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## Optimal Design or Rehabilitation of an Irrigation Project's Pipe Network

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### 1. Introduction

This chapter deals with the optimal design of the hydraulic part of an irrigation project. It is mainly focused on the design or management of the sprinkler irrigation method.

A typical sprinkler irrigation system usually consists of the following components:

- Source of the water (reservoir, river, well, waste water)
- Conduit to irrigation area (for instance, a canal or pipe system)
- Pump unit
- Pipe network (mainline and submainlines)
- Sprinklers or various types of irrigators (center pivot sprinkler system, linear move system, traveling big gun system, portable hand-move lateral pipe system, solid-set irrigation system, etc.)

This chapter deals with the optimal design of the most expensive part of a pressurised irrigation system, i.e., its pipe network. The problem of calculating the optimal pipe size diameters of an irrigation network has attracted the attention of many researchers and designers. During the process of designing an irrigation pipe network, the hydraulic engineer will face the problem of determining the diameters of the pipes forming the distribution network. For economic reasons, the pipe diameter should be as small as possible; on the other hand, the diameter must be large enough to ensure service pressure at the feed points (Labye et al., 1988; Lammadalena and Sagardoy, 2000).

Many optimization models based on linear programming (LP), non-linear programming (NLP) and dynamic programming (DP) techniques are available in the literature. Among them Labye's method is especially well known in the design of irrigation systems (Labye, 1966, 1981). This approach initially assigns the minimum possible diameter to each link without infringing on the maximum velocity restriction. From this initial situation, it is based on the concept of economic slope  $\beta_s$ , which is defined as the quotient between the cost increase ( $P_{s+1} - P_s$ ) produced when the diameter of the link is increased and the consequent gain in head loss ( $J_s - J_{s+1}$ ). The economic slope enables the characteristic curve of each sub-network to be established. Each increase in diameter is decided while trying to minimize the associated cost increase in an iterative process that ends when all the pressure heads in the network coincide with the design head.

The linear programming method is also still accepted as an approach for the optimal selection of the diameters of pipes in branched irrigation networks. Mathematical models based on LP were initially developed and used in the irrigation network design process in the former Czechoslovakia in the early 1960s (Zdražil, 1965).

Various methods for optimizing branched irrigation networks - Labye's method, the linear programming method and a simplified nonlinear method - were compared in (Theocharis, et al., 2010).

The above-mentioned methodologies are suitable only for networks without loops, which are typical in the irrigation industry. However, there are frequent situations where the presence of loops in the network is useful, e.g., when redundant parallel pipes in the network's supply are needed or the interconnection of branches to correct shortages or equalize pressure solves some design problems. A possible approach for increasing the hydraulic capacity of branch systems in the rehabilitation process is to convert them to looped networks (thereby providing alternative pathways) and increase their hydraulic capacity with a minimum capital investment. In the majority of cases the requirement to increase the hydraulic capacity of the system could be based on the following requirements, e.g.:

- To increase pressure and water demands at hydrants due to upgrading the irrigators (with increased pressure and demand characteristics).
- To provide sufficient pressure within the pipeline system with an increased number of demand points as well as grouping them in selected parts of the irrigation system.
- To expand the system by adding new branches.
- To eliminate a system's deficiencies due to its aging.

The methodologies for optimizing looped water distribution systems (WDS) mainly evolved for drinking water distribution systems, but, with some modifications, they are also applied in the irrigation industry. Alperovits and Shamir (Alperovits & Shamir, 1977) extended the basic LP procedure to looped networks. Kessler and Shamir (Kessler & Shamir, 1989) used the linear programming gradient method as an extension of this method. It consists of two stages: an LP problem is solved for a given flow distribution, and then a search is conducted in the space of the flow variables. Later, Fujiwara and Khang (1990) used a two-phase decomposition method extending that of Alperovits and Shamir to non-linear modelling. Also, Eiger, et al. (1994) used the same formulation as Kessler and Shamir, which leads to a determination of the lengths of one or more segments in each link with discrete diameters. Nevertheless, these methods fail to resolve the problems of large looped systems.

Researchers have focused on stochastic or so-called heuristic optimization methods since the early 1990s. Simpson and his co-workers (1994) used basic genetic algorithms (GA). The simple GA was then improved by Dandy, et al. (1996) using the concept of the variable power scaling of the fitness function, an adjacency mutation operator, and gray codes. Savic and Walters (1997) also used a simple GA in conjunction with an EPANET network solver.

Other heuristic techniques have also been applied to the optimization of a looped water distribution system, such as simulated annealing (Loganathan, et al, 1995; Cunha and Sousa, 2001); an ant colony optimization algorithm (Maier, et al., 2003); a shuffled frog leaping algorithm (Eusuff & Lansey, 2003) and a harmony search (Geem, 2002), to name a few.

The impetus for this work is that significant differences from the known global optimums are referred to even for single objective tasks and simple benchmark networks, while existing algorithms are applied. Reza, et al. (2008) evaluated the performance of several meta-heuristic techniques - genetic algorithms, simulated annealing, tabu search and iterated local search. He compared these techniques by applying them to medium-sized benchmark networks. For the Hanoi network (which is a well-known benchmark often used in the optimization community), after ten different runs with five heuristic search techniques he obtained results which varied in a range from 6,173,421 to 6,352,526. These results differ by 1.5 - 4.5 % from the known global optimum for this task (6,081,128), which is a relatively large deviation for such a small network (it consists of 34 pipes). Similar results were presented by Zecchin, et al. (2007) and Cisty, et al. (1999).

