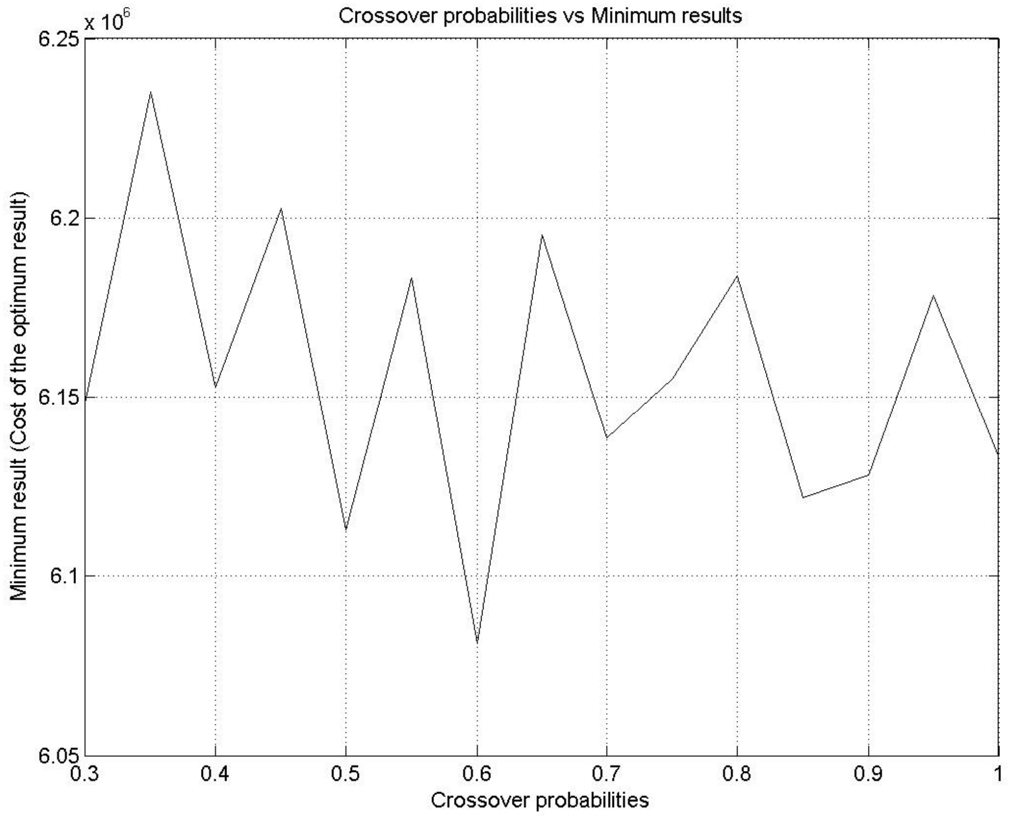

Figure 5.21. Crossover Probabilities vs. Minimum System Costs

5.3.2.5 Investigating the crossover type

To find the optimum crossover type, a similar process to the determination of previous parameters has been applied. While keeping other parameters constant, the crossover type values are varied and NOGA was run 25 times for each set. The crossover type means the crossover process that is defined in the third chapter. The crossover type value changes from 1 to 4 with steps of 1. If type 2 crossover is chosen it means that the parents will exchange their genes from two points on the chromosome. The set of all parameters are given below in Table 5.17. After the sets of trials are completed; the system costs, system penalty costs and minimum costs are plotted (see Figures 5.22 and 5.23).

Table 5.17. Parameter Set for Crossover Type Investigation

Parameter	Value
Pressure penalty constant	45000$
Mutation rate	0.0175
Elitism rate	0.04
Crossover probability	0.60
Crossover type	[1, 4] points
Population size	50 chromosomes
Number of allowed generations	5000
NOGA trial number	25
Tolerable pressure interval	[30, 80] m

Similar to the previous investigations, system is not penalized in any of the runs. When the mean system costs are considered (Figure 5.22), there can be seen a trend of increase as the crossover type value increases. The lowest mean cost is achieved with the first crossover type. Similarly, in Figure 5.23, the lowest minimum again achieved with the first crossover type. In Figure 5.23, the trend of increase is more obvious as the crossover type value increases. By considering both figures, it is preferred to choose 1 point crossover type.

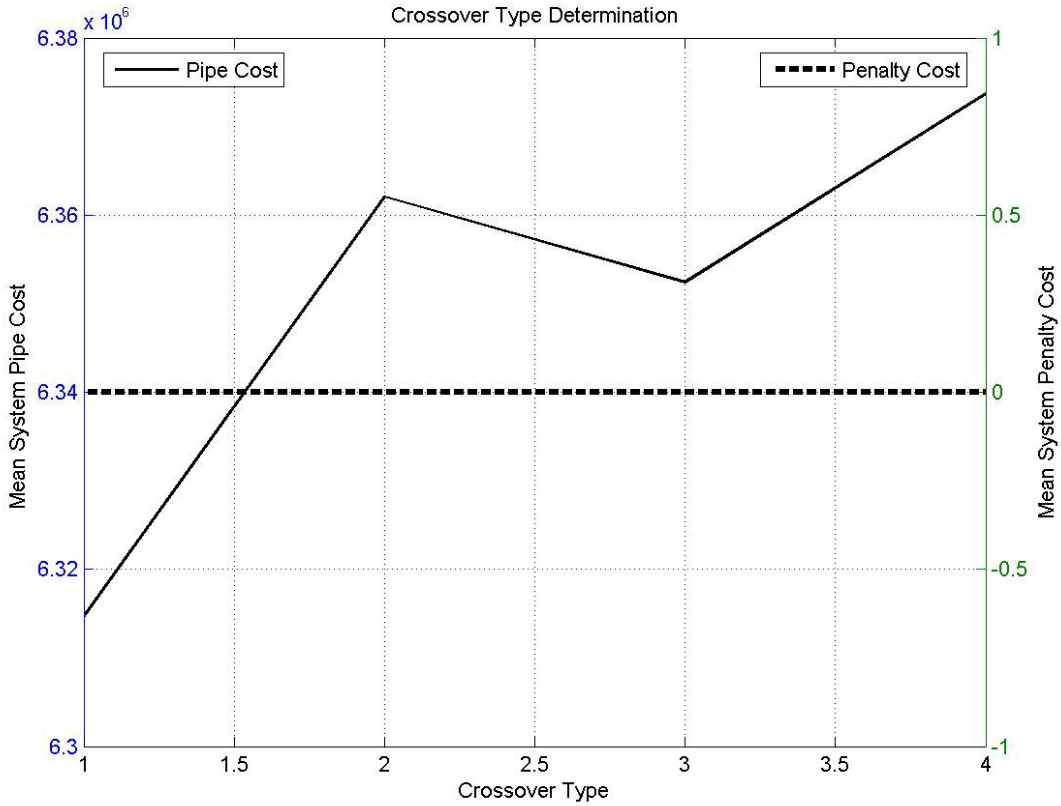

Figure 5.22. Crossover Types vs. Mean System Costs

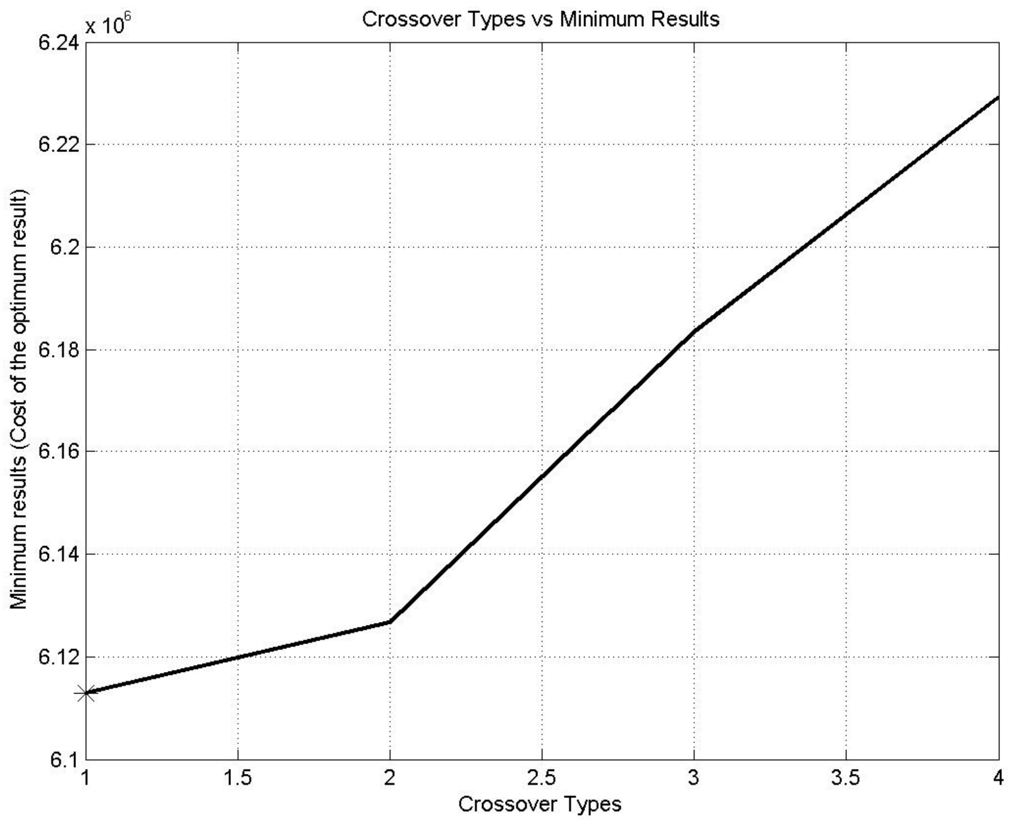

Figure 5.23. Crossover Types vs. Minimum System Costs

5.3.3 Final set of parameters for Hanoi network

In Section 5.3.2, the parameters for Hanoi network for NOGA tried to be found. By fixing all the parameters except one and releasing that exception parameter, a methodology is applied. After these investigations for each parameter, a final set of parameters is reached (Table 5.18).

Table 5.18. Final Parameter Set for Hanoi Network for NOGA

Parameter	**Value**
Pressure penalty constant	45000$
Mutation rate	0.0175
Elitism rate	0.04
Crossover probability	0.60
Crossover type	1 point

Different from Shamir's network, in Hanoi network pressure penalties are abandoned more successfully. This is basically depending on the character of the network and the performance of the parameters on the network. Among these sets of trials NOGA hit 6,081,127$ and 6,096,099$ capital costs. These values are under 6,100,000$ limit and good results compared with the past studies.

5.3.4 Comparison of NOGA with other researchers' programs

As mentioned earlier, Hanoi network is studied by many researchers. Its relatively large search space attracted so many researchers and also they used this network to test their algorithm since there are many studies to compare. Other than traditional methods, Savic and Walters, (1997); Abebe and Solomatine, (1998); Cunha and Sousa, (1999); Liong and Atiquzzaman, (2004); Neelakantan and Suribabu, (2005); Güç (2006) tested their genetic algorithm based programs on this network. The optimum pipe diameters of these researchers' studies are listed below with corresponding capital costs.

Table 5.19. Final Results of Researchers on Hanoi Network

	Pipe diameters (inch)						
Pipe No	Savic & Walters	Cunha & Sousa	Abebe & Solomatine	Liong & Atiquzzaman	Neelakantan & Suribabu	Güç	This Study
1	40	40	40	40	40	40	40
2	40	40	40	40	40	40	40
3	40	40	40	40	40	40	40
4	40	40	40	40	40	40	40
5	40	40	30	40	40	40	40
6	40	40	40	40	40	40	40
7	40	40	40	40	40	40	40
8	40	40	30	30	40	40	40
9	40	40	30	30	40	40	40
10	30	30	30	30	30	24	30
11	24	24	30	30	24	24	24
12	24	24	30	24	24	24	24
13	20	20	16	16	20	12	20
14	16	16	24	12	16	12	16
15	12	12	30	12	12	16	12
16	12	12	30	24	12	12	12
17	16	16	30	30	16	20	16
18	20	20	40	30	24	30	24
19	20	20	40	30	20	20	20
20	40	40	40	40	40	40	40
21	20	20	20	20	20	20	20
22	12	12	20	12	12	12	12
23	40	40	30	30	40	40	40
24	30	30	16	30	30	30	30
25	30	30	20	24	30	30	30
26	20	20	12	12	20	30	20
27	12	12	24	20	12	20	12
28	12	12	20	24	12	16	12
29	16	16	24	16	16	16	16
30	16	12	30	16	12	20	12
31	12	12	30	12	12	16	12
32	12	16	30	16	16	20	16
33	16	16	30	20	16	16	16
34	20	24	12	24	24	24	24
Total Cost (Million $)	**6,07**	**6,05**	**7,00**	**6,22**	**6,08**	**6,33**	**6,08**

In Table 5.19, when the capital costs are considered, results of Cunha and Sousa (1999) and Savic and Walters (1997) are below the other researchers. However, their hydraulic network solver is not EPANET. When their systems are hydraulically solved by EPANET, some pressure violations emerge. The nodal pressures corresponding to the researchers' system's pipe diameters are listed below (see Table 5.20).

