Ant-colony-based simulation–optimization modeling for the design of a forced water pipeline system considering the effects of dynamic pressures

H. Abbasi, A. Afshar and M. R. Jalali

ABSTRACT

Valve and pump shut-off in water pipeline systems lead to transient flow. This flow is a complex phenomenon and is potentially a very serious problem causing extra dynamic pressure in the system. Within the last few decades, the evolutionary and meta-heuristic algorithms, such as genetic algorithms, simulated annealing. More recently, however, ant-colony optimization algorithms have received considerable attention. In this paper the procedure and application of the ant-colony optimization algorithm to the design of a water supply pipeline system, considering dynamic pressures arising from valve closure, is presented. A simulation–optimization interaction loop (SOIL) is defined that cycles between the steady-state and transient flow modules to describe the hydraulics of the pipeline and ant colony optimization algorithm. A hydraulic simulation module is coupled with the ant colony optimization algorithm to form an efficient and powerful software program which locates the pumping stations at any possible or predefined locations while optimizing their specifications, along with pipe diameters, at each decision point. The model may equally regard or disregard the dynamic pressures.

Two examples are provided to illustrate the proposed methodology which is limited to the solution of any gravity and/or forced water supply pipeline which is typical for water supply systems.

Key words | ant colony, conveyance system, optimum design, simulation–optimization, transient flow

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NOTATION

The following symbols are used in this paper:

C set of costs associated with the options $\{c_{ij}\}$
D set of decision points $\{d_i\}$
G graph (D,L,C)
$G^{k^*_{gb}}$ value of the objective function for the ant with the best performance within the past total iterations
L set of options $\{l_{ij}\}$
α, β parameters that control the relative importance of the pheromone trail versus a heuristic value
η_{ij} heuristic value representing the cost of choosing option l_{ij} at decision point i
ρ pheromone evaporation coefficient
τ_0 initial value of pheromone
$\tau_{ij}(t)$ concentration of pheromone on arc (i,j) at iteration t
k^*_{gb} ant with the best performance within the past total iterations
$P_{ij}(k,t)$ probability that ant k selects option l_{ij} for decision point i at iteration t
q random variable uniformly distributed over [0, 1]
q_0 tunable parameter $\in [0, 1]$
$f_i(D_i)$ cost function for pipes with diameter D_i at reach i
$g_j(HP_j)$ cost function for pumping station with pumping HP_j head at node j

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NR number of reaches
NN number of nodes
V_{min}, V_{max}, H_{min}, H_{max} the minimum and maximum allowable velocities at all reaches and minimum and maximum allowable piezometric head at all nodes, respectively
NI number of SOIL

INTRODUCTION

Minimization of the capital and operational costs of water conveyance systems has received considerable attention during the last few decades (Gupta 1969; Martin 1997; Jabbari & Afshar 2002). Dynamic programming has successfully been used to determine the optimal solution to an approximation of the complete pipeline design problem (Martin 1990). The selected design specifies the number and sizes of the pumping stations, length, diameter and the pressure classes of the pipeline at the beginning of each stage interval over the planning period.

Luettinger & Clark (2005) developed a geographical information system based route selection process to provide a rational basis for narrowing the existing potential alternatives into a final alignment corridor. Afshar et al. (1990) developed a dynamic programming model to optimally integrate hydropower plant into a water supply main.

Within the past decade the focus has shifted to the use of search-based evolutionary and meta-heuristic algorithms, such as genetic algorithms, simulated annealing and, more recently. honey bees mating optimization and ant colony optimization (ACO) algorithms (Bozorg Haddad et al. 2008). The search-based optimization algorithms seem to be more easily coupled to computationally expensive simulation models. They are also more powerful in handling nonlinear, non-convex problems.

ACO algorithms, using principles of communicative behavior occurring in real ant colonies, have successfully been applied to solve various combinatorial optimization problems. Examples include: the traveling salesman problem (Dorigo et al. 1996), the quadratic assignment problem (Gamberdella et al. 1999; Maniezzo & Colorni 1999), the job shop scheduling problem (Colorni et al. 1994) and the resource-constraint project scheduling problem (Merkle et al. 2000). For an excellent overview on ant algorithms see Dorigo & Di Caro (1999).

However, very few applications of ACO algorithms to water resources problems have been reported. Abbaspour et al. (2001) employed an ACO algorithm to estimate the hydraulic parameters of unsaturated soils. Maier et al. (2003) used ACO algorithms to find a near-global optimal solution to a water distribution system. They concluded that ACO algorithms might form an attractive alternative to genetic algorithms for the optimal design of water distribution systems. Jalali et al. (2006) employed the ACO procedure to operate optimally a multi-reservoirs system. Abbasi et al. (2006) developed an ACO-based approach to optimally design a water pipeline system under static flow regime. Kobayashi et al. (2008) presented a challenge to real-world simulation–optimization modeling in a development of multi-phase systems in the subsurface.

Search-based meta-heuristic ACO algorithms seem quite suitable for simulation–optimization problems. Successful coverage of the search space with a limited number of search points results in a near-optimal solution with a limited number of highly expensive simulation runs.

In this paper, the procedure and application of ACO algorithms to the design of a water supply pipeline system, considering dynamic pressures arising from valve closure, is presented. A simulation–optimization interaction loop (SOIL) is defined that cycles between the steady-state and transient flow modules to couple the hydraulic behavior of the pipeline (i.e. the simulator) and the ant colony optimization algorithm (the optimizer). The exchange of information between the simulator and the optimizer in the interaction loop facilitates convergence to a near-optimal solution. The coupled hydraulic simulation module and the ACO algorithm locate the pumping stations at any possible or predefined locations and optimize their specifications along with pipe diameters at each decision point. The model may equally regard or disregard the dynamic pressures resulting from the valve closure.