The main concern of this paper is to propose a method which is more dependable and converges more closely to a global optimum than existing algorithms do. The paper proposes a new multiphase methodology for solving the optimal design of a water distribution system, based on a combination of differential evolution (DE) and particle swarm optimization (PSO) called DEPSO (Zhang & Xie, 2003). DEPSO has a consistently impressive performance in solving many real-world optimization problems (Xu, et al., 2007; Moore & Venayagamoorthy, 2006; Luitel & Venayagamoorthy, 2008; Xu, et al., 2010). As will be explained in the following text, the search process in PSO is based on social and cognitive components. The entire swarm tries to follow the global best solution, thus improving its own position. But for the particular particle that is the global best solution, the new velocity depends solely on the weighted old velocity. DEPSO adds the DE operator to the PSO procedure in order to add diversity to the PSO, thus keeping the particles from falling into a local minimum.

The second base improvement proposed, which should determine the effectiveness of the proposed methodology, is the application of a multi-step procedure together with the mentioned DEPSO methodology. The multi-step optimization procedure means that the optimization is accomplished in two or more phases (optimization runs) and that in each further run, the optimization problem comes with a reduced search space. This reduction of the search space is based on an assumption of the significant similarity between the flows in the sub-optimal solutions and the flows in the global optimal solution. The details are described later in this paper.

This chapter is structured as follows: In the "Methodology" section, WDS optimization is explained and formally defined. This section subsequently describes PSO, DE, and DEPSO, together with DEPSO's multi-phase application to WDS optimal design. The experimental data, design, and results are presented and discussed in the "Application and Results" section. The "Conclusion" section describes the main achievements.

## 2. Methodology

### 2.1 Optimal design of a water distribution network

Given a water network comprised of  $n$  nodes and  $l$  sizable components (pipes, valves, pumps and tanks), the general least-cost optimisation problem may be stated mathematically in terms of the various design variables  $x$ , nodal demands  $d$ , and nodal pressure heads  $h$ . Here  $x$  is a vector of the selected characteristic values (or physical

dimensions) for the  $l$  sizable system components;  $d$  is a vector of length  $n$  specifying the demand flow rates at each node, and  $h$  is a vector of length  $n$ , whose entries are the pressure head values for the  $n$  nodes in the system (note that the head depends on  $x$  and  $d$ ). Here  $x$  may include, for example, the diameter of the pipes, the capacity of the pumps, valve types and settings, and the tank volume, diameter and base elevation (Rossman, 2000). In our work the least cost optimal design problem is solved, and the decision variables are the diameters of the pipelines, which must be selected from a discrete set of commercially available pipe diameters.

The design constraints are typically determined by the minimal pressure head requirements at each demand node and the physical laws governing the flow dynamics. The objective is to minimize the cost function  $f(h, d, x)$ . This cost function may include installation costs, material costs, and the present value of the running costs and/or maintenance costs for a potential system over its entire lifetime. For optimisation methods that cannot explicitly accommodate constraints, it is a common practice to add a penalty term to the cost function, in order to penalize any constraint violations (such as deviation from the system's pressure requirements) (Lansey, 2000). This technique requires a penalty factor to scale the constraint violations to the same magnitude as the costs.

The WDS design optimization problem is therefore to minimize

$$f(h, d, x),$$

subject to

$$g(q, d, x) = 0,$$

$$e(h, d, x) = 0,$$

$$h_{\min} \leq h(d, x) \leq h_{\max},$$

$$j_{\min} \leq j(x) \leq j_{\max} \quad (1)$$

where a set of at least  $n$  conservation of mass constraints  $g(q, d, x) = 0$  includes the conservation of the flow equation for each of the nodes in the system, incorporating the nodal water demands  $d$  and the flows  $q$  for all the pipes branching from a node; the system of equations  $e(q, d, x) = 0$  are energy equation constraints, specifying that energy is conserved around each loop, which then follows the pressure head constraints. The design constraints of the form  $j_{\min} < j(x) < j_{\max}$  on the variables  $j(x)$  specify the physical limitations or characteristic value sets from which the components may be selected (Lansey, 2000). These constraints may represent restrictions on discrete variables such as pipes which come in a range of commercial diameters.

The main design constraints (pressure head requirements) in the present work were determined by the EPANET 2 (Rossman, 2000) simulation model. For the purpose of the optimal design the model is first set up by incorporating all the options for the individual network components. The DEPSO then generates trial solutions, each of which is evaluated by simulating its hydraulic performance. Any hydraulic infeasibility, for example, failure to reach a specified minimum pressure at any demand point, is noted, and a penalty cost is



calculated. The operational (e.g. energy) costs can also be calculated at this point if required. The penalty costs are then combined with the predicted capital and operational costs to obtain an overall measure of the quality of the trial solution. From this quality measure the fitness of the trial solution is derived. The process will continue for many thousands of iterations, and a population of good feasible solutions will evolve.

## 2.2 Particle swarm optimization

Particle swarm optimization (PSO) is a meta-heuristic method inspired by the flocking behaviour of animals and insect swarms. Kennedy and Eberhart (Kennedy et al., 2001) proposed the original PSO in 1995; since then it has steadily gained popularity. In PSO an individual solution in a population is treated as a particle flying through the search space, each of which is associated with a current velocity and memory of its previous best position, a knowledge of the global best position and, in some cases, a local best position within some neighbourhood - defined either in terms of the distance in decision/objective space or by some neighbourhood topology. The particles are initialized with a random velocity at a random starting position.

