# Climate Change Adaptation in Multi-Reservoir Systems through Revising Operation Policies

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**Abstract**

Many river-reservoir systems have been significantly affected by climate change. Karun and Dez multi-reservoir system is the largest reservoir system in Iran, which has experienced significant decline of surface runoffs in the past 10 years. Currently, the system contains six multi-purpose hydropower reservoirs and 8 more dams have been studied to be built on these two rivers. In this study, potential impacts of climate change on the optimal operation policies of the reservoirs were assessed. For this purpose, time series of reservoir inflows under A2, B1 and A1B emission scenarios were projected using outputs of HadCM3, CGCM3 and ECHAM5 Atmosphere-Ocean General Circulation Models (AOGCM). In order to formulate the optimal operation policies for the Karun-Dez multi-reservoir system, a stochastic optimization model, namely Stochastic Dual Dynamic Programming (SDDP), was utilized. Comparison between the simulation of operation policies proposed based on the historical and projected inflows, showed that by considering the climate change projections, the performance of the policies could be improved by up to 30%. The results also showed that a relatively important share of negative impacts of climate change on Karun and Dez multi-reservoir system can be mitigated by utilizing the operation policies derived based on the climate change projections.

**Keywords: Climate change, optimal operation, hydropower, Karun and Dez reservoir system, Stochastic Dual Dynamic Programming.**

## 1. INTRODUCTION

Climate change has affected the hydrologic conditions of the water systems throughout the world. Adapting to the changing hydrologic conditions is essential to mitigate the negative impacts of the climate change. In particular, hydropower generation has been significantly impacted by change in the hydrologic conditions [1]. Adaptation to climate change, to some extent can be achieved by taking into account the changing conditions in the process of developing operation policies for hydropower systems.

Optimization methods are common tools for developing optimal operation policies for multi-reservoir systems. Stochastic Dynamic Programming (SDP) is one of the most commonly used methods for developing optimal operation policies in reservoir systems. However, the curse of dimensionality, which is the exponential increase in runtime needed with the increase in the dimensions of the optimization problem, restricts the application of SDP to systems with 3-4 reservoirs [2]. Different approaches have been proposed to circumvent the curse of dimensionality, with Stochastic Dual Dynamic Programming (SDDP) [3] being supposedly the most successful of these approaches.

SDDP is one of the most commonly used approaches for the problem of optimal operation of multireservoir systems. Pereira and Pinto [3] developed SDDP for the problem of hydrothermal scheduling. SDDP uses the dual information of one-stage optimization to approximate the expected cost-to-go function in each stage of the problem. In this sense, SDDP could be regarded as an extension of Benders decomposition, and each approximation of the cost-to-go function, is a Benders cut. The accuracy of this approximation is increased through an iterative simulation-optimization process. Philpott and Guan [4] has given a mathematical proof of convergence for SDDP.

SDDP has been largely used in hydrothermal scheduling [5, 6]. Tilmant and Kelman [7] utilized SDDP in order to analyze trade-offs between agricultural development scenarios and hydropower benefits in a big water resources system. Tilmant et al. [18] proposed a method for incorporating irrigation benefits in the objective function of SDDP in order to assess the marginal value of water. Goor et al. [9] proposed a method based on the convex hull approximation of the true hydropower function in order to take into account the variable productivity of hydropower plants. Rouge and Tilmant [10] provided a discussion on the existence of multiple near-optimal solutions in SDDP and proposed a periodic reoptimization algorithm to stabilize the policies developed from SDDP. Poorsepahy-Samian et al. [11] proposed a method for incorporating box-cox transformation in the inflow modelling of SDDP. The results showed that inflow modelling significantly affects the quality of the policies from SDDP.

This paper studies the potential impacts of climate change on operation policies developed by SDDP for Karun-Dez hydropower multi-reservoir system in Iran. The remaining of this paper is organized as follows. Section 2 presents a brief description of the stochastic dual dynamic programming and the one-stage problem. Karun-Dez Multireservoir system is introduced in Section 3 followed by a summary of the results from inflow projections in climate change scenarios. Section 3 finishes by presenting and comparing the results from the simulation of optimal policies. Finally, Section 4 presents the concluding remarks.

