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OPTIMIZATION OF ELECTRICITY PRODUCTION OF A HYDROPOWER PLANT POWERED FROM A MULTIPLE USE RESERVOIR, USING AN ADAPTED SSO ALGORITHM

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One of the most important issues related to electricity production from hydropower is that of the multiple use of the reservoir of the hydropower development. Recently, there were developed metaheuristic algorithms for approaching this kind of very complex optimization problems which are difficult to be solved with the usual methods of operational research.

This paper presents an adapted shark algorithm for the long-term optimization of the operation of a reservoir with multiple use: electricity production, flood protection and water supply considered as a monthly required flow. The goal is to realize an imposed monthly electricity production complying with the other two uses of the reservoir. The results are consistent with those obtained using dynamic programming, the gain is the simplicity of the use of this evolutionary algorithm.

Keywords: metaheuristic algorithms, hydropower optimization, electricity production, shark algorithm

1. Introduction

In Romanian National Power System (NPS), almost one third of the installed capacity and one quarter of the electricity is produced in hydropower plants (HPPs). Often, large hydropower plants share the reservoir with other water uses as: water supply for population, industry and agriculture, flood protection, inland navigation etc. Frequently, water use for hydropower is subordinated to the other water uses which introduce constraints in the operation of HPPs. Also considering the stochastic nature of reservoir inflows and of the demand of electricity and the nonlinearity of some equations describing the system, the optimization problems become difficult to be solved with usual methods of operational research. Alternatively, there were developed metaheuristic algorithms for approaching this kind of very complex optimization problems [1]. Compared, considering energy consumption, urbanization, and GDP for modelling, and forecasting residential energy consumption looks even more complex [2].

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In [2], the authors define metaheuristic algorithms as higher-level heuristic algorithms applied with success for solving burdensome problems. They provide good solutions for very difficult problems which do not need for an exact solution and have practical execution times.

Those metaheuristic algorithms search for best solutions or agents and replace those which do not have a good competence, described with the help of a fitness function, [4]. There are many such metaheuristic algorithms so: how to choose one for solving a certain problem? Same authors remind the no-free-lunch (NFL) theorem that states that there no universal algorithm for all problems.

Regarding the huge number of metaheuristic algorithms conceived by different researchers, in [5] there were identified not less than 192, introduced between 1961 and 2019. Among these, the author listed Shark Smell Optimization (SSO) algorithm as being developed and first time presented in [5].

The authors present SSO algorithm as being based on the ability of shark, one of the best hunters, for finding prey [6]. Thus, the behaviors of shark within his environment are mathematically modeled to solve the real-world engineering optimization problems. Results were consistent compared with many other heuristic optimization methods and confirm the validity of SSO algorithm.

For a broad spectrum of engineering problems SSO was chosen as metaheuristic algorithm to be applied. From the latest research using SSO algorithm can be mentioned one which uses new improved version of SSO algorithm for solving the optimization problem of obtaining an enhanced contrast of medical images [7]. Obtained results were examined with the help of five measure indexes and are compared with five methods. It was demonstrated the superiority of SSO algorithm among the other methods.

In the same register, in [8] the optimization of Gabor filters, statistic-based approaches, is done using a SSO algorithm. The authors analyze the lesion photographs and realize a powerful, unmonitored, and high-performance division method which detect the lesion on the skin for medical purposes. The results demonstrate the validity of the used optimization method.

Other very recent paper proposed an improved multi-objective SSO algorithm using composite angle cosine for automatic train operation [9]. At the end, it was demonstrated that their improved SSO algorithm has better optimization performance than other two optimization algorithms: traditional improved particle swarm optimization and traditional improved SSO.

Regarding power engineering, besides [6] when it was first time proposed SSO algorithm for load frequency control problem in electrical power system, in [10] a new multi-objective SSO algorithm is applied for the settings of continuous and discrete control parameters namely tap location of tap changing transformers, voltage of generator, and the reactive compensation devices value to solve three objectives at the same time as: voltage deviation, the total voltage stability and real power loss. Their model was applied on different test cases and the results demonstrate his superiority as well as his good potential in handling the multi objective problems in power systems.

A recent paper presents a combination of the grey wolf and SSO algorithms for optimizing objective functions under several boundary constraints for responsive load integration in residential applications [11]. The related microgrid was also evaluated related to the effect of adding renewable energy sources as wind power and photovoltaic power, and an energy storage system. The results were very good.

Most complex optimization problems related to electricity, suitable for being solved with metaheuristic algorithms, could be for example: simultaneous optimization of price of electricity from renewables and construction of new power plants [12], or optimization of the integration of distributed generation and electric vehicles in smart residential district [13].

Coming back to hydropower engineering in Romania, first time metaheuristic algorithms were mentioned in [1] as a good alternative to traditional optimization methods: linear programming and dynamic programming. As metaheuristic algorithms were mentioned: genetic algorithm, neural network algorithm, simulated annealing algorithm, fuzzy algorithm. The algorithms were described and applied to different optimization problems in hydropower and the results were compared with those obtained with traditional methods. The authors underlined that metaheuristic algorithms do not need complicated equations to be solved and lead to elegant solutions to difficult optimization problems.

Since then, a large number of papers were published presenting metaheuristic algorithms applied for solving an optimization problem in hydropower: Firefly Algorithm, Cuckoo Search and Bat Algorithm [14], Honey Bees Mating Optimization Algorithm [15], Genetic Algorithm, Particle Swarm Optimization (PSO), Flower Pollination Algorithm, and SSO [16] all applied to the same hydropower development, Vidraru, one of the most important in Romania. In all papers, results are compared with the exact solution obtained using Newton-Raphson method solved with dynamic programming in regressive scheme [1] and with the metaheuristic algorithms applied in papers published before. The overall conclusion of these papers is that metaheuristic algorithms are appropriate to solve optimization problems in hydropower and that among the 8 tested algorithms PSO is the most efficient one.

In the mentioned papers, Vidraru hydropower development (HPD) was considered only for hydropower use of water from the reservoir which, in fact, has multiple use: hydropower production, flood protection and water supply. This paper presents an adapted SSO algorithm for solving the hydropower optimization of Vidraru reservoir operation, namely, to realize an imposed monthly energy generation in Vidraru HPP considering the multipurpose use of the reservoir.

2. Case study data and hypothesis

The data used is related to Vidraru HPD, namely to the reservoir and to the hydropower plant, and were presented in the papers having as case study this HPD, e.g. in [1, 14-16], meaning: data regarding Vidraru HPP, the capacity curve of Vidraru reservoir, the variation of the specific energy production with respect to water level, etc.

We specifically present the data which slightly changed, new data and the hypothesis used. We considered the mean hydrological year, the driest year, and the wettest year, with mean flows: 19.67, 11.74 and 28.53 m^3/s, respectively.

In Table 1 are presented: monthly inflows in Vidraru reservoir, Q_m, Q_d and Q_w, and monthly imposed energy generations in Vidraru HPP, E_m, E_d and E_w, for mean hydrological year, driest year, and wettest year respectively. There are also presented monthly imposed outflows from Vidraru reservoir for water supply, Q_{ws}, minimum and maximum allowed storage in Vidraru reservoir, $V_{\min}$ and $V_{\max}$ [1], that were used for simulation. Thus, the flood control is considered imposing a maximum water level and corresponding volume in the reservoir.

Table 1

Data used for the simulation

Month	1	2	3	4	5	6	7	8	9	10	11	12
Q_m (m^3/s)	8.55	8.22	11.41	27.47	47.62	37.63	24.23	17.61	15.65	13.93	12.99	10.76
E_m (GWh)	40	36	34	32	28	28	28	28	30	36	40	40
Q_d (m^3/s)	5.77	5.66	10.86	17.76	27.70	20.96	15.66	8.63	7.18	7.24	6.52	7.00
E_d (GWh)	24	21	20	19	17	17	17	17	18	21	24	24
Q_w (m^3/s)	5.97	5.92	8.93	18.92	54.40	92.66	52.08	30.94	19.15	22.49	20.49	10.37
E_w (GWh)	58	52	49	46	41	41	41	41	44	52	58	58
Q_{ws} (m^3/s)	9.13	9.13	5.48	5.48	4.87	6.08	14.60	24.33	14.60	10.95	7.91	9.13
$V_{\min}$ (mil.m^3)	250	210	170	140	100	140	140	140	140	140	200	250
$V_{\max}$ (mil.m^3)	465	460	450	440	400	400	450	465	460	455	465	465

It can be noted that the monthly mean inflows slightly changed related to previous papers [1] due to considering a larger period, 58 years of monthly inflows, 1950-2007. From the same period were considered monthly inflows for the driest and the wettest year, 1990 and 1991, respectively.

For energy generations it was admitted the same monthly repartition for the three types of years, as considered in [1], with 400 GWh annual production.

The water supply downstream is considered as an imposed constant annual volume of water to be released from the reservoir, 320 mil.m^3, with monthly ratios, as in [1].

3. Adapted Shark Smell Optimization algorithm

For solving the desired optimization problem, it was used a SSO algorithm inspired from [17], adapted for minimizing the squared difference of the realized energy generation with respect to planned energy:

$$\min\left\{ f(x) = \sum_{k=1}^{12} \left(E_k - E_k^*\right)^2 \right\}, \tag{1}$$

where $f(x)$ is the objective function, E_k – planned energy and E_k^* – energy generation, and k – index for the month of the year.

As in [1], for the volume in the reservoir at the end of each month, V_k^f, it was imposed to be within the minimum and the maximum imposed volumes, $V_k^{\min}$ and $V_k^{\max}$, respectively, as in relation (2):

$$V_k^{\min} \le V_k^f \le V_k^{\max}. \tag{2}$$

In contrast to [1], it was added for the monthly water volume for HPP, $V_{\mathrm{HPP}k}$, the restriction to be at least equal with the monthly volume imposed downstream for water supply, V_{ws}, thus, with V_k^i the volume in the reservoir at the beginning of the month, and V_k the inflow, as monthly volume, the balance equation in the reservoir becomes as in (3):

$$V_{\mathrm{HPP}k} = V_k^i + V_k - V_k^f \ge V_{ws}. \tag{3}$$

Besides the traditional SSO algorithm presented in [17], the improvement is a deep search of the shark before to move to the next position, meaning supplementary rotations for searching the solution.

4. Results

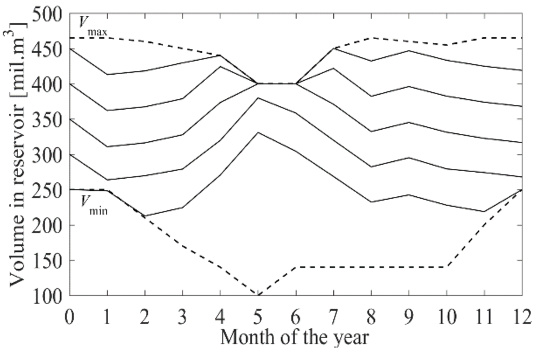
There are presented results for planned energy 400 GWh, for mean hydrological year in fig. 1, driest year in fig. 2 and wettest year in fig. 3, for five values for the volume of water in Vidraru reservoir at the beginning of the year: 250, 300, 350, 400 and 450 mil. m^3.

Figures contain, for five hypotheses for the volume at the beginning of the year: 250, 300, 350, 400 and 450 mil.m^3, as it follows:

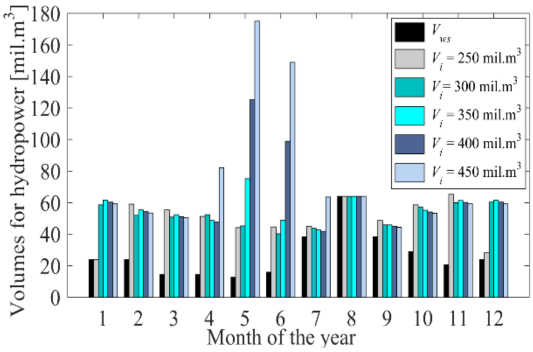
a) variation of volumes in the reservoir during the year;

b) volume of water imposed downstream for water supply (in black) and volumes of water for the HPP;

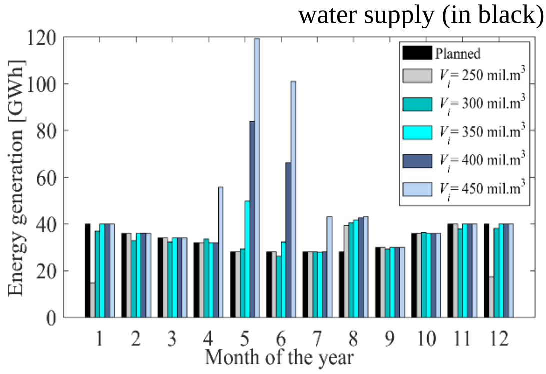
c) planned energy generation (in black) and realized energy generation.



a) variation of volume in reservoir;



b) volume of water imposed downstream for water supply (in black) and of water for HPP;



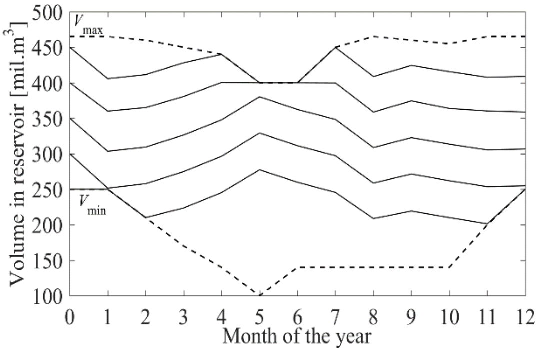
c) planned (in black) and realized energy generation

Fig. 1. Results for the mean hydrological year

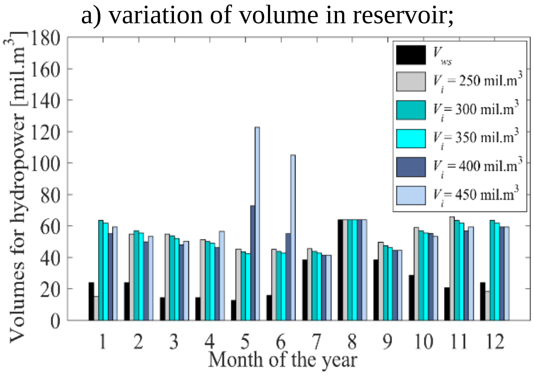
6. Comments and conclusions

From all the figures, 1 to 3, a), it can be noted that the volume of water in Vidraru reservoir is evolving between the minimum and the maximum allowed levels. It means that the water reserve for water supply and the volumes reserved for flood protection, respectively, are respected. It can be also noted from b), that the volumes of water for HPP are greater than the monthly imposed values for water supply. Thus, HPP operation is done respecting also this restriction.

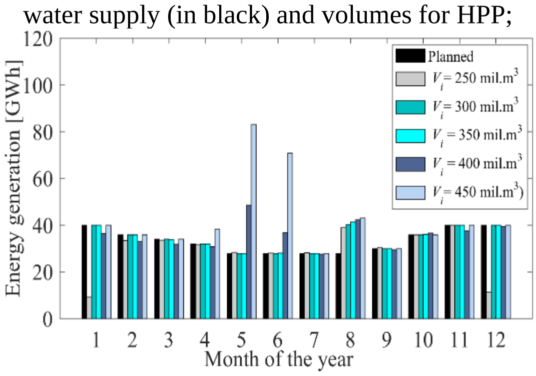
From figures c), it can be observed that the imposed energy generation is realized if volume of water for hydropower is not smaller that the volume imposed for water supply downstream and if the volume in reservoir respect the limit volumes: smaller than the minimum or greater than the maximum allowed.



a) variation of volume in reservoir;

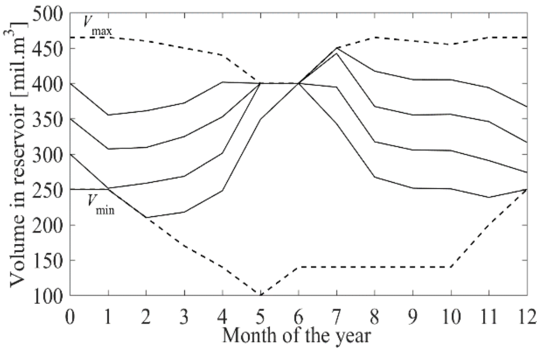


b) volumes of water imposed downstream for water supply (in black) and volumes for HPP;

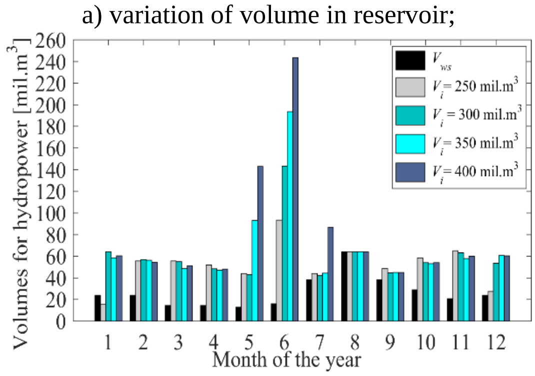


c) planned (in black) and realized energy generation

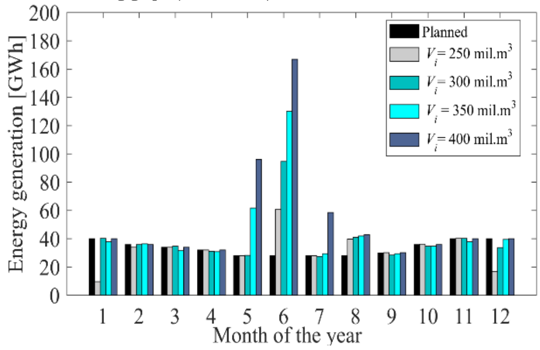
Fig. 2. Results for the driest year



a) variation of volume in reservoir;



b) volumes of water imposed downstream for water supply (in black) and volumes for HPP;



c) planned (in black) and realized energy generation

Fig. 3. Results for the wettest year

The overall conclusion of the paper is that the adapted SSO algorithm applied for this particular optimization problem in hydropower: to realize an imposed monthly energy generation in a HPP supplied with water from a multipurpose use reservoir: hydropower, flood control and water supply downstream, gives good results, respecting the imposed restrictions regarding volumes in the reservoir and discharge released downstream for water supply.

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