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OPTIMIZATION OF LOW-ENTHALPY GEOTHERMAL HEATING SCHEMES BY MEANS OF GENETIC ALGORITHMS

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ABSTRACT

The application of genetic algorithms to the optimization of certain aspects of low-enthalpy geothermal district heating schemes is presented. In particular, minimization of the cost due to pumping and amortization of the construction of the pipe network inside the geothermal field is investigated. An outline of the optimization code is given and its performance is evaluated through application examples to geothermal fields with uniform and non-uniform water temperature distribution. In addition, a procedure to decide the number of new wells that should be drilled is discussed. It has been concluded that the use of the proposed technique may result in substantial cost reduction, thus promoting the direct use of geothermal energy.

Keywords: amortization cost, cost minimization, direct use, genetic algorithms, geothermal energy, pumping cost.

1 INTRODUCTION

Geothermal energy, together with other renewable energy sources, constitutes in the long term the only viable solution for a sustainable future. The earth will provide us with heat in the next million years at predictable rates [1]. Our task is to harness and manage it properly, in other words, to manage the heat transportation means, namely water or steam, in a sustainable way.

Geothermal and other soft energy sources meet another crucial criterion for a sustainable future: very low environmental impact – soil, water and air pollution (e.g. emission of greenhouse gases) is low even from high-enthalpy geothermal fields compared to the impact of fossil fuels.

Moreover, an increased share of renewable energy in the energy market promotes global stability, as it reduces the dependence of energy consumers on remote oil producers, on the mode of oil transfer (tankers or pipes) and on big oil companies.

High-enthalpy geothermal energy looks more attractive since it can be transformed to electricity. On the other hand, low-enthalpy geothermal sources are much more abundant. Distributed in most areas of the world, they can provide heat for space heating and other direct uses, thus covering an important part of energy demand. Analysis of their financial performance is rather complex [2]. A comprehensive report is offered by Lund and Freeston [3]. Their current contribution to the energy balance is probably underestimated, as very often their use is not adequately recorded, at least quantitatively. It is certain, though, that their share can substantially increase in many areas of the world, including the energy importing part of Europe. Greece is one of the countries with a large unexploited potential [4].

While the cost of energy production from renewable sources has generally declined, it has remained higher than that of oil and coal plants [5]. This comparatively high cost (when environmental and social factors are not taken into account) is a major obstacle to the wider use of geothermal and other renewable energy sources. Thus, optimization of their financial performance is crucial. This is not an easy task since many different factors are involved.

Genetic algorithms, outlined in the following paragraphs, constitute a very flexible optimization tool for such multiparametric problems. This paper deals with their application to cost minimization of some major components of geothermal district heating schemes, which are probably the most promising application of low-enthalpy geothermal energy [6].

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2 THE OPTIMIZATION TOOL

Genetic algorithms, initially introduced by Holland [7], are a mathematical tool with a very wide range of applications. They are particularly efficient in optimization problems, especially when the respective objective functions exhibit many local optima or discontinuous derivatives.

There are already extensive books [8–11], which deal with the theoretical background, the perspectives, the computational details and the applications of genetic algorithms (and other evolutionary techniques). Their main concepts, together with the features of the particular code used in this paper, are briefly described in the following paragraphs.

Genetic algorithms are essentially a mathematical imitation of a biological process, namely that of evolution of species. They start with a number of random, potential solutions of the investigated problem. These solutions, which are called chromosomes, constitute the population of the first generation. In binary genetic algorithms, each chromosome is a binary string of predetermined length.

Each chromosome of the first generation undergoes evaluation by means of a pertinent function or process, which depends entirely on the specific application of genetic algorithms. Then, the next generation is produced by means of certain operators which imitate biological processes and are applied to the chromosomes of the first generation. The main genetic operators are: (a) selection, (b) crossover and (c) mutation. Many other operators have also been proposed and used.

Selection is used first. It leads to an intermediate population in which better chromosomes have statistically more copies. These copies eventually replace some of the bad chromosomes. Then, the other operators apply to a number of randomly selected members of this intermediate population. The result is an equal number of new chromosomes, i.e. new solutions, which replace the old ones. Thus, the next generation is formed.

The whole process, i.e. evaluation–selection–crossover–mutation–other operators, is repeated for a predetermined number of generations. It is anticipated that at least in the last generation a chromosome will prevail, which represents the optimal (or at least a very good) solution to the examined problem.

The features of the genetic operators, which have been used in this paper for the minimization of the sum of certain important cost elements of a geothermal district heating scheme, are outlined in the following paragraphs.

2.1 Selection

Selection can be accomplished in many ways. The most common processes are: (a) the biased roulette wheel and (b) the tournament method. The latter has been preferred because it applies equally well to maximization and to minimization problems, while the former applies naturally (namely, without a definite need of scaling) to maximization problems only.

