



Research Article / Araştırma Makalesi

**OPTIMIZATION OF PRODUCTION PLANTS WITH POLLUTION CONTROL
IN WATER RESOURCES: A CASE STUDY**

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ABSTRACT

Recent years, one of the biggest problems of water resources that become strategic and critical issues is pollution. In this study, Genetic Algorithm-based optimization of a nonlinear and constrained problem on water resources was performed for maximum profit of production plant. The obtained results are compared with the results of Lagrange Multipliers method. It has been observed that the genetic algorithm method gives consistent and precise results.

Keywords: Genetic algorithm, lagrange multipliers, nonlinear problems, optimization.

1. INTRODUCTION

Water is one of the most important natural resources that enable sustainable natural life. Pollution has become one of the most important problems of water resources especially in recent years. Polluted stream water is one of the most important environmental problems. The water pollution problem arises from industrial wastes and untreated sewage discharged directly to streams [1]. In the literature, expert systems constitute a large majority of applications in water resource engineering.

Also many numerical optimization methods have been developed in order to reach the optimum solution for problems. In recent years, with the development of computer hardware and software systems that can process data much faster, machines that can learn and make decisions have been intended [2]. Artificial intelligence issues are the milestones of these intentions which many of them are achieved. The most obvious common feature of artificial intelligence methods is that they are based on imitating human, nature and social environment structures [3]. One of these nontraditional optimization methods is Genetic Algorithm (GA). The GA works with natural selection logic and it has a wide range of applications in different fields but not much on water resources. Aras et al proposed A GA-based model designed to optimize wastewater treatment costs in river basins. The model was applied to a contaminated river system by three

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determined discharge sources [4]. In a different study about additional chlorination optimization of drinking water networks, GA was used to find locations for chlorination, injection rates and scheduling of chlorine [5].

In this study, maximum profit of production plant is considered having taken water resources pollution control into account. The configuration of mathematical model is taken from [6]. The results are verified by comparing to Lagrange Multipliers which is a traditional optimization method.

2. DEFINITION OF THE PROBLEM

Figure 1 shows the system of production and treatment plant partially taken from [6]. For the unit quantity of the products (x_1) produced in the production plant, unit quantity of waste $3x_1^{0.5}$ is formed. The part of the resulting waste (x_2) is directly supplied to the stream without any pre-process at the treatment plant. The other part is supplied to the stream after it is treated in the treatment plant. Eventually, the water quality of the stream must be within certain limits.

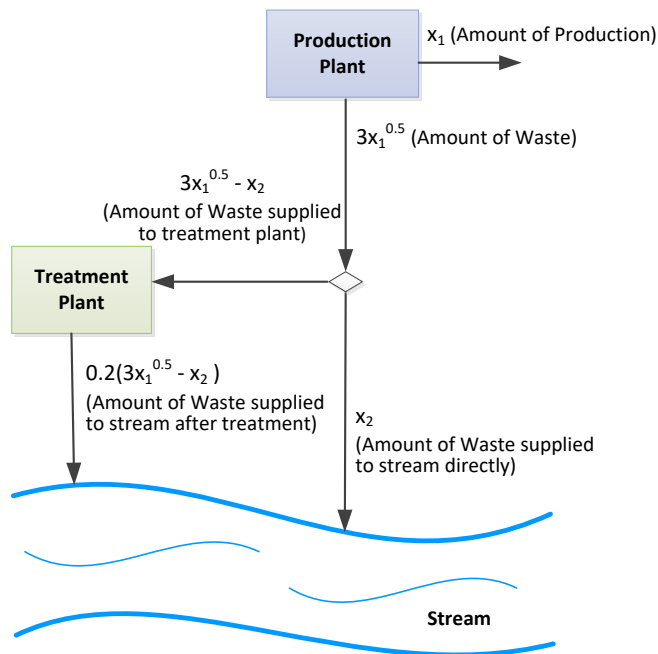


Figure 1. Schematic representation of the problem (partially taken from [6]).

2.1. Objective Function

The unit quantity of product (x_1) that can be produced on the production plant and the part of resulting waste (x_2) that can be directly supplied to the stream are variables in order to maximize the total net profit of the production plant without disturbing the desired water quality of the stream.