ANT-COLONY OPTIMIZATION

An interesting and very important behavior of ant colonies is their foraging behavior and, in particular, their ability to find the shortest route between their nest and a food source, provided that they are almost blind. The path taken by individual ants from the nest to the food source is essentially random (Dorigo *et al.* 1996). However, when they are traveling, ants deposit a communication substance, named a pheromone. The pheromone trail forms an indirect means of communication. As more ants choose a path, the pheromone on the path builds up and makes it more attractive for other ants to follow the path.

Presentation of the problem as a graph seems essential for the successful application of ACO algorithms to real-world engineering problems. Let's define a graph $G = (D,L,C)$, in which $D = \{d_i\}$ is the set of decision points at which some decisions are to be made, $L = \{l_{ij}\}$ identifies the set of options $j = 1, \ldots,$ NC, at each decision point $i = 1, \ldots,$ NT and $C = \{c_{ij}\}$ is the set of rewards or costs associated with option $L = \{l_{ij}\}$. A feasible path on the graph is called a solution $(\phi)_k$ and the path with maximum reward or minimum cost is called the optimum solution $(\phi*)_k$. In the ACO algorithm, artificial ants are permitted to release pheromone while a solution is developing, after a solution has been fully developed, and/or both. The amount of pheromone deposited is made proportional to the goodness of the solution an artificial ant develops. Rapid drift of all ants towards the same part of the search space is avoided by employing a stochastic component of the choice decision policy and the numerous mechanisms, such as pheromone evaporation, explorer ants, local search and pheromone re-initiation (Montgomery & Randall 2002).

The transition rule used in the original ant system is defined as (Dorigo *et al.* 1996)

$$P_{ij}(k,t) = \begin{cases} \frac{[\tau_{ij}(t)]^{\alpha}[\eta_{ij}]^{\beta}}{\sum_{j=1}^{J}[\tau_{ij}(t)]^{\alpha}[\eta_{ij}]^{\beta}} & \text{if } j \in N_k(i) \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

where P_{ij} (k,t) is the probability that ant k selects option l_{ij} for decision point i at iteration t, $\tau_{ij}(t)$ is the pheromone concentration on arc (i,j) at iteration t, η_{ij} is the heuristic value associated with choosing option l_{ij} at decision point i, $N_k(i)$ is the feasible neighborhood of ant k when located at decision point i, and α and β are two parameters that control the relative importance of the pheromone trail and heuristic value. The heuristic value η_{ij} is analogous with providing the ants with artificial sight and is sometimes called visibility (Dorigo *et al.* 1996). In static problems, the heuristic value is calculated once at the start of the algorithm and remains unchanged during the computation process. In this study, the heuristic value is determined as

$$\eta_{ij} = 1 - \frac{C_{ij}}{\sum_{j=1}^{J} C_{ij}} \quad \text{if } j \in N_k(i) \quad (2)$$

The next node j where ant k chooses to move may be selected as (Dorigo & Gambardella 1997*a*)

$$j = \begin{cases} \arg\max_{l \in N_k(i)}\{[\tau_{il}(t)]^{\alpha}[\eta_{il}]^{\beta}\} & \text{if} \quad q \le q_0 \\ J & \text{otherwise} \end{cases} \quad (3)$$

where J is a value of a random variable selected according to the probability distribution of $P_{ij}(k,t)$ (see Equation (1)), q is a random variable uniformly distributed over [0,1] and $q_0 \in [0,1]$ is a tunable parameter. The ants are guided to move towards the optimal regions of the search space using probabilistic decision policy defined by Equations (1) and (2). The balance between the exploration of new points in the state-space and the exploitation of accumulated knowledge is determined by the level of stochasticity in the policy and the strength of the updates in the pheromone trail (Dorigo & Gambardella 1997*b*). The global trail updating is done as follows:

$$\tau_{ij}(t+1) = (1-\rho)\tau_{ij}(t) + \rho\Delta\tau_{ij}(t) \quad (4)$$

where $\tau_{ij}(t+1)$ is the amount of pheromone trail on option l_{ij} of the ith decision point at the $(t+1)$th iteration, $0 \le \rho \le 1$ is a coefficient representing the pheromone evaporation rate and $\Delta\tau_{ij}(t)$ is the change in pheromone concentration associated with arc (i,j) at iteration t. The amount of pheromone $\tau_{ij}(t)$ associated with arc (i,j) is intended to represent the learned desirability of choosing option l_{ij} when at decision point i.

Various methods have been suggested for calculating the pheromone changes. The method used here was originally suggested by Dorigo & Gambardella (1997*a*) in which only the ant which produced the globally best solution from the beginning of the trail (ACS_{gb}) was allowed to contribute to pheromone change:

$$\Delta\tau_{ij}(t) = \begin{cases} 1/G^{k^*_{gb}} & \text{if } (i,j) \in \text{tour done by ant } k^*_{gb} \\ 0 & \text{otherwise} \end{cases} \quad (5)$$

where $G^{k^*_{gb}}$ is the value of the objective function for ant k^*_{gb} with the best performance within the past total iterations.

In this problem, decision points are attributed both to nodes and arcs. Specifically, the pumping head and pumping station locations are attributed to the nodal decision points, whereas pipe diameters and/or energy losses per unit length of the nominated pipes forming another set of decision variables are attributed to the arc decision points. Therefore, the decision graph includes a combination of nodal and arc decision points as depicted in Figure 1.

