Larhyss Journal, ISSN 1112-3680, n°51, Sept 2022, pp. 145-160

DAM RESERVOIR OPERATION OPTIMIZATION USING GENETIC ALGORITHM AND PRINCIPAL COMPONENT ANALYSIS SIMULATION MODEL - CASE OF DAM GHRIB RESERVOIR

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Research Article – Available at http://larhyss.net/ojs/index.php/larhyss/index
Received July 28, 2022, Received in revised form…, 2022, Accepted…, 2022

ABSTRACT

The study of the eighteen-year monthly operating budget of the Ghrib Reservoir from 1999 to 2016 shows an important deficit in satisfying water demand partly due to the uncertainty of stochastic water inflows. In this context, the main objective of the present research work is to overcome this shortcoming by reducing it and improving the current reservoir operation. Therefore, the optimization of this last using a genetic algorithm (GA) is carried out based on historical and simulated water inflows. The performance of the classical GA in optimizing the multipurpose reservoir operation based on the simulated water inflows using the principal component analysis (PCA) model is highly demonstrated given a significant decrease in the water deficit from 47% to 8%. The developed model could help operators make decisions for operating dam reservoirs more efficiently.

Keywords: Reservoir operation, Genetic Algorithm, Optimization, Simulation, Principal Component Analysis.

INTRODUCTION

Water resource operation is a relevant issue, with a view to better satisfying the ever-increasing water demand. In semiarid zones, water resources are scarce and more vulnerable to climate change, and operators must have a common concern about how to tackle water stress and uneven precipitation. From Ghrib Reservoir, situated in Ain Defla city, a rural semiarid region, the volumes allocated to drinking, industrial and irrigation water supply do not generally cover an increasing water demand; this is partly attributed to uncertain inflows to the reservoir, a stochastic variable whose reliable knowledge is necessary for deriving the reservoir operating rules. Therefore, because of

the water deficit observed in the water demand satisfaction in 2016, it was decided to increase the Ghrib reservoir capacity, and the reservoir heightening works using fuse gates lasted more than three years from 2016 to 2019 or later. In this respect, our search work attempted to confirm that the water deficit issue occurred from poor knowledge in the current reservoir operation, and it was not necessary to implement the costly reservoir heightening plan. Therefore, the need for improving the current multipurpose reservoir operation holds the way in the measure where the reservoir operators could have reliable decision support tools.

Then, optimization of the current reservoir operation in an uncertain future intends to maximize downstream releases so that the difference between the latter and the real demand is minimized. In this context, a large number of optimization models have been developed worldwide, ranging from linear optimization models to more complex deterministic and stochastic dynamic models. Reservoir operation is considered a problem of linear optimization and stochastic dynamics with a curse of dimensionality (Cheong et al, 2010; Rieker and Labadie, 2012; Stedinger et al., 2013; Xu et al., 2014; Lin and Rutten, 2016).

With the development of artificial intelligence applied to reservoir operations, another category of metaheuristic evolutionary algorithms has emerged, namely, genetic algorithms (GA), particle swarm algorithms, moth search algorithms, etc., based on biological imitation. Genetic algorithms (GAs) are widely used for optimizing reservoir operations; starting from a random population set, there is a greater chance of finding the optimum through the successful use of an approximate hybrid model developed from the genetic algorithm and nonlinear programming, which demonstrates its robustness in the derivation of multipurpose reservoir operating policies (Leela et al., 2019). By defining the fitness function of the GA model with noise, the calculation time is reduced by 90%, and a high reliability of the water supply from the optimization of a single reservoir operation is obtained (Yu et al., 2019). The constrained GA is successfully applied in optimizing multipurpose reservoir operation; a decrease in the low flow rate leads to an increase in the ecological flow during dry periods (Chang et al., 2010). The superiority of hierarchical adaptive GA is proven on the deterministic dynamic programming for reservoir operation optimization and that, regarding the convergence properties, power generation benefits and computational efficiency (Zhang et al., 2019). The classical GA is improved more conveniently by reducing the number of penalty functions and optimizing flood control operations. (Ren et al., 2022). Chang and Guo (2020) presented state-of-the-art high-level research papers implementing practically artificial intelligence techniques in hydrological modeling, forecasting and optimizing for accurate flood control and reservoir operation.