These components are represented in terms of the two best locations during the evolution process: one is the particle's own previous best position, recorded as vector  $p_i$ , according to the calculated fitness value, which is measured in terms of the clustering validity indices in the context of the clustering, and the other is the best position in the entire swarm, represented as  $p_g$ . Also,  $p_g$  can be replaced with a local best solution obtained within a certain local topological neighbourhood. The corresponding canonical PSO velocity and position equations at iteration  $t$  are written as

$$v_i(t) = w \cdot v_i(t-1) + c_1 \cdot \varphi_1 \cdot (p_i - z_i(t-1)) + c_2 \cdot \varphi_2 \cdot (p_g - z_g(t-1)) \quad (2)$$

$$z_i^t(t) = z_i(t-1) + v_i(t) \quad (3)$$

where  $w$  is the inertial weight;  $c_1$  and  $c_2$  are the acceleration constants, and  $\varphi_1$  and  $\varphi_2$  are uniform random functions in the range of  $[0,1]$ . Parameters  $c_1$  and  $c_2$  are known as the cognitive and social components, respectively, and are used to adjust the velocity of a particle towards  $p_i$  and  $p_g$ .

PSO requires four user-dependent parameters, but accompanied by some useful rules. The inertia weight  $w$  is designed as a trade off between the global and local searches. The greater values of  $w$  facilitate global exploration, while the lower values encourage a local search. Parameter  $w$  can be fixed to some certain value or can vary with a random component, such as:

$$w = w_{\max} - \varphi_3/2, \quad (4)$$

where  $\varphi_3$  is a uniform random function in the range of  $[0,1]$  and  $w_{\max}$  is a constant. As an example, if  $w_{\max}$  is set as 1, Eq. 4 makes  $w$  vary between 0.5 and 1, with a mean of 0.75. During the evolutionary procedure, the velocity for each particle is restricted to a limit  $w_{\max}$ , as in velocity initialization. When the velocity exceeds  $w_{\max}$ , it is reassigned to  $w_{\max}$ . If  $w_{\max}$  is too small, the particles may become trapped in the local optima, where if  $w_{\max}$  is too large, the particles may miss some good solutions. Parameter  $w_{\max}$  is usually set to around 10 - 20% of the dynamic range of the variable on each dimension (Kennedy et al., 2001).

Izquierdo et al. (2008) applied PSO to the water distribution system design optimization problem in his work. They developed an adaptation of the original algorithm, whereby the solution collisions (a problem that occurs frequently in PSO) are checked using several of the fittest particles, and any colliding solutions are randomly regenerated with a new position and velocity. This adaptation greatly improves the population diversity and global convergence characteristics. Finally, they adapted the algorithm to accommodate discrete variables by discretizing the velocities in order to create discrete step trajectories for these variables. Izquierdo et al. tested their algorithm on the NYTUN and HANOI WDS benchmarks and achieved large computational savings (an order of magnitude better than the previous methods), whilst closely approximating the known global optimum solutions.

### 2.3 Differential evolution

In 1997 Storn and Price (1997) first proposed differential evolution (DE), as a generic metaheuristic for the optimization of nonlinear and non-differentiable continuous space functions; it has proven to be very robust and competitive with respect to other evolutionary algorithms. At the heart of its success lies a very simple differential operator, whereby a trial solution vector is generated by mutating a random target vector by some multiple of the difference vector between two other random population members. For the three distinct random indices  $i, j$  and  $k$ , this has the form:

$$y_i = x_i + \hat{f} \times (x_j - x_k), \quad (5)$$

where  $x_i$  is the target vector;  $y_i$  is the trial vector; and  $\hat{f}$  is a constant factor in the range  $[0, 2]$  which controls the amplification of any differential variation, typically taken as 0.5. If the trial vector has a better objective function value, then it replaces its parent vector. Storn and Price also included a crossover operator between the trial vector and the target vector in order to improve convergence.

### 2.4 Hybrid DEPSO methodology

The DEPSO algorithm involves a two-step process. In the first step, the original PSO as previously described is applied. In the second step, the DE mutation operator is applied to the particles. The crossover rate for this study is given as one (Zhang & Xie, 2003). Therefore, for every odd iteration, the original PSO algorithm is carried out, while for every even iteration, the DEPSO algorithm is carried out. The procedure for the implementation of DEPSO is summarized in the following steps:

1. Initialize a population of particles with random positions and velocities. Set the values of the user-dependent parameters.
2. For every odd iteration, carry out the canonical PSO operation on each individual member of the population.
  - a. Calculate the fitness function  $Fit(z_i)$  for each particle  $z_i$ ;
  - b. Compare the fitness value of each particle  $Fit(z_i)$  with  $Fit(p_i)$ . If the current value is better, reset both  $Fit(p_i)$  and  $p_i$  to the current value and location;
  - c. Compare the fitness value of each particle  $Fit(z_i)$  with  $Fit(p_g)$ . If the current value is better, reset  $Fit(p_g)$  and  $p_g$  to the current value and location;

- d. Update the velocity and position of the particles based on Eqs. 6 and 7.
3. For every even iteration, carry out the following steps:
  - a. For every particle  $z_i$  with its personal best  $p_i$ , randomly select four particles,  $z_a$ ,  $z_b$ ,  $z_c$ , and  $z_d$ , that are different from  $z_i$  and calculate  $\Delta_1$  and  $\Delta_2$  as,

$$\Delta_1 = p_a - p_b, a \neq b, \quad (6)$$

$$\Delta_2 = p_c - p_d, c \neq d, \quad (7)$$

where  $p_a$ ,  $p_b$ ,  $p_c$ , and  $p_d$  are the corresponding best solutions of the four selected particles.

