A Dynamic Programming Model Coupled with Fuzzy Rule Base for Reservoir Operation Optimization

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Abstract: A dynamic programming fuzzy rule-based (DPFRB) model for optimal operation of reservoirs system is presented in this paper. A deterministic Dynamic Programming (DP) model is used to develop the optimal set of inflows, storage volumes, and reservoir releases. These optimal values are then used as inputs to a Fuzzy Rule-Based (FRB) model to derive the general operating policies. Subsequently, the operating policies are evaluated in a simulation model while optimizing the parameters of the FRB model. The algorithm then gets back to the FRB model to establish the new set of operating rules using the optimized parameters. This iterative approach improves the value of the performance function of the simulation model and continues until the satisfaction of predetermined stopping criteria. The DPFRB performance is tested and compared to a model which uses the multiple regression based operating rules. Results show that the DPFRB performs well in terms of satisfying the system target performances.

Keywords: reservoir operations, dynamic programming, and fuzzy inference system

1. Introduction

Implicit stochastic methods (ISMs) are commonly used for optimizing reservoir systems operation. However, one important difficulty in ISMs is to combine the large set of results obtained from an implicit stochastic method to derive general operating policies. Implicit stochastic programming has been widely used to derive the general operating policies for reservoir systems. Young (1967) proposed the use of linear regression procedure to find the operational rules from the results of a deterministic optimization method. Bhaskar and Whitlach (1980) used a multiple linear regression to derive the operating rules as a function of inflows to reservoir and storage volumes. Karamouz and Houck (1982) extended this approach in a model called DPR, in which dynamic programming releases are progressively constrained to become close to the operating rule values.

Along with regression or using simple statistics and diagrams and tables to infer the operating policies (Lund & Ferreira, 1996), other methods including the Artificial Neural Networks (ANN) (Raman & Chandramouli, 1996; Chandramouli and Raman, 2001; Cancelliere et al., 2002), and fuzzy rule-based (FRB) technique (Russel and Campbell, 1996; Shrestha et al., 1996; Panigrahi and Mujumumdar, 2000; Dubrovin et al., 2002) and the combination of FRB and ANN (Ponnambalam et al., 2001; Ponnambalam, et al., 2003) have been used. Raman and Chandramouli (1996) showed in a case study that ANN-based policies have better performance compared to multiple regression-based policies. There are other models dealing with the use of operational rules in multi-reservoir control models such as Johnson et al. (1991), Koutsoyiannis and Economou (2003), Lund and Guzman (1999), Oliveira. and Loucks (1997), and Philbrick and Kitanidis (1999). In the DPFRB model proposed in this paper, the optimal values obtained from a deterministic

DP model are used in an FRB model to derive the operating policies. These fuzzy rules are then tested in a simulation model for evaluation of their performance. Also, an iterative method is proposed to find the best values of the FRB parameters, based on the results of the simulation model. The DPFRB and DPR models are applied to Dez and Karoon reservoir system and the results are compared. This paper is organized as follows: In Section 2, the deterministic DP model used in the first step of DPFRB and DPR models is described. Section 3 outlines the principles of the FRB method. The complete description of proposed DPFRB model is presented in Section 4. Analysis of the results after applying the above models to the case study is discussed in Section 5. Finally, we conclude in section 6 by summarizing the findings and providing suggestions for improvement.

2. Dynamic Programming Based Modeling

Dynamic programming (DP) is a widely used numerical tool for optimization of reservoirs operation. In this method, an *N* multi stage mathematical model, which has a separable objective function, is divided to *N* sub-problems and the value of objective function is evaluated at each stage, recursively. We use a deterministic DP model for optimization of a multiple site reservoir system. The recursive function and constraints of such a system may be mathematically presented as follows:

$$f_{t+1}(S_{t+1}) = \min\ [Loss(R_t, D_t) + f_t(S_t)] \qquad t=1,...,T \qquad [1]$$

Subject to: typical constraints of a reservoir operation model including flow (mass balance) equations, lower and upper bounds of the state (storage volumes) and decision (release volumes) variables and so on $f_t(S_t)$ is the total minimum losses of operation from stage 1 to stage t when the state of storage volumes of reservoirs at the beginning of season t is S_t , T is the time horizon, S_t is the vector of storage volumes of a system of *n* reservoirs at the beginning of season *t* , R_t is the vector of release volumes from corresponding reservoirs during season *t* , D_t is the amount of the water demand in season *t* , and $Loss(R_t, D_t)$ is the immediate loss of operation during the season *t* .

