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Application of Cluster Analysis for Finding Operational Patterns of Multireservoir System during Transition Period

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Abstract

Operational objectives and/or constraints of a reservoir system may need to be shifted at certain periods (i.e. transition periods) due to seasonal considerations of human interest and ecological benefits. Despite the fact that operational schemes in the transition periods are critical and of great interest to reservoir operation practice, the problem has received little attention in the literature. This paper presents a study on cluster analysis for identifying patterns of operational schemes during a transition period. The test case corresponds to ten major reservoirs of the Federal Columbia River Power System (FCRPS) in the United States. The operation horizon consists of two weeks during which the objectives of the reservoir system are shifted based on seasonal consideration for fish migration and survival. An optimization model based on evolutionary algorithm is used to derive the optimal operational schemes under various inflow scenarios. A K-Spectral Centroid algorithm (K-SC) is applied on the resulting operational schemes to find clusters of the schemes based on similarities of their temporal shapes. By investigating the relations between the clusters and the inflow scenarios, general patterns of operational schemes are

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identified. Our analyses offer insights into the operational schemes during the transition period and broaden the understanding of short-term reservoir operation with shifting operational objectives.

Author keywords: Cluster analysis; Multi-reservoir system; Operational patterns;; Shifting objectives;

Introduction

Reservoir operation normally provides multiple benefits to human interests including flood control, hydropower generation, irrigation, etc. Recently, restoration of river ecosystems are being considered in reservoir operation to address growing concerns on ecological and environmental protection. Flow requirements for the biota in the river i.e., fish community (Cardwell et al. 1996; Chen et al. 2013), riparian vegetation (Morrison and Stone 2015; Richter and Richter 2000), and macro-invertebrate community (Maynard and Lane 2012) are considered for adapting reservoir operation. However, some of the requirements regarding the river ecosystem are seasonal, e.g., fish migration, and they are normally emphasized only during specific time periods. As a result, the operational considerations (either the objectives or constraints or both) are shifted at specific times (i.e., transition periods). Reservoir operation schemes during a transition period are expected to achieve an optimal trade-off between the operational objectives both before and after the transition.

Shifting operational objectives have been frequently discussed in the context of long-term planning studies (Lund 1996; Wurbs 1991). The shifts occur mostly because the original objectives and/or constraints are replaced with others that can better serve the new requirements for the reservoir system. These changes of the operational considerations are due to regional economic development or climate impacts (Jager and Smith 2008; Li et al. 2009; Loucks 1992; Raje and

Mujumdar 2010), which typically happen during a relatively long time frame such as decades. The shift of objectives and/or constraints in this long time frame context may have influence on the short-term reservoir operation due to the connection between long-term water control plans and the prescribed rules for short-term operation. However, the influence is mostly significant for a long time scale such as years. For a short term operation, the shift of operational objectives and/or constraints within the long-term planning are not considered.

In the context of short-term reservoir operation (i.e., within a year), many studies considering ecological interests have been made. However, most of these studies highlight the implementation of ecological interests in reservoir operations (Chen et al. 2015; Homa et al. 2005) and focus on achieving an optimal trade-off between the original human interests, e.g., power generation, and the added ecological interests e.g., ecological flow (Olivares 2008; Suen and Wang 2010). Very few studies have been conducted on reservoir operation in a transition period during which the objectives and/or constraints are shifted from one set to another due to seasonal requirements of the river ecosystem. Eschenbach et al., (2001) emphasized the need of reservoir managers to adapt quickly to changing objectives. Smith et al. (2007) argued that shifting operational objectives and constraints on ecological interests is a future challenge of reservoir operation for meeting dynamic and changing requirements. These discussions show the need for investigating optimal schemes for reservoir operations during a transition period.