- b. Calculate the mutation value  $\delta_i$  by Eq. 8 and create the offspring  $o_{ij}$  by Eq.9,

$$\delta_i = (\Delta_1 + \Delta_2) / 2, \quad (8)$$

$$o_{ij} = p_{ij} + \delta_{ij}, \text{ if } \varphi \leq p_r \text{ or } j = r \quad (9)$$

where  $j$  corresponds to the dimension of the individual, and  $r$  is a random integer within 1 and the dimension of the problem space.

- c. Once the new population of offspring is created using steps a) and b), their fitness is evaluated against that of the parent. The one with the higher fitness is selected to participate in the next generation.
- d. Recalculate the  $p_g$  and  $p_i$  of the new population.
4. Repeat steps 2) to 3) until a stopping criterion is met, which usually occurs upon reaching the maximum number of iterations or discovering high-quality solutions.

## 2.5 Multi-step approach to WDS design

The proposed approach to the WDS optimization methodology involves refining the optimization calculations in a multiple-step approach, where the search space from the first optimization run is reduced for the second optimization run. In every run the DEPSO methodology is applied. The size of the search space depends on the number of possible diameters for each link from which the optimal option could be selected. In the first phase for all the links, all the available diameters are usually considered. In this case the size of the search space is  $n^l$ , where  $n$  is the number of possible diameters and  $l$  is the number of links. In the second phase the size of the search space is  $n_1.n_2.n_3 \dots n_l$ , where  $n_i$  is the number of possible diameters for link  $i$ , which is a smaller number than in the first phase if some of the  $n_i$  are less than  $n$ .

On the basis of the flows computed in the pipes of the suboptimal solution in the first phase, it is possible, with the help of the known design minimum and maximum flow velocities, to calculate the maximal and minimal pipeline diameter considered for a given link of the WDS network. The prerequisite for undertaking such a step is the ability of modern heuristic algorithms to approximate the global optimum with a sufficient degree of accuracy, which could now, after two decades of their development, be expected. It is therefore assumed that the resulting suboptimal solution already has flows sufficiently close to the flows in the global optimum design of the WDS. This assumption is empirically verified by the author in this paper, but it also has a logical basis, since it is known that for a given distribution of the flows in a water distribution network, multiple solutions for the design of the diameters (the main design parameter in our definition of WDS optimization) could be found to comply with the technical requirements of the system.



One of the diameter designs for flow distribution in a network is best with regard to the cost of the network. This means that there are fewer variations in the flows than there are variations of the possible diameters, so if the diameters proposed by the heuristic search engine (e.g. DEPSO) differ from the optimal diameters searched for, the flows could be quite close to them, especially when a suboptimal solution close enough to the global optimal one is considered. There is some degree of intuition in this theorem, but the proposed idea was tested with positive results (as will be referred to hereinafter). The subsequent task is to find the corresponding optimal diameters for this distribution of the flows.

A reduction of the search space is accomplished for the second optimisation run with the assistance of the minimum and maximum pipeline flow velocities allowed. These parameters allow for the calculation of the anticipated minimum and maximum diameter for every network segment. These two values set an upper and lower boundary to the new range of acceptable diameters for each pipe segment, from which the algorithm will choose the optimal values in the second run. With the above-mentioned reduction of possible particle values a smaller search space is obtained, and better search results can be expected.

3. Application and results

The Tomasovo irrigation network was used as a case study in this work. Its layout is shown in Figure 1. This is one of the irrigation facilities in Slovakia which has medium-size area coverage, and the sprinkler type of irrigation is applied. Its construction was completed at the beginning of the 1960s; the whole facility is therefore approaching the end of its service life and can be selected as a suitable model for testing the proposed optimization methods which could also be easily applied for the rehabilitation of the hydraulic system.