## 2. STOCHASTIC DUAL DYNAMIC PROGRAMMING

In SDDP, the multistage optimization problem is decomposed into a set of one-stage optimization sub-problems. Then starting from the last one-stage sub-problem, the sub-problems are solved and the value of the objective function for each time stage is approximated using a linear approximation. As the number of these linear approximations increases, the accuracy of the approximation improves and algorithm reaches the convergence when the approximation is a good representation of the real objective function. In a reservoir operation optimization problem, taking the reservoir storages and the inflow to the reservoirs in the last $p$ time stages as the state variables, in a system with $J$ reservoirs, each linear approximation has the following form:

$$F_t^* \leq \sum_{j=1}^{J} \alpha_{t,j} s_{t,j} + \sum_{j=1}^{J}\sum_{i=1}^{p} \beta_{t,j}^{i} q_{t-i,j} + \delta_t \tag{1}$$

Where $\alpha_{t,j}$ is the approximation parameter associated to the water storage in reservoir $j$ in the beginning of the time stage $t$ , $\beta_{t,j}^{i}$ is the approximation parameter associated to the inflow to reservoir $j$ in the time stage $t-i$ and $\delta_t$ is the approximation offset. Therefore, the one-stage optimization sub-problem in SDDP has the following general form:

$$\textbf{minimize} \qquad F_t = f_t + F_{t+1}^* \tag{2}$$

Subject to: $$\mathbf{s}_{t+1} - \mathbf{C}^R(\mathbf{r}_t + \mathbf{r}_t^{spill}) - \mathbf{C}^I \mathbf{w}_t = \mathbf{s}_t + \mathbf{q}_t \tag{3}$$

$$\underline{\mathbf{s}}_{t+1} \leq \mathbf{s}_{t+1} \leq \bar{\mathbf{s}}_{t+1} \tag{4}$$

$$\mathbf{r}_t \leq \mathbf{rmax} \tag{5}$$

$$\begin{cases} F_{t+1}^* \leq \sum_{j=1}^{J} \alpha_{t,j}^{1} s_{t,j} + \sum_{j=1}^{J}\sum_{i=1}^{p} \beta_{t+1,j}^{1,i} q_{t-i,j} + \delta_{t+1}^{1} \\ \vdots \\ F_{t+1}^* \leq \sum_{j=1}^{J} \alpha_{t,j}^{L} s_{t,j} + \sum_{j=1}^{J}\sum_{i=1}^{p} \beta_{t+1,j}^{L,i} q_{t-i,j} + \delta_{t+1}^{L} \end{cases} \tag{6}$$

$$\mathbf{o}_t + p_t^{ins} \geq \mathbf{Ins}_t \tag{7}$$

$$\mathbf{w}_t + p_t^{consumptive} = \mathbf{demand}_t \tag{8}$$

$$G_{j,t} + p_t^{power} \geq pf_j \times pmax_j \quad \forall j = 1,\ldots,J \tag{9}$$

$$f_t = z_{ins} p_t^{ins} + z_{consumptive} p_t^{consumptive} + z_{power} p_t^{power} \tag{10}$$

Where $F_t$ is the total expected penalty from the beginning of the stage $t$ to the end of planning horizon; $f_t$ is the penalty at the stage $t$; $\mathbf{w}_t$ is the $(D \times 1)$ matrix of the allocations to different consumptive demands in the stage $t$ $(m^3)$; $\mathbf{r}_t$ is the matrix of the reservoir releases in the stage $t$ $(m^3)$; $\mathbf{q}_t$ is the matrix of the reservoir inflows in stage $t$ $(m^3)$; $\mathbf{r}_t^{spill}$ is the matrix of the spills in the stage $t$ $(m^3)$; $\mathbf{rmax}$ is the upper bound of reservoir releases in the stage $t$ $(m^3)$; $\bar{\mathbf{s}}_{t+1}$ and $\underline{\mathbf{s}}_{t+1}$ are the upper and lower bound matrixes of reservoir storages at the end of stage $t$, respectively; $pf_j$ is the plant factor for the reservoir $j$; $G_{j,t}$ is the amount of power generated in reservoir $j$ (MWh); $\mathbf{o}_t$ is the matrix of discharges from the point of instream flow demands in the stage $t$; $\mathbf{Ins}_t$ is the matrix of instream flow demands; $\mathbf{demand}_t$ is the amount of consumptive demands; $p_t^{power}$ is the amount of reliable energy production deficit in the stage $t$ (MWh); $p_t^{consumptive}$ is the matrix of the consumptive demand deficit; $p_t^{ins}$ is the matrix of the instream flow demand deficit in the stage $t$; $z_{power}$ is the penalty factor for deficit in supplying hydropower demand; $z_{consumptive}$ is the matrix of the penalty factors for deficit in supplying the consumptive demands and $p_t^{ins}$ is the matrix of penalty factors for deficit in supplying instream flow demands.

