Hydraulic Optimization of Transient Protection Devices Using GA and PSO Approaches

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Abstract: The purpose of this paper is to optimize the preliminary selection, sizing and placement of hydraulic devices in a pipeline system in order to control its transient response. A global optimal solution is sought using both genetic algorithm (GA) and particle swarm optimization (PSO) approaches involving an unknown combination of hydraulic devices to cope effectively with water hammer conditions. In this exploratory study, three simple objective functions are considered: (1) to minimize the maximum head; (2) to maximize the minimum head; and (3) to minimize the difference between the maximum head and minimum head in the system. Several case studies are tested numerically using different protection strategies. This study shows that the integration of a GA or PSO with a transient analysis technique can improve the search for hydraulic protection devices in a pipe network. This study also shows that the selection of an optimum protection strategy is an integrated problem, involving consideration of loading conditions, device and system characteristics, and protection strategy. Significantly, simpler transient control strategies are often found to perform better than more complex ones.

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Introduction

As water is an essential element for the survival of human beings, so distribution networks are an essential ingredient of all water supply systems. The annual construction and maintenance of these pipeline systems cost many millions of dollars. Traditionally, optimizing procedures for the design of fluid transmission pipelines have tended to focus on the steady (or nearly steady) state requirements of the system. Consideration of transients often takes place with the tacit assumption that the cost of controlling transients represents a small portion of the overall pipeline cost. At the same time it is generally recognized that pipe costs constitute a major portion of the total system expenditure. Yet the selection of pipe diameter, pipe material, and pipe wall thickness strongly influences the nature of the pipeline transient response. These in turn, along with other devices which may be present, usually establish the critical design conditions for the pipeline. Therefore transient considerations are often fundamental, not incidental, in determining the ultimate system cost. Any optimized design which fails to properly account for water hammer effects is likely to be, at best, suboptimal and, at worst, completely inadequate.

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Another motivation for exploring transient issues that is becoming progressively important is water quality concerns. For many years, it was simply assumed that the quality of water that entered a distribution system was essentially equivalent to that leaving the system. Moreover, it is still often assumed that water quality models can account for the key mechanisms of transformation by considering nearly steady state considerations alone. However, one challenging water quality problem is that contaminants can intrude into a pipe through a leak when induced by transient low or negative pressures. In reality, since all pipeline systems leak and since hydraulic transients occur almost continuously in distribution systems, it is not surprising that low pressure transient waves offer considerable potential to draw untreated and possibly hazardous water into a pipeline system (Karim et al. 2003; Karney 2003).

Unfortunately, designing these critical transient protection systems is a challenging problem and a variety of strategies is commonly suggested. Protection approaches range from installing specialized devices such as pressure relief and reducing valves, air chambers and tanks, to the selection of pipe properties and the modification of operational procedures (Boulos et al. 2004). However, the selection, installation, and operation of these hydraulic devices strongly depend on the specifics of the particular pipe system as well as on the experience/comfort of the designer/operator. Unfortunately, systematic exploration of such alternatives has been impractical in the past due to inherent computational challenges, due both to the analysis burden of individual options and due to the multidimensional nature of the search space. However, improved algorithms and faster computers have been gradually changing this situation, making the optimal determination of protection devices (position, size, and device characteristics) a more pressing and practical problem.

Recently, genetic algorithm (GA) search procedures have become popular optimization choices, particularly since GAs may sometimes solve problems that are difficult for traditional gradient-based optimization methods (Goldberg 1989; Simpson et al. 1994; Dandy et al. 1996; Back et al. 1997). The main advantage of these evolutionary algorithms is their ability to find the global optimum. In essence, in GA and other evolutionary strategies, a population of potential solutions explores the search space simultaneously, exchanging information from the trials and often using only functional values (i.e., not derivatives) of the objective function. A new (and somewhat related) optimization method to GA is also discussed and applied in this paper. This method is called a particle swarm optimization (PSO) approach, and it uses a "swarm intelligence" (SI) technique (Kennedy and Eberhart 1995; Shi and Eberhart 1998, 1999; Kennedy and Eberhart 2001). In this technique, the population of potential solutions is called a "swarm" and it explores the search space rather like a flock of intelligent birds might search for food. As in the GA approach, there is a global exchange of information between the individuals. Both the GA and the PSO approaches are proving to be efficient algorithms for solving hard optimization engineering problems.

In this research, the optimum selection of hydraulic devices for water hammer control in a water distribution system is considered. Before exploring the numerical simulation, some essential background relating to transient analysis and pipeline optimization considering transients is briefly described. Both a GA and a PSO approach are then used to obtain an optimal selection of hydraulic devices taking into account water hammer events in the system. Reliability issues like pipe failure are not directly included in this paper but rather the system hydraulics, relating to the maximum and minimum pressure, are applied to represent the system's performance. The paper shows not only that the proper protection approach is important to relieve water hammer, but that the selections of basic pipe properties such as wall thickness or pressure rating are influenced by transient considerations (see also Jung and Karney 2004). In other words, system operation and design form an integrated set of interdependencies.