SYSTEM IDENTIFICATION AND MODEL STRUCTURE

The proposed system for modeling is a pressurized water supply pipeline system with a predefined layout. A water supply pipeline may consist of n pipe segments and $n+1$ nodes, with the possible inclusion of a pumping station at each node (Figure 1). Control valves may be located at each turnoff point on the main line, as well as at the termination node. The turnoff points are assumed to be at the end of each pipe segment. Control valves at the turnoff points may be used for water division and delivery to offline demand points, if needed.

In design offices, it is common practice to prepare a preliminary hydraulic design with steady state assumptions. The resulted preliminary pipe diameters are used in a transient flow model to estimate the pressure build-up due to sudden valve closure and/or pump failure. The sum of the static pressure and transient pressure build-up is usually used as the maximum possible pressure for determining the pipe characteristics, such as the type of pipe and/or its thickness. It is quite clear that this one-cycle loop may result in a more or less conservative design.

The proposed optimization model intends to find the best combination of pipe diameters at each section and location of the possible pumping stations as well as their design specifications. Realizing the formation of transient flow by valve closure and/or pump failure, the model must couple a transient flow simulator and an optimization module. The optimizer intends to optimize the hydraulic elements of the system in a static mode, using the ACO algorithm. In fact, considering pipe diameters, location of pumping stations and their characteristics as decision variables, the optimizer minimizes the total cost of the system to satisfy a pre-defined demand and assumed

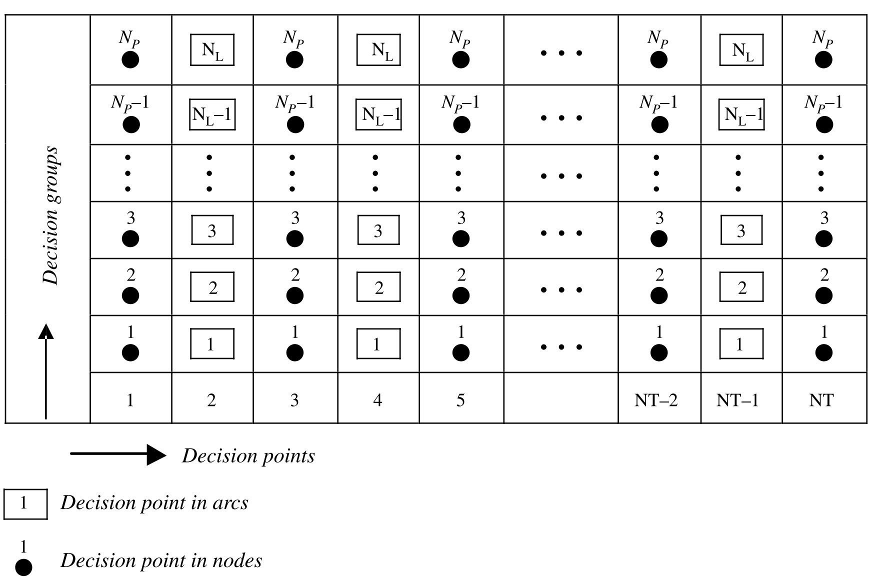

Figure 1 | Decision graph in water conveyance system design.

hydraulic constraints under a static flow regime. The design parameters developed in the first stage forms the input to the transient flow simulator to calculate the maximum and minimum pressures resulting from the assumed valve(s) closure policy. To describe the cycle between the steady-state flow model, the transient flow model and the proposed optimization algorithm, a SOIL is defined (Figure 2). In an iterative scheme, the maximum pressure violation from the maximum allowable pressure may now be determined. For the next SOIL, the associated constraints in the static model are relaxed by the maximum pressure violation computed in the previous SOIL.

In this study, the target function is the total investment cost. In a mathematical formulation, one may define the model as

$$\text{Min cost} = \sum_{i=1}^{\text{NR}} f_i(D_i) + \sum g_j(\text{HP}_j) \tag{6}$$

subject to:

$$f_k = 10.7 \times L_k \times \left(\frac{Q}{C_H}\right)^{1.852} \times \frac{1}{D_k^{4.87}} \quad k = 1, \ldots, \text{NR} \tag{7}$$

$$H_j - H_i - f_k + \text{HP}_j = 0 \quad k = 1, \ldots, \text{NR} \tag{8}$$

$$V_{\min} \leq V_k \leq V_{\max} \quad k = 1, \ldots, \text{NR} \tag{9}$$

$$D_{\min} \leq D_k \leq D_{\max} \quad k = 1, \ldots, \text{NR} \tag{10}$$

$$H_{\min} \leq H_l \leq H_{\max} \quad l = 1, \ldots, \text{NN} \tag{11}$$

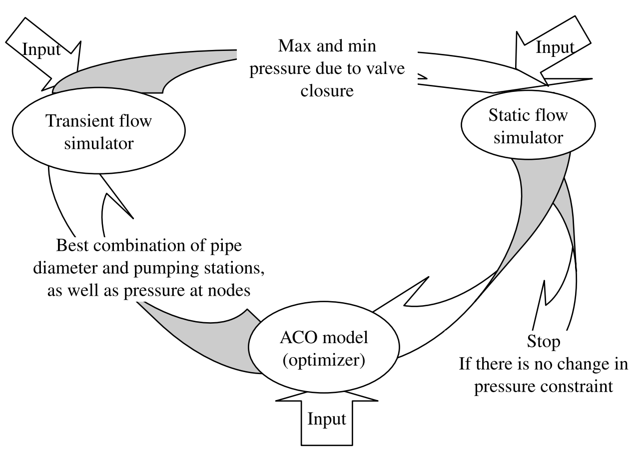

Figure 2 | Interaction between the static and transient simulator and the ant colony optimization model (optimizer).

where $f_i(D_i)$ is the cost function for pipe with diameter D_i at reach I, $g_j(\text{HP}_j)$ is the cost function for pumping station with pumping head HP_j at node j, f_k is the friction head loss at reach k; L is the length of the pipe at reach, C_{H} is the Hazen–William's coefficient, H is the piezometric head, V_k is the velocity at reach k, NR is the number of reaches, NN is the number of nodes and $V_{\min}$, $V_{\max}$, $H_{\min}$, $H_{\max}$ are the minimum and maximum allowable velocities at all reaches and minimum and maximum allowable piezometric head at all nodes, respectively.