The use of GA methods for optimizing Ghrib reservoir operation attempted to explore the possibilities of expressing objective function and penalty function so that operating rules would be improved, taking into account the uncertainty of stochastic inflows, whose simulation intends to reproduce future scenarios, whose the most accurate one is taken.

Different types of models have been proposed for the simulation of hydrological data, stationary or nonstationary, for instance, autoregressive models with moving average ARMA, autoregressive integrated with moving average (ARIMA), and seasonal autoregressive integrated moving average (SARIMA) (O'Connell and O'Donnell, 2014; Babamiri et al., 2022). The use of these models is conditioned by chronological continuity, the autocorrelation of data, even by the stationary character and normality of the historical series to be reconstituted. To overcome these shortcomings, a model called « GESTOP » based on principal component analysis (PCA) was developed at different time steps (Dechemi et al, 1994). PCA methods are generally used worldwide to reduce the number of variables or parameters. Repeated PCA is applied to a multiple regression model to establish an initial reservoir operation function model before optimization by excluding colinear dependent and independent parameters (Wang et al., 2019). In a matter of hydrological simulation related to reservoir operation using PCA, no cases were noted.

MATERIAL AND METHODS

Study Area and data used

Ghrib Reservoir

The Ghrib Reservoir is an embankment-type dam located on the Cheliff River in Aïn Defla city, 120 km southwest of Algiers (Fig. 1).

It is 74 meters in height and 270 meters in crest length. The maximal capacity is approximately 180 million cubic meters (MCM), while the dead volume is 30 MCM. Topographically, the watershed feeding the Ghrib Reservoir consists of hills; its main characteristics are detailed in Table 1.

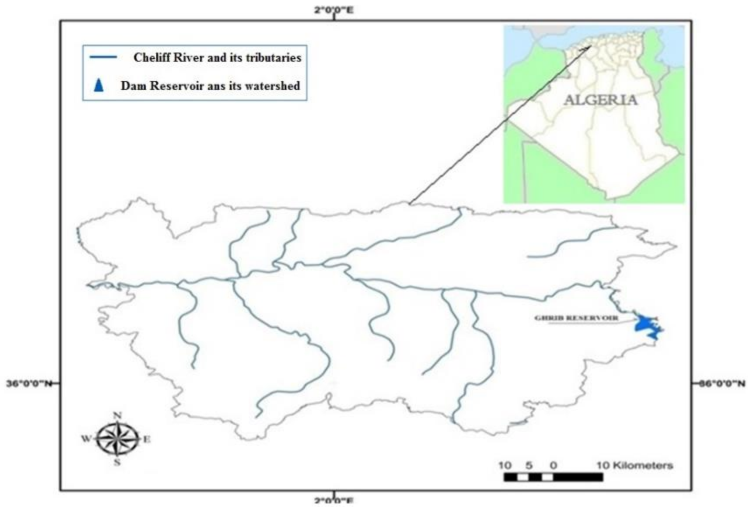

Figure 1: Location map of Dam Ghrib Reservoir

Table 1: Ghrib watershed characteristics

Catchment Characteristics	Units	Value
Area	km^2	2800
Perimeter	km	34
Altitude	m	460
Roche Slope Index		0.5
Drainage Density	km/km^2	5.6
Time Concentration	Hour	15
Forestation Ratio	%	50

Hydrological Characteristics of the Ghrib Reservoir

The Ghrib Reservoir watershed area is 2800 square kilometers with a high variability in rainfall, with an average of 400 mm/year. The average monthly inflow to the reservoir is 89 MCM and varies between maximal and minimal inflows corresponding to 186 and 14.5 MCM, respectively. Generally, December and January are the rainiest months with higher inflows to the reservoir, and September and August are the months that record the least inflows relative to other months, while the average annual evaporation is 8.2 MCM corresponding to an evaporated water leaf of 1300 mm.

The hydrological characteristics of the Ghrib Reservoir are reported in Table 2.

