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A simple model of storage control for a reservoir system using a novel intelligent state dropping mechanism

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ABSTRACT

Dynamic programming (DP) models have been proposed by a number of researchers to develop optimal reservoir operation. In this paper, we propose to eliminate the fixed threshold values, specifically the maximum allowable release and reservoir storage from the DP model and replace them with dynamic dependent values calculated by a fuzzy inference engine. For this purpose, a simple model of DP is modified based on a novel intelligent state dropping (ISD) mechanism. The ISD mechanism is designed based on fuzzy logic theory. Although the proposed methodology is widely used for broadband satellite based internet protocol network congestion control, its application in water resources management has not been reported to date. Application of the ISD mechanism incorporates the inflow uncertainty in reservoir optimization model in a simpler way than the stochastic DP-based optimization models (SDP). Furthermore, the multi-purpose objective function of DP-model is changed to a single objective function. The simulation results showed that the newly proposed model reduces the shortfall in supplying demand and improves the reservoir operation performance indices, i.e., the reservoir reliability indices, as compared with the results by the DP and SDP models.

Key words | fuzzy logic, optimal reservoir operation, state dropping mechanism, uncertainty

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INTRODUCTION

Reservoir operating rules should stabilize the release of water from the reservoir to mitigate problems of flood and drought. Designing operating rules necessary for optimal water allocation and maintaining the reservoir in a normal condition are complex, since predictability of the system state (water storage in reservoir systems) is affected by external factors such as inflow variability (Loucks *et al*. 1988; Ganji *et al*. 2008). In a reservoir system, when a high flow situation occurs due to excessive precipitation, the reservoir capacity is full and this consequently leads to loss of water and increasing the flooding risk. This is due to the inability to predict and react properly to future inflow situations (Chang & Chang 2006). Our approach to tackling the presented problem space is to implement a fuzzy controlled dynamic programming (DP) model. The DP model has been developed based on Bellman's principle of optimality (Bellman & Dreyfus 1962), and is generally used as an optimization tool for reservoir operation. Two fixed threshold values, the maximum allowable release and reservoir storage which are used in the DP model, are replaced with dynamic dependent values calculated by a fuzzy inference engine. The inference engine dynamically keeps calculating the threshold values of the DP model based on the reservoir state variables and inflows. The DP model, which is modified based on a novel intelligent state dropping (ISD) mechanism, is termed DP-ISD. The ISD mechanism was developed using fuzzy logic theory (Zadeh 1965).

The DP-ISD mechanism, as a simple structure model, incorporates inflow uncertainty (current and forecasted inflows) into the optimization process without including

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any additional state variables. It reduces the problem of dimensionality, since the number of explored states at each stage of the DP optimization model is decreased. The problem of dimensionality (also known as the curse of dimensionality) is the problem caused by the exponential increase in volume associated with adding state variables to a (mathematical) space in the DP model. In a broad sense, this algorithm uses dynamic inflow and storage conditions as input to engineer an adaptive system operation that provides the maximum allowable release for a DP optimization model. Although the application of fuzzy logic in reservoir operation and optimization has been widely investigated by many researchers (Russell & Gampbell 1996; Teegavarapu & Simonovic 1999; Chang *et al.* 2002; Ganji *et al.* 2008), the proposed intelligent method has not been used to date. As an alternative, stochastic dynamic programming (SDP) is used in reservoir operation. Many researchers have used DP and SDP models for reservoir optimization, for example, Su & Deininger (1974), Huang *et al.* (1991) and Ganji *et al.* (2007*a*, *b*, 2008). Nevertheless, the applicability of DP/SDP models is confined to a few state variables due to the problem of the curse of dimensionality (Loucks *et al.* 1988; Huang *et al.* 2002). According to Loucks *et al.* (1988) four state variables with many discrete values increased the computation time of computer. As a result, a number of researchers introduced modified DP-type approaches (Kelman *et al.* 1990; Saad *et al.* 1994) and continues state models (Fletcher & Ponnambalam 2008; Ganji & Shekarrizfard 2009) to cope with this problem.

