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Selection of Genetic Algorithm Parameters for Optimization of Storm-Sewer Networks Using Taguchi Method

Yağmur Suyu-Kanalizasyon Şebekelerinin Optimizasyonunda Taguchi Yöntemi ile Genetik Algoritma Parametrelerinin Seçimi

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Abstract

Genetic algorithm is one of the most referred optimization techniques for the hydraulic optimization of stormwater and sewer system design. The genetic algorithm has different parameters affecting its performance such as population sizes, crossover methods, crossover rates, elitism rates, mutation rates and comparative values for the tournament selection algorithm. By the nature of the genetic algorithm, different values of these parameters should be tried to get the optimum values for them. But checking all possible values of these parameters that is a full factorial design is too much time consuming. Therefore, in this study, the Taguchi method is proposed for the first time in the literature to determine the most suitable parameter values of the genetic algorithm used for the hydraulic optimization of stormwater and sewage system design. The L16 Taguchi orthogonal array that involves 16 experiments was employed. Each experiment was replicated six times. Only 16x6=96 runs were carried out to determine the significance of the factors instead of running a full factorial design with 4^4x6=1536 runs. As a result, the cost value obtained with the Taguchi method is very close (0,15%) to the cost value obtained with the full factorial design. Moreover, with the Taguchi method, the results are obtained in a shorter time (7 days instead of 4 months) with much fewer attempts.

Keywords: Storm-sewer networks, optimization, genetic algorithm, taguchi

Öz

Genetik algoritma, yağmursuyu ve kanalizasyon sistem tasarımının hidrolik optimizasyonu için en çok başvurulan optimizasyon tekniklerinden biridir. Genetik algoritma, performansını etkileyen popülasyon büyüklüğü, çaprazlama yöntemleri, çaprazlama oranları, elitizm oranları, mutasyon oranları ve turnuva seçim algoritması için karşılaştırma değerleri gibi farklı parametrelere sahiptir. Genetik algoritmanın doğası gereği bu parametrelerin optimum değerlerini elde etmek için, parametrelerin farklı değerleri denenmelidir. Fakat tam faktöriyel tasarım olan bu parametrelerin tüm olası değerlerini denemek, çok fazla zaman alır. Bu nedenle, yağmursuyu ve kanalizasyon sistem tasarımının hidrolik optimizasyonu için kullanılan genetik algoritmanın en uygun parametrelerini belirlemek için Taguchi Yöntemi, literatürde ilk defa bu çalışmada önerilmektedir. Taguchi yönteminin 16 deney anlamına gelen L16 ortogonal dizisi kullanılmıştır. Her deney altı kez tekrarlanmıştır. Faktörlerin anlamlılığını belirlemek için tam faktöriyel tasarımda 4^4x6=1536 defa çalıştırma yerine sadece 16x6=96 defa çalıştırılmıştır. Sonuç olarak, Taguchi yöntemiyle elde edilen maliyet değeri, tam faktöriyel tasarımla elde edilen maliyet değerine oldukça yakındır (0,15%). Üstelik Taguchi yöntemi ile çok daha az denemeyle daha kısa sürede (4 ay yerine 7 gün) sonuç elde edilmektedir.

Anahtar Kelimeler: Yağmur suyu-kanalizasyon şebekeleri, optimizasyon, genetik algoritma, taguchi

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1. Introduction

Urban stormwater drainage and sewer systems are essential parts of municipal infrastructure as building a new network has a high cost of investment. Therefore, optimization techniques are used to minimize the cost while the infrastructure design is complex.

The optimization of storm-sewer systems can be performed in three parts: the layout optimization (Haghighi 2013, Turan et al. 2019), the hydraulic optimization of the given layout (Liang et al. 2004, Afshar 2006, Afshar et al. 2006, Cetin and Yurdusev 2017) and the optimization of both layout and hydraulic designs (Pan and Kao 2009, Moeini and Afshar 2017, Duque et al. 2020).