Transient Analysis of Pipeline Systems

A transient event disturbs the flow of water in a pipeline system and causes a short-term imbalance in the steady state flow equations. This imbalance can only be accommodated within confines of a pressurized flow system through the dramatic but subtle forces of fluid compressibility and pipe extension. But, as water is not easily compressed, significant pressure forces result: pressures that are quickly established and rapidly propagate to other portions of the system, communicating to them information about change in flow and pressure. Through a complex process of pressure and flow adjustments, the transient waves gradually decay and the system gradually evolves to a more steady state. However, the precise way the system comes into this new equilibrium, often in a convoluted and jerking manner, is one that is sensitive to many of the physical characteristics of the system. Of course, this background is routine and well known. So too is the fact that these transient events can be significant, with flow adjustments sometimes creating pressure changes that are large enough to fracture or weaken the pipe or its supports. Yet these events have consequences that are often forgotten or too little appreciated (Karney 2003).

Two equations, a momentum equation and a relation of mass conservation, are generally used to model transient flow in closed conduits (Wylie and Streeter 1993; Ghidaoui 2004). If x is distance along the centerline of the conduit, t is time, and partial derivatives are represented as subscripts, these equations can be written as:

momentum equation

$$V_t + gH_x + \frac{f_p V|V|}{2D_p} = 0 \tag{1}$$

continuity equation

$$H_t + \frac{a^2}{g} V_x = 0 \tag{2}$$

in which $H=H(x,t)$=piezometric head; $V=V(x,t)$=fluid velocity; D_p=inside pipe diameter; f_p=Darcy–Weisbach friction factor; a=celerity of the shock wave; and g=acceleration due to gravity. To be compatible, x and V must be positive in the same direction. Eqs. (1) and (2) are generally applicable if the flow is one dimensional, the conduit properties (diameter, wave speed, temperature, etc.) are constant, the convective and slope terms are small, and the friction force can be approximated by the Darcy–Weisbach formula for steady flow.

The popular method of characteristics (MOC) is a simple and numerically efficient way of solving the unsteady flow equations (Wylie and Streeter 1993). In essence, the MOC combines the momentum and continuity expressions to form the following compatibility equation in discharge Q and head H

$$dH \pm BdQ \pm \frac{R}{\Delta x} Q|Q| dx = 0 \tag{3}$$

in which $B=a/gA_p$ where A_p=cross-sectional area of the pipe; and $R=f_p\Delta x/2gD_pA_p^2$. Eq. (3) is valid only along the so-called C^+ and C^- characteristic lines defined by $dx/dt=\pm a$. To satisfy these characteristic relations, the x-t grid is usually chosen to ensure $\Delta x=\pm a\Delta t$. Once initial conditions and the space-time grid have been specified, Eq. (3) can be integrated along characteristic lines (Karney and McInnis 1992; Wylie and Streeter 1993). This procedure is the one numerically adopted in this paper.

There are many applications of transient analysis in pipeline systems. One of them is to estimate the worst-case events in the water distribution system, which is often the starting point of a transient study. If the protection strategy is well designed, the combination of various transient events that creates the pressure force will dissipate; conversely, if poorly conceived, it could harm or significantly damage the water distribution system. The transient model can simulate the transient events in the pipeline system and keep track of which set of conditions is worst from the point of view of the system's transient response (Filion and Karney 2002; Karney 2003).

Optimization of Pipeline Systems

Pipeline systems abound throughout the world and vary tremendously in form, function, complexity, and cost. They are used to transport a wide variety of fluids and slurries and may be subject to radically different operating environments. It is not surprising then that a host of optimization techniques, some general and others specific, have evolved in order to achieve economy of design, construction, operation, and maintenance of these systems. It would be difficult to list comprehensively all the methods employed to find near-optimal solutions to pipeline problems, but these methods range from linear and dynamic programming to the use of GAs. As representative researches, Anperovits and Shamir (1977) applied linear programming and Lansey and Mays (1989) suggested using nonlinear programming to optimize component sizing and the operational decisions arising in water distribution systems. Simpson et al. (1994) compared a GA approach to both complete enumeration and nonlinear programming in the context of pipeline optimization.

However, for the current purpose it suffices to say that most of the pipeline optimization methodology has been concerned with the optimization of systems under steady or nearly steady flow conditions. Popular techniques have been used extensively in numerous variant forms to great advantage on the most complex of systems but an obvious potential disadvantage to many methods is that they may disregard operating conditions that are crucial to system integrity, safety, and performance. Moreover, the steady or nearly steady techniques leave the critical choice of pipe wall thickness (that so largely influences the cost and strength of a pipeline) to an afterthought, or at best a suboptimization problem.

Despite this general neglect, a few optimization approaches have considered transients. Laine and Karney (1997) applied an optimization scheme for a simple pipeline connecting a pump and a storage reservoir. A complete enumeration scheme as well as a probabilistic selection procedure was incorporated with both transient and steady state analysis. Lingireddy et al. (2000) show that a surge tank design model obtains an optimal set of decision variables while satisfying a specified set of pressure constraints. The model was developed based on a bilevel optimization framework and it employs a genetic algorithm in minimizing a nonlinear objective function. The impact of transient conditions on the question of diameter selection was considered in Jung and Karney (2004).