The net income of the production plant is determined by:

- i. Sale Price of Finished Product: $10x_1$
- ii. Production Cost: $4x_1$

- iii. Treatment Plant Cost: $0.8(3x_1^{0.5} - x_2)$
- iv. Waste Tax Price: $2(x_2 + 0.2(3x_1^{0.5} - x_2))$

The maximum profit for the production plant is obtained by subtracting the total cost of the product from the sales price of the product. As a result, the objective function to be maximized can be expressed as in Eq. (1):

$$F(x_1, x_2) = 6x_1 - 3.6x_1^{0.5} - 0.8x_2 \quad (1)$$

2.2. Constraints

The daily capacity limit of the treatment plant in the system is expressed in Equation (2) as 12 units while the maximum amount of waste in order to ensure that the river water quality remains within certain limits is given Eq. (3) as 4 units:

$$3x_1^{0.5} - x_2 \leq 12 \quad (2)$$

$$x_2 + 0.2(3x_1^{0.5} - x_2) \leq 4 \quad (3)$$

Also, the daily maximum production capacity of the production plant is specified as 25 units. Furthermore, since the variable values defined for the presented problem and amount of waste supplied to the treatment plant cannot be negative, $0 \leq x_1 \leq 25$ and $x_2 \geq 0$ and $3x_1^{0.5} - x_2 \geq 0$ conditions should be provided.

3. OPTIMIZATION OF THE PROBLEM WITH LAGRANGE MULTIPLIERS

In the Lagrange Multipliers method, first of all, the inequality constraints in the problem are brought to equality and a Lagrange function is created. Afterwards, the Kuhn-Tucker (K-T) conditions are applied to obtain the results [7]. The Lagrange function (L) is expressed in Eq. (4) to represent λ_j Lagrange Multipliers.

$$\begin{aligned} &max. F(x_i) \\ &g_j(x_i) \leq C_j \quad j = 1, 2, \dots, m \quad (m: \text{number of constraints}) \\ &L = F(x_i) - \sum \lambda_j (g_j(x_i) - C_j) \end{aligned} \quad (4)$$

In this case, the following necessary and sufficient conditions (K-T) must be provided,

$$\frac{\partial L}{\partial \lambda_j} = 0 \quad (5)$$

$$\frac{\partial L}{\partial x_j} = \frac{\partial F}{\partial x_j} - \sum_j^m \lambda_j \frac{\partial g_j(x_i) - C_j}{\partial x_i} = 0 \quad (6)$$

$$\lambda_j (g_j(x_i) - C_j) \leq 0 \quad (7)$$

$$g_j(x_i) - C_j \leq 0 \quad (8)$$

where, F is objective function, x_i is design variables, g_j is constraints and C_j is constants.

4. OPTIMIZATION OF THE PROBLEM WITH GENETIC ALGORITHM

The GA starts working with a group of initial populations that are initially generated randomly and displayed with codes. The suitability of each solution in the initial population is assessed and the best ones are sent directly to the next generation with the elitism operator. The remaining individuals are selected according to the fitness value using a selection mechanism. The selected good individuals are subjected to crossover and mutation operators to form better individuals. The resulting new individuals are replaced by older individuals, and genetic operators are reapplied and then evaluation process is repeated according to the fitness function genetic [8].

The loop continues until the termination criterion is met. The termination criterion is determined by the number of generations in this study.

4.1. Genetic Algorithm Parameters

The GA needs to code the problem variables. Although there are different types of coding, binary {0,1} coding is most commonly used. In this technique all solutions are represented by bit arrays with the same dimensions and each of these arrays is a random point in the space of the possible solution of the problem [9]. In the problem, the number of bits of the variables called string (chromosome) length (SL) can be calculated by Eq. (9) to represent the upper bound $x_{(i)upper}$ and the lower bound $x_{(i)lower}$ for the variable i . [10].

$$2^{SL} \geq [(x_{(i)upper} - x_{(i)lower})/\varepsilon] + 1 \quad (9)$$

For the binary coding of the variables x_1 and x_2 used in this study, the total number of bits was calculated as 19 for each individual in the population. The first 10 bits represent the variable x_1 and the next 9 bits represent the variable x_2 . There are 2^{19} potential solutions in solution space of a 19 bits array.

In the GA, firstly a random initial population must be generated and the size of this population determines the number of search points in each generation. The optimum population size P , proposed by Goldberg, can be calculated by the equation given in Eq. (10) [11]. The size of the average population has been identified as 26 for an array of 19 bits in our problem.

$$P = 1.65 * 2^{0.21*SL} \quad (10)$$

4.2. Genetic Algorithm Operators

Together with the GA operators which are elitism, selection, crossover and mutation, a new population is created in each generation. With elitism, individuals with the best fitness value of the population are protected and these individuals are transferred to the next generation. This process continues for other generations. Other individuals are also subject to selection process according to their fitness values. Although there are many selection operators in the literature, the most common of these are roulette wheel and tournament selection operators [9].

