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Research Article

Detection of Pipes Causing Pressure Loss in Water Distribution Networks via Artificial Immune Systems

Miraç ERYİĞİT[a,*]

[a] *Department of Environmental Engineering, Faculty of Engineering, Bolu Abant Izzet Baysal University, Bolu, TURKEY*
** Corresponding author's e-mail address: miraceryigit@hotmail.com*
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ABSTRACT

This paper proposes the optimization model using Artificial Immune Systems, depending on a model calibration, in order to determine worn out pipes with low Hazen-Williams roughness coefficient causing pressure loss in the water distribution networks. The modified Clonal Selection Algorithm, a type of Artificial Immune Systems, was used as a heuristic optimization method. In order to evaluate its performance, the model was implemented to the four-loop hypothetical water distribution network under steady-state conditions. According to the results, the model appeared to be promising in the detection of old pipes causing high pressure losses in the water distribution networks.

Keywords: *Pressure loss, Water Distribution Networks, Optimization, Model Calibration, Artificial Immune Systems*

Su Dağıtım Şebekelerinde Basınç Kaybına Neden Olan Boruların Yapay Bağışıklık Sistemleri ile Tespit Edilmesi

ÖZ

Bu çalışmada, su dağıtım şebekelerinde basınç kaybına neden olan düşük Hazen-Williams pürüzlülük katsayısına sahip eskimiş boruların belirlenmesi için model kalibrasyonuna bağlı Yapay Bağışıklık Sistemlerini kullanan bir optimizasyon modeli önerilmektedir. Sezgisel optimizasyon yöntemi olarak Yapay Bağışıklık Sistemlerinden biri olan modifiye Klonal Seçim Algoritması kullanılmıştır. Modelin performansını test etmek için, sürekli-kararlı koşullar altında dört gözlü farazi (sanal) bir su dağıtım şebekesinde model uygulanmıştır. Elde edilen sonuçlara göre, su dağıtım şebekelerindeki yüksek basınç kayıplarına neden olan eskimiş boruların tespit edilmesinde modelin gelecek vaat ettiği görülmüştür.

Keywords: *Basınç kaybı, Su Dağıtım Şebekeleri, Optimizasyon, Model Kalibrasyonu, Yapay Bağışıklık Sistemleri*

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I. INTRODUCTION

The pipes in water distribution networks (WDNs) become worn out over time. Consequently, in addition to a public health risk due to corrosion, sufficient pressure heads can not be provided at nodes (junctions) of the WDN due to low roughness coefficients increase friction (head) losses. This may cause water failing to reach up to upper floors of buildings, and forcing the use of the water boosters. In this context, a detection of pipes causing pressure loss in the WDNs comes into prominence to restore. In order to achieve this task, model calibration is utilized. The model calibration is the minimization process of the difference between the model estimations and field observations of flows and pressures to specify the physical and operational hydraulic characteristics of the existing system. The hydraulic characteristics comprise model parameters such as nodal water demand, roughness of pipes, operation status of valves, pipes, tanks, pumps and emitters in the WDNs [1]-[4].

In the literature, several studies based on model calibration were carried out to determine pipe roughness (friction) in the WDNs (compiled by [4], [5]). De Schaetzen et al. [1] applied methods of the optimal sampling design for the model calibration of pipe roughness coefficients using genetic and entropy algorithms, shortest path algorithm. Kapelan et al. [6] improved the inverse transient model based on the hybrid search method for a roughness calibration. Wu et al. [3], Lingireddy and Ormsbee [7], Jamasb et al. [8], Boczar et al. [9], Prasad [10], Dini and Tabesh [11] proposed optimization models depending on the model calibration using Genetic Algorithm (GA), Clonal Selection Algorithm (Clonalg) and Ant Colony Optimization to obtain pipe roughness coefficients, respectively. Kang and Lansey [12] performed the demand and roughness calibration based on a two-step method. Similarly, Koppel and Vassiljev [13], Alvisi and Franchini [14], Vassiljev et al. [15], Piller et al. [16], Xie et al. [17], Du et al. [18], Jadhao and Gupta [19], Zhang et al. [20] studied pipe roughness calibration in the WDNs by using different methods.