In constraint (11), the values of H_{l} are determined using a static flow simulation model. However, to revise the upper and lower bounds on the maximum and minimum allowable heads in Equation (11), the transient flow simulation model is employed at each SOIL (Figure 2). For the given design vector from the ACO model, the transient flow simulation model is executed and the maximum pressure associated with any valve closure rule is determined. The maximum deviation from the assumed $H_{\max}$ in the previous SOIL is used to relax the upper limit on H_{l} to be used in the next SOIL. In other words, the maximum allowable pressure, $H_{\max}$, is no longer a fixed value; it varies at different SOIL as the new head distribution results from the transient flow simulation model. The SOIL ends if the maximum pressure resulting from the transient flow simulation model approaches the relaxed maximum allowable head in the previous SOIL.

It is important to note that, within each SOIL, the minimum and maximum allowable pressures are tightened based on the final solution of the ant-colony optimization solver. In another words, in each SOIL, the ACO model is executed as many times as required for the static optimization model to converge to a desirable near-optimal solution. Therefore, a limited number of cycles are needed for adjusting the ACO solution to account for the dynamic pressure changes resulting from the transient flow simulation module. The cycles on SOIL are terminated when all constraints with newly modified right-hand side values (i.e. tightened minimum and maximum allowable pressure) are fully satisfied.

To make the problem solvable with the proposed ACO algorithm, the search space has to be discretized. In fact, ACO algorithms have been developed and extended for

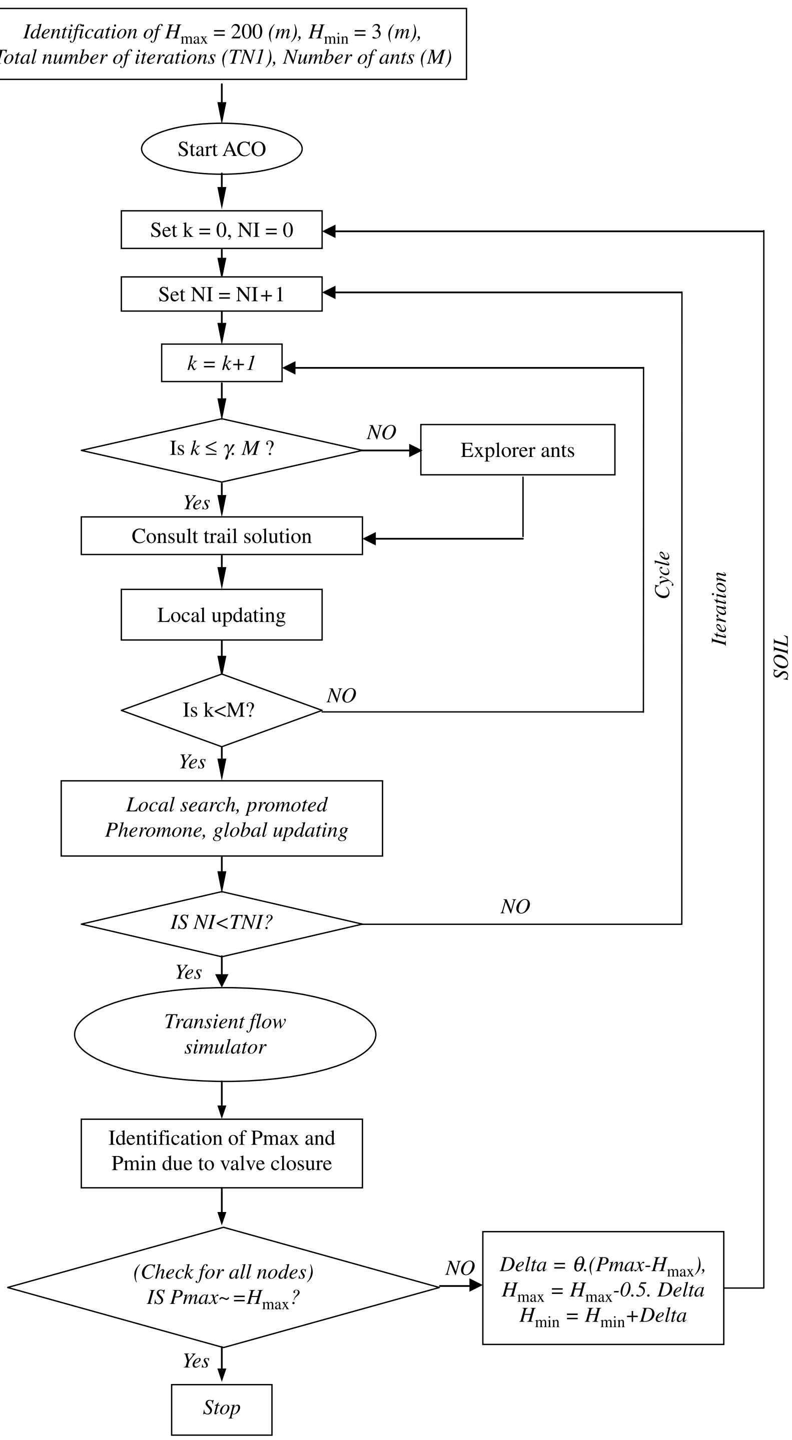

Figure 3 | The details of the interaction between simulation and optimization models.

