

APPLICATION OF CHARGED SYSTEM SEARCH ALGORITHM TO WATER DISTRIBUTION NETWORKS OPTIMIZATION

R. Sheikholeslami^a, A. Kaveh^{b, 1, †}, A. Tahershamsi^a and S. Talatahari^c

^a *Department of Civil and Environmental Engineering, Amirkabir University of Technology (Tehran Polytechnic), Tehran, Iran*

^b *Centre of Excellence for Fundamental Studies in Structural Engineering, Iran University of Science and Technology, Narmak, Tehran-16, Iran*

^c *Department of Civil Engineering, University of Tabriz, Tabriz, Iran*

ABSTRACT

A charged system search algorithm (CSS) is applied to the optimal cost design of water distribution networks. This algorithm is inspired by the Coulomb and Gauss's laws of electrostatics in physics. The CSS utilizes a number of charged particles which influence each other based on their fitness values and their separation distances considering the governing law of Coulomb. The well-known benchmark instances, Hanoi network, double Hanoi network, and New York City tunnel problem, are utilized as the case studies to evaluate the optimization performance of CSS. Comparison of the results of the CSS with some other meta-heuristic algorithms indicates the performance of the new algorithm.

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1. INTRODUCTION

One of the main components of urban water systems is the pipe networks. Pipe networks are complex systems that require a high level of investment for their construction and maintenance. Nearly 80% to 85% of the cost of a total water supply system is contributed

¹Corresponding author: A. Kaveh, School of Civil Engineering, Iran University of Science and Technology, Tehran-16, Iran.

[†]E-mail address: alikaveh@iust.ac.ir (A. Kaveh)

toward water transmission and the water distribution network. A traditional design process for a water distribution network is the use of a trial and error approach; however, this approach does not necessarily provide a least-cost solution for the problem. Though this process leads to safe designs, however, the cost of the water distribution networks is highly dependent on the experience of the designer. Thus in order to economize the cost of the water distribution networks under design constraints; it is advantageous to cast the problem as an optimization problem.

On the other hand water distribution network design is a large-scale problem, complicated by the wide range of possible system operating conditions and the existing uncertainties. From a mathematical point of view, significant difficulties are involved due to the discrete nature of the pipe diameters and the nonlinearity of the head-loss relationship. These lead to a mixed integer nonlinear problem, corresponding to the NP-hard class [1] which implies that an optimal solution is not feasible in a polynomial time. Two different types of optimization are applied to solve this problem. The first type consists of linear programming (LP) and nonlinear programming (NLP). Pipe network optimization problem has a degree of nonlinearity due to dependence on unknown pipe discharges, which satisfy the nodal demands and hydraulic constraints on unknown pipe diameters. The general idea of LP is to relax the non-linearity by assuming a particular flow pattern (or removing one pipe from each loop). Then, applying LP to obtain the gradient of the objective function and best pipe diameters. Using gradient of the objective function, the flow pattern must be revised. The two stage iterative procedure is continued until no further reduction in cost can be observed. In NLP, the unknown pipe discharges are represented as a function of the unknown pipe diameters by satisfying the hydraulic conditions. Then pipe network is optimized to achieve the minimum cost under hydraulic and design constraints [2]. In general, the main drawback of these approaches is the nature of optimized domain conformation. Sonak [3] proved that this domain in general is convex between the points representing minimum values of objective function corresponding to sequential assumptions of zero flow rate for one selected pipe from every loop, the optimized domain between these points are represented by a concave surfaces. Thus the optimized domain is a concavo convex. The final solution achieved by these methods is always dependent on the starting point and the complexity of the optimized domain. In order to moderate the unpleasant behavior of the LP and NLP methods, the optimization procedure must be repeated with different starting points.

The second type of optimization approaches is the random-based meta-heuristic algorithms. Meta-heuristic algorithms often perform well for most of the optimization problems. This is because these methods refrain from simplifying or making assumptions about the original form. All of these algorithms attempt to find the optimal solution in a stochastic manner and avoid local optimum solutions. Meta-heuristics utilize fewer mathematical formulas and do not require very well defined mathematical models. They also provide efficacious solutions to the high-scale combinatorial and non-linear problems [4].

The objective of this paper is to employ the recently developed meta-heuristic optimization algorithm which is based on principles from physics and mechanics, known as Charged System Search (CSS), for optimal cost design of water distribution networks

considering the pressure and demand constraints. Here, the numerical simulation is based on the CSS method including benchmark problems, and the results are compared with those of other existing heuristic approaches. This demonstrates the effectiveness of the present algorithm. The CSS is inspired by the governing laws of electrostatics in physics and the governing laws of motion from the Newtonian mechanics. The CSS contains some agents or charged particles (CPs) that affect each other according to the laws of Coulomb and Gauss from electrostatics. The optimization process in the CSS algorithm progresses by determining the resultant force affecting on each CP, and then agents are moved toward their new positions according to the Newtonian laws of motion. These successive movements of the CPs direct the algorithm toward optimum solutions. This algorithm is proposed by Kaveh and Talatahari [5]. The CSS method has been applied to a diverse range of optimization problems including optimal design of frame structures, geodesic domes, and truss structures [6], and optimum design of composite open channels [7]. The diversity of the applications will naturally continue grow as the algorithm becomes more widely known. The first multi-objective optimization problem appears to have been tackled in [8] in which a new multi-objective optimization algorithm, named as CSS-MOPSO, is proposed. The proposed algorithm is a hybrid method which is a combination of particle swarm (PSO) method and charge system search (CSS). Finally as a new variant of the algorithm Talatahari *et al.* [9] introduced an efficient CSS approach employing the chaos theory (CCSS) to solve mathematical global optimization problems.