Table 2: Dam Ghrib reservoir characteristics

Reservoir Characteristics	Units	Value
Reservoir Capacity	MCM	180
Dead volume	MCM	30
Annual Siltation	MCM	3,2
Maximal Dam Height	m	74
Crest Length	m	270
Average Annual Inflows	MCM	89
Average Annual Rainfall	mm	400

Optimization Issue Formulation

The main objective of the Ghrib Reservoir operation optimization issue is to find the water allocations that adequately satisfy the respective water demands without compromising the system. The objective function is written as follows:

$$minimize\ (f) = \sum_{i=1}^{n}\left(\frac{R_i - D_i}{D_i}\right)^2 \quad (1)$$

where i is the month index; N is the operating future in months; andR_i and D_i are the releases and demand in month *i*, respectively. Storage at each period is expressed through the continuity equation as follows:

$$S_i = S_{i-1} + I_i - E_i - R_i - Seep_I - Sp_i; \quad (2)$$

where $S_i$is the reservoir storage at the end of month i when *i*= 1, $S_{i-1}$is equal to S_0 (the initial reservoir storage); I_i and $E_i$are, respectively, water inflows and evaporation during month *i*; $Seep_i$ is a seepage during month i; and $Sp_i$is the spill volume during month *i*. The water system is defined by the lower and upper bounds of the release, storage and spill values as follows:

$$R_{min} \leq R_i \leq R_{max}\ ; \quad (3)$$

$$S_{min} \leq S_i \leq S_{max}\ ; \quad (4)$$

$$SEEP_i \geq 0, Sp_i \geq 0; \quad (5)$$

where $S_{min}$is the minimum storage corresponding to the dead storage and S_{max} is the maximum reservoir capacity. The maximum, average and minimum water demands are considered to be the most difficult variables to assess in reservoir operation.

In optimizing the reservoir operation, the following two inflow-to-reservoir cases are considered:

a) Optimization with historical inflows;

b) Stochastic optimization: in which we consider inflows to the reservoir as uncertain variables, generated by a simulation model that enables the generation of different scenarios of simulation taking into account randomness and uncertainty of these parameters that characterize the semiarid hydrological regime of the region.

The used GA consists of randomly initializing a population of 50 individuals, satisfying constraints, depending exclusively on the design parameters and with a parent selection rate of 80%. After obtaining new individuals from the crossover, the applied mutation rate is 5%.

Thus, for optimizing historical reservoir operation, the "objective" function is given by:

$$\mathrm{G(i,j)} = \sum_{\mathrm{j=1}}^{\mathrm{T}} \left(\mathrm{D_i} - \mathrm{R_{ij}}\right)^2 \tag{6}$$

where i= 1,… n months, j=1,…T population

T : Population size, T= 50 among 200 generations.

Di: Water demand at month i

Rij: Release at month i for water need j.

The penalty function is given by:

$$\mathrm{h(i,j)} = 0.5\mathrm{x}1000^{2*\sum_{\mathrm{j=1}}^{\mathrm{T}} \mathrm{G(i,j)}} \tag{7}$$

The penalty function in Eq. (7) is expressed in relation to the active reservoir storage bounds, namely, the maximum and minimum. The objective function G*(i,j)* expressing the optimization of the multipurpose reservoir operation in an uncertain future is subject to the following constraints:

$$\text{If } S_{i,j} < \mathrm{S_{i-1}} \text{ then } \quad \mathrm{G(i,j)} = \left(\mathrm{S_{i-1}} - \mathrm{S_{i,j}}\right)^2 \quad \text{Else } \mathrm{G(i,j)} = 0 \tag{8}$$

That guarantees having the penalty function $\mathrm{h(i,j)}$ higher than zero, and a solution that violates the given constraints is called unfeasible.

Regarding the stochastic optimization, the used model “GESTOP” for simulating inflows is automated and structured into three modules: the first enables transforming the collected data files with different time steps, the second enables preparing data for simulating each of all variable types with principal component analysis and calculates the different simulation parameters (covariance, residuals, etc.). The third enables simulating the different parameters of the raw and normalized models with the different distribution probabilities.

This powerful PCA model (Dechemi et al., 1994) enables the simulation of cyclic and random variables, including truncated time series, at different time steps. PCA is a linear factorial method that enables variables correlated each other to be replaced by new variables called “principal components”, being linear combinations of the uncorrelated variables with a maximum variance.

Principal components, being linear combinations of the initial variables, are expressed by:

$$C_l = \sum_{j=1}^{P} a_{lj} \times X_j \tag{9}$$

where

C_l: Principal Component (PC);

a_{lj}: Direction cosines, elements of eigenvalues matrix;

X_j: j order variable.