discrete optimization problems (Dorigo *et al.* 1999). Although new developments on ACO have provided a promising environment for the solution of continuous problems (Socha & Dorigo 2006; Jalali *et al.* 2007), in this study the discrete version of the algorithm has been employed. The possible ranges of the hydraulic grade line have been identified as the search space. Therefore, assuming a minimum and maximum allowable pressure on the pipeline, the hydraulic grade line assumes a maximum and minimum value at each node. Based on the minimum pressure requirement at each node and the maximum tolerable pressure by the pipe (i.e. 3 and 200 m in this example, respectively), and considering the maximum possible pressure build-up due to the valve closure, the range of possible hydraulic grade lines at each node has been discretized into classes with 3 m intervals. Ideally the finer discratization scheme should result in more precise and desirable values for the decision variables (i.e. pipe diameters and/or pumping heads): however, an extremely fine discretization scheme of the ACO application may result in inferior solutions due to the dramatic increase in possible paths to be taken by the ants.

For transient flow, two basic equations–Newton's second law of motion and the continuity equation–are applied to different segments of the fluid to obtain the governing differential equations. The dependent variables are the elevation of hydraulic grade line, H, above a fixed datum and the average velocity, V, at a cross section. The independent variables are distance, x, along the pipe segment measured from the upstream end and time t; hence, $H = H\ (x, t)$, $V = V\ (x, t)$. The unsteady continuity

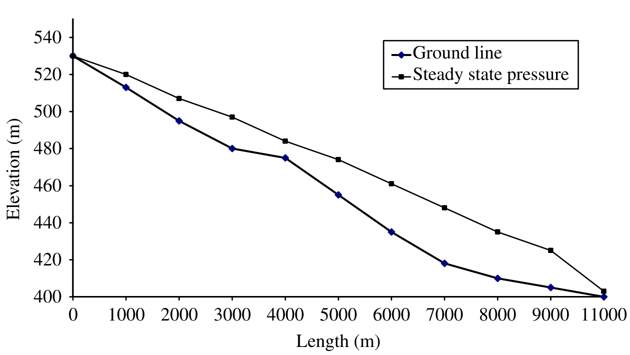

Figure 4 | The optimal design of the gravity system under steady state flow (first example).

Table 1 | Results of ACO applied to the gravity system (continuous solution) (first example)

No. pipe segment	Diameter (m)	Length (m)	V (m³/s)
1	0.43	1,000	2.1
2	0.40	1,000	2.4
3	0.43	1,000	2.1
4	0.40	1,000	2.4
5	0.43	1,000	2.1
6	0.40	1,000	2.4
7	0.40	1,000	2.4
8	0.40	1,000	2.4
9	0.43	1,000	2.1
10	0.48	2,000	1.7
Total cost			1,112,777

equation and equation of motion is applied to the control volume (Streeter & Wylie 1998):

$$\frac{a^2}{g}\frac{\partial V}{\partial x} + V\frac{\partial H}{\partial x} + \frac{\partial H}{\partial t} = 0 \qquad (12)$$

$$g\frac{\partial H}{\partial x} + V\frac{\partial V}{V} + \frac{\partial V}{\partial t} + \frac{fV|V|}{2D} = 0 \qquad (13)$$

where a is the wave velocity, f is the Darcy–Weisbach friction factor and D is the pipe diameter. In this study, uniform valve closure has been assumed and the associated boundary conditions, based on the resulting velocity distributions at the outlet, have been defined. Other boundary conditions, such as reservoirs and pumps, may also be easily considered in the hydraulic simulator and/or optimizer.

No general analytical solution to these equations is available; however, the equations may be solved, using the method of characteristics as practiced in this model (Chaudhry 1979). The numerical simulation module is coupled with the ACO module to form a simulation–optimization model for the optimal design of a forced pipeline under a transient flow condition. The details of the interactions between the simulation and optimization modules, as well as the concept of $H_{\max}$ relaxation are presented as a flow chart in Figure 3.

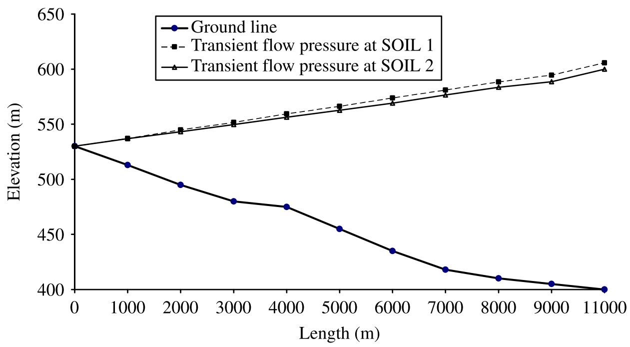

Figure 5 | Longitudinal profile of the path and transient flow pressure lines at the first and final SOIL (first example: 60 s).

MODEL APPLICATION

To examine the performance of the proposed algorithm in developing an optimum design of a water supply system under a transient flow regime, two examples are provided. The first example consists of a gravity system with no pumping station. The second example is a system in which the inclusion of pumping stations at every node is possible. For both systems, the static optimal design model is also solved, and the results are compared with those of the dynamic design model.

After conducting appropriate sensitivity analysis, a total number of 50 ants (M) were assigned to the problems, with $\rho = 0.1$, $\alpha = 1$, $\beta = 3$ and $q_0 = 0.8$. To start with a generalized initial condition, the pheromone was uniformly distributed all over the defined paths (i.e.$\tau_0 = 1$). For both examples the turnoff nodes were located at the end of the pipelines.