In the following, first a brief bibliographical review is presented. Then, the statement of the optimal design of water distribution networks is formulated. Review of the CSS is presented in section 4. Section 5 contains some illustrative examples. Finally, the conclusion is drawn in section 6 based on the reported results.

2. A BRIEF BIBLIOGRAPHICAL REVIEW

In the last three decades, a significant number of optimization methods have been applied to water distribution network design and maintenance planning, including linear, nonlinear, dynamic and mixed integer programming or enumeration techniques [10-16]. The algorithms are a combination of primal and dual processes and stop when the difference between the best solution and the global lower bound falls within a prescribed tolerance. Since the optimization problem is nonlinear, the gradient information may not be attained in many instances. This results in failure to reach the optimal solution [17].

Recently, researchers have focused on meta-heuristic optimization methods. Many of these methods are created by the simulation of the natural processes. Genetic algorithms (GAs), simulated annealing (SA), particle swarm optimization (PSO), ant colony optimization (ACO), harmony search (HS), and charged system search algorithm (CSS) are some familiar examples of meta-heuristic algorithms. Simpson *et al.* [18], Cunha and Sousa [19], and Lippai *et al.* [20] were the first to apply meta-heuristic algorithms, such as GA, SA, and tabu search (TS) to water network design. Geem *et al.* [21] developed HS algorithm and tackled the design of a water distribution network using this method. Maier *et al.* [22] used ACO for water distribution optimization and found that the ACO can be

computationally efficient. Vairavamoorthy and Shen [23] tested PSO on the benchmark problems and concluded that the method identified correctly the optimal solutions.

Also there is some software for optimum design of water distribution networks. Savic and Walters [24] developed the practical software GANET, which applies the GA to water network design problems. Reza and Martínez [25] developed the GENOME model, a GA based model. They analyzed the performance of this algorithm by applying it to several benchmark networks and to a complex real-sized irrigation water distribution network. A new computer model called meta-heuristic pipe network optimization model (MENOME) has been developed by Reza and Martínez [26]. The MENOME model is an extension of the previously developed GENOME model. This computer program includes several additional meta-heuristic optimizers. OptiDesigner is other software which applies the GA to water network design optimization problems. The program uses EPANET (a hydraulic simulator distributed by the US EPA) for the drawing and analyzing the system. This software can design the network pipes and find their minimal cost under a set of constraints. The review presented here should be considered only as a representative sample of the studies, and the reader is also referred to the references in those studies.

3. PROBLEM FORMULATION

A typical design problem of water distribution network consists of sizing, i.e., determining the size of as many pipes as the equations allow to meet specified pressures and discharges throughout the network. Generally the optimization problem can be defined as: how to supply an adequate water quantity in order to cover the needed demand for each node through a highly interconnected system of pipes, and through using network elements such as pumps, reservoirs and tanks. In this study we want to minimize cost of the water network design subject to continuity equation, conservation of energy equation, and minimum pressure requirements. We assume that the pipe layout, nodal demands, head and velocity requirements are all known. The mathematical statement of the optimal design problem can be written as:

$$\text{Minimize: } f_{\text{cost}} = \sum_{i=1}^{N_p} f(D_i, L_i) \quad (1)$$

$$\text{Subject to: } \begin{cases} \sum Q_{in} - \sum Q_{out} = \sum Q_e & \rightarrow \text{continuity constraint} \\ \sum h_f - \sum E_p = 0 & \rightarrow \text{energy constraint} \\ H_j \geq H_j^{\min} & \rightarrow \text{minimum pressure constraint} \end{cases} \quad (2)$$

where $f(D_i, L_i)$ is the cost of pipe i with diameter D_i and length L_i , and N_p is the number of pipes in the network. In continuity constraint Q_{in} is the flow rate to the node, Q_{out} is the flow rate out of the node, and Q_e is the external inflow rate at the node. In energy constraint h_f is the head loss computed by the Hazen-Williams or Darcy-Weisbach formulae and E_p is the

energy added to the water by a pump. Also H_j is the pressure head and H_j^{min} is the minimum required pressure head at node j in which $j=1, 2, \dots, N_n$. N_n is the number of nodes in the network.

Different forms for the head loss formula have been developed for practical pipe flow calculations. In this study, the head loss (h_f) in the pipe is expressed by the Hazen-Williams formula:

$$h_f = \omega \frac{L}{C^\alpha D^\beta} Q^\alpha \quad (3)$$

Here $\omega = 10.6668$, $\alpha = 1.85$, $\beta = 4.87$, Q_i is the pipe flow (m^3/s), C_i is the Hazen-Williams roughness coefficient which ranges from 150 for smooth-walled pipes to as low as 80 for old, corroded cast iron pipes, D_i is pipe diameter (m), and L_i is pipe length (m). Higher ω values require larger diameters to deliver the same amount of water, because these can violate the minimum pressure requirements, while the lower ω values may just meet the constraint. Thus, higher ω values eventually require more expensive water network designs [27].