As an alternative to the related literature, the optimization model depending on the model calibration, using the modified Clonal Selection Algorithm (modified Clonalg) was improved to detect worn out pipes with low roughness coefficient of Hazen-Williams (C) causing pressure loss in the four-loop hypothetical WDN under steady-state conditions in this study. The results indicated that the model seems to be practicable for the detection of old pipes causing pressure losses in the WDNs.

II. MATERIAL AND METHOD

A. MODEL FORMULATION

The objective function applied in the model calibration was optimized by minimizing the difference between the model estimated and the field observed (measured) pipe flow and junction (node) pressure values under the boundary conditions for obtaining the model parameter values (pipe roughness etc.) in the WDN. The objective function (f) defined by Wu et al. [3] as shown below was used in this study.

$$\textit{minimize} \quad \frac{\sum_{nh=1}^{NH}\left(\frac{Hsim_{nh}-Hobs_{nh}}{Hpnt}\right)^2+\sum_{nf=1}^{NF}\left(\frac{Fsim_{nf}-Fobs_{nf}}{Fpnt}\right)^2}{NH+NF} \tag{1}$$

where $Hsim_{nh}$ is the *nh*-th model simulated pressure head (hydraulic head), $Hobs_{nh}$ is the *nh*-th observed pressure head, $Fsim_{nf}$ is the *nf*-th simulated flow rate, $Fobs_{nf}$ is the *nf*-th observed flow rate, *Fpnt* is the flow per the fitness point and *Hpnt* is the hydraulic head per the fitness point, *NF* is the number of the observed pipe flow rates, *NH* is the number of the observed pressure heads. *Hpnt* and

Fpnt were assigned as 0.3 m and 0.63 l/s, respectively [21]. In order to detect pipes having low roughness coefficient, the following constraints were considered for minimizing the objective function:

The continuity equation should be fulfilled for each node;

$$\sum Q_{in} - \sum Q_{out} = Q_e \tag{2}$$

where Q_e is the external inflow rate or water demand at the junction (node), Q_{in} and Q_{out} are the inflow and outflow rate of the junction, respectively. The minimum required pressure head for each junction is defined as the following:

$$H_j \geq H_j^{\min} \qquad j = 1,...,M \tag{3}$$

where H_j is the pressure head at junction j, H_j^{min} is the minimum required pressure head at junction j, M is the number of junctions (nodes) in WDN. In addition to the objective function (f), the penalty function was described for avoiding violation of the constraints. The penalty function is as below:

$$If\ \ H_j < H_j^{\min} \rightarrow\ |H_j| + f \qquad j = 1,...,M \tag{4}$$

In this study, H_j^{min} was assigned as zero for preventing the occurrence of negative pressures in the junctions. The modified Clonalg improved by Eryiğit [22], a type of Artificial Immune Systems (AIS), was used to minimize the objective function above (Equation 1) since the algorithm is highly capable to solve optimization problems. The modified Clonalg was shown for optimization problems in Figure 1, where Ab is the randomly created antibody set (population), f is the antigenic affinity of the antibody representing the objective function for each antibody, C is the population of cloned antibodies, $C*$ is the population of matured (mutated) antibodies following the cloning process.