There are several optimization algorithms used for the hydraulic optimization of storm-sewer networks such as ant colony algorithm (Afshar 2010, Moeini 2019), cellular automata (Guo et al. 2007, Zaheri et al. 2020), cuckoo search algorithm (Cetin and Turan 2022), grey wolf optimization algorithm (Masoumi et al. 2021), and particle swarm optimization algorithm (Afshar 2008; Navin and Mathur 2016).

Besides these optimization algorithms, genetic algorithms, and genetic programming (Ekmekcioğlu et.al 2023) have been widely used for the hydraulic optimization of storm-sewer networks by many researchers. To find the global optimum value, the genetic algorithm provides the necessary solution by getting the least cost with several trials. The genetic algorithm has different parameters affecting the performance such as population sizes, crossover methods, crossover rates, elitism rates, mutation rates and comparative values for the tournament selection algorithm. By the soul of the genetic algorithm, different values of these parameters should be tried to determine the most suitable values for them.

Afshar (2006) and Afshar et al. (2006) used the genetic algorithm for the hydraulic design optimization in some benchmark networks in the literature. Afshar (2006) used nodal elevations as decision variables and examined the effects of four different selection methods. Afshar et al. (2006) examined the effects of using nodal elevations and pipe diameters together as decision variables and using only nodal elevations as a decision variable. In both studies, genetic algorithm parameters are given only for the case where the best results are obtained. Siriwardene and Perera (2006) emphasized the importance of the proper selection of genetic algorithm parameters for the hydraulic optimization of sewer networks. They investigated the effects of different genetic algorithm parameters such as seven population sizes, two selection methods, four crossover rates, eight mutation rates in addition to impervious and pervious model parameters. Brand and Ostfeld (2011) used the genetic algorithm to determine the optimal design of sewer network with searching the diameter size and the flow distribution of the network, the number, size and location of treatment plants, the pump power, and the required excavation work. They conducted experiments by assigning one value to each genetic algorithm parameter. Afshar (2012) studied on the hydraulic optimization of storm-sewer networks with rebirthing procedure to overcome the discretization problems of the continuous decision variables. He used the genetic algorithm and tried four population sizes and assigned one value for each of the other genetic algorithm parameters. Haghighi and Bakhshipour (2012) studied on the hydraulic optimization of storm-sewer networks with the adaptive decoding strategy to satisfy all constraints of the sewer system by using the genetic algorithm. They assigned one value for each genetic algorithm parameter. Cimorelli et al. (2013) studied on the hydraulic optimization by using the genetic algorithm.

Cetin and Yurdusev (2017) studied on the hydraulic optimization of storm-sewer networks by using the genetic algorithm. They used pipe diameters and pipe slopes as decision variables. They tried different genetic algorithm parameters such as five population sizes, four elitism rates, two tournament rates, three cross methods, four crossover rates and six mutation rates to find the optimum cost value. Since checking all parameter combinations (2880) as a full factorial design was too much time consuming, they suggested the dynamic mutation rate method to reduce the number of trials for the mutation rates. They used the stormwater network taken from a real project in the hydraulic optimization. The real project was prepared without any optimization procedure and based on engineering experience only. They found the dynamic mutation rate method is effective instead of trying all mutation rates.

In some of the studies mentioned above a value is directly assigned to each genetic algorithm parameter without carrying out any experiments. There are also studies in the literature that use the full factorial design to determine the best possible values of genetic algorithm parameters. However, it is obvious that checking all alternative values of the genetic algorithm parameters is too much time consuming.