4. CHARGED SYSTEM SEARCH ALGORITHM

4.1. General concepts

The charged system search (CSS) is a population-based search approach, where each agent (CP) is considered as a charged sphere with radius a , having a uniform volume charge density which can insert an electric force to the other CPs. The magnitude of forces for the CP located in the inside of the sphere is proportional to the separation distance between the CPs, and for a CP located outside the sphere it is inversely proportional to the square of the separation distance between the particles. The resultant forces or acceleration and the motion laws determine the new location of the CPs. The pseudo-code for the CSS algorithm can be summarized as follows:

Step 1: Initialization. The initial positions of CPs are determined randomly in the search space and the initial velocities of charged particles are assumed to be zero. The values of the fitness function for the CPs are determined and the CPs are sorted in an increasing order of fitness values. The best CP among the entire set of CPs will be treated as \mathbf{X}_{best} and its related fitness will be fit_{best} . Similarly, the worst CP will have fit_{worst} . A number of the first CPs and their related values of the fitness function are saved in a memory, so called charged memory (CM).

Step 2: Forces determination. Calculate the force vector for each CP as

$$\mathbf{F}_j = q_j \sum_{i, i \neq j} \left(\frac{q_i}{a^3} r_{ij} \cdot \mathbf{i}_1 + \frac{q_i}{r_{ij}^2} \cdot \mathbf{i}_2 \right) ar_{ij} p_{ij} (\mathbf{X}_i - \mathbf{X}_j) \begin{cases} j = 1, 2, \dots, N \\ i_1 = 1, i_2 = 0 \Leftrightarrow r_{ij} < a \\ i_1 = 0, i_2 = 1 \Leftrightarrow r_{ij} \geq a \end{cases} \quad (4)$$

where \mathbf{F}_j is the resultant force acting on the j th CP; N is the number of CPs. The magnitude of charge for each CP (q_i) is defined considering the quality of its solution as:

$$q_i = \frac{fit(i) - fitworst}{fitbest - fitworst}, \quad i = 1, 2, \dots, N \quad (5)$$

where $fitbest$ and $fitworst$ are the best and the worst fitness of all the particles; $fit(i)$ represents the fitness of the agent i ; and N is the total number of CPs. The separation distance r_{ij} between two charged particles is defined as follows:

$$r_{ij} = \frac{\|\mathbf{X}_i - \mathbf{X}_j\|}{\|(\mathbf{X}_i + \mathbf{X}_j)/2 - \mathbf{X}_{best}\| + \varepsilon} \quad (6)$$

where \mathbf{X}_i and \mathbf{X}_j are the positions of the i th and j th CPs respectively, \mathbf{X}_{best} is the position of the best current CP, and ε is a small positive number to avoid singularities. Here, p_{ij} is the probability of moving each CP towards the others and is obtained using the following function:

$$p_{ij} = \begin{cases} 1 & \frac{fit(i) - fitbest}{fit(j) - fit(i)} > rand \vee fit(j) > fit(i) \\ 0 & \text{otherwise} \end{cases} \quad (7)$$

where $rand$ is a random number uniformly distributed in the range of (0,1).

As mentioned before, each CP is considered as a charged sphere with radius a , having a uniform volume charge density. A suitable value for a is defined considering the size of the search space as:

$$a = 0.01 \times \max(\{x_{i,max} - x_{i,min} \mid i = 1, 2, \dots, n_v\}) \quad (8)$$

in which $x_{i,max}$ and $x_{i,min}$ are the lower and upper bound of the i th decision parameter respectively; and n_v is the number of design variables.

Step 3: Solution construction. Each CP moves to the new position and the new velocity is calculated as:

$$\begin{aligned} \mathbf{X}_{j,new} &= rand_{j1} \cdot k_a \cdot \mathbf{F}_j + rand_{j2} \cdot k_v \cdot \mathbf{V}_{j,old} + \mathbf{X}_{j,old} \\ \mathbf{V}_{j,new} &= \mathbf{X}_{j,new} - \mathbf{X}_{j,old} \end{aligned} \quad (9)$$

where k_a is the acceleration coefficient; k_v is the velocity coefficient to control the influence of the previous velocity; and $rand_{j1}$ and $rand_{j2}$ are two random numbers uniformly distributed in the range of (0,1).

The effect of the previous velocity and the resultant force affecting a CP can be controlled by the values of k_v and k_a , respectively. Excessive search in the early iterations may improve the exploration ability; however it must be decreased gradually in order to increase the exploitation ability. Since k_a is the parameter related to the attracting forces, it works as a control parameter of the exploitation property [5]. Therefore, choosing a linear incremental function (from 1 in initial to 1.5 at last) can improve the performance of the algorithm. Also, the direction of the previous velocity of a CP is not necessarily the same as the resultant force. This shows that the velocity coefficient k_v controls the exploration process and therefore a linear decreasing function (from 2 in the start to 0.5 in the end) can be selected.