Given a network system and a set of specified demands at nodes, the optimal design of surge protection devices is defined here by the set of devices which results in either maximizing the minimum head or minimizing the maximum head. In order to take both objectives into account, the goal of minimizing the difference between the maximum head and minimum head is also selectively applied. The overall optimization problem can be stated mathematically as follows where one of the following three objective functions is selected:

$$\min H_{\max}(i,j,k,t) \tag{4}$$

where $\forall i$, $\forall t$

$$\max H_{\min}(i,j,k,t) \tag{5}$$

where $\forall i$, $\forall t$

$$\min\left|H_{\max}(i,j,k,t) - H_{\min}(i,j,k,t)\right| \tag{6}$$

where $\forall i$, $\forall t$ subject to the governing transient Eqs. (1) and (2) and a set of algebraic constraints:

$$H^{*}_{\min}(i) \leqslant H(i,t) \leqslant H^{*}_{\max}(i) \tag{7}$$

$$H(i,t) = C_1, \quad Q(i,t) = C_2 \tag{8}$$

where $t=0$, $\forall i$

$$f(H(i,t),Q(i,t)) = C_3, \tag{9}$$

where $t>0$, i=boundary nodes

$$j \in L \tag{10}$$

$$k \in S \tag{11}$$

where $H_{\max}$ and $H_{\min}$=maximum and minimum predicted heads; $H^{*}_{\max}$ and $H^{*}_{\min}$=maximum permissible heads (say representing pipe ratings or health concerns for negative pressures); i=node index; t=time index; j=location of surge protection devices; k=size of the devices; S=available sizes of the devices; and L=available locations to install the devices, which are all nodes except the location of tanks and demands in the case study. Two hyperbolic partial differential equations in Eqs. (1) and (2) are subject to initial conditions in Eq. (8) and boundary conditions in Eq. (9), where C_1, C_2, and C_3=constants. Initial conditions are typically taken as steady. Simple boundary conditions of constant-level reservoir and demand can be constant head and flow, respectively, but combined relationships between H and Q are general for most boundaries.

Evolutionary Approaches to Optimization

Evolutionary computation (EC) algorithms provide solutions to many hard optimization problems that are difficult to solve using the traditional gradient based methods, as their nature may imply discontinuities of the search space, nondifferentiable objective functions, imprecise arguments, and function values (Back et al. 1997). The main advantage of these algorithms is the usage of a population of potential solutions that explore the search space simultaneously, exchanging information among alternatives, and using only function values of the objective function. The EC algorithms often make it possible to provide global solutions to many hard optimization problems.

Genetic Algorithm Approach

Probably the most well known and widely applied EC paradigm is the GA. According to GA theory, genetic operators, inspired by biological DNA evolution procedures, cause a population of solutions to evolve from it and thereby to explore the search space efficiently. The GA approach does not require certain restrictive conditions (e.g., continuity, differentiability to the second order, etc.), properties that can seldom be guaranteed for water distribution problems, particularly under transient states.

Since 1990, a number of researchers have applied the GA technique to distribution system optimization problems. Relatively comprehensive approaches for the use of genetic algorithm for steady state pipe network optimization have been developed (Goldberg 1989; Simpson et al. 1994; Dandy et al. 1996; Montesinos et al. 1999). The specific goal of this paper is to develop a more comprehensive hydraulic devices optimization model using GA, considering transient conditions.

Particle Swarm Approach

In the last decade, the research field of SI has arisen (Kennedy and Eberhart 1995). The SI argues that intelligent cognition derives from the interaction of individuals in a social environment and that the main ideas of sociocognition can be effectively applied to develop stable and efficient algorithms for optimization tasks (Kennedy and Eberhart 2001).

The PSO technique is a SI technique developed by Kennedy and Eberhart (1995) and is mainly used for continuous optimization tasks. In this technique, the population of potential solutions (a "swarm") explores the search space by simulating the movement of a flock of birds searching for food. There is a global exchange of information among all individuals or "particles," and each particle can profit from the discoveries of the rest of the swarm. The PSO has been shown to be efficient in solving hard optimization problems and engineering applications, including neural network training and Human Tremor analysis (Kennedy and Eberhart 2001).

There are many variants of the PSO technique. In this paper, a version of the algorithm derived by adding an inertial weight to the original PSO dynamics has been used (Shi and Eberhart 1998). Assuming that the search space is D-dimensional, we denote by $X_i=(x_{i1},x_{i2},\ldots,x_{iD})$ the position of the ith particle of the swarm and by $P_i=(p_{i1},p_{i2},\ldots,p_{iD})$ its historically best position in the search space. Let g be the index of the best particle in the swarm and $V_i=(v_{i1},v_{i2},\ldots,v_{iD})$ the velocity (position change) of the ith particle. The swarm is manipulated according to the equations as follows:

$$v_{id}=wv_{id}+c_1r_1(p_{id}-x_{id})+c_2r_2(p_{gd}-x_{id}) \tag{12}$$

$$x_{id}=x_{id}+v_{id} \tag{13}$$

where $d=1,2,\ldots,D$; $i=1,2,\ldots,N$ and N=size of the population; w=inertial weight; c_1 and c_2=positive constants; and r_1 and r_2=random values in the range [0,1]. Eq. (12) is used to calculate the ith particle's new velocity, a determination that takes into consideration three main terms: the particle's previous velocity, the distance of the particle's current position from its own best position, and the distance of the particle's current position from the swarm's best experience (position of the best particle). Thus, the particle moves to a new position according to Eq. (13) with a step size determined by Eq. (12). The performance of each particle is measured using a predefined fitness function. The inertial weight w plays an important role in the convergence behavior of the technique. It is used to control the impact of the previous history of velocities on the current velocity of each particle, regulating in this way the tradeoff between the global and local exploration abilities of the swarm: large values of w facilitate the global exploration of the search space (visiting new regions) while small values facilitate local exploration (i.e., fine tuning the current search area). The swarm is initialized using a uniform distribution over the search space. By gradually decreasing the inertial weight from a relatively large value initially to a small value through the course of the PSO run, the PSO tends to evolve from a more global search ability to a more local search one as the simulation continues.