The above mathematical model is solved by discretizing the reservoir storage levels after which optimal sequence of inflows, storage volumes, and releases are obtained for t=1 to t=T.

3. Fuzzy Rule-Based (FRB) Modeling

The FRB modeling could be regarded as a substitute for representing the operational policies. In this method, the human reasoning is easily incorporated in the decision making process and therefore human operators are better able to apply the results of the model. They should also be able to incorporate their experimental findings through membership functions, the basic concept of fuzzy set theory. The FRB method is a mathematical model in which the rule-based system is defined by fuzzy rules. A fuzzy rule is an "if-then" proposition where "if" is associated with the premise variables and "then" is associated with the fuzzy or crisp consequences such as:

If S_t *is* A_{1i} *and* I_t *is* A_{2i} *then* R_t *is* B_i

where, I_t , S_t , and R_t are inflow to reservoir, storage volume, and release from reservoir, respectively and A_{ki} is the k^{th} linguistic explanatory variable and B_i is the consequences of rule " *i* ". A linguistic variable is a variable represented by a label such as small, medium, or large. Each value of a linguistic variable is represented by a fuzzy set. Therefore, A_{ki} is a fuzzy set, which is defined through its membership function. These fuzzy rules are the linguistic representation of an inference engine of a Fuzzy Inference System (FIS) and are determined by well-trained experts or through a learning mechanism using available input-output data. We have used the optimal solutions derived from the DP as input-output data to train the fuzzy rules. In our FIS, the inflow and storage are taken as the fuzzy premises while the releases from reservoirs are considered as the crisp consequent variables. This is a simple form of the well-known Sugeno-type (Sugeno,1985) FIS. To establish a FIS, the lower and upper limits of each premise variable are determined from the training data set. Then, the range between upper and lower limits of each premise variable is divided into a set of overlapped classes in which each class is a fuzzy number. Here we used Triangular Fuzzy Numbers (TFN). Figure (1) shows the partitioning of inflow into reservoirs, as one of our premise variables.

Two different methods were used to determine the supports (the range between minimum and maximum) of each fuzzy number. In the first method, the premise variables are divided into equally distant classes where different number of training data exists for each class. In the second method, the supports of the fuzzy numbers are determined in such a way as to have equal frequencies of the training data located in the

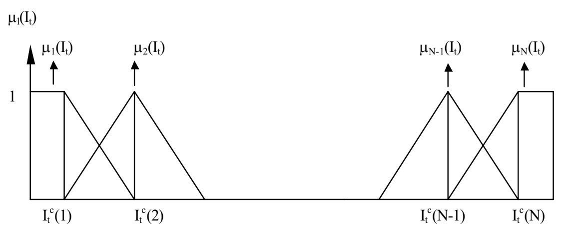

Figure 1. Discretization of inflows to reservoirs and their membership functions

different classes. The two methods were also used to determine the mean value of fuzzy numbers. In the first method, the mean value of each fuzzy number would be the expected value of all training data located on the support of this number and is independent of other premise variables. In the second method, the mean value of each fuzzy number in rule " i " depends on the other premise variables of this rule. Suppose each fuzzy rule " i " has m premise variables. Then, the set P_i is defined as

$$P_i = \left\{ \begin{array}{l} a_{1i}(s),\, a_{2i}(s),\dots,\, a_{ki}(s),\dots,\, a_{mi}(s);\, b_i(s), s = 1,\dots,n_i \\ \Big|\ a_{ki}(s) \in [l_i^-(k), l_i^+(k)] \end{array} \right\}$$

and the mean value of fuzzy numbers are calculated as:

$$m_i(k) = \frac{\sum_{s=1}^{ni} a_{ki}(s)}{n_i} \qquad i = 1,\dots, NR \qquad [2]$$

where n_i is the number of elements belonging to P_i and $a_{ki}(s)$ is the s^{th} $(s=1,\dots,n_i)$ element of P_i . Each of these elements is located on the support of the $k^{th}(k=1,\dots,m_i)$ premise variable of rule "i ". This support is the range between $l_i^-(k)$ and $l_i^+(k)$. Therefore $a_{ki}(s)$ is the input part and $b_i(s)$ is the output part of the training data of the set P_i . If the k_{th} premise variable of the fuzzy rules is divided into nn_k fuzzy numbers, the total number of rules NR is then given by:

$$NR = nn_1 * nn_2 * \dots * nn_m \qquad [3]$$

The consequent of each fuzzy rule " i " is calculated by combining the outputs of all the data which belong to Pi and then satisfy at least partially this rule. The degree to which the sth element of Pi belongs to the rule " i " is measured by the so-called degree of fulfillment (dof). In fact, the dof represents the weight or degree with which each input data satisfies each fuzzy rule. An input data

$(a_{ki}(s))$ consists of m elements each of which belongs to a fuzzy set by the degree of $\mu(a_{ki}(s))$. Therefore, the final weight *(dof)* of this input data can be selected as the minimum degree of satisfaction among these elements ("min" operator) or product of different weights ("product" operator). In general, any T-norm operator, could be used. Here we apply a parametric "product" operator as follows:

$$dof_i(s) = \left[\prod_{k=1}^{m} \mu(a_{ki}(s))\right]^g \quad if \quad dof_i(s) \geq e \qquad [4]$$

where $\mu(a_{ki}(s))$ is the membership function of the s^{th} element of P_i in the k^{th} premise variable of the rule " i "and " g " and " e " are the parameters of the dof values. The consequence of the rule "i" (B_i) is then calculated through aggregation of all the output data belonging to P_i by using a weighed average method given by:

$$B_i = \frac{\sum_{s=1}^{ni} dof_i(s) * b_i(s)}{\sum_{s=1}^{ni} dof_i(s)} \qquad [5]$$

Parameters " g "and " e " are two important parameters which are described in the next section.

4. DPFRB Model

As mentioned before, the DPFRB model is a combination of dynamic programming, fuzzy rule-based, and simulation models. In DPFRB, the monthly historical inflows to reservoirs are divided to two different sets. One set is used for the DP and FRB models as training inflows while the other is used for the simulation model as test inflows. At first, the DP optimization model is executed and an optimal set of reservoir releases and storage volumes are determined. These