Step 4: Updating process. If a new CP exits from the allowable search space, a harmony search-based handling approach is used to correct its position. According to this mechanism, any component of the solution vector violating the variable boundaries can be regenerated from the CM (charged memory) or by randomly choosing one value from the possible range of values. This mechanism will only be used for the CPs which exist from the allowable search space to become their solution practical. For more details, the reader may refer to [28]. In addition, if some new CP vectors are better than the worst ones in the CM, they are included instead of the worst ones in the CM.

Step 5: Terminating criterion control. Steps 2–4 are repeated until a terminating criterion is satisfied. The terminating criterion is one of the following conditions (the one which occurs earlier):

- 1) *Maximum distance of CPs:* the maximum distance between CPs is less than a pre-determined value ($3 \times a$ in this paper); or
- 2) *The maximum number of iterations:* the optimization process is terminated after a fixed number of iterations.

For many heuristic algorithms it is a common feature that if all the agents get gathered in a small space, i.e., if the agents are trapped in part of the search space, escaping from this may be very difficult. Since prevailing forces for the CSS algorithm are attracting forces, it looks as if the above problem has remained unsolved for this method. However, having a good balance between the exploration and the exploitations, and considering three steps containing self-adaptation, cooperation and competition, can solve this problem [5]. These three essential concepts are considered in this algorithm. Moving towards good CPs provides the self-adaptation step. Cooperating CPs to determine the resultant force acting on each CP supplies the cooperation step and having larger force for a good CP, compared to a bad one, and saving good CPs in the CM provide the competition step.

4.2. CSS algorithm-based water distribution network optimization procedure

Application of meta-heuristics falls into a large number of areas; one of them is optimal pipelines sizing for water distribution systems. As it was mentioned previously in Section 3, size optimization of water distribution systems involves determining optimum values for pipe diameters that minimize the cost. This minimum design should also satisfy the conservation of mass and energy and minimum pressure requirements, Eqs. (1 and 2).

The CSS algorithm initiates the design process by selecting random values for the design variables. Then the algorithm checks the pressure head at each node and calculates the cost

(Figure 1). In this procedure choosing design parameters that fulfill all design requirements and have the lowest possible cost is concerned, i.e. the main objective is to comply with basic standards but also to achieve good economic results.

In order to handle the constraints, a penalty approach is utilized. If the constraints are between the allowable limits, the penalty is zero; otherwise the amount of penalty is obtained by dividing the violation of allowable limit to the limit itself. After analyzing a model, the pressure of each node is obtained then these values are compared to the allowable limits to calculate the penalty functions as:

$$\begin{cases} H_j^{\min} \leq H_j & \Rightarrow \Delta^{(j)} = 0 \\ H_j^{\min} > H_j & \Rightarrow \Delta^{(j)} = \frac{H_j^{\min} - H_j}{H_j^{\min}} \end{cases} \quad j = 1, 2, \dots, N_n \quad (10)$$

In this method, the aim of the optimization is redefined by introducing the cost function as:

$$F_{\text{cost}} = (1 + \varepsilon_1 \cdot \sum \Delta^{\varepsilon_2}) \times f_{\text{cost}} \quad (11)$$

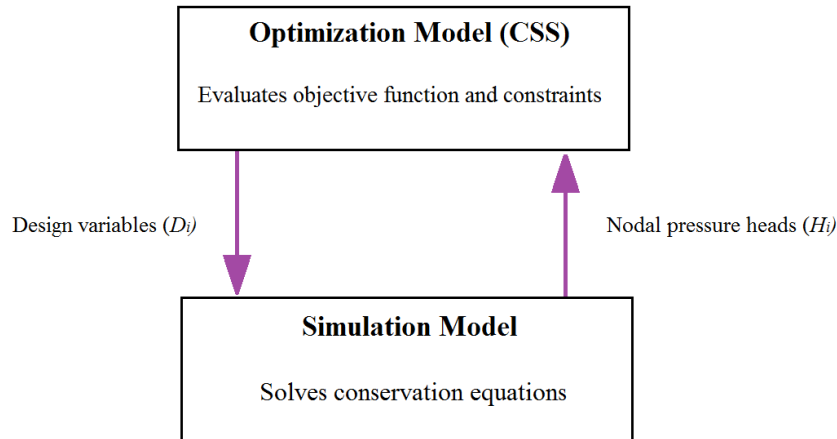


Figure 1. Optimization-simulation model link for the CSS method

The penalty function method has certain drawbacks, for example penalty parameters are problem dependent and needs proper parameter tuning to converge to the feasible domain. When the penalty parameters are large, penalty functions tend to be ill-conditioned near the boundary of the feasible domain and this may result in a local optimal solution or an infeasible solution [29]. In this case, repeated runs are suggested by varying the penalty parameter until satisfactory results are obtained. Here the constant ε_1 and ε_2 are selected considering the exploration and the exploitation rate of the search space. ε_1 is set to unity and ε_2 is selected in a way that it decreases the penalties and reduces the variables. Thus, in the first steps of the search process, ε_2 is set to 1.05 and ultimately increased to 1.2.