The first example is a proposed 11,000 m gravity system with 11 nodes (Figure 4). The hydraulic grade line is divided into 50 classes with 1 m intervals. The minimum and maximum velocities are defined as 0.6 and 2.4 m/s, respectively. The results for steady state flow conditions, along with geometrical input data, are presented in Figure 4 and Table 1. As is clear from column 4 of Table 1, the maximum allowable velocity of 2.4 m/s restricts the lower bound of the pipe diameters to the small value of 0.40 m. Therefore, there is no possibility to further decrease the total cost from $111,227.

The same problem was approached considering transient flow condition with uniform valve closure times of 60, 120, 240, 360 and 480 s. The minimum and maximum allowable pressures were set as 3 and 200 m, respectively. Clearly, in the first SOIL, the additional pressure due to the sudden valve closure at 60 s may make the solution developed by the ACO model and steady state flow simulator non-feasible. For the maximum allowable pressure of 200 m, however, in the second SOIL, as illustrated in Table 2, the solution to the model has converged to a feasible near-optimal solution. The results are presented in Figure 5. More detailed information is provided in Tables 2 and 3.

Table 2 | Results of coupled ACO and transient flow model applied to the gravity system (continuous diameter) (first example: 60 s valve closure time)

		Diameter (m)		V (m^3/s)	
No. pipe segment	Length (m)	SOIL 1	Last SOIL	SOIL 1	Last SOIL
1	1,000	0.43	0.43	2.1	2.1
2	1,000	0.4	0.43	2.4	2.1
3	1,000	0.43	0.43	2.1	2.1
4	1,000	0.4	0.43	2.4	2.1
5	1,000	0.43	0.43	2.1	2.1
6	1,000	0.40	0.43	2.4	2.1
7	1,000	0.40	0.40	2.4	2.4
8	1,000	0.40	0.40	2.4	2.4
9	1,000	0.43	0.46	2.1	1.8
10	2,000	0.48	0.48	1.7	1.7

Table 3 | Results of coupled ACO and transient flow model applied to the gravity system (continuous diameter) (first example: 60 s valve closure time)

		Pressure head (m), steady state condition		Pressure head (m), transient flow condition	
No. node	Elevation (m)	SOIL 1	Last SOIL	SOIL 1	Last SOIL
1	530	0	0	0	0
2	513	7	7	23.99	23.89
3	495	12	15	49.78	48.24
4	480	17	20	71.74	69.63
5	475	9	15	84.45	81.27
6	455	19	25	111.3	107.71
7	435	26	35	138.79	134.2
8	418	30	39	162.96	158.52
9	410	25	34	178.41	173.5
10	405	20	32	189.61	183.61
11	400	3	15	205.67	200
			Total cost	111,227	114,070

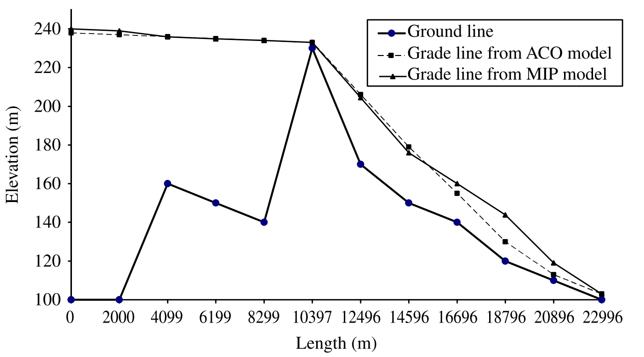

Figure 6 | Longitudinal profile of the path and the steady state grade lines resulted from ACO and MIP models (second example).

As shown in Table 3, consideration of the transient flow has increased the total cost from $111,227 to $114,070. In fact, minor increases in pipe diameters at segment numbers 2, 4, 6 and 9 have made the solution feasible with $2843 extra cost. Uniform valve closure times of 120, 240, 360 and 480 s cause no further pressure increase; hence, the design for 60 s valve closure time remains valid for larger valve closure times.

The second example is a forced-water conveyance system in which the inclusion of a pumping station at each node is permitted (Figure 6). Assuming steady state flow conditions, Jabbari & Afshar have approached the problem employing a mixed integer programming (MIP) model (Jabbari & Afshar 2002). The present study examines the same problem, including the formation of transient flow and pressure build-up due to valve closure at the terminal node with uniform valve closure times of 60, 120, 240, 360 and 480 s. For this example, the hydraulic grade line was divided into 80 classes with 3 m interval. Figure 6 compares the hydraulic grade lines resulted from the MIP algorithm with that of the ACO model for the steady state modeling condition. More detailed information may be found in Table 4. Once again, the minimum and maximum permissible pressures and velocities are defined as 3 m, 200 m, 0.4 m/s and 2.4 m/s, respectively. As Table 4 shows, the overall results are in the same order. The minor differences may be due to (1) the discretization scheme in the ACO algorithm and/or (2) the possibility of employing pipes with different diameters in any reach by MIP (see, for example, pipe segments 2 and 10 in Table 5). Moreover, linearization of the pumping cost function is a major problem with MIP modeling of any water conveyance system. The present study does not intend to compare the performances of the MIP and ACO algorithms. In fact, the MIP algorithm may not efficiently be employed for coupling with the computationally expensive transient flow simulation models. Search-based algorithms are more suitable to be coupled with the computationally expensive simulation models. This paper employs results of the MIP model for simple and

Table 4 | Pipe diameters for steady state solution (second example)