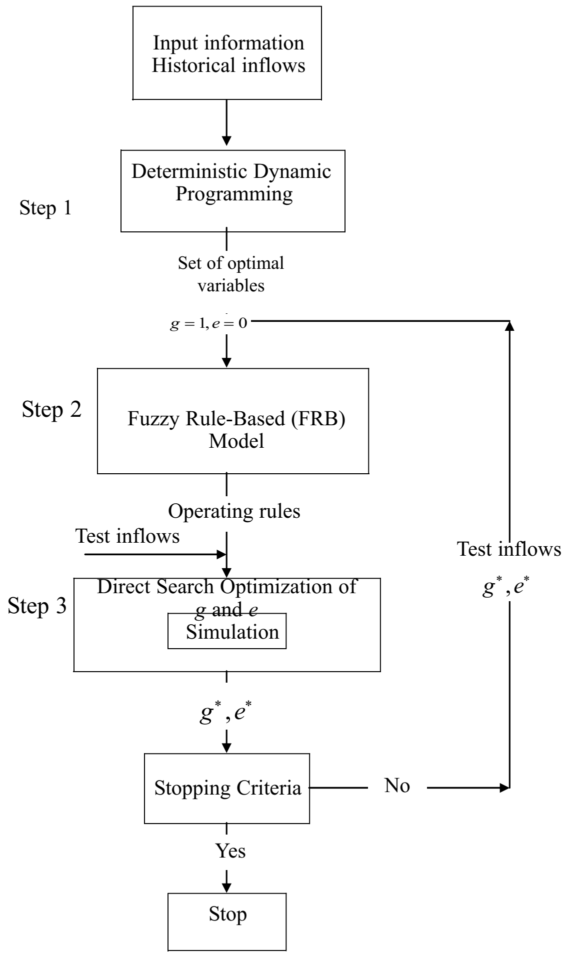

Figure 2. The flow chart of the DPFRB model

optimal storage and reservoir volumes as well as training inflows are then taken as the input values of the FRB model to derive the operating policies in the second step. The inflows and optimum storage volumes are taken as the fuzzy premise variables while the reservoir releases are taken as the consequences of fuzzy rules.

Figure 2 shows the flow diagram of the DPFRB model. The rule system was trained for each month of a year, separately. The parameters " g " and " e " are set equal to 1.0 and 0.0, respectively in the first iteration of DPFRB model. Following this, the operating policies or fuzzy rules, determined from the FRB model, are tested in a simulation model. Initial reservoir volumes are supposed known and inflows to reservoirs are presumed available from the set of test data. The reservoir releases are then calculated using the weighted average method similar to the way the consequences of fuzzy rules are determined:

$$R_t = \frac{\sum_i dof_i(v_t).B_i(FRB)}{\sum_i dof_i(v_t)} \qquad \forall i \,|\, dof_i(v_t) \geq e \qquad [6]$$

In equation [6], R_t is the vector of the reservoir releases during the season t. For our case study of two reservoirs system; $v_t = [I_{1t}, I_{2t}, S_{1t}, S_{2t}]$ is the vector of the state fuzzy variables and $B_i(FRB) = [R_{1t}, R_{2t}]$ is the vector of responses of rule " i " obtained from the FRB model. After calculating the reservoir releases in each time period, the reservoir storage volumes are determined from the continuity equation for the next period and the process is repeated over the simulation horizon. To find the best values of the " g " and " e " parameters, the simulation model was imbedded in a direct search optimization procedure to minimize the value of the objective function in the simulation. Subsequently, the best values of these parameters as well as the test inflows are fed back to the FRB model, and the fuzzy rules are established again by the new values of " g " and " e " and the inflows. This iterative procedure continues until the best value of the objective function in the simulation model is obtained. The DPFRB algorithm can be summarized as follows:

(i) Derive optimal releases and storages using DP

(ii) Derive operating rules using FRB. The input data and the parameters " g " and " e " of the FRB model are obtained from (i) initially and from (iii) during iteration.

(iii) Determine the optimal parameters " g^* " and " e^*" using a direct search of " g " and " e " in simulation.

(iv) Check for satisfaction of stopping criterion.

(v) If yes then stop else go to step (ii).

In this model, the operating policies are parameterized in a way as to be able to find the best values of parameters even for different objective functions in simulation. For example, the reliability of meeting the different types of demands under any other risk or reliability consideration could be taken into account as the objective function in the search algorithm.

Nalbantis and Koutsoyiannis (1997) have discussed the advantages of parameterized operating rules. In addition to the flexibility of parameterized operating rules in satisfying the different objectives of the system, we use these parameterized policies as an interface between the DP and the simulation model.

Usually, after a few iterations, the best value of the simulated objective function is obtained and further iteration doesn't result in further improvement. The stopping criterion was selected when the value of objective function has no improvement in successive iterations. Although, the objective function shows further improvement if we use a finer grid search around the best obtained values of " g " and " e ", we observed that the rate of these later improvements is very slow and doesn't warrant further computations.

5. Implementation and Discussion

The DPFRB model was applied to the reservoirs system of Dez and Karoon in Iran. Dez and Karoon drainage basins are located in the SouthWest region of Iran, carrying more than one fifth of the surface water available in the country. Total area of these basins is about 45,000 square kilometers. The reservoirs are constructed on Karoon and Dez rivers and they are named after them.