Optimal schemes for reservoir operation are typically obtained by intensive simulation or, alternatively, by optimization algorithms. In addition to traditional optimization approaches such as Newton methods, evolutionary algorithms, e.g., Genetic Algorithms, have been receiving increasing attention on reservoir operation (Atiquzzaman et al. 2006; Prasad and Park 2004; Reed et al. 2013; Yandamuri et al. 2006; Yin and Yang 2011) due to their ability to find global (and not just local) optima. Data mining techniques are also applied frequently for identifying operational schemes of reservoir operation (Bessler et al. 2003; Wei and Hsu 2008). Among them, cluster analysis has been found to have many applications in reservoir operation due to its advantage for identifying patterns from massive data (Ponnambalam et al. 2002; Suen 2011).

The main purpose of this study is to use a cluster analysis approach to identify operational scheme patterns for reservoir operation during a transition period. A case study of ten reservoirs in the Columbia River, United States is considered. Fifty-one different inflow hydrograph scenarios based on historical records from 1965 to 2015 are used. For each inflow scenario, the optimal operational scheme is derived using a Genetic Algorithm and then a clustering method is used to group and identify patterns of operational schemes.

The remainder of the paper is organized as follows. In the section on Optimization Model Setup, the study case i.e., the Big-ten reservoir system of the Federal Columbia River Power System (FCRPS), is briefly introduced. The objective and the constraints of the optimization model during a transition period, as well as modelling of the reservoir system, are described. The inflow scenarios used for the optimization model are introduced and their statistics are briefly discussed. The Cluster Analysis Method section introduces the K-Spectral Centroid algorithm (K-SC), which is an efficient clustering technique recently developed (Yang and Leskovec 2011). By comparing to the K-means method, which is widely used for cluster analysis, advantages of applying the K-SC on reservoir operational schemes are discussed. The index for determining the number of clusters in the K-SC is also described. In the Results and Discussions section, the optimal operational schemes and the identified patterns are presented. The practical benefits of the identified operational patterns are also discussed. Finally, the main results are summarized in the Conclusions section.

Optimization Model Setup

Study case

The Big-ten reservoir system, i.e., ten large reservoirs of the Federal Columbia River Power System (FCRPS) in the United States is considered as a study case. Grand Coulee reservoir (GCL), located in upper Columbia River, is of storage type and dominates the system by accounting for nearly 80% of the storage. Other reservoirs are mostly run-of-river type, characterized for having relatively small storage. The river-reservoir network and some of the reservoir characteristics are presented in Fig.1.

(Fig.1. is here)

The Big-ten reservoir system provides multiple benefits, e.g., power generation, flood control and fish migration. However, some of the reservoirs have seasonal requirements and the operational objectives are only required during specific periods (Chen et al. 2016; Schwanenberg et al. 2014). From April to August, the reservoir system is operated to help migration of juvenile anadromous fish by maintaining specific operation pool levels (SOPs) and spilling a certain amount of flow (called fish flow). The reservoir system no longer has the fish flow nor the SOP requirements during September. Therefore, the objectives of reservoir operation are shifted after August 31st (called the shift date).

Objectives

An hourly optimization model is used for finding the optimal operational schemes during the transition period. The time horizon for operating the reservoir system as short-term is normally two weeks (Chen et al. 2016). In order to investigate the overall performance of the reservoir system during the transition period, the optimization period in the study is set to two weeks with one week before and after the shift date. The decision variables in the model are the total outflows at each reservoir and at each time interval (i.e., hour). The Non-dominated Sorting Genetic Algorithm (NSGA-II, (Deb et al. 2002)), one of the most widely-used Evolutionary Algorithms, is selected as the optimization method. The population (i.e., candidate solutions) of the NSGA-II is set to 50 and the generation (i.e., iteration times) is set to a relatively large number (10,000) to ensure convergence.