For clarity, the term "population" is defined here for both the GA and PSO approaches as a simultaneous group of individuals (trial solutions) that may interact or mate to produce a new population. The two terms "generation" (common in the GA literature) and "iteration" (from the PSO literature) are herein replaced by the single term "iteration" to denote the process of going from one population to a new one.

Case Study

The optimization of a pipeline system considering transient condition can be a difficult task since it possesses both highly nonlinear and complex aspects. In this paper, a case study is presented to illustrate a suitable optimization procedure. The network system shown in Fig. 1 comprises three reservoirs at Nodes 1, 6, and 16, 29 pipes, 23 nodes, and four valves. This is a gravity flow system that draws water from the higher reservoir to the downstream network. All nodal elevations are at datum. Three $0.3\ m^3/s$ demands at Nodes 3, 14, and 23, and one $0.2\ m^3/s$ demand at Node 17 are considered for the specific case consid-

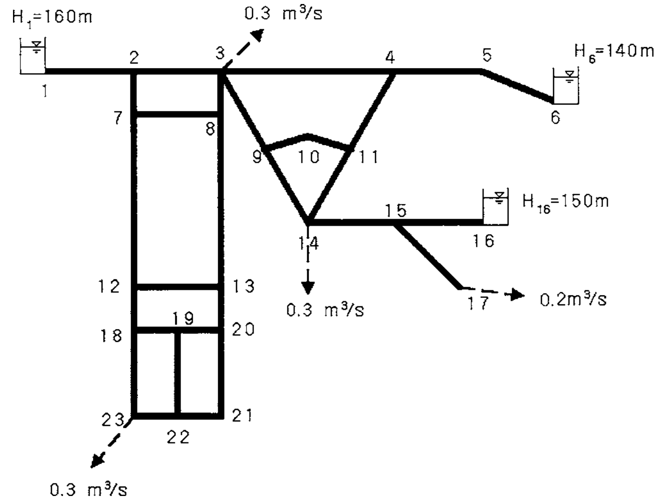


Fig. 1. Pipe network

ered here. The length, diameter, Darcy–Weisbach (DW) friction factor, and wave speed of the pipes are given in Table 1.

In order to introduce transient conditions, a variety of possible causes could be selected. For convenience and illustration, a rather severe transient event caused by a rapid closing of a set of valves at Nodes 3, 14, and 23 in a 1/2 s is chosen to characterize the performance of the system. Without any protection devices, the maximum pressure head (278.0 m) is generated at Node 21 at 1.7 s and the minimum pressure head (45.7 m) is generated at Node 21 at 4.3 s after closing of the valve.

Evolutionary approaches including GA and PSO are used to obtain the optimal system performance considering the cost of high and low pressures as described earlier. Fig. 2 shows the composition of optimal hydraulic device model with GA and PSO. In this paper, Carroll's (1999) genetic algorithm is applied to obtain an optimum selection of hydraulic devices for water hammer control. Specifically, the GA includes binary coding for the individuals, the probability of (jump) mutation is 0.02, the probability of (uniform) crossover is 0.5, the population size is 20, the length of each chromosome is 30, and simulations are run for 50 iterations. The genes in the chromosome represent the location and size of surge protection devices depending on the case studies. Tournament selection (size 2) and elitism (in which the best individual is copied to the next iteration) are selected. As a decision variable, the size, location, and number of hydraulic devices are selected in GA program, and the transient program analyzes the pipeline system with hydraulic devices. In a manner similar to the GA approach, the decision variables of PSO are the same as the ones used for GA. In this paper, the population size and the maximum velocity are 20 and 3, respectively. Following an empirical study of PSO (Shi and Eberhard 1999), a linearly decreasing inertial weight is used which starts at 0.9 and ends at 0.4 and $c_1=2$ and $c_2=2$. A total of 50 iterations for each experimental case are conducted.

To demonstrate the interrelated character of the transient problem, several specific combinations of surge control devices and objective functions are explored and compared. Moreover, to allow the understanding to evolve more naturally, several explorations of relatively limited scope are first undertaken.

Table 1. Network Data

Pipe number	Upstream node	Downstream node	Length (m)	Diameter (m)	Darcy–Weisbach friction factor	Wave speed (m/s)
1	1	2	200	0.5	0.04	1,000
2	2	3	200	0.5	0.04	1,000
3	3	4	400	0.5	0.04	1,000
4	4	5	200	0.5	0.04	1,000
5	5	6	200	0.5	0.04	1,000
6	2	7	100	0.5	0.04	1,000
7	7	8	200	0.5	0.04	1,000
8	3	8	100	0.5	0.04	1,000
9	3	9	200	0.5	0.04	1,000
10	9	10	100	0.5	0.04	1,000
11	10	11	100	0.5	0.04	1,000
12	4	11	200	0.5	0.04	1,000
13	9	14	200	0.5	0.04	1,000
14	11	14	200	0.5	0.04	1,000
15	14	15	200	0.5	0.04	1,000
16	15	16	200	0.5	0.04	1,000
17	15	17	200	0.5	0.04	1,000
18	7	12	400	0.5	0.04	1,000
19	8	13	400	0.5	0.04	1,000
20	12	13	200	0.5	0.04	1,000
21	12	18	100	0.5	0.04	1,000
22	13	20	100	0.5	0.04	1,000
23	18	19	100	0.5	0.04	1,000
24	19	20	100	0.5	0.04	1,000
25	20	21	200	0.5	0.04	1,000
26	19	22	200	0.5	0.04	1,000
27	18	23	200	0.5	0.04	1,000
28	21	22	100	0.5	0.04	1,000
29	22	23	100	0.5	0.04	1,000

Case 1: Two Surge Tanks

The relatively simple problem of sitting two surge tanks to relieve the water hammer is first considered. The diameter of each surge tank is 3 m and the length, Darcy friction factor, and diameter of an assumed connector pipe are 30 m, 0.04, and 0.1 m, respectively. The decision variables of GA and PSO are the locations of two surge tanks. The objective function of GA and PSO is to minimize the maximum head [Fig. 3(a)] and, in a second run, to maximize the minimum head [Fig. 3(b)] in the system. Although the size of the search space is small enough to allow complete enumeration, this problem is optimized using both GA and PSO for consistency with all case studies (Cases 1–6). After only nine iterations, both GA and PSO solutions show the same result that the optimal locations of two surge tanks for both objectives are Nodes 21 and 22, and the minimized maximum head is 252.8 m (a 25.3 m improvement) and the maximized minimum head is 81.5 m (a 35.8 m increase). Not surprisingly, given the small search size, the solution converges rapidly to the final answer.

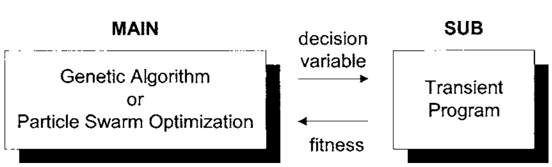
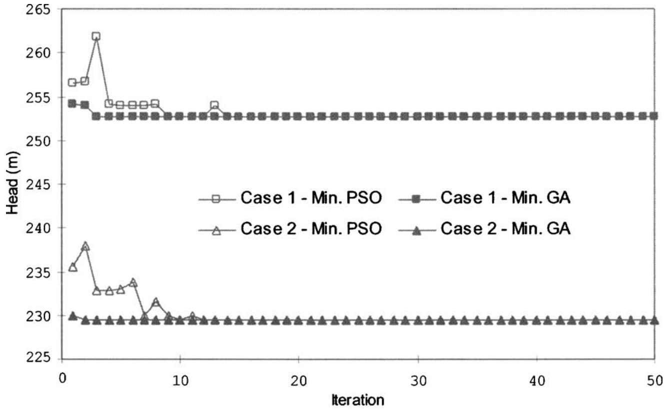


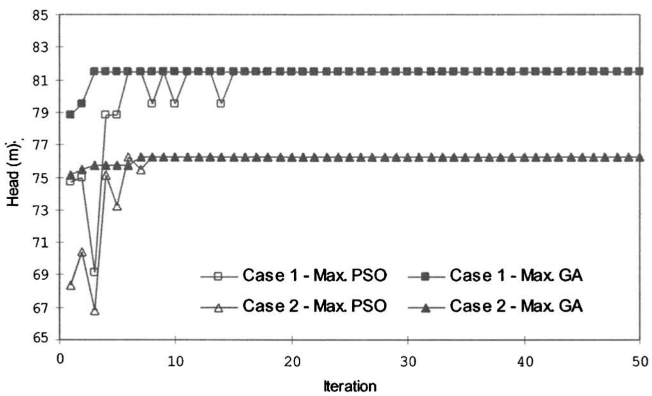
Fig. 2. Optimization of hydraulic device in pipeline system

Case 2: One Surge Tank and One Pressure Relief Valve

Although effective, the tanks considered in Case 1 are expensive, and it is often cheaper to use pressure relief valves (PRVs). The basic pipe system is the same as Case 1 except that one surge tank and one PRV replace the two surge tanks. The explicit algorithm of PRV is derived from a general hydraulic element called an external energy dissipator (Karney and McInnis 1992). The PRV operation or activation head is set at 180 m, the full opening area of PRV is 0.01 m^2, and the opening and closing time are 2 and 30 s, respectively. The decision variables of GA and PSO are simply the locations of one surge tank and one PRV. After only ten iterations, the GA and PSO solutions again show the same result that the optimal locations of the PRV and surge tank to minimize the maximum head are Nodes 22 and 13, and the minimized maximum head is 229.5 m. The optimal locations of the PRV and surge tank to maximize the minimum head are Nodes 22 and 18, and the maximized minimum head is 76.2 m. Figs. 3(a and b) show the convergence when minimizing the maximum head and when maximizing the minimum head in the system for Cases 1 and 2. Interestingly, the PRV is more efficient for minimizing the maximum head than the surge tank. This is likely due



(a)



(b)

Fig. 3. Evolution procedure for Cases 1 and 2

to the improved energy dissipation characteristics of the PRV compared to the surge tank, since a tank primarily stores energy rather than dissipating it. However, this dissipating characteristic of PRV is most effective for upsurge events and thus has a detrimental effect when controlling the minimum pressure.

