# EVOLUTIONARY ALGORITHM PSO AND HOLT WINTERS METHOD APPLIED IN HYDRO POWER PLANTS OPTIMIZATION

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**Abstract:** Forecasting power generation hydro production system is essential for optimum planning of electricity. Many researchers over the years have experimented with different techniques for optimal planning between the constituent institutions of a country Electric Power Corporation. Among these we can mention the time series models and optimization techniques PSO.

Time series models used mostly for predicting the factors affecting the production of electricity are: SARIMA, ETS, exponential smoothing (Holt-Winters) etc. In our country the most important factor in the production of energy are natural water inflow, characteristics of which are seasonality and periodicity. One of the models suitable to handle with these qualities is exponential smoothing PSO algorithm is among algorithms with efficiency in solving the optimization problem with non-linear nature which are used in modeling the problem of electricity generation. PSO algorithm variables in this case are volume and natural water inflow. The values of these variables, to the problem of optimizing the electrical power, are obtained from time-series forecasting techniques. Using PSO for the above problem we derive predictions for the short term electricity production in Albania.

Keywords: PSO, optimization, time series, Holt-Winters, HPP, forecast

# I. Introduction

The electricity production is one of the important indicators for economic and social development of a country. So the studyand forecast of the main factors affecting the production of electricity in hydro power generation system has a great importance. Since that the problem of electricity is important, its study is essential. Interpretation of this problem as a linear or non-linear optimization helps in solving problems in this area.

Various optimization techniques are used in water resources planning and management to model and study different types of problems relating to water supply, flood control, reservoir systems, hydropower operation, irrigation, etc. Traditional methods to predict hydrological variables of the optimization problem in hydro power plant are time-series analysis.

There are many authors who have given different formulations and solution methodologies applied to optimal operation problem for solving hydropower plants (HPP) Habibollahzadeh & Bubenko (1986); Wei L., *et.al.*, 2008); Jian *et.al.*, 2008); Zhou *et.al.*, 2013). Zhou and Yang (2013) have presented a method which combines the random simulation with the optimal operation of reservoirs group.

Zheng and Fu (2013) have done the evaluation of power generation efficiency in cascade hydropower plants of China. Mahor and Rangnekar (2012) have used the Time Varying Acceleration Coefficients PSO (TVAC\_PSO) to study the optimal generation schedule of real operated cascaded located at Narmada river in, India.

Holt-Winters was proposed in (1960) as an improvement of Holt method (1957), to take account of seasonality. (also known as triple exponential smoothing).

We consider the production of electricity in Albania hydro power generating system. The most important hydrological system in Albania has been built on the Drin river. Analysis of natural inflow time series for three HPP take in consideration helps in the selection of a suitable model for forecasting purposes. In this paper we present a combination of optimization techniques and time series models to have an optimal administration of hydroelectric resources.

## II. Case study

In this work we consider the Albanian hydro-electric system, especially the Drin Cascade where are located the most important HPP, Fierza, Koman, Vau i Dejes. Drin cascade is positioned in the north side of the county. It's the second most important cascade in Balkan based on productivity of hydroelectric power, it covers 92 % of the total production in the country which is only 50% of the total load. The main resource of energy production in Albania are natural water inflow. Due to its geographic position and her basin, Fierza is the most important HPP.Since the Fierza HPP is situated above Koman HPP, water discharge from gates or turbines are not considered as losses. Fierza discharges serves as the water inflow for Koman HHP and discharges of Koman are water inflow for Vau-Deja HPP which is the smaller of the two hydroelectric stations mentioned above. Figure 1 provided pictures of three most important HPP-s.



a) Fierza b) Komanc) Vau-Dejes

Figure 1. Geographic position of Fierza, Koman and Vau Dejes.

Production of electricity of the Drin basin depends directly from the rainfall, snowfall and other natural causes. The predictions made are based on a real database. This database is available since the construction of the cascade. Based on this data we could manage to obtain better predictions, which will help us to plan the production of electricity for the year that follows. Considering that the country demand for electricity is always increasing, our aim is to deal with the optimal planning problem.