An important objective of the reservoir system is to meet power load in the region, as well as gain maximum revenue from power generation. Power generated that exceeds the load can be sold in the power market. On the other hand, energy needs to be purchased if a load deficit occurs. Net electricity is defined as hydropower generated minus the load. The revenue is then quantified by multiplying the net electricity by real-time prices from the power market. The revenue objective is expressed as:

$$\max \sum_{t=1}^{T} \left(\left(\sum_{i=1}^{Nr} PG_t^i \right) - PL_t \right) * PR_t \qquad (1)$$

where PG is hydropower generated in the system (MWh), *PL* is the power (MWh) that is needed for meeting the load (MW) in the region, and *PR* is the market price for hydropower (dollar/ MWh). The variable t is time, e.g., in hours; T denotes the optimization period, i.e., 3,360 hours (14 days), the index i indicates individual reservoirs in the system, and N_r is the total number of reservoirs. The price of hydropower for the two weeks period was pre-determined by an economic model (Chen et al. 2014) and is treated as a deterministic parameter in this study. It should be noted that the formulation of the objective is mainly for demonstrating the effect of objective shifting on the reservoir operation. The operating agency, i.e., the Bonneville Power Administration primarily aims to reduce the total operational cost rather than to make a profit, as is true of other non-profit federal agencies. An alternative objective can be formulated for reducing the operational cost.

Other constraints of reservoir operation, such as maintaining the SOP and the fish flow are described below.

Constraints

In order to assist juvenile salmon and steelhead species in surface passage past the dams, most of the reservoirs in the system are required to spill a certain amount of flow through non-turbine structures such as sluices or gates (Schwanenberg et al. 2014). These flow requirements are expressed as either a fixed flow rate or a percentage of the total outflow of a reservoir (NOAA Fisheries 2014), as follows:

$$Q_{s,i}^{t} = Q_{sr,i} \quad \text{(for } i = 5,7,8,9\text{)} \tag{3}$$

$$Q_{s,i}^{t} = \frac{q_{s,i}}{100} Q_{out,i}^{t} \quad \text{(for } i = 3,4,6,10\text{)} \tag{4}$$

where Q_s is the spill flow, Q_{sr} is the fixed fish flow requirement, q_s is the flow rate and Q_{out} is the total outflow from reservoir. According to the Biological Opinion issued by the National Oceanic and Atmospheric Administration (NOAA), the Grand Coulee (i=1) and Chief Joseph (i=2) reservoirs are not required to satisfy any fish flow requirement.

Also with the purpose of assisting fish migration, the forebay elevations of reservoirs in the system are required to be kept within specific ranges, i.e., the SOP. The SOP requirements are expressed as follows:

$$SOP_{lower,i} \le H_{r,i}^{t} \le SOP_{upper,i} \tag{5}$$

where H_r is forebay elevation, and SOP_{lower} and SOP_{upper} are lower and upper boundaries for the SOP requirement, respectively.

Other operational constraints considered in the model include lower and upper limits on forebay elevations, on turbine flows, on power outputs and ramping limits on reservoir outflows, on forebay elevations, and on tail water elevations. These constraints are considered as common practice for reservoir operation and therefore are not listed for brevity.

The short-term operation of reservoirs is known to be greatly dependent on initial and ending conditions (Lund 1996) such as reservoir forebay elevations (FB). Different initial and ending FB conditions often lead to various operational schemes that are too different to compare. To exclude the effects of initial and ending conditions, a fixed initial FB and a restriction on ending FB are considered. In the study, the historical FB elevation of a normal year (the year of 1986) at the end of August 24th (the day before beginning date of optimization) is used as initial condition. On the other hand, the reservoir FBs at the end of optimization period are expected to stay within a target range in order to fulfill their future obligations. These target ranges are commonly decided by middle-term or long-term optimization models (Lund 1996), which are not included in this study. Instead, the historical FB elevation of 1986 at the end of September 7th (end date of optimization) is used as a reference ending condition. In order to avoid equality constraints, a small deviation is allowed for the FB elevation at the end-of-period, to approximate the reference ending condition:

$$H_{tar,i} - \Delta \cdot D_{w,i} \leq H_{r,i}^{t} \leq H_{tar,i} + \Delta \cdot D_{w,i} \tag{6}$$

where H_{tar} is the reference FB at the end-of-period; Δ is deviation percentage; D_w is maximum water depth at reservoir i. The deviation percentage for Grand Coulee reservoir is set to 0.25%, due to its large storage, corresponding to only 0.04 m in water depth. For the other reservoirs the deviation percentage is set to 10%.