The approximation parameters for each time stage are calculated by exploiting the dual variables associated to the constraints. The solution algorithm in SDDP involves two main phases: (1) Backward recursion and (2) Forward simulation. In backward recursion, starting from the last stage, the one-stage optimization sub-problem is solved by assuming a trial value for the state variables and then an approximation is built for that trail value. The backward recursion is followed until the first stage and then the forward simulation phase is executed where starting from the first stage, the optimization sub-problems are solved. The value of state variables from the forward simulation are then fed into the next backward recursion as the new trial values. The algorithm is repeated until reaching convergence. For more information about the solution algorithm, see [7] and [11].

The inflow uncertainty in SDDP is generally handled by fitting an Autoregressive or Periodic Autoregressive model to the inflow time series. The fitted inflow model is used to generate inflow scenarios for both backward recursion and forward simulation phases. Gjelsvik et al. [12] proposed that an Autoregressive model of order one (i.e. AR(1)) is a good trade-off between speed and accuracy.

## 3. CASE STUDY AND RESULTS

Karun-Dez Multireservoir system is located southwest Iran. Six hydropower reservoirs, namely Karun4, Karun3, Karun1, Godarlandar, Gotvand and Dez are under operation in the system, and eight more dams are planned to be built in the near future. The location map and the schematic of the system are shown in Figure 1.