Table 5.20. Nodal Pressures of Hanoi Network

	Node Pressures (m)						
Node	Savic & Walters	Cunha & Sousa	Abebe & Solomatine	Liong & Atiquzzaman	Neelakantan & Suribabu	Güç	This Study
1	100,00	100,00	100,00	100,00	100,00	100,00	100,00
2	97,14	97,14	97,14	97,14	97,14	97,14	97.14
3	61,67	61,67	61,67	61,67	61,67	61,67	61.67
4	56,88	56,87	58,61	57,54	56,92	57,54	56.92
5	50,94	50,92	54,84	52,43	51,02	52,44	51.02
6	44,68	44,64	39,51	47,13	44,81	47,14	44.81
7	43,21	43,16	38,71	45,92	43,35	45,93	43.35
8	41,45	41,39	37,93	44,55	41,61	44,57	41.61
9	40,04	39,98	35,73	40,27	40,23	43,51	40.23
10	39,00	38,93	34,37	37,24	39,20	42,77	39.2
11	37,44	37,37	32,81	35,68	37,64	38,15	37.64
12	34,01	33,94	31,65	34,52	34,21	34,72	34.21
13	29,80	29,74	30,23	30,32	30,01	30,51	30.01
14	35,13	35,01	36,43	34,08	35,52	30,08	35.52
15	33,14	32,95	37,24	34,08	33,72	30,08	33.72
16	30,23	29,87	37,70	36,13	31,30	30,59	31.3
17	30,33	30,03	48,14	48,64	33,41	44,05	33.41
18	43,97	43,87	58,63	54,00	49,93	51,97	49.93
19	55,58	55,54	60,64	59,07	55,09	54,00	55.09
20	50,44	50,49	53,89	53,62	50,61	49,58	50.61
21	41,09	41,14	44,54	44,28	41,26	40,23	41.26
22	35,93	35,97	44,11	39,11	36,10	35,07	36.1
23	44,21	44,30	39,89	38,79	44,53	42,62	44.52
24	38,90	38,57	30,62	36,37	38,93	36,53	38.93
25	35,55	34,86	30,61	33,16	35,34	32,52	35.34
26	31,53	30,95	32,23	33,44	31,70	31,66	31.7
27	30,11	29,66	32,71	34,38	30,76	31,23	30.76
28	35,50	38,66	33,61	32,64	38,94	32,62	38.94
29	30,75	29,72	31,56	30,05	30,13	30,62	30.13
30	29,73	29,98	30,55	30,10	30,42	30,06	30.42
31	30,19	30,26	30,50	30,35	30,70	30,09	30.7
32	31,44	32,72	30,28	31,10	33,18	30,98	33.18

The pressures lower than 30m are shaded

While considering Table 5.19 and 5.20, the results of Neelakantan and Suribabu (2005) and this study are the lowest among the researchers' results.

5.4 Comparison of NOGA in terms of parameter performance

As mentioned in the previous section, Hanoi is one of the well known networks in the literature. Many researchers tried their algorithm on this network. Savic and Walters (1997) also tried their algorithm on this network. They have clarified most of their parameters and the method used by their program.

They used standard genetic algorithm for the optimization. They used fitness, crossover and mutation operators. Additionally, the pipe diameters and the pipe costs are all same. On the contrary, they did not prefer to use EPANET and they used their own hydraulic network solver. They preferred to use population size as 100 and the number of allowed generations is 10000. Moreover they used Gray coding (Goldberg, 1989) instead of binary coding that is supposed to be performing better than binary coding. More important than any other distinctions Savic and Walters did not preferred to use elitism operator in their runs.

They did not prefer to use roulette wheel selection; they used linear ranking selection instead. Although, the penalty function is well described, the pressure penalty constant value is not clarified in their publication (Savic and Walters, 1997). Their reproduction algorithm is not available in NOGA so that, best reproduction type that is found in this chapter (one point crossover type) is applied. Although some of the parameters are not described - or do not exist - to compare the performance of NOGA with the parameters of Savic and Walters' the optimum parameters found in this study are used. In other words, some of the parameters are completed in order to perform in the NOGA kernel. The final parameter set of Savic and Walters for Hanoi network is given in Table 5.21.

It can be declared that, the main difference between the operators of the researchers' is the existence of elitism operator. The other parameters are less effective compared to the elitism operator.

Table 5.21. Final Parameter Set of Savic and Walters for Hanoi Network

Parameter	**Value**
Pressure penalty constant	45000$
Mutation rate	1/102
Elitism rate	Not exist
Crossover probability	1.00
Crossover type	1 point
Population size	100 chromosomes
Number of allowed generations	10000

After the completion of the parameter set of Savic and Walters for NOGA, NOGA was run 20 times on Hanoi. To compare the performance of the parameters of researchers, NOGA was run additionally 20 times with the parameter set of this study. The results are compared in terms of mean system costs and mean penalty costs (figures 5.24, 5.25 and 5.26). In all figures the X axis only indicates the trial number.

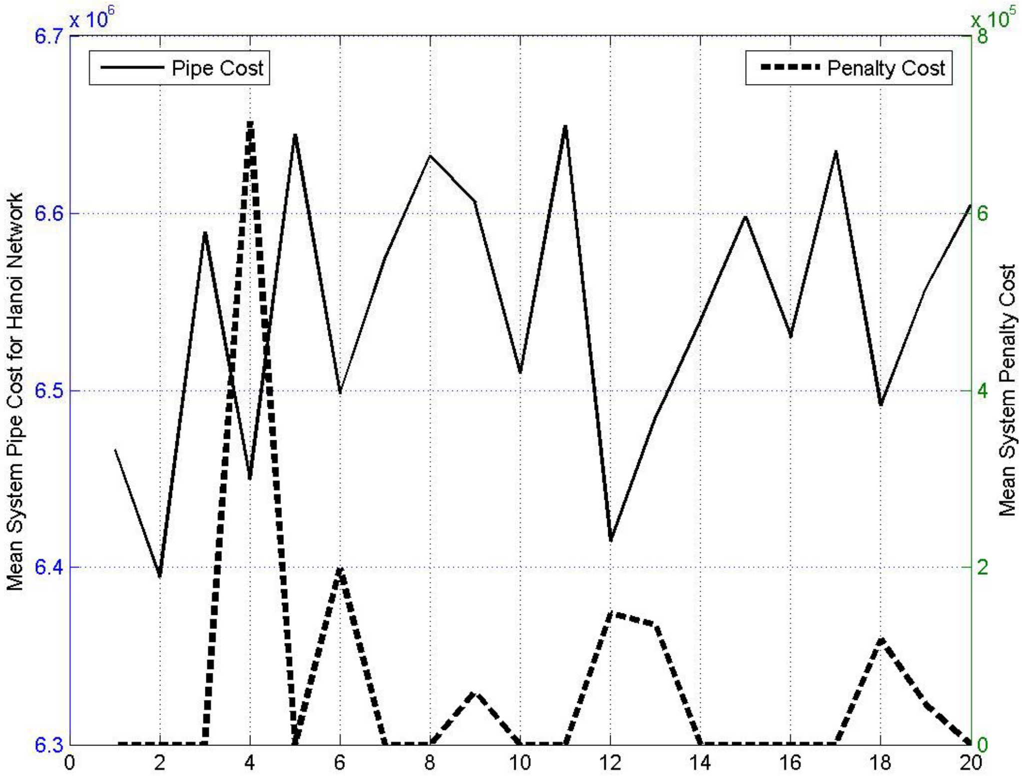

Figure 5.24. System Pipe Costs and Penalty Costs for Savic and Walters' Parameters

Figure 5.24 shows the results of NOGA with Savic and Walters' parameters. As can be seen, system is penalized in 6 of 20 runs. Among 20 runs the minimum result is about 6.4 million \$. Different than this result, the first 5 best results are all penalized. Figure 5.25 shows the results of NOGA with the parameter set found in the previous section. System is not penalized in any of the runs and among 20 trials, the minimum result is about 6.1 million \$. Additionally, the difference of the results of these parameter sets is more obvious in Figure 5.26. In this figure the system pipe costs of the researchers are plotted on the same area in an ascending order. For the minimum results, the difference is about 0.3 million \$. While considering the 4 of 5 best results are penalized with Savic and Walters' parameters, the difference between the results of each parameter set is obvious.

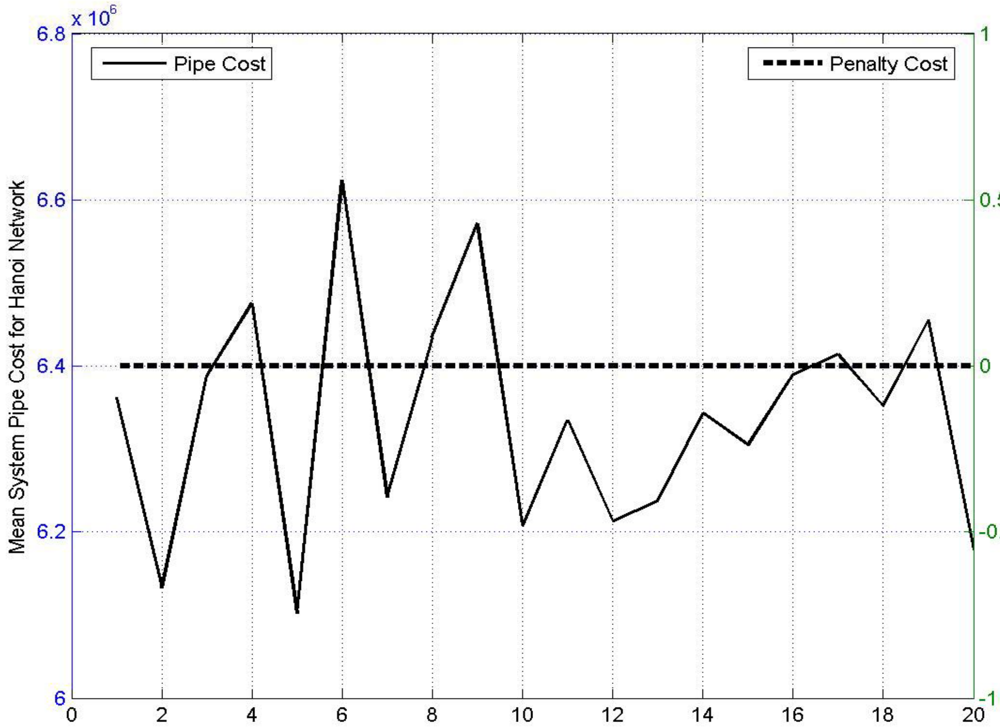

Figure 5.25. System Pipe Costs and Penalty Costs for NOGA's Parameters

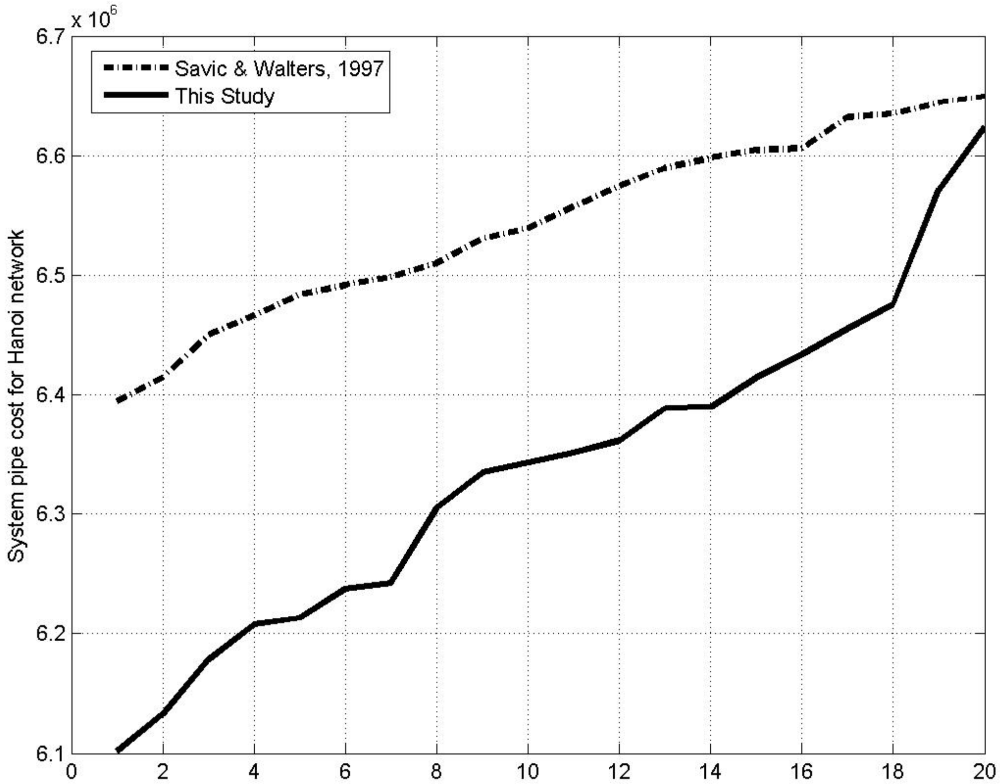

Figure 5.26. Results of Different Parameter Sets in an Ascending Order

The differences between the results of each parameter set may be related with many parameters. Most probably, the main source of that much difference is the elitism operator. This comparison is a solid fact that the elitism operator helps the program to find the global optimum. Another solid fact is that, any program is unique and characteristic to its author. The small differences in the structure of operators may affect the results of the main program. This means that no ideal parameter set can be proposed for any network and for any computer program.