A similar procedure to the ISD mechanism, i.e., intelligent packet dropping, was previously used for broadband satellite based internet protocol (IP) network congestion (Vallamsundar 2007). The ISD mechanism was originally developed based on active queue management (AQM) theory (Yanfei *et al.* 2003; Hadjadj Aoul *et al.* 2004; Vallamsundar 2007; Chu *et al.* 2008). The AQM algorithm is one existing method to control quality of service (QoS). QoS is also defined as 'A set of service requirements to be met by the satellite network while transporting a flow' (Hardy 2001). One of the most well-known AQM techniques is random early discard (RED) which is an algorithm that was previously used in satellite networks and transmissions to provide predictable and reliable services. The key point of RED is to avoid network congestion by controlling the queue length within a reasonable range, by setting the minimum and maximum thresholds for queues and handling newly arrived packets according to the predefined maximum and minimum thresholds. Vallamsundar (2007) proposed a fuzzy-based packet dropping mechanism to tune the maximum and minimum thresholds of the RED algorithm and discard arriving packets considering the uncertain external factors affecting the satellite-based system. This algorithm showed a considerable improvement in satellite network transmission. A similar algorithm is proposed to discard higher levels of state values of release at each stage of a DP optimization model in this study. More discussion on the RED and the proposed algorithm are mentioned in the section on 'DP-based intelligent state dropping mechanism (DP-ISDm)'.

In this study, a fuzzy logic model is developed to tune the maximum state of release at each stage (month) during a DP optimization process. Our proposed fuzzy logic model includes three fuzzy lookup tables. Each lookup table deals with one of specific variable (i.e., storage at time t, inflow at time t, and storage values at time $t+1$, respectively). The outputs of the first and second lookup tables are considered as an input to the next lookup table. The output of the last lookup table is considered as a dynamic threshold (maximum allowable release) to discard the higher level of release states at each stage of DP optimization model.

As background for this research, intelligent system and fuzzy logic theory are discussed briefly, and is followed by the presentation of the simple algorithm model. Then, the proposed optimization methodology (DP-ISD model) is applied to water allocation in the Zayandeh-rud river basin and the results are compared with those obtained using a simulation model and simple dynamic programming. The results of the proposed optimization model are shown to be better than those of classical DP models because of using the proposed ISD mechanism during the optimization process.

MATERIALS AND METHODS

Fuzzy logic

Fuzzy logic as a soft computing technique (Zadeh 1965) is based on fuzzy sets theory. Fuzzy set theory considers the degree of "belongingness" to a set or category using a membership number between 0 and 1. The set of membership numbers is represented by a *membership function* (MF). A membership function is a curve that defines how each point in the input space is mapped to a membership value between 0 and 1. It provides the degree of membership within a set of any element that belongs to the universe of discourse. Fuzzy logic usually uses IF/THEN rules that are statements used to formulate the conditional statements that comprise the fuzzy logic. The conditional rules are stored in the knowledge base and fuzzy inferencing is done on the stored rules. Fuzzy logic programming can be used in two ways: as a way of trying to model the behavior of a human expert and as a way of relating a set of outputs to a set of inputs in a model-free way, i.e., the fuzzy inference model. To model the thinking of a human expert, input variables are specified by category (i.e., "large" and fuzzy rules outlined in the preceding sections) and are developed on the basis of the expert's knowledge and experiences.

Fuzzy rule-based modeling

A fuzzy rule-based model is a mathematical model which includes a set of rules, each rule consists sets of n input variables $X = \{X_i \,|\, X_i = x_{ij},\ i = 1,\ldots, n;\ j = 1,\ldots, m\}$ in the form of fuzzy sets with membership function $\mu(x_{ij})$ and a set of n consequences y_i also in the form of a fuzzy set which can be presented as follows:

$$\textit{If } X_1 \textit{ is } x_{i1} \bullet X_2 \textit{ is } x_{i2} \bullet \ldots \bullet X_m \textit{ is } x_{im} \textit{ then } y_i \tag{1}$$