## **Problem formulation**

The optimization problem that models the optimal electricity production is a maximization problem [8, 10]:

**Objective function:** The goal is generating the maximum power from the whole system, so the objective function can be described as *Maximum Hydropower Generation* 

$$MaxE = \sum_{t}^{T} P_{t}\Delta t \quad \text{where} \quad P_{i,t} = g\eta_{i,t}\rho Q_{i,t}H_{i,t}$$
(1)

where *T* is the total number of the computation time interval index; *n* is the total number of reservoirs in the multi-reservoir system; *i* is the index for the number of reservoirs;  $\Delta t$  is the time interval; *t* is the index for the current period;  $P_{i,t}$  is the output of power in the *t*th period;  $\eta_{i,t}$  is the hydropower generation efficiency of *i*-th reservoir in *t*-th period;  $Q_{i,t}$ ' is the release through the reservoir turbines of the *i*th reservoir in the *t*-th period;  $H_{i,t}$ , is the difference between reservoir water level and tail-racewater level of *i*-th reservoir in *t*-th period; *E* is the sum of the hydropower generation of the reservoir.

*Head equation*: The head is defined as the difference between the water levels in the upstream and downstream reservoirs of the hydro power plant, depending on the water storages in the respective reservoirs

$$H_{i,t} = X_{i,t} - X_{i+1,t}, i = 1, 2, 3$$
  
$$H_{4,t} = \omega, \text{ where } \omega = 23$$
 (2)

**Constraints.** The optimal value of the given objective function is computed subjected to constraints of two kinds; equality constraints and inequality constraints or simple variable bounds as given below.

**Equality constraints:** *Water balance equation*. The water balance equation, which contribute directly in water level, for each reservoir is given:

$$M_{i,t} = M_{i,t-1} + I_{i,t} + (\sum_{m \in M_i} q_{t,m} + s_{t,m}) - q_{i,t} - s_{ki,t}$$
(3)

Where  $M_{i,t}$  is the water storage of reservoir j at end of period k;  $l_{i,t}$  the natural inflow to reservoir j during the period k;  $q_{k,j}$  the water discharge of plants j;  $s_{k,j}$  is the water spillage by reservoir j; Mj is the set of reservoir upstream to reservoir j;  $s_{k,m}$  is the water quantity discharged from the upper reservoir gates;  $q_{k,m}$  is the water quantity discharged from the upper reservoir turbines.

**Inequality constraints:** Reservoir storage, turbine discharges rates, spillages and power generation limit should be in minimum and maximum bound.

*Reservoir storage bounds*: Generally in the hydro power plants the volume of water available is between the minimum draw down level and full reservoir level.

$$M_{i,\min} \le M_{i,t} \le M_{i,\max} \quad \text{(4)}$$

 $M_{i,t}$  water content of reservoir i at the end of position t;  $M_{i,max}$  installed storage capacity of a hydro power unit;  $M_{i,min}$  min storage contento of a hydro power unit;  $X_{i,t}$  water level of reservoir i at the end of position t;  $X_{i,max}$  max water level of reservoir i during position t;  $X_{i,min}$  min water level of reservoir i during position t.

*Water Discharge Bounds*: This is a minimum and maximum bound on the release of the hydro power plant through turbine.

$$Q_{i,\min} \le Q_{i,t} \le Q_{i,\max} \quad m/s^2 \tag{5}$$

 $Q_{i,t}$  water discharge of reservoir i during position t;  $Q_{i,max}$  max discharge of a hydro power plant;  $Q_{i,min}$  min discharge of a hydro power plant.

*Power Generation Bounds:* Power generated through hydro power plants should be minimum and maximum bounds.

$$P_{i,\min} \le P_{i,t} \le P_{i,\max} \qquad MW \tag{6}$$

 $P_{i,t}$  generated power of hydro unit i during position t (MW);  $P_{i,max}$  max generated power of a hydro plant (MW);  $P_{i,min}$  min generated power of a hydro plant (MW).