Selection through the tournament method requires the determination of the respective selection constant KK. Then it proceeds in the following way: KK chromosomes are randomly selected from the current generation and their fitness values are compared to each other. The chromosome with the best (smallest in the investigated case) fitness value passes to the intermediate population. This process is repeated PS times, PS being the population size. In this way, the intermediate population is formed. Moreover, in our genetic code, we have adopted an elitist approach – the best chromosome of each generation is separately passed to the new one.

2.2 Crossover

Crossover applies to pairs of chromosomes, which are binary strings of length SL. Two chromosomes, which are named parents, are randomly selected from the intermediate population. An integer number

XX, between 0 and (SL−1), is randomly selected, too. Then each parent binary string is cut into two pieces, immediately after the position XX. The first piece of each parent is combined with the second piece of the other. In this way, two new chromosomes are formed, which are called offsprings and replace their parents in the next generation.

Crossover aims at combining the best features of both parents in one offspring. All chromosomes of the intermediate population have equal probability of undergoing crossover. But this probability is actually larger for the better chromosomes of the parent generation because they have more copies in the intermediate population.

2.3 Mutation

Mutation applies to characters (genes), which form the chromosomes. In binary genetic algorithms, the gene selected for mutation is changed from 0 to 1 and vice versa. This process aims at: (a) extending the search to more areas of the solution space (mainly in the first generations) and (b) helping local refinement of good solutions (mainly in the last generations). The mutation probability is equal for all genes of all chromosomes. Its magnitude depends on the chromosome length SL, but generally is much smaller than the respective crossover probability because the latter refers to chromosomes and not to genes.

2.4 Antimetathesis

Many additional operators have been proposed in the literature to further improve the performance of genetic algorithms. A number of them are problem specific, while others are for general use. In this application, one more operator of general use has been included. This operator has been proposed by Katsifarakis and Karpouzos [12] and Katsifarakis *et al*. [13]. It applies to pairs of successive positions (genes) of a chromosome. Any position (except for the last one) can be selected with equal probability p_a. If the value of the selected gene equals 1, it is set to 0, while that of the following gene is set to 1 (irrespective of its original value). The opposite happens if the value of the selected gene is 0. Thus, the proposed operator is equivalent either to simple mutation or to the mutation of two successive genes. Moreover, it can be interpreted as a limiting case of the inversion operator. The operator has been called antimetathesis, based on its function (when different from simple mutation). This name is in line with the tradition in genetic algorithms terminology, which calls for terms of Greek origin. Antimetathesis and mutation are used interchangeably (in the even and odd generations, respectively). It has been anticipated that this combination is the most effective, as the two operators are complementary to each other, both in refinement of good solutions and in exploring different areas of the solution space.

2.5 Handling constraints

In many applications, optimization is subject to constraints. This means that chromosomes, which result from genetic operators, may represent infeasible solutions. The usual way to deal with constraints is to include penalty functions in the evaluation process. Each penalty function affects the fitness value of chromosomes, which violate the respective constraint, increasing it in minimization problems and decreasing it in maximization ones. Repair of chromosomes, in order to fulfill the constraints, is the best choice in certain cases. Other approaches include rejection of infeasible chromosomes and modification of genetic operators, in order to produce feasible solutions only.

Handling of constraints depends essentially on the particular problem. For this reason, it is further discussed in the frame of the application to optimization of geothermal heating schemes.

3 OPTIMIZATION OF GEOTHERMAL DISTRICT HEATING SCHEMES

To illustrate the application of genetic algorithms to optimization of geothermal district heating schemes, we considered minimization of the combined cost of two major geothermal components: (a) annual pumping (operation) cost and (b) amortization of the construction cost of the pipe network carrying hot water from the wells to a central station. Two examples are presented. In the first, the temperature of water produced is constant, while in the second it depends on the location of each producing well.

3.1 Geothermal field with uniform temperature distribution

A low-enthalpy geothermal field, stretching over an area of 3000×3000 m, produces water of 80°C, which is suitable for house heating. The water will be used by a nearby small town, requiring an average flow rate of $Q_T = 500$ l/s during the heating period. There are already four wells in the field and six more will be constructed. The coordinates of the existing wells are shown in Fig. 1.

The optimization problem is to find the positions of the 6 new wells and the distribution of the total flow rate Q_T to the 10 wells (old and new), which minimizes a cost function including: (a) operation (pumping) cost and (b) amortization of the construction cost of the pipe network that connects the wells with a central station at the edge of the field (its coordinates are $x_{st} = 0$, $y_{st} = 2000$). The central station is also shown in Fig. 1.