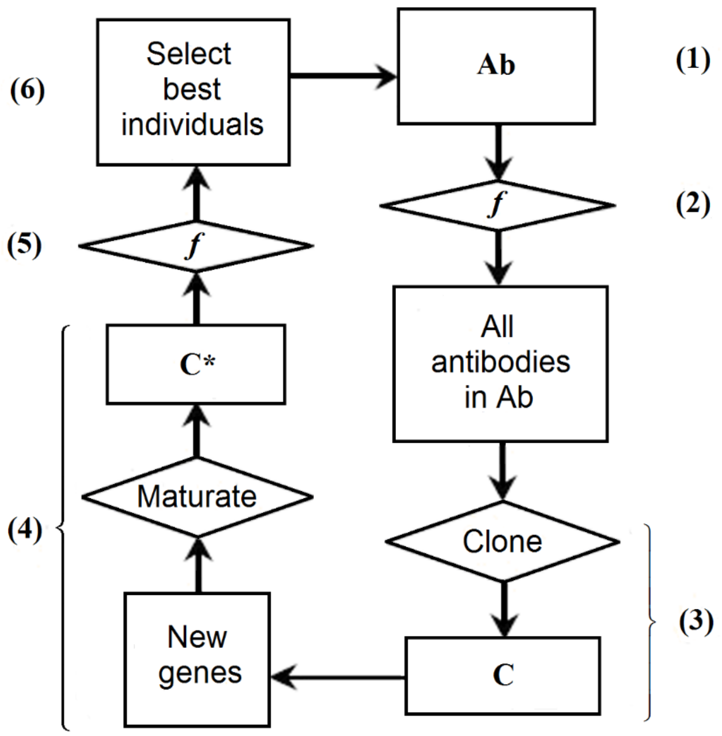

Figure 1. *The flow diagram of the modified Clonalg for the optimization problems [22].*

The steps of the algorithm are as follows:

(1) An antibody set (Ab) is randomly generated.
(2) For each antibody in Ab, an objective function (f) is calculated to be optimized (maximized or minimized).
(3) All antibodies are cloned.
(4) All clones (C) are exposed to the maturation process (mutation) inversely proportional to their antigenic affinities (objective function values). Also, new genes are generated for the clones in this step.
(5) For each matured clone in C*, an objective function (f) is computed again.
(6) The matured clones, which have the highest affinity (best individuals) are selected to replace the antibodies which have the lowest affinity in Ab. This loop continues until the iteration reaches a maximum number. Hence, the best result can be obtained.

According to the certain probability called as "probability rate" based on a given problem, new genes are created for each antibody clone in the modified Clonalg (Step 4). The number of the created clones for all the antibodies can be computed as shown below [23]:

$$N_C = \sum_{i=1}^{N_{Ab}} round\left(\beta \cdot N_{Ab}\right) \qquad i = 1,\ldots,N_{Ab} \tag{5}$$

where *Nc* is the total number of the antibody clones in population *C*, *β* is the multiplying coefficient, "*round*" is the rounding operator for the integer.

The mutation rate can be calculated as given below [23]:

$$\alpha_i = \exp\left(-\rho \cdot f_i\right) \tag{6}$$

where α_i is the mutation rate for the antibody clones exposed to the mutation (maturation) process, ρ is the decay coefficient, and f_i is the antigenic affinity value (objective function value) normalized over the interval [0-1]. Definition of Ab is as follows:

$$\overbrace{\begin{bmatrix} Ab_1 = & x_{11} & \cdots & x_{1j} & \cdots & x_{1nd} \\ \vdots & \vdots & & & & \vdots \\ Ab_i = & x_{i1} & & \ddots & & x_{ind} \\ \vdots & \vdots & & & & \vdots \\ Ab_{N_{Ab}} = & x_{N_{Ab}1} & \cdots & x_{N_{Ab}j} & \cdots & x_{N_{Ab}nd} \end{bmatrix}}^{Ab} \rightarrow \overbrace{\begin{bmatrix} f_1 \\ \vdots \\ f_i \\ \vdots \\ f_{N_{Ab}} \end{bmatrix}}^{f} \qquad i = 1,\dots,N_{Ab} \qquad j = 1,\dots,nd \tag{7}$$

where N_{Ab} is the total number of the antibodies in population Ab, x_{ij} is the gene of Ab_i, representing the decision variable of the objective function, *nd* is the number of the genes (decision variables) of Ab_i. In this study, x_{ij} represents Hazen-Williams pipe roughness coefficient (C). *f* was minimized by basing on the roughness coefficients (genes) generated and maturated (mutated) during the modified Clonalg processes. Lower and upper limits for determining the pipe roughness coefficients were assigned as 70 and 100, respectively.

B. APPLICATION OF THE FOUR-LOOP WDN

This hypothetical WDN composes of 10 nodes involving junctions 1-9 and the reservoir, 13 pipes within four loops, and it is fed by the gravity from the reservoir with a 60 m fixed hydraulic head. Project roughness coefficient (C) was assigned as 100 in all the pipes. The properties of the network scenario were selected randomly. Project data, operational data (actual data), and the layout of the Four-loop WDN were given in Table 1, Table 2 and Figure 2, respectively. Flow rates in all the pipes except pipe 1, and pressure heads in node 1, 4, 5, 7 and 9 were assumed to observe.

