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Contrastive analysis of three parallel modes in multi-dimensional dynamic programming and its application in cascade reservoirs operation

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SUMMARY

The "curse of dimensionality" of dynamic programming (DP) has always been a great challenge to the cascade reservoirs operation optimization (CROO) because computer memory and computational time increase exponentially with the increasing number of reservoirs. It is an effective measure to combine DP with the parallel processing technology to improve the performance. This paper proposes three parallel modes for multi-dimensional dynamic programming (MDP) based on .NET4 Parallel Extensions, i.e., the stages parallel mode, state combinations parallel mode and hybrid parallel mode. A cascade reservoirs of Li Xiangjiang River in China is used as the study instance in this paper, and a detailed contrastive analysis of the three parallel modes on run-time, parallel acceleration ratio, parallel efficiency and memory usage has been implemented based on the parallel computing results. Results show that all the three parallel modes can effectively shorten the run-time so that to alleviate the "curse of dimensionality" of MDP, but relatively, the state combinations parallel mode is the optimal, the hybrid parallel is suboptimal and the stages parallel mode is poor.

1. Introduction

With the rapid propulsion of cascade hydropower development, cascade reservoirs operation optimization (CROO) is attracting more and more attention of people all over the world (Jiang et al., 2014). CROO is a multivariate coupled and complicated nonlinear programming problem, which needs to consider not only the hydraulic and electrical connection between upstream and downstream reservoirs, but also a lot of constraints (Ji et al., 2015). It has the characteristics of high dimensionality, strong coupling, and uncertainty, etc. Over the past decades, a wide range of comprehensive methods have been used to deal with the CROO problems, which mainly involve various modern heuristic random search algorithms and traditional optimization algorithms.

Modern heuristic random search algorithms such as the Genetic Algorithm (GA) (Baskar et al., 2003; Chiang, 2007; Dariane and Momtahen, 2009), Particle Swarm Optimization (PSO) (Cai et al., 2001; Nagesh Kumar and Janga Reddy, 2007; Zhang et al., 2014), Ant Colony Optimization (ACO) (Zhou and Ji, 2007; Ji et al., 2011; Moeini and Afshar, 2013), Simulated Annealing (SA) (Basu, 2005), Evolutionary Programming (EP) (Basu, 2004; Malekmohammadi et al., 2009), Fuzzy Neural Network (FNN) (Chaves and Kojiri, 2007; Deka and Chandramouli, 2009) and Differential Evolution algorithm (DE) (Yuan et al., 2008; Yuan and Wu, 2012) have been extensively used to solve the CROO problems with nonlinear and non-convex objective functions. Many heuristic random search algorithms have been proved to possess a global convergence, while as they are affected by stochastic characteristics, they cannot guarantee a global optimum with finite iterations.

Those traditional optimization methods include Linear Programming (LP) (Marino and Mohammadi, 1983; Jabr et al., 2000; Reis et al., 2006; Lu et al., 2011; Li et al., 2013), Nonlinear Programming (NLP) (Martin, 1983; Lund and Ferreira, 1996; Barros et al., 2003; Chen, 2007), Lagrangian Relaxation (LR) (Hindi and Ghani, 1991; EI-Keib et al., 1994), Quadratic Programming (QP) (Papageorgiou and Fraga, 2007), Network Flow Algorithm (NFA) (Braga and Barbosa, 2001), and Dynamic programming (DP) (Johnson et al., 1993; Raman and Chandramouli, 1996; Eum et al., 2010; Goor et al., 2011; Shokri et al., 2013), etc. They are all elitist algorithms, and have already received different degrees of success in solving CROO problems.

DP is a powerful multi-stage decision-making method, and is a suitable optimization method for CROO problems as the structure of the optimization problem conforms to a multi-stage decision-making process which can be formulated as a DP problem