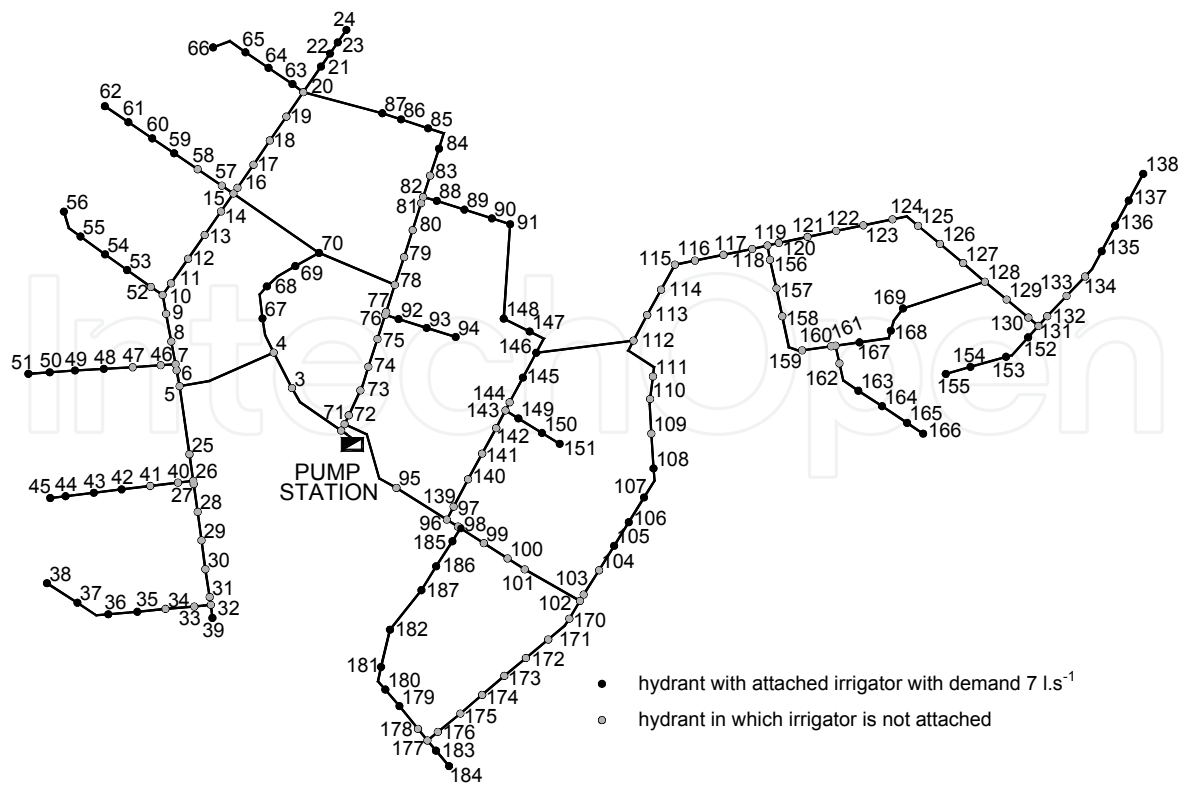


Fig. 1. Tomasovo irrigation system layout with positions of demands marked

The irrigated area of this system amounts to 700 ha. The hydraulic part of the irrigation system consists of the irrigation water take-off structure from the canal, a pump station, a pressurized network for the delivery of irrigation water, and sprinklers. For the purpose of this study it is necessary to describe only the pipeline network in detail (which is available from the author of this chapter in the form of an EPANET input file). The pump station and sprinklers represent the boundary conditions for the system analysed. Only their basic parameters (the pressure and output flow of the pump station, the required sprinkler pressure and demand flow) are taken into account in the optimization computations. A concept of irrigation with hose-reel irrigators with an optimum demand flow of  $7.0 \text{ l.s}^{-1}$  and an optimal inlet pressure of 0.55 MPa is proposed for this system. In addition, it is assumed that a battery of such sprinklers will be used, i.e., there will be a set of four machines which operate as a whole on the adjacent hydrants – this approach has some advantages while managing the system, and similar operational rules could also be defined in other systems. Water is supplied through a pump station with an output pressure of 0.85 MPa and a flow of  $392 \text{ l.s}^{-1}$ . This means that 56 irrigators with a demand flow of  $7.0 \text{ l.s}^{-1}$  could simultaneously work on the network (14 groups of irrigators). These irrigators could be placed in various hydrants of the network during the operation of this system. The worst case for their placement should be used for the design of the diameters. In Figure 1 the placement of the irrigators is displayed, the positions of which were used in searching for the optimal pipe diameters in this study. In some of the nodes the input of the water to the network is imitated in the EPANET inputs with the aim of reducing the overall flow to the maximal possible flow from the pump station and concurrently having in each part of the network such a flow which could be expected in this place during the system's operation.

This network has a total of 186 nodes supplied by one source node (the pump station). There are 193 pipes arranged in 7 loops, which are to be designed using a set of 7 asbestos cement pipes with diameters of 100, 150, 200, 300, 350, 400 and 500 mm and an absolute roughness coefficient of  $k = 0.05 \text{ mm}$ . When searching for the optimal diameters for this system, a total enumeration of all possible alternatives from which the optimal solution should be chosen is not possible. The amount of possible combinations could be evaluated from a number of the above-mentioned proposed diameters powered on a number of pipes – it reaches the impressive amount of  $7^{193}$ , which is a number with 163 digits before the decimal point. That is why the optimization methodologies described in the methodology part were applied for solving this task. The Darcy–Weisbach equation has been adapted to calculate the head losses, using EPANET 2 (Rossman, 2000). The minimum required pressure head in this network is 0.55 MPa for each demand node (which the proposed hose-reel sprinkler needs for its operation).