If only the first PC is considered, taking into account the unexplained variance by the residual ε_j, the final expression of the standardized or normalized model is written as follows (Souag et al., 2007):

$$\hat{X}_j = \beta_{j0} + \sum_{l=1}^{Q} \beta_{jl} \times C_l^{'} + \mathrm{E}_{.j} \tag{10}$$

where

The matrix $[\beta]$ consists of a first vector β_0 , comprising averages of historical series; the other vectors of the matrix have, as components, the regression coefficients between the variables and PC.

$[C^{'}]$: The principal components matrix

$[E]$: The residuals matrix

Based on this structure, different simulation methods are offered, providing several possible combinations and therefore a variety of possible scenarios. In the case of a stochastic simulation, probabilistic distribution methods such as lognormal, GEV or Goodrich fit distributions are used.

Performance Metrics assessment of the water system

To assess the performance of the Ghrib Reservoir operation before and after optimization, the following metrics are considered:

- The water demand satisfying ratio (WDSR)
- Deficit Ratio (DFR);

- The loss ratios (LR) express the difference between the observed and optimized reservoir storage.

The water demand satisfaction ratio is expressed by:

$$\mathrm{Prob}[R_i \geq D_i] \geq \mathrm{WDSR} \qquad (i=1,\ldots, n) \qquad (11)$$

where WDSR is the water demand satisfying ratio, corresponding to the probability that there is no failure (Hashimoto et al., 1982) or when the system fails to satisfy a target.

The deficit ratio expresses the rate of deficit relative to water demand satisfying during the planning period (DFR). Thus:

$$\mathrm{DFR} = \frac{\sum_{i=1}^{T}(D_i - R_i)}{\sum_{i=1}^{T} D_i} \text{ When } R_i < D_i \qquad (12)$$

RESULTS AND DISCUSSION

Monthly historical records of states and decision variables, from September 1999 to August 2016, considered in optimizing reservoir operation are water inflows, storage, evaporations calculated by the method of Colorado tank - class A (Remenieras, 1986), and releases.

The study of monthly observed inflows from 1999 to 2016 identifies two distinct periods, namely, a dry period from May to September, where monthly inflows are generally very low (< 1 MCM), and a wet period. From October to April, they generally exceed 10 MCM, with high peaks recorded during the months of December and January.

In terms of the monthly filling ratio (FR) (Fig. 2), the reservoir operating balance sheet reveals 10 and 40 months of drought from May 2002 to January 2003 and from June 2005 to October 2008, respectively, where the average FR is between 32% and 22%. However, during the rest of the reservoir operating period, the average FR is 45% with the highest reservoir regularization ratio during the months of February and March.

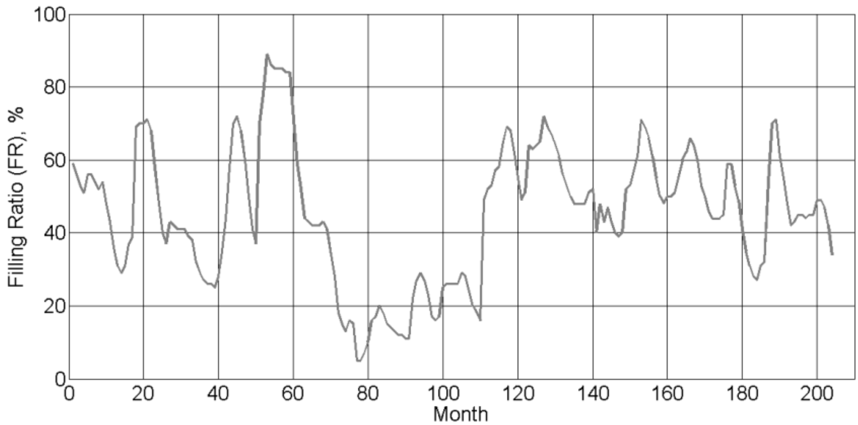

Figure 2: Observed reservoir filling ratio

The average monthly water demand satisfying ratio (WDSR) and deficit ratio (DFR) are 53% and 47%, respectively. During drought periods (April-August), the DFR increases on average from 52% to 80% for some months.

Therefore, in view of the lowest WDSR and the significant DFR, the optimization of the current reservoir operation by taking into account the stochastic inflows to the reservoir is necessary to bring a significant improvement to the actual reservoir operating system.