In this study, roulette wheel selection mechanism is used. In the selection of roulette, the chromosomes belonging to each population individual create the slices of a wheel by grouping according to their fitness function values. The value of fitness function which is close to the desired value will have a greater slice in the wheel. In this case, the selection probability of these individuals in the population increases.

The individuals who are sent to the temporary population with the selection operator are subjected to the crossover operation. There are different crossover operators which are functional as single point, double point and multi point. In our study, crossing method from single point is used. In this crossover process, a random point is selected on the genes of the individuals that are matched in pairs and chromosomes are separated from the identified point. The starting parts of the separated chromosomes remain the same, but the second parts are exchanged between themselves. In the literature, it is recommended to select the probability of crossover for the crossover operator within range of 0.5 and 1.0. For this study, optimal value for the crossover rate is determined to be 0.7 as a result of trials.

The mutation is the other operator that is used after the crossover in the GA. This operator is used to expand the search space and to increase variety by making random changes in the genes of individuals. The recommended correlation for the rate of mutation is shown in Eq. (11) [12].

$$\frac{1}{P} \leq P_{Mutation\ Rate} \leq \frac{1}{SL} \quad (11)$$

The GA parameters used in the study are summarized in Table 1.

Table 1. GA Parameters.

The total number of bits for each individual in the population	19
Population size	26
Generation number	100
Crossover rate	0.7
Mutation rate	0.04

4.3. Penalty Function

The GA is an unconstrained optimization technique and the use of the GA in constrained optimization problems can be overcome by penalty functions. When a situation occurs outside the limits of the constraints, the fitness value of the relevant solution is penalized by the penalty function. So, the objective function values of solution space are kept within the desired limits. The penalty function correlation is given in Eq. (12) where n is the number of constraints, r_j is the penalty coefficient and g_j is the constraints [13].

$$PF = \sum_{j=1}^n r_j * [0, g_j]^2 \tag{12}$$

The square of the g_j is taken against the probability of a negative value of the penalty function. Since the r_j coefficient which is used to control the penalty process directly affects the results, it should be selected appropriately for each constraint.

5. RESULTS

Figure 2 shows the values of the problem variables during the operation of the algorithm. The places where the points get compact show that the variables go optimally in that area. Accordingly, it is observed that the production amount is about 20 quantity and the waste amount is about 1.6 quantity.

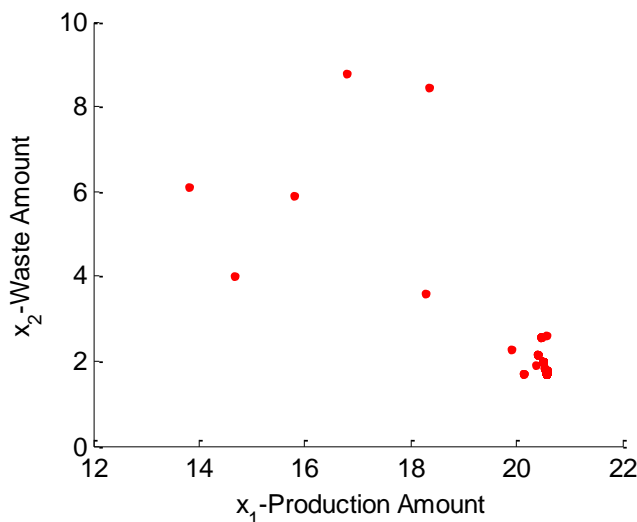


Figure 2. The values of the variables.