An experimental design technique known as the Taguchi method, developed by Genichi Taguchi, can be used to reduce the number of total runs (Taguchi 1986) required to determine the best values of genetic algorithm parameters. In the literature, many researchers used the Taguchi method to reduce the number of trials required for the determination of the best parameter values. Turton (1994) proposed a genetic algorithm approach for the solution of the traveling salesman problem and used the Taguchi method to tune the values of genetic algorithm parameters. Bayrak and Hınıslıoğlu (2013) used the Taguchi method to determine the optimal conditions for the concrete pavement. Zhang et al. (2015) investigated the usage of the Taguchi method for soil erosion experiments. They found that the Taguchi design could replace full factorial designs. Moosavi and Sadeghi (2021) used the Taguchi method for the modeling and optimization of the soil loss process. Zhang et al. (2021) studied the Taguchi method's applicability to soil erosion experiments. Akkuş and Yaka (2018) prepared an experimental design for machining the steel on CNC lathes and used the Taguchi method to find the best values of cutting parameters. Lafifi et al. (2019) used the Taguchi method to estimate the geotechnical parameters of the Mohr–Coulomb model obtained from the pressuremeter test. Xia et al. (2019) optimized the performance of the genetic algorithm for determining the pollutant source fluxes by tuning the parameters with the Taguchi method. George and Tembhurkar (2020) took the advantage of the Taguchi method to optimize the defluoridation of water using Ficus glomerata. Gisbert et al. (2020) proposed the application of Taguchi's orthogonal arrays to calibrate the parameters of the Descent Local Search algorithm to optimize the tensioning process of cable-stayed bridges. Jalees (2020) optimized the adsorption condition of the drinking water using the Taguchi method. Liu et al. (2021) studied the influences of Taguchi designed structural factors on the water quality of the green roof runoff. Naghedifar et al. (2020) used the Taguchi method to optimize performance of an irrigation system by means of numerical modeling. Seifi et al. (2020) optimized time series models of the wastewater treatment and reuse plants with the help of the Taguchi method. Sharifi et al. (2020) improved the Taguchi method to model the high strength self-consolidating concrete's ideal mix design. Chanda and Bhattacharyya (2021) studied the Taguchi method to find the ideal combination of the parameters during profile forming. Chen et al. (2021) investigated the usage of the Taguchi method to explore the feasibility of producing low-strength material for the waste management. Elsheikh et al. (2021) used the Taguchi method to optimize the kerf geometry. Gholizadeh-Tayyar et al. (2021) adjusted the key factors in project planning with the Taguchi method. Hiwarkar et al. (2021) used the Taguchi method to tune operating parameters in order to attain the maximum rate of degradation for nitrogenous substances in the mineralization. Pham et al. (2021) used the Taguchi method to optimize the treatment performance associated with the removal of the total organic carbon. Kechagias et al. (2022) presented the Taguchi method to optimize the parameters of artificial neural networks designed for the prediction of quality characteristics of cut surfaces. Puneeth and Ganesha Prasad (2022) carried out the Taguchi method to optimize the coating parameters of membranes.

Although it has been seen in the literature that the Taguchi method is used in many areas, the usage of the Taguchi method has not been encountered in the storm-sewer optimization. In this study, the Taguchi Method is proposed for the first time in the literature to lessen time to be spent during the optimization process, to decrease the number of trials and to tune different genetic algorithm parameters of the hydraulic design optimization. For this purpose, the genetic algorithm-based storm-sewer network design proposed by Cetin and Yurdusev (2017) was considered as the case study. The Taguchi method was applied to this problem and the obtained results were compared with the results of Cetin and Yurdusev (2017).

2. Material and Methods

2.1. Optimization Of Hydraulic Calculations with a Genetic Algorithm

The genetic algorithm is a natural selection-based search and optimization technique. A new generation is obtained after performing crossover and mutation operations on the population of chromosomes. The total cost of the system is used to determine the best solution. The cost function (C_t) is given in Equation 4:

$$C_p = \sum_{i=1}^{n} L_i x M_p \tag{1}$$

$$C_m = \sum_{i=1}^{m} X_i x M_m \tag{2}$$

$$C_b = \sum_{i=1}^{n} L_i x h_i x M_b + \sum_{i=1}^{m} X_i x M_b \tag{3}$$

$$C_t = C_p + C_m + C_b \tag{4}$$

where C_p is the total pipe cost, n is the total number of lines in the network, L_i is the pipe length, M_p is the unit price of a pipe per meter length, C_m is the total manhole cost, m

is the total number of manholes in the network, X_i is the buried depth of each manhole, M_m is the unit price of a manhole per meter depth, C_b is the burying cost, h_i is the average buried depth of each line and M_b is the unit price of the burying per meter depth. (Cetin and Yurdusev 2017)

Decision variables are pipe diameters and pipe slopes. The population size, the crossover rate, the elitism rate, and the mutation rate are the genetic algorithm parameters. The flow chart of the algorithm used in this study is given in Figure 1.