5. DESIGN EXAMPLES

In this section, common design examples as benchmark problems are optimized with the proposed method. The final results are compared to the solutions of other methods to demonstrate the efficiency of the present approach. In order to investigate the effect of the initial solution on the final result and because of the stochastic nature of the algorithm, each example is independently solved 20 times. The initial population in each of these runs is generated in a random manner. These examples include three well-known networks:

- Hanoi network
- Double Hanoi network
- New York Water Supply System

The first problem is proposed by Fujiwara and Khang [13]. This network consists of 32 nodes, 34 pipes and 3 loops. The network has no pumping station as it is fed by gravity from a reservoir with a 100 m fixed head. The second design example is double Hanoi network. Because this network is derived from the basic Hanoi network, its optimal cost is known. All the parameters for the reservoir, nodes and lines in the double Hanoi water distribution network are the same as in the original Hanoi network. The third test problem concerns the rehabilitation of the New York City water supply network with 21 pipes, 20 demand nodes, and one reservoir. This example first presented by Shaake and Lai [30], in which the existing gravity flow tunnels are inadequate to meet the pressure requirements, therefore new pipes can be added in parallel to the existing ones.

5.1. Hanoi Water Distribution Network

For this example the system data are presented in Table 1. Hanoi network (Figure 2.) requires the optimal design of 34 pipes, allowing a minimum hydraulic head of 30 m for all its 32 nodes, by means of 6 available diameters. The total solution space is then equal to $6^{34} = 2.87 \times 10^{26}$. The cost of commercially available pipe sizes {12, 16, 20, 24, 30, 40; in inches} is {45.73, 70.40, 98.38, 129.30, 180.80, 278.30 in dollar/meter}.

Table 1: Hanoi network data

Node number	Demand (m ³ /h)	Pipeline	Length (m)	CSS optimal diameter (in)
01	–	01	100	40
02	890	02	1350	40
03	850	03	900	40
04	130	04	1150	40
05	725	05	1450	40
06	1005	06	450	40
07	1350	07	850	40
08	550	08	850	40
09	525	09	800	40
10	525	10	950	30
11	500	11	1200	24
12	560	12	3500	24

13	940	13	800	20
14	615	14	500	16
15	280	15	550	12
16	310	16	2730	12
17	865	17	1750	16
18	1345	18	800	24
19	60	19	400	20
20	1275	20	2200	40
21	930	21	1500	20
22	485	22	500	12
23	1045	23	2650	40
24	820	24	1230	30
25	170	25	1300	30
26	900	26	850	20
27	370	27	300	12
28	290	28	750	12
29	360	29	500	16
30	360	30	2000	12
31	105	31	1600	12
32	805	32	150	16
		33	860	16
		34	950	24

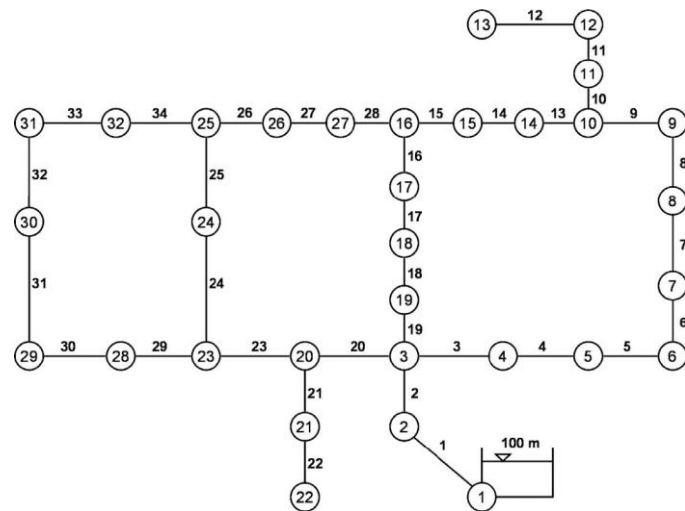


Figure 2. Network layout for the Hanoi problem

Table 2 reports the best results and the required number of analyses for convergence in the present algorithm and some of other heuristic methods. In this example, a population of 30 individuals is used and CSS found the best feasible solution of 6.081×10^6 \$ after 548 iteration (16,440 analysis). The hydraulic head for each node is shown in Figure 3. As shown in this figure the minimum value for pressure head is equal to 30.0061 m (in node 11). The best cost of the SCE [17], ACO [31], MENOME [26], and PSO [32] is 6.220,

6.134, 6.173, and 6.093 million dollars, respectively. Also the minimum cost obtained by the GENOME [25], TS [33], PSHS [34], and GHEST [35] is 6.081×10^6 \$ after 50000, 40200, 17980, and 16,600 function evaluations, respectively. The convergence history of the results obtained by the CSS algorithm is shown in Figure 4.