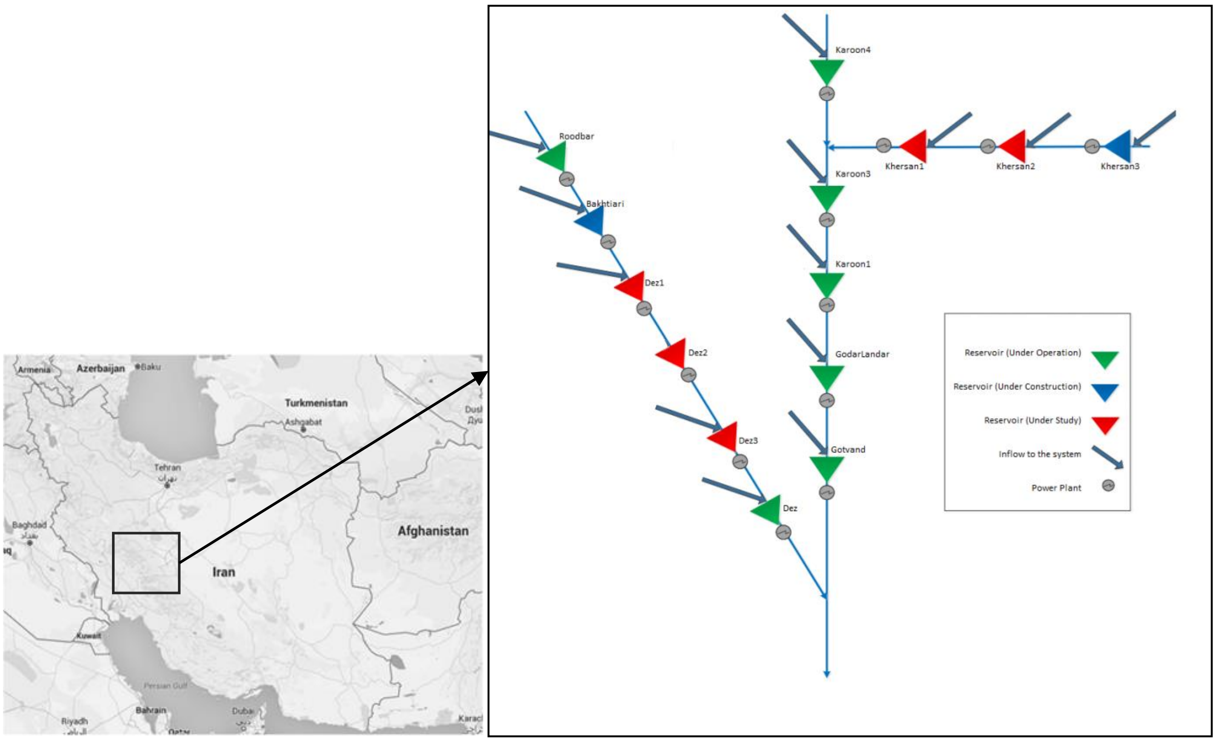


**Figure 1. Location map and Schematic of the Karun-Dez Multireservoir system**

The system has experienced a significant decline in the amount of inflows in the past 10-15 years period compared with the long-term mean and part of this decline is identified as a consequence of climate change. More specifically, the total inflow to the Karun and Dez river basins have declined by 24% and 30% respectively, in the 2001-2010 period compared with the long-term 1975-2000 period.

In order to assess the impact of the climate change on the optimal operation policies in the system, time series of the inflows to the system in the 2000-2050 were projected under A2, B1 and A1B emission scenarios using the outputs of HadCM3, CGCM3 and ECHAM5 Atmosphere-Ocean General Circulation Models. Figure 2 presents the comparison between the mean annual inflows to the Karun and Dez basins in the historical period with the climate change projections [13].

Figure 2 reveals that the annual inflow to the system is expected to decline in the future compared with the 1975-2000, in both basins. However, in Karun basin it could be expected that the future inflows will increase compared with the inflow of 2001-2010 period. Furthermore, HadCM3 AOGCM model has resulted in higher inflow projections compared with the ECHAM5 and CGCM3 Models. Based on the observed patterns in the system, it could be deduced that HadCM3 model results in implausible inflow projections. Therefore, HadCM3 model is omitted from the subsequent analysis.

Based on the historical inflow of the 1975-2000 period and the inflow projections under the different climate scenarios, seven different sets of optimal operation models were developed in this study utilizing SDDP algorithm, one of which was developed based on the historical inflows of the 1975-2000 period and the six others were developed based on the climate change projections. Following suggestions in [12], the inflow time series for the climate change projections and the historical time series were modelled using AR(1) model.

Afterwards, the extracted operation policies were simulated based on the inflows of the 2001-2010 period and the results were compared. More specifically, the performance of the operation policies derived for the inflow data of 1975-2000 period were compared with the policies derived for the inflow projections based on climate change scenarios. The results are presented in Table 1. The reliability, resiliency and vulnerability indexes proposed by Hashimoto et al. [12] were utilized to quantify the efficiency of the operation policies.

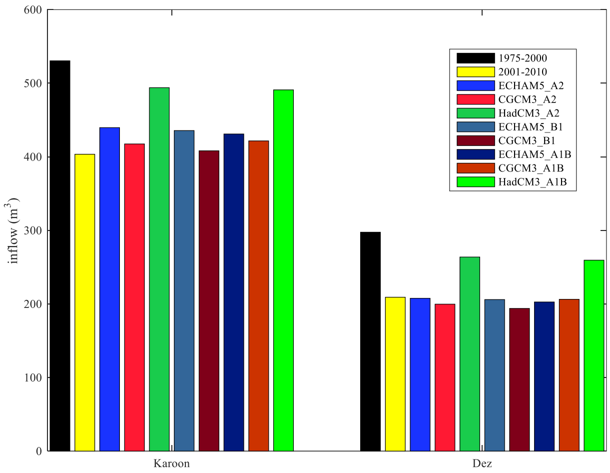


**Figure 2. Comparison of the mean total inflows to the Karun and Dez River basins in the historical period with the climate change projections**