2.2. Taguchi Experimental Design

The traditional experimental design requires an extensive number of runs to determine the impact of various factors on the system performance. Hence, the implementation of this technique in real-life problems is time-consuming and expensive. Genichi Taguchi, developed an alternative experimental design technique called Taguchi experimental design which can reduce the number of runs by using orthogonal arrays (OAs) (Taguchi 1986).

An OA is a special matrix in which columns are factors or factor interactions and rows are factor levels for a particular run. OAs are highly fractioned factorial experiments that permit the estimation of the greatest number of main effects in an orthogonal manner with the fewest possible runs in the experiment. (El-Haik and Shaout 2010). It is necessary to choose an appropriate p-value and resolution level if a conventional fractional factorial design is used. Furthermore, there may not be a fractional factorial design with the requisite resolution for the number of factors considered (Law 2007). In ready-to-use tables, all design points in OAs are defined. Because of this, they are exempt from the requirement to determine the p-value and the resolution level. (Ilgin and Gupta 2010).

Signal to Noise ratios (SNR) are calculated based on the experimental results obtained using OAs. In the Taguchi technique, the terms "signal" and "noise" stand for the desired and unwanted values, respectively, for the output characteristic known as "mean" and "standard deviation," respectively. That is why, the SNR can be considered as the ratio of the mean to the standard deviation (Yang and Tarng 1998). One of the following three equations is often used to calculate SNR depending on the category of the output characteristic:

Category 1: Smaller is the better characteristic:

$$SNR = -10 \log \frac{1}{n} \left(\sum y^2 \right) \tag{5}$$

Category 2: Larger is the better characteristic:

$$SNR = -10 \log \frac{1}{n} \left(\sum \frac{1}{y^2} \right) \tag{6}$$

Category 3: Nominal is the best characteristic:

$$SNR = 10 \log \left(\frac{\bar{y}}{s_y^2} \right) \tag{7}$$

A larger SNR indicates a better test result regardless of the category of the output characteristic.

Following the determination of SNRs, statistical analysis of variance (ANOVA) is conducted to determine the significant parameters. Furthermore, optimal parameter settings can be predicted by analyzing SNRs and the results of ANOVA. Figure 1 presents the steps of the Taguchi experimental design.

2.3. Case Study

The stormwater network previously mentioned by Cetin and Yurdusev (2017) is used in this study. This stormwater network taken from a real project having 193 manholes and 192 lines having 15,318 m long is shown in Figure 2. (Cetin and Yurdusev 2017).

2.4. Genetic Algorithm Parameter Optimization Using Taguchi Experimental Design

In this study, the population size, the crossover rate, the elitism rate, and the mutation rate are chosen to be analyzed for their impacts on the genetic algorithm performance. The parameters (factors) and their levels are presented in Table 1. According to Table 1, a full factorial experimental design requires 256 different experiments (Yang and Tarng 1998) assuming that each experiment is replicated once. If the number of replications increases, the number of experiments will also be much larger.

Table 1. Levels of each factor.

Factors	Levels			
	Level 1	Level 2	Level 3	Level 4
Population size	80	100	120	140
Crossover rate	30%	50%	70%	90%
Elitism rate	1%	2%	3%	5%
Mutation rate	1%	3%	5%	7%

A great reduction in the number of experiments can be achieved by using an appropriate Taguchi orthogonal array. An L16 orthogonal array which accommodates five factors with four levels was employed in this study. As a result, placing factor levels' numerical values into the L16

