MAXIMIZING HYDROPOWER PRODUCTION FROM RESERVOIRS: THE CASE STUDY OF MARKABA

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ABSTRACT

Hydropower is a form of renewable energy that is clean and cheap. Under uncertain climatic conditions, maximization of hydropower production becomes a challenging task. Stochastic Dynamic programming (SDP) is a promising optimization algorithm that is used for complex non-linear reservoir operational policies and strategies. In this research, a combined simulation-SDP optimization model is developed and verified for maximizing large-scale hydropower production in a monthly time step. The model is developed to generate optimal operational policies for the Qarawn reservoir in Lebanon and test these policies in real time conditions. The model is used to derive operational regimes for the Qarawn reservoir under varying flows using transitional probability matrices. Simulating the derived rules and the generated operational policies proved effective in maximizing the hydropower production from the Markaba power plant. The model could be successfully applied to other hydropower dams in the region.

Keywords: hydropower, reservoirs, optimization, simulation, non-linear programming

INTRODUCTION

In arid and semi-arid regions, reservoirs are used to store seasonal river waters for periods when it is required most. Operational policies for reservoirs need to be derived to maximize the net benefit out of the reservoir objectives. This is by no means a simple task. How to come up with operational procedures heavily rely on the available storage, the possible net inflow or more accurately the probability of a certain inflow range, the reservoir losses, and of course the importance of the satisfied objective. Mathematical models have been used to simulate reservoir operation, but each reservoir remains a peculiar case, with the exercise repeated for different reservoirs and different scenarios.

Optimization techniques for reservoir operation have been extensively reviewed by Yeh (1985). Stochastic Dynamic Programming is one technique takes into consideration the probability distribution functions and successive probabilities of random variables and incorporates them into a model that transforms multistage decision-making problems into a series of single stage problems that are interrelated together. This capability enhances the suitability and usefulness of DP operation for the optimization of water resources system operation that is stochastic and non-linear in nature. In explicit SDP, the uncertainties of the random hydrologic variables are integrated in the model in the form of probability matrices that directly affect the optimization procedure. Clainos *et al.* (1972) tested the implementation of discrete transitional probability matrices in a stochastic DP model and discussed their role in arriving at optimal operational policies. To obtain an optimal policy, he concluded, conditional probability dependency matrices in an SDP model should be derived from historical inflow data. Trezos and Yeh (1987) developed an optimization model that uses a stochastic DP approach to optimize the production of a hydropower system by solving a series of quadratic programming problems. Lee *et al.* (1992) used a modified SDP model and concluded that rather than adopting commonly used rigid operation rule curves, it would be more appropriate to adopt a flexible operational policy, which would include transition periods between winter and summer storage levels. Huang and Wu (1993) developed a procedure to test the convergence of SDP models in reservoir operation. They considered that an SDP model is convergent if a linearly independent coefficient matrix that represents the uniqueness of conditional inflow probabilities exists. The rank of this matrix should be equal to the number of inflow states for the solution to be unique. Recent advances include Fuzzy Logic based SDP (Mousavi *et al*. 2004), and Metamodelling (Galelli & Sancini-Sessa, 2010) who combined SDP with a meta-model based on physical irrigation demand parameters for generating optimal solutions. Newer models include artificial neural networks (Deka & Chandramouli, 2009). However, application of these networks involve the presence of an expert system from which the networks can be trained to generate policies, something usually lacking in areas where reservoir operation is not based on expert opinion.

