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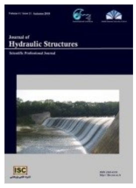

Enhancing Cellular Automata via Tabu Search for Optimal Operation of Hydropower Systems

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Abstract

One of the environmentally-friendly solutions to meeting energy consumption is multi-reservoir hydropower systems. The operation of a multi-reservoir hydropower system is an entirely complex problem due to a wide range of decision variables. Classic algorithms often get stuck in the local optimum and cannot successfully address these problems. Modern algorithms are more effective than classic ones, although their computational time is very high. In this study, an innovative hybrid model is proposed, called cellular automata-tabu search (CA-TS) to optimally operate multi-reservoir systems. For simplification, CA divides the problem into several sub-problems, which the number of them is the same as the length of operation period. Each sub-problem is solved by TS so that the net benefit of the power generation is maximized. For comparison purpose, a non-linear four-reservoir benchmark problem is considered to evaluate the proposed method. Finally, the results are compared with the existing results obtained by GA, PSO, and CA-NLP, showing the efficiency of CA-TS.

Keywords: Tabu Search, Optimization, Hydropower Operation, Cellular Automata

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1. Introduction

The optimal operation of multi-reservoir systems is a completely complex issue for the researchers due to a wide range of decision variables. In the last decades, different classic and modern algorithms are employed by researchers to overcome the complexity of the problem.

Variety of classic methods like linear programming (LP) [1-2], non-linear programming (NLP) [3-5] and dynamic programming (DP) [6-11] were applied to address different types of problems.

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Recently, different methods of modern optimization were presented and applied in the field of water resources management due to their capability to solve complex problems. The well-known genetic algorithm (GA) is employed to solve a host of optimization operation problems [12-16]. Ant colony optimization (ACO) [17-19], particle swarm optimization (PSO) [20-23], Simulated annealing algorithms [24-26], honey bee algorithm [27-28], differential evolution algorithm [29-30] and weed optimization [31-32] were used to solve optimal reservoir operation problems.

Recently, an innovative optimization method called cellular automata (CA) is used by Afshar and Shahidi [33] to meet demand, especially in the field of water and hydropower supply. Afshar and Shahidi [33] applied CA in the field of water supply and hydropower in the Dez reservoir and compared their results with the other algorithms, including GA, PSO, and ACO. The results showed the efficiency of the CA in comparison with meta-heuristic algorithms. Afshar [21] developed this method from a single reservoir to a multi-reservoir to assess the capability of the model in operating multi-reservoir hydropower systems. The results revealed that the developed model was more potent than both GA and PSO in maximizing produced energy. Afshar and Azizipour [34] proposed a reliability-based version of the CA model for water supply operation. Azizipour and Afshar [35] also developed a hybrid GA-CA method for solving reliability-based hydropower reservoir operation. In the following, Azizipour and Afshar [36] developed the model to an adaptive GA-CA model to solve more intricate problems.

In this study, an innovative hybrid method called cellular automata-tabu search (CA-TS) is presented to optimally address solving multi-reservoir hydropower problems. In the present study, the CA method is employed to divide the original problem into several sub-problems with the number equal to the length of operation period. Afterward, the TS method tackles these sub-problems separately and the achieved solutions replaced in the CA when all of the sub-problem are solved. This procedure continues until the satisfaction of the convergence criteria. For comparison purposes, the presented method is validated by solving a common benchmark problem, including four reservoirs, and then the capability of the model is compared with metaheuristic algorithms such as GA, PSO, and CA-NLP [21].

2. Proposed Hybrid Cellular Automata - Tabu Search (CA-TS) model

Hydropower systems are typically operated such that the maximum total energy generation is achieved, while existing limitations are met. In this research, maximizing of total benefit of energy generation is considered with the following mathematical model.

$$Maximize\ P = \sum_{d=1}^{D} \sum_{t=1}^{T} B_{d,t} E_{d,t} \tag{1}$$

$$S_{t+1} = S_t + I_t - MR_t \qquad t = 1,2,3,\ldots,T \tag{2}$$

$$S_{d,t}^{min} \le S_{d,t} \le S_{d,t}^{max} \qquad t = 1,2,3,\ldots,T+1, d = 1,2,3,\ldots,D \tag{3}$$

$$R_{d,t}^{min} \le R_{d,t} \le R_{d,t}^{max} \qquad t = 1,2,3,\ldots,T\ , \quad d = 1,2,3,\ldots,D \tag{4}$$

$$E_{d,t} = R_{d,t} h_{d,t} \qquad t = 1,2,3,\ldots,T\ , \quad d = 1,2,3,\ldots,D \tag{5}$$

$$h_{d,t} = \left(\frac{H_{d,t} - H_{d,t+1}}{2}\right) - TWL_{d,t} \qquad t = 1,2,3,\ldots,T\ , \quad d = 1,2,3,\ldots,D \tag{6}$$

$$H_{d,t} = H_{d,t} = a_d + b_d S_{d,t} + c_d S_{d,t}^2 + e_d S_{d,t}^3 \qquad t = 1,2,3,\ldots,T\ , \quad d = 1,2,3,\ldots,D \tag{7}$$

Where, P is objective function, $B_{d,t}$ is benefit in reservoir d at time step t, $E_{d,t}$ is energy generation in reservoir d at time step t, S_t, R_t and I_t are the vectors of storage, release, and inflow volumes, respectively. M is a $D*D$ matrix that connected the reservoirs network. $S_{d,t}^{min}$ is the minimum acceptable storage volume in reservoir d at time step t, $S_{k,t}^{max}$ is maximum acceptable storage volume in reservoir d at time step t, $R_{k,t}^{min}$ is minimum acceptable release in reservoir d at time step t, $R_{,t}^{max}$ is maximum acceptable release in reservoir d at time step t, $h_{d,t}$ is net head in reservoir d at time step t for calculating energy generation, $H_{d,t}$ is reservoir water level in reservoir d at the beginning time step t and $H_{d,t+1}$ is the reservoir water level in the reservoir d at the end of the time step t, $TWL_{d,t}$ is tailwater level in reservoir d at time step t. a_d, b_d, c_d, and e_d are constants coefficients. D and T are the number of reservoirs and time periods, respectively.
Using CA capabilities in each problem requires defining four main components, namely cell, cell state, which is generally considered as the decision variable, cell neighborhood, and updating rule. In this problem, the starting and the endpoint of any time step, indicated via separate points on the operation horizon, is considered as cells, and the corresponding reservoirs' storage volume as the cell states [21]. The neighborhood component for each cell is determined as the previous and the following time step. The determination of the updating rule is a vitally important part of the CA method. Here, for a random cell state t, the updating rule should be found as a procedure of assigning the proper amount for the decision variable $\boldsymbol{S}_{k,t}$ to maximize system energy production over neighboring periods of t-1 and t

$$Maximize\ P_t = \sum_{d=1}^{D} (B_{d.t-1}E_{d.t-1} + B_{d.t}E_{d.t}) \tag{8}$$

It is noteworthy that cell state t and t-1 is subjected to:

$$S_{d.t}^{min} \le S_{d.t} \le S_{d.t}^{max} \qquad t = 1,2,3,\dots,T\ ,\ d = 1,2,3,\dots,D \tag{9}$$
$$S_{d,t} = S_{d,t-1} + I_{d,t-1} - M_{d,j}R_{j,t-1} \qquad t = 1,2,3,\dots,T\ ,\ d = 1,2,3,\dots,D \tag{10}$$
$$S_{d,t+1} = S_{d,t} + I_{d,t} - M_{d,j}R_{j,t} \qquad t = 1,2,3,\dots,T\ ,\ d = 1,2,3,\dots,D \tag{11}$$
$$R_{d,t-1}^{min} \le R_{d,t-1} \le R_{d,t-1}^{max} \qquad t = 1,2,3,\dots,T\ ,\ d = 1,2,3,\dots,D \tag{12}$$
$$R_{d,t}^{min} \le R_{d,t} \le R_{d,t}^{max} \qquad t = 1,2,3,\dots,T\ ,\ d = 1,2,3,\dots,D \tag{13}$$

These sub-problems can be solved by any optimization method. However, it is clear the selected optimization method for solving sub-problems plays an important role in success of the algorithm. Recently, Afshar [21] hired the NLP method to address these sub-problems lead to an efficient CA-NLP method. However, employing a classic method to solve this part of the problem could cause trapping to the local optimum. Using evolutionary algorithms may avoid trapping to the local optimum and also can improve the performance of the CA model. Therefore, a well-known evolutionary algorithm, namely tabu search (TS), proposed by Glover [37], is selected to optimally solve each sub-problem. TS as a prestigious optimization method was effectively implemented to a wide range of hybridization optimization problems. The method makes the most of searching strategies that even accept poor solutions to avoid getting stuck in a local optimum. The main components of TS algorithm are:

1. **Move**
   TS can produce a neighborhood using the current solution and evaluate it [38]. The move action is a movement from the current condition toward a new one. There are different methods of movement, namely, swamp, insert, add/drop, and increase/decrease that could be employed according to the type of the problem [37]. In this study increase/decrease type is employed to build new neighborhoods.
2. **Tabu List**
   Considering a memory including a set of moves at each neighborhood called tabu list, which is the main feature of the TS [38]. The tabu list keeps a record of selected moves to avoid getting stuck in a local optimum. The length of the tabu list can be specified by experience. The length of the tabu list can also affect intensification and diversification [39].
3. **Aspiration Criteria**
   Aspiration criteria are applied to prevent a solution's tabu state till the solution is proper enough based on quality or diversity. A well-known aspiration criterion permits solutions that are better enough than the current best solution.

The proposed CA-TS model begins with a randomly generated set of reservoirs storage over the operation horizon. At each time step, a vector of reservoirs storage is defined as a sub-problem. This sub-problem is solved by the TS components according to Eqs 8-13. Once solving all of the sub-problems by the TS, then new storages volumes are superseded into the CA part. This interaction between CA and TS keeps on until the convergence criteria are met.

3. Case study

The capability of the model is evaluated by solving a benchmark problem called 4-reservoir non-linear problem. The schematic representation of the problem is shown in Fig. 1. The related data of the modified version of the 4-reservoir problem, including maximum/minimum storages and releases volumes, can be found in Afshar [21]. According to this fact that solving the original linear form of the 4-reservoir problem proposed by Chow and Cortes-Rivera [40] cannot validate the effectiveness and efficiency of the model, the modified non-linear version of the 4-reservoir problem proposed by Afshar [21] employed here. The original linear form of the 4-reservoir problem defined over 12 months operation period having 12 decision variables. The proposed modified non-linear version of 4-reservoir consists of 12, 60, and 240 short, medium, and long-term operations having 44, 236, and 956 decision variables, respectively. Therefore, it can evaluate the ability of the model to tackle different scales of non-linear problems.

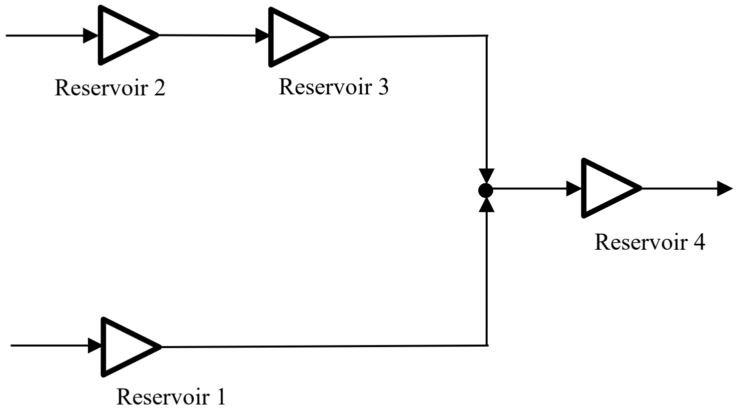

Figure 1. Schematic representation of the 4-reservoir problem

4. Result and discussion

The 4-reservoir nonlinear problem was solved by proposed CA-TS method and the minimum, average, and maximum obtained objective functions over 10 runs are shown in Table 1. The table also presents the average required computational time to converge. The computational effort for solving the problems, especially long-term problem, proves the efficiency of the proposed algorithm. As shown in the table, the number of run-time increases linearly with enlarging the problem.

Table 1. Results of proposed model for different operation periods

Period	Total Benefit			Average CPU Time (Sec)
	Max	Average	Min	
12	34200	33260	32000	11
60	172000	168000	166000	63
240	687000	667000	655000	255

Table 2 compares the results of the proposed method with those of reported by Afshar [21]. It is obvious in the table that the proposed method can produce superior results in comparison with other optimization algorithms in all operation periods, with relatively less computational effort. The CA-TS model could obtain better solutions by 2.4%, 4.87%, and 5.69% than GA in 12, 60, and 240- operation periods, respectively. It is also seen that the model's superiority increases by increasing the scale of the problem. While associated the run-time with the GA increases exponentially with enlarging the scale of the problem, the run-time which belongs in the proposed model increases linearly. For instance, the proposed method requires roughly one-sixth of the run-time of the GA to converge to its optimal solution over a 240-month operation period. It is noteworthy to mention that different tuning parameters related to the GA and PSO can be found in [21].

Although the run-time of the CA-NLP model is less than the proposed model, the CA-NLP model is prone to get stuck in local optima. As shown in the table, the obtained result of CA-NLP in a 60-month operation period is inferior to the both of GA and proposed model.

Table 2. Comparison between proposed model and Afshar [21] models

Periods	Method	Best solution	Average CPU Time (Sec)
12	CA-TS	3.42E+04	11
	CA-NLP*	3.34E+04	0.34
	GA*	3.34E+04	6.90
	PSO*	3.34E+04	9.60
60	CA-TS	1.72E+05	63.00
	CA-NLP*	1.62E+05	12.50
	GA*	1.64E+05	126.70
	PSO*	1.49E+05	181.80
240	CA-TS	6.87E+05	255.00
	CA-NLP*	6.59E+05	73.50
	GA*	6.50E+05	1487.00
	PSO*	5.89E+05	2208.90

*The results reported in [21].

Convergence curves for 12 and 240-month operation period are shown in Fig. 2 and Fig. 3, respectively. As it is clearly seen, the number of CA iterations is independent of the scale of the problem; so, increasing the operation period cannot affect the number of iterations. The model can not only produce better solutions than modern algorithms, but the most crucial characteristic of the model is the high rate of convergence in large-scale problems.

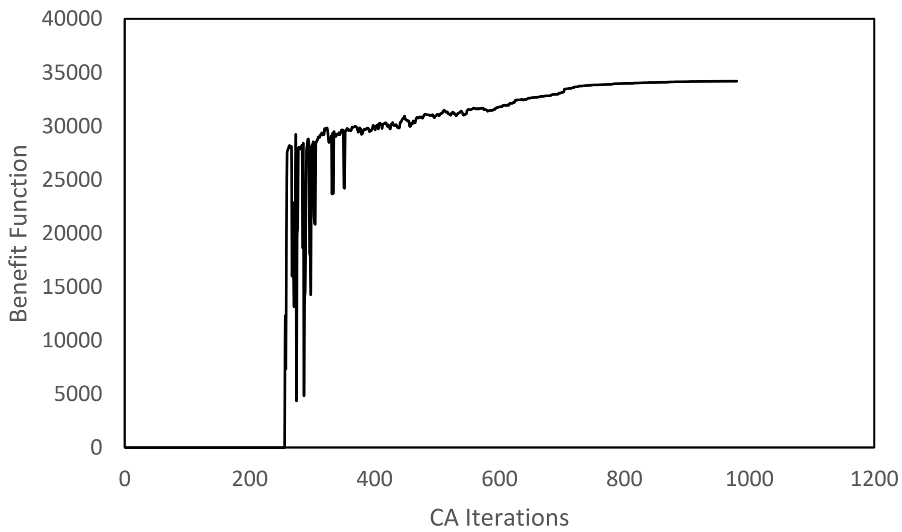

Figure 2. Convergence curve for 12 Months of operation

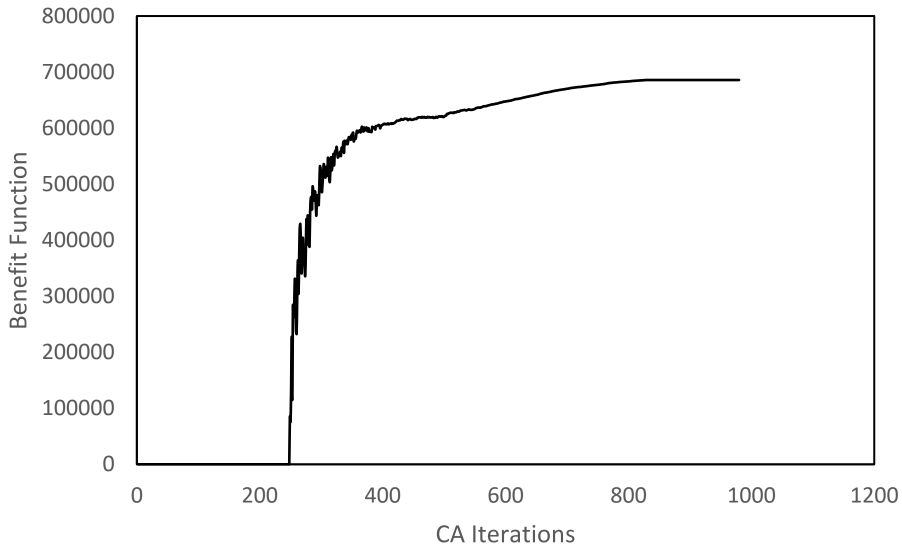

Figure 3. Convergence curves for 240 months of operation

5. Conclusion

For optimal hydropower operation, an innovative hybrid model, called cellular automata-tabu search (CA-TS) was developed to maximize the produced energy. For simplification, the original problem was divided into several sub-problems, which the number of them is the same as the length of the operation period, and each of these sub-problems was addressed by a well-known algorithm called tabu search algorithm.

The capability of the model was investigated by comparing obtained results of the model with those reported by Afshar [21] in solving a benchmark non-linear four-reservoir problem for different operation periods (12, 60, and 240 months). The results indicated that the proposed model could optimally address various scales of problems in comparison with GA, PSO, and CA-NLP methods.

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