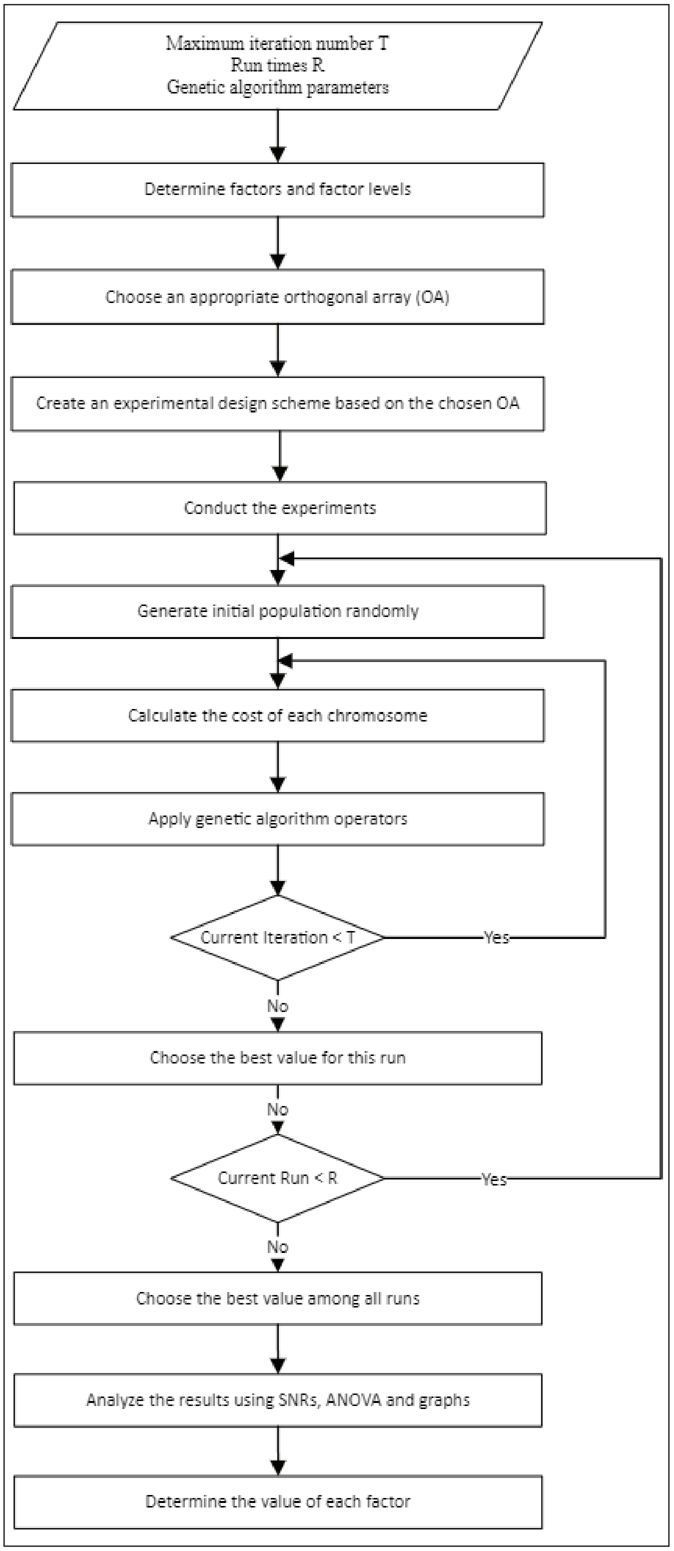

Figure 1. Steps of the Taguchi experimental design based genetic algorithm parameter determination approach.

Figure 2. The network of the case study.

orthogonal array creates the experimental design shown in Table 2. The last column of Table 2 was left blank since there are four factors in our study. It must be noted that keeping one column empty does not damage the orthogonality of the array. (Gologlu and Sakarya 2008) Each experiment was replicated six times. This means that 16x6=96 runs were carried out to determine the significance of the factors. If a full factorial design was used, the number of runs would be 1536 (4^4x6).

All trials were performed on a computer with an Intel 2.8 GHZ Pentium Core i7 CPU. On average, one run lasted approximately 6300 seconds. 96 runs that are the total number of runs in the experimental design created by the L16 orthogonal array, lasted approximately 7 days. If the total number of runs (1536) of the full factorial design were used, it would take approximately 112 days, in other words approximately 4 months.

Equation 5 is used to calculate SNRs. Table 3 displays the average SNRs for each of the four levels of factors. In this table, delta (Δ) represents the difference between a factor's maximum and minimum average SNRs and denotes the impact of that factor. The factor with the greatest delta

Table 2. L-16 Orthogonal array-based experimental design used in this study.

