Hydro Power Plant optimization using the HBV model

Arthur Bagourd & Aigerim Baitassova

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Introduction

Hydro power plants are fast to get started and very flexible, thus they can react to peak demands or shortfalls from wind power and other types of energy. This is why they are considered as essential by power market players. Modeling the optimization of hydro power plants is of course critical to hydro power plants managers but is also essential to any actor in the power market. Indeed, power traders aim at modeling the entire power network and assets in order to deduct from it the supply and thus the power price. The optimization of hydro power plants is a complex process that requires to estimate several parameters, and in particular the inflows of water to the reservoir. Power traders tend to only look at the forecasted water level at the reservoir in order to determine the energy production for a given hydro power plant.
In this paper we aim to extend the hydro power plant optimization model by introducing a hydrological model to improve the forecasted usage of the plant and therefore of the supply. We use an existing hydrological model: the HBV model in which we allow for some simplifications.
We first introduce and explain the HBV model. In a second part we define the optimization problem for the hydro power plant. In a third part we discuss the results obtained from using the HBV model versus using the standard TSO (Transmission system operator) forecasts.

NB: This paper is destined to practitioners who want to improve their optimization and is not meant to extend the existing academic theory.

1 HBV model

The HBV model (Hydrologiska Byrns Vattenbalansavdelning) is an hydrological model meant to predict the river's runoff. The model aims at simulating daily discharge by using rainfall, temperature and estimates of potential evaporation. It comprises of four routines representing snow, soil water and evaporation, groundwater and routing routine. The HBV model (Bergstrm 1976) was first developed by the Swedish Meteorological and Hydrological Institute and initially was used for runoff simulations in Sweden. Since 1976, different versions of this model have been applied in more than 40 countries. The uses of this model in different countries are very various: flood forecasting, computing design flood for dam safety, simulation discharge from ungauged catchments, water resources evaluation etc. Here we use a simplified version of HBV model to simulate water runoff which is discharged in the reservoir. Practitioners are free to tweak it and to add parameters, this will not fundamentally change the results.

1.1 Notation

We define the following model variables:

- $a(t)$ the total water runoff on day t in m^3
- $a_0(t)$ the surface runoff in m^3
- $a_1(t)$ the interflow in m^3
- $a_2(t)$ the baseflow in m^3
- β the shape coefficient for the moisture deficit
- $E_a(t)$ the actual daily evapotranspiration
- F the degree-day factor
- FC the Field Capacity, ie the maximum storable soil moisture
- $K_0(t)$ the recession coefficient associated to the surface runflow
- $K_1(t)$ the recession coefficient associated to the inflow
- $K_2(t)$ the recession coefficient associated to the baseflow
- $PE_a(t)$ the daily adjusted potential evapotranspiration
- P_{eff} the effective precipitation that contributes to the surface runoff
- PE_m the long term monthly mean potential evapotranspiration
- $P(t)$ the volume of rainfall water in L
- PWP the soil Permanent Wilting Point, ie the minimal soil moisture a plant requires not to wilt
- $S_m(t)$ the snow melting rate
- $SM(t)$ the soil moisture in L
- $\frac{SM(t)}{FC}$ the soil moisture deficit
- T the last day of the model
- $\theta(t)$ the temperature on day t
- $\tilde{\theta}$ the temperature threshold for the processing of inputed precipitations
- $\bar{\theta}(t)$ the mean daily temperature
- θ_m the long term monthly mean temperature

1.2 Model

The HBV model comprises of four main modules:

1. The snow melting and accumulation module
2. The soil moisture and effective precipitation module
3. The evapotranspiration module
4. The runoff module

The model is illustrated in Figure 1.