*Spillage:* Spillage from the reservoir is allowed only when to be released from reservoir exceeds the maximum discharge limits. Water spilled from reservoir i during time t can be calculated as follows

$$S_{i,t} \ge 0 \text{ and } S_{i,t} = \begin{cases} Q_{i,t}^{,} - Q_{i,t} & Q_{i,t}^{,} > Q_{i,t} \\ 0 & otherwise \end{cases}$$
(7)

*Initial & end reservoir storage volume:* The level of water in the reservoir after we operate must be the same as in the beginning. If we want to take an optimal choice than we should preserve the amount of water available in the reservoir.

$$\begin{split} X_j^0 &= X_j^{\text{begin}} \text{ and } X_j^T = X_j^{\text{end}} \end{split} \tag{8} \\ X_j^T - X_j^0 &= d \text{ where } |d| \leq 0.90. \end{split}$$

## III. Particle Swarm Optimization (PSO)

It was developed in 1995 by James Kennedy (social-psychologist) and Russell Eberhart (electrical-engineer).



Figure 2. Picture of birds flying and floating fish.

PSO is a robust stochastic optimization technique based on the movement and intelligence of swarms. It is inspired by social behavior and movement dynamics of insect's, birds and fish. PSO techniques Has successfully been applied to a wide variety of problems (Optimization of Electric Power Distribution, Neural Networks, Structural Optimization, Shape Topology Optimization) [8,9]. It uses a number of particles that constitute a swarm moving around in the search space looking for the best solution. Each particle is treated as a point in a D-dimensional space which adjusts its "flying" according to its own flying experience as well as the flying experience of other particles. Each particle in D- dimensional search space The basic concept of PSO lies in accelerating each particle toward its Pbest and the Gbest locations, with a random weighted acceleration at each time step as shown in figure[8]. The change of position of the particle in the step (k+1) use the velocity vector in the current step and the position of the previous step.



Figure 3. Concept of modification of a searching point by PSO

The modification of the particle's velocity can be mathematically modeled according the following equation [11].

$$V_{id}^{k+1} = w \times V_{id}^{k} + C_1 \times rand_1() \times (Pbest_{id} - X_{id}^{k}) + C_2 \times rand_2()(Gbest_{id} - X_{id}^{k})$$
(9)  
where  $i = 1, 2, ..., N_p$ ;  $d = 1, 2, ..., N_q$ 

The modification of the particle's position  $X_{id}^{k+1} = X_{id}^k + V_{id}^{k+1}$  (10)

The steps of PSO algorithm involved in optimization are as follows [8]:

- Step 1: Initialize velocity of discharge particles between
- Step 2: Initialize position of discharge particle between for population size PS.
- Step 3: Initialize dependent discharge matrix.
- **Step 4:** Initialize the *Pbest(i)* and *Gbest*.
- Step 6: Calculate reservoir storage *Xj*,*t* with the help of eq. (4).
- Step 7: Check whether is within limit *X j*, min and Xj, max.
- **Step 8:** Evaluate the fitness function given with eq (1):
- **Step 9:** Is fitness value is greater than *Pbest(i)*?
  - If yes, set it as new *Pbest* (*i*) & go to the step10.
  - else go to the next step.
- **Step 10:** Is fitness value is greater than *Gbest*?
  - If yes, set it as new *Gbest* & go to the next step.
  - else go to next step
- Step 11: Check whether stopping criteria reached?
  - If yes then got to step 19.
  - else go to next step.
- Step12: Calculate acceleration coefficients using.
- Step 13: Update velocity of discharge particle using eq. (9).
- Step 14: Check whether Vjt is within limit Vj,min, Vj,max.
- Step 15: Update position of discharge particles using eq. (10).
- **Step 16:** Check whether *Uj*,*t* is within limit *Uj*,min,*Uj*,max.

Step 17: Update dependent discharge matrix considering hydraulic coupling.Step 18: Check for stopping criteria

- If *iter <it* \_max then increase iteration count by 1 & go to step 6.
- Else go to step 19.

Step 19: Last Gbest position of particles is optimal solution.

# IV. Time Series Of Water Inflow In Drin Cascade

Time series of water flow in Drin river cascade is an interesting one, it is influenced in her behavior by many external factors. Water flows in the Drin river cascade depend on weather conditions as for example high temperatures in the period of spring and summer affect the melting of snow in heights of the mountains and thus increase the water level of the HPP; precipitation in wet periods also increase the water level of the HPP. The rise of water level affects positively the production of electricity. By observing the time series of water inflow we may say that seasonal patterns are appropriate to model the electricity production in the short term.