where • denote a logic operator which is "and" in this study, as in the reservoir operation, every data point appears to play an equally important role. For example, in this study the inputs consist of the current water storage, inflows, and demand, and consequence is the maximum allowable release to meet the various demands. The design of a rule base is based on the user's expertise and experience on the behavior of the system. As the second stage, after designing linguistic rules, the membership values of the input-output fuzzy sets are determined. Generally, to define linguistic rule curves of a fuzzy variable (both input and output), triangular, trapezoidal, or Gaussian membership functions are used. In our work on fuzzy logic controller design for dynamic reservoir operation, triangular membership functions are used since they were proven to be extremely effective in reservoir operation (Shrestha *et al.* 1996) and also for to their computational simplicity. It should be noted that several rules may give different consequences for the same set of inputs in a fuzzy rule-based model. In this case, the degree of fulfilment is used to measure the extent to which data apply to a give rule, and can be determined using min-max and/or product inference methods (Bardossy & Duckstein 1995). Here, the product inference is selected, as it may interpret the physical nature of the reservoir operating system in a better way than the minimum inference. In the case of fuzzy consequence number, it is generally transformed into an ordinary number, using a so-called defuzzification method. Defuzzification was done here by using fuzzy median, which is a appropriate location number, when one needs to show the fuzzy number by a single crisp number. More discussions on fuzzy rule-based systems can be found in Shrestha *et al.* (1996).

The primary key in designing a meaningful rule base system is to achieve an optimal performance. Ongoing studies suggest that techniques such as neural networks, neuro-fuzzy systems and/or genetic algorithms are of assistance in tuning the fuzzy parameters online with the aid of measurements from the system. In this study, however, a conventional trial and error method was used to design our fuzzy rule base. The rule base is fine-tuned by observing progress of simulation and the output performance (e.g., allocation and reservoir storage reliability indices). Reliability is the ability of a system or component to perform its required functions under stated conditions for a specified period of time (Hashimoto *et al.* 1982). Reliability is widely used in performance analysis of water resource systems (Dockner & Van Long 1993; Cai 1999; Ganji 1999; Karamouz *et al.* 2003; Li *et al.* 2008; Park *et al.* 2009). More information about the reliability indices has been provided in "Results and Discussion". Fine tuning can be performed in various ways, keeping in mind the different trade-offs that are observed in the output performance. For example, any decrease in reservoir storage reliability (as resulted from higher threshold values of release) should be traded off against a possible increase in allocation reliability. Rules are tuned in a manner that would strike a balance between these two conditions. The proposed rule base in conjunction with a simple DP model can be used to improve reservoir operation. It eliminates the fixed threshold value of release, and transition probability matrix from the DP model and replaces it with dynamic threshold values calculated by the fuzzy inference engines. Below, the overall structure of the proposed model is discussed.

DP-based intelligent state dropping mechanism (DP-ISDm)

Providing appropriate services for satellite-based networks using the RED algorithm is complex since predictability of service in satellite-based systems is affected by external factors such as weather. Presently, in satellite networks, when excessive precipitation occurs, the capacity of the ground terminal is lost and this consequently leads to loss of service. In addition, the hub does not have any intelligence to assist the ground terminals during rain fade situations. Lately, QoS (i.e., RED) is being adopted in both ground terminals and satellite hubs so that higher priority packets with more stringent service level agreements (SLAs) get services at the cost of low priority packets, when there is contention for bandwidth. SLAs are fundamental to both providers and recipients of services and are intended to provide guaranteed response or resolution time for incidents. To solve this problem, a fuzzy-based packet dropping algorithm has been proposed by Vallamsundar (2007) that can be implemented as a system-based intelligent algorithm in the ground terminals to discard arriving packages. This algorithm is used to tune the RED algorithm by changing the value of maximum and minimum thresholds.

Shekarrizfard & Ganji (2010) used a similar intelligent mechanism for irrigation scheduling, where the next rainfall amount is not exactly predictable. In this case, the maximum allowable soil moisture content of the simulation model is tuned (as a threshold for irrigation depth) using a novel fuzzy intelligent mechanism. This threshold may decrease the depth of an irrigation event to save the soil capacity for rainfall or discard it when soil moisture content is higher than the threshold value. An intelligent dropping mechanism can also be used to improve a discrete dynamic optimization process (i.e., DP-based model). In this case, the intelligent model determines a threshold for decision/state variable (i.e., release) and discards violated state values from the optimization process. This is the first time, a dropping mechanism has been proposed for use in a DP-base optimization process.

Figure 1 shows the flowchart of the DP-ISDm model. The proposed framework includes the intelligent and simple DP sub-models. For the DP sub-model, discretizing the state variables (Vasiliadis & Karamouz 1994) is the first step. The DP part of model uses the simple algorithm of the Bellman equation (Bellman & Dreyfus 1962) for dynamic optimization. For the fuzzy sub-model, three lookup tables were designed to tune the maximum allowable release which is discussed below.