3.1.1 Chromosome construction

Each chromosome represents a solution to the problem. In our case, the solution is a combination of the flow rate values Q_i of 10 wells and 12 coordinate values (x and y for the 6 new wells). It is reasonable to assume that no single well will pump more than half the total flow rate Q_T. Each Q_i then ranges from 0 to 250 and each coordinate from 0 to 3000, requiring, in binary form, 8 and 12 digits (genes), respectively. The resulting total chromosome length is $8 \times 10 + 12 \times 12 = 224$ digits.

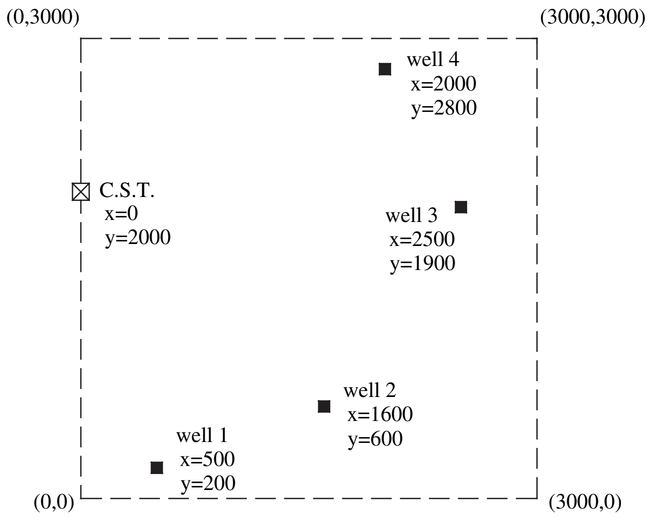

Figure 1: Layout of the existing wells and the central station (CST).

3.1.2 Observance of the constraints

There are two main constraints: (a) the sum SQ of the 10 Q_i should be equal to $Q_T = 500$ and (b) coordinate values should be smaller than 3000.

Each chromosome, when decoded, renders Q_i values from 0 to 255. Thus, SQ ranges from 0 to 2550, practically never fulfilling the first constraint. To 'repair' the solution, each Q_i is multiplied by the factor Q_T/SQ. In this way, the proportions between the well flow rates are preserved.

Coordinate values resulting from the chromosomes range from 0 to 4095. To observe the second constraint, two procedures have been tried: (a) to set the values larger than 3000 equal to 3000 and (b) to multiply each 'raw' coordinate value by 3000/4095. The second procedure was finally adopted to avoid any bias towards larger coordinate values.

3.1.3 The evaluation procedure

The fitness value of each chromosome solution equals the respective total (pumping and network amortization) cost. Pumping cost C_p depends on the piezometric level drawdown at the wells. It is reduced when the mutual interference of the wells decreases, i.e. it obtains lower values when the wells are fairly spread over the entire field. Network amortization cost C_a is directly proportional to the initial network cost. The latter depends on the total length (and the diameter) of the pipes. It is reduced with the distance of the wells from the central station, i.e. it obtains lower values when the wells are clustered around the central station. Thus, small C_p values correspond to large C_a values and vice versa. C_p is given by the following simple formula:

$$C_p = A_p \cdot \sum_{i=1}^{10} Q_i \cdot H_i, \tag{1}$$

where A_p is a pumping cost coefficient, incorporating the duration of pumping (set equal to 5 months), pump efficiency (set equal to 0.8) and an electricity cost of 0.06€ per kW h. It follows that $A_p = 2.7$, when Q_i, namely well flow rates, are expressed in l/s. Finally, H_i is the distance between the water level at well i and a predefined level, e.g. water level at the central station (the additional piezometric head to carry water from each well to the central station is considered negligible). Then

$$H_i = d_i + s_i, \tag{2}$$

where d_i is the distance between the initial piezometric level and the predefined reference level and s_i is the piezometric level drawdown at the perimeter of well i. To calculate s_i, the following assumptions have been made: (a) the confined geothermal aquifer is horizontal, homogeneous and isotropic and (b) the aquifer is 'infinite' and flow is due to the operation of the geothermal wells only. Then the drawdown s at any point x, y is given as:

$$s = \frac{1}{2\pi T} \cdot \sum_{i=1}^{n} Q_i \cdot \ln \frac{\sqrt{(x - x_i)^2 + (y - y_i)^2}}{R}, \tag{3}$$

where T is the aquifer transmissivity, n is the number of wells affecting the piezometric level at the point of interest, x_i and y_i are the coordinates of well i and R is the radius of influence of the wells. The values of T and R used in all application examples are 0.001 m^2/s and 3000 m, respectively.