The objective of this research is to develop a combined optimization-simulation dynamic model with the following aims:

- To generate an optimal operational policy for maximizing hydropower production, in which the monthly water release would be a function of available storage as well as the possible inflow
- To test the performance of these policies by simulating them using historic reservoir inflows
- To compare the generated policies with the currently adopted policies for reservoir operation
- To determine the benefits of implementing the optimization-simulation model

The model is designed as a dynamic structure rather than inflexible, in the sense that the stochasticity of the reservoir inflows is incorporated in a way that will periodically update the generated policies using an SPD approach. The Qarawn reservoir in Lebanon is used as a case study. The reservoir is designed to generate hydropower from several power plants. Since the final stages of its construction in 1965, the reservoir has been operated with a sub optimal policy. The Litani Authority, established by the Lebanese Government in 1954, is responsible for the management, operation, and maintenance of the reservoir. Currently, the reservoir releases are done with a main purpose of trying to meet the energy demands of Electricite du Liban, the exclusive electrical power supplier in Lebanon. These releases are not made based on a systematic consideration of both the available storage and the possible inflow. The current operational procedure of the reservoir does not include any optimization consideration as to maximizing energy production. This study presents a short-term stationary operational policy for maximizing hydropower production.

METHODOLOGY

General

A stochastic dynamic programming model is developed to generate optimum operational policies that would minimize the deficit for irrigation while optimizing hydropower production. The model is validated by testing the performance of the generated operating rules within a simulation model using generated inflows that preserve the statistical moments of historic inflows records. The current operational policy of the reservoir is also simulated and compared to the SDP generated policy. Figure 1 shows the proposed general modeling approach.

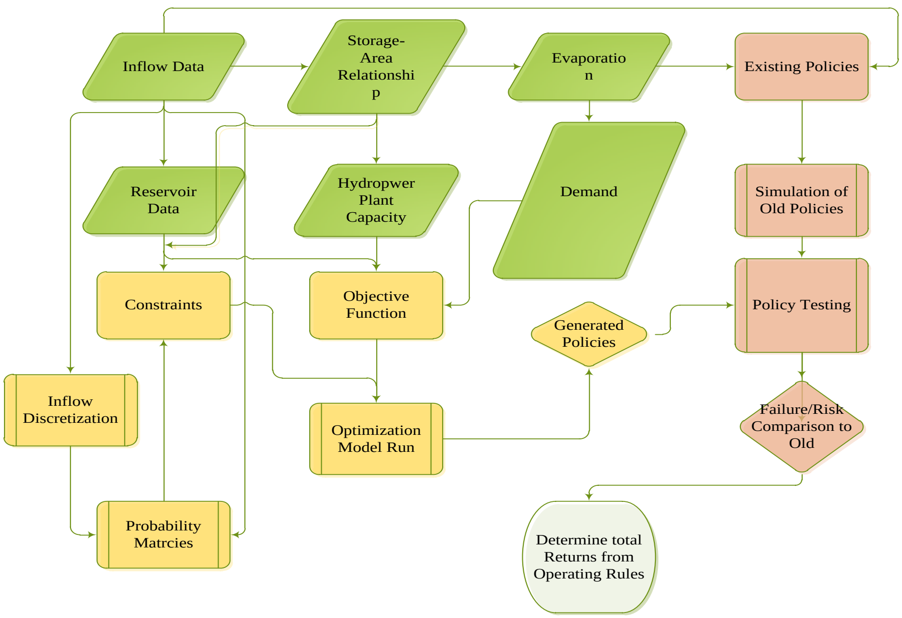

Figure 1. Optimization-simulation flowchart for the proposed model.

System configuration

Litani river

The Litani river (Figure 2) rises south of Baalbak in North Beqaa and flows 161 km to reach the Mediterranean sea 9 km North to Tyr in South Lebanon. The average precipitation per year over the riverbasin area (2175 km^2) sums up to 1665 MCM (770 mm). The river has been characterized by having high potential for irrigation and energy production. In order to use this potential of the river, the Lebanese government has been working on the development and implementation of the famous Litani Project since the mid-1950s.