Reservoir System Modelling

The reservoir storages at each time step are modelled through the following equation (i.e., continuity equation) in order to conserve the mass:

$$V_i^{t+1} - V_i^t = ((Q_{in,i}^t + Q_{in,i}^{t+1})/2 - (Q_{out,i}^t + Q_{out,i}^{t+1})/2) \cdot \Delta t \tag{7}$$

where V is reservoir storage; Q_{in} and Q_{out} are inflow to and outflow from reservoirs, respectively; Δt is time step. The inflows are input to the model and the outflows are the decision variables. Water losses due to evaporation are not considered in the model due to the short time frame under consideration.

The forebay elevations are obtained from the established forebay-storage curves. The tail waters are obtained using a regression equation involving the reservoir outflow and the forebay elevation of the downstream reservoir. The turbine flow is modelled by relating the outflow with the fish flow requirement through the following procedures:

$$Q_{tb}^t = \begin{cases} Q_{tb\_\min} & if \;\; Q_{tb\_\min} \le Q_{out,i}^t < Q_{sr,i} + Q_{tb\_\min} \\ Q_{out,i}^t - Q_{sr,i} & if \;\; Q_{sr,i} + Q_{tb\_\min} \le Q_{out,i}^t < Q_{sr,i} + Q_{tb\_\max} \\ Q_{tb\_\max} & if \;\; Q_{sr,i} + Q_{tb\_\max} \le Q_{out,i}^t \\ Q_{out,i}^t & else \end{cases} \tag{8}$$

where Q_{tb} is turbine flow, Q_{tb_min} and Q_{tb_max} are allowed minimum and maximum turbine flows, respectively;

The power generation is computed based on the turbine flow and the water head (a function of forebay elevation and tail water elevation) with project-aggregated coefficients:

$$N_{d,i}^t = K_i (H_{r,i}^t - TW_i^t) \times Q_{tb}^t \tag{9}$$

where N_d is power output, TW is the tail water elevation and K is the coefficient to express the overall efficiency of turbine which is aggregated as one value for each project (reservoir).

The flow propagation within the reservoir-river network is modelled using the Muskingum-Cunge routing method with calibrated coefficients. Most of the propagation times in the river between two reservoirs are 1-3 hours except the river reach between CHJ reservoir and MCN reservoir with an average propagation time of 21 hours.

Inflow Scenarios

There are two inflows to the reservoir system, one is the inflow from upstream of the GCL reservoir (GCL inflow), and another is the inflow from upstream of the LWG reservoir (LWG inflow). Other inflows, mostly side inflows from small tributaries, provide relatively small water volumes, and hence are omitted in this study. Historical records on the two inflows with six-hour interval from 1965 to 2015 (Fig. 2) are used as the multiple inflow scenarios. The period considered in the study is two weeks ranging from August 25th to September 7th. Since the optimization model is hourly time step, we linearly interpolated the inflow data.

(Fig.2. is here)

To better characterize the inflow scenarios, two indexes are proposed in the study. The total inflow volume of the two weeks period is certainly important for fulfilling objectives/constraints of reservoir operation. Inflow volumes of week one and that of week two are also important because shifting of reservoir operation involves temporal water usage competition. The first index is the total volume ratio (TVR), which is defined as the ratio of total inflow volume in a given year for the two week period to that of a benchmark year for the same period. The year of 1986, the normal water year, is used as the benchmark year. If the TVR value of one inflow is larger than one, the total inflow volume for the two week period is larger than the benchmark year, implying relative water abundance, and vice versa. Another index, termed as weekly volume ratio (WVR), is defined as the ratio of inflow volume of week one to that of week two. The WVR index aims to represent temporal distribution of the inflow between week one and week two.