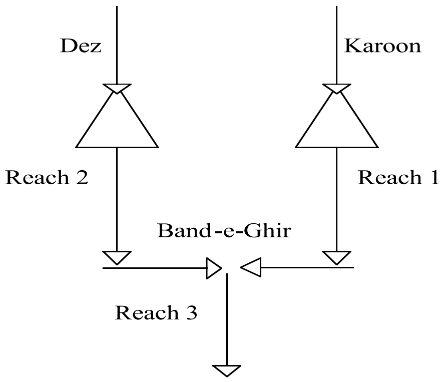

Figure 3. The shematic of karoon and Dez system

The two rivers are joined together at a location called Band -e- Ghir, in the north of the city of Ahwaz and form the "Great Karoon River ". This river passes Ahwaz and reaches the Persian Gulf in the south of the city of Ahwaz. Average annual streamflow to Dez and Karoon reservoirs are 8.5 and 13.1 Billion Cubic Meters (BCM), respectively. Figure (3) shows the schematic representation of this system. These two rivers downstream of Karoon and Dez dams supply water for the domestic, industrial, agricultural, and agro-industerial sectors.

Total irrigated land, downstream of Dez and Karoon dams are estimated to be about 250,000 hectares. Besides the irrigation benefit from the lands, which are the main consumer of water in these basins, these two rivers supply domestic water demand for cities and towns as well as to main industrial units such as steel industries and termal power plants. Total water demand from Dez and Karoon rivers for all purposes is estimated to be 1.91 BCM. Thirty five percent of this amount is allocated to the downstream of Karoon dam between Karoon reservoir and Bande-Ghir (first reach), 42 percent is allocated to downstream of Dez dam (second reach), and the rest to downstream of Band - e - Ghir to Persian Gulf (third reach).

To evaluate the DPFRB model, we also applied the DPR model to this system. The DPR uses multiple linear regression analysis to derive the general operating rules. In this model, the set of optimal solution of DP is regressed and operating policy is presented by a linear equation. These regression equations are then tested in a simulation model. Following the first iteration, the DP is repeated by imposing an additional constraint in which the DP releases are constrained in a bound of linear releases of the previous iteration. Using this iterative procedure, the value of the objective function is improved. Forty years of historical monthly inflows into each reservoir are available. Of that, thirty years of data is used in the DP and the FRB models and the remaining ten years' data are used in the simulation model. Statistical characteristics of these inflows show the first ten years of the data belong to a dry period and the last ten years to a wet period. Table 1 compares the mean and the standard deviation values of the first and last ten years of inflows with the value of these statistics for the total forty years of available inflows.

Because of significant differences between the statistics of these two parts of inflow time series, the DPFRB and DPR models are evaluated under two scenarios. In one of them, the first thirty years of inflows are used in the DP model and the last ten years in the simulation model. In the other scenario, the first ten years of inflows are used in the simulation model while the last thirty years of inflows are used in the DP model. In another test and under each of the mentioned scenarios, we have also increased all of the water demands by multiplying them with a demand factor of two (demfact=2) to make it more challenging for the DPFRB and the DPR models. Table 2 shows the results obtained from the DPFRB and the DPR models in each of the scenarios. It should be noted that from the different types of water demands, the domestic, industrial, and agro-industrial usages were satisfied over all the

Table 1. Statistics of different parts of historical inflows

Statistics	First 10 years of Inflows			Last 10 years of Inflows			Total 40 years of Inflows		
	Mean	SD	CV	Mean	SD	CV	Mean	SD	CV
Karoon	632.0	336.5	0. 53	1211.8	842.3	0.70	972.6	729.1	0.75
Dez	493.1	355.8	0.72	885.50	784.4	0.89	724.8	652.0	0.90

Table 2. Comparison between DPFRB and DPR models
For first scenario, 10 last years' inflows as test data and demfact=1 (or demfact=2)

Model	Demand Factor	NS*	NI=	DP Cost	Simulation Cost	Demand Reliability
DPFRB	1 (2)	3 (3)	4 (4)	0.00 (2070)	0.00 (2180)	100.0 (87.5)
DPR		—	—		459 (3840)	97.9 (84.2)
For second scenario, 10 first years' inflows as test data						
DPFRB	1 (2)	3 (3)	4 (4)	0.00 (324)	0.00 (22500)	100.0 (54.2)
DPR		—	—		7020 (58400)	93.3 (49.8)

times of the simulation period. Therefore, we have reported only the reliability of meeting the agricultural water demand.

In Table 2, NF is the number of representative discrete storage volumes in the DP model, NS and NI are respectively the numbers of fuzzy intervals of storage and inflow premise variables in the FRB model. Optimization and Simulation costs are the average monthly loss of reservoir operation in DP and simulation models, respectively and the demand reliability is the percentage of time the target demand has been satisfied during the simulation horizon. It should be noted that the NF , NS , and NI values were set the same for each reservoir. To avoid the discretization error in the case of demfact=2 for which the optimization cost is not equal to zero, we used thirty discrete storage states for each reservoir in the DP model. However, we observed that dividing each premise variable into only three to five fuzzy numbers is sufficient in the FRB model. This is due to the fact that the rule-based system tends to be incomplete and most of the rules are not applicable if finer discretization is used.

Both methods described in section 3 for discretizing the premise variables had approximately similar results. Also, the first method of determining the mean value of each fuzzy number showed better results. Therefore, the mean values of the k^{th} fuzzy number of each premise variable are the same for all the rules. From Table 2 and in the case of usual demands (demfac=1), we see scenarios in which the value of objective function is zero under both optimization and simulation of the DPFRB model. For the DPR model, there is significant difference between the values of the objective function in the DP and the simulation models where the simulation costs for two wet and dry scenarios are equal to 459 and 7020, respectively. Also, the reliability of meeting the agricultural water demand in the DPFRB model is higher than what it is for the DPR model. We can observe in Table 2 that the DPFRB performs better than the DPR with respect to the value of the objective function in simulation as well as in terms of the reliability in meeting the demands. The results of both the DPFRB and the DPR

Table 3. Effect of the uncertainty of inflows on the value of simulated cost in DPFRB and DPR models for demfact=1 (demfact=2)Optimum cost in DP= 0.00 (324)

	Same inflows in DP and simulation		Different inflows in DP and simulation	
	A11=	A12=	B11==	B12==
K*	DPFRB	DPR	DPFRB	DPR
1	15.6 (2930)	1080 (10200)	309 (30900)	7110 (66700)
2	4.36 (2640)	1080 (10200)	0.00 (22500)	7020 (58400)

* K=1 is corresponding to the first iteration and K=2 is corresponding to the best
= A11/A12 are the values of simulation cost when the first 30 years' inflows are used both in the DP and the simulation in the DPFRB/DPR models
== B11/B12 are the values of simulation cost when the first 30 years' inflows are used in the DP and the last 10 years' inflows in the simulation the in DPFRB /DPR models.

models in the second scenario are not as good as the first scenario, especially for demand factor=2.0, as can be expected but still DPFRB does perform much better than DPR. It should be noted that the difference between the values of the objective functions in DP and simulation sub-models of DPFRB and DPR comes from two sources. The first is due to difficulties of not fitting the operating rules to optimal values. In fact, the actual relation between release, storage and inflow may be highly nonlinear and this non-linearity should be adequately modeled through the operating rules.

When the inflows in the DP and the simulation models are the same, the operating rules are used for interpolation. However, when these inflows are different, we may have some inflows in simulation beyond the range of the inflows used in the training of the operating rules. Therefore, in addition to the capability of policies to fit to a complex and nonlinear pattern of data, the capability of operating rules for extrapolation should also be explored. This extrapolation can be converted into interpolation if the policies could be retrained when subjected to new data. Therefore, there are two different characteristics of an interface model (FRB or regression) that are important for developing the operating rules: its capability to fitting optimal data obtained from DP and its flexibility in retraining due to uncertainty of inflows.

To distinguish between the above aspects, Table 3 compares the DPFRB and the DPR models in two different cases: when the inflows into reservoirs are supposed to be the same in the DP and the simulation sub-models and when they are not. This table shows the results of the first and the best iterations of the models in the two above cases.