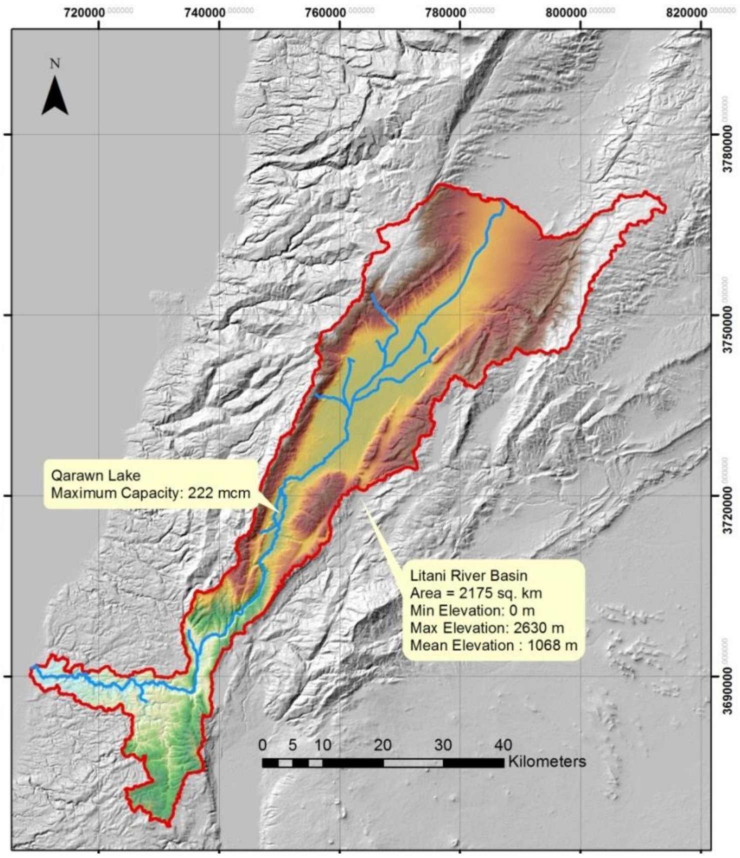

Figure 2. Elevation map of the Litani river basin.

Current Qarawn reservoir operation

In the original plans, the reservoir was designed as a multipurpose facility to supply water for irrigation, domestic use, and hydropower production. The current operational policy of the reservoir is to release water to meet the highly variable demand of Électricité du Liban (EDL) - the exclusive electrical power supply distributor in Lebanon - during peak hours of power consumption. EDL mainly depends on thermally generated energy, and it uses the hydropower system at Qarawn only as a supplemental source of energy. Therefore, the release neither depends on current reservoir storage nor on preceding inflow.

A short-term policy is herein developed to maximize hydropower production from the reservoir and optimize its current single purpose operation.

Hydropower production

Hydropower within the Litani Project is produced at three power plants. The first power plant downstream to the Qarawn reservoir is the one at Markabe (Abd El-Al Power Plant). It consists of 2 turbines with a total capacity of 34 MW. The plant uses an average of 265 MCM annually to produce 115 MKWh in a moderately wet year. The other two power plants are both located at Awali river downstream to Markabe plant. These power plants are the Awali (Paul Arcache) power plant (108MW) and or Joune (Charles El Helou) power plant (48 MW). Therefore, the three power plants have a total capacity of 192 MW. Electricity from hydropower varies during years. The average is 700 MKWh, which is less than 6% of the annual electricity distributed during the last twelve years. It is worthwhile mentioning that the power demand in Lebanon is not currently met from the existing system. At this stage of this study, hydropower production from the Markabe power plant is optimized.

Data collection and processing

Hydrologic data

Daily records of inflows, releases, and storages for 31 years were obtained from the Litani Authority. The data is converted to monthly values to be compatible for use within the developed simulation model that works with a monthly time step. The time step is very important for the development of the operational policies. Evaporation is calculated from average climatic data using the Penman method. The average monthly evaporation depth from the reservoir surface is determined and used in the simulation of the system throughout the optimization horizon.

Area-Head-Storage relationships

Available reservoir data gives the storage for each elevation of water in the reservoir above sea level. The following relationship was derived from the available data by quadratic regression:

$$H = -a\,(S)^2 + b\,(S) + c \quad \ldots\ldots\ldots\ldots\ldots \quad (1)$$

where H and S are the elevation of water from sea level (m) and the storage level in the reservoir (MCM), respectively; a, b and c are to be determined. This is used in the calculations of the evaporation rate and the objective function of the optimization model. An area-head relationship is derived through linear regression:

$$A = d\,H - e \qquad (2)$$

where A is the surface area (ha) and H is the elevation of water from sea level (m), and *d* and *e* are to be determined. The surface area at the beginning and the end of the time stage is calculated as a function of the storage using equations (1) and (2), simultaneously. The monthly average surface area of the reservoir is determined as:

$$\overline{A}(S_i, S_{i+1}) = \frac{\left[\ A(S_i) + A(S_{i+1})\ \right]}{2} \qquad (3)$$

After calculating the average evaporation rates for all time stages, the average monthly evaporated volume is calculated by multiplying this rate by the surface area of the reservoir:

$$E\text{ (MCM)/month} = \text{Evaporation rate mm/(month)} \times A(S_i, S_{i+1})\text{ (ha) } / C_f \qquad (4)$$

Where C_f is a conversion factor = 10^5

MODEL FORMULATION

Recursive equation

In a reservoir operation optimization model the state, decision, and hydrologic random variables are represented by the volume of water stored in the reservoir, the release, and the stream inflow to the reservoir, respectively. The objective function used is usually additive, and the optimization is usually based on a monthly time step. In hydropower systems, the return function reflects the amount of energy generated from the system as a function of the release and the available head for the turbine.

The stochastic dynamic programming model that is used is a backward-moving algorithm. The monthly inflow into the reservoir is considered as a first-order Markov process. The transition probabilities of different inflow classes is calculated from a large set of generated stream-flow data based on the 40 year historic record. The general form of the recursive equation that is optimized in the model is the following (Yeh, 1985):

$$f_t^u(S_t, I_{it}) = \underset{S_{t+1}}{optimize}\left\{\sum_j P_{ij}^{t+1}\left[B_t(S_t, I_{jt}, R_t) + f_{t+1}^{u-1}(S_{t+1}, I_{jt+1})\right]\right\} \qquad (5)$$

where:

$B_t(S_t, I_{jt}, R_t)$ is the value of the system performance (return function) in period t pertaining to an initial storage S_t, an inflow I_t of state (class) j and a release decision R_t; B_t can be a function of hydropower production, water demand shortage, or both.
$f_t^u(S_t, I_{ti})$ is the expected value of the objective function of the problem; t is the monthly time stage, within one year period; u is the total number of periods considered up to the current stage; S_t is the storage at the beginning of stage t; I_i and I_j are inflow variables at stage t of states i and j respectively; P^t_{ij} is the transitional inflow probability specifying the conditional probability that the current discrete inflow class in period t is at state j, given that the previous inflow in period t+1 is at state i.

Constraints

The above recursive equation is subject to the following constraints. The state transformation equation is used in its inverted form in order to keep all S_{t+1} terms on one side of the equation (Labadie, 1990):

$$R_t = S_t - S_{t+1} + I_{it} - E_t \times [A_t(S_t) + A_{t+1}(S_{t+1})]/2 \qquad (6)$$

where: E_t is the evaporation rate during period t (mm/week)

Any uncontrolled release beyond the monthly demand or turbine capacity is taken as spill. Seepage is considered negligible because grouting and treatment of the reservoir minimized the amount of water lost to infiltration. Constraints on the minimum and maximum release and storage variables are defined by the turbine capacity.

Recursive equation elements

Storage and release constraints

The minimum allowable storage $S_{t,\,min}$ in the model constraints is set at the value of the dead storage in the reservoir left for sedimentation and water supply augmentation in extremely dry years. The maximum storage $S_{t,\,max}$ is considered as the maximum capacity of the reservoir at its spillway level. For release constraints, the minimum bounds on the monthly releases $R_{t,min}$ is set to be equal to the least non-zero release increment that is chosen for DP calculations.

Inflow classes

The number and ranges of monthly inflow classes is chosen based on the full range of the historical sequence of inflows, their minimum and maximum values, and their standard deviation. The inflows were divided into discrete values (low, medium low, medium high, high) which will differ from week to week

The conditional probability that represents the monthly inflow transition from state to state is an n*n matrix of the following form:

$$\begin{bmatrix} P_{11} & P_{12} & P_{1..} & P_{1n} \\ P_{21} & P_{22} & P_{2..} & P_{2n} \\ P_{..1} & P_{..2} & P_{....} & P_{..n} \\ P_{n1} & P_{n2} & P_{n..} & P_{nn} \end{bmatrix}$$

One matrix is calculated for each monthly inflow class using the Lag-one Markov model.

Optimization

The optimization routine aims at maximizing hydropower production as a single purpose for the reservoir. The return function of the optimization equation (5) represents the hydropower production from the reservoir:

$$B_t = Hp_t \qquad (7)$$

$$Hp_t = T_{eff} \times PWRREL_t \times \left\{\frac{(H_t+H_{t+1})}{2} - f_{1t}\right\} \times T_{op} \times K \times \gamma \quad (8)$$

where Hp_t is the hydropower produced per week in MKWh:

Where:
T_{eff} = Turbine efficiency (fraction)
$PWRREL$ = the minimum value between the release at time t and the maximum turbine capacity (Turmax).

H_t = Head on turbine at the beginning of time stage t (m)
T_{op} = operating hours of the turbine /month = 600 hrs
γ = Specific weight for water = 9.81 KN/m^3
K = a constant including conversion units
Head on turbine is calculated in relation to the storage from equation (9):

$$H_t = a(S_t)^2 + b(S_t) + c - EL \quad (9)$$

Where: EL is the elevation of turbine above sea level. a, b, and c are coefficients determined by quadratic regression and f_{1t} is the friction loss during the time stage determined The hydropower produced in million kilowatt-hours (MKWh) during time stage t is calculated by relating turbine efficiency to the operating hours, the head of water and the release for power.

GENERATION AND SIMULATION OF OPERATING POLICIES

Operating policies

Monthly operating rules are generated from the optimization rules that give the end-of-week best storage as a linear function of the beginning-of-week storage. An optimal end-of-period storage S^*_{t+1} is given as a function of initial storage S_t for each inflow class. These rules are simulated to test their performance using the historic as well as generated inflow data preserving the historic moments.

Simulation model description

A simulation model is formulated based upon the state transformation equation.

When the current operational policy of the Qarawn reservoir is simulated, the end of-week storage is given by the simulation equations. When the generated policies are simulated, the end-of-week storage S_{t+1} is determined obtained from the operation rules. The inverted form of the state equation is used to calculate the monthly release R_t:

$$R_t = S_t - S_{t+1} + I_t - Ev_t - Sp_t \quad (10)$$

where Ev_t is the evaporated volume in week t

Simulation of current operation

Evaluation of the currently existing operational policy is based upon the spill failures, the violation of the minimum storage bound failures, and the hydropower produced (monthly and per annum). At each stage t, the end of week storage S_{t+1} was calculated using real values of historical releases. When this calculated S_{t+1} was greater than S_{max}, S_t of the next week was set equal to S_{max} and a spill failure $F_{sp} = 1$ was counted. Failure for minimum storage violation was counted also as $F_{smin} = 1$ when the calculated S_{t+1} was less than S_{min}. The percentage of spill failure and the percentage of minimum storage violation failure is determined:

The percentage of spill failure was determined as follows:

$$\%F_{sp} = \sum F_{sp} / n \tag{11}$$

The percentage of minimum storage violation failure was calculated as:

$$\%F_{min} = \sum F_{min} / n \tag{12}$$

Where n = the total number of stages t along the simulation horizon. The total failure percentage was then calculated as:

$$\%F_T = \%F_{min} + \%F_{sp} \tag{13}$$

Simulation of generated policies

The linear operational policies are integrated in the simulation model to determine the optimal target S_{t+1}. The state transformation equation is used in the simulation. The state equation was used in the inverted form, and S_{t+1} was given by the operational policy for given values of S_t and I_{t-1}. The needed operational policy was selected based upon the inflow class of the preceding time stage:

If $I_{t-1} \in$ class n, then use OP_{tn} to determine S_{t+1}

Where n = number of inflow classes

OP_t is the operational policy derived from the optimization procedure.

The determined S_{t+1} is used to calculate an initial value of the release:

If $R_{tcalc} < R_{min}$ or $R_{tcalc} > R_{max}$,

$$R_{tcalc} = S_t - S_{t+1} + I_t - E_i (S_t , S_{t+1}) \tag{14}$$

Then R_t R_{min} or $R_t = R_{max}$, respectively, and S_{t+1} is adjusted accordingly. The adjusted S_{t+1} is then tested against the upper and lower bounds of storage:

If adjusted $S_{t+1} > S_{max}$, then $S_{t+1} = S_{max}$. (15)

The spill Sp_t in the current time stage was calculated as: $Sp_t = S_{t+1} - S_{max}$ and the spill failure is counted as $F_{sp} = 1$. If calculated $S_{t+1} < S_{min}$, then minimum storage violation failure is counted as $F_{mins} = 1$, otherwise $F_{mins} = 0$. The adjusted S_{t+1} is used to serve as S_t for the next stage and the operational policy of the next week was chosen accordingly. The release R_t was used to calculate Hp_t as in the DP procedure.

RESULTS AND DISCUSSION

The generalized dynamic programming software CSUDP (Labadie, 1990) was the programming tool used for the optimization process. Three user-defined subroutines and one input data file were developed and compiled within the general CSUDP algorithm. In the first subroutine (subroutine state), the state transformation equation of the system was defined and used in the inverted form. The subroutine was also used to present the head-storage relationship, the area-head relationship, as well as the evaporation volume as a function of the evaporation rate and the reservoir area. The second subroutine (subroutine object) contained the objective function used in each scenario. The third subroutine (subroutine read-in) was used to input additional data required for the two subroutines like the maximum turbine flow, monthly evaporation rates, and water demand when necessary. The input data file requires information about:

- Dimension of the problem
- Type of state equation (inverted or non-inverted)
- Number of stages involved
- Minimum and maximum bounds on the releases and storages at each stage
- Desired number of iterations
- Type of objective function used (additive, multiplicative, or min-max)
- Kind of optimization (stochastic or deterministic).
- Kind of operational policies sought (stationary or non-stationary)
- Discretization of state and decision variables
- Transitional probability matrices (derived from inflow classes (Table 1))

In this case the developed problem was one-dimensional (one state variable was involved), and it was solved along twelve stages (monthly time step). Stationary stochastic policies were sought, and additive objective functions were chosen for all scenarios. Discretization of the state and decision variables (DELX) was controlled by the maximum limit of computational activities at each stage dictated by the capacity of the software. For the storage bounds of the reservoir, DELX was rounded up to 2 MCM. Convergence occurred in no more than 13 iterations. Output of the run included a file giving the optimal end of month storage Si+1 for each discrete value of beginning storage Si. It also yielded the additive optimal objective function value for each state increment. This information was used to develop the monthly operating rules using regression analysis. End results that are directly used for the reservoir operation are presented in Table 2. Table 3 shows the regression coefficients for the operational rules relationships. It is clear that the rules follow a linear pattern, making their application by the reservoir operator fairly simple.

TABLE 1

Inflow Classes for Operational Rules

	Inflows MCM							
	Class I		Class II		Class III		Class IV	
	Disc.	Range	Disc.	Range	Disc.	Range	Disc	Range
Jan	30	< 45	60	45-75	90	75-105	120	>105
Feb	30	< 45	60	45-75	90	75-105	120	>105
Mar	30	< 50	70	50-90	110	90-130	150	>130
Apr	20	<35	50	35-65	80	65-95	110	>95
May	10	<20	30	20-40	50	40-60	70	>60
June	2	<7	12	7-17	22	17-27	32	>27
July	1	<3	5	3-7	9	7-10.5	12	>10.5
Aug	1	<3	5	3-7	9	7-10.5	12	>10.5
Sep	1	<2.5	4	2.5-5.5	7	5.5-8.5	10	>8.5
Oct	4	<6.5	9	6.5-11.5	14	11.5-16.5	19	>16.5
Nov	8	<11.5	15	11.5-18.5	22	18.5-25.5	29	>25.5
Dec	10	<20	30	20-40	50	40-60	70	>60

TABLE 2

Operating Rules for the New Policy

	IT-1 ∈ CLASS I	IT-1 ∈ CLASS II	IT-1 ∈ CLASS III	IT-1 ∈ CLASS IV
Jan	0.69*S+ 50.90	0.71*S+53.42	0.72*S + 53.80	0.65*S +58.77
Feb	0.83*S+41.82	0.83*S+41.94	0.68*S + 77.60	0.83*S + 59.15
Mar	0.89*S+37.85	0.91*S+37.05	0.59*S+104.21	0.45*S+135.66
Apr	0.81*S+31.55	0.95*S+21.90	0.80*S + 67.0	0.57*S+ 114.55
May	0.80*S+22.32	0.83*S+20.94	0.84*S+39.90	0.77*S+ 66.48
June	0.81*S+10.04	0.79*S+20.28	0.84*S + 11.25	0.77*S + 39.33
July	0.79*S+7.20	0.79*S+8.37	0.79*S + 13.20	0.77*S + 16.49
Aug	0.77*S+5.98	0.77*S+6.30	0.77*S + 9.14	0.78*S+12.12
Sep	0.74*S+7.31	0.76*S+5.79	0.75*S+ 9.93	0.75*S + 9.93
Oct	0.75*S+5.57	0.78*S +3.37	0.79*S + 1.77	0.82*S + 2.30
Nov	0.80*S -0.88	0.83*S +0.056	0.84*S - 0.79	0.80*S + 6.55
Dec	0.80*S+13.21	0.82*S +19.22	0.82*S + 19.22	0.92*S+ 27.44

TABLE 3

Regression Coefficients for Operating Rules

	IT-1 ∈ CLASS I	IT-1 ∈ CLASS II	IT-1 ∈ CLASS III	IT-1 ∈ CLASS IV
Jan	0.9773	0.9665	0.9585	0.9334
Feb	0.9925	0.9927	0.9839	0.9705
Mar	0.9871	0.9896	0.9224	0.9045
Apr	0.997	0.9989	0.9516	0.8934
May	0.9844	0.9848	0.9713	0.9471
June	0.99	0.9808	0.9583	0.9426
July	0.9706	0.9523	0.9454	0.9502
Aug	0.9349	0.9302	0.9285	0.9335
Sep	0.9419	0.9305	0.9305	0.9335
Oct	0.944	0.9623	0.9393	0.9516
Nov	0.9688	0.9931	0.9929	0.9693
Dec	0.9804	0.9925	0.9927	0.9931

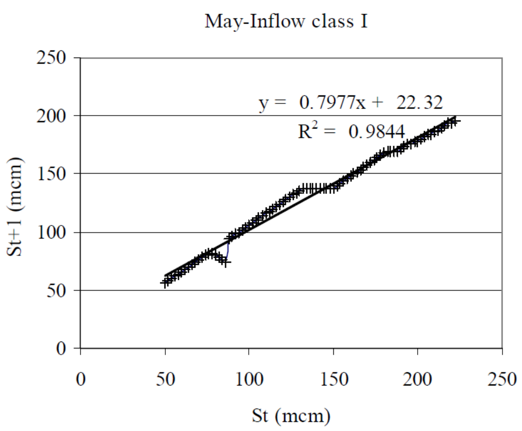

Figure 3. Operational rule for May, inflow class 1.

Figure 3 shows how the rules were derived. For a certain inflow class, the set of best releases (decision variables)

The old policy was simulated for hydropower production and reliability. Table 4 shows the simulation results. Table 5 shows a comparison between the spill and minimum storage violations (failures) for the two policies.

TABLE 4

Simulation Results for the Old and the Newly Generated Policy

Month	Mean Past Hydropower Production (MKWh)	Mean Hydropower Production (MKWh) (Proposed Policy)	Spill (Existing)	Spill (new)(mcm)
January	7.1	6.73	6.9	0
February	5.31	11.58	12	0.5
March	6.16	13.12	18	0.4
April	7.4	11.81	19.9	1.6
May	8.83	9.8	11.1	1.7
June	9.79	10.24	2.3	0
July	11.75	10.18	0.5	0
August	11.67	9.65	0	0
September	10.42	9.13	0	0
October	10.1	9.34	0	0
November	8.86	10.38	3.1	0
December	7.92	8.8	5	0
Sum	105.31	120.76	78.8	4.2

TABLE 5

Average Annual Failures and Shortages

Type of Failure (% of times)	Old Policy	Proposed Policy
Spill Failure	9	4.6
Minimum Storage Failure	18	2.4
Total failure	27	7

The total failures of the current policy are very high (27%). It is evident from the results of simulating the current operation that a new policy needs to be developed with a more robust approach than currently on-going. The new policy decreased the total failure to 7%. Comparing the simulations of the new policies and the existing policy for average annual hydropower production (Figure 4) yields the following: the average annual hydropower produced over 31 years of Qarawn reservoir operation was 105.3 MKWh/year. New operating policy yielded 120.7 MKWh/year (an increase of about 15 %).

Hydropower production for the old policy is highest in summer (11.75 MKWh in

July) and lowest in winter (5.31 MKWh in February). The production was inversely related to the inflow volume into the reservoir. This is because the hydropower release is independent of the preceding inflow, the occurring inflow and the existing storage. The release depends only on the demand of the Lebanese Company of Electricity (Electricite du Liban). On the contrary, the scenario1 policy tends to have a more stable hydropower production. The production was lowest in January (6.73 MKWh). In other months, hydropower production ranged from 8.8 MKWh up to 13.12 MKWh. The monthly distribution was a little bit different: the power production decreased in fall months (October and November), but remained almost constant throughout other year months.

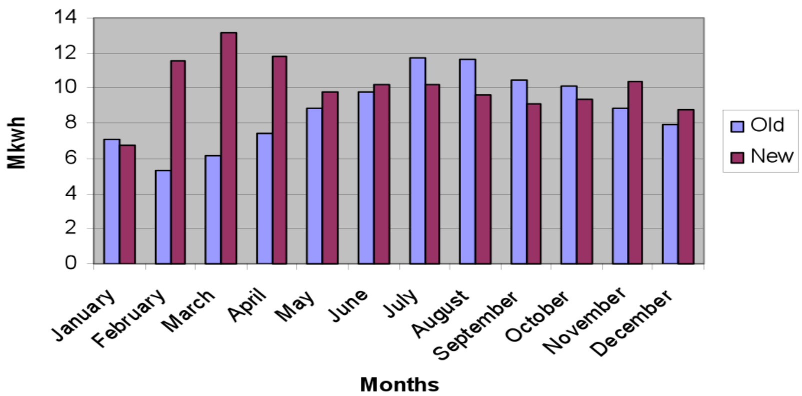

Figure 4. Average monthly hydropower production for the current policy (old) and new.

CONCLUSION

Population increase and the rising need for food production pauses tremendous shortage risks on energy supply systems. In this work a model that aims at maximizing hydropower production from reservoirs and simulating results in real time is presented. The resulting operational policies from the model are guaranteed to generate an optimal solution for the problem of interest. Implementing these policies increased hydropower production by 15% This will amount to more than 15 MKWH of clean energy, equivalent to an annual net income increase of more than $3.75 Million USD at the current diesel price and average diesel consumption of 250 g/KWh. This will also help reduce the pollution from power generated using fossil fuel. This research is fundamental for promoting the economic development as well as food production and security as the simple method can be easily applied to other proposed dams in Lebanon and elsewhere in the region. Future work includes optimizing operation to satisfy the multiple objectives from the whole system (including other downstream power plants and proposed reservoirs).

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