Time series of water inflow in each of three HPP of Drin cascade show *periodicity* and *seasonality*. Observations of water inflow for Fierza HPP are shown in Figure 4.



Figure 4. Fierza water inflow time series (1991-2015).

To understand seasonality patterns in a time series we have used *Seasonality plot*.. Seasonality plot superimpose shorter time series in a coordinate system for all seasons observations recorded which enables the underlying seasonal pattern

to be seen more clearly, and also allows any substantial departures from the seasonal pattern to be easily identified. For example the series of water inflows have monthly observations so they overlap each year from January to December. Figure 5 show the seasonality plot for each of the time series of water inflow in Fierza, Koman and Vau-Dejës HPP. Observing carefully (especially Fierza HPP) we see repeated behavior almost each year from January to December.



Figure 5. Seasonality plot for Fierza, Koman, Vau-Dejes water inflow

**Seasonal methods for time series.** Selecting an appropriate method to forecast is important because we estimate how the time series of observations will continue into the near future. There are many simple forecast methods such as: *Average method* in which the forecast of all future values is equal to mean of observed data; *Naïve method* in which the forecast is equal to last observed value; *Seasonal naïve method* where the forecast is equal to the last value from same season etc.

In our previous work we have constructed forecasting model for time series of water inflow based on it's seasonality pattern [1,2]. A seasonal ARIMA model was developed and then used to forecast the water inflow in upcoming months combined with PSO. In this work we have tried to develop and construct another seasonal model based on seasonality pattern of the time series. In this work we propose an exponential smoothing method. The classic exponential smoothing method proposed by Holt (1957) assigned weights to observations based on the time of registration. The older the observation the smaller it's impact in forecast. The Holt-Winters method was proposed by Holt (1957) and latter developed by winters (1960). It takes into consideration trend as well as seasonality of the time series. A taxonomy of exponential smoothing methods is given by R.J.Hyndman et.al (2002). Three smoothing equations of Holt-Winters are:

one for the level, 
$$0 \le \alpha \le 1$$
  
one for trend,  $0 \le \beta^* \le 1$   
one for seasonality.  $0 \le \gamma \le 1 - \alpha$ 

where, m=period of seasonality (in our case m=12, because of monthly observations).

The equation to obtain the forecasted values of Holt-Winters with additive trend are:

$$\begin{array}{l} & \swarrow \\ y_{t+h|t} = l_{t} + hb_{t} + s_{t-m+h_{m}^{+}} \\ y_{t} = l_{t-1} + b_{t-1} + s_{t-m} + e_{t} \\ l_{t} = l_{t-1} + b_{t-1} + \alpha e_{t} \\ b_{t} = b_{t-1} + \beta e_{t} \\ s_{t} = s_{t-m} + \gamma e_{t} \end{array}$$

Additive and multiplicative versions give the same point forecasts but different Forecast intervals.

(*Note: fpp*, *forecast, expsmooth, HW packages in R offer the graphical view and other results of the constructed models*)

**Model selection.** Model selection is based on many error measure or informaton criteria. We have based our "best model selection" procedure on Akaike Information criterion (AIC, AICc), Bayesian Information criterion (BIC), MSE, MAPE, MASE, MAD etc.

Akaike Information Criterion

$$AIC = -2\log(Likelihood) + 2p$$

where p is the number of estimated parameters in the model. Minimizing the AIC gives the best model for prediction.

Because AIC does not have much meaning by itself so it is useful in comparison to AIC value for another model fitted to same data set. It is recommended to consider several models (on same data set) with AIC values close to the minimum. (a difference in AIC values of 2 or less is not regarded as substantial and we may choose the simpler but non-optimal model.).

AIC corrected (for small sample bias): 
$$AIC_c = AIC + \frac{2(p+1)(p+2)}{n-p}$$
  
Schwartz' Bayesian:  $BIC = AIC + p(\log(n) - 2)$ 

Other goodness of fit we have considered to select the best model are:

$$MAE = T^{-1} \sum_{t=1}^{T} |y_t - y_{t|t-1}|; \qquad MSE = T^{-1} \sum_{t=1}^{T} (y_t - y_{t|t-1})^2;$$

$$RMSE = \sqrt{T^{-1} \sum_{t=1}^{T} (y_t - y_{t|t-1})^2}; \qquad MAPE = 100T^{-1} \sum_{t=1}^{T} \frac{|y_t - y_{t|t-1}|}{|y_t|}$$

The Holt Winters models are selected from the R software results based on the accuracy measure and goodness of fit tests mention above.