When the paper of Savic and Walters (1997) is examined, their computer program is performing well while compared the result found by them. This means that, the main parameters used in their program is unique to that program only. When their parameter set is applied to NOGA the results are worse. Also, the parameter set of

NOGA for Hanoi network is unique for NOGA only. Any other program of another author may result in different optimal results with the parameter set of NOGA.

CHAPTER 6

CASE STUDY

Throughout this chapter the proposed methodology will be applied on a large network (N8-1 of Ankara water distribution network) as a case study; then, the results of NOGA concerning N8-1 will be compared with the dimensions of this existing network.

6.1 Case Study: Ankara Network, N8-1

6.1.1 Characteristics of N8-1 network

The network to be studied is a skeletonized form of N8-1 pressure zone of the Northern Supply zone of Ankara Water Distribution network. N8-1 pressure zone serves about 30,000 people living in Keçiören county. For the effectiveness of NOGA, N8-1 network is needed to be skeletonized; the skeletonized form of N8-1 network has been taken from Akkaş (2006). The network contains 2 tanks, 181 pipes and 141 nodes. Throughout this chapter this network will be named according to its zone number (N8-1).

The layout of N8-1 network is given with node numbers in Figure 6.1 and the pipe numbers in Figure 6.2. Hazen – Williams coefficient is assumed to be as 130 for all pipes. There are 11 commercially available pipe sizes for N8-1 network. The pipe unit prices are taken from Keleş (2005). The available pipe diameters and corresponding unit prices are given in Table 6.1. The pipe lengths are given in Table 1 and nodal demands and node elevations are given in Table 2 in Appendix A.

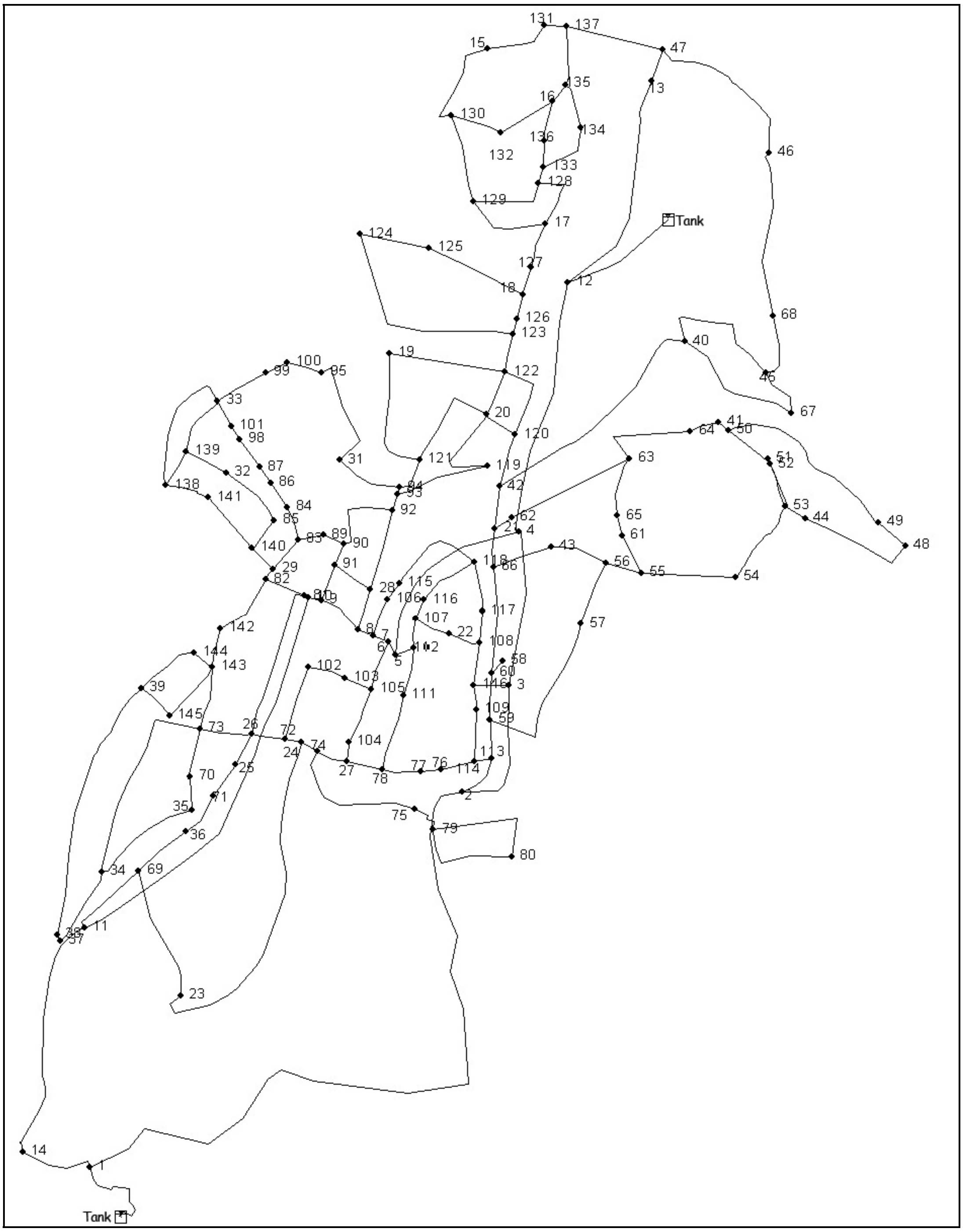

Figure 6.1. Layout of N8-1 Network with Node IDs

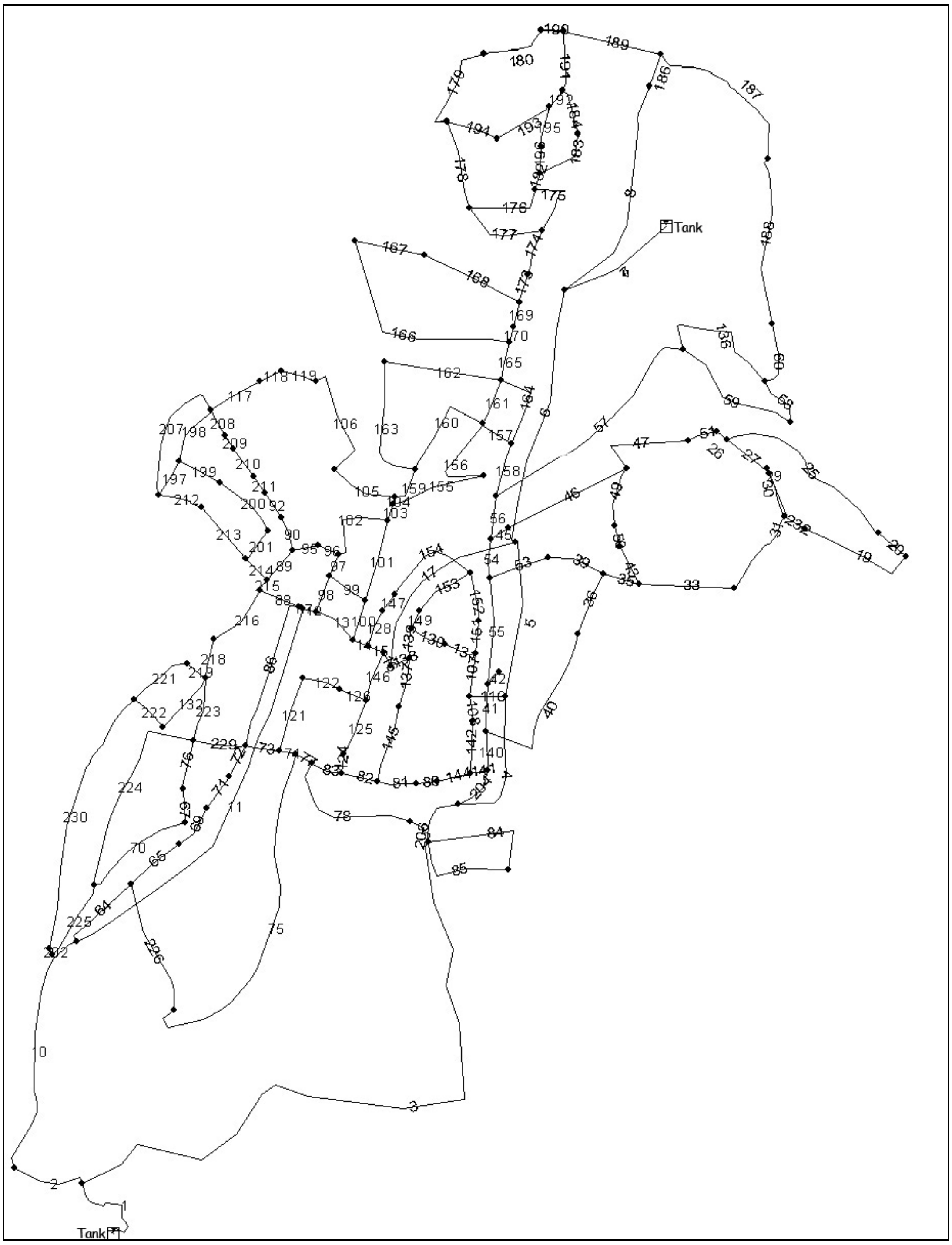

Figure 6.2. Layout of N8-1 Network with Pipe IDs

Table 6.1. Available Pipe Diameters and Corresponding Unit Prices

Diameter (mm)	Unit Price ($/m)
100	16.19
125	17.51
150	19.04
200	24.98
250	31.43
300	37.86
350	45.96
400	51.78
450	65.88
500	71.27
600	93.57

6.1.2 Application of the methodology

As mentioned earlier, N8-1 has 181 pipes. Since there are 12 different available pipe diameters, each pipe diameter is defined in 4-bits genes. One chromosome consists of 724 (181*4) binary bits. 4-bits gene composition requires 16 different pipe diameters. However, 12 different available pipe sizes exist. It is preferred to use middle sized pipe diameters instead of unreal diameters for extra genes (from 13th to 16th) as performed for Hanoi network. Using middle sized diameters saves time during computation since all individuals among the population have real pipe diameters. If unreal pipe diameters are replaced instead; the program would have spent more time to converge and this will decrease the performance of the algorithm.

For N8-1 network both low and high pressures tried to be abandoned. To achieve this, upper and lower pressure limits are required. These limitations are chosen as 90 and 30 meters respectively. Since N8-1 network has high pressure limitation, the penalty function should have been changed for N8-1 network. Note that, for Shamir's and Hanoi networks no upper pressure requirement exists. For N8-1 network, the pressure penalty function is modified from equation 3.3 to equation 6.1.

$$P_j = \left(\sum_i^n \left(\begin{array}{cc} \left| \sqrt{(pl_l + 1)}^k - p_i \right|^2 * u; & \Leftrightarrow p_i \le 0 \\ \left| (pl_l + 1) - p_i \right|^k * u; & \Leftrightarrow 0 < p_i < 30 \\ 0; & \Leftrightarrow 30 \le p_i \le 90 \\ \left| p_i - (pl_u - 1) \right|^k * u; & \Leftrightarrow 90 < p_i \end{array} \right) \right) \quad (6.1)$$

Note that, accustomed terms in equation 6.1 were defined in Section 3.4.4. In order to illustrate better, the penalty function is plotted for pressures varying from 20 to 100 in Figure 6.3. Similar to earlier studies, no velocity constraint is taken into account for this network.