No. pipe segment	Length	Diameter ACO	MIP
1	2,000	0.80	0.8
2	840.9	0.80	0.55
	1,159.1		0.8
3	2,000	0.80	0.8
4	2,000	0.80	0.8
5	2,000	0.80	0.8
6	2,000	0.40	0.4
7	2,000	0.40	0.4
8	2,000	0.40	0.45
9	2,000	0.40	0.45
10	1,421.8	0.45	0.4
	578.2		0.45
11	2,000	0.50	0.45
Total cost		304,287	287,795

Table 5 | Results of coupled ACO and transient flow model applied to the forced system (continuous diameter) (second example: 60 s valve closure time)

		Diameter (m)		*V* (m/s)	
No. pipe segment	**Length (m)**	**SOIL 1**	**Last SOIL**	**SOIL 1**	**Last SOIL**
1	2,000	0.8	0.8	0.6	0.6
2	2,000	0.8	0.8	0.6	0.6
3	2,000	0.8	0.8	0.6	0.6
4	2,000	0.8	0.8	0.6	0.6
5	2,000	0.8	0.8	0.6	0.6
6	2,000	0.40	0.63	2.4	1.0
7	2,000	0.48	0.8	1.7	0.6
8	2,000	0.40	0.69	2.4	0.8
9	2,000	0.40	0.8	2.4	0.6
10	2,000	0.42	0.63	2.2	1.0
11	2,000	0.45	0.63	1.9	1.0

Table 6 | Results of coupled ACO and transient flow model applied to the forced system (second example: 60 s valve closure time)

		H_{pump} (m)		Pressure head (m), steady state condition		Pressure head (m), transient flow condition	
No. node	Elevation (m)	SOIL 1	Last SOIL	SOIL 1	Last SOIL	SOIL 1	Last SOIL
1	100	138	138	138	138	227	194
2	100	0	0	137	137	224	192
3	160	0	0	76	76	166	130
4	150	0	0	85	85	176	140
5	140	0	0	94	94	184	148
6	230	0	0	3	3	87	56
7	170	0	0	36	60	172	118
8	150	0	0	45	79	207	140
9	140	0	0	27	87	230	153
10	120	0	0	20	106	256	174
11	110	0	0	8	113	270	186
12	100	0	0	3	120	284	198
					Total cost	305,350	360,838

steady state cases to verify the performance of the proposed algorithm in solving nonlinear and non-convex optimization problems.

To consider the transient flow condition and dynamic pressure build-up, the design parameters resulting from the solution to the steady state flow condition with the ACO model were used as the first trial solution. Due to the transient flow condition, the real pressure in different nodes of the system exceeded those of the static flow condition which violated the maximum permitted pressure. For example, with a valve closure time of 60 s at the first SOIL, the maximum pressure constraint was violated at nodes 1, 2, 8, 9, 10, 11 and 12 with a maximum violation of 84 m at node 12. Results of the model at different iterations (i.e. SOIL numbers) for 60 s valve closure time are displayed in Figure 5. The model converged to a near-optimal solution after 13 SOILs in which all constraints were satisfied. Accounting for the transient flow condition and dynamic pressure in the system through hydraulic treatment (i.e. diameter changes) resulted in more than $55K extra cost compared to the static flow regime (Table 6).

As column 5 of Table 6 shows, the least total cost for the steady state problem has been determined as $305,350. This solution, however, has violated the head constraints on nodes 1, 2, 8, 9, 10, 11 and 12 by 27, 24, 7, 30, 56, 70 and 84 m, respectively. After 12 more SOIL cycles, the model converged to a feasible near-optimal solution as presented in Figure 7 and Tables 5 and 6. As column 6 of Table 6 indicates, all pressure heads are in the permissible ranges and, hence, no constraint violation has been recognized. This improvement was achieved by increasing pipe diameters at segments 6, 7, 8, 9, 10 and 11. In fact, the increased diameters resulted in lower velocities at segments and smaller dynamic pressure in the pipeline. The results for different valve closure times are presented in Tables 7 and 8, which clearly show how the solutions converge to

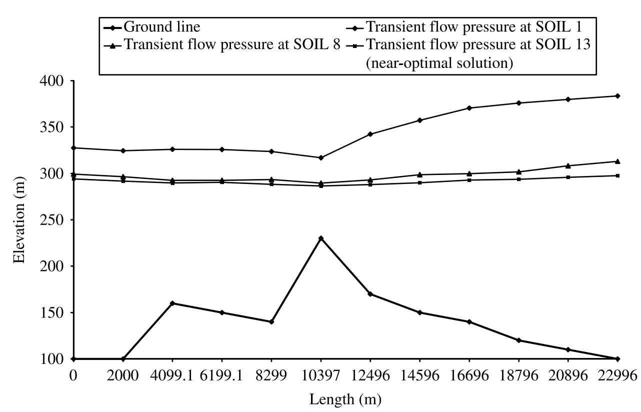

Figure 7 | Longitudinal profile of the path and transient flow pressure at some successive SOILs with valve closure time of 60 s.

Table 7 | Results of coupled ACO and transient flow model applied to the forced system (continuous diameter) (second example: 120, 240, 360 and 480 s valve closure time)