The A11 and A12 portions of Table 3 show the performance of the DPFRB and the DPR models in fitting the optimal solutions of the DP model because the inflows into reservoirs are the same for both the DP and the simulation models. Comparison between the results of A11 with A12 shows that the DPFRB outperforms the DPR with respect to fitting capability. For example the best values of simulation cost are 4.36 (2640) in A11 (DPFRB) and 1080 (10200) in A12 (DPR) cases. We see that the minimum value of the simulation cost in the DPFRB is less than the DPR cost for all the cases. This implies that the fuzzy rules and the tuning of their parameters in successive iterations results in a good fitness to the optimal solution of the

DP model and hence the fuzzy rules can fit to a nonlinear structure of optimal data better than the regression based rules.

Comparing B11 to B12 is similar to the results of Table 2, but comparing the A11 to B11 or A12 to B12 shows the effect of adding uncertainty on the performance of models in addition to the fitting capability. As we expect in this case, by adding the effect of uncertainty, the value of simulation cost is increased in the first iteration. For example in the DPFRB model, the simulation cost has increased from 15.6 (2930) to 309 (30900). After a few iterations, this effect has been compensated in the DPFRB model and the simulation cost has reached 0.0 (22500). This shows that for demfact=1, the iterative procedure used in the DPFRB model result in a simulation cost of 0.0, which is equal to the value of optimization cost. On the other hand, we observe that even in the case of not including the uncertainty effect (A11), the best value of the simulation cost of the DPR model is equal to 4.36, which is greater than 0.0. For demfact=2, the iterative method has improved the simulation cost from 30900 to 22500, but this value is still larger than 2640, which is the best value of the simulation cost when the uncertainty is not included.

This shows the significant effect of the uncertainty in the case of demfact=2. Similarly, if we compare the results of A12 with B12, it could be observed that the simulation cost of the DPR model is also increased due to the effect of uncertainty. For example, the simulation cost has been changed from 1080 (10200) to 7110 (66700) in the first iteration. These values have been decreased to 7020 (58400) in the best iteration that is not as good as the improvement due to iterative procedure of the DPFRB model. This advantage of the DPFRB over the DPR is important, because in the DPFRB model, the time consuming DP sub-model has to be executed only in the first iteration, while in the DPR model it is executed in all the iterations. This feature of the DPFRB is attractive in terms of minimal computational resources required, especially when it is applied to a large-scale optimization problem.

6. Summary and Conclusions

A three step Dynamic Programming Fuzzy Rule-Based (DPFRB) model was presented and tested in this paper. This model integrates dynamic programming, fuzzy rule base and a simulation model. The DP solutions are trajectories of optimal release and storage volumes over the planning horizon which may not be completely useful for real operators. Closed-loop operating rules are thus required which are built by using those trajectories as inputs to an interface model inferring general operating rules. The interface model could be a regression, ANN or any function approximator model which is able to extract linear or nonlinear relationships between input and output data set. In this paper, fuzzy rule base has been used as the above-mentioned interface model. Thus, optimal solutions of the DP model are used to establish the general operating policies in the FRB model and the policies obtained are then evaluated in a simulation model. As the FRB-based policies have some parameters whose values can be tuned in simulation, a direct search optimization method is used to find the best values of the parameters of the FRB model. The tuned optimal parameters are sent back to FRB to create a new set of fuzzy rules and the procedure continues until the satisfaction of the stopping criteria. This model is compared to a model, which uses multiple linear regression to derive the operating rules.

The simulated objective function shows how effective the derived rules are if they would have used in system operation. On the other hand the reliability of meeting demands in simulation measures how frequent the failures and successes would occur if the derived rules were to be used. Thus, the better values of the simulated objective function and the higher reliability of meeting the demand shows the capability of the DPFRB model in satisfying the objectives of the system when compared to the regression-based model. Moreover, the derived operating rules are in form of fuzzy “if-then” rules which are easy to understand by human operators as they are based on linguistic terms like high inflow, low demand and so on.

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