Experiment Number	Column				
	1	2	3	4	5
1	80	30%	1%	1%	-
2	80	50%	2%	3%	-
3	80	70%	3%	5%	-
4	80	90%	5%	7%	-
5	100	30%	2%	5%	-
6	100	50%	1%	7%	-
7	100	70%	5%	1%	-
8	100	90%	3%	3%	-
9	120	30%	3%	7%	-
10	120	50%	5%	5%	-
11	120	70%	1%	3%	-
12	120	90%	2%	1%	-
13	140	30%	5%	3%	-
14	140	50%	3%	1%	-
15	140	70%	2%	7%	-
16	140	90%	1%	5%	-

value has the greatest influence on the response. The last row of Table 3 presents the ranking of the factors based on the delta values. The two most important factors are the crossover rate and the mutation rate. The least important factor is the population size.

An ANOVA study was also conducted on SNRs. Table 4 presents the results of this analysis. According to the ANOVA results, the two most important factors are the crossover rate and the mutation rate due to their low p values. The crossover rate is significant at 90% confidence level while the mutation rate is significant at 85% percent confidence level. If the factors are ranked according to p values, the same ranking in Table 3 is obtained.

The average SNRs listed in Table 3 are graphically represented in Figure 3. For each factor, the highest SNR is desired. The value of each parameter was determined based on this principle and presented in Table 5.

3. Results and Discussion

In this study, the Taguchi's L16 orthogonal array was used to determine the parameter values of a genetic algorithm constructed for the storm-sewer hydraulic optimization. After all Taguchi experiments, the values of the population size, the crossover rate, the elitism rate, and the mutation

Table 3. Signal to noise ratios (SNRs).

Levels	SNR			
	Population Size	Crossover Rate	Elitism Rate	Mutation Rate
First Level	-135,112	-135,053	-135,084	-135,185
Second Level	-135,076	-135,052	-135,071	-135,043
Third Level	-135,089	-135,090	-135,089	-135,069
Fourth Level	-135,140	-135,222	-135,173	-135,120
Δ	0.06	0.17	0.10	0.14
Rank	4	1	3	2

Table 4. ANOVA Table for SNRs.

Source	DF	SS	MSS	F	p
Population Size	3	0.009609	0.003203	0.830557	0.55884345
Crossover Rate	3	0.077826	0.025942	6.726940	0.07589487
Elitism Rate	3	0.026004	0.008668	2.247647	0.26158664
Mutation Rate	3	0.046994	0.015665	4.061969	0.13989030
Residual Error	3	0.011569	0.003856		
Total	15	0.172003			