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Nomenclature

A	punish coefficient
E	total hydropower generation for all stages over the entire planning horizon (in kWh)
Ev_t^i	evaporation capacity of the ith reservoir in the tth stage (in m^3/s)
D_t	decision variables set in the tth stage
$f_t^*(V_{t-1}^{Sb})$	optimal cumulative output of beginning state Sb at the tth stage
$f_{t+1}^*(V_t^{Se})$	optimal cumulative output of end state Se at the tth stage
$F_t^*()$	optimal cumulative output vector function of cascade system at the tth stage
H_t^i	average water head of the ith hydropower station in the tth stage
I_t^i	inflow of the ith reservoir in the tth stage (in m^3/s)
i	reservoir index
K^i	efficiency coefficient of the ith hydropower station
M	total number of discretized points for the state variable in a stage
n	total number of reservoirs in the cascade system
N_t^i	output of the ith hydropower station in the tth stage (in kW)
$N_{t,\min}^i$	lower output limit of the ith hydropower station in the tth stage (in kW)
$N_{t,\max}^i$	upper output limit of the ith hydropower station in the tth stage (in kW)
$N_t()$	output function of the tth stage
Q_t^i	total outflow of the ith reservoir in the tth stage, including q_t^i and W_t^i (in m^3/s)
q_t^i	outflow through the turbines of the ith reservoir in the tth stage (in m^3/s)
$Q_{t,\max}^i$	upper outflow limit of the ith reservoir in the tth stage (in m^3/s)
$Q_{t,\min}^i$	lower outflow limit of the ith reservoir in the tth stage (in m^3/s)
Sb	beginning state index of a stage, where $Sb = 1, 2, \ldots, M$
Se	end state index of a stage, where $Se = 1, 2, \ldots, M$
T	total number of stages over the entire planning horizon
t	stage index
TN	total guaranteed output of the cascade system
V_t^i	storage of the ith reservoir at the end of the tth stage (in m^3)
V_{t-1}^i	storage of the ith reservoir at the beginning of the tth stage (in m^3)
$V_{t,\max}^i$	upper storage limit of the ith reservoir in the tth stage (in m^3)
$V_{t,\min}^i$	lower storage limit of the ith reservoir in the tth stage (in m^3)
V_0^i	storage of the ith reservoir at the beginning of the first stage (in m^3)
V_b^i	storage of the ith reservoir at the beginning of entire planning horizon (in m^3)
V_T^i	storage of the ith reservoir at the end of the Tth stage (in m^3)
V_e^i	storage of the ith reservoir at the end of entire planning horizon (in m^3)
W_t^i	outflow through flood discharge gate of the ith reservoir in the tth stage (in m^3)
Δt	duration of an operation stage, (in second)
θ	exponent
σ_t	0–1 variable

(Liang and Hsu, 1995). Moreover, DP imposes no restrictions on the unsmooth and non-convex nature of CROO problems, which makes it boasting high popularity among the conventional optimization techniques for reservoir operation. Over the past decades, DP had been used extensively in the optimization of reservoir management and operation (Huang and Wu, 1993; Travers and Kaye, 1998; Chen et al., 1999).

In discrete DP model, the storage volume of each reservoir in each stage is discretized into a finite number of points. By the exhaustive enumeration over all possible combinations of these discrete points, the global optimality can be assured. The most significant characteristic for DP is able to obtain the global optimal solution and no requirement for the initial trajectories. However, the well-known "curse of dimensionality" (Bellman, 1961) poses difficulties and limits the application of DP in CROO problems, especially for large-scale hydropower system.

In solving CROO problems on large and complex hydropower systems, a general idea is to adopt suitable methods to avoid or alleviate the "curse of dimensionality" of DP. Therefore, a variety of improved DP algorithms have been extensively used (Zhao et al., 2014), such as Discrete Differential Dynamic Programming (DDDP) (Heidari et al., 1971; Chow et al., 1975; Liao and Shoemaker, 1991; Tospornsampan et al., 2005), Incremental Dynamic Programming (IDP) (Mathlouthi and Lebdi, 2009), Dynamic Programming with Successive Approximation (DPSA) (Larson and Korsak, 1970; Opan, 2011), Incremental Dynamic Programming and Successive Approximations (IDPSA) (Trott and Yeh, 1973), Progressive Optimality Algorithm (POA) (Turgeon, 1981; Cheng et al., 2012; Lu et al., 2013), and so on. These improved DP algorithms have effectively avoided the "curse of dimensionality" problem. However, they also have some disadvantages, for example, POA and DDDP are sensitive to initial trajectories for each state variable, and may converge to a local optimum in some situations. DPSA is difficult to be applied to solution of non-convex problems, and there is also no assurance of convergence to the global optimum.

Therefore, in order to avoid the "curse of dimensionality" and at the same time obtain the global optimal solution of CROO problems, there is a lot of work needs to be done, and the most important and effective is to improve the computational efficiency of DP. Generally, there are two basic approaches to improve the computational efficiency of DP. One is to improve the classical DP algorithm in the case of guarantee the global convergence, the other is to use new computer techniques including hardware and software.

For the first approach, related researches have been done by some scholars. For example, Mousavi et al. (2004) reduced the computational time of a DP model for a multi-reservoir system by diagnosing infeasible storage combinations and removing them from further computations. This method has a certain effect, but the computational time consuming still enormous and intolerable when the scale of hydropower system reaches a certain large degree. Zhao et al. (2012) proposed an improved DP model for reservoir operation optimization (ROO) by taking the advantage of the monotonic relationship between reservoir storage and the optimal release decision. However, the model can only be applied to reservoir operation with a concave objective function. Ji et al. (2015) proposed a new multi-layer nested multi-dimensional