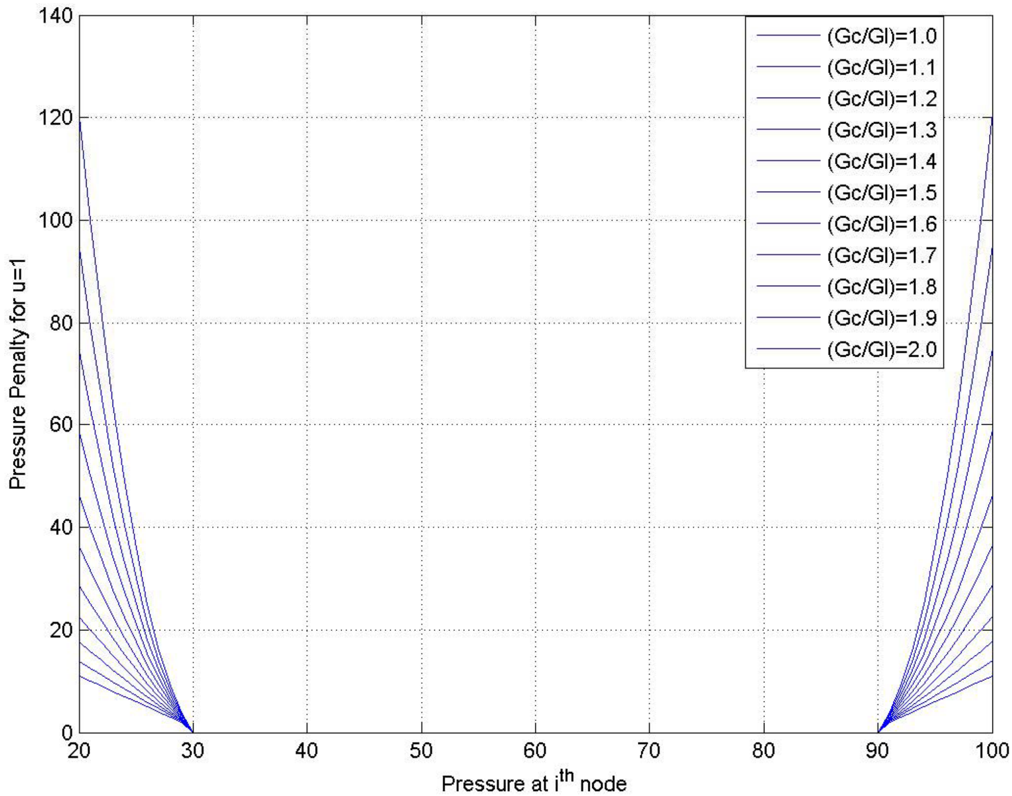

Figure 6.3. Penalty Function for Pressures: [20:100] for N8-1 Network

As introduced in the previous section, N8-1 has more pipes than the tested networks in chapter 5. When the search spaces Shamir's and Hanoi networks are compared with N8-1's search space the distinction becomes appreciable. Hanoi network has a search space of 6^{34} ($2.87 * 10^{26}$) solutions. On the other hand N8-1 network has a search space of 12^{181} ($2.15 * 10^{195}$) solution. N8-1 has a search space almost $7.50 * 10^{168}$ times bigger than Hanoi. This phenomenon brings the necessity of allowing high generation numbers compared to earlier studies. Since there is no restriction on the allowed number of generations, it is preferred to use 50,000.

6.2 Developing the methodology on N8-1 network

In the previous chapter, a methodology has been developed to find the optimal parameter set for NOGA for any water distribution network. It should be emphasized that, all of the steps of the methodology may take long time; sometimes, it may be ineffective to run every step. Especially while working with large networks, computation times may be tiresome to go over all the steps of the proposed methodology. As a result, while applying the methodology to N8-1 network, some steps of the main methodology are eliminated. Pressure penalty constant, mutation rate and the crossover rate investigations are accomplished however; elitism rate and crossover type investigations are not applied.

Similar to the main methodology, after deciding on an initial set of parameters, firstly, pressure penalty constant is investigated; then, by fixing the pressure penalty constant, mutation rate is determined. After determining these two parameters, crossover probability investigation is accomplished. No more iteration has been done further, and the other parameters (elitism rate and crossover probability) are tried to be estimated.

6.2.1 Investigating the pressure penalty constant

To find the suitable pressure penalty constant, all other parameters are fixed to initially estimated values. The first set of all parameters are given in Table 6.2. All these values are formed according to the experience on the Shamir's and Hanoi networks.

The pressure penalty constant (PPC) takes the value from the interval of [5000, 50000] with steps of 5000$. That means PPC = {5000, 10000, 15000, … , 45000, 50000}$. NOGA was run only 1 time for each pressure penalty constant and the system pipe costs and system pressure penalties are calculated. The results of these runs are sketched (Figure 6.4 and 6.5).

For N8-1 network, while drawing the pressure penalties the violations below the lower pressure limit (30 m) and the violations above the upper pressure limit (90 m) are considered. Note that, for Shamir's and Hanoi networks, only the pressures below lower pressure limit (30 m) are considered while plotting the pressure violations. Although, higher pressure violations are considered while running the program, due to the characteristics of the network, upper pressure requirement (90 m) can not be satisfied everywhere.

Table 6.2. Parameter Set for Pressure Penalty Constant Investigation

Parameter	Value
Pressure penalty constant	[5000, 50000]$
Mutation rate	1 %
Elitism rate	4 %
Crossover probability	60 %
Crossover type	1 point
Population size	50 chromosomes
Number of allowed generations	50000
NOGA trial number	1
Tolerable pressure interval	[30, 90]m

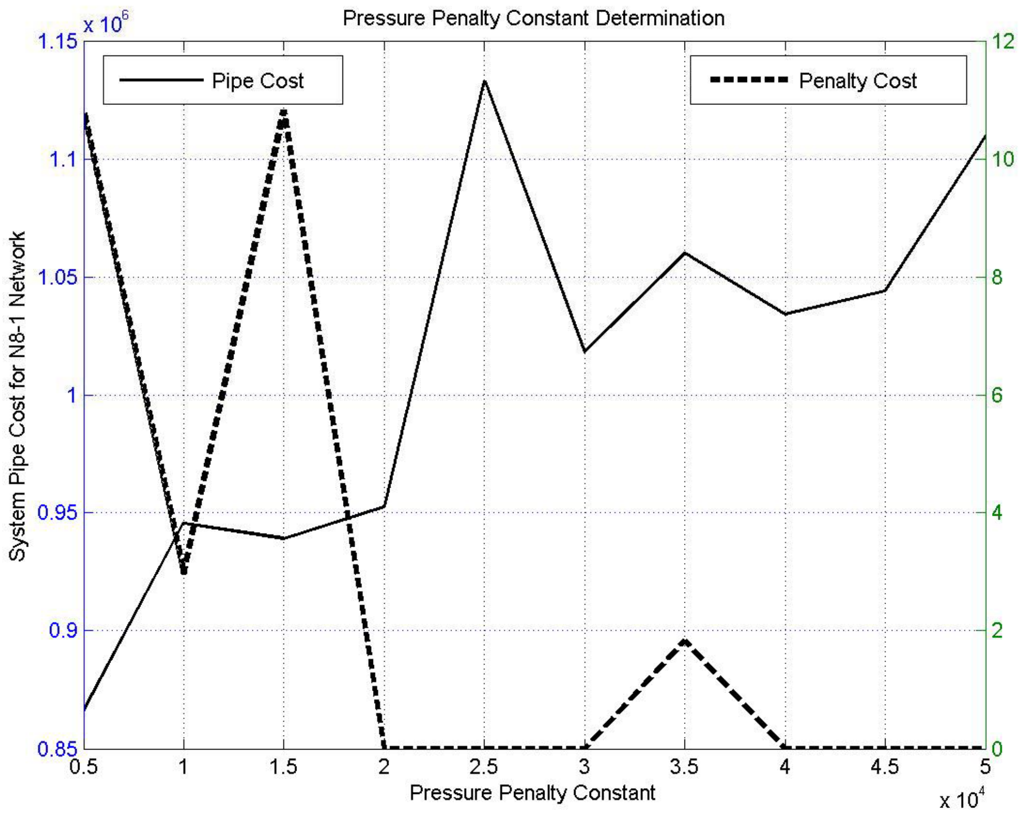

Figure 6.4. Pressure Penalty Constants vs. System Costs

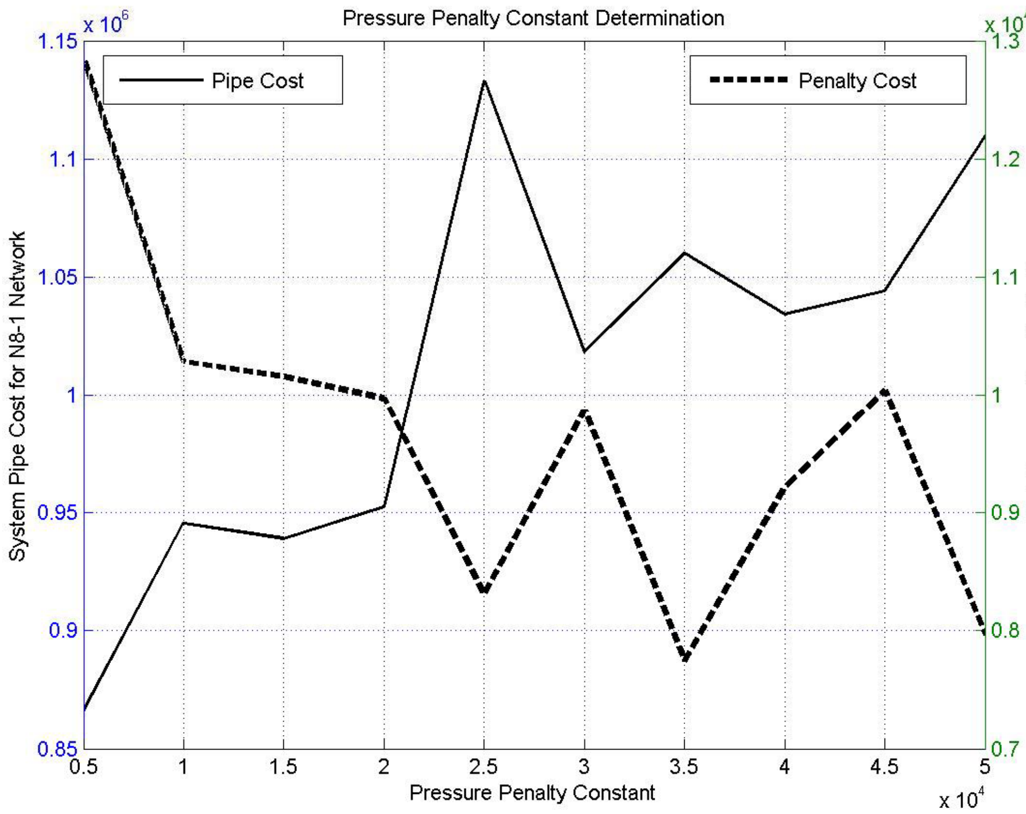

Figure 6.5. Pressure Penalty Constants vs. System Costs

When Figure 6.4 is investigated, it can be seen that for 6 pressure penalty constant values (20,000; 25,000; 30,000; 40,000; 45,000; 50000)$ the system is not penalized when only low pressure violations are considered. With another look, it is also clear that, after 20,000$ pressure penalty constant value, system is penalized only one time at 35,000$. In addition, after 20,000$ pressure penalty constant value, there is a trend of increase at the system pipe costs. Actually, there is a general trend of increase at the system pipe costs as pressure penalty constant values increase.

On the other hand, when Figure 6.5 is investigated, it is obvious that all the networks are penalized when high pressure violations are considered. Although there is a decrease at the penalty values after pressure penalty constant is equal to 20,000$, the penalty values are very greater (about 1000 times) that the values in Figure 6.4.

Since, high pressure violations can not be avoided; it is not preferred to consider these penalties while giving the decision to the appropriate pressure penalty constant value. So, while considering Figure 6.4, it is preferred to use 20,000$ pressure penalty constant for the next investigations.

Despite choosing 20,000$ any other value that is greater than 20,000$ can be chosen but this may result in penalizing the promising individuals just at the beginning of the program. So, choosing the lowest value, among non-penalized solutions is the best for the network.

To avoid from the high pressure problem at the nodes, pressure reducing valves (PRV) can be placed on appropriate pipes.

6.2.2 Investigating the mutation rate

Similar to the investigation of pressure penalty constant, to find the optimum mutation rate, all other parameters are fixed and only mutation rates are varied. The mutation rate takes the value from an interval of [0.0025, 0.0200] with steps of 0.0025, which means mutation rate = {0.0025, 0.0050, 0.0075, … , 0.0175, 0.0200}. The set of all parameters are given below in Table 6.3. NOGA was run only one time for each mutation rate and the system costs and penalty costs are calculated. Similar to the pressure penalty constant investigation, both low pressure and high pressure violations are drawn with respect to the mutation rates in Figures 6.6 and 6.7 respectively.

