

Effects of Multipath ATS's Parameter on Solving an Hydro-Thermal Economic Operation Scheduling Problem

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Abstract. This paper investigated an influence of an important parameter, namely discarding mechanism (DM), of the efficient Multipath Adaptive Tabu Search algorithms (MATS) on solving the well-known hydro-thermal economic operation scheduling problem with four hydro power plants and one thermal plant. The aim of this problem is to minimize fuel cost for the thermal plant by controlling the water discharge rate of each hydro plant under restricted constraints eg. water managements, power generator limits and power balance criterion. Nine types of DM has been tested and the results indexed by score which contain solution quality and search performance, show that DM with one invoking at the 1000th iteration, has the highest score 71 that make it be most suitable DM with MATS for solving this problem.

Keywords: Adaptive Tabu Search Algorithm, Multipath Adaptive Tabu Search Algorithm, Hydro-thermal economic operation scheduling problem

1. Introduction

Hydro-thermal generation scheduling problem is an hard-to-solve problem in electrical engineering because of the strict constraints such as reservoir volume limit, capacity limits of hydropower plants and thermal power plants, electricity demands, power losses and other security constraints. Due to these reasons, many heuristic search methods have been applied to solve the problem, eg. neural network [1], simulated annealing [2], genetic algorithms [3]-[4] and differential evolution [4]. As with other search methods, the proposed multipath adaptive tabu search algorithms (MATS) has also been applied to the hydro-thermal scheduling problem [9]. In this work, we focused on the influences of a key parameter of MATS, namely discarding mechanism (DM) on solving the problem.

This paper is organized as follows. First section overviews Hydro-thermal generation scheduling problem, second section reviews the proposed algorithms and its interesting parameter, third section is computational results and the last section is conclusion.

2. Problem formulation

Hydro-thermal generation scheduling problem selected here can be easily described by Fig. 1. It consists of two subsystems, hydro power plants (P_h) with four generating units and a thermal power plant. The output power of the hydro plants depend on variables in equation (1)

$$P_{h,i}(t) = c_{1,i}V_{h,i}^2(t) + c_{2,i}Q_{h,i}^2(t) + c_{3,i}V_{h,i}(t)Q_{h,i}(t) + c_{4,i}V_{h,i}(t) + c_{5,i}Q_{h,i}(t) + c_{6,i} \quad (1)$$

where $V_{h,i}$ is volume of i th reservoir, $Q_{h,i}$ is water discharge rate through the generating i th unit and $c_{j,i}$ parameters which can be found in [3].

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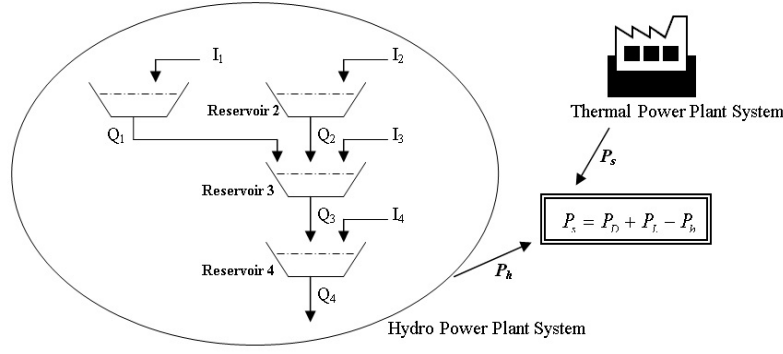


Fig. 1: Tested system with four hydro power plants at each reservoir and one thermal power plant [2].

The only one thermal power plant can generate output power (P_s) according to equation (2)

$$P_s(t) = P_D(t) + P_L(t) - P_h(t) \quad (2)$$

where PL is power loss which is zero for this case and PD is demand power in each hour for a day given in Table 1 from [3]. The output power from thermal unit can only be generated in range of 500 to 2500 MW and its fuel cost in US dollar (\$) can be written in general quadratic form shown in equation (3)

$$F_s(P_s(t)) = 5000 + 19.2P_s(t) + 0.002P_s^2(t) \quad (3)$$

Table 1: Load demands in MW.

Hour	Load	Hour	Load	Hour	Load	Hour	Load	Hour	Load	Hour	Load
1	1,370	5	1,290	9	2,240	13	2,230	17	2,130	21	2,240
2	1,390	6	1,410	10	2,320	14	2,200	18	2,140	22	2,120
3	1,360	7	1,650	11	2,230	15	2,130	19	2,240	23	1,850
4	1,290	8	2,000	12	2,310	16	2,070	20	2,280	24	1,590

The main objective function of this problem is to minimize the fuel cost of thermal plant while load demand in each hour are kept by feeding power from hydro plants under considering many constraints. The objective function can be formulated in general optimization problem form as follows,

$$\begin{aligned} \min J(Q_1, Q_2, Q_3, Q_4, t) \\ \text{subject to } Q_{\min} < Q_i < Q_{\max} \end{aligned} \quad (4)$$

where

$$J = P_s(Q_1, Q_2, Q_3, Q_4, t) + \sum \alpha L \quad (5)$$

L and α is penalty terms and weighting factors which interested readers can see more details in [9]. Next section will review concept of multipath adaptive tabu search algorithms and its key parameter.

3. Mulipath Adaptive Tabu Search (MATS)

Adaptive tabu search (ATS) [7] is an efficient metaheuristic search algorithm which has been modified from the naïve tabu search algorithms (TS) [5]-[6]. TS bases on two main strategies, diversification and intensification. To enhance search performance of TS with two mechanisms, namely back-tracking (BT) and adaptive search radius (AR) mechanisms can obtain ATS at the end. Multipath adaptive tabu search algorithms (MATS) has been launched recently [8]. Its concept lays on idea to administrate many ATS with a few mechanisms under higher performance approaches. Three mechanisms, partitioning mechanism (PM) to initialize ATSSs, sequencing mechanism (SM) to allow all ATS working in sequential manner and lastly discarding mechanism (DM) to cancel low quality ATSSs out of the main loop, have been used to construct MATS. This paper is interested in the effect of DM on solving an hydrothermal scheduling problem so that various DMs have been elaborated experimentally.

4. Computational results

A Single ATS and ATSS in MATS were set with the same parameters. AR consists of five steps, if $J < 2 \times 10^8$ then $R_{new} = 0.2R_{old}$, if $J < 1 \times 10^8$ then $R_{new} = 0.02R_{old}$, if $J < 1.3 \times 10^6$ then $R_{new} = 0.002R_{old}$, if $J < 9.7 \times 10^5$ then $R_{new} = 0.0002R_{old}$ and if $J < 9.6 \times 10^5$ then $R_{new} = 0.00002R_{old}$. BT will bring ATS backward to the 10th visited solution when five iteration of unimproved solutions are occurred. Number of neighbor solutions is fixed to 10. MATS began with four search paths of ATSSs by PM and then controlled all ATS operating in series by SM. For DM has been classified into nine types, let see in the first column of Table 2. DM (100, 400) means that the first DM will be invoked in the 100th iteration to reduce a half number of ATS from four to two and then the second DM in the 400th iteration. Similarly, DM (1000, 6000) means that the first and second DMs will be invoked in the 1000th and 6000th iterations respectively. Difference may be happen in DM (1000, -), it means that the only one DM will be invoked in the 1000th iteration and reduce number of ATSSs from four to one. The other one DM invoked were also tested at the 2000th iteration and the 3000th iteration, but not including 4000th iteration or more than since it may be over 150,000 function evaluation limit.

ATS, MATS and tested problem were coded in MATLAB® and run on PC with CPU dual core 2.6 GHz and RAM 1 GB for 25 random trials. The experimental results in the best objective function values have been shown in Table 2 with respect to the previous methods, genetic algorithms (GA) and differential evolution (DE).

Table 2: Computational results in the obtained objective function values.

Methods	Obtained objective function value ($\times 10^5$ \$)					
	Minimum	Median	Mean	Maximum	Standard dev.	
GA [4]	9.49500	9.69605	9.71289	9.95042	0.10387	
DE [4]	9.43215	9.49159	9.48921	9.57220	0.03914	
ATS [9]	9.39131	9.46218	9.46548	9.55447	0.03676	
MATS	DM(100, 400)	9.38668 (6)	9.47128 (1)	9.48145 (1)	9.61992 (1)	0.04551 (1) (10)
	DM(1000, 2000)	9.38452 (7)	9.44025 (8)	9.44697 (7)	9.51312 (5)	0.03480 (4) (31)
	DM(1000, 3000)	9.40043 (2)	9.45294 (4)	9.45668 (3)	9.52146 (4)	0.03041 (5) (18)
	DM(1000, 4000)	9.39504 (4)	9.43414 (9)	9.44364 (9)	9.52592 (3)	0.03528 (3) (28)
	DM(1000, 5000)	9.39903 (3)	9.45074 (5)	9.45338 (4)	9.50017 (7)	0.02559 (8) (27)
	DM(1000, 6000)	9.41274 (1)	9.45445 (3)	9.45276 (5)	9.48967 (9)	0.01940 (9) (27)
	DM(1000, -)	9.38213 (9)	9.46503 (2)	9.46261 (2)	9.53978 (2)	0.04157 (2) (17)
	DM(2000, -)	9.38383 (8)	9.45005 (6)	9.44779 (6)	9.50562 (6)	0.02943 (7) (33)
DM(3000, -)	9.38769 (5)	9.44200 (7)	9.44592 (8)	9.49837 (8)	0.03007 (6) (34)	

If we consider the averaged objective function values in the fourth column of Table 2, all ATS and MATS can obtained lower values than the other previous methods. To compare between ATS and MATSs, some of MATSs can be better than ATS's does and the best or the lowest objective function of MATS is of DM (1000, 4000) with $J=9.44364 \times 10^5$ which is lower than of ATS ($J=9.46548 \times 10^5$). Among these of MATS, ranking score was applied here for comparative quality approach. For example in minimum objective values column, MATS with DM(1000,-) has obtained the lowest value with $J=9.38213 \times 10^5$, it got the top score (9) but MATS with DM(1000,6000) has returned the highest value with $J=9.41274 \times 10^5$, so that the minimum score (1) belongs with it. The other columns is also assigned the score from (9) to (1) for the ranking down-top style. The last column contains summation of the scores for each row in the bold letters, eg DM(3000,-) got score (34) but DM(1000,4000)'s score was (28).

Table 3 illustrates searching time of ATS and MATSs. It has been analyzed with the same way of Table 1 by scoring from (9) to (1) for the ranking down-top style and sum up at the end column.

Table 3: Searching time under 150,00 functions evaluation limits.

Methods	Search time (seconds)					
	Minimum	Median	Mean	Maximum	Standard dev.	
ATS	609.7961	611.5549	613.0564	622.9270	3.3817	
MATS	DM(100 ,400)	575.1360 (1)	577.5422 (1)	577.4698 (1)	579.7491 (1)	0.9050 (2) (6)
	DM(1000,2000)	454.7540 (3)	456.4700 (3)	456.3377 (3)	457.1989 (3)	0.5612 (6) (18)
	DM(1000,3000)	433.4950 (4)	434.2360 (4)	434.3219 (4)	436.7574 (4)	0.7698 (4) (20)
	DM(1000,4000)	419.6814 (5)	421.5634 (5)	421.3704 (5)	422.3600 (5)	0.7276 (5) (25)
	DM(1000,5000)	405.3939 (7)	405.9770 (7)	405.9749 (7)	406.6292 (7)	0.3777 (9) (35)
	DM(1000,6000)	399.3869 (8)	400.4883 (8)	400.4008 (8)	401.2549 (8)	0.4680 (8) (40)
	DM(1000, -)	483.5793 (2)	484.5790 (2)	484.6087 (2)	486.3450 (2)	0.5175 (7) (15)
	DM(2000, -)	408.2392 (6)	410.5295 (6)	410.3181 (6)	412.5687 (6)	0.8754 (3) (27)
	DM(3000, -)	366.3175 (9)	369.7090 (9)	369.2753 (9)	371.0262 (9)	1.2527 (1) (37)

Fig. 2 shows total scores from summation of Table 2 and Table 3 classified by type of DM, eg. DM(1000,3000) have the score (18) from Table 2 and the score (20) from Table 3, so that its total score is (38). We can see that the total score contains both solution quality index and search performance index of each DMs. The high score imply that its DM has ability to find solution with high quality and spend less seaching time. From Fig.2, DM(3000,-) has the highest score (71) and it is elite candidate to be with MATS on solving the hydro-thermal economic operation scheduling problem.

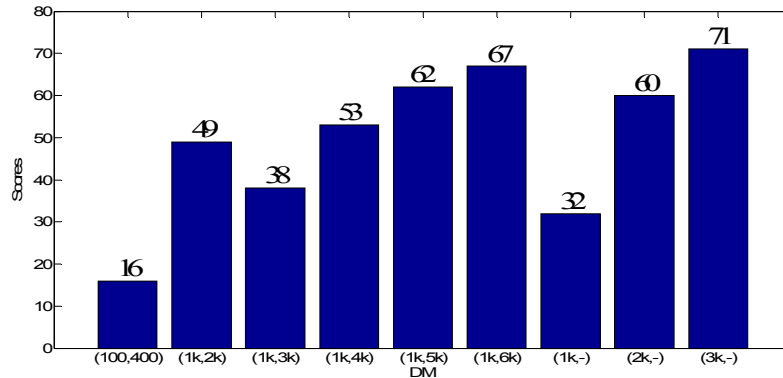


Fig. 2: Total scores of DM from solution quality obtained and searching time spent.

Convergence property of these MATS can be studied in Fig. 3, it is of DM(1000,-) as an example. In Fig.3, MATS#4 or MATS path 4th has searched non-stop 12,000 iterations and also spent 484.1457 seconds. Starting by randomly guessing solution, $J=1.9055 \times 10^5$, 2.0212×10^5 , 1.8355×10^5 and 2.0447×10^5 are initial costs of MATS#1 to #4 respectively. Until the 1000th iteration, DM was invoked and then its internal process operated by ranking and discarding the low quality paths (MATS#2, #1 and #3).

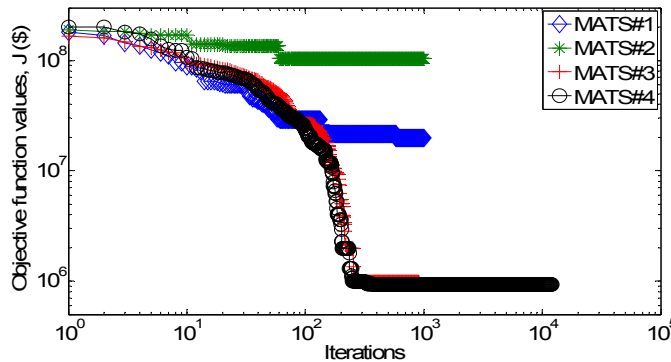


Fig. 3: Convergence curves of MATS with DM(1000,-).

5. Conclusions

This paper has studied the effects of DM of MATS on solving the short-term hydro-thermal economic operation scheduling problem by computational experiments. Nine types of DMs have been performed 25 independent runs. Through the proposed scoring which contain both solution quality obtained and searching

time spent, The results show that the DM(3000,-) is the best candidate to MATS for solving the problem with the highest score 71 than the of others.

6. Acknowledgements

Authors would like to thank Rajamangala University of Technology Lanna Tak for partial financial supports for the research.

7. References

- [1] R.H. Liang and Y.Y. Hsu. Scheduling of hydroelectric generation units using artificial neural networks. *Proc. IEE, Pt. C*, 1994: 452-458.
- [2] K.P. Wong and Y.N. Wong. Short term hydrothermal scheduling. Part I: Simulated annealing approach. *Proc. IEE, Pt. C*. 1994: 497-501.
- [3] S.O. Orero and M.R. Irving. A genetic algorithm modeling framework and solution technique for short term optimal scheduling. *IEEE Trans. on Power System* 1998, 13(2): 501-518.
- [4] URL: http://www.ntu.edu.sg/home/epnsugan/index_files/cec-benchmarking.htm
- [5] F. Glover. Tabu search-Part-I. *ORSA J Computing* 1989, 1(3): 190-206.
- [6] F. Glover. Tabu search-Part-II. *ORSA J Computing* 1990, 2(1): 4-32.
- [7] S. Sujitjorn, Kulworawanichpong T., Puangdownreong D. and Areerak K-N. Adaptive tabu search and applications in engineering design, *Integrated Intelligent Systems for Engineering Design*, chapter 12. IOS Press the Netherlands 2006.
- [8] J. Kluabwang, D. Puangdownreong and S. Sujitjorn. Multipath adaptive tabu search for a vehicle control problem. *J Appl Math* 2012; Article ID 731623, 20 pages.
- [9] J. Kluabwang. Economical operation of hydro-thermal power system based on multi-path adaptive tabu search. *WASET J of Sci & Tech* 2012, 65(34): 170-172.



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