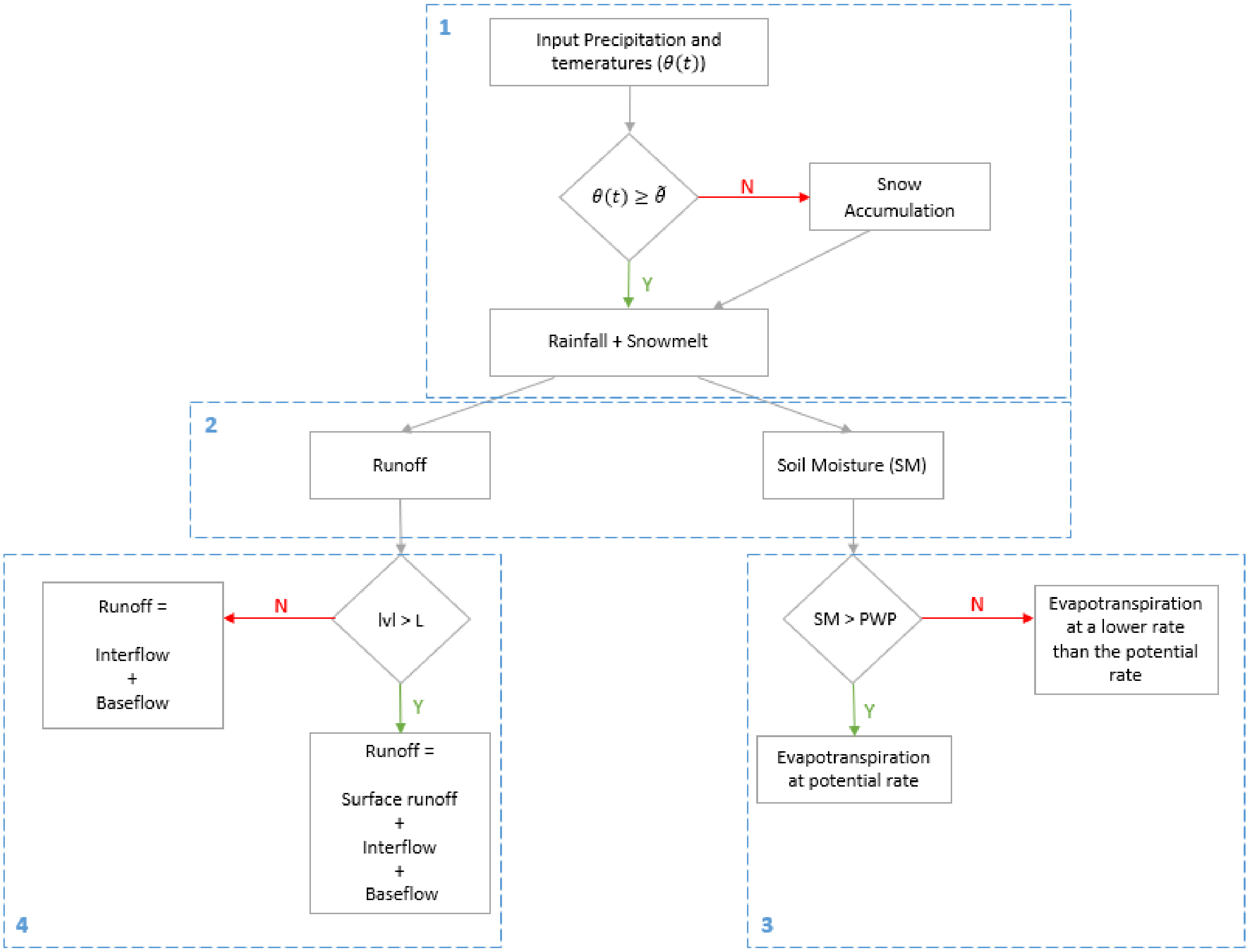

Figure 1: The HBV model

The inputs of the model are the following:

- precipitations as a time series: $P(t)\ \forall t \in [0, T]$
- temperatures as a time series: $\theta(t)\ \forall t \in [0, T]$
- long-term estimates of monthly temperatures for each month $\forall \text{m} \in \{1, ..., 12\}$
- long-term estimate of potential evapotranspiration rates $\forall \text{m} \in \{1, ..., 12\}$

The model works as follows:

1. The model first processes the input precipitations $P(t)$, if the input temperature $\theta(t)$ is higher than a given threshold $\tilde{\theta}$, the precipitation are processed as rainfalls, else they contribute to the snow accumