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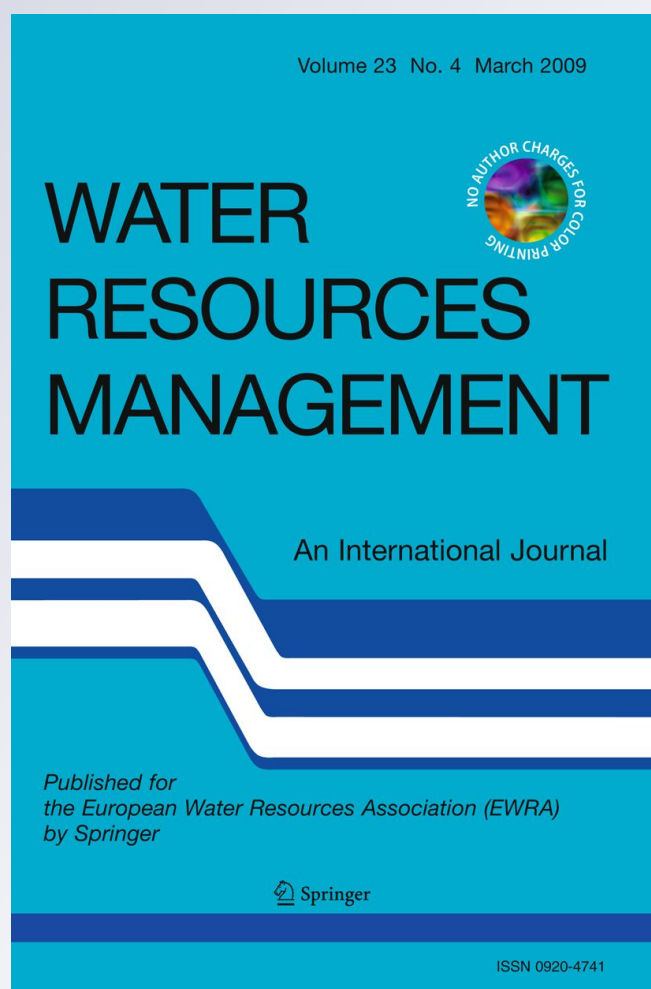
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Detection of Leakage Freshwater and Friction Factor Calibration in Drinking Networks Using Central Force Optimization

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Abstract Inverse Transient Analysis (ITA) is a powerful approach for leak detection and calibration of friction factors in pressurized pipes. Through this method, a transient flow is initiated and pressures are measured somewhere in the system. Then, a nonlinear programming (NLP) problem with a least-squares criterion objective function is developed to minimize discrepancies between the measured and calculated pressures at measurement sites. Solving the raised NLP results in the problem's unknowns being leakage specifications and pipe friction factors. For this purpose, various optimization techniques may be utilized. This issue is a major challenge for ITA-based methods. The present work aims at applying the new method of Central Force Optimization (CFO) to the problem of ITA. CFO is a deterministic metaheuristic inspired by gravitational kinematics in which small objects in space are dragged by bigger ones. Herein, the concept and main structure of CFO are represented as well as of CFO. A reference pipe-network is considered to be solved using the ITA equipped with CFO. The results are then discussed compared to the previous works. It is concluded that CFO is easy to implement, computationally efficient and has a remarkable performance in solving leak detection problem.

Keywords Transient analysis · Leak · Drinking networks · Central force optimization

1 Introduction

An urgent requirement for new methods of leak detection in drinking networks has motivated many researchers to develop model-based techniques. Leakages, economically and environmentally impose significant costs on piping systems. The relevant losses are estimated from 20% to, in some cases, more than 50% of the supplied freshwater based on the system's age and

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location (AWWA 1990; Weil 1993). This indicates that academic investigations and industrial developments are highly required in this regard. Leak detection methods are to find leak parameters including the number, location and area size of leaks. In addition, pipe friction factors increase with the system's age because of deposition and corrosion. During operation, new changed friction factors can play a significant role in validity of the leak detection results. Therefore, they should be simultaneously calibrated with leaks.

In recent years, several leak detection and calibration methods for piping systems have been developed and discussed. With a glimpse into the literature, it is found that investigators have so far tried to deal with the problem in various ways. Accordingly, the presented methods may be classified in several categories. Some methods focus on status assessment of pipe networks and generally evaluate water losses in system by means of monthly or annual water balances and statistical techniques (Tabesh *et al.* 2009; Christodoulou *et al.* 2010). Some other methods deal with the operational aspects of drinking networks to control water losses, better management and rehabilitation of the system (Liberatore and Sechi 2009; Zarghami 2010; Araujo *et al.* 2006). In addition, some methods aim at developing experimental facilities (Meniconi *et al.* 2011) or mathematical tools for precisely detecting leaks as well as calibrating pipe friction factors. The present work is placed in this category whose methods vary from simple visualizations to complex model-based techniques. The later are classified into steady or unsteady flow methods where the unsteady or transient methods are more preferred and extended in recent years. Based on the nature of wave propagation in transient flows, they contain more information about the system at hand. Leakages and pipe friction factors are the unknown variables in a pipe network under operation. In a transient flow condition, when a wave travels along a pipe, it is under the influence of pipe features including leak and frictional losses resulting in particular changes in the transient flow responses. These changes can be used to assess the network's function. On the other hand, transient flow responses, like pressure variations, for a leaky old system are obviously different with those for its original intact situation. These differences and the ways to interpret them led to develop various transient-based leak detection methods. In a classification, transient analysis for leak detection may be done in frequency domain (Mpesha *et al.* 2001, 2002; Wang *et al.* 2002; Covas *et al.* 2005; Kim 2005; Lee *et al.* 2005, 2007; Sattar and Chaudhry 2008; Sattar *et al.* 2009; Ferrante *et al.* 2009) or time domain (Liggett and Chen 1994; Brunone 1999; Vitkovsky *et al.* 2000, 2003; 2007; Brunone and Ferrante 2001; Kapelan *et al.* 2003; Covas and Ramos 2001; Al-Khomairi 2008; Shamloo and Haghighi 2009, 2010). In accordance with the system's configuration, some methods can be only applied to single (or very simple) pipelines (most frequency methods) whilst some others can be also used for water distribution networks (most time domain methods). For drinking pipe-networks, Inverse Transient Analysis (ITA) is presently the most efficient approach. ITA is capable of detecting leaks simultaneously with calibrating the pipes for friction coefficients. The main concept behind the ITA-based methods is that; the transient flow properties of pressurized pipes are affected by leaks, similar to other pipe features. This fact is used as a key guide in developing an inverse problem to find the system's unknowns being leaks and friction factors. In what follows, the main steps of the ITA method for pressurized pipes are outlined:

- (1) A transient flow is initiated by causing a change in a consumption outflow. This could be practically done by closing or opening an available regulating valve,
- (2) Transient pressures are then sampled somewhere in the network namely measurement sites. In general, the number of measurement sites is much fewer than the number of nodes in the network.

- (3) Afterwards, the network is numerically modeled for transient flow analysis. The model is developed as a function of leak parameters and pipe friction factors which are the decision variables in this study.
- (4) A nonlinear programming (NLP) problem with a least-squares criterion objective function is then defined to minimize the absolute differences between the observed and calculated pressures at measurement sites.
- (5) A nonlinear optimization technique is finally utilized to solve the problem. Being computationally efficient, capable of solving large problems and of course of finding the global optimum, are major concerns with the applied optimization method.

Each of the aforementioned steps plays a remarkable role in success of ITA method. In this context, many theoretical and experimental studies have been so far proposed (Liggett and Chen 1994; Vitkovsky *et al.* 2000, 2007; Kapelan *et al.* 2003; Covas and Ramos 2001; Al-Khomairi 2008; Shamloo and Haghighi 2009; 2010). This work focuses on the last step in the ITA procedure referred to as the applied nonlinear optimization method. When implementing the ITA for a pipe network, imagine that all of the primary steps, 1–4, are perfectly provided and the problem is properly defined to be solved. If the applied optimization solver is not able at reaching to the global solution, the whole process of ITA fails and results in wrong leaks and friction factors. This very probably happens when gradient-based (mathematical) or local search optimization methods are used. In the two last decades, developments in nature inspired metaheuristics besides the great advances in computers have considerably helped researchers optimize complex engineering problems in which decision spaces are often highly multimodal. Genetic Algorithms (GA), Simulated Annealing (SA), Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO) are well-known examples in this regard. Nevertheless, since these methods are inherently stochastic there is no guarantee in reaching to the global solutions. Further, most metaheuristics are inspired by random movements and gradual evolution in nature accordingly, they are not computationally efficient. It is worth noting that analyzing a pipe network under transient flow inherently includes heavy computations taking a lot of time. Through an inverse transient analysis, the optimization solver numerously calls the flow simulator model for analyzing the network to evaluate the objective function. Obviously, this part of ITA is complex and time-consuming however, applying more efficient optimization methods can significantly lessen the burden of calculations.

Based on what briefly discussed two important aspects of the applied optimization methods in this study are: (1) the ability to find the global solution (2) with a computationally efficient mechanism. Among the available techniques, there is not a clear way to conclude which one is better with respect to the mentioned aspects. However, applying different methods to ITA and solving benchmark examples could be very helpful in this regard. This work utilizes central force optimization method newly introduced by Formato (2007). CFO is a deterministic metaheuristic that works based on the metaphor of gravitational kinematics. Herein, CFO is combined with the ITA procedure as its optimization solver in step 5. The model is then applied against a reference pipe network taken from literature. Solving the example provides a good platform for comparing different methods so far applied to ITA problems.

2 Literature Review

The present study concentrates on the optimization technique applied to ITA for leak detection and calibration of pipe friction factors in drinking networks. On this basis, the previous researches are reviewed as follows:

Liggett and Chen (1994) introduced the principles of inverse transient analysis method. They theoretically developed an ITA-based approach for pressurized pipe networks. For solving the raised inverse problem, they utilized Levenberg–Marquardt (LM) method which is a classical gradient-based optimization technique. In dependence on the starting point, LM searches in the problem's decision space for better local solutions. This fact limits the use of classical (mathematical) methods in solving many engineering problems which are often non-convex and including several local optima. However, that work showed that LM has a good performance in the ITA. This was concluded from an example pipe network, having 11 pipes and 7 junctions, solved there and thereafter in later researches.

Vitkovsky *et al.* (2000) paid more attention to the role of optimization in ITA. They considered the non-convexity of the problem and proposed a metaheuristic to tackle with that. Instead of LM in previous work, they developed a genetic algorithm (GA) with new schemes for crossover and mutation operators. In that work, the method of Liggett and Chen (1994) was generally adopted but the problem solution method was improved using GA. Although the obtained results were satisfactory but the applied GA, compared to LM, was computationally inefficient. In general, GA takes a lot of time for objective function evaluations as well as for its inner computations. Moreover, because of random searches, GA's parameter setting is hard and needs several trial-and-error runs. These issues were also highlighted in that work by this phrase: “there is a trade-off between the fast speed of a derivative method of optimization and the slower but more robust and comprehensive GA search.” In practice, for large networks with many pipes and junctions, the problem becomes more difficult to solve as the decision space of ITA becomes more complex and multimodal.

Kapelan *et al.* (2003) considered the limits and benefits of each mathematical and nature inspired optimization method and developed a novel solution procedure for ITA. They introduced a hybrid optimization model composed of two previously used methods of LM and GA to reduce the volume of computations as well as to obtain more reliable results. Using the GA-LM scheme, those researchers analyzed the benchmark network and discussed the results. It was concluded that the hybrid ITA is more stable and precise than LM and much faster than GA.

Later on, Jung and Karney (2008) applied two metaheuristics, GA and Particle Swarm Optimization (PSO) to solve the ITA problem. The previous benchmark pipe network was also solved there. It was shown that both GA and PSO are capable of solving the problem however; PSO slightly provided faster convergence and resulted in more accurate results compared with GA.

Shamloo and Haghighi (2009) developed an ITA-based method for single pipelines, namely inverse backward transient analysis (IBTA) in which they used Sequential Quadratic Programming (SQP) as the problem solver. SQP is a mathematical gradient-based method that depends on the initial guess to start optimization. The method exhibited a good performance in terms of accuracy in results and the speed of calculations. These merits encouraged those researchers to extend their work for leak detection and calibration of pipe-networks. In 2010 they proposed some features to improve the ITA procedure. They introduced a method to optimally generate the transient flow in the network. This had a remarkable role in producing a fast-enough and informative transient flow. The pressure measurement sites were also optimally allocated in the system resulting in sensitive data which is really essential to ITA. These pre-optimizations make the inverse problem of leak detection more tractable to solve so that even a mathematical solver like SQP would be able to find the global optimum. They also applied their methods to the benchmark example introduced in the previous works.

Haghighi and Shamloo (2011) dealt with the importance of quantity and quality of the generated transient flow for ITA in pipe networks. They presented a simple GA to optimize

the transient excitation parameters which are the location and method of maneuver of the valve as a transient generator. In that work the method of SQP was also adopted to solve the nonlinear problem of ITA.

As a conclusion, it seems that the optimization technique applied to ITA-based methods is still a challenge and requires more investigations. For this purpose, one practical approach is to develop and test different algorithms to solve the problem. This makes it possible to better compare the methods and to conclude which one is better suited to the ITA. The present work intends to add a recently developed metaheuristic namely central force optimization to the list of optimization methods so far applied to the ITA method.

3 Governing Equations

Two conservative rules of mass continuity and momentum govern transient flows in pressurized pipes. For most hydraulic engineering applications, these equations are written as (Chaudhry 1987),

$$\frac{\partial H}{\partial t} + \frac{a^2}{gA} \frac{\partial Q}{\partial x} = 0 \quad (1)$$

$$\frac{\partial Q}{\partial t} + gA \frac{\partial H}{\partial x} + \frac{fQ|Q|}{2DA} = 0 \quad (2)$$

where x = distance along the pipe, t = time, a = wave speed, g = gravitational acceleration, A = pipe cross-sectional area, D = pipe diameter, Q = instantaneous discharge, H = instantaneous piezometric head, and f = Darcy–Weisbach friction factor. The governing equations are often solved using the method of characteristics (MOC). In MOC, the equations are linearly combined and then integrated resulting in two positive and negative characteristic equations. For the pipe network at hand, pipes are discretized and the characteristic equations are developed at each calculation node. Especial equations are also introduced to boundary conditions which are generally reservoirs, junctions, valves, pumps and leakages most of which are found in (Chaudhry 1987; Wylie and Streeter 1993). Leak effects in pipes are also simulated by the orifice equation as follows,

$$Q_L = \xi A_e \sqrt{2g|H_L - Z_L|} \quad (3)$$

where Q_L = leak discharge, $A_e = C_d A_L$ effective leak area, C_d = coefficient of discharge, A_L = apparent leak area, Z_L and H_L = respectively, elevation and instantaneous piezometric head at the leak location and $\xi = 1$ if $H_L > Z_L$ and $=0$ otherwise. Since the number and location of leaks are initially unknown, all junction nodes are assumed as leakage candidates, of course with unknown sizes. Equation 3, along with the positive and negative characteristic equations, is introduced to leaky nodes. On this basis, a numerical model was developed by Shamloo and Haghighi (2010) to analyze transient flow in pipe networks which is also exploited herein.

4 Inverse Transient Analysis

In general, transient flows are modeled in piping systems being designed or evaluated for waterhammer effects. In those conditions, the initial flow, boundary conditions and

all other specifications of pipes are completely known while transient flow responses including pressure variations are calculated. In ITA, by contrast, some parts of the boundary conditions or pipe features such as leak parameters and friction factors are unknown. However, a few number of transient pressure signals are available from measurements. In practice, the number of unknown variables in a piping system is much more than the known ones. As a result, the ITA problem is mathematically under determined and consequently needs optimization methods to be solved. To this end, a direct transient analysis model is set up for the network in which flow specifications are computed as a function of unknown variables including nodal leak areas A_e and pipe friction factors f . This model is used herein to evaluate the following objective function in inverse transient analysis method,

$$C(A_e, f) = \sum_{j=1}^{MS} \sum_{i=1}^M (H_{ij} - H'_{ij})^2 \quad (4)$$

where C = objective function, M = number of sampled quantities in transient pressure signals, MS = number of measurement sites and H_{ij} and H'_{ij} = respectively, calculated and observed pressure heads at measurement sites. Applying a nonlinear optimization method, the objective function C is minimized resulting in optimum leak areas and pipe friction factors. In this situation, C is theoretically close to zero. Finally, the nodes with non-zero leak sizes indicate the number and location of leaks. In the next section, the optimization method applied to solve Eq. 4 is introduced.

5 Central Force Optimization (CFO) Method

Small objects in our universe can become trapped in close orbits around highly gravitating masses (Formato 2009). This is the main concept behind the central force optimization method which searches in a decision space for the biggest object i.e., the global optimum of the problem. CFO is a new nature-inspired metaheuristic originally developed by Formato (2007). This method works based on the metaphor of gravitational kinematics, a branch of physics that deals with the motion of masses moving under the influence of gravity. Because of this metaphor utilized by CFO, all movements in the problem's decision space are governed by deterministic rules taken from the vector mechanics. As a consequence, CFO is a deterministic method which means that every initial starting point, named as probe herein, travels on a certain trajectory to reach the answer. In other words, CFO is not influenced by random-based operators which play a major role in most stochastic metaheuristics like GA, PSO and SA. In this view, CFO looks like mathematical methods which are deterministic too. Besides, CFO seems to be capable of escaping from local solutions as shown through several test functions by Formato (2007 and 2009). CFO is basically a maximization algorithm that starts to optimize an objective function; Eq. 4 herein, by flying a limited number of probes through the decision space. Every probe, p , is a feasible solution to the problem that has N_d coordinates in a N_d -dimensional problem. The position vector is therefore $\vec{R}_j^p = \sum_{m=1}^{N_d} x_j^{p,m} \hat{e}_m$ where $x_j^{p,m}$ is m^{th} coordinate (decision variable) of probe p at time step j and $\hat{e}_m$ is the unit vector along the x_m axis. As a comparison, probes in CFO are equivalent to chromosomes in GA. As each probe position represents a solution to the problem, it also takes a fitness value, mass M herein,

from the objective function. In the problem's decision space, smaller probes are dragged by bigger ones and experience new accelerations making them flying through the space over time. As time progresses, probe position vectors are changed by some rules taken from the equations of motions until all probes settle around the largest mass found in the decision space.

Based on the Newton's universal law of gravitation, each probe p with position vector $\vec{R}_{j-1}^p \in R^{N_d}$ at time step $j-1$ experiences an acceleration vector $\vec{a}_{j-1}^p$ under the influence of gravitational central forces caused by other probes,

$$\vec{a}_{j-1}^p = G \sum_{\substack{k=1 \\ k \neq p}}^{N_p} U(M_{j-1}^k - M_{j-1}^p) (M_{j-1}^k - M_{j-1}^p)^\alpha \frac{(\vec{R}_{j-1}^k - \vec{R}_{j-1}^p)}{|\vec{R}_{j-1}^k - \vec{R}_{j-1}^p|^\beta} \quad (5)$$

where N_p = the number of probes, $p=1, 2, 3, \dots, N_p$ the probe number name, j = time step of calculations which is in fact the optimization iteration number, α, β and G = the CFO constants, $M_{j-1}^p = C(\vec{R}_{j-1}^p)$, the objective function value against probe p at time step $j-1$ and U is the unit step function that gives $U(x)=1$ if $x \geq 0$ and $= 0$ otherwise. In fact, U keeps the CFO's gravity always attractive that means the attractive forces from bigger probes are only adopted for modifying probe position vectors. The position distance $|\vec{R}_{j-1}^k - \vec{R}_{j-1}^p|$ between two probes k and p , is obtained from the following relationship,

$$|\vec{R}_{j-1}^k - \vec{R}_{j-1}^p| = \sqrt{\sum_{m=1}^{N_d} (R_{j-1}^{k,m} - R_{j-1}^{p,m})^2} \quad (6)$$

For more clarification, Fig. 1 demonstrates the utilized gravitational metaphor for a 3-dimensional space with 4 probes. Probe position vectors at time step j are then updated by applying the accelerations computed in previous time step as follows,

$$\vec{R}_j^p = \vec{R}_{j-1}^p + \frac{1}{2} \vec{a}_{j-1}^p \Delta t^2 \quad (7)$$

in which Δt = time step increment which is considered to be unity here. Using Eq. 7, the probes move to new locations that may be outside the feasible decision space. The method used for returning the errant probes can be very important to a CFO's performance. Formato (2007) suggested the following equation to repair infeasible components of errant probes,

$$\begin{aligned} \text{if } \vec{R}_{j,i}^p < x_i^{\min} \text{ then } \vec{R}_{j,i}^p &= x_i^{\min} + F_{rep} (\vec{R}_{j-1,i}^p - x_i^{\min}) \text{ and,} \\ \text{if } \vec{R}_{j,i}^p > x_i^{\max} \text{ then } \vec{R}_{j,i}^p &= x_i^{\max} - F_{rep} (x_i^{\max} - \vec{R}_{j-1,i}^p) \end{aligned} \quad (8)$$

where $x_i^{\min}$ and $x_i^{\max}$ = respectively, the lower and upper bounds of decision variables and F_{rep} = the reposition factor which is a user-specified parameter in range of 0–0.9.

Since CFO is deterministic and there is no randomness in it, finding an optimum set for its constants is easier than stochastic metaheuristics. Formato (2009) comprehensively investigated the CFO's parameters by running it against several complex

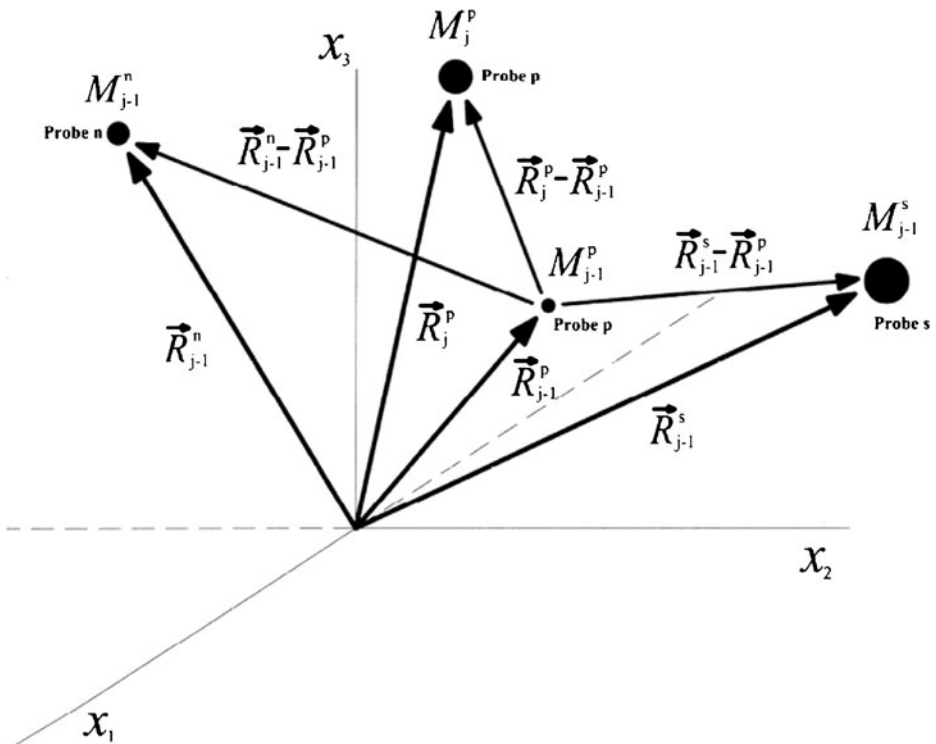


Fig. 1 Typical 3-D CFO decision space (Formato 2007)

multi-dimensional test functions. It was concluded that setting α , β and G to be 2 and F_{rep} to be 0.5 provides the best performance in most cases. However, N_p and F_{rep} require receiving more attention to be assigned. Another important factor in CFO is the initial spatial distribution of probes that in accordance with N_p determines how much CFO knows about the decision space topology at the beginning of a run. For this purpose, several approaches may be applied, for example; probes may be uniformly distributed on each coordinate axis or on a pre-defined grid or they may be randomly generated. Another strategy can also be a combination of the aforementioned probe distribution methods. In fact, for a successful and efficient parameter setting it is necessary to be mathematically acquainted with the problem at hand as well as with the CFO's behavior.

Similar to other heuristic methods, convergence of a CFO run must be systematically checked through its iterations. This is essential to prevent ineffectual computations. In general, a large number of time steps N_t is initially considered which determines the end of computations. However, the optimization may be sooner terminated for the sake of "fairly static probe distribution over several time steps" or "saturation of the best fitness over many time steps". Adding to these, in ITA problems, the global optimum value of objective function is already known which is theoretically equal to zero. This fact helps one introduce another stopping criteria to the CFO algorithm applied to ITA problems.

Based on what described about the central force optimization method, Fig. 2 as a flowchart is also presented here to better show how the method works.

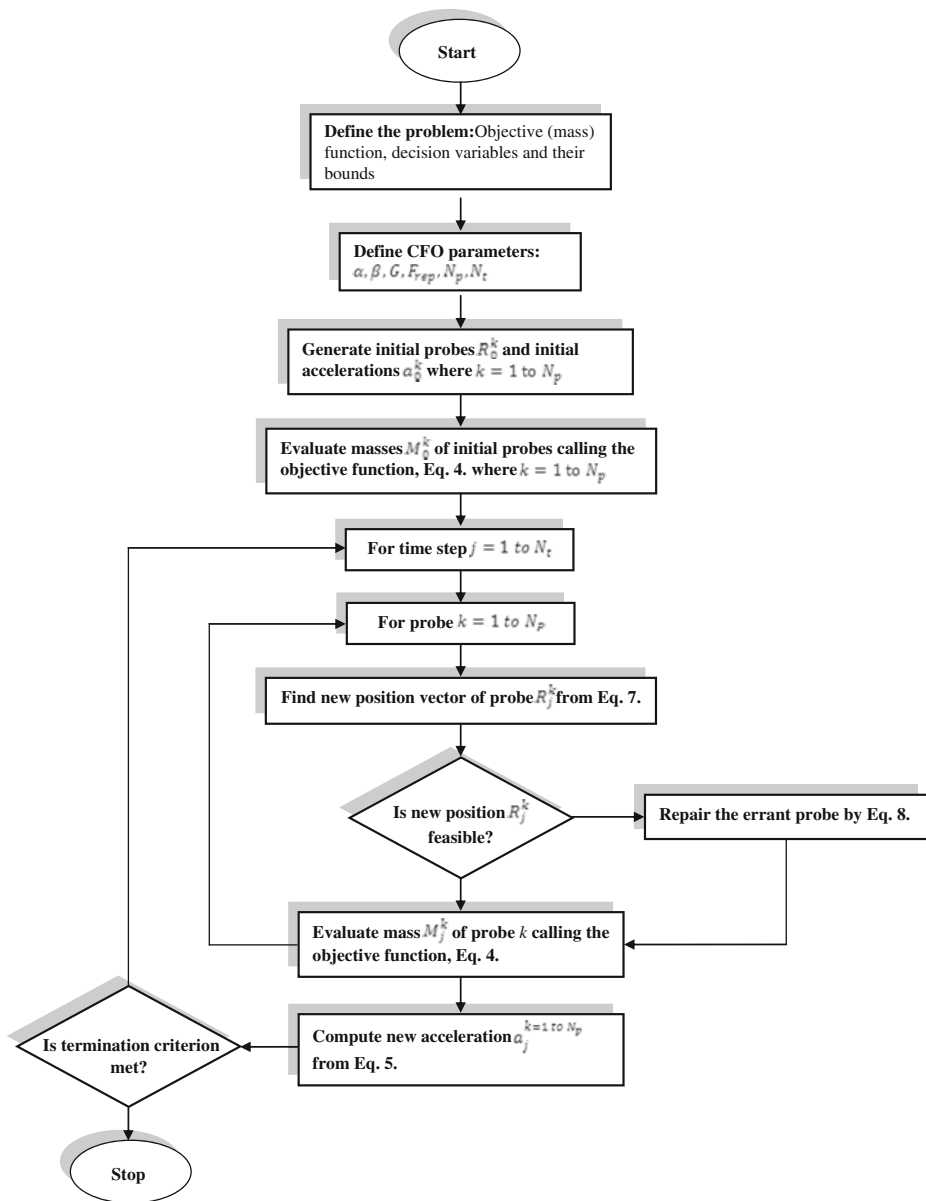


Fig. 2 CFO algorithm

6 Example

6.1 Problem Description

As an example, a reference pipe network is taken into account from literature for leak detection and calibration for friction factors. The example is based on a hypothetical drinking network originally introduced by Pudar and Liggett (1992) which was also used

by Liggett and Chen (1994), Vitkovsky *et al.* (2000, 2003), Kapelan *et al.* (2003), Jung and Karney (2008) and Shamloo and Haghighi (2010). The network is composed of 11 pipes and 7 nodes with a 30 m height reservoir at node 1 which gravitationally feeds the system. A constant inflow with $0.058 \text{ m}^3/\text{s}$ flow rate at node 7 also supplies the network. For all pipes, diameter is 254 mm, length is 762 m and wave speed is 1316 m/s. A small leak with 1 cm^2 effective area size is located at node 2. Figure 3 depicts the network's layout in which node numbers, pipe names and their actual Darcy–Weisbach friction factors f are included.

6.2 Inverse Transient Analysis

To carry out the inverses transient analysis, a transient flow is initiated in the system and the pressure fluctuations are sampled at measurement sites. In this pipe network, node 4 is defined as the transient generation point. As seen in Fig. 3, there is initially a $0.058 \text{ m}^3/\text{s}$ steady outflow discharges from node 4. As a transient excitation according to Fig. 4, the outflow from node 4 is decreased to $0.028 \text{ m}^3/\text{s}$ within 10 s time period and is then increased to $0.058 \text{ m}^3/\text{s}$ in the same time. Nodes 4 and 7, two out of seven junction nodes in the

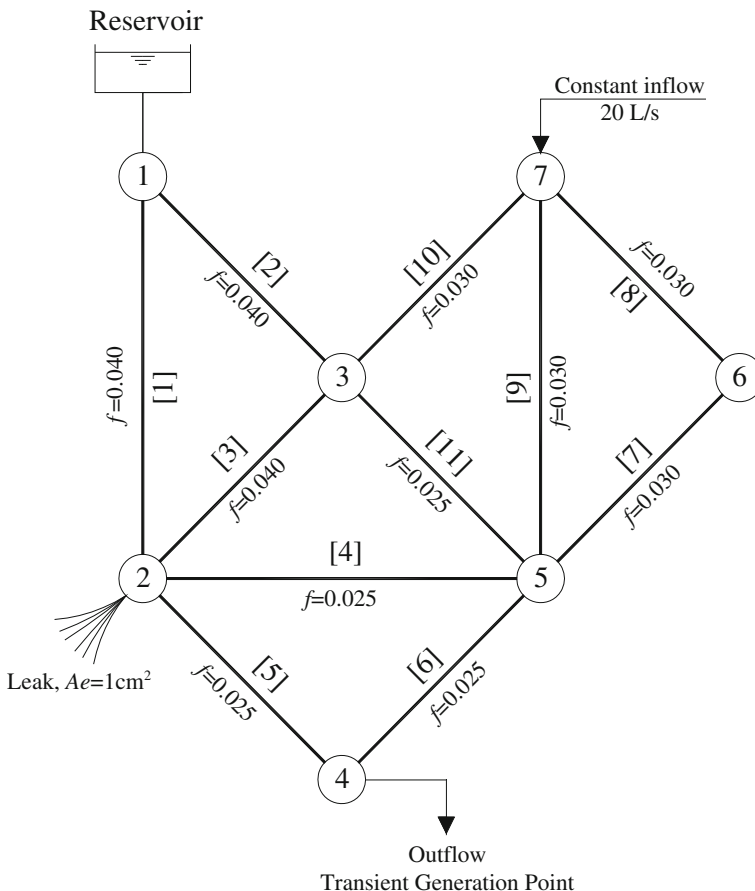
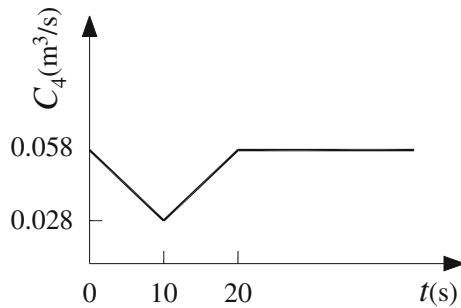


Fig. 3 Benchmark pipe-network

Fig. 4 Triangular transient excitation at node 4



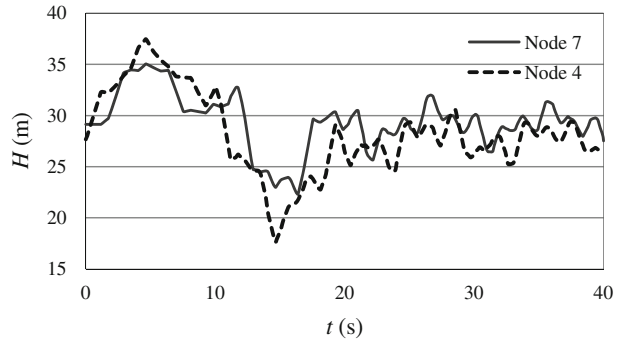
network, are chosen as the measurement sites at which the transient pressures are sampled for 40 s as shown in Fig. 5.

In order to carry out ITA, the problem is so developed that all junctions but the reservoir node are assumed to be leaky with unknown area size ($NL=6$, number of leaks). All pipe friction factors are unknown too ($NP=11$, number of pipes), resulting in 17 unknowns in total. The network is then numerically modelled as a function of the unknown variables. Using the transient simulation model and the sampled data, the objective function, Eq. 4, is defined and the ITA problem is formed to be solved.

Following Fig. 3, CFO is prepared for optimizing the problem. Only constraints on nodal leak areas and pipe friction factors are respectively $0 \leq A_e \leq 10 \text{ cm}^2$ and $0.01 \leq f \leq 0.08$ which represent boundaries of the problem's search space. In general, the number of probes is decided depending on the number of decision variables and extent of decision space. For this example with 17 variables, 36 probes are initially introduced to CFO among which 34 probes are uniformly distributed on decision variables (2 probes on each axis) and 2 remaining probes are randomly allocated in the decision space. The CFO's constants, α , β and G , are set to be 2 as proposed by Formato (2007 and 2009). Then, several pre-runs were carried out to set F_{rep} by changing it over range of 0–0.9. It was concluded that $F_{rep}=0.26$ is the best choice in this example. Now, CFO is ready to start optimization by flying its probes through the decision space. Using the objective function in Eq. 4, the probe masses are evaluated and their positions are updated over time until the biggest probe i.e., the global optimum is achieved. Figure 6 demonstrates the trend of objective function minimization versus CFO time steps. To see the effects of F_{rep} on the method's performance some sample runs with different values of F_{rep} are also shown in Fig. 6. In only 9 time steps corresponding to 360 evaluations, the objective function C became 6.61 m^2 from 429.86 m^2 in the beginning. After that, the optimization dramatically advanced until time step 75 corresponding to 2736 evaluations where C was obtained 0.031 m^2 . This value remained permanent in next iterations so that the search process was terminated after next 25 iterations through which no change was seen in the best obtained result. Table 1 presents a comparison between CFO and the previous methods applied to this example. From this table, CFO is found to be computationally much more efficient than GA, slightly weaker than SQP which is a derivative method and close to the hybrid model of GA-LM. As a consequence, it seems that CFO similar to hybrid methods like GA-LM exploits the advantages of both mathematical and heuristic methods respectively in terms of efficiency (speed of computations) and accuracy. However, it is worth mentioning that implementing CFO and its parameter setting are significantly easier than the aforementioned methods.

Tables 2 and 3 respectively represent the optimum detected nodal leak areas and pipe friction factors in comparison with their precise values. The results show that how well CFO

Fig. 5 Transient pressure heads at measurement sites



can help the ITA method detect the leakage and calibrate the pipe friction factors in pipe networks.

7 Discussion and Conclusions

Inverse Transient Analysis (ITA) is a model-based technique for pressurized pipes leak detection and calibration for friction factors. ITA is an inverse problem in which transient pressures are known somewhere in the pipe network while nodal leaks and pipe friction factors are unknown. This problem is mathematically underdetermined consequently; it needs to be solved using optimization methods. A least-squares criterion objective function is defined to evaluate the discrepancies between the measured and calculated pressure heads at measurement sites. A nonlinear optimization method is then utilized here to calibrate the problem decision variables, leak areas and pipe friction factors, to minimize the objective function.

Each objective function evaluation requires a transient flow analysis in the system which itself includes heavy numerical computations and takes a lot of time especially in large scale problems. Adding to this, topology of ITA problem's decision space may be multimodal which means that the problem at hand may consist of several local solutions. Success of the ITA to get reliable results is highly dependent on ability of the applied optimization method to find the global optima. Consequently, two important aspects of the optimization method in this work are computational efficiency (speed) and results reliability (accuracy).

Fig. 6 Trend of C minimization versus iteration number

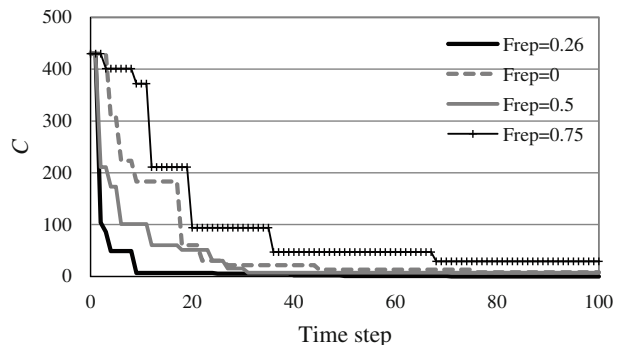


Table 1 Comparison of different optimization methods applied to the example

Optimization method	Number of evaluations	Investigated by
GA	50000	Kapelan et al. 2003
GA-LM	3000	Kapelan et al. 2003
SQP	1830	Shamloo and Haghighi 2010
CFO	2736	Current work

The present study adopted main framework of ITA method and exploited a newly developed metaheuristic namely Central Force Optimization as the problem solver. CFO is a search-based technique inspired by the metaphor of gravitational kinematics in physics. In CFO, each decision variable is considered as a coordinate axis in the search space. Each solution is also defined as a probe which has a position vector and a fitness value, mass, obtained from the problem's objective function. At the beginning, CFO flies a limited number of probes over the problem's decision space. Based on the Newton's universal law of gravitation, each probe experiences a vector of acceleration under the influence of gravity of other probes. Consequently, small probes are attracted to bigger ones and this continues until all probes become trapped in close orbits around highly gravitating masses. The biggest mass and its position vector eventually indicate the optimum solution.

As a case study, a benchmark network was taken into account from the literature which has been previously solved using different methods including LM, GA, GA-LM, and SQP. Among these methods, LM and SQP are mathematical or gradient-based solvers, GA is a stochastic population-based metaheuristic and GA-LM is a hybrid model. Herein, CFO as a deterministic metaheuristic was also applied to the benchmark example and exhibited a good performance in terms of efficiency and accuracy, based on which CFO can be compared to the previously used methods.

- Similar to LM and SQP there is no randomness in CFO's procedure and this is why CFO is a deterministic method. Therefore, every optimization run yields the same results so that the solved examples so far (in Formato's papers and herein) can be utilized as validation cases for investigators who intends to develop their own code. LM and SQP are two classical local search methods that work based on gradients of objective function in decision space. These methods start with an initial guess and then searches for the best solution in neighborhood of the current solution. Through successive iterations the solution is getting better and better until no better solution is found in the current solution's vicinity. Use of derivatives in LM and SQP makes it possible to determine the steepest slope in each current solution's neighborhood so that the best neighbor

Table 2 Leak areas detected by ITA

Node	True A_e (cm ²)	Detected A_e (cm ²)	Absolute difference ($\times 10^{-2}$)
2	1.00	0.99	1.00
3	0.00	0.00	0.00
4	0.00	0.00	0.00
5	0.00	0.00	0.00
6	0.00	0.00	0.00
7	0.00	0.00	0.00

Overall average differences in leak areas is 1.7×10^{-3}

Table 3 Darcy–Weisbach friction factors calibrated by ITA

Pipe	True f	Calibrated f	Absolute difference ($\times 10^{-2}$)
1	0.0400	0.0390	0.10
2	0.0400	0.0390	0.10
3	0.0400	0.0400	0.00
4	0.0250	0.0260	0.10
5	0.0250	0.0260	0.10
6	0.0250	0.0245	0.05
7	0.0300	0.0310	0.10
8	0.0300	0.0320	0.20
9	0.0300	0.0300	0.00
10	0.0300	0.0310	0.10
11	0.0250	0.0250	0.00

Overall average difference in friction factors: 8×10^{-4}

solution is quickly found. This potentiality avoids blind searches and unnecessary objective function evaluations in mathematical methods while significantly speeds up the optimization commutations. The example solved here shows that CFO is computationally efficient too (referring to Table 1), in particular, it is far faster than GA. This is related to the metaphor of gravitational kinematics used in CFO such that this method can be considered as a type of gradient-like optimization. In the model developed here the CFO exponents α and β are considered to be 2. As seen in Eq. 5, with these quantities the ratio of the difference of masses divided by the distance between probes very look like the square of a directional derivative of objective function which is utilized by SQP and LM to quickly recognize the position of local optima. This may be a reason for explaining how CFO is a fast search like gradient-based methods. Another point is that in contrast with other nature-inspired metaheuristics like GA, CFO's algorithm and ingredients are strictly in accordance with the mathematical and physical rules.

- Similar to GA, PSO and ACO, CFO is a population-based metaheuristic which means that it starts to search in a decision space with multiple initial solutions, probes herein. This is an important feature of the aforementioned methods which maintains the diversity of search in the decision space. Consequently, CFO by flying multiple initial probes has the potentiality to escape from local optima. However, the number of probes and how they are distributed in the decision space are very effective in CFO. This is because there is no randomness in CFO as for example there is in GA in which random operators can depreciate the effects of initial solutions' quality. In this work, after a few trial-and-error runs for the benchmark network, it was concluded that 2 probes uniformly distributed on each decision variable axis are enough however; 2 other probes were also randomly generated for more reliability. Through solving several complex multimodal test functions, Formato (2009) found that for uniform probe distribution approach, CFO is mostly sensitive to F_{rep} and N_p which was also concluded by the authors of this work from solving the ITA problem. This is while GA is significantly sensitive to more parameters such as mutation and crossover ratios, population size, and method of pairing, method of chromosomes representation and so on. Since CFO is deterministic, its parameter setting like deciding the number of probes or F_{rep} is much simpler than GA. For the example network, only 10 time steps were taken into account for sensitivity analysis of N_p and F_{rep} while the other parameters were kept constant. In GA, for

example, tuning mutation and crossover ratios is not that easy. It needs several pre-runs with significant number of generations to find an optimum set of parameters.

Like other metaheuristics, there is no doubt that CFO can become trapped in local optima or premature solutions. In spite of random movements which are used in GA, CFO exploits deterministic strategies to escape from local solutions. How well CFO performs this is still an open question and needs more developments and discussions in future. It seems that flying multiple initial probes with a diversified distribution is the first strategy to rid of local optima. A few additional randomly distributed probes can be also helpful in this regard as shown in the benchmark example. The second stagey is related to the function of F_{rep} which was introduced as a crucial factor in CFO. In accordance with the other constants in the method, F_{rep} has a remarkable role in restarting the search when some probes stick to boundaries or are thrown out. Another strategy is that when a probe becomes trapped in a local optimum it can be moved away from there under the influence of other probes flying over the decision space. On the other hand, if the initial probes are well distributed over the decision space they help each other escaping from local solutions through a CFO run. This is quite different with local trapping in mathematical methods in which the local optimum is only compared with its neighbor solutions which all are in a same hill. The aforementioned strategies are what currently work in the standard CFO algorithm for handling local trapping problem however other approaches can be also introduced. For instance, in the authors' opinion the unit step function U in Eq. 5 can play a significant role in rescuing probes trapped in local optima. U keeps the CFO's gravity always attractive which means that probes are only accelerated to move to better positions (toward bigger masses). To avoid local trapping, for a limited number of iterations, it would be useful to accept unattractive accelerations too which appear in a CFO implementation when U is dropped from Eq. 5. This strategy looks a lot like the aspiration mode in tabu search method that lets some tabu moves be adopted in search. This idea is still immature and needs to be more investigated through solving several multimodal test functions. However, it indicates that CFO as a novel metaheuristic is still open to receive new ideas and modifying features.

- Table 1 shows that the number of objective function evaluations (number of times that the transient analysis model is called) in CFO is very close to in GA-LM which is a hybrid optimization model. GA-LM utilizes the mathematical advantages of LM in term of speed as well as the heuristic advantages of GA in term of capability of finding global optima. Based on what explained about CFO and concluded from the case study, it seems that the method systematically exploits the both aforementioned advantages, at least in solving ITA problems.

In general, CFO is found to be an interesting metaheuristic which exhibited a good performance in solving the complicated problem of ITA in pipe networks. The method is still in its preliminary steps with many questions waiting to be replied. Further investigations in various fields of engineering are required to improve the method's performance. Deciding about the number and the distribution method of probes and parameters setting, handling the problem's constraints and escaping from local optima are major aspects of CFO that need more investigations in future.

In this paper the inverse transient analysis method was introduced as a powerful approach for parameter estimating in pressurized pipe-networks. This consequence has been also highlighted in previous researches. However, except Covas and Ramos (2001) and Vitkovsky *et al* (2007) which are experimental investigations, other works are theoretical. ITA method for leak detection and calibration of pipe-networks although is theoretically very promising but in

practice it includes some limitations. First of all, the piping system needs to be numerically modeled, which can be a difficult task for real-life systems especially for old ones. Data gathering for ITA is time-consuming and may include significant uncertainties which influence the reliability of the method. Success of ITA is greatly dependent on the quality and quantity of the measured data as well as accuracy of the numerical model. Implementing the field parts of the method including transient generation and pressure heads sampling is very crucial. Finding the most appropriate locations for initiating transient flow and measuring data is very important in ITA method. Furthermore, for a successful ITA it is recommended that the transient flow must be very quickly generated. Faster transients contain more information about the system and consequently result in more reliable leak detection. Besides, very fast transients may cause practical problems to the system such as undesirable waterhammer pressures or cavitations. Therefore, there are still major practical and theoretical aspects of ITA method which need to be more investigated in future.

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