The computational experiments were accomplished in the following manner: Firstly, 100 testing runs of the first phase of the proposed algorithm (without reducing the search space) were computed for the Tomasovo network; the results are summarised in Figure 2. In this stage various DEPSO settings were used (DE factor =  $0.3 \div 0.8$ , CR =  $0.5 \div 1.0$ , PSO C1 = C2 =  $0.5 \div 1.5$ ;  $N_{\text{population}} = 100 \div 250$  and  $N_{\text{generation}} = 500 \div 1000$ ). The histogram in Figure 2 shows that the minimal (best) obtained cost of the optimized network in this phase was 510,469.5 €; the maximal (worst) network price was 544,464.8 €; and the most frequently obtained result was 515,000 € – 525,000 €. The original search space was reduced by the procedure explained in section 2.5 from the original  $7^{193}$  to a value of  $7^{100}$  on the basis of the

flows in the most frequently obtained result (or average result) from this interval (the cost of this solution was 521,536.9 €). The mentioned one hundred runs of the first phase of the algorithm were performed with the intention of verifying the probability of obtaining this result (a reduction of the search space to approximately  $7^{100}$  alternatives), which is a prerequisite for the next computational phase, e.g., this amount of the computations was accomplished only for testing purposes. In actual computations this is not necessary: five to ten runs would be enough, and the best solution in a real case could be taken as the basis for reducing the search space.

Thus in our testing computations, the reduced search space with an average reduction (which is also the most likely result obtained according to Figure 2) was chosen and entered into the second optimization run. The leading factor determining the search space reduction and affecting the accuracy of the calculations are, in addition, the mentioned result of the computations from the first phase of the algorithm and also the minimum and maximum flow velocities mentioned in section 2.5. The values of the velocity for the search reduction were  $0.1\text{ m.s}^{-1}$  ( $v_{\min}$ ) and  $3\text{ m.s}^{-1}$  ( $v_{\max}$ ). One hundred runs of the second phase were conducted similarly as in the case of the first phase computations in order to verify the probability of obtaining the final result, which is also reported in Figure 2. It is possible to see there that almost all the results from the second phase are on the left side of the results from the first phase, i.e., they are better. This means that it is better to apply our proposed two-phase algorithm than to refine or accomplish more computations without a reduction of the search space as is usual. The minimal (best) obtained cost of the optimized network in this final phase was 507,148.3 €; the maximal (worst) network cost was 513,462.0 €; and the average result was 508,970.5 €.

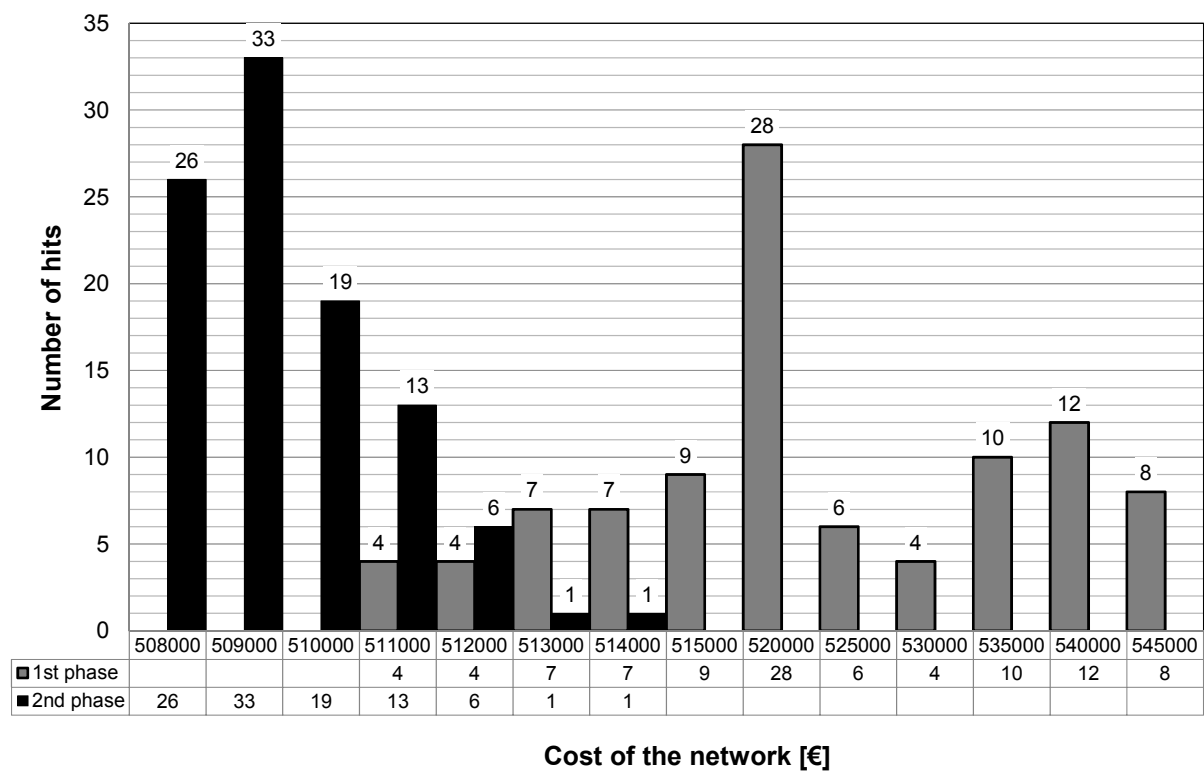


Fig. 2. Histogram of first and the second phases of the optimization computations

This procedure works fully automatically and does not need an expert's assistance in the optimization calculations. The EPANET input file of this water distribution network and all the results of the computations are not presented here in the table form in detail, because an inappropriately large space would be needed for such a presentation and is available from the author of this chapter.