Table 1 gives the parameter estimation of three water inflow time series in Fierza, Koman and Vau-Dejës.

Table 1.

	Fierza HPP	Koman HPP	Vau-Dejës HPP
Holt Winters	alpha: 0.543	alpha: 0.176	alpha: 0.488
Parameter	beta : 0	beta : 0	beta : 0
estimation	gamma: 0.461	gamma: 0.144	gamma: 0.276
	-	-	-

The forecasted values and confidence intervals for water inflow in Fierza HPP are then obtained and plotted as shown in figure 6. We clearly observe the seasonality patterns which are preserved in the coming months.



**Figure 6.**Smoothed values of water inflow in Fierza HPP and forecasted values for 24 months with confidence intervals.

#### V. Results and Discussions

Using the observed value from 1991 to 1015, we predict the value the natural water inflow with Holt-Winters methods for the time period 24 month (given in the first row of the table 1 and table 2). The forecasted value for the natural water inflow are used as input variables in PSO technique to provide the energy produced (given in the second row of the table 1 and table 2). Also we have used

Holt-Winters to predict the values of production in Fierza HPP (given in the third row of the table 1 and table 2).

**Table 1.** Production of Fierza HPP with PSO and H-W in time period March 2015 - February 2016.

Fierza <b>2015-2016</b>	Marc	Apr	May	June	July	Aug	Sept	Oct	Nov	Dec	Jan	Feb
Natural inflowHw	365	409	289	151	52	39	71	131	203	309	309	347
Prod (MW)PSO	120	190	200	100	140	135	150	50	65	150	160	180
Prod (MW)HW	191.37	182.86	161.91	134.08	121.19	122.52	102.78	113.9	118.23	161.44	197.15	182.717

**Table 2.** Production of Fierza HPP with PSO and H-W in time period March2016 -February 2017

Fierza 2016-2017	Marc	Apr	May	june	July	Aug	Sept	Oct	Nov	Dec	Jan	Feb
Natural inflow HW	394	437	318	180	81	68	99	160	232	337	337	376
Prod (MW) PSO	190	210	170	110	140	150	100	90	75	170	180	200
Prod (MW) HW	170.36	161.85	140.9	113.06	100.18	101.51	81.766	92.92	97.212	140.43	176.13	161.703

As we seen from the results in table 1 and table 2, the value of production taken from the combination of HW and PSO techniques and the value of production taken only from HW, are near to each other. The results of H-W are more smoothed than the obtained values by PSO technique.

**Comparing Holt-Winters and PSO Forecasted Values.** Predicted values obtained from PSO utilize forecasted values of water inflow from Holt-Winters method of time series, so these forecasted values are more accurate than the forecasted values based only in H-W models of production.





*Figure 6.* Forecasted values of energy production with PSO technique and H-W model.

As we see from the figure 6, the line obtained by of PSO techniques combined with HW maintains seasonality which are characteristic of natural water in flows, as well as spikes in extremes months (months wet or dry). While the HW forecast only provides estimates hammered without taking into account the extremes values, which are important in the prediction because of being repeated in seasonally.

## VI. Conclusion

In this work we propose a combination of optimization technique and time series models in order to obtain the optimal schedule of energy production. The PSO technique utilizes the forecasted value from HW as variables of the optimization problem which models hydropower plant energy production.

We have considered the Albanian hydro-electric system, especially the Drin Cascade where are located the most important HPP, Fierza, Koman, Vau i Dejes. We worked with Holt-Winters method to capture seasonality because in our country the most important factor in the energy production are natural water inflow, characteristics of which are *seasonality and periodicity*.

The variables values for the problem of optimizing the electrical power, where obtained from Holt-Winters forecasting techniques and then used as variables in PSO algorithm.

The obtained values from PSO algorithm results more accurate than the forecasted values based only in Holt-Winters models of production.

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