Table 2. Performance comparison for the Hanoi network

Method*	Cost (10^6 \$)	No. of analysis
SCE [17]	6.220	25,402
MENOME [26]	6.173	26,457
ACO [31]	6.134	85,600
PSO [32]	6.093	6,600
GENOME [25]	6.081	50,000
TS [33]	6.081	40,200
PSHS [34]	6.081	17,980
GHEST [35]	6.081	16,600
CSS (<i>present work</i>)	6.081	16,440

* For all methods $\omega = 10.6668$

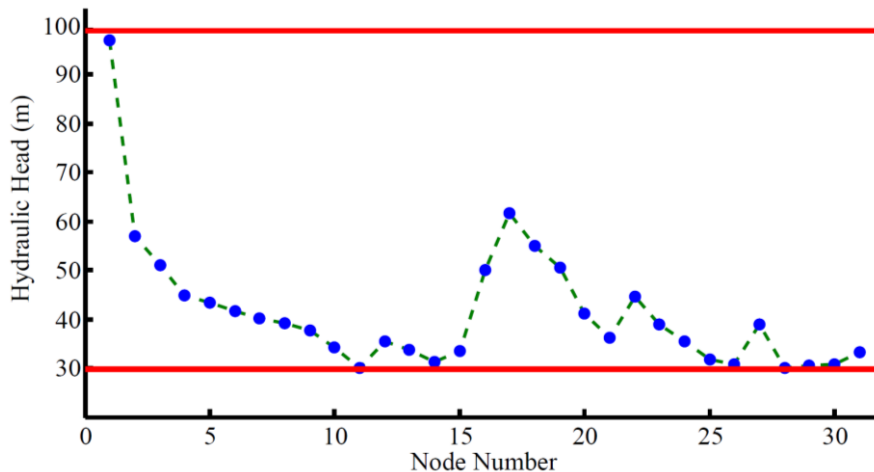


Figure 3. Comparison of the allowable and existing hydraulic head for the nodes of the Hanoi network using CSS

5.2. Double Hanoi network

Network layout for this problem is shown in Figure 5. All the parameters for the reservoir, nodes and lines in the double Hanoi water distribution network are the same as in the original Hanoi network on both mirrored parts except for the first pipe (from the reservoir to node 2), which is shortened from the original 100 to 28.9 m. This change was made for the sake of obtaining the same head in node 2 (with a diameter of 40 in, which will certainly be proposed here by any optimization method) as in the original Hanoi network. In such conditions the optimal solution for the double Hanoi network should have the same diameters on the corresponding pipes as in the original Hanoi network (on both mirrored

parts). The total solution space is then equal to $6^{67} = 1.37 \times 10^{52}$.

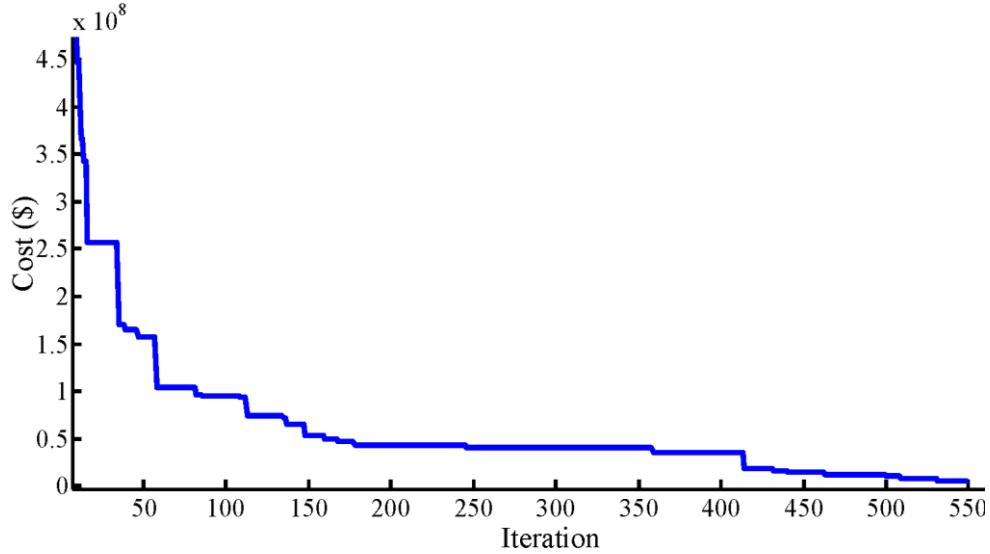


Figure 4. The convergence history for the Hanoi network using the CSS algorithm

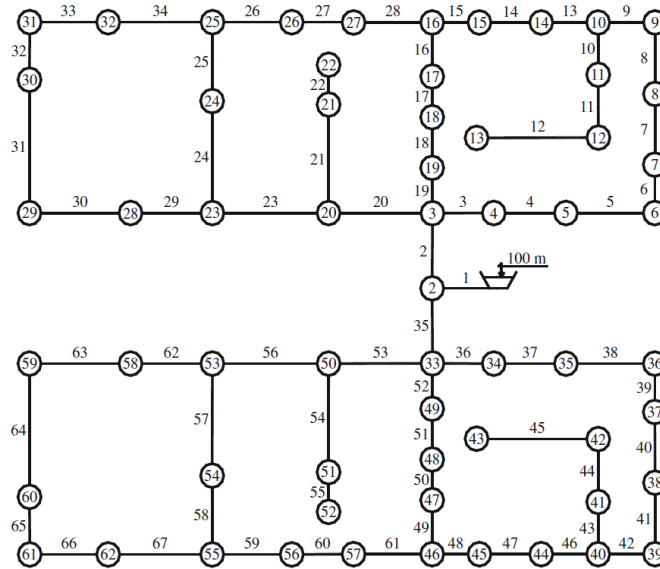


Figure 5. Double Hanoi network

In node 2 the same demand is as in the original Hanoi network; it is not doubled. Under these conditions the *reference* optimal solution (global) could be evaluated as follows [36]:

$$C_{DH} = 2C_H - 2L_1C_1 + 28.9C_1 \quad (12)$$

in which C_{DH} is the optimal cost of the double Hanoi network; C_H is the reference optimal

cost of the Hanoi network (6.081×10^6 \$); L_1 is the length of the first pipe on the original network (100 m); and C_1 is the unit price of diameter 40 in (278.28 \$).