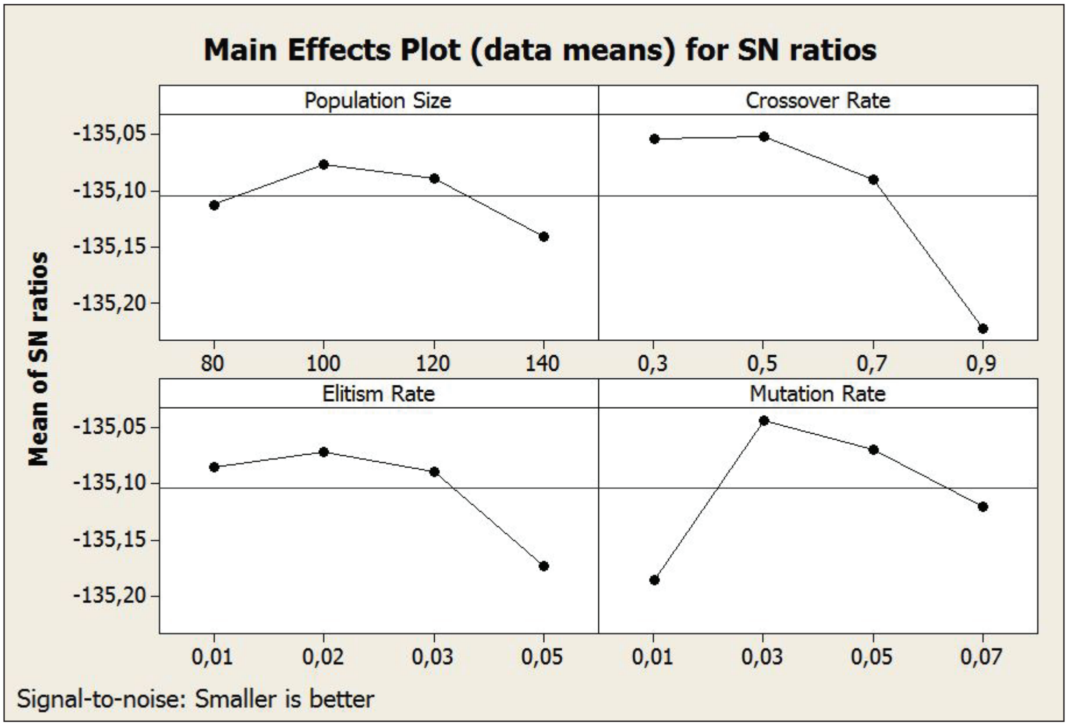

Figure 3. Main effect plot for SNRs.

Table 5. Genetic algorithm parameter values.

Parameter	Value
Population Size	100
Crossover Rate	50%
Elitism Rate	3%
Mutation Rate	2%

rate were determined as 100, 50%, 2% and 3%, respectively. A cost value of 2.766.566,11 EUR was obtained with these parameter values.

Cetin and Yurdusev (2017) applied the full factorial design for the determination of the parameter values of the genetic algorithm designed for the same storm-sewer network. Based on this analysis, they determined the values of the population size, the crossover rate, the elitism rate, and the mutation rate as 100, 50%, 1%, and 7%, respectively. (Cetin and Yurdusev 2017).

Table 6 summarizes the results obtained in this study and the results of Cetin and Yurdusev (2017). According to this table, the optimum genetic algorithm parameter values obtained by the Taguchi method are very close to the optimum parameter values obtained by the full factorial design of Cetin and Yurdusev (2017). The difference in cost values between the Taguchi method and the full factorial design is only 0,15%.

By using the Taguchi method, only 96 runs were carried out to determine the significance of the factors instead of implementing 1536 runs required by the full factorial design. Although, the cost values of the full factorial design and the

Table 6: Results.

Study	Cost Value (EUR)	Population size	Crossover rate	Elitism rate	Mutation rate
Taguchi L16 (this study)	2,766,566.11	100	50%	2%	3%
Cost with full factorial design (Cetin and Yurdusev 2017)	2,762,534.00	100	50%	1%	7%
Cost without optimization (Cetin and Yurdusev 2017)	2,913,750.00				

Taguchi method were very close to each other, there was a dramatic difference between the operation times of both design methods. The processing time in the full factorial design is four months while the Taguchi method provides the results in only 7 days. In other words, the Taguchi design provides a dramatic decrease in the processing time although its cost value is 0,15% higher.

4. Conclusion and Suggestions

The aim of this study is to lessen the number of runs to be carried out for the determination of the genetic algorithm parameter values while getting the optimum cost value of a storm water and sewer network. For this purpose, the Taguchi Method has been proposed for the first time in the literature for the determination of the genetic algorithm parameter values to be used in the hydraulic design optimization of stormwater and sewerage networks. Taguchi experimental design is an alternative experimental design technique which can reduce the number of runs by using orthogonal arrays.

The developed algorithm has been run on a real network optimized by the genetic algorithm. The population size, the crossover rate, the elitism rate, and the mutation rate were chosen to be analyzed for the impact of these parameters on the genetic algorithm performance. The L16 Taguchi orthogonal array that involves 16 experiments was employed. As a result, the optimum genetic algorithm parameters values were determined for this network.

The outcome of this study has shown that, the genetic algorithm parameter values and the cost value obtained by using the Taguchi Method are approximately the same with the values provided by the full factorial design. This leads to the fact that the optimum values of the genetic algorithm parameters can be determined with less trials in less time without deteriorating the performance of the genetic algorithm.

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