Table 6.3. Parameter Set for Mutation Rate Investigation

Parameter	Value
Pressure penalty constant	20000$
Mutation rate	[0.0025, 0.0200]
Elitism rate	4 %
Crossover probability	60 %
Crossover type	1 point
Population size	50 chromosomes
Number of allowed generations	50000
NOGA trial number	1
Tolerable pressure interval	[30, 90]m

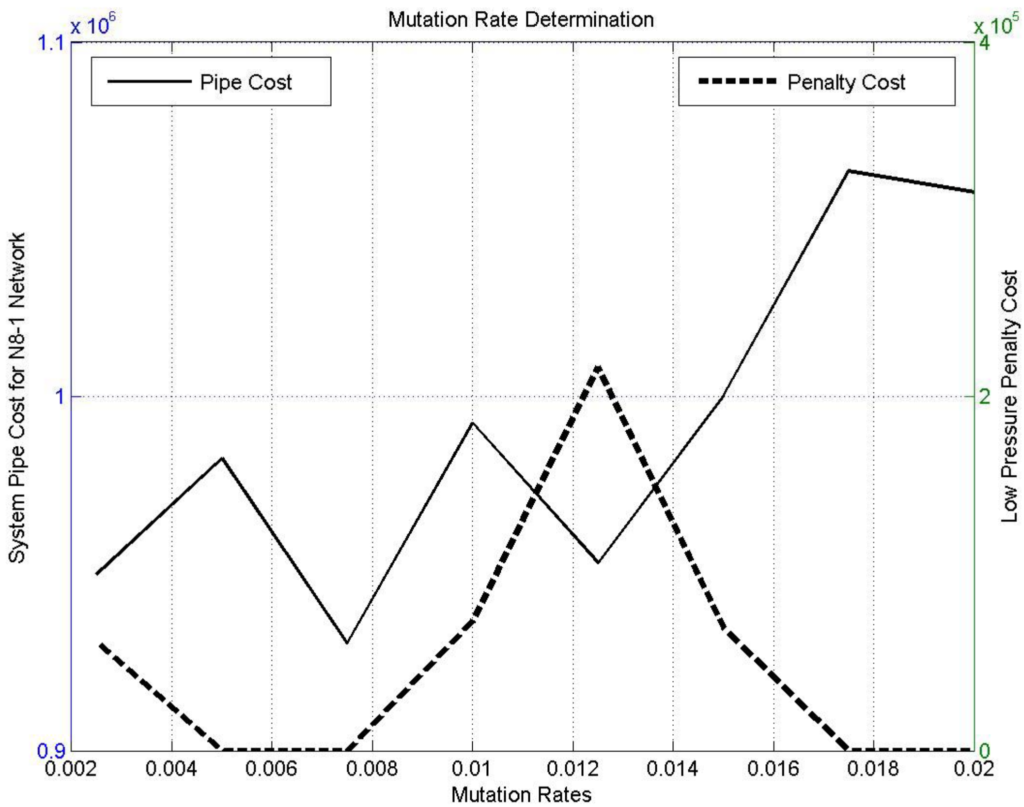

Figure 6.6. Mutation Rates vs. System Costs

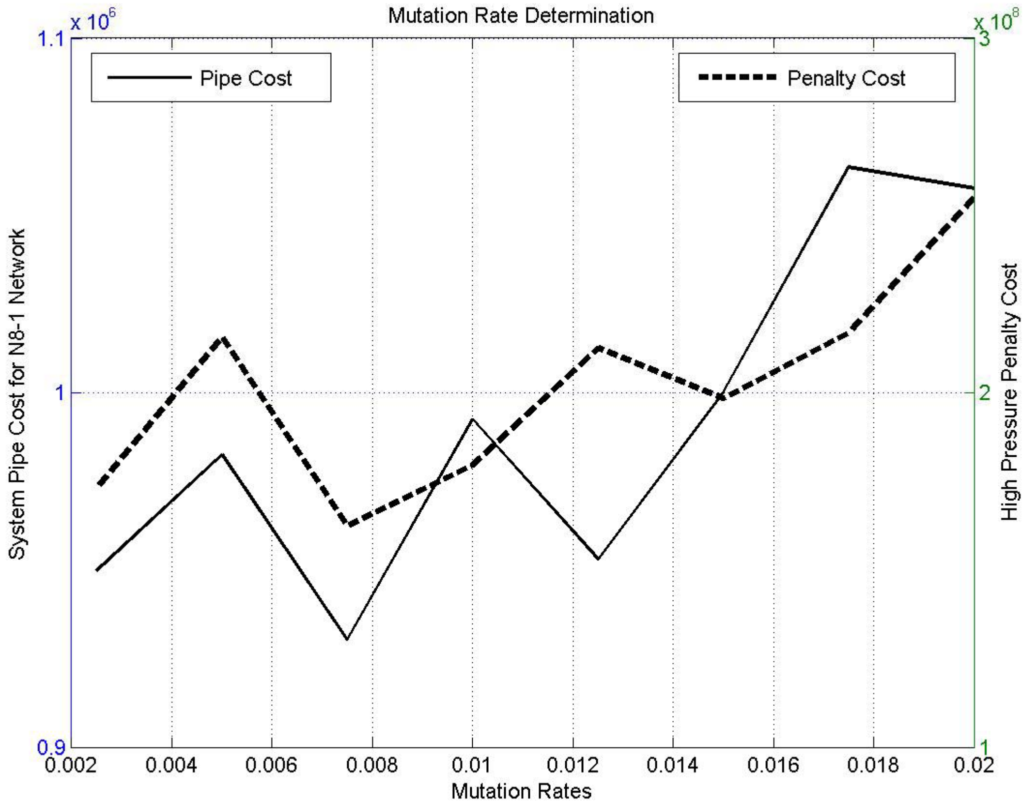

Figure 6.7. Mutation Rates vs. System Costs

When Figure 6.6 is investigated, it can be seen that for 4 mutation rates system is not penalized while considering the low pressure violations. If divided into two, there are two regions of non-penalized solutions. These intervals are; [0.0050, 0.0075] and [0.0175, 0.0200]. When system pipe costs of these two intervals are compared, the first group significantly differs from the other one. When the corresponding system pipe costs of 0.0050 and 0.0075 are compared, corresponding system pipe cost for 0.0075 is lower. It is also obvious that, after 0.0075, there is a trend of increase at the system pipe costs. Moreover, when referred to Sections 5.2.2.2. and 5.3.2.2 and the preferred mutation rates for Shamir's and Hanoi networks are compared, it can be interpreted that, as network size increases there can be a trend of decrease at the mutation rate. Remember that, for Shamir's network 0.0675 mutation rate was chosen while this value is 0.0175 for Hanoi. When looked at the previous studies, researchers (Savic and Walters, 1997; Goldberg, 1989) have a tendency to decrease the mutation rate as the network size increases.

When Figure 6.7 is investigated, all networks are penalized while considering the high pressure violations. Although high pressures can not be avoided, there is a tendency of increase at the system pipe costs and penalty costs after mutation rate is equal to 0.0075.

Both considering the previous studies in the literature and the investigations done for N8-1 network, it is preferred to choose 0.0075 mutation rate for N8-1 network for NOGA while considering low pressure violations only. However, when high pressure violations are considered, again 0.0075 mutation rate seems the appropriate value. For the next investigation, 0.0075 mutation rate will be used.

6.2.3 Investigating the crossover probability

To find the optimum crossover probability value, a similar process to the determination of previous parameters has taken. While keeping all other parameters constant, the crossover probability parameter varied in a range and NOGA was run one time for each set. The crossover probability takes its value from an interval of [0.3, 1.0] with steps of 0.05 that means crossover probability = {0.30, 0.35, ... , 0.95, 1.0}. The set of all parameters are given below in Table 6.4. Similar to the mutation rate investigation, both low pressure and high pressure violations are drawn with respect to the crossover probabilities in Figures 6.8 and 6.9 respectively.

Table 6.4. Parameter Set for Crossover Probability Investigation

Parameter	Value
Pressure penalty constant	20000$
Mutation rate	0.0075
Elitism rate	0.04
Crossover probability	[0.3, 1.0]
Crossover type	1 point
Population size	50 chromosomes
Number of allowed generations	50000
NOGA trial number	1
Tolerable pressure interval	[30, 90]m

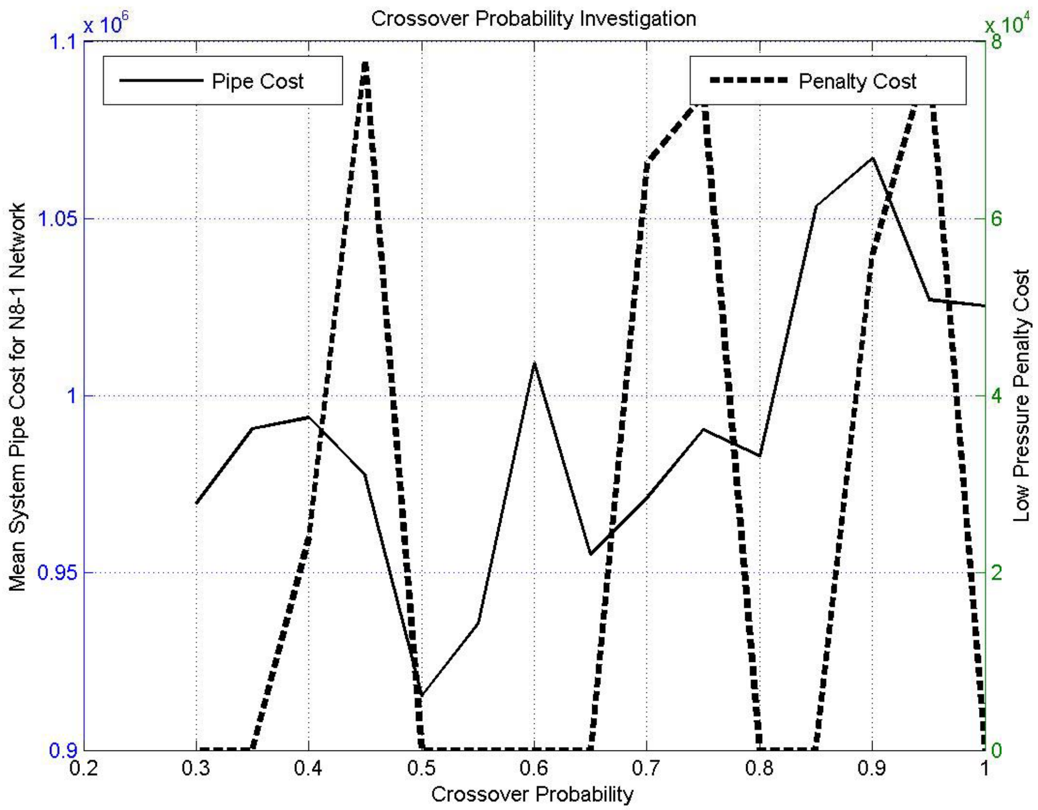

Figure 6.8. Crossover Probabilities vs. System Costs

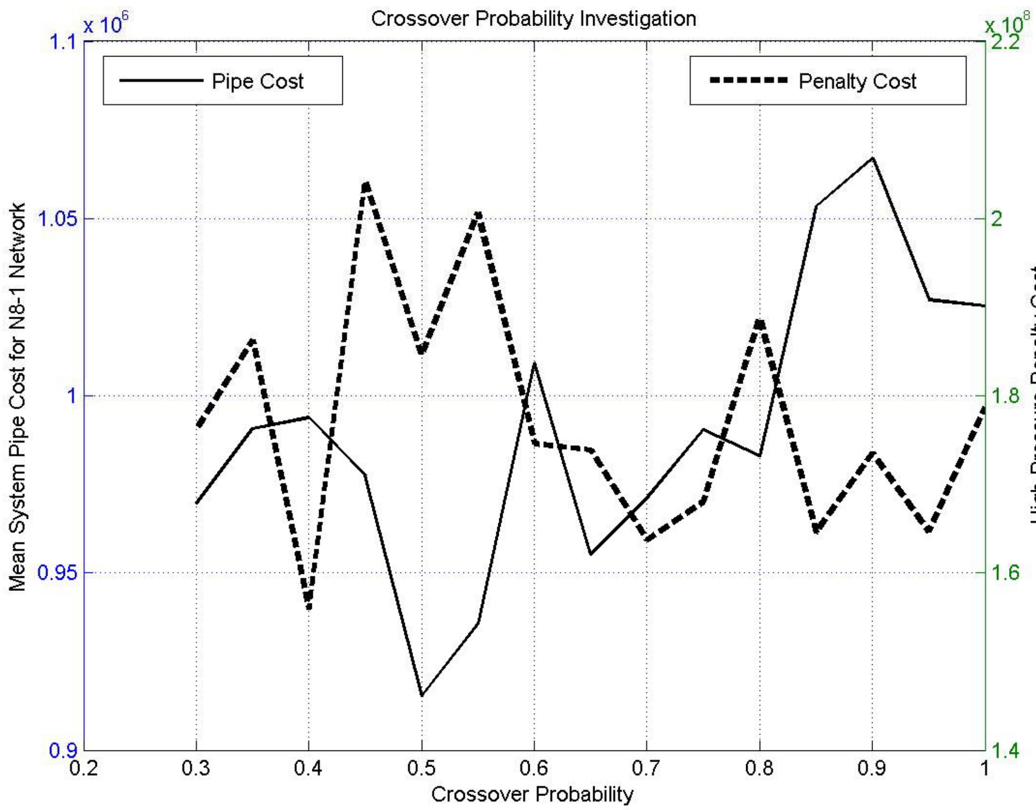

Figure 6.9. Crossover Probabilities vs. System Costs

When Figure 6.8 is investigated, it can be seen that for [0.5 – 0.65] interval system is not penalized when low pressure violations are considered only. When the system pipe costs of this interval are compared, 0.5 crossover probability seems to be appropriate. Also it is obvious that, before and after 0.5 crossover probability, there is a trend of increase at the system pipe costs.

When Figure 6.9 is investigated, individuals are penalized when high pressure violation is considered. Although the corresponding penalties of [0.45, 0.55] interval is higher, there is not a tendency of increase or decrease at any point. The penalties show a variation among the crossover probabilities and this variation is not possible to be interpreted.

By considering the low pressure violation, it is preferred choose 0.5 crossover probability for N8-1 network for NOGA.

Crossover probability investigation for Shamir's and Hanoi networks were done in Sections 5.2.2.4 and 5.3.2.4 respectively. For Shamir's network, it was preferred to use 90% crossover probability. When the network is enlarged as in Hanoi case, the preferred crossover probability value dropped to 60%. Moreover, for N8-1 network 50% crossover probability is appropriate. While considering this variation within network expansion, it can be interpreted that; as network size increases the crossover probability decreases. Since N8-1 is a very large network, the change of crossover probability can be defined in a range of [0.5, 0.9].