The proposed fuzzy inference system has two inputs and one output for each of the three lookup tables, which use separate linguistic rule sets for the process of inferencing. Triangular membership functions were adopted for both of the input and output sets. The fuzzy linguistic rule base was designed taking into consideration the time varying conditions of storage and inflow and water user demand. The inferencing in the three lookup tables was performed-based on 76 rules.

The first lookup table (Figure 2) deals with the dynamic monthly reservoir storage volume and demand at time t. Normalization is performed on the storage and demand and fuzzy logic is invoked. The input variables for the first lookup table are relative monthly demand and relative reservoir storage. The relative monthly demand is a fraction of maximum demand that should be supplied at time t and the relative storage is determined as a ratio of reservoir storage at time t to the reservoir capacity. The output variable that constitutes the table is the normalized values of the maximum release which is the ratio of maximum allowable release to maximum release by a classic DP model. For convenience, the inputs and output are divided into five fuzzy intervals, i.e., very low (VL), low (L), medium (M), high (H), and very high (VH), respectively. Figure 2 shows the output surface of lookup Table 1 and interaction between the input-output based on rule set containing the 26 IF-THEN conditional rule set. A sample rule base is shown below. Equal weight has been given to each rule.

IF (RS_t is ***Low***) AND (D_t is ***Normal***) THEN (Re_t is ***Low***)

where RS_t is the relative storage volume at time t which is presented as $RS_t = S_t/CAP$, and CAP is the reservoir capacity. D_t is the relative demand that represents a fraction of maximum water demand at the reservoir downstream. Re_t is the relative maximum allowable release at time t. All variables are fuzzy and are presented as $RS_t, D_t, Re_t \in \{VL, L, M, H, VH\}$.

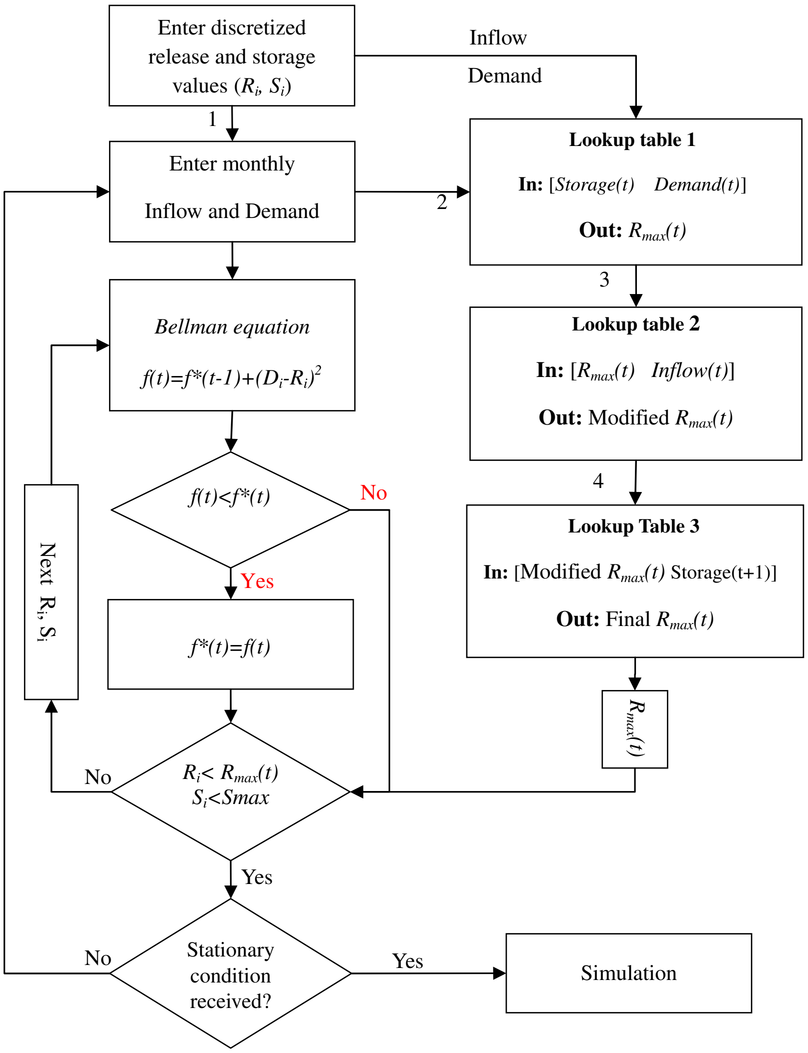

Figure 1 | The overall structure of DP-ISD. $R_{max}(t)$:Maximum allowable release; *Smax:* Maximum allowable storage (reservoir capacity); *Ri:* Monthly release as a decision variable; S_i: Monthly storage as a state variable; D_i: Monthly demand