Table 1. *The project data of the Four-loop WDN.*

Node	**Elevation** *(m)*	**Base demand** *(l/s)*	**Initial Pressure** *(m)*	**Pipe**	**Length** *(m)*	**Diameter** *(mm)*	**C** *(Unitless)*
Reservoir	60	-	-	1	1500	600	100
1	0	50	51.50	2	1000	500	100
2	0	45	48.44	3	1000	250	100
3	0	45	48.44	4	1000	500	100
4	0	55	34.25	5	1000	250	100
5	0	45	31.86	6	1000	250	100
6	0	50	28.33	7	1000	250	100
7	0	45	31.86	8	1000	250	100
8	0	50	28.33	9	1000	250	100
9	0	60	25.60	10	1000	250	100
				11	1000	250	100
				12	1000	250	100
				13	1000	250	100

Table 2. *The operational data of the Four-loop WDN.*

Node	**Operating Pressure Head** *(m)*	**Pipe**	**Operating Flow Rate** *(l/s)*	**C** *(Unitless)*
Reservoir	-	1	445.00	100
1	51.50*	2	201.64*	78
2	46.46	3	86.21*	100
3	46.36	4	193.36*	74
4	24.41*	5	73.48*	71
5	19.30*	6	28.48*	100
6	16.82	7	30.57*	92
7	27.17*	8	41.21*	73
8	18.37	9	29.43*	72
9	13.52*	10	74.88*	81
		11	38.23*	83
		12	70.43*	76
		13	52.08*	100

*Observed pressure heads and flow rates.

EPANET 2, a commonly known WDN simulation software, was used/preferred for the hydraulic calculations because it is simple and efficient (also, it can be linked with Matlab). It was developed as a tool for understanding the movement and fate of drinking water constituents within water distribution systems, and can be used for many different types of applications in distribution systems analysis [24]. The optimization model was run 30 times for the Four-loop WDN within the maximum iteration number in each run. Random seed process (random number generation) was carried out while generating the initial set of pipe roughness coefficients in each run. The PC with Intel I5 Core 2.5 Ghz (3.1 Ghz with Turbo Boost) and Matlab R2014a software were used for the analyses in the study (the optimization model was coded in Matlab and linked with EPANET 2).