6.2.4 Comments for the rest of the methodology

As mentioned at the beginning of this section, for N8-1 network the proposed methodology is applied. This part includes the pressure penalty constant investigation, the mutation rate investigation and the crossover probability investigation. The other investigations which are elitism rate and crossover type investigations are not made. There are some reasons behind this phenomenon. When referred to Sections 5.2.2.3 and 5.3.2.3, the chosen elitism rates are the minimum rates for both Shamir's and Hanoi networks. Remember that, as elite members should be even numbers, the minimum elitism rate is 4 percent for the population with 50 chromosomes. When Figures 5.6 and 5.18 are investigated again, for both networks 0.04 elitism rate is the desirable value which represents the minimum required elitism rate for also N8-1 network. So, it is estimated that the elitism rate will be 0.04 for N8-1 network since 50 chromosomes are used for the optimization.

When crossover type is considered, a similar view like the elitism rate occurs. When referred to Sections 5.2.2.5 and 5.3.2.5, the chosen crossover types are the same and the minimum. When Figures 5.10, 5.22 and 5.23 are investigated again, for both networks, one point crossover is preferable. When Figures 5.10 and 5.22 are compared, there can be seen a difference at the trends of increase. In Figure 5.10, the difference at the results of different crossover types is slight. On the contrary, in Figure 5.22 the trend of increase at the mean system costs is obvious. This difference can be interpreted as; when size of the network increases, one point crossover is more preferable. If this approach is correct, choosing one point crossover for N8-1 is also advisable. Due to these figures and the interpretations, it is preferred to choose one point crossover for N8-1 network.

With the investigations of parameters and some additional assumptions based on the previous studies for Shamir's and Hanoi networks, the parameter set for N8-1 for NOGA is completed. The final set of parameters is tabulated below in Table 6.5.

Table 6.5. Final Parameter Set for N8-1 for NOGA

Parameter	Value
Pressure penalty constant	20000$
Mutation rate	0.0075
Elitism rate	4 %
Crossover probability	50 %
Crossover type	1 point

6.3 Comparing the results with existing network

After completing the set of parameters for N8-1 network for NOGA; the program was run 10 times with the parameter set given in Table 6.5. To compare the results of NOGA and the existing network, the existing network is solved by EPANET. The existing network's pipe diameters are given in Table 3 in Appendix A. After solving the network with these diameters, the nodal pressures for each node are listed in Table 4 in Appendix A.

In Table 4, the highlighted cells indicate the nodes which violate the pressure requirements. Existing system violates the minimum pressure requirement at 29 nodes and maximum pressure requirement at 8 nodes. The minimum and maximum pressures calculated are 21.26 m and 113.84 m respectively. To prevent the high pressures at the nodes, PRVs can be placed on appropriate pipes. The capital cost of the existing network can be calculated using the given diameters as 972,870 $.

To summarize the results of the runs of NOGA, system pipe costs are visualized in Figure 6.10.

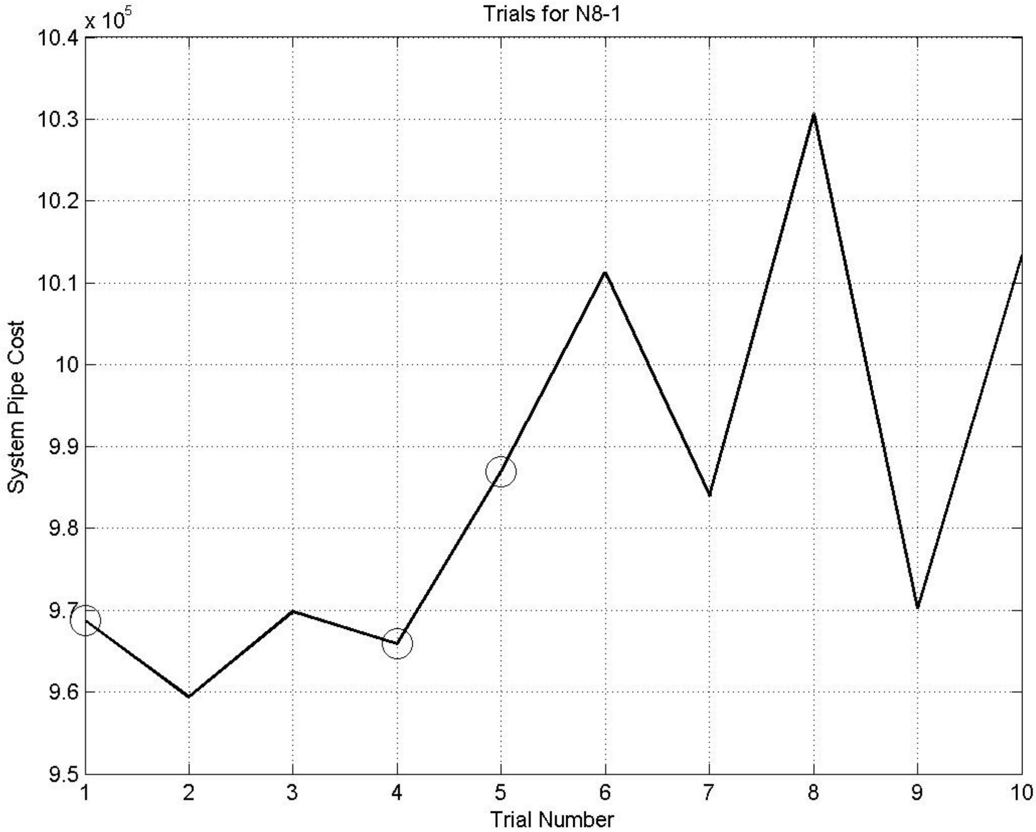

Figure 6.10. System pipe costs for N8-1

In the above figure (Figure 6.10), the pipe costs for each trial are plotted. There is a variation within a range of minimum 959,345$ and maximum 1,030,654$. The standard deviation is 24,280$. In the figure, the circle signs indicate the networks which violate the low pressure requirement. There are three penalized networks among 14 trials when low pressure violation is considered only.

When the results of NOGA and the existing system are compared, NOGA's optimal network (trial number 2) is about 2.5% cheaper than the existing one. Moreover there is no lower pressure limit violation at the node pressures. Upper pressure violation exists at 9 nodes. The optimal pipe diameters of the result of NOGA and the nodal pressures are tabulated in Tables 5 and 6 respectively in Appendix A.

CHAPTER 7

CONCLUSIONS AND RECOMMENDATIONS

7.1 Conclusions

The realization of planning, design, construction, operation and maintenance of water supply systems pictures one of the largest infrastructure projects of municipalities; the cost of water supply projects may reach values at the order of million dollars for greater cities. As a result, water supply system projects should be designed very meticulously.

For four decades, researchers try to design water distribution networks in the optimal way. Genetic algorithm (GA), being one of the global optimization tools, is a well conditioned method for the optimization. GA consists of standard operators; these operators are related with the main parameters of the algorithm. It is proposed that the values of the parameters of genetic algorithm directly affect the performance of the program concerning each operator. Since, the characteristics or the cases to be optimized are different for each network, the parameters of GA for each network can not have ideal values. Although the meta-heuristic is preserved, the solutions formed still depend on the values of parameters. So, the values of the parameters such as pressure penalty constant, mutation rate, elitism rate etc. should be determined for each network, each case to be optimized and each computer program specifically. Although many researchers used GA for the optimization of water distribution networks, not much attention has been given for determination of these parameters in the field of water distribution network optimization studies.

This work represents one of the rare studies in this field in which parameter selection is investigated and presented very meticulously. Throughout this study, a novel methodology is developed to determine the appropriate set of parameters which is specific to network, the case to be optimized and the computer program. To apply the methodology, a computer program (NOGA) is developed. NOGA is a MATLAB based computer program that includes EPANET Programmer's Toolkit as the hydraulic network solver. To acquire the appropriate set of parameters for each network, the methodology is applied as described below;

- After deciding on the initial values of parameters using own experience and searching the literature; NOGA was run several times with varying target parameter while the other parameters are kept constant. Target parameter is varied in a predefined range and the results of all runs are saved.
- Then, both considering the hydraulic conformities and system's capital costs, the appropriate value of target parameter is determined and passed to the next parameter investigation.

For this study, the sequence of the investigations of parameters are chosen as; pressure penalty constant, mutation rate, elitism rate, crossover probability, and crossover type investigations.

By applying the proposed methodology on two well known networks that are Shamir's network and Fujiwara's Hanoi network, the appropriate parameter set for the related network is tried to be found. Then, the methodology is applied to the third network (N8-1 of Ankara).

Evaluation of the results has shown that, the parameters of the algorithm are related with the network, the case to be optimized and the developed computer program. Since, the characteristics of each network are different; the parameters of GA for each network can not have ideal values. The results have shown that, the pressure penalty constant value varied depending on the pipe costs and the network characteristics. The mutation rate is found to vary in a range of [0.0075 – 0.0675] for three networks. Elitism rate is determined as the minimum value for the corresponding population size. Crossover probability is found to vary in a range of [0.5 – 0.9]. Roulette wheel method is applied for the selection process. Variable power scaling is used for the penalty function. The exponent introduced into the penalty function is increased in magnitude as the GA computer program run proceeds.

When the parameters are related with the networks individually, it can be concluded that;

- Pressure penalty constant is increased with increasing capital cost of network.
- Mutation rate is decreased with increasing chromosome length (network size).
- Elitism rate is kept constant (the minimum value for corresponding population size).
- Crossover probability is decreased with increasing chromosome length (network size).
- Crossover type is kept constant.

The methodology should be applied to determine the appropriate parameter set of genetic algorithm for each optimization study. Using the method described, fairly well results are obtained when compared with the literature and the existing system.

7.2 Further studies

The developed methodology yields the appropriate set of parameters for any network; however, depending on the size of the network, the computation time for a single run may be longer than one day. With the developing technology, computation time may decrease; additionally, various smart modifications on the optimization steps can result in shorter computing times. Designing the computer program in a well structured manner and improving using algorithmic analysis can decrease the computational time as well. Most of the computation time for NOGA is spent for solving the network with the hydraulic network solver. Thus, developing a hydraulic network solver algorithm that is integrated to NOGA may reduce the computation time.

The objective function of the algorithm is to minimize the capital cost of the network. During the optimization, the program determines the pipe diameters only considering the availability of the pipe and the hydraulic conformity of the network. However while constructing the actual network, placing different sized diameters side by side in an undesirable occasion; it increases the construction cost. Also, some components of networks, i.e. main transmission line is designed exterior to network and the pipe diameters can not be different throughout. When these kinds of limitations are not added to the optimization algorithm, the optimal networks can be unserviceable and inefficient in terms of construction. This problem can be eliminated by grouping the pipes of the networks according to their priorities. When the pipes are grouped, each group will have its own set of candidate pipe sizes. By reducing the available pipe sizes, the search space of the algorithm decreases significantly. So, grouping the pipes with a smart method can help the algorithm to find optimal and serviceable networks within relatively short computing time. Another way of avoiding unserviceable solutions may be modifying the crossover operator.

The developed methodology is applied on the standard operators of the algorithm; however, GA contains more parameters than the investigated ones that are related with the operators. These parameters can be any of the variables in the algorithm. For example, the pressure penalty function (eqn. 3.3) contains more than one parameter itself. The methodology can be modified for these parameters as well. First of all, the penalty function and its components should be determined since penalty function is the most important operator that affects the algorithm. Throughout this study, the structure of the algorithm is not discussed. The applications of operators such as mutation, selection and crossover should be discussed using various techniques. Next to GA, other adaptive search methods such as ant colony, tabu search, and simulated annealing methods can be applied.

NOGA runs under static loading only; however making extended period simulation (EPS) analysis for the network, may result in better designs. By adding certain extensions to the EPANET Programmer's Toolkit in the NOGA, the program can be used to find the optimum case under EPS conditions.

While applying the proposed methodology, the variations among the parameters were studied in relation to the characteristics of the networks. These variations can be classified by investigating more networks meanwhile; the interpretations can be stored in a digital library for NOGA. If the parameters of the algorithm can be related to the characteristics of the network, the appropriate parameter set of any new network can be estimated for the optimization process.

The proposed methodology is applied on a predefined sequence for the parameters. By changing the order of parameters, the same methodology should be applied. This may result in different appropriate set of parameters for each network. While applying the methodology only one loop for the investigation of parameters is completed as a result of limited computational time. Although applying the methodology for one loop only, the lowest results are found when compared with the literature.

User interface of NOGA can be developed and it can be a stand alone application and can be executable in all computers. Various modifications related with the integration of NOGA and EPANET can be added. To improve the performance in terms of convergence and computation time; Gray coding, Lamarck's evolution theory can be applied. Making some additional modifications on the main GA operations or adding some operators such as migration may also increase the performance of NOGA. Using another optimization algorithm with GA, NOGA can become a hybrid optimization program. Different than known operators, heuristic operators that rests on the natural evolution can be found and integrated.