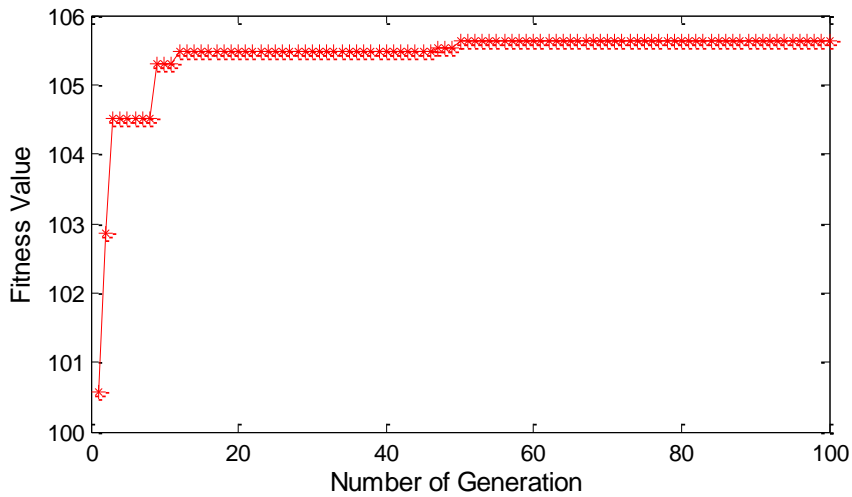


Figure 3. The plot of fitness value vs. number of generation

Figure 3 shows the plot of fitness value versus number of generation for the maximized total net profit of the plant maximized with GA. The result converged at generation 51.

Table 2. Optimum results for profit of the production plant.

Profit Value of the Production Plant with Pollution Control in Water Resource	Optimization Method	
	<i>Lagrange Multipliers</i>	<i>Genetic Algorithm</i>
<i>Problem Variables</i>		
Production Amount	20.5511	20.5492
Waste Amount	1.6000	1.5945
<i>Objective Function Values</i>		
Maximum Profit	105.7067	105.7005

The results of the problem variables and the maximum profit values obtained by the Genetic Algorithm and the Lagrange Multipliers methods are presented in Table 2. The results were obtained using MATLAB programs.

6. CONCLUSIONS

Most engineering problems are hard to solve using conventional optimization methods such as Lagrange Multipliers due to many specific constraints imposed. The results have shown that the GA can provide successful solutions to constrained engineering problems and solve them quickly and optimally reveals highly sensitive and accurate results. It can be concluded that the GA is proven to be robust and capability to obtain an efficient solution for engineering problems.

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REFERENCES / KAYNAKLAR

- [1] A. M. Yüceer, (2005) Akarsularda Su Kalitesinin İzlenmesine Yönelik Yeni Bir Dinamik Benzetim Yazılımı, Doktora Tezi, Fen Bilimleri Enstitüsü, Ankara Üniversitesi, Ankara, Türkiye.
- [2] A. Baylar, M. Öztürk, A. Arslan, (1998) Su Kaynakları Sistemlerinde Lineer Olmayan Problemlerin Genetik Algoritma ile Çözümü, Pamukkale Üniversitesi Mühendislik Bilimleri Dergisi, 4(3), 777-785.
- [3] P. Erdoğan, (2016) Parçacık Sürü Optimizasyonu ile Doğrusal Olmayan Denklem Köklerinin Bulunması ve Genetik Algoritma ile Mukayesesi, İleri Teknoloji Bilimler Dergisi, 5(1), 1-14.
- [4] E. Aras, V. Toğan, M. Berkun, (2007) River Water Quality Management Model using Genetic Algorithm, Environmental Fluid Mechanics, 7(5), 439-450.
- [5] M. E. Uçaner, O. N. Özdemir, (2002) Genetik Algoritmalar ile İçme Suyu Şebekelerinde Ek Klorlama Optimizasyonu, Gazi Üniversitesi, Mühendislik Mimarlık Fakültesi Dergisi, 17(4), 157-170.
- [6] L. W. Mays, Y. K. Tung, (2002) Hydrosystems Engineering and Management, Water Resources Publications, LLC.
- [7] H. Bal, (1995) Optimizasyon Teknikleri, Gazi Üniversitesi.
- [8] H. Saruhan, (2004) Genetic Algorithms: An Optimization Technique, Technology, 7(1), 105-114.
- [9] M. Yaman, H. Saruhan, F. Mendi, (2006) Genetik Algoritma Yardımıyla Kardan Mil Çapı Minimasyonu, Tasarım İmalat Analiz Kongresi (TİMAK), 77-88.
- [10] C. Y. Lin, P. Hajela, (1992) Genetic Algorithms in Optimization Problems with Discrete and Integer Design Variables, Engineering Optimization, 19(4), 309-327.
- [11] D. E. Goldberg, (1985) Optimal Initial Population Size for Binary Coded Genetic Algorithms, The Clearinghouse for Genetic Algorithms, University of Alabama, TCGA Rept. 85001, Tuscaloosa.
- [12] T. Bäck, (1993) “Optimal Mutation Rates in Genetic Search”, Proceedings of the 5th International Conference on Genetic Algorithms, 2-8.
- [13] A. Homaifar, C.X. Qi, S.H. Lai, “Constrained Optimization via Genetic Algorithms”, Simulation, 1994, 62(4), 242-254.