For our solution described in the previous example (6.081×10^6 \$), according to Eq. 13 the global optimum solution of the double Hanoi network should be 12.114×10^6 \$. The best results obtained with CSS, GALP, GA, OptiDesigner, and the HS [36] are summarized in Table 3. The reference optimal cost of the Hanoi network for CSS, HS, and GA is 6.081×10^6 \$. But CSS found the best feasible solution of 12.119×10^6 \$ after 100,000 analysis (a population of 50 CPs is used) and the best cost for the HS and GA are 12.405 and 12.601 million dollars, respectively. In addition, deviation from global optimum (12.114×10^6 \$) for the CSS algorithm is 0.04%, while it is 2.39% and 4.01% for the HS and GA, respectively. This result demonstrates that the CSS algorithm is better in term of closeness to the global minimum. The Convergence history for double Hanoi network using the CSS algorithm is shown in Figure 6.

Table 3: Performance comparison for the Double Hanoi network

Method	Hanoi network	Double Hanoi network	Deviation from reference global optimum (%)
CSS (<i>present work</i>)	6,081,087	12,118,706	0.04
GALP [36]	6,057,697	12,073,039	0.04
HS [36]	6,081,087	12,404,680	2.39
GA [36]	6,081,087	12,600,624	4.01
OptiDesigner [36]	6,115,055	12,795,541	5.62

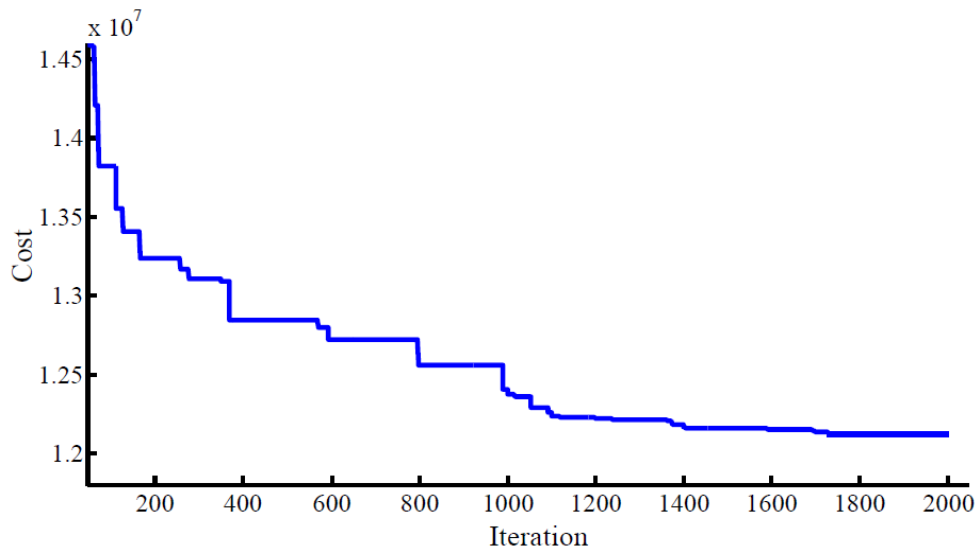


Figure 6. The convergence for the double Hanoi network using CSS algorithm

5.3. The New York City water supply tunnels

A number of studies in pipe network optimization have examined the expansion of the New York water supply system. The common objective of the studies was to determine the most economically effective design for additions to the then-existing system of tunnels that constituted the primary water distribution system of the city of New York (Figure 7). For each of the tunnels there is the option to leave the tunnel (e.g. a null option) or the option to provide a duplicate tunnel with one of fifteen different diameter sizes. i.e., 16 possible decisions including the do nothing option and 21 pipes to be considered for duplication, the total solution space is $16^{21} = 1.93 \times 10^{25}$ possible network designs. The Hazen-Williams coefficient value for new pipes is taken as 100. For summaries of system data and unit costs of tunnel network, please refer to [37].

Table 4 shows the best cost and the required number of analyses for convergence of the present algorithm and some other meta-heuristic algorithms. The CSS-based algorithm needs 2000 analyses to find the best solution while this number is equal to 7014, 4475, 3373, 2400 and 2100 analyses for ACO [22], PSHS [34], HS [34], PSO [38] and GHEST [35], respectively. It means that, CSS algorithm appeared really fast, since the required number of analysis is the best performance published to date. CSS approach obtained the best cost of 38.64×10^6 \$, this optimal solution indicates an excellent agreement with the previous designs reported in the literature. In addition the difference between the best and the worst results of this problem for CSS in 20 tests is 3.61% and the average cost is 40.08×10^6 \$. The minimum nodal pressure requirement for all nodes, except 16 and 17, is 255 ft and for nodes 16 and 17 it is 260 ft and 272.8 ft, respectively, while the pressure heads for these critical nodes (16, 17, and 19) obtained by CSS is 260.08 ft, 272.87 ft, and 255.05 ft, respectively.