The histograms of the indexes from the 51 inflow scenarios are shown in Fig. 3. For the GCL inflow, the observed mean and standard deviation of the TVR index are 1.00 and 0.18, respectively. It follows that, on average, the total inflow volume of the two weeks is equal to that of the benchmark year, although large variability was observed among the different scenarios. On the other hand, the observed mean and standard deviations of the WVR index for GCL inflow are 1.10 and 0.14, respectively. This suggests that, on average, the inflow volume of week one is significantly larger than week two, showing a important variability of inflows during the two weeks period. For LWG inflow, the observed means of the TVR and the WVR indexes are 0.99 and 1.0, respectively. These values suggest that the total inflow volume of the two weeks for the LWG inflow is (on average) a little less than that of the benchmark year, but the inflow volumes of the first and second week are (on average) nearly the same.

(Fig.3. is here)

The study considers multiple inflow scenarios in order to identify general patterns of reservoir operation during the transition period. Each optimization for a given inflow scenario is called an experiment. Each experiment results in a set of outflows and associated forebay elevation trajectories. The trajectory of the forebay elevation is one of the primary means to represent operation of reservoirs and each of these trajectories is an operational scheme for reservoir operation. For a given reservoir system, the forebay elevation trajectory is influenced by the initial and ending conditions of the forebay elevation, as well as the inflow. Since the initial and ending forebay elevation of the optimization model are almost invariant in each experiment (described in the Constraints section), the study solely focuses on the relationships between forebay elevation trajectories and reservoir inflows.

Cluster Analysis Method

Cluster Analysis (CA) refers to the group of techniques that are designed to separate a set of objects or observations into different groups or *clusters* according to their similarities or proximities. Due to its generality, the problem has been extensively studied and a number of solutions and methodologies have been proposed in the literature going back to Hartigan's Rule (see Fuentes and Casella 2009; John A. Hartigan 1975; Sugar and James 2011; Tibshirani et al. 2001 for a few examples). Among different techniques, the K-means clustering algorithm (Dhillon and Modha 2001; Hartigan and Wong 1979) has been a widely-used method for CA. More recently, with the advances in genetics, image processing and machine learning, new variations of the problem have become increasingly popular, including clustering and classification of curves, with the obvious implications in pattern recognition, as discussed in (Zhang et al. 2015). The operational schemes of reservoir operation are time-series data (i.e., curve) which may have similar patterns even under different inflow conditions. Identifying patterns of operational schemes helps to gain a generalized understanding on reservoir operation during the transition period.

K-Spectral Centroid (K-SC) algorithm

The K-SC algorithm (Yang and Leskovec 2011) is a recently developed method for finding distinct temporal patterns of time-series data. For a given N set of time series and the number of clusters K, the goal of the K-SC is to find an assignment of each time series, and the centroid of each cluster, so that a function of a distance metric is minimized. In a similar way to the K-means clustering algorithm, the K-SC iterates a two-step procedure: assignment step and refinement step. The K-SC algorithm starts with a random initialization of the cluster centers. In the assignment step, each data time series is assigned to the closest cluster, and in the refinement step the cluster centroids are updated. By alternating the two steps, the sum of the distances between the members of the same cluster is minimized, and the assignment of N sets of time series into K clusters is completed. The MATLAB code of the K-SC algorithm can be found at the Stanford large network dataset collection (SNAP Datasets) that is provided by (Leskovec and Krevl 2015).

K-SC algorithm VS K-means

The two clustering methods are compared based on their applications to reservoir operational schemes. In our study, the operational schemes are time series, each representing specific actions or decisions over time. Similar shapes of these operational schemes suggest similar decisions on reservoir operation that can be grouped on the same cluster. Therefore, it is essential to have a metric that can appropriately measure the shape similarity of two time series. For K-means, a simple distance metric, i.e., Euclidean, is adopted. The Euclidean metric measures the overall distance between two curves and tends to focus on only the global peaks of the curves. Under this metric, two time series may have a large distance due to a scale (in volume) or shifting (in position) effect, even if their temporal shapes are similar. On the contrary, the K-SC uses a distance metric $D(x_j, x_k)$ that is invariant to scaling and shifting (Yang and Leskovec 2011), defined as:

$$D(x_j, x_k) = \min_{\lambda, q} \frac{\left\| x_j - \lambda \cdot x_{k(q)} \right\|}{\left\| x_j \right\|} \tag{10}$$

where $\|\cdot\|$ is the l_2 norm, λ is the scaling coefficient, q is the shifting coefficient measured by q time units that are used to shift x_k. The metric works by finding the optimal value of the alignment q and the scaling coefficient λ for matching the shapes of the two time series.

To compare the K-means and K-SC, we designed 6 artificial operational schemes, in some of them with similar shapes (Fig. 4). However, the volume (i.e., scale) within those with similar shapes are different. For example, Scheme 1 and Scheme 2 have a difference of 20% in terms of scale. Also some shapes are very close in terms of scale such as Scheme 5 and Scheme 6 with only 3% difference. For reservoir operation, we define two operational schemes to be similar if their temporal shapes are similar despite their scales and shift. The rationale for the definition is discussed in relation to the clusters that are found by K-means and K-SC which are shown in Fig.4.

The six artificial operational schemes should be easily classified into four clusters by direct observation. The members in each cluster are {①, ②}, {③, ④}, {⑤}, {⑥}. The scheme ① and scheme ② are different in scale but are very similar in terms of temporal shape. From the reservoir operator's perspective, these two share a similar operational pattern which decreases (either water level or outflow) along with time, hits a valley point, and then increases after that. In the same manner scheme ③ and scheme ④ are similar. Scheme ⑤ and scheme ⑥ should be considered different operational patterns even though they are very close in magnitude. As shown in Fig.4, K-means clusters the six operational schemes as {①, ②}, {③}, {④,⑥}, {⑤}. It turns out that K-means fails to recognize the relation between schemes ③ and ④, producing incorrect clusters. On the other hand, the K-SC method is able to find the desirable clusters.

(Fig.4. is here)

Another advantage of K-SC is the robustness in presence of outliers. K-means is more sensitive to outliers, because it considers the average of time series for a cluster center. Instead, K-SC scales each time series differently to find a cluster center, and therefore the influence of outliers is largely decreased.

Number of Clusters

Similar to most clustering methods,K-SC also needs to be specify the number of clusters in advance. The Silhouette (Kaufman and Rousseeuw 2009), an index to measure how well each object lies within its cluster, is used for determining the number of clusters. The Silhouette index for the i_{th} point, S_i, is defined as $S_i = (x_i-y_i)/ \max(x_i,y_i)$, where x_i is the average distance from the i_{th} point to the other points in the same cluster, and y_i is the minimum average distance from the i_{th} point to points in a different cluster, minimized over clusters. The index is within the range of [-1, 1], and the higher the value the better the clustering. For the case study, we measure how the Silhouette index (on average) varies with the number of clusters for the operational schemes of each reservoir and determine the number of the clusters with the highest Silhouette index. Fig.5 shows the relations between the Silhouette index and different number of clusters for three reservoirs in the Big-ten system, as an example. From these relations, the optimal number of clusters for GCL reservoir, LWG reservoir and MCN reservoir can be determined as 2, 2 and 3, respectively.

(Fig.5. is here)

Results and Discussion

Optimal operational schemes and clusters

Among the ten reservoirs, the GCL and the LWG are the two most upstream reservoirs and their operation certainly influences the downstream reservoirs. The MCN, which is located immediately downstream of the confluence of the Snake River and the Upper Columbia River (see Fig. 1), also plays an important role in the system. Therefore, these three reservoirs are selected to demonstrate the operation of the ten reservoirs. Most of the other reservoirs except the three selected ones are run-of-river reservoirs, which pass inflow from the upstream reservoir. For simplicity, the operation of these reservoirs are not discussed herein although all ten reservoirs are considered in the modeling. The optimal forebay elevation of the selected reservoirs under multiple inflow scenarios is obtained from the optimization model and is shown in Fig.6.

The groups of the forebay elevation that are clustered by the K-SC algorithm are also shown in Fig.6. The centroid of each group, which demonstrates a mean result of the corresponding cluster, is illustrated as well.

(Fig.6. is here)

Two distinctive clusters or groups (Fig. 6a) are found in the collection of forebay elevations of GCL reservoir. For Group 1, the forebay elevation gradually decreased (with oscillation) in week one and increased in week two. In contrast, the forebay scenarios in Group 2 show that the forebay elevation increases (with oscillation) in week one achieving a maximum elevation at the end of week one or at the beginning of week two. After the maximum forebay elevation is attained, the forebay elevation decreases until the end of week two.

The forebay elevations of the LWG reservoir are also clustered into two groups (Fig. 6b). Even though the forebay elevations in week one are all restrained in certain range because of the SOP requirement, the trajectories have clear patterns. For Group 1, the forebay elevations initially decreased and then increased in week one. The forebay elevations are maintained at a high level in week two. For group 2, during the first week, the forebay elevation is initially increased and then decreased until the end of week two, resulting in an opposite operational strategy to that of Group 1.

Three clusters are identified for the forebay elevation of MCN reservoir (Fig. 6c). For Group 1, the forebay elevations mainly decreased in week one and then increased in the first half of week two. After that, the forebay elevations decreased until the end of week two. Group 2 and Group 3 are similar in terms of temporal shape for week two, during which the forebay elevations are mainly decreased (with oscillation). However, these two groups adopt different operational schemes for week one. The forebay elevations of Group 2 rapidly increase and then decrease while for Group 3 the forebay elevations maintain a constant level in the first half week and then decrease.

Relations between inflow scenarios and clusters

Based on the forebay elevation clusters of each reservoir, the TVR and WVR indexes of the inflows, namely GCL inflow and LWG inflow, can be grouped accordingly. Note that each inflow has these two indexes. For instance, two groups are identified in the GCL forebay elevation (Fig. 6a) with 38 solutions in Group 1 and 13 solutions in Group 2. Since each forebay elevation curve (one member in a group) is associated with one inflow scenario, we can then put the TVR index of all the 38 inflow scenarios that are associated with Group 1 in one group. The other 13 inflow scenarios that are associated with Group 2 are classified as another group, shown in Fig. 7 (a). Similarly, the WVR index is classified into two groups shown in Fig. 7 (d). Correspondingly, the TVR and WVR index of the two inflows can also be classified based on the forebay elevation groups of the LWG reservoir and the MCN reservoir (shown in Fig. 7 (b&e) and Fig. 7 (c&f)).

(Fig.7. is here)

The groups on the TVR index show no interesting results. However, clearly separated clusters (or regions) are found for the WVR index. As can be seen in Fig. 8(d), the WVR index of the GCL inflow in Group 1 mostly adopts values lower than 1.0 and in Group 2 these values are mostly higher than 1.0. Interesting results are also found for the WVR index of the LWG inflow (Fig. 7 (e)). In Group 1, the WVR index of the LWG inflow adopts values lower than 1.0 and in Group 2 these values are mostly higher than 1.0. Three groups are found for the WVR index based on the three groups of the forebay elevations for the MCN reservoir (Fig. 7(f)). Members of Group 1 are all in the upper-right region in which the WVR index of the GCL inflow and that of the LWG inflow are both higher than 1.0. Most of the scenarios of Group 2 are located in the lower-left region in which the WVR index of the GCL inflow is lower than 1.0 and the WVR index of the LWG inflow is mostly lower than a value of 1.05. Most of the members in Group 3 are in the lower-right region in which the WVR index of the GCL inflow is higher than 1.0 while the WVR index of the LWG inflow is lower than 1.0.

Patterns of reservoir operation

By linking the definition of WVR index with the two groups of the forebay elevation for GCL reservoir, it is clear that different operational schemes need to be adopted when the volume of GCL inflow in week one is smaller or greater than that of week two. When the volume of GCL inflow in week one is smaller than week two (i.e., WVR lower than 1.0), the operation would adopt the scheme of Group 1, which would use the storage of this reservoir (forebay elevation is decreased) during week one to increase its outflow. This would decrease the power generation (and power revenue) in this reservoir as flow is released when water level is relatively low. However, the outflow increases in the GCL reservoir during week one for meeting the fish flow requirement. This operational scheme tries to obtain a balanced solution between human interests and ecological benefits. Contrastingly, when the volume of GCL inflow in week one is larger than week two (i.e., WVR greater than one), the system would adopt the scheme of Group 2, which would store water in week one (forebay elevation is increased) when inflow is relatively high during this week. The high inflow from upstream of GCL ensures that fish flow requirements for the four reservoirs on the lower Columbia River (MCN, JDA, TDA and BON) are satisfied in week one. Continuing to release water from the GCL reservoir would no longer be needed for fish flow because the other four reservoirs with fish flow requirement (LWG, LGS, LMN and IHA) are on the Snake River. Therefore, the optimal operation of the system under this situation is to store the excess water (after satisfying fish flow requirements) during week one to produce more power during week two.

Another pattern is identified for the operation of LWG reservoir. The association between forebay elevation groups with the WVR index shows that the LWG reservoir should adopt a different operational scheme when the volume of LWG inflow in week one is smaller or greater than that of week two. When the volume of LWG inflow in week one is smaller than week two (i.e., WVR index lower than one), the LWG reservoir should release more water in week one to fulfill the fish flow requirement. Thus its forebay elevation is decreased, as shown in Fig. 6b (Group 1). During week two, the forebay elevation maintains a high level for generating more power with the same outflow, which helps to compensate the power loss in week one. On the other hand, the LWG reservoir would store some water in week one when the volume of LWG inflow in week one is larger than week two (WVR index is higher than one), after the fish flow requirement is met. Higher forebay elevations can be obtained in this way, as shown in Fig. 6b (Group 2). This resulting high forebay elevations and the increased outflow in week two help to produce more power.

The operation of the MCN reservoir is influenced by the operation of reservoirs on the upper Columbia River (GCL and CHJ) and the operation of reservoirs on the Snake River (LWG and the other three reservoirs). Patterns for the MCN reservoir result from three combinations of the GCL reservoir operation and the LWG reservoir operation. For instance, the scheme of Group 3 needs to be adopted for the MCN reservoir when the GCL reservoir operation adopts its Group 2 scheme (when WVR index of GCL inflow is higher than one) and the LWG reservoir operation adopts its Group 1 scheme (when WVR index of LWG inflow is lower than one). In this case, as the fish flow requirement for downstream reservoirs can be fulfilled by the operation of upstream reservoirs, the scheme would only pass the inflow from GCL and LWG in week one. A relatively high forebay elevation can also be maintained in this way. More water would be released in week two for generating more power thus maximizing revenue. The rational of this scheme is to improve the power objective when fish flow requirements are met.

The identified patterns offered an insight to the various operational schemes during the transition period. Reservoir operators can benefit from these patterns as they could choose an operational scheme depending on a forecasted hydrological regime. Noted that the accuracy of the forecast influences the selection of the patterns. These patterns can also be used as prior information for online optimization, which will diminish the effort for finding optimal solutions. The identified patterns provide a good initial starting point for the optimization model. Therefore, the efficiency of optimization models can be improved with the assistance of the patterns.

Conclusions

Different patterns of operational schemes are identified for the ten-reservoir system of the Federal Columbia River Power System (FCRPS) during a transition period. These patterns are found to be highly correlated with the index of weekly volume ratio (WVR) which represents a ratio between volume of water in week one and that of week two. Contrastingly, the patterns show nearly no correlation with the index of total volume ratio (TVR) which represents a ratio between total water volume for the two-week period of a specific year and that of a benchmark year. The comparison indicates that reservoir operation during objective shifting is more sensitive to temporal distribution of the inflow (i.e., WVR index) than to the total volume of the inflow (i.e., TVR index). Therefore, the WVR index is the main driver for adopting different operational schemes.

The identified patterns help to provide a general understanding for the operational schemes during the transition period, which can be used as prior knowledge for a better online optimization performance. The method of the K-SC is found to outperform the widely used K-means for clustering reservoir operational schemes with more informative patterns.

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