Moreover, the performance metrics deduced from the observed records of water demand and releases collected from the eighteen-year reservoir operating budget (1999-2016) confirm the need to improve the current reservoir operation, as shown in Table 3.

Table 3: Performance metrics of Ghrib historical reservoir operation

	Sep	**Oct**	**Nov**	**Dec**	**Jan**	**Feb**
WDSR (%)	49.38	57.86	61.43	62.18	57.83	51.47
DFR (%)	50.62	42.14	38.57	37.82	42.17	48.53
	Mar	**Apr**	**Mai**	**Jun**	**Jul**	**Aug**
WDSR (%)	48.26	48.08	52.72	46.75	47.88	46.30
DFR (%)	51.74	51.92	47.28	53.25	52.12	53.70

Regarding the increasing water demand, the expected objective is to satisfy it for each month and to reduce the observed deficit as much as possible in satisfying it. The optimization of the current reservoir operation was carried out according to two cases of observed and simulated inflows.

Optimization with GAs in a certain future (Historical records 1999-2016)

In the first case of observed inflows and for the algorithm initialization, releases from the reservoir are considered random; the performance metrics of the optimization results are reported in Table 4.

Table 4: Performance metrics of the optimized reservoir operation using GA

	Sep	Oct	Nov	Dec	Jan	Feb
WDSR. %	76.76	77.71	82.89	80.11	79.41	81.19
DFR. %	23.24	22.29	17.11	19.89	20.59	18.81
LR.%	-7	-31	-18	3	61	18
	Mar	**Apr**	**Mai**	**Jun**	**Jul**	**Aug**
WDSR. %	80,14	76,83	76,75	75,38	75,03	78,52
DFR. %	19,86	23,17	23,25	24,62	24,97	21,48
LR.%	-1	24	49	31	19	10

The results obtained from optimizing the current multipurpose reservoir operation are encouraging, regarding a significant increase in the average monthly WDSR reaching 78.4%, while it is 53% for historical releases. It exceeds 75% (Fig. 3) for each month, even in the summer period (June to August).

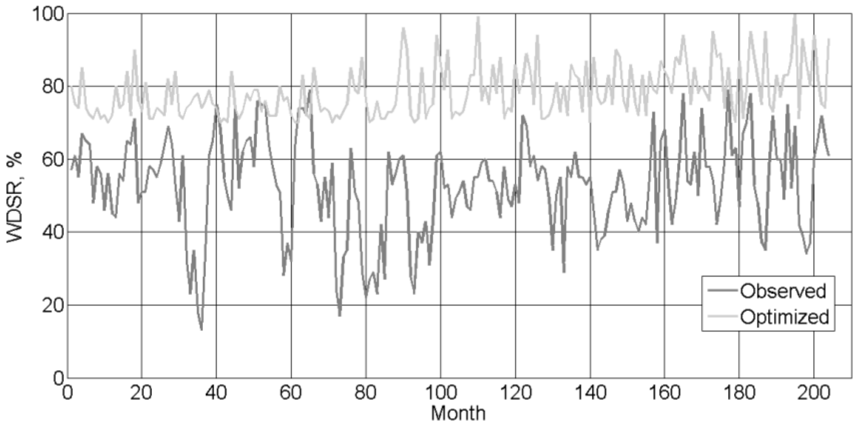

Figure 3: Comparison between observed and optimized WDSR

Likewise, the average monthly FR is clearly better than that calculated from the historical records (Fig. 4). It is 49.5% against an observed ratio of 45%, resulting in an additional storage of 11% relative to historical storage (Fig. 5).

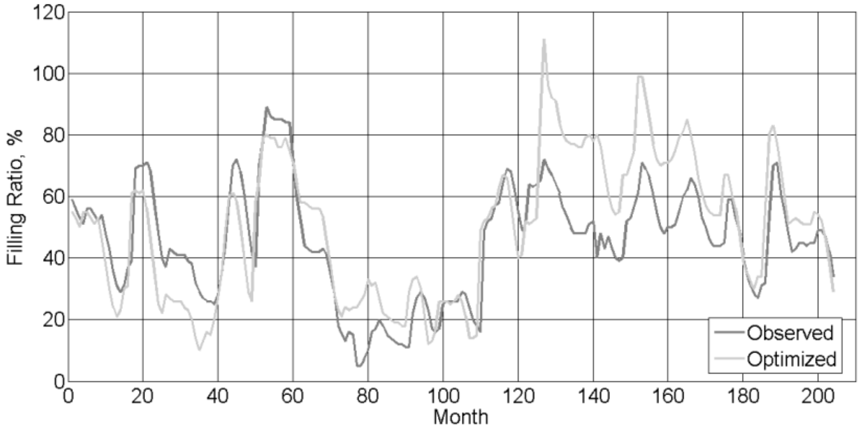

Figure 4: Comparison between observed and optimized reservoir filling ratios

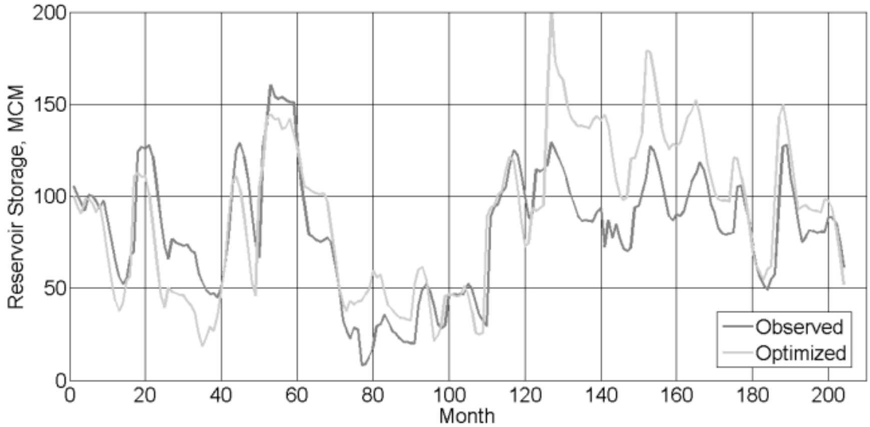

Figure 5: Comparison between observed and optimized reservoir storage

Moreover, during the summer, the average regularized volume remains higher, corresponding to more than 40% of the reservoir capacity, with a WDSR higher than 75%.

Stochastic Optimization of Reservoir Operation in an Uncertain Future

Monthly inflows simulation over a period of 70 years shows the generated values very close to the observed data. Nearly 75% of the total variance is explained by the first four principal components (PC) (Table 5).

Table 5: Contribution of each simulated water inflow PC to the total variance

Number of Dimensions (PC)	1	2	3	4
Eigenvalues	4.426	2.194	1.205	1.136
(%) of Principal components	36.88	18.28	10.04	9.47
(%) cumulated (PC)	36.88	55.16	65.20	74.67

To validate the simulated inflows relative to the observed inflows, their mean and standard deviation are compared (Table 6); the means are practically similar, and the standard deviations are relatively close from September to January. For the dry months (May-August), a consistent reproduction of the statistical inflow characteristics is noted.

The simulation of hydrological parameters using GESTOP enables us to generate different future scenarios and alternatives by anticipating all eventualities of probable events that may threaten water system safety or operation.

Table 6: Inflow mean and standard deviation values

	Observed		**Simulated**	
	Mean	**Std**	**Mean**	**Std**
September	2.48	3.24	2.76	3.88
October	12.11	20.27	11.60	24.88
November	5.25	6.08	6.60	7.90
December	7.30	11.31	7.99	17.37
January	7.33	13.69	6.45	11.42
February	10.93	17.86	6.51	10.96
March	13.68	15.30	11.32	11.99
April	8.59	10.69	8.60	9.79
May	2.81	3.07	3.19	4.19
June	2.72	4.11	4.03	8.86
July	0.60	0.85	0.84	2.82
August	0.50	0.57	0.52	0.50

The stochastic optimization of multipurpose reservoir operation using the simulated inflows brought a consistent improvement to the actual water system operating, according to the achieved performance metrics; it is highly efficient and convincing given the achieved results, as shown clearly in Table 7, where the average monthly WDSR is significantly better than that of the historical records (92% against 53%) and the monthly deficit is much lower.

Table 7: Performance metrics of the optimized reservoir operation in an uncertain future

	Sep	Oct	Nov	Dec	Jan	Feb
WDSR %	93.91	90.61	75.84	93.47	80.74	92.88
DFR %	6.09	9.39	24.16	6.53	19.26	7.12
LR%	-1	-50	-46	-83	-141	82
	Mar	**Apr**	**Mai**	**Jun**	**Jul**	**Aug**
WDSR %	96.12	95.66	95.86	94.39	96.27	92.11
DFR %	3.88	4.34	4.14	5.61	3.73	7.89
LR%	9	-46	-35	-35	13	57

However, the average monthly reservoir FR is 43%; this is relatively correct since the optimization procedure is carried out with drought scenarios. Even Fig. 6 shows some monthly periods where optimized storages are less than observed values because the optimization computation is implemented with a maximum water demand, increasing more than 20% relative to observed records. Nevertheless, we obtained a significant WDSR of approximately 92%, resulting in an LR of 23%, which is quite normal in the case of semiarid regions.

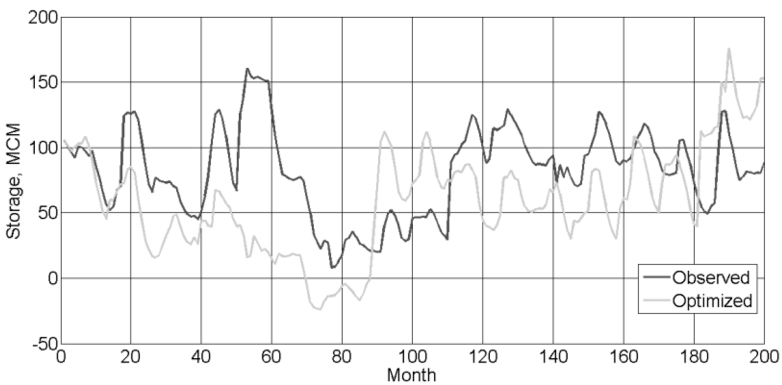

Figure 6: Reservoir storage after stochastic optimization

The performance of the results achieved in optimizing multipurpose reservoir operation through the GA and PCA models is highly demonstrated. Fig. 7 shows the fitness function in relation to the number of generations, where the convergence of the GA model to the optimum is reached with fewer iterations.

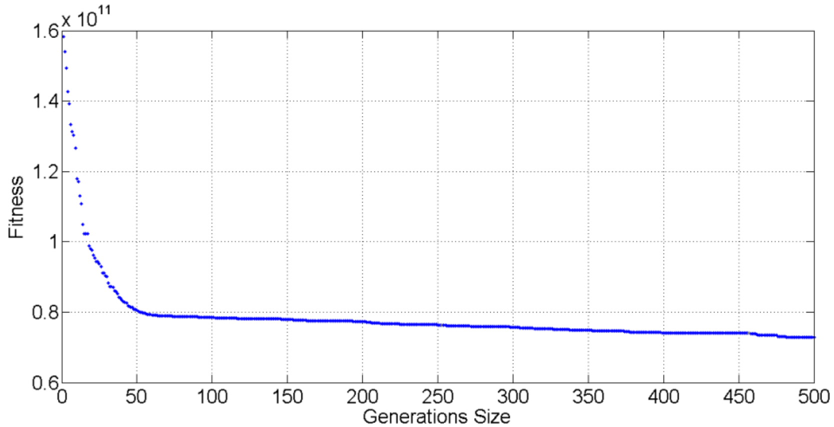

Figure 7: GA Algorithm converging

CONCLUSION

The reservoir operation optimization is very complex given numerous decision variables. This paper presented a search work for optimizing the operation of the Ghrib Reservoir, situated in a semiarid region (Algeria), where a consistent water supply from the reservoir is a difficult task.

The stochastic optimization model based on GA and PCA has demonstrated its robustness in improving the water demand satisfying ratio and in reducing the water deficit; the development of this optimized operation model in an uncertain future represents a decision support tool that could contribute to the improvement of the current reservoir operation by adequately supplying the increasing water demand and that, for a rational conservation of the active reservoir volume.

The optimized reservoir operation comprising the simulated water inflows enables the anticipation of water deficits while satisfying the water demand and reservoir storage with a high ratio, which is the reached research work target.

Therefore, it would be desirable to use the optimized operation model as a decision-making tool in terms of systematic knowledge of the filling ratio, release from the reservoir and reduction in water loss. In perspective, this model could be developed, improved and generalized to all multipurpose water systems in Algeria.

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