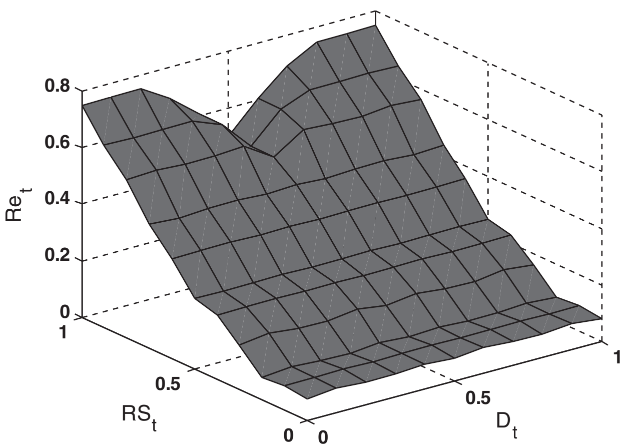

Figure 2 | Output surface by the first lookup table.

The second lookup table (Figure 3) deals with the uncertainties contributed by monthly inflow conditions. Input variables are monthly relative inflow (RI_t) and maximum allowable (Re_t) release which Re_t is the output variable by the first lookup table. The output variable is the modified maximum allowable release (MRe_t). Figure 3 presents the output surface of lookup Table 2 and interaction between the input and output based on the set containing the 25 IF-THEN conditional rule set.

The input values for the third lookup table (Figure 4) are the relative reservoir storage at time $t+1$, and the modified maximum release that resulted from the second lookup table. The output is the modified value of maximum monthly

Table 1 | The comparison of system reliability indices among DP-ISDm, and DP models

Reliability index	DP-ISDm	DP
Shortage ratio	64.7	68.1
R^T_{v-all}	65	59.8
R^T_{n-st}	100	100
R^T_{v-st}	100	100
Demand	898.9	898.9

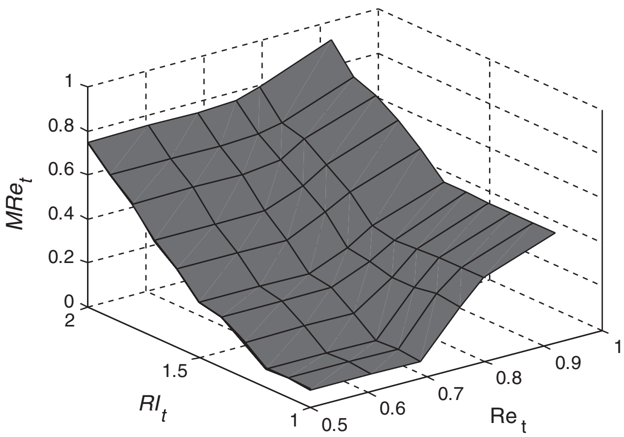

Figure 3 | Output surface by the second lookup table.

allowable release. Applying the modified monthly maximum allowable release, the feasible solution space is limited for the release state variable. It means the optimization process is limited to an imposed threshold by the ISD mechanism at each stage of dynamic programming.

If there are variables (e.g., inflow at time $t+1$) that should be considered for decision on maximum allowable release, additional lookup tables can be designed in a same way. The DP-ISD optimization process terminates when a stationary condition is achieved that means the optimal state variables