Case 3: Three Pressure Relief Values

In this case, to avoid the complication and investment of the surge tank, protection is explored using three PRVs only. The size and operation of each PRV is same as that of Case 2. The decision variables of both GA and PSO are the locations of three PRVs. The objective function of the GA and PSO is to minimize the difference between the maximum head and minimum head in the system. Fig. 4 shows the convergence to a minimum head difference of 170.5 m. The GA and PSO show the optimal solution with up to three PRVs is, in fact, to have only one at Node 21; the maximum head and minimum head are 234.2 and 63.7 m, respectively. Fig. 5 shows the head traces of Node 21 with no surge control devices, two surge tanks (Case 1), one surge tank and one PRV (Case 2), and one PRV (Case 3). All traces show the abrupt head increase in the beginning of transient due to the rapid valve closure, but the systems with optimized surge control devices present a significant "quieting" of the transient response and visually demonstrates the effectiveness of surge control devices as a transient protection strategy. It also shows that the transient response of one PRV (Case 3) is actually better than for the two

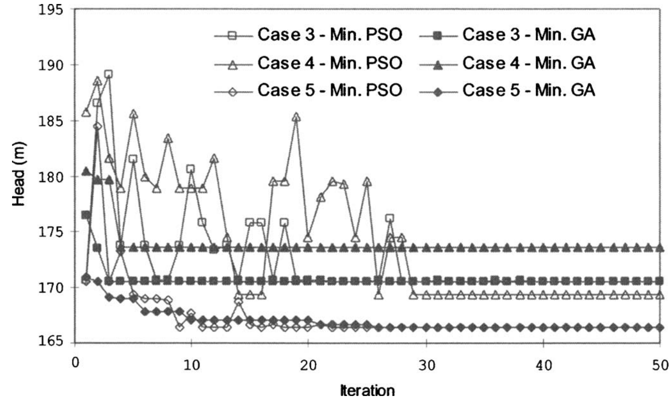


Fig. 4. Evolution procedure for Cases 3, 4, and 5

surge tank (Case 1) solution and is roughly as effective as the one involving a combined surge tank and PRV (Case 2).

Case 4: Two large Pressure Relief Valves and Two Small Pressure Relief Valves

The hypothesis from Case 3 is that only one PRV was selected because the valve area was too large, and that the valve operation itself introduced unwanted transients into the system. Thus, two kinds of PRV are considered in this test. The full opening areas of the large and small PRVs are 0.02 and 0.005 m^2, respectively. The decision variables of GA and PSO are the location of two large PRVs and two small PRVs. Fig. 4 shows the evolution procedure of GA and PSO to minimize the difference between the maximum head and minimum head in the system. The GA show the minimum difference is 173.7 m and the optimal location of PRVs is Node 22 with one large PRV only and the maximum head and minimum head are 229.3 and 55.6 m, respectively. In contrast to the previous cases, the PSO shows a slight improvement: the minimum difference is 169.4 m and the optimal locations of four PRVs are Nodes 21 and 22 with two small PRVs only; the maximum head and minimum head are 234.4 and 65.0 m, respectively.

Case 5: Two Pressure Relief Valves with Variable Valve Size

As two different valve areas are considered in Case 4, the size of PRV is one of the major elements affecting a transient response.

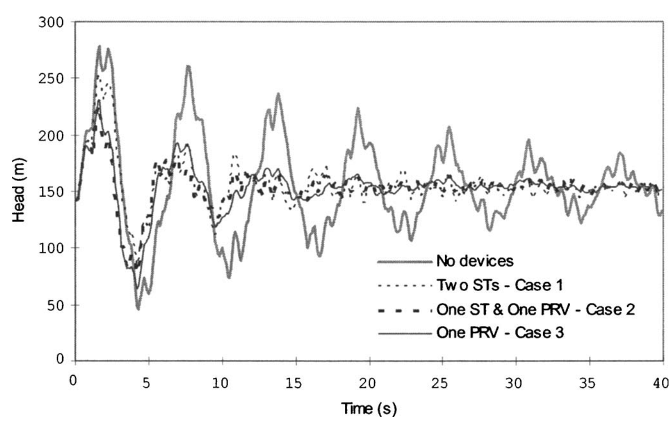


Fig. 5. Head trace at Node 21 (Cases 1, 2, and 3)