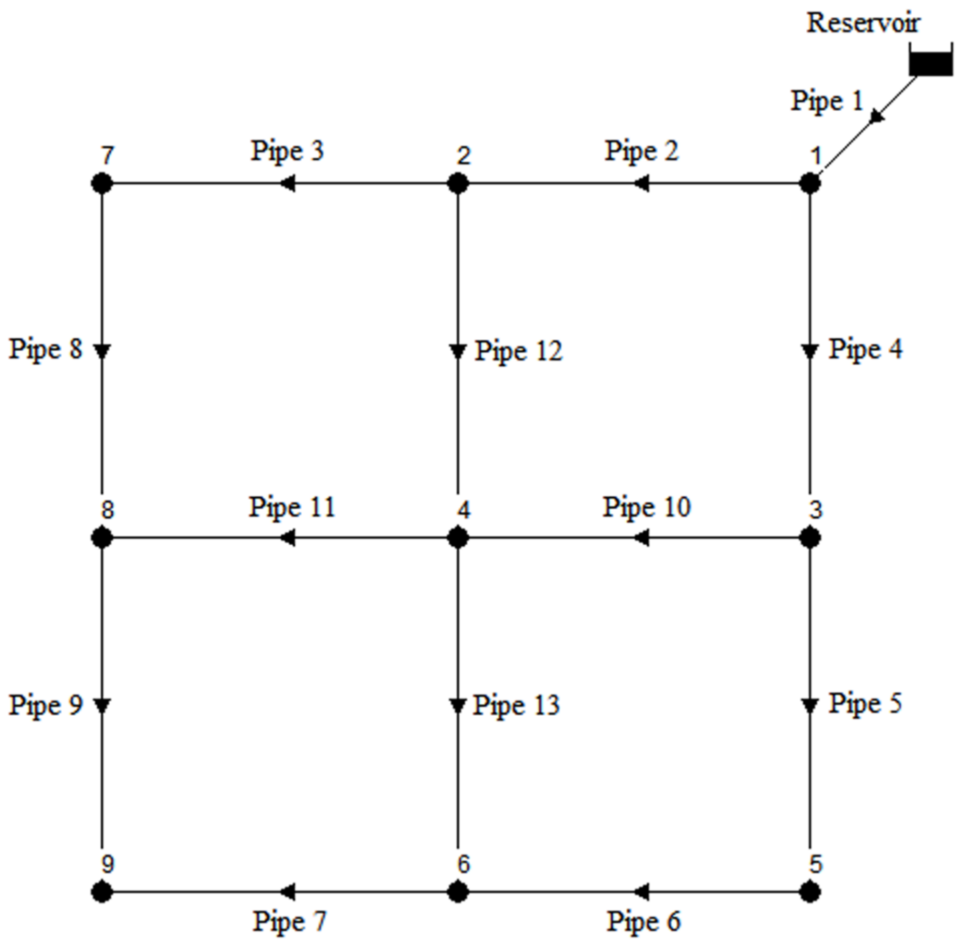

Figure 2. *The Four-loop WDN layout.*

III. RESULTS AND CONCLUSION

Table 2 presents the worn out pipes with low pipe roughness coefficient (C) causing pressure loss in the WDN. The model using modified Clonalg was run 30 times, and forced to minimize the objective function (f) for detecting these pipes. The average of best (fittest) *f* values after 30 runs converged to zero (see Table 3). Different C coefficient sets minimizing *f* to zero were obtained for the pipes of the WDN in each run because *f* is based on model calibration using pressure heads observed in only 5 nodes (not all nodes). However, as it is seen in Table 4, mean predicted and actual roughness coefficients are approximate with each other (Also, they are illustrated in Figure 3). A mean run time is short which is approximately 8 minutes (see Table 3). Furthermore, the pressures in all the nodes were obtained properly within the hydraulic computations, and any negative pressure did not exist in the junctions. Consequently, the results demonstrated that the model can easily determine the old pipes reducing pressure heads in the nodes of the Four-loop WDN.

Table 3. *Parameters and performances of the modified Clonalg used for the optimization problem.*

N_{Ab}	β	ρ	**Probability Rate**	**Iteration Number**	**Minimum *f***	**Maximum *f***	***Mean *f***	***Mean Run Time *(min)***
30	1	13	0.1	1000	6.21×10^{-10}	4.09×10^{-6}	2.8×10^{-7} $\pm8.4\times10^{-7}$	8.2 ±0.02

N_{Ab}: Number of population Ab. β: Multiplying coefficient for the cloning. ρ: Decay coefficient.

Table 4. Comparison of mean predicted and actual pipe roughness coefficients.

Node	*Mean Pressure Head *(m)*	Pipe	*Mean Flow rate *(l/s)*	*Mean Predicted C *(Unitless)*	Actual C *(Unitless)*
1	$51.50 \pm 3.42 \times 10^{-4}$	1	445 ± 0	100.0 ± 0.002	100
2	$47.14 \pm 5.22 \times 10^{-1}$	2	$201.64 \pm 1.07 \times 10^{-4}$	84.9 ± 5.6	78
3	$46.54 \pm 5.25 \times 10^{-1}$	3	$86.21 \pm 5.1 \times 10^{-5}$	98.2 ± 1.4	100
4	$24.41 \pm 9.43 \times 10^{-5}$	4	$193.36 \pm 1.07 \times 10^{-4}$	75.8 ± 4.3	74
5	$19.30 \pm 3.74 \times 10^{-4}$	5	$73.48 \pm 2.78 \times 10^{-4}$	70.7 ± 0.7	71
6	$16.55 \pm 1.83 \times 10^{-1}$	6	$28.48 \pm 2.77 \times 10^{-4}$	94.6 ± 3.4	100
7	$27.17 \pm 4.62 \times 10^{-5}$	7	$30.57 \pm 1.17 \times 10^{-4}$	96.6 ± 3.2	92
8	$18.02 \pm 3.31 \times 10^{-1}$	8	$41.21 \pm 5.11 \times 10^{-5}$	71.5 ± 1.4	73
9	$13.52 \pm 2.18 \times 10^{-4}$	9	$29.43 \pm 1.17 \times 10^{-4}$	75.1 ± 2.9	72
		10	$74.88 \pm 1.79 \times 10^{-4}$	80.7 ± 1.0	81
		11	$38.23 \pm 9.19 \times 10^{-5}$	80.6 ± 2.3	83
		12	$70.43 \pm 7.55 \times 10^{-5}$	74.8 ± 0.9	76
		13	$52.08 \pm 1.77 \times 10^{-4}$	98.1 ± 1.2	100