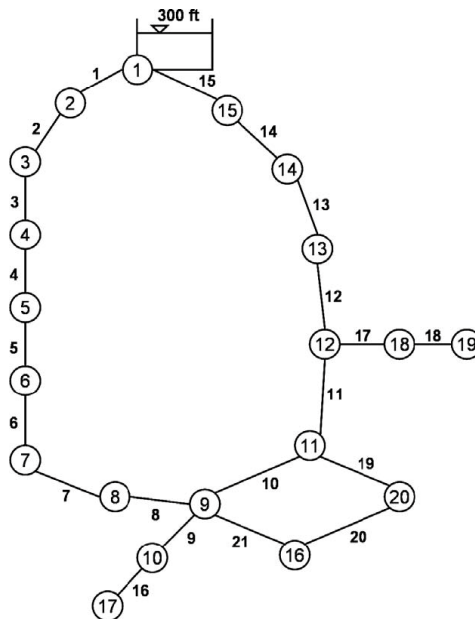


Figure 7. General layout of New York network

Table 4. Performance comparison for the New York Tunnel problem

Method*	Cost (10 ⁶ \$)	No. of analyses	ω
GA [24]	40.42	10 ⁶	10.9031
TS [33]	40.42	35,300	10.9031
ACO [22]	38.64	7014	10.6668
PSHS [34]	38.64	4475	10.6668
HS [34]	38.64	3373	10.6668
PSO [38]	38.64	2400	N/A
GHEST [35]	38.64	2100	10.6668
CSS (<i>present work</i>)	38.64	2000	10.6668

6. DISCUSSION AND CONCLUSION

This paper applies a new algorithm for discrete cost optimization of water distribution networks, so called the charged system search (CSS) based on some basic laws of physics and mechanics. The optimal network design algorithms are computationally complex and generally belong to a group of NP-hard problems. Thus the new population based algorithms can be more promising. In this direction in this article we have used the CSS-based model which contains three levels and some sub-levels as follow:

Level 1: Initialization

- **Step 1: Initialization.** Initialize CSS algorithm parameters; Initialize an array of Charged Particles with random positions and their associated velocities.
- **Step 2: CP ranking.** Evaluate the values of the fitness function for the CPs, compare with each other, and sort increasingly.
- **Step 3: CM creation.** Store CMS number of the first CPs and their related values of the objective function in the CM.

Level 2: Search

- **Step 1: Attracting force determination.** Determine the probability of moving each CP toward others, and calculate the attracting force vector for each CP.
- **Step 2: Solution construction.** Move each CP to the new position and find the velocities.
- **Step 3: CP position correction.** If each CP exits from the allowable search space, correct its position using a harmony search-based handling approach.
- **Step 4: CP ranking.** Evaluate and compare the values of the objective function for the new CPs, and sort them increasingly.
- **Step 5: CM updating.** If some new CP vectors are better than the worst ones in the CM, include the better vectors in the CM and exclude the worst ones from the CM.

Level 3: Terminating criterion controlling

The terminating criterion is one of the following:

- **Maximum number of iterations:** the optimization process is terminated after a fixed

number of iterations.

- Number of iterations without improvement: the optimization process is terminated after some fixed number of iterations without any improvement.
- Minimum objective function error: the difference between the values of the best objective function and the global optimum is less than a pre-fixed anticipated threshold.

Compared to ACO, both CSS and ACO are randomized search techniques which contain a number of agents. The ant algorithms are based on the indirect pheromone communication capabilities of the ants, while CSS is based on the direct effect of the electrical forces. The quality of the solutions can affect the optimization process in both algorithms. The ACO is a discrete algorithm while the CSS is essentially a continuous one. In the ACO method, the probability of selecting a good section is higher than the others and the pheromone of a good section will increase favoring the section to be selected by more ants. Similarly, for the CSS, a good solution creates a bigger force than others and attracts more CPs. This results in having more searches around the good solution and increases the probability of finding better solution vectors.

The HS algorithm, similar to CSS, includes a memory storing the feasible vectors. A new harmony vector is generated from the harmony memory, the memory considerations, pitch adjustments, and randomization. In the HS, in each iteration only one solution vector is generated, while in the CSS a number of CPs is created. The HS utilizes the stored vectors in HM to create new vectors directly, while CSS uses the stored vectors in determining the electrical forces. Only when a CP swerves from the search space, the charged memory is utilized directly. In special conditions, the CSS works as a HS method and uses some of operators of the HS algorithm as an auxiliary tool.

In order to demonstrate the performance of the CSS, it is applied to the design of three water distribution networks (Hanoi, Double Hanoi, and New York network). Compared to other meta-heuristics such as GA, TS, PSO, HS and ACO, the CSS has less computational cost and can determine the optimum result with a smaller number of analyses. The comparison of the results of the CSS results with those of the other heuristics shows the performance of the present algorithm and demonstrates the efficiency of the algorithm in finding the optimum design of water distribution networks. The future works should focus on expanding the CSS-based algorithm to other fields of optimization due to high potential of the algorithm in solving difficult optimization problems. Simultaneous optimization of topology and geometry of pipe networks is one of these problems.

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