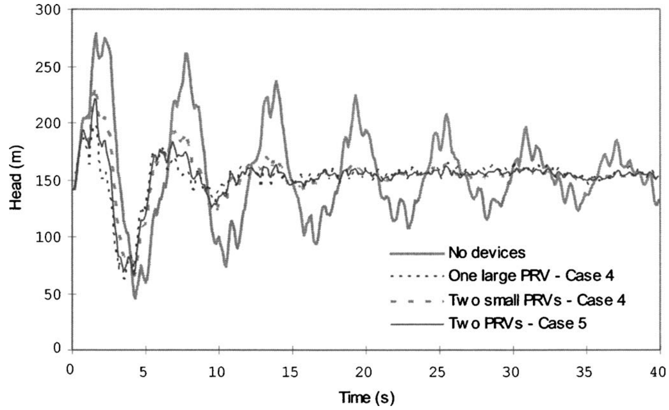


Fig. 6. Head trace at Node 21 (Cases 4 and 5)

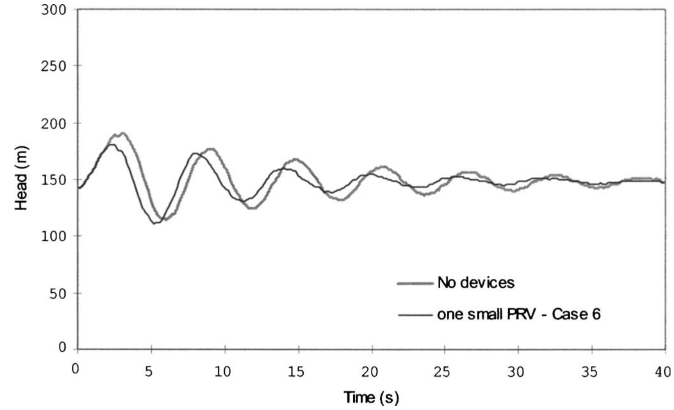


Fig. 7. Head trace at Node 21 with slow transient (Case 6)

In order to explore the impact of valve size on the transient response, two PRVs with variable valve sizes are considered in this test. Four possible PRV sizes are assumed (0.005, 0.01, 0.015, and 0.02 m^2). The decision variables of GA and PSO are the locations and sizes of two PRVs. The objective function of GA and PSO is to minimize the difference between the maximum head and minimum head in the system; the resulting minimum difference is 166.4 m (Fig. 4), a better outcome than that of Case 4. Both the GA and PSO approaches achieve the same solution, specifically that the locations of PRVs are Node 20 with 0.005 m^2 valve area and Node 22 with 0.01 m^2 valve area and the maximum and minimum heads are 230.6 and 64.2 m, respectively. The head trace at Node 21 in Fig. 6 shows, not surprisingly, that not only is the transient with surge control devices improved from the no protection case, but that the response for both the optimized location and size of surge control devices (Case 5) is better than that for the optimized location only (Case 4).

Case 6: Two Large Pressure Relief Valves and Two Small Pressure Relief Valves with Milder Transient Event

One of the challenges of surge analysis, and indeed of many designs, is to select an appropriate design event (or events). Up until now, we have used a simple and quite severe surge loading associated with simultaneously and suddenly arresting demand. What impact would it make if this initiating event were better controlled? This hints of the kind of impact a well-trained operator might have on the system, and thus points to the possibility of external control of transient loading.

The test condition is still the same as in Case 4 except that a slower closing of the valve at Node 23 in 3 s is chosen to characterize the transient performance of the system. The maximum and minimum head without four PRVs are 194.7 m at 2.8 s (Node 23) and 114.8 m at 6.0 s (Node 21). The objective function of GA and PSO is to minimize the difference between the maximum and minimum heads in the system and the minimum difference is 74.3 m. After 50 iterations, GA and PSO show the same result, namely that the optimal location of four PRVs is Node 22 with one small PRV only and the maximum head and minimum head are 184.2 and 109.9 m, respectively. Fig. 7 shows the head traces at Node 21 with no surge control device and one small PRV. They show a more gradual and smooth head increase compared with the sudden valve closure; but the one with an optimized PRV shows a further attenuated response, indicating the more controlled nature of the system's reaction.

Outcomes and Discussion

Surge analysis is a complex topic and no attempt has been made here to be comprehensive. A more global and comprehensive approach would couple an economic evaluation of the protection system (considering capital and operating costs) with an economic assessment of system performance (taking into account the cost of high and low pressures). Moreover, it would involve a more complete range of surge protection strategies. The optimization for a pipeline system may ultimately consider the transient characteristics (operation speed) and system characteristics (system topography, pipe size, material, and thickness), as well as transient protection devices. At present such an approach is difficult since decision parameters are challenging to evaluate and enumerate as they cover a vast range of approaches. In this paper, although the case studies are limited to the transient protection devices and operation speed of transient event, they do suggest certain tendencies.

Table 2 summarizes the surge control devices, objective functions, optimization method, converging iteration to the best solution, optimal locations, maximum, and minimum heads for each case study. The selection of hydraulic devices is clearly sensitive to the specific transient event assumed. Interestingly, some hydraulic devices actually deteriorate the water hammer response. Several specific observations arise from the case study.