### 3.1 A Comparison of the branched and looped alternatives of the irrigation network design

Irrigation systems were usually designed with branch layout. Because we proposed in this study procedure for design of the looped irrigation networks in this chapter are optimal designs for this two possibilities evaluated. The looped layout of the tested irrigation network is reduced to branch one by removing pipes between nodes 15-70, 20-87, 70-78, 91-148, 112-146, 128-169, 182-187. The linear programming (LP) method is accepted as an approach for the optimal selection of the diameters for pipes in branched networks. For the clarity purposes we briefly describe the optimisation procedure of the pipeline network rehabilitation using linear programming. The mathematical formulation of this problem is as follows:

$$A_{11}x_1 + A_{12}x_2 + \dots + A_{1n}x_n = B_1$$

$$A_{21}x_1 + A_{22}x_2 + \dots + A_{2n}x_n = B_2$$

etc.

$$A_{m1}x_1 + A_{m2}x_2 + \dots + A_{mn}x_n = B_m \quad (10)$$

$$c_1x_1 + c_2x_2 + \dots + c_nx_n = \min \quad (11)$$

Solution has to comply with inequalities:

$$x_1 > 0; x_2 > 0 \text{ etc. up to } x_n > 0 \quad (12)$$

When in order to resolve pipeline networks optimization task linear programming is applied, unknown are the lengths of individual pipeline diameters. In conditions (10) should be mathematically expressed the requirement that the sum of unknown lengths of individual diameters in each section has to be equal to its total length. The second type of the equation in constraints (10) represents the request that the total pressure losses in a hydraulic path between the pump station and critical node (the end of the pipeline, extreme elevation inside the network) should be equal or less than the known value. This constraint is based on the maximum network pressure requirement needed for the operation of the system. Given the investment costs minimisation requirement, the objective function (11) sums the products of individual pipeline prices and their required lengths. Four possible diameters (base of  $v_{\min}$  a  $v_{\max}$ ) are selected for each section. Further details on LP optimisation can be found in available literature, e.g., Cisty et al., (1999). The results of optimal design of the branch network by LP is summarised in the Table 1.

The results obtained indicate that the optimal design of a branched network using linear programming provides better results from an investment cost point of view (504,574.5 €)

than the calculations using DEPSO on a looped network (507,148.3 €). This follows from the fact that LP is a deterministic algorithm, which provides a real global minimum of the problem, which was defined by equations (10, 11, 12). The DEPSO method is a heuristic algorithm, which can provide results closer to a global minimum. The main reason is, of course, that there are fewer pipes in the branched alternative than in looped one. Considering the operation of an irrigation network, there are some advantages in using a looped layout, which is illustrated by evaluating the set of the real operation situations of the Tomasovo irrigation network both with branched and looped optimal designs.

The pressure assessment of the pipeline network was done in such a way that a set of realistic operational situations was analysed. These demand situations are proposed to have maximum hydraulic requirements (compatible with those used for the design of the network), and 320 various possibilities with different placements of the irrigators on the network were generated and evaluated. The next step was to run a simulation calculation of the branched and looped network configurations for all of these operational situations. In these alternatives we have assessed the minimal, maximal and average pressures at all the demand points. These values are shown in the diagram (Figure 3), where the data is sorted according to size.