To conclude, this study represents a methodology for the application of genetic algorithm optimization for designing water distribution networks. Inspired from the natural evolution, a computer program is developed and applied to three networks. Although the methodology and NOGA have strong analytical capabilities, they should be improved to use for the network designs of modern cities.

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APPENDIX A

DETAILS OF N8-1 NETWORK

Table 1. Pipe Numbers and Lengths of N8-1 Network

Pipe ID	Length (m)		Pipe ID	Length (m)		Pipe ID	Length (m)
Pipe 1	30		Pipe 81	225		Pipe 161	135
Pipe 2	202		Pipe 82	32		Pipe 162	341
Pipe 3	2202		Pipe 83	137		Pipe 163	383
Pipe 4	357		Pipe 84	359		Pipe 164	248
Pipe 5	418		Pipe 85	309		Pipe 165	114
Pipe 6	796		Pipe 86	433		Pipe 166	526
Pipe 7	266		Pipe 87	11		Pipe 167	189
Pipe 8	668		Pipe 88	123		Pipe 168	156
Pipe 10	737		Pipe 89	112		Pipe 169	73
Pipe 11	1218		Pipe 90	101		Pipe 170	45
Pipe 12	39		Pipe 92	84		Pipe 173	46
Pipe 13	141		Pipe 95	76		Pipe 174	172
Pipe 14	48		Pipe 96	66		Pipe 175	232
Pipe 15	50		Pipe 97	67		Pipe 176	160
Pipe 16	56		Pipe 98	110		Pipe 177	149
Pipe 17	422		Pipe 99	128		Pipe 178	251
Pipe 19	386		Pipe 100	124		Pipe 179	253
Pipe 20	16		Pipe 101	238		Pipe 180	169
Pipe 25	674		Pipe 102	246		Pipe 182	61
Pipe 26	16		Pipe 103	52		Pipe 183	204
Pipe 27	164		Pipe 104	19		Pipe 184	118
Pipe 29	21		Pipe 105	198		Pipe 186	11
Pipe 30	131		Pipe 106	343		Pipe 187	579
Pipe 31	430		Pipe 107	114		Pipe 188	519
Pipe 33	55		Pipe 108	70		Pipe 189	7
Pipe 35	12		Pipe 110	20		Pipe 190	49
Pipe 36	144		Pipe 117	163		Pipe 191	49
Pipe 39	124		Pipe 118	70		Pipe 192	63
Pipe 40	472		Pipe 119	104		Pipe 193	52
Pipe 41	137		Pipe 121	220		Pipe 194	119
Pipe 42	48		Pipe 122	113		Pipe 195	118

Table 1. (continued)

Pipe ID	Length (m)		Pipe ID	Length (m)		Pipe ID	Length (m)
Pipe 43	58		Pipe 124	58		Pipe 196	29
Pipe 45	58		Pipe 125	168		Pipe 197	115
Pipe 46	313		Pipe 126	84		Pipe 198	185
Pipe 47	111		Pipe 128	116		Pipe 199	132
Pipe 49	177		Pipe 130	124		Pipe 200	201
Pipe 50	60		Pipe 131	110		Pipe 201	113
Pipe 51	87		Pipe 132	189		Pipe 202	21
Pipe 53	161		Pipe 136	256		Pipe 204	137
Pipe 54	114		Pipe 137	142		Pipe 206	99
Pipe 55	312		Pipe 138	14		Pipe 207	396
Pipe 56	123		Pipe 139	86		Pipe 208	86
Pipe 57	653		Pipe 140	113		Pipe 209	45
Pipe 58	148		Pipe 141	9		Pipe 210	99
Pipe 59	467		Pipe 142	139		Pipe 211	58
Pipe 60	189		Pipe 144	96		Pipe 212	134
Pipe 64	250		Pipe 145	245		Pipe 213	194
Pipe 65	184		Pipe 146	148		Pipe 214	88
Pipe 67	28		Pipe 147	58		Pipe 215	38
Pipe 69	133		Pipe 149	62		Pipe 216	201
Pipe 70	330		Pipe 151	112		Pipe 218	117
Pipe 71	203		Pipe 152	171		Pipe 219	68
Pipe 72	17		Pipe 153	236		Pipe 221	192
Pipe 73	87		Pipe 154	357		Pipe 222	116
Pipe 74	48		Pipe 155	276		Pipe 223	184
Pipe 75	1031		Pipe 156	297		Pipe 224	602
Pipe 76	214		Pipe 157	106		Pipe 225	239
Pipe 77	24		Pipe 158	158		Pipe 226	358
Pipe 78	430		Pipe 159	113		Pipe 229	166
Pipe 80	53		Pipe 160	311		Pipe 230	777
						Pipe 232	10

Table 2. Nodal Demands and Node Elevations of N8-1 Network

Node ID	Elevation (m)	Demand (lt/s)		Node ID	Elevation (m)	Demand (lt/s)
Junc 1	1037.48	0.00		Junc 73	1105.21	1.69
Junc 2	1065.89	0.61		Junc 74	1092.36	0.86
Junc 3	1089.00	0.03		Junc 75	1066.11	1.03
Junc 4	1105.60	0.00		Junc 76	1087.62	0.47
Junc 5	1119.27	0.02		Junc 77	1091.04	0.87
Junc 6	1118.54	0.22		Junc 78	1108.38	0.73
Junc 7	1116.29	0.38		Junc 79	1054.80	1.11
Junc 8	1115.63	0.18		Junc 80	1030.83	0.97
Junc 9	1115.95	0.16		Junc 81	1116.17	0.82
Junc 10	1116.10	0.02		Junc 82	1113.56	0.53
Junc 11	1092.90	0.36		Junc 83	1112.77	0.42
Junc 12	1109.56	0.00		Junc 84	1101.13	0.35
Junc 13	1105.12	36.12		Junc 85	1103.75	0.53
Junc 14	1044.58	0.00		Junc 86	1092.53	0.21
Junc 15	1103.85	0.61		Junc 87	1086.65	0.53
Junc 16	1093.71	0.34		Junc 89	1109.18	0.70
Junc 17	1098.08	0.80		Junc 90	1105.42	0.55
Junc 18	1096.12	0.40		Junc 91	1109.26	0.44
Junc 19	1056.11	1.05		Junc 92	1090.35	0.78
Junc 20	1091.68	1.23		Junc 93	1085.38	0.50
Junc 21	1105.41	0.43		Junc 94	1084.30	0.48
Junc 22	1112.71	0.80		Junc 95	1058.89	1.61
Junc 23	1101.69	4.28		Junc 98	1075.14	0.67
Junc 24	1092.02	1.60		Junc 99	1057.95	0.69
Junc 25	1099.32	0.43		Junc 100	1059.87	0.25
Junc 26	1099.07	1.02		Junc 101	1069.93	0.54
Junc 27	1107.69	0.33		Junc 102	1101.39	0.48
Junc 28	1109.54	0.71		Junc 103	1102.58	0.93
Junc 29	1114.47	0.35		Junc 104	1109.69	0.76
Junc 31	1085.43	1.77		Junc 105	1111.44	0.58
Junc 32	1079.94	0.61		Junc 106	1114.95	0.40
Junc 33	1059.96	1.21		Junc 107	1119.17	0.54
Junc 34	1100.97	1.70		Junc 108	1100.78	0.49
Junc 35	1112.96	0.66		Junc 109	1089.28	0.76
Junc 36	1109.91	0.60		Junc 111	1118.17	1.03
Junc 37	1085.72	0.38		Junc 112	1119.27	0.35
Junc 38	1084.95	3.89		Junc 113	1077.41	0.38
Junc 39	1094.95	1.58		Junc 114	1078.57	0.36
Junc 40	1107.67	2.00		Junc 115	1114.38	0.73
Junc 41	1061.82	0.67		Junc 116	1119.35	0.87

Table 2. (continued)

Node ID	Elevation (m)	Demand (lt/s)		Node ID	Elevation (m)	Demand (lt/s)
Junc 42	1108.38	1.13		Junc 117	1105.76	0.72
Junc 43	1091.19	0.92		Junc 118	1107.05	1.11
Junc 44	1026.55	1.72		Junc 119	1110.03	0.83
Junc 45	1106.77	0.86		Junc 120	1109.47	0.52
Junc 46	1101.54	1.60		Junc 121	1077.93	1.17
Junc 47	1105.45	0.87		Junc 122	1089.08	1.22
Junc 48	1047.82	2.04		Junc 123	1091.53	1.00
Junc 49	1049.58	3.76		Junc 124	1058.35	1.04
Junc 50	1059.68	1.24		Junc 125	1068.67	1.19
Junc 51	1040.73	1.07		Junc 126	1094.10	0.57
Junc 52	1038.45	0.85		Junc 127	1097.84	0.61
Junc 53	1027.74	0.22		Junc 128	1084.11	0.66
Junc 54	1073.64	1.55		Junc 129	1077.79	0.81
Junc 55	1077.24	0.97		Junc 130	1080.63	0.91
Junc 56	1078.26	0.41		Junc 131	1108.94	0.60
Junc 57	1073.43	1.31		Junc 132	1089.28	0.53
Junc 58	1093.79	0.99		Junc 133	1084.39	0.43
Junc 59	1086.05	1.05		Junc 134	1100.95	0.61
Junc 60	1095.45	0.72		Junc 135	1099.92	0.33
Junc 61	1079.02	0.65		Junc 136	1086.40	0.36
Junc 62	1101.83	1.02		Junc 137	1105.59	0.15
Junc 63	1092.90	0.87		Junc 138	1046.33	0.94
Junc 64	1082.14	1.42		Junc 139	1060.41	0.63
Junc 65	1080.18	0.96		Junc 140	1106.02	1.01
Junc 66	1106.83	0.85		Junc 141	1077.46	0.60
Junc 67	1082.61	3.50		Junc 142	1104.26	0.90
Junc 68	1109.23	1.03		Junc 143	1095.95	0.81
Junc 69	1101.21	1.15		Junc 144	1088.30	0.84
Junc 70	1112.62	0.52		Junc 145	1104.70	0.44
Junc 71	1106.78	0.65		Junc 146	1093.56	0.30
Junc 72	1094.38	0.52		Tank 147	1021.49	N/A
				Tank 148	1134.27	N/A

Table 3. Existing Pipe Diameters

Pipe ID	Diameter (mm)		Pipe ID	Diameter (mm)		Pipe ID	Diameter (mm)
Pipe 1	500		Pipe 81	125		Pipe 161	125
Pipe 2	500		Pipe 82	125		Pipe 162	125
Pipe 3	500		Pipe 83	125		Pipe 163	125
Pipe 4	500		Pipe 84	125		Pipe 164	125
Pipe 5	500		Pipe 85	125		Pipe 165	125
Pipe 6	500		Pipe 86	125		Pipe 166	125
Pipe 7	500		Pipe 87	125		Pipe 167	125
Pipe 8	500		Pipe 88	125		Pipe 168	125
Pipe 10	250		Pipe 89	125		Pipe 169	125
Pipe 11	250		Pipe 90	125		Pipe 170	125
Pipe 12	250		Pipe 92	125		Pipe 173	125
Pipe 13	250		Pipe 95	125		Pipe 174	125
Pipe 14	250		Pipe 96	125		Pipe 175	125
Pipe 15	250		Pipe 97	125		Pipe 176	125
Pipe 16	250		Pipe 98	125		Pipe 177	125
Pipe 17	250		Pipe 99	125		Pipe 178	125
Pipe 19	125		Pipe 100	125		Pipe 179	125
Pipe 20	125		Pipe 101	150		Pipe 180	125
Pipe 25	125		Pipe 102	125		Pipe 182	125
Pipe 26	125		Pipe 103	125		Pipe 183	125
Pipe 27	125		Pipe 104	125		Pipe 184	125
Pipe 29	125		Pipe 105	125		Pipe 186	150
Pipe 30	125		Pipe 106	125		Pipe 187	150
Pipe 31	125		Pipe 107	125		Pipe 188	150
Pipe 33	125		Pipe 108	125		Pipe 189	150
Pipe 35	125		Pipe 110	125		Pipe 190	150
Pipe 36	125		Pipe 117	125		Pipe 191	150
Pipe 39	125		Pipe 118	125		Pipe 192	150
Pipe 40	125		Pipe 119	125		Pipe 193	150
Pipe 41	125		Pipe 121	125		Pipe 194	150
Pipe 42	125		Pipe 122	125		Pipe 195	150
Pipe 43	125		Pipe 124	125		Pipe 196	150
Pipe 45	125		Pipe 125	125		Pipe 197	150
Pipe 46	125		Pipe 126	125		Pipe 198	150
Pipe 47	125		Pipe 128	125		Pipe 199	150
Pipe 49	125		Pipe 130	125		Pipe 200	150
Pipe 50	125		Pipe 131	125		Pipe 201	150
Pipe 51	125		Pipe 132	100		Pipe 202	150
Pipe 53	125		Pipe 136	125		Pipe 204	200
Pipe 54	125		Pipe 137	125		Pipe 206	200

Table 3. (continued)