1. Various kinds of objective functions can be targeted for specific purposes. In this paper, three kinds of objective functions are used: (1) to minimize the maximum head; (2) to maximize the minimum head; and (3) to minimize the difference between the maximum head and minimum head in the system. In the case study, the objective functions to minimize the maximum head and to maximize the minimum head predict a similar optimal location for hydraulic devices. Therefore, the objective function to minimize the difference between the maximum head and minimum head would sometimes be a more logical selection to consider. Significantly, at least in this case, any one of these choices effectively targets the transient envelope of the response and thus produces similar outcomes and decisions in the test system. Objectives could also be set to minimize various cost functions that treat pressure violations as penalty terms
2. As optimization methods, GA and PSO are applied to minimize the maximum head and maximize the minimum head in the pipeline system. Both programs are population-based stochastic optimization approaches and show similar evolution in their quest to obtain the optimal location, size, and number

Table 2. Summary of Case Studies

Case	Protection	Objective function	Method	Number to convergence[a]	Optimal location (node)	Maximum head (m)	Minimum head (m)
		None (rapid transient)				278.0	45.7
1	Two surge tanks	Minimum H_{max}	GA	3	21, 22	252.8	81.5
			PSO	9			
		Maximum H_{min}	GA	3	21, 22	252.8	81.5
			PSO	6			
2	One surge tank, one PRV	Minimum H_{max}	GA	2	22 (PRV)	229.5	72.5
			PSO	10	13 (surge tank)		
		Maximum H_{min}	GA	7	22 (PRV)	231.7	76.2
			PSO	6	18 (surge tank)		
3	Three PRVs	Minimum $H_{max}-H_{min}$	GA	3	21	234.2	63.7
			PSO	22	(one PRV only)		
4	Two large PRVs, two small PRVs	Minimum $H_{max}-H_{min}$	GA	4	22 (one large PRV only)	229.3	55.6
			PSO	30	21, 22 (two small PRVs only)	234.4	65.0
5	Two PRVs (variable size)	Minimum $H_{max}-H_{min}$	GA	10	20(0.005 m^2)	230.6	64.2
			PSO	9	22(0.01 m^2)		
		None (slow transient)				194.7	114.8
6	Two large PRVs, two small PRVs (slow transient)	Minimum $H_{max}-H_{min}$	GA	3	22 (one small PRV only)	184.2	109.9
			PSO	25			

[a]Number of iterations to convergence; both optimizations are run for 50 iterations.

of hydraulic devices. In order to use consistent parameters for all case studies, the population size and the number of iterations for both GA and PSO are fixed at 20 and 50. The corresponding number of evaluations is greater than the total numbers of combinations for Cases 1 and 2; thus Fig. 3 shows rapid convergence within 3–10 iterations (60–200 evaluations). After 50 iterations, both approaches show the same optimal result except for Case 4. In this one case, the GA shows a minimum difference of 173.7 m with one large PRV (0.02 m^2) while the PSO solution shows a slightly better result of 169.4 m with two small PRVs (0.005 m^2) only. It is difficult to say generally which approach performs better because each optimization method has its own characteristics with different operators; however, when the same population size and number of iterations are applied in the case studies, the PSO has tended to discover a better solution, although with slower convergence, than the GA approach.

3. After several iterations, Fig. 4 of Cases 3 and 4 shows that the minimum fitness decreases rapidly by about 20 m. This behavior suggests a high sensitivity to the "location" gene, and thus that an improper location of hydraulic devices could be useless or even harmful to the transient response. Clearly this locational sensitivity represents a challenging criterion when facing a range of forcing events in complex systems.
4. In Cases 3 and 4, having more PRVs actually caused a more severe minimum head in the system; having only one PRV at the ideal location showed superior protection for water hammer in this system. Particularly, Cases 5 and 6 showed that a large PRV is sometimes worse than a small one, since the valve operation itself could deteriorate the system's response. These studies show an ill-advised hydraulic protection system itself could cause negative pressures and thus is capable of introducing contamination into a pipeline, thus creating a water quality problem. Selecting both the optimal number and size of hydraulic devices is crucial to creating the best water hammer protection.
5. Not surprisingly, the case study shows that the selection of hydraulic devices to prevent water hammer is sensitive to the nature of the transient condition or loading considered. If a fixed number of devices are forced into the solution, such as by using a given number of relief valves, the transient response often deteriorates.
6. Overall, it is clear that a suitable selection of hydraulic devices is crucial if water hammer pressure is to be effectively controlled.

Conclusions

This paper optimizes the selection and location of hydraulic protection devices considering transients in water distribution networks. The evolutionary approaches of genetic algorithm and particle swarm optimization are used as optimization methods to obtain the location, size, and number of hydraulic devices in a pipeline system. Both optimization programs, inspired by natural evolution and adaptation, show excellent performance for solving moderately complex real-world problems. In this application, both approaches show similar evolution histories and optimal results. A set of case studies shows that reckless installation of protection devices can be ineffective for relieving water hammer events, and may even degrade system response. The proper size, location, and number of hydraulic devices to prevent water hammer are highly dependent on the transient condition and the specific characteristics of the system being considered. The optimal selection of hydraulic devices is not only crucial to system performance and reliability, but also effective in decreasing costs.

Even though evolutionary approaches show excellent performance for reasonably complicated systems, they also have several disadvantages including an often-noted slow final convergence. However, one of the desirable characteristics of the evolutionary computational approaches is that they are easy to hybridize with other optimization strategies. Quick convergence of a local search method would help to increase the overall convergence speed of the evolutionary computation. Hybridization of evolutionary computation with local search methods is an attractive subject for future work.

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