		Diameter (m)							
		120 s		240 s		360 s		480 s	
No. pipe segment	Length (m)	SOIL 1	Last SOIL	SOIL 1	Last SOIL	SOIL 1	Last SOIL	SOIL 1	Last SOIL
1	2,000	0.8	0.8	0.8	0.8	0.8	0.8	0.8	0.8
2	2,000	0.8	0.8	0.8	0.8	0.8	0.8	0.8	0.8
3	2,000	0.8	0.8	0.8	0.8	0.8	0.8	0.8	0.8
4	2,000	0.8	0.8	0.8	0.8	0.8	0.8	0.8	0.8
5	2,000	0.8	0.8	0.8	0.8	0.8	0.8	0.8	0.8
6	2,000	0.4	0.69	0.42	0.43	0.4	0.44	0.42	0.4
7	2,000	0.4	0.63	0.42	0.47	0.4	0.4	0.4	0.42
8	2,000	0.41	0.63	0.4	0.4	0.41	0.52	0.4	0.4
9	2,000	0.41	0.43	0.46	0.4	0.41	0.4	0.44	0.46
10	2,000	0.41	0.53	0.4	0.79	0.44	0.43	0.49	0.48
11	2,000	0.49	0.4	0.44	0.46	0.49	0.43	0.41	0.42

near-optimum solutions as the number of SOIL increases while satisfying the constraints. As the number of SOIL increases, the total non-feasibilities of the system decrease and the total cost increases. Therefore, a near-optimal solution is obtained when the solution converges with zero non-feasibility. Figure 8 clearly shows the convergence history of the minimum solution cost for the first and last SOIL for the second example with 60 s valve closure time.

The trade-off between uniform valve closure times of 60, 120, 240, 360 and 480 s, as well as the total system cost for optimum feasible solutions, are presented in Figure 9, indicating that the cost of the conveyance system increases as the closure time decreases. For the system under consideration, increasing valve closure time from 60 to 120 s results in more than 8% reduction in total system cost, which exceeds $30K.

Table 8 | Results of coupled ACO and transient flow model applied to the forced system (second example: 120, 240, 360 and 480 s valve closure time)

		H_{pump} (m)		Pressure head (m)							
				120 s		240 s		360 s		480 s	
No. node	Elevation (m)	SOIL 1	Last SOIL	SOIL 1	Last SOIL	SOIL 1	Last SOIL	SOIL 1	Last SOIL	SOIL 1	Last SOIL
1	100	138	138	219	183	209	181	198	176	190	174
2	100	0	0	217	180	205	179	196	174	186	172
3	160	0	0	156	117	142	120	132	113	123	111
4	150	0	0	167	125	152	128	141	122	134	121
5	140	0	0	173	133	162	139	154	132	145	130
6	230	0	0	79	42	74	47	64	40	54	39
7	170	0	0	156	105	149	106	132	103	121	103
8	150	0	0	191	128	183	132	166	131	153	129
9	140	0	0	214	142	206	149	186	145	173	146
10	120	0	0	245	168	228	176	214	172	199	171
11	110	0	0	259	182	243	186	226	187	212	184
12	100	0	0	271	199	250	199	234	200	226	198
			Total cost	304,287	330,582	304,725	318,200	305,362	307,225	304,075	305,850

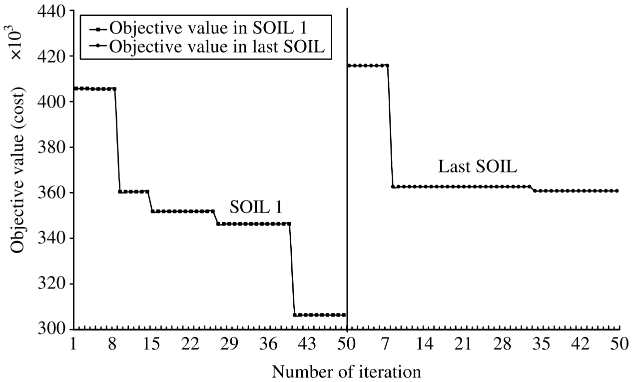

Figure 8 | Convergence history of the minimum solution cost for the first and last SOIL (second example with 60 s valve closure time).

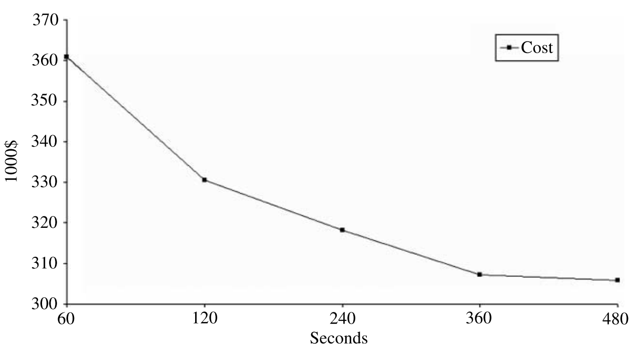

Figure 9 | Costs of the feasible solution with uniform valve closure time of 60, 120, 240, 360 and 480 s for the second example.

CONCLUDING REMARKS

To apply ACO algorithms to water conveyance systems, one has to define the problem as a graph formed with decision points, options and costs associated with the options. In the water conveyance system, the hydraulics grade line and pumping head must be discretized into intervals, deciding on the hydraulics grade line and pumping level at each decision point with respect to an optimality criterion. Feasible paths for artificial ants to follow may be constrained by defining feasible diameter sets or feasible hydraulics grade lines and pumping heads at each decision point.

The application of the model to some hypothetical problems provides promising results. Test analysis showed that the ant colony system-global best, along with explorer ants, pheromone promotion and local search operators performs quite satisfactory in coupling simulation–optimization techniques in water supply pipeline designs. The results obtained compare well with those resulting from the MIP algorithm in steady state conditions. However, there were no data or benchmarks to check the performance of the model for transient flow conditions. Yet, the convergence pattern, as well as the results and the improvements over steady state flow conditions, may be employed to assess the performance of the proposed modeling system.

Definition and application of a simulation–optimization interaction loop establishes a logical relationship between the transient flow model and the ant colony optimization algorithm. The coupled simulation and optimization modules provide a powerful and computationally efficient design environment for the optimal design of water conveyance systems, considering the dynamic pressures resulting from the valve closure. The proposed algorithm can be easily extended to branched-supply systems.

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