Pipe ID	Diameter (mm)		Pipe ID	Diameter (mm)		Pipe ID	Diameter (mm)
Pipe 55	125		Pipe 138	125		Pipe 207	200
Pipe 56	125		Pipe 139	125		Pipe 208	200
Pipe 57	125		Pipe 140	125		Pipe 209	200
Pipe 58	125		Pipe 141	125		Pipe 210	200
Pipe 59	125		Pipe 142	125		Pipe 211	200
Pipe 60	125		Pipe 144	125		Pipe 212	200
Pipe 64	125		Pipe 145	125		Pipe 213	200
Pipe 65	125		Pipe 146	125		Pipe 214	200
Pipe 67	125		Pipe 147	125		Pipe 215	200
Pipe 69	125		Pipe 149	125		Pipe 216	200
Pipe 70	125		Pipe 151	125		Pipe 218	200
Pipe 71	125		Pipe 152	125		Pipe 219	200
Pipe 72	125		Pipe 153	125		Pipe 221	200
Pipe 73	125		Pipe 154	125		Pipe 222	200
Pipe 74	125		Pipe 155	125		Pipe 223	200
Pipe 75	125		Pipe 156	125		Pipe 224	200
Pipe 76	125		Pipe 157	125		Pipe 225	200
Pipe 77	125		Pipe 158	125		Pipe 226	200
Pipe 78	125		Pipe 159	125		Pipe 229	200
Pipe 80	125		Pipe 160	125		Pipe 230	200
						Pipe 232	100

Table 4. Nodal Pressure Heads of Existing System

Node ID	Pressure Head (m)		Node ID	Pressure Head (m)		Node ID	Pressure Head (m)
Junc 1	113.84		Junc 49	84.5		Junc 99	80.97
Junc 2	76.8		Junc 50	74.89		Junc 100	78.92
Junc 3	52.58		Junc 51	93.82		Junc 101	69.37
Junc 4	34.74		Junc 52	96.1		Junc 102	38.72
Junc 5	21.16		Junc 53	106.6		Junc 103	37.61
Junc 6	21.9		Junc 54	61.74		Junc 104	30.6
Junc 7	24.17		Junc 55	58.32		Junc 105	28.84
Junc 8	24.84		Junc 56	57.41		Junc 106	25.51
Junc 9	24.65		Junc 57	62.85		Junc 107	21.35
Junc 10	24.58		Junc 58	44.12		Junc 108	40.07
Junc 11	52.92		Junc 59	52.87		Junc 109	52.3
Junc 12	28.26		Junc 60	42.46		Junc 111	22.23
Junc 13	32.58		Junc 61	56.45		Junc 112	21.17
Junc 14	106.69		Junc 62	34.16		Junc 113	64.42
Junc 15	33.66		Junc 63	42.39		Junc 114	63.17
Junc 16	43.76		Junc 64	52.7		Junc 115	26.08
Junc 17	39.22		Junc 65	55.22		Junc 116	21.17
Junc 18	41		Junc 66	29.4		Junc 117	34.94
Junc 19	81.2		Junc 67	53.48		Junc 118	33.48
Junc 20	45.54		Junc 68	27.18		Junc 119	27.72
Junc 21	30.76		Junc 69	40.3		Junc 120	27.52
Junc 22	27.95		Junc 70	26.91		Junc 121	59.75
Junc 23	39.65		Junc 71	33.62		Junc 122	48.05
Junc 24	48.03		Junc 72	45.62		Junc 123	45.58
Junc 25	40.54		Junc 73	34.38		Junc 124	78.74
Junc 26	40.75		Junc 74	47.69		Junc 125	68.42
Junc 27	32.61		Junc 75	73.62		Junc 126	43.02
Junc 28	30.23		Junc 76	53.7		Junc 127	39.31
Junc 29	25		Junc 77	50.07		Junc 128	53.26
Junc 31	52.92		Junc 78	32.01		Junc 129	59.57
Junc 32	59.4		Junc 79	84.93		Junc 130	56.82
Junc 33	79.33		Junc 80	108.89		Junc 131	28.64
Junc 34	38.54		Junc 81	24.33		Junc 132	48.18
Junc 35	26.57		Junc 82	25.95		Junc 133	53.04
Junc 36	30.91		Junc 83	26.68		Junc 134	36.52
Junc 37	53.78		Junc 84	38.23		Junc 135	37.6
Junc 38	54.54		Junc 85	35.63		Junc 136	51.04
Junc 39	44.55		Junc 86	46.77		Junc 137	32
Junc 40	28.46		Junc 87	52.65		Junc 138	93
Junc 41	72.79		Junc 89	30.29		Junc 139	78.92

Table 4. (continued)

Node ID	Pressure Head (m)		Node ID	Pressure Head (m)		Node ID	Pressure Head (m)
Junc 42	27.98		Junc 90	34.09		Junc 140	33.4
Junc 43	44.68		Junc 91	30.55		Junc 141	61.9
Junc 44	107.75		Junc 92	48.73		Junc 142	35.26
Junc 45	29.39		Junc 93	53.02		Junc 143	43.57
Junc 46	35.3		Junc 94	54.01		Junc 144	51.21
Junc 47	32.16		Junc 95	79.73		Junc 145	34.8
Junc 48	86.26		Junc 98	64.16		Junc 146	47.96

Table 5. Optimal Pipe Diameters

Pipe ID	Diameter (mm)		Pipe ID	Diameter (mm)		Pipe ID	Diameter (mm)
Pipe 1	350		Pipe 81	200		Pipe 161	300
Pipe 2	100		Pipe 82	150		Pipe 162	125
Pipe 3	600		Pipe 83	250		Pipe 163	125
Pipe 4	600		Pipe 84	100		Pipe 164	100
Pipe 5	400		Pipe 85	100		Pipe 165	450
Pipe 6	150		Pipe 86	350		Pipe 166	100
Pipe 7	150		Pipe 87	250		Pipe 167	100
Pipe 8	100		Pipe 88	250		Pipe 168	100
Pipe 10	200		Pipe 89	200		Pipe 169	300
Pipe 11	150		Pipe 90	100		Pipe 170	500
Pipe 12	150		Pipe 92	125		Pipe 173	350
Pipe 13	350		Pipe 95	100		Pipe 174	250
Pipe 14	300		Pipe 96	100		Pipe 175	200
Pipe 15	150		Pipe 97	200		Pipe 176	300
Pipe 16	350		Pipe 98	100		Pipe 177	250
Pipe 17	300		Pipe 99	150		Pipe 178	125
Pipe 19	250		Pipe 100	200		Pipe 179	125
Pipe 20	125		Pipe 101	200		Pipe 180	125
Pipe 25	100		Pipe 102	350		Pipe 182	200
Pipe 26	100		Pipe 103	200		Pipe 183	300
Pipe 27	100		Pipe 104	150		Pipe 184	250
Pipe 29	125		Pipe 105	250		Pipe 186	100
Pipe 30	100		Pipe 106	250		Pipe 187	200
Pipe 31	100		Pipe 107	450		Pipe 188	200
Pipe 33	100		Pipe 108	100		Pipe 189	300
Pipe 35	100		Pipe 110	350		Pipe 190	125
Pipe 36	100		Pipe 117	250		Pipe 191	300
Pipe 39	100		Pipe 118	250		Pipe 192	250
Pipe 40	100		Pipe 119	250		Pipe 193	100
Pipe 41	100		Pipe 121	125		Pipe 194	100
Pipe 42	100		Pipe 122	125		Pipe 195	250
Pipe 43	100		Pipe 124	100		Pipe 196	200
Pipe 45	100		Pipe 125	200		Pipe 197	100
Pipe 46	100		Pipe 126	250		Pipe 198	125
Pipe 47	100		Pipe 128	125		Pipe 199	125
Pipe 49	100		Pipe 130	400		Pipe 200	100
Pipe 50	100		Pipe 131	300		Pipe 201	100
Pipe 51	100		Pipe 132	250		Pipe 202	150
Pipe 53	100		Pipe 136	100		Pipe 204	100
Pipe 54	100		Pipe 137	250		Pipe 206	100

Table 5. (continued)

Pipe ID	Diameter (mm)		Pipe ID	Diameter (mm)		Pipe ID	Diameter (mm)
Pipe 55	125		Pipe 138	300		Pipe 207	150
Pipe 56	100		Pipe 139	350		Pipe 208	100
Pipe 57	250		Pipe 140	100		Pipe 209	100
Pipe 58	100		Pipe 141	125		Pipe 210	100
Pipe 59	100		Pipe 142	150		Pipe 211	250
Pipe 60	100		Pipe 144	250		Pipe 212	100
Pipe 64	200		Pipe 145	100		Pipe 213	100
Pipe 65	150		Pipe 146	200		Pipe 214	100
Pipe 67	100		Pipe 147	200		Pipe 215	150
Pipe 69	150		Pipe 149	100		Pipe 216	100
Pipe 70	250		Pipe 151	200		Pipe 218	100
Pipe 71	125		Pipe 152	250		Pipe 219	100
Pipe 72	100		Pipe 153	125		Pipe 221	100
Pipe 73	300		Pipe 154	250		Pipe 222	100
Pipe 74	300		Pipe 155	400		Pipe 223	100
Pipe 75	100		Pipe 156	400		Pipe 224	100
Pipe 76	100		Pipe 157	200		Pipe 225	100
Pipe 77	300		Pipe 158	100		Pipe 226	125
Pipe 78	100		Pipe 159	250		Pipe 229	100
Pipe 80	250		Pipe 160	100		Pipe 230	100
						Pipe 232	100

Table 6. Nodal Pressure Heads of Optimum System

Node ID	Pressure Head (m)		Node ID	Pressure Head (m)		Node ID	Pressure Head (m)
Junc 1	113.76		Junc 49	80.80		Junc 99	84.43
Junc 2	84.17		Junc 50	71.69		Junc 100	82.50
Junc 3	60.90		Junc 51	90.47		Junc 101	72.92
Junc 4	44.07		Junc 52	92.75		Junc 102	46.40
Junc 5	30.07		Junc 53	102.71		Junc 103	46.04
Junc 6	30.69		Junc 54	59.96		Junc 104	38.74
Junc 7	30.18		Junc 55	56.86		Junc 105	37.20
Junc 8	30.68		Junc 56	56.13		Junc 106	33.98
Junc 9	30.33		Junc 57	62.02		Junc 107	30.28
Junc 10	30.09		Junc 58	44.29		Junc 108	49.00
Junc 11	53.58		Junc 59	54.38		Junc 109	58.02
Junc 12	30.15		Junc 60	42.64		Junc 111	31.17
Junc 13	32.72		Junc 61	54.89		Junc 112	30.09
Junc 14	102.43		Junc 62	34.38		Junc 113	69.24
Junc 15	35.94		Junc 63	40.65		Junc 114	68.10
Junc 16	46.10		Junc 64	50.06		Junc 115	34.68
Junc 17	42.73		Junc 65	53.59		Junc 116	30.03
Junc 18	45.41		Junc 66	30.02		Junc 117	43.73
Junc 19	85.78		Junc 67	55.66		Junc 118	42.30
Junc 20	50.26		Junc 68	30.14		Junc 119	32.10
Junc 21	31.44		Junc 69	45.18		Junc 120	32.36
Junc 22	36.81		Junc 70	31.08		Junc 121	64.36
Junc 23	44.39		Junc 71	39.53		Junc 122	52.62
Junc 24	54.31		Junc 72	51.93		Junc 123	50.14
Junc 25	46.95		Junc 73	39.00		Junc 124	83.13
Junc 26	47.19		Junc 74	53.98		Junc 125	72.81
Junc 27	38.81		Junc 75	79.28		Junc 126	47.56
Junc 28	35.19		Junc 76	59.04		Junc 127	43.66
Junc 29	30.90		Junc 77	55.62		Junc 128	56.35
Junc 31	56.89		Junc 78	38.24		Junc 129	62.75
Junc 32	62.68		Junc 79	90.49		Junc 130	59.32
Junc 33	82.45		Junc 80	114.44		Junc 131	30.79
Junc 34	42.68		Junc 81	30.02		Junc 132	50.56
Junc 35	30.69		Junc 82	32.40		Junc 133	55.56
Junc 36	36.43		Junc 83	32.44		Junc 134	38.92
Junc 37	57.62		Junc 84	43.03		Junc 135	39.85
Junc 38	58.38		Junc 85	39.53		Junc 136	53.49
Junc 39	49.07		Junc 86	51.36		Junc 137	34.12
Junc 40	30.71		Junc 87	57.23		Junc 138	96.18
Junc 41	69.65		Junc 89	35.05		Junc 139	82.10

Table 6. (continued)

Node ID	Pressure Head (m)		Node ID	Pressure Head (m)		Node ID	Pressure Head (m)
Junc 42	30.01		Junc 90	38.10		Junc 140	37.73
Junc 43	44.12		Junc 91	34.54		Junc 141	65.48
Junc 44	103.84		Junc 92	53.06		Junc 142	40.44
Junc 45	31.72		Junc 93	56.93		Junc 143	48.22
Junc 46	37.95		Junc 94	58.01		Junc 144	55.80
Junc 47	34.26		Junc 95	83.46		Junc 145	39.46
Junc 48	82.56		Junc 98	67.99		Junc 146	56.28