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The genetic algorithm and its application to optimise energy utilization of a water reservoir

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Abstract

The study presents the results of genetic algorithm application to optimize energy utilization of the reservoir Sance on the river Ostravice. The aim of our research was a proposal of operational rules for reservoir management in real time to obtain the maximum of hydropower energy. Our solution has shown that proposed technique with operators of selection and crossing is very effective and can approach the optimum area more rapidly than other methods.

1 Introduction

Drinking water for the population in the region Ostrava is the main purpose of the reservoir. The supply of drinking water has recently significantly decreased contrary to the project assumptions, because the Czech Republic has embarked on new economic conditions of market economy. This brings about an opportunity for the decision makers to utilize the remaining target release for hydropower production. It is also possible to increase in this way the minimum discharges below the dam. The scheme of reservoir utilization is shown in Fig. 1.

The problem of the finding of the maximum hydropower production has the character of an optimization problem for two main reasons. First, the head conditions deteriorate with the increase of the absorption capacities of turbines contributing to major output (the reservoir has wider utilization). But on the other hand the disposable output decreases and from this reason the hydropower production decreases too. The second reason is a specific one for the reservoir Sance. Two small turbines of different types (Banki and Francis types) with different ranges of absorption capacity and with various operational characteristics are installed in the hydropower plant. That is why the synchronous working of both turbines need not reach the maximum production.

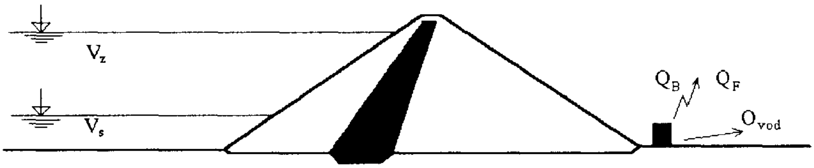

Fig. 1 The Scheme of Reservoir Utilization

Energy generation can be expressed as

$$E = 9.81 \cdot \eta_B \cdot Q_B \cdot H \cdot t_B + 9.81 \cdot \eta_F \cdot Q_F \cdot H \cdot t_F \rightarrow \max, \tag{1}$$

where E is energy [kWh] generated by the plant, η_B and η_F are the efficiences of the turbines, Q_B and Q_F are the immediate absorption capacities of the turbines [$m^3 \cdot s^{-1}$], H is the head of the turbines [m], t_B and t_F are the operation periods [h].

The extreme of the objective function (1) had to be found by constraints. These constraints are given first of all by the mutual relation of the water and energy utilization of the reservoir, the required reliability of the target release, the quantity of the storage capacity available and the parametres of either turbines.

Constraints can be expressed as

$$\begin{aligned} & Q_B + Q_F = Q_t = Q_n - O_{vod}, \\ & 0.150 \le Q_B \le 0.648, \\ & 0.500 \le Q_F \le 1.600, \\ & Q_t \le Q_n = f(V_z, P_o) = 2.300 \\ & P_o = 98.8\ \%,\ V_z = 44.176 \text{ mil. m}^3 \\ & V_z \ge V_d \end{aligned} \tag{2}$$

where Q_n is the target release of the reservoir [$m^3 \cdot s^{-1}$], Q_t is the usable flow through turbines [$m^3 \cdot s^{-1}$], O_{vod} is the quantity of the water supply [$m^3 \cdot s^{-1}$], V_z is the usable reservoir storage [mil. m^3], V_d is the minimum dispatch reservoir storage for water supply [mil. m^3], P_o is the reliability in terms of failure years [%].

The form of the objective function (1) and of the constraints (2) indicates a problem of nonlinear programming, because the efficiencies and the absorption capacity of the turbines depend on the head, being nonlinear functions. The analytical solution of the function (1) extreme by e.g. Lagrange's multiplicators is difficult and slow, because it is necessary to derive first the analytical form of the function.

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We found the extreme of function (1) by the simulation technique in the first phase of our research. Although this methodological approach is acceptable it makes necessary a large number of alternatives on the basis of which the optimal solution is to be found.

2 Methodology of the research

The genetic algorithms are convenient for the solution of finding the extreme of the multiple-peak function. The method of genetic algorithm is a search procedure based on the mechanics of natural selection and natural genetics. The genetic algorithm has been applied to a numerous problems including search, optimization and machine learning; e.g. Austin [1], Goldberg [2], Holland [3], Wang [4].

We used this methodology in the process of our solution:

1. The definition interval of absorption capacities of the turbines comprised in the objective function (1) are the unknown parameters x_1 and x_2. We discretizated them by 2^l points according to

$$\Delta x_i = \frac{b_i - a_i}{2^l - 1}, \tag{3}$$

where l is the number of attributes (bits) of a variable, which represents the original variables x_i ; a_i , b_i are bounds of the definition interval of absorption capacities according to constraints (2).

The genetic algorithm works with the binary coding of the parametres. Each point in space is to be found at random e.g. by the generator of random numbers. In our case, we chose l = 4 and l = 5 due to the narrow range of absorption capacities of the turbines. The example of coding for l = 5 is shown in Table 1.

Table 1. Coding of parameters for l = 5.

Binary Code	Integer Value	Parameter value x_i
00000	0	a_i
00001	1	$a_i + \Delta x_i$
00010	2	$a_i + 2\Delta x_i$
00011	3	$a_i + 3\Delta x_i$
•••	•••	•••
11110	30	$a_i + 30\Delta x_i$
11111	31	$a_i + 31\Delta x_i = b_i$

2. We formed the initial population set in the space by a random choice of m points, each of them being defined by co-ordinates (in the given case $n = 2$). For these co-ordinates functional values E were calculated and then they were arranged in descendant order. Probability p_j was ascribed to each point $j = 1, 2, \ldots, m$ according to expression (Wang [4])

$$p_j = p_1 + \frac{p_m - p_1}{m - 1} \cdot (j - 1), \tag{4}$$

where $j = 1$ is liable to the best point in the space, $j = m$ is liable to the worst point.
3. The operators of selection and crossing are of essential significance in the genetic algorithm. They produce new generations of points. In our problem, we included one third and alternatively one half of the highest values E into the reproduction process. This turned out as convenient both from the doing of convergence to the optimum point of view, and of the magnitude of divergence from the theoretical value of the optimum. Considering that in this case the function E has only two parametres, the process of crossing was simple. It was based on the random change of one parameter the other parameter remaining unchanged.

In the formation of the individual generations of energy production values as regards both turbines it is necessary to choose an allowable divergence of maximum values in two neighbouring generations. The forming of subsequent generations will terminate when we are satisfied with a larger divergence. That is why a danger of a considerable divergence of the theoretical maximum can occur. Therefore we chose in our iteration process this divergence only as 0.001 GWh per year. This made the reproduction process continue by means of further generations thus approaching the extreme.

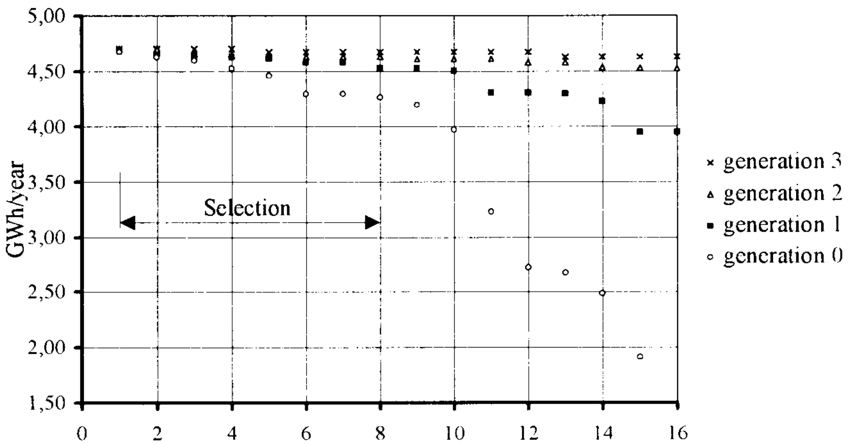
The operating singularities are also important for engineering applications of the design method, when for different reasons one or both turbines can be put out of operation. It is necessary to associate also zero values of x_1 and x_2 parametres during the process of discretization of absorption capacities of turbines according to expression (3).

3 Results of the research

The synthetic series of 500 years of average monthly flows was the groundwork for the calculation of hydropower production. This synthetic series was generated by means of a mathematical model derived from short flow series of observation flows. The advantage of long flow series is primarily a major reliability of hydroenergetic calculations as it includes considerably larger number of various hydrological situations than a short flow series. The calculated values of average monthly hydropower productions can be statistically further elaborated; e.g. it is easy to deduce a probability distribution or statistic characteristics of produced energy in the individual months, years, etc.

The alternative of O_{vod} = 1.300 m^3·s^{-1} and Q_t = 1.000 m^3·s^{-1} is the nearest to the up-to-date operational situation of the reservoir Sance. Eight experiments of generation of the initial population set have been processed. They differ only in the initial numbers of the random generator. The initial populations are termed briefly "Generation 0". They are formed by random selection of 16 pairs of absorption capacity of turbines and of the corresponding values of average year energy generation.

Experiment No. 2



Experiment No. 6

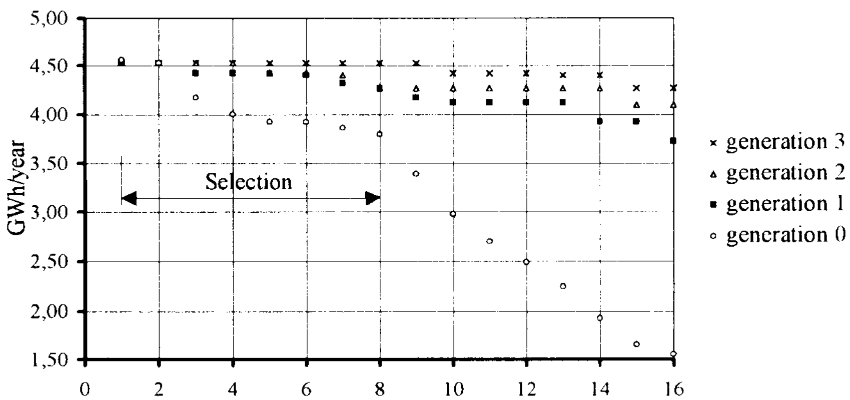


Fig. 2 Results of Two Characteristic Experiments

The results of two characteristic experiments are shown in Figure 2. Experiment No. 2 is typical for the method of genetic algorithm owing to the fact that the values of energy production increase in the next generations. Consequently the selection and crossing gradually proceed to the extreme. It is interesting that the range of values rapidly decreases in the superior generations and it converges to maximum values. This is a logical consequence of the selection because only one half of the values enters further reproduction. The maximum average energy production has been found to equal 4.869 GWh a year.

Experiment No. 6 showed that the initial population need not always be of good quality. This manifests itself by the fact that the discretized absorption capacities of the turbines giving rise to the maximum energy production do not occur in the next generations. In the other words, the values of maximum energy production are not higher than these values in the generations before. That is why these values occur in the following generations either, and only the worst alternatives became improved by crossing.

In all the 8 experiments 4 generations were sufficient at most. Thus it was demonstrated that an optimum zone can be reached by a relatively fast process. Divergences of the maximum in the respective experiments did not exceed 5 % of the maximum derived from the simulation model.

Optimum operational rules concerning the reservoir could be easily suggested on the basis of the ascertained maximum of energy production and corresponding to the absorption capacities of the turbines. Table 2 illustrates the dependence of hydropower production on the utilization of the turbines in all 8 experiments. As the most convenient the utilization of both turbines on full output only during wet (full-water) periods with the full contents of the reservoir has been found. During dry periods only the Francis turbine is in operation, and in the critical dry periods only the Banki turbine is in service merely for the process of the minimum outflow treatment below the dam.

Table 2. Dependence of Hydropower Production in Generated Sets on the Utilization of the Turbines.

Experiment No.	max. E_{year} [GWh/year]	Q_B [$m^3 \cdot s^{-1}$]	Q_F [$m^3 \cdot s^{-1}$]
1	4.628	0.000	1.453
2	4.704	0.482	1.600
3	4.628	0.582	1.527
4	4.701	0.515	1.600
5	4.691	0.548	1.600
6	4.558	0.515	1.380
7	4.620	0.548	1.453
8	4.869	0.000	1.600

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4 Conclusions

For the engineering application of the proposed techniques the achieved research results are inspiring, as they indicate possibilities of new metodological processes of application for the solution of optimization problems. These new metodological processes are efficient and they rapidly approach the optimum range. It may be expected that the advantage of genetic algorithm, in contrast to other numerical methods, is going to increase along with increase in the complexity of the problem. This holds true even if we solved only the extreme of a two-dimensional function.

The relevance of the proposed metodological process results first of all from the optimization character of the given problem. An application of the traditional methods can cause difficulties (e.g. the "curse of dimensionality", a large number of alternatives in simulation technique, etc.). The genetic algorithm proceeds from a population, which also corresponds to the character of the given problem, and many other methods start from a single point. The transition rules of genetic algorithm are stochastic but many other methods are governed by deterministic transition rules.

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