Due to the aforementioned assumptions, only s_i values enter the optimization procedure and the respective pumping cost is given as:

$$C_{p1} = A_p \cdot \sum_{i=1}^{10} Q_i \cdot s_i. \tag{4}$$

The amortization cost C_a is estimated in the following way: the network construction cost, based on average conditions in Greece, is taken equal to 45 and 60€ per meter for small and large pipe diameters, respectively. The threshold is set at $Q = 50$ l/s, since the pipe diameter is selected according to the flow rate. Assuming an amortization period of 10 years and an interest rate of 5%, the amortization cost per meter is $A_{a1} = 6$ and $A_{a2} = 8$€ for small and large pipe diameters, respectively. Thus, C_a is given by the following formula:

$$C_a = \sum_{i=1}^{10} A_{ai} \cdot L_i, \tag{5}$$

where A_{ai} is equal either to A_{a1} or to A_{a2} and L_i is the length of the pipe that carries water away from well i. Given the well coordinates, the task is: (a) to produce the shortest tree-type pipe network, connecting the wells to the central station and (b) to calculate the flow rate QL_i through each pipe i, in order to select the proper A_{ai} value. To accomplish this, the wells are labeled according to their distance from the central station. The label of the most distant well is set equal to 1. Thus, to find the shortest L_i from well i, only wells with larger label values are checked. Moreover, QL calculations start from the most distant well and proceed towards an increasing label order.

In summary, the evaluation procedure includes the following steps: (a) calculation of s_i for each well by means of eqn (3), which is used $n = 10$ times, (b) calculation of C_{p1} using eqn (4), (c) calculation of L_i and QL_i, (d) calculation of C_a using eqn (5) and (e) calculation of the sum $C_T = C_{p1} + C_a$.

3.1.4 Preliminary tests

Before addressing the main problem, three preliminary tests were conducted, to check the optimization tool and to increase our insight into the problem. In the first, the evaluation function included network amortization cost only. The program was run many times. Typical best results are summarized in Table 1 and shown in Fig. 2. All of them exhibit the following basic features: (a) All the new wells (shown as small circles) have been placed inside the polygon defined by the existing ones and the central station. (b) Some new wells (6, 7 and 9 in Fig. 2) have almost zero contribution to the cost, since they are located on the pipe connecting a more distant well (5 in Fig. 2) to the central station. (c) The largest part of Q_T is pumped from wells 7 and 9, which are the closest to the central station. Thus, only QL_7 and QL_9 exceed the threshold of 50 l/s and only L_7 and L_9 are multiplied by the largest cost coefficient A_{a2}.

The same evaluation function was used in the second test, but the pumping scheme included six new wells only. All of them have been placed very close to each other and to the central station, as expected.

In the third test, the evaluation function included pumping cost only (for the complete set of wells). In all the runs, all the new wells were placed on the field boundaries (four of them exactly on the four field corners). Typical best results are summarized in Table 1 and shown in Fig. 3. It is worth mentioning that differences between s_i values are very small, indicating a near optimum outflow rate distribution.

3.1.5 Main results

The complete program (including both pumping and amortization costs in the evaluation function) was conducted many times to derive a statistically sound estimate of its efficiency. All runs resulted in similar final costs (between 205,000 and 207,000€ and final cost differences did not exceed 1%). Cost reductions for the cheapest solution of the respective first generation (which can be considered to represent unoptimized planning) ranged between 13% and 17%.

Table 1: Typical best solutions.

	Amortization cost only				Pumping cost only			
	x_i	y_i	Q_i	s_i	x_i	y_i	Q_i	s_i
Well 1	500	200	7.97	62.26	500	200	47.04	99.49
Well 2	1600	600	1.14	47.84	1600	600	43.84	99.35
Well 3	2500	1900	4.56	32.39	2500	1900	43.11	98.84
Well 4	2000	2800	5.69	40.40	2000	2800	48.28	99.65
Well 5	749	1453	6.83	151.20	3000	790	47.04	99.27
Well 6	723	1474	4.56	155.64	0	3000	57.64	99.47
Well 7	546	1598	200.46	377.18	3000	3000	54.93	99.52
Well 8	985	733	11.39	86.97	0	1989	51.23	99.89
Well 9	94	1922	256.26	442.07	0	0	53.20	99.72
Well 10	1990	2251	1.14	45.37	3000	0	53.69	99.34
Cost	$C_p = 520{,}045$; $C_a = 35{,}430$; $C_T = 555{,}475$				$C_p = 134{,}281$; $C_a = 84{,}059$; $C_T = 218{,}340$			

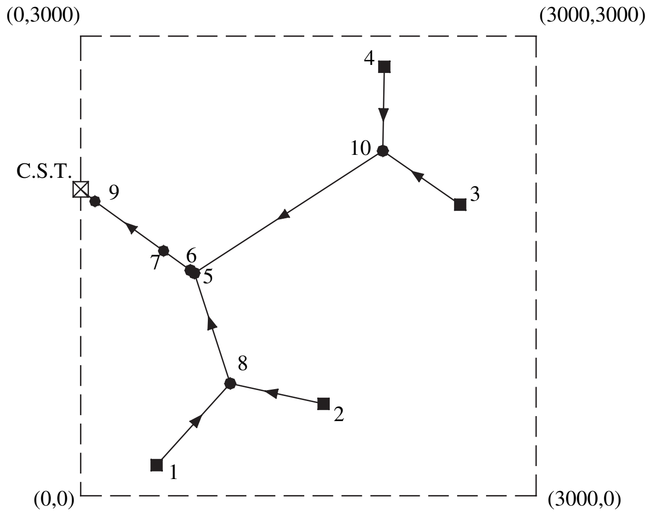

Figure 2: Typical best solution (pipe network amortization cost only).