**Table 1. Comparison between the performances of different operation policies based on the simulation of 2001-2010 period**

| Policy | Total Penalty | Total Power Generation (GWh) | Reliability | | | Resiliency | | | Vulnerability | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Reliable Energy | Consumptive demand | Instream Flow | Reliable Energy | Consumptive demand | Instream Flow | Reliable Energy | Consumptive demand | Instream Flow |
| Historical | $10.02\times10^7$ | 232180 | 47.0 | 81.6 | 98.9 | 27.5 | 62.9 | 97.2 | 1427 | 852 | 39 |
| CGCM3-A2 | $9.08\times10^7$ | 238400 | 63.3 | 83.3 | 94.5 | 32.4 | 63.3 | 81.2 | 1123 | 775 | 43 |
| CGCM3-B1 | $7.50\times10^7$ | 238670 | 63.4 | 83.4 | 94.3 | 32.6 | 66.5 | 85.2 | 980 | 771 | 74 |
| CGCM3-A1B | $8.92\times10^7$ | 235380 | 63.9 | 83.0 | 94.2 | 32.1 | 68.9 | 86.4 | 1183 | 812 | 18 |
| ECHAM5-A2 | $7.70\times10^7$ | 237580 | 63.2 | 84.1 | 95.7 | 35.0 | 65.8 | 88.5 | 892 | 802 | 24 |
| ECHAM5-B1 | $7.23\times10^7$ | 235640 | 61.1 | 83.7 | 96.0 | 29.8 | 65.9 | 88.3 | 975 | 878 | 4 |
| ECHAM5-A1B | $7.70\times10^7$ | 243190 | 65.3 | 84.8 | 94.7 | 32.0 | 70.7 | 87.8 | 889 | 740 | 20 |

The results indicate that by considering the climate change projections, the total simulated penalty (which is the main performance index as it is the objective function of the optimization to derive the optimal operation policies), has improved by 10% to 30% compared with the policies developed using historical inflows. The reliability of supplying reliable energy and consumptive demands have also increased 34% and 2.5%, respectively. Meanwhile, the reliability of supplying instream flow demand has decreased by 4% when using the policies derived for climate change projections. The better instream flow demand supply reliability based on the historical optimal operation policy is due to the overestimation of the inflow in this policy. In other words, this policy over-predicts inflows to the system and as a result, reservoirs released more water downstream in order to supply instream flow demand. However, by doing so, the reliability of supplying other demands, in particular energy demand, decreased significantly.

The resiliency and vulnerability indexes, also reveal that by using the policies derived based on the climate change projections, the performance could be improved significantly. Furthermore, the policies derived based on the projections of ECHAM5 AOGCM model performed better when compared with the policies derived based on the CGCM3 model projections. The operation policies for B1 scenario performed better in the period of 2001-2010 in comparison to A2 and A1B scenarios. Hence, it can be concluded that the ECHAM5-B1 projections provided best operation policies for the period of 2001-2010 and performed better in capturing the inflow decrease in this period.

## 4. CONCLUSIONS

In this paper, the potential impacts of the climate changes on the optimal operation policies in Karun-Dez multireservoir system were analyzed. The mean annual inflow to the system was decreased by 27% in the 2001-2010 period compared with the long-term 1975-2010 period. The optimal policies derived for 1975-2010 period were compared with the optimal policies derived based on the inflow projections of A2, B1 and A1B emission scenarios and ECHAM5, CGCM3 AOGCM models.

Based on the results, it was shown that by considering the inflow projections based on climate change scenarios, the reliability of supplying reliable energy and consumptive demands in the dry period of 2001-2010 could be improved by 34% and 2.5%, respectively. However, this was accompanied by a 4% decrease in the reliability of supplying the instream flow demand. The main performance index, namely the total penalty (which have been the objective function in the optimal operation models), could be improved by up to 30% when utilizing the policies derived for the climate change scenarios.

Also based on the results, it could be concluded that projections of the ECHAM5 AOGCM model for B1 emission scenario provides a better understanding of the behavior of the system in the 2001-2010 period, compared with the projections of CGCM3 and HadCM3 models for A2, B1, and A1B scenarios.

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