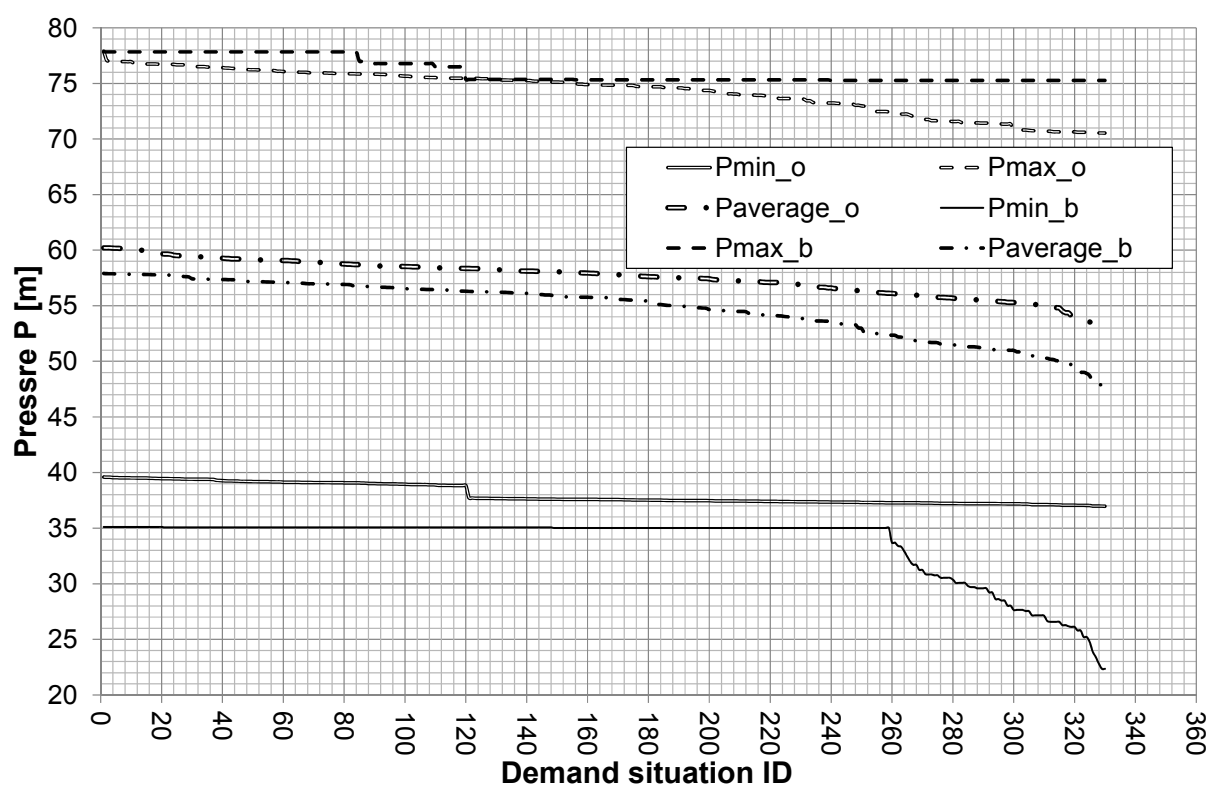


Fig. 3. Comparison of the pressures in 320 demand situations in the branched and looped alternatives

The simulation results prove the benefit of looping in hydraulic terms (better pressure ratios, lower maximal pressures, higher minimal pressures) and in economic terms – looped network rehabilitation is not much more expensive than a branched solution. There are unacceptably low pressures in branch networks in approximately 25% of the demand



situations investigated, which is why a looped network should be preferred to a branched one from an operational point of view. One can assume that the results described are also applicable when designing other systems.

| Diameter | unit cost | Branch network |           | Looped network first phase |            | Looped network second phase |           |
|----------|-----------|----------------|-----------|----------------------------|------------|-----------------------------|-----------|
|          |           | length         | cost      | length                     | cost       | length                      | cost      |
| mm       | €/m       | m              | €         | m                          | €          | m                           | €         |
| 100      | 15.5      | 5,049.6        | 78,268.8  | 8,679.7                    | 134,535.35 | 8,582.2                     | 133,024.1 |
| 150      | 20        | 7,509.8        | 150,196   | 5,671.1                    | 113,422    | 6,302                       | 126,040   |
| 200      | 12        | 6,629.8        | 79,557.6  | 8,523.9                    | 102,286.8  | 8,273.7                     | 99,284.4  |
| 300      | 36.5      | 3,756.4        | 137,108.6 | 3,194.7                    | 116,606.55 | 3,015.5                     | 110,065.7 |
| 350      | 47        | 1,171          | 55,037    | 834.3                      | 39,212.1   | 730.3                       | 34,324.1  |
| 400      | 55        | 35.3           | 1,941.5   | 35.3                       | 1,941.5    | 35.3                        | 1,941.5   |
| 500      | 72.5      | 34             | 2,465     | 34                         | 2,465      | 34                          | 2465      |
| SUM      |           | 24,185.9       | 504,574.5 | 26,973                     | 510,469.3  | 26,973                      | 507,144.3 |

Table 1. Costs of the optimal design from linear programming and the first and second phase of the DEPSO algorithm

4. Conclusion

In this study the application of the DEPSO optimization algorithm for the design of a pressurised irrigation water distribution network is proposed. Its effectiveness is determined by the proposed multiple-step approach with application of the DEPSO heuristic methodology, where the optimized problem with a reduced search space is entered into each subsequent run. This reduction was obtained with the help of the assumption of a significant closeness between cost flows in the suboptimal and global optimal solutions. This assumption was empirically verified at the large Tomasovo irrigation network where this methodology was applied. The calculation results for this network show the better performance of the proposed methodology compared to the traditional, one-step application of the various heuristic methods. The benefit of designing the looped alternative versus the branch one is demonstrated by comparing the operational flexibility of networks designed by DEPSO and by linear programming.

The focus of the work was aimed at simplifying the calculations for practical use. The proposed optimization procedure could work fully automatically and does not need an expert's assistance in the optimization calculations (e.g., for choosing the various parameters of the heuristic methodology). Various improvements are possible in future research, e.g., the direct inclusion of the operation evaluation into the optimization procedure by applying a multi-objective approach.

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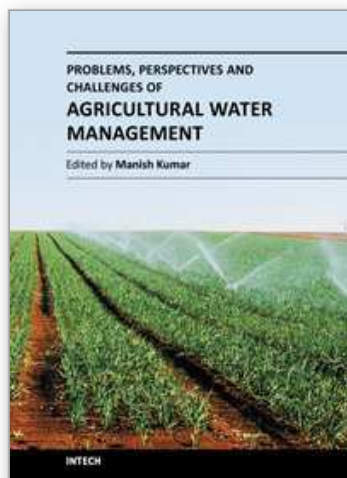
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## **Problems, Perspectives and Challenges of Agricultural Water Management**

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Food security emerged as an issue in the first decade of the 21st Century, questioning the sustainability of the human race, which is inevitably related directly to the agricultural water management that has multifaceted dimensions and requires interdisciplinary expertise in order to be dealt with. The purpose of this book is to bring together and integrate the subject matter that deals with the equity, profitability and irrigation water pricing; modelling, monitoring and assessment techniques; sustainable irrigation development and management, and strategies for irrigation water supply and conservation in a single text. The book is divided into four sections and is intended to be a comprehensive reference for students, professionals and researchers working on various aspects of agricultural water management. The book seeks its impact from the diverse nature of content revealing situations from different continents (Australia, USA, Asia, Europe and Africa). Various case studies have been discussed in the chapters to present a general scenario of the problem, perspective and challenges of irrigation water use.

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