Well locations and pipe network patterns of the aforementioned best solutions could be easily classified in two groups, which are adequately represented by the two typical solutions shown in Fig. 4a and b. The respective well flow rates, coordinates and piezometric level drawdowns are summarized in Table 2.

3.1.6 Additional constraints

An additional constraint, which may be imposed in certain cases is that the drawdown values should not exceed a certain limit $s_{\max}$. The reasons can be: (a) to avoid ground subsidence and (b) to avoid inflow of colder water to the geothermal aquifer.

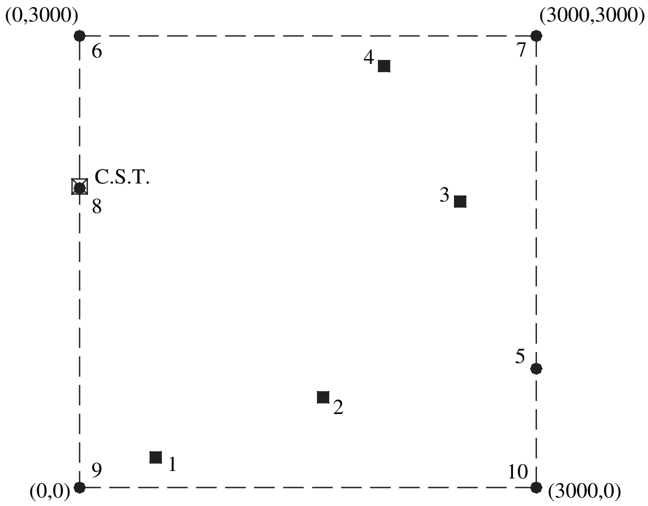

Figure 3: Typical best solution (pumping cost only).

Table 2: Typical best solutions ($C_a + C_p$).

	Solution A				Solution B			
	x_i	y_i	Q_i	s_i	x_i	y_i	Q_i	s_i
Well 1	500	200	49.67	112.57	500	200	50.49	110.34
Well 2	1600	600	49.97	110.84	1600	600	49.71	107.26
Well 3	2500	1900	49.97	106.58	2500	1900	49.97	111.70
Well 4	2000	2800	48.15	109.81	2000	2800	49.71	110.19
Well 5	1057	3000	49.67	112.08	0	1234	49.97	111.17
Well 6	0	934	51.18	112.87	375	2987	52.06	111.11
Well 7	0	2090	49.67	111.85	96	0	49.97	103.87
Well 8	253	2812	51.79	111.95	1218	3000	48.41	111.09
Well 9	2857	3000	49.97	97.70	0	2343	49.97	110.84
Well 10	947	97	49.97	112.25	3000	1688	49.71	100.41
Cost	205,174				205,344			

The effect of the constraint depends on the magnitude of s_{max}, relative to the s_i values of the optimum solution of the unconstrained case. If s_{max} exceeds all s_i, then the constraint has no effect at all. If, on the contrary, s_{max} is comparatively small, it might be impossible to observe the constraint without increasing the number of new wells.

The best way to deal with such constraints is to introduce a penalty function to the evaluation procedure. In our case, we simply add a fictitious cost, Pen, to the total cost, C_T, rendering the final fitness value worse. A strong dependence of Pen on the magnitude of the violation at each particular well is desired in order to 'attack' larger violations first. If $s_{max} < s_i$ at m wells, an efficient form of the penalty function is:

$$\text{Pen} = B_{\text{pen}} \cdot \sum_{i=1}^{m} (s_i - s_{\max} - 1)^2. \quad (6)$$

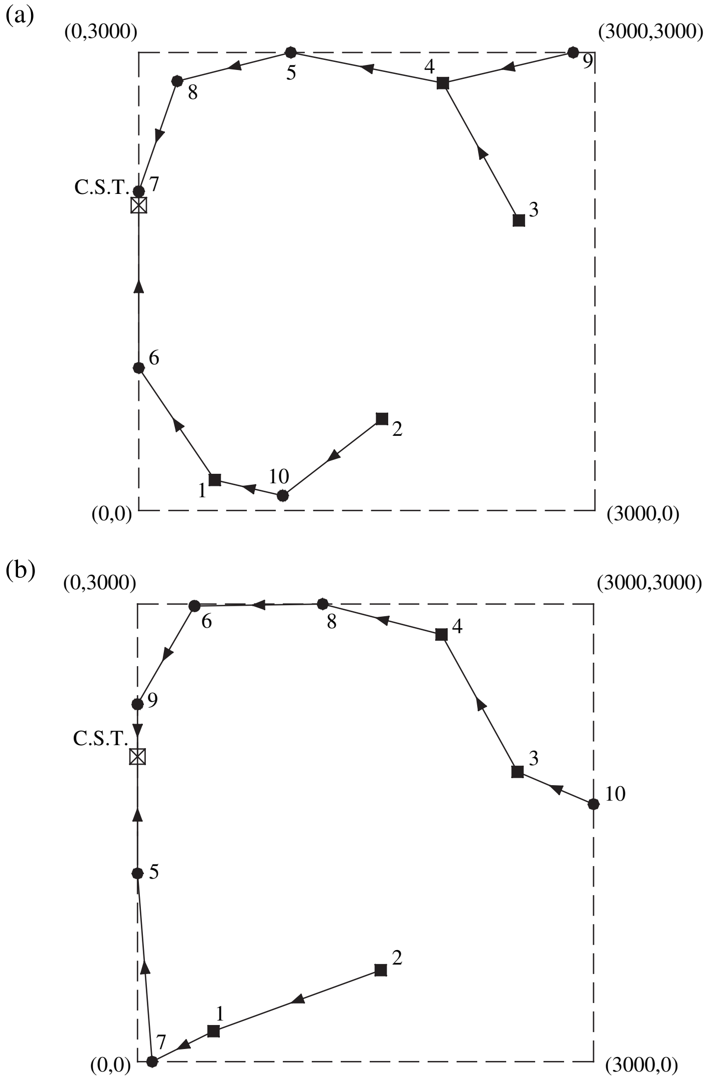

Figure 4: (a) Type A best solution (for both pumping and amortization cost) and (b) Type B best solution (for both pumping and amortization cost).

Subtraction of 1 in the last term of eqn (6) guarantees that each term included in the sum is greater than 1, even if s_i exceeds $s_{\max}$ slightly only. So, if the value of the constant B_{pen} is large enough, the constraint is guaranteed, provided that its observance is possible, of course.

In certain cases, the constraints are ‘soft’, that is, small violations can be tolerated. For such constraints, smaller B_{pen} values should be used, with the following form of the penalty function:

$$\text{Pen} = B_{\text{pen}} \cdot \sum_{i=1}^{m} (s_i - s_{\max})^2. \tag{7}$$

To illustrate the aforementioned procedure, we consider the solutions depicted in Fig. 4a and b. According to Table 2, the respective s_i values do not exceed 113 m. Then, if $s_{\max} > 113$, the constraint

Table 3: Typical best solutions for $s_{max} = 105$ m.

	Rigid constraint				Soft constraint			
	x_i	y_i	Q_i	s_i	x_i	y_i	Q_i	s_i
Well 1	500	200	46.73	104.39	500	200	53.17	105.08
Well 2	1600	600	43.92	104.96	1,600	600	43.36	104.29
Well 3	2500	1900	49.80	104.20	2,500	1900	47.89	104.7
Well 4	2000	2800	53.12	104.99	2,000	2800	51.28	105.25
Well 5	2719	434	47.50	104.08	0	1012	47.89	99.24
Well 6	3000	21	54.65	104.98	2,977	0	56.18	104.88
Well 7	0	1125	48.77	103.16	2,250	12	49.40	105.11
Well 8	92	2813	55.16	104.45	2,934	3000	47.89	90.07
Well 9	0	0	48.77	98.49	374	2956	55.05	105.11
Well 10	935	3000	51.58	104.78	0	2251	47.89	99.12
Fitness	209,582				209,387			
Cost	209,582				209,348			

will not actually affect the optimization procedure. Suppose now that $s_{max} = 105$ m. Use of eqn (6) with $B_{pen} = 2{,}000$ guarantees strict observance of the constraint. Use of eqn (7) with $B_{pen} = 400$ permits small constraint violations. Typical results are summarized in Table 3.

Finally, it should be mentioned that control points may not coincide with wells. If the drawdown constraint is applied to a sub-area of the geothermal field, control points should be placed on the perimeter of this sub-area, too.

3.1.7 Number of new wells

In the case studied so far, the number of new wells was included in the data set. In many actual studies though, it belongs to the output list. An extra new well will certainly reduce the pumping cost C_p, while its impact on C_a may be negligible (e.g. if the well is added along an existing pipe). Of course, it introduces an additional cost for the amortization of its construction and equipment.

Inclusion of the number of new wells to the chromosome of the genetic algorithm gives rise to substantial technical problems (like increased chromosome length and step changes in the evaluation function). A more efficient approach is the following: (a) calculate the amortization cost C_w for construction and equipment of one well and (b) run the program for different successive numbers of new wells. The cost of the optimum solution C_T will generally decline with the increase in the number of wells. But, if this cost reduction is smaller than C_w, no additional well should be drilled. This approach is efficient if C_w is larger than the acertainty in the calculation of best C_T. In our example, if $C_w = 4000$€, we have found with reasonable confidence that the optimum number of new wells is 7.

It should be mentioned, though, that the number of new wells may be restricted by the availability of initial capital or by plans for stepwise development of the energy source.

3.1.8 Brief sensitivity analysis

Each optimum solution results as a compromise between the optimization processes of C_p and C_a. Thus, it is affected by their relative importance, namely, the relative magnitude of A_p versus

Table 4: Well outflow rates.

Well	1	2	3	4	5	6	7	8	9	10
Q_i	50	50	50	50	50	52	50	48	50	50

A_{a1} and A_{a2}. Errors will shift the point of compromise resulting in a smaller than calculated cost reduction.

Overestimation of aquifer transmissivity has the same result as an equal percentage of underestimation of A_p. On the contrary, selection of the radius of influence does not affect seriously the optimization process, provided that the selected value is large enough.

Accuracy to two decimal digits in the values of well flow rates is practically meaningless. To investigate the effect of round off, the optimum solution of Fig. 4b is considered, where the total cost is equal to 205,344€. Rounding off well outflow rates, namely using Q_i values from Table 4, one obtains practically the same cost.

3.2 Geothermal field with non-uniform temperature distribution

In most geothermal fields, temperature distribution is not uniform. As an example, we consider a geothermal aquifer with three distinct temperature zones, as shown in Fig. 5. Temperature ranges from 80°C in the central area to 70°C and 60°C in the two perimetric zones. All other aquifer features are the same as in the previous example. The positions of the central station and of the existing wells and the number of new wells are also the same.

In this case, thermal power provided by the system of wells depends both on total well flow rate Q_T and on the average geothermal water tepmperature T_{av}. We assume that the required Q_T varies linearly from 500 to 600 l/s, as T_{av} varies from 80°C to 60°C respectively. Since Q_T depends on T_{av}, the latter affects the pumping cost C_p and probably C_a, too. To handle the respective constraints, we proceed in the following way: (a) we calculate the average water temperature for the 'raw' well flow rates Q_i, which result from chromosome decoding, (b) we calculate the required total well flow rate Q_{TT} for this particular water temperature and (c) we multiply each 'raw' Q_i by the factor Q_{TT}/SQ (SQ being the sum of Q_i, as mentioned in Section 3.1.2).

A necessary input to the aforementioned calculations is the temperature zone in which each new well lies. This is achieved by means of a rather simple technique introduced by Katsifarakis and Latinopoulos [14].

The program has been run many times. Well locations and pipe network patterns of the respective best solutions could be easily classified into three groups, which are represented by the three typical solutions shown in Fig. 5a, b and c. The respective well flow rates, coordinates and piezometric level drawdowns are summarized in Table 5. All runs resulted in similar final costs (between 240,300 and 244,300€ and the final cost differences did not exceed 1.7%). The most prominent feature of all the best solutions is that no new well is located at the lowest temperature (60°C) zone, while in the best pattern of all (shown in Fig. 5c), two new wells are placed just inside the hottest field zone. This is their major difference from the best solution patterns achieved for the uniform temperature field. Moreover, the total cost is around 17% higher for the non-uniform temperature field, because: (a) piezometric level drawdowns at the wells are larger since they are placed closer to each other in order to avoid the lowest temperature field areas and (b) the required total flow rate is larger. Actually Q_{TT} is equal to 554.5 l/s for patterns A and B (which have many similarities) and a little lower at 543.8 l/s for pattern C.