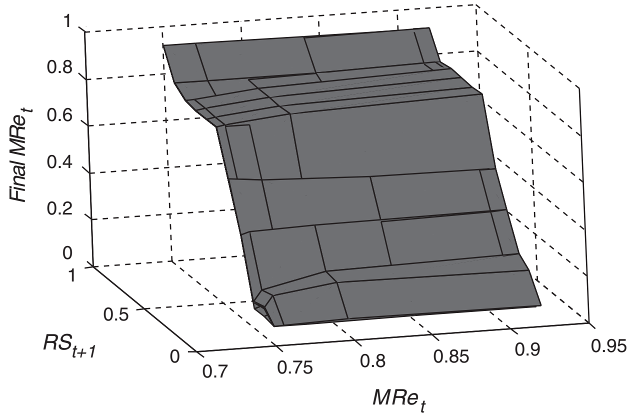

Figure 4 | Output surface by the third lookup table.

do not change in successive stages. The proposed optimization model is used for a real case study and the results are compared with a simple DP model. In order to evaluate the performance and robustness of the proposed algorithm, a simulation model is proposed.

Study area

The Doroodzan dam with 993 million m^3 capacity is located in the North Western part of Shiraz on the Kor River. The Kor River lies between 29°01′ and 31°15′ N latitude and 51°45′ and 54° 30′ E longitude (Figure 5). Different objectives are considered for Doroodzan dam operation (i.e., crop water supply, supplying urban and industrial water demands, flood control and energy generation). The dam supplies irrigation water for 46,000 ha of agricultural land using an irrigation network consisting of a main canal and three subsidiary canals. The climate of the study area is cold with rainy winters and dry summers. The mean yearly streamflow and variance of the Kor River are 26.3 and 698.3 million m^3, respectively. A 29-year monthly inflow series was collected from a hydrological

Table 2 | Monthly volumetric reliability ($R^{m(a)}_{v-all}$) from DP-ISDm, DP and SDP models

	Month (from August)											
Models	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
DP-ISDm	73.6	100	100	100	100	100	72.6	37.1	13.3	16.2	13.3	51.2
DP	54.8	96.5	96.5	93.8	92.4	85.1	57.0	49.4	19.3	14.7	12.9	18.4
SDP	27.5	100.0	100.0	100.0	100.0	100.0	63.1	49.4	21.8	10.6	8.1	22.4

Figure 5 | The study area, Doorodzan dam.

station at Doorudzan dam to evaluate the capability of proposed optimization model. Also, the SPIGOT streamflow software (Grygier & Stedinger 1991) was used to generate a 29-year monthly synthetic flow. The synthetic streamflow series is used for a simulation model to evaluate the result of optimization model in a real time situation.

RESULTS AND DISCUSSION

The DP-ISDm model was applied to derive an optimal operating policy for Doorodzan dam using a 29-year monthly historical streamflow series. Also, a simple DP model was used for optimization at Doorodzan dam, and the results are compared with the proposed model. Although both of the models have the same optimization procedure, the storage state variable should be included in the DP objective function to control the reservoir storage, as opposed to DP-ISDm model. This means that the DP-ISDm does not use a multi-purpose objective function, and the level of storage is controlled indirectly using the imposed monthly thresholds (i.e., maximum allowable release) by ISDm algorithm. The maximum allowable release for different levels of storage state variable is determined for each stage of optimization using the ISDm part of the model.

Figure 6 shows the monthly maximum allowable release resulting from the ISDm (continuous line) and maximum release as used by the simple DP model. The maximum allowable release shows variability that results from inflow and reservoir storage uncertainty. This threshold limits the release states and discards a number of superior levels of release states. Although the maximum demand could not be supplied by both models completely, comparison of the reliability indices (Ganji *et al.* 2007*a*, *b*) showed that supplying a higher level of demands is possible using the DP-ISDm model. The results of the reliability analysis are provided in the following.

As the first step to evaluate the reliability indices, the optimal operating rules (from the DP-ISDm and DP models) are used to simulate the reservoir storage and release using a 29-year series of monthly synthetic inflows. Figures 7 and 8

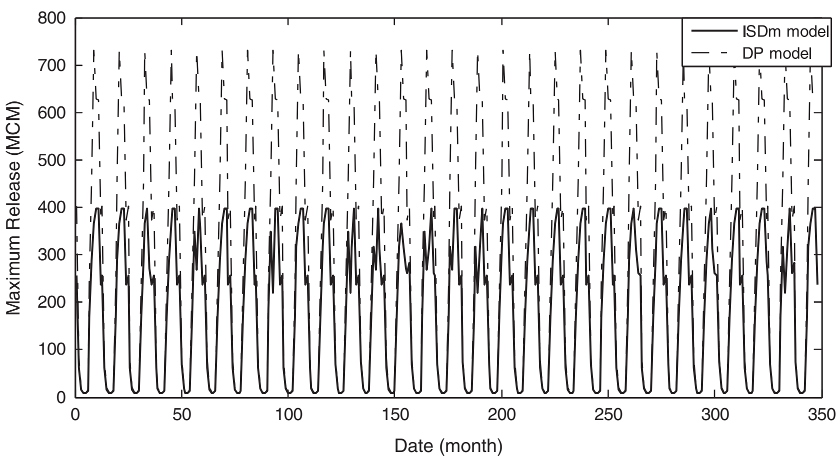

Figure 6 | Maximum allowable release resulting from the intelligent part of model.

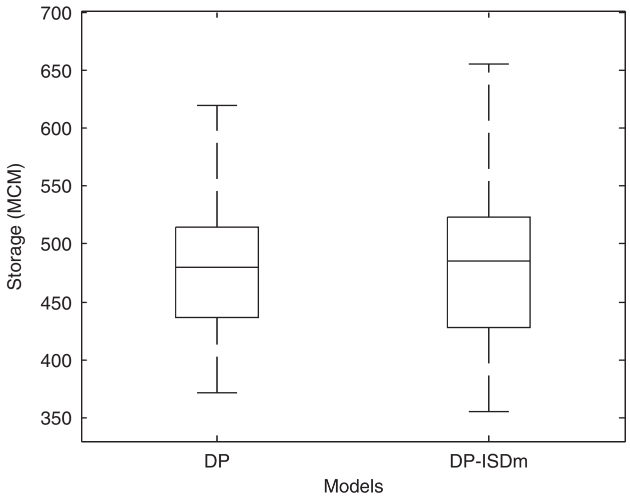

Figure 7 | Box plot of simulated monthly storage as resulted from optimal operating rule of DP-ISDm and simple DP model.

show the box plots for the simulation values of reservoir storage and release. In the box plot, the topmost line corresponds to 99%, the upper part of the box corresponds to 75%, the lower part corresponds to 25%, and lastly the lowest line corresponding to 1% value (storage and/or release). Figure 8 indicates that the level of release has been increased as a result of using the DP-ISDm model compared to the DP model. However, a numerical comparison among the simulation results is only possible using the proposed indices of reliability (Ganji *et al.* 2007*a*).

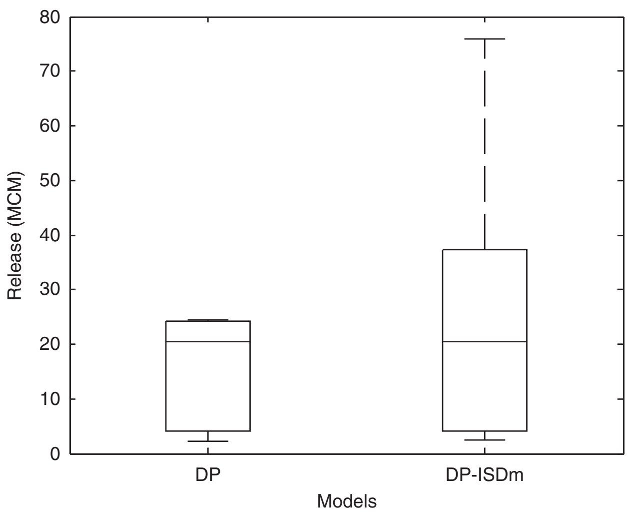

Figure 8 | Box plot of simulated monthly release as resulted from optimal operating rule of DP-ISDm and simple DP model.

To compare the capability and efficiency of the proposed model in reservoir storage management, the occurrence and volumetric reliabilities (Ganji *et al.* 2007*a*) of the reservoir system are used. Occurrence storage reliabilities (total and monthly reliability) are defined as:

$$R^T_{n-st} = \left(1 - \frac{\text{The number of } \textit{monthly} \text{ failures in design period}}{\text{The number of months in design period}}\right) \times 100 \tag{2}$$

where, the dimension of both numerator and denominator are the number of times (the number of months). R^T_{n-st} is the overall storage reliability of the reservoir system as percentage. The failure is defined as violating the storage limit bounds (maximum and minimum allowable storage values). Shortfall or the overflow of reservoir storage water over the reservoir planning horizon (as percentage) can be used as an index of reservoir volumetric reliability (Ganji *et al.* 2007*a*):

$$R_{v-st} = \frac{\text{Total storage shortfall or overflow}}{\text{Total available water into the reservoir system during the planning horizon}} \tag{3}$$

where the units of numerator and denominator are m^3. Furthermore, the capability of both models to supply the water demand is determined using occurrence and volumetric allocation reliability as proposed by Ganji *et al.* (2007*a*). Occurrence allocation reliability of the reservoir system (R^T_{n-all}) is the reliability of not violating the total required allocation of water users in the study area. It is defined the same as the occurrence storage reliability of Equation (2) when failure is defined not to violate total required allocation of water users. The volumetric reliability of reservoir system for water allocation (total reliability):

$$R^T_{v-all} = \frac{100}{nm} \sum_{i=1}^{nm} \left(\frac{\text{Monthly supplied water}}{\text{Monthly demand}}\right) \tag{4}$$

where, nm is the number of months for the planning horizon and the units of numerator and denominator in the bracket are m^3.

The value of R_{v-st} changes from zero to values larger than 1 and it may become 2 or even 3. The zero value shows failure did not occur, indicating a system volumetric reliability of 100%. Values larger than 1 indicate that sum of volume of failures is more than the total available water in the reservoir system during the planning horizon. Equation (4) can also be used to determine the monthly reliability of reservoir system for water allocation after a little modification.

Table 1 shows the resultant values of reliability indices for DP-ISD and DP models on a yearly basis. The results indicate that the occurrence storage reliability (Equation (2)) is 100% (R^T_{n-st}) during the planning horizon and the average volumetric reliability of system (R^T_{v-st}) is also 100%. The same values resulted from the simple DP model. For the proposed model, R^T_{v-all} is estimated to be about 65%, which shows that a 65% of allocation of maximum demand can be achieved. Shortage ratio is also determined that shows shortage in supplying demand over the planning horizon to the sum of monthly demand over the planning horizon (see Table 1). It shows that 64.7% of total demand cannot be supplied over the planning horizon, considering the simulation results for DP-ISDm model. For the simple DP model, 59.8% of R^T_{v-all} was achieved and the shortage ratio was 68.1% (Table 1). This shows the proposed model has improved the reservoir operation and optimization results.

Water allocation reliability index (R^T_{v-all}) varies on a monthly basis and is shown as $R^{m(a)}_{v-all}$. Table 2 shows timely variation of monthly average reliability indices ($R^{m(a)}_{v-all}$). $R^{m(a)}_{v-all}$ of water allocation for DP-ISDm are higher than that of the DP model. Also $R^{m(a)}_{v-all}$ values are reported for the SDP model. This uses the Markov transition probability of inflow to determine the expected value function of the Bellman equation in a DP-based optimization process. According to Table 2, water deficit can be clearly seen during March untill July which is due to higher level of demand. Comparing the results, it is shown that DP-ISDm is a powerful tool and can significantly improve the allocation reliability with respect to the alternative models.

In DP-type models state variables must be discretized. A fine discretization increases the runtime and causes dimensionality problems, while it does not necessarily lead to better results. The proposed ISD model decreases the computation of the DP-based model by discarding higher states. It also incorporates the uncertainty in reservoir operation and improves the reservoir reliability indices. In spite of SDP modeling, considering the inflow uncertainty does not add any other state variable to the optimization model. Applying the proposed framework may not model overall uncertainty of the problem, but it certainly gets closer to a stochastic model. Also, by considering the advanced methodologies available for reservoir operation, extending the current algorithms to the multi-reservoir case seems to be applicable.

SUMMARY AND CONCLUSIONS

In this research, a novel fuzzy dynamic optimization model has been developed for reservoir operation and water allocation. As opposed to alternative models, i.e., simple DP-based and SDP models, the proposed model generates appropriate operating policy rules for reservoir operation using a fuzzy ISDm. The ISD mechanism is designed based on a fuzzy logic. Application of the ISD mechanism incorporates the uncertainty of inflow in reservoir optimization model, in a simpler way than the stochastic DP-based optimization models and reduces the dimensionality problem. In this research, model capability was evaluated in terms of reliability indices for reservoir operation. It is shown that the proposed model significantly improves the reliability in demand allocation as compared with the alternative model.

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