*Average of 30 runs

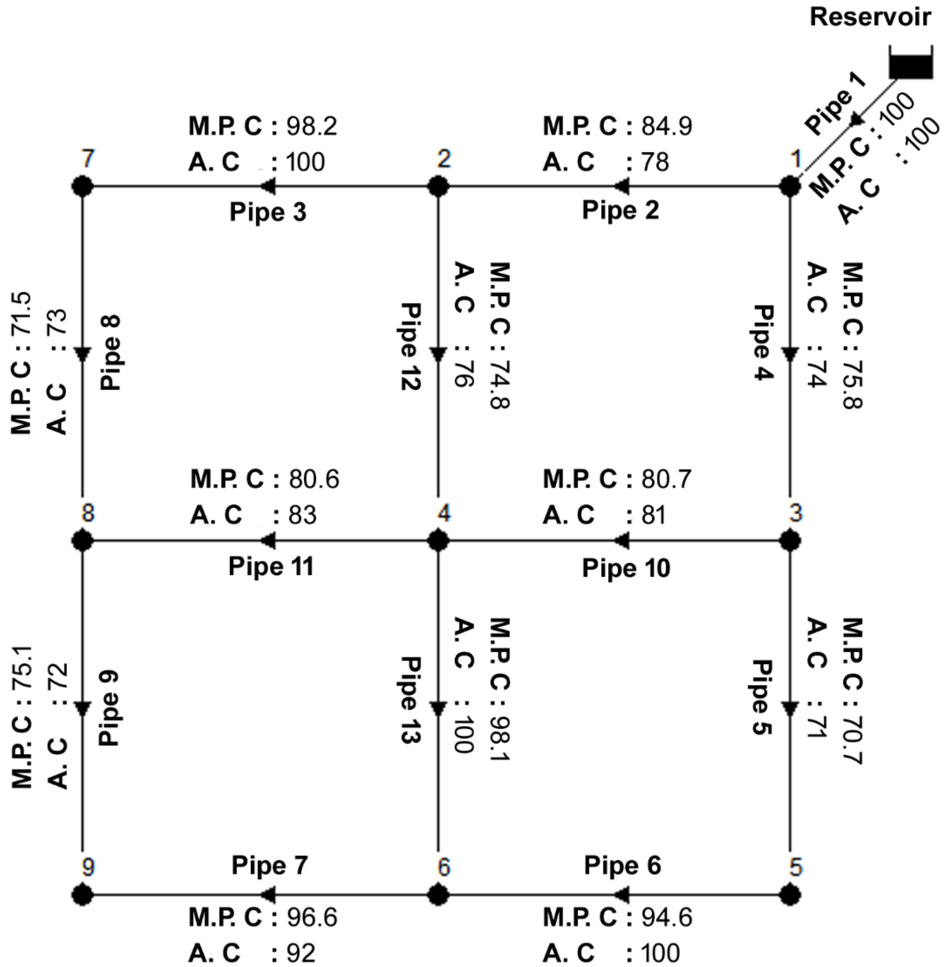

Figure 3. *Mean predicted and actual pipe roughness coefficients of each pipe (M.P. C: Mean Predicted C, A. C: Actual C)*

Model calibration depends on field observations. Therefore, actual C coefficients of the pipes can be predicted more accurately by the optimization model using more observed data (flow rate and pressure head) in each run. But more observation data mean more expensive task. On the contrary, the model was able to detect worn out pipes with less observed field data in the short run times. Thus, the model could be used as an alternative to the other models in the related literature. In the future studies, the model may be tested for the WDNs consisting of more loops or different complex systems (combined dendritic-looped networks, irrigation systems etc.). Also, the model can be applied by using the roughness coefficients of the other head loss formulas (Darcy-Weisbach, Chezy-Manning) to detect the old pipes in the WDN.

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