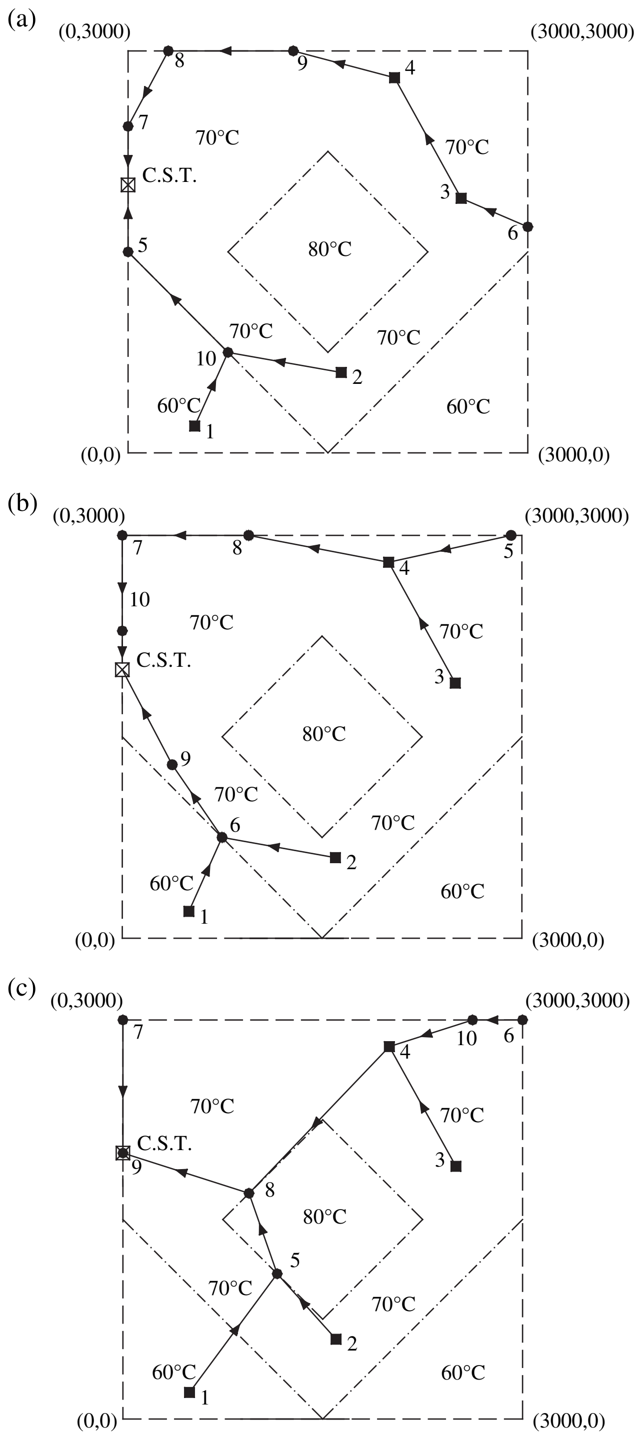

Figure 5: (a) Type A best solution for geothermal field with non-uniform temperature distribution; (b) Type B best solution for geothermal field with non-uniform temperature distribution and (c) Type C best solution for geothermal field with non-uniform temperature distribution.

Table 5: Typical best solutions (non-uniform temperature distribution).

	x_i (m)	y_i (m)	Q_i (l/s)	s_i (m)	T (°C)
Type A best solution					
Well 1	500	200	49.99	107.39	60
Well 2	1600	600	49.99	115.45	70
Well 3	2500	1900	55.48	129.40	70
Well 4	2000	2800	56.06	127.24	70
Well 5	0	1500	56.64	127.22	70
Well 6	3000	1687	65.30	127.90	70
Well 7	0	2437	55.19	127.00	70
Well 8	302	3000	57.79	126.67	70
Well 9	1242	3000	55.48	129.07	70
Well 10	750	750	52.59	127.10	70
			554.51		
Type B best solution					
Well 1	500	200	49.36	108.49	60
Well 2	1600	600	49.68	111.74	70
Well 3	2500	1900	50.00	112.85	70
Well 4	2000	2800	56.41	128.69	70
Well 5	2919	3000	69.23	126.02	70
Well 6	749	751	54.16	130.73	70
Well 7	1	3000	61.85	127.61	70
Well 8	949	3000	54.16	127.02	70
Well 9	375	1292	51.60	128.58	70
Well 10	0	2289	58.01	131.66	70
			554.46		
Type C best solution					
Well 1	500	200	49.63	103.31	60
Well 2	1600	600	49.63	117.09	70
Well 3	2500	1900	49.63	121.10	70
Well 4	2000	2800	50.67	127.14	70
Well 5	1158	1092	61.43	146.62	80
Well 6	3000	3000	60.73	128.54	70
Well 7	0	3000	49.97	98.82	70
Well 8	947	1697	55.53	141.51	80
Well 9	0	2000	61.77	129.02	70
Well 10	2645	3000	54.83	130.28	70
			543.82		

4 CONCLUSIONS

Improvement of financial performance of a geothermal district heating scheme has been investigated by means of genetic algorithms. Two significant cost elements have been studied, namely operation (pumping) cost and amortization of construction of the pipe network inside the geothermal field. Optimization has been achieved through: (a) proper location of new wells in the geothermal area and (b) proper distribution of total water demand (flow rate) to the individual wells. Application examples to geothermal fields with uniform and non-uniform water temperature distribution indicate that genetic algorithms can be used efficiently in geothermal problems too. In all the cases, a cost reduction larger than 10% was achieved, with respect to unoptimized planning of well and pipe network layout. Such cost reductions can contribute to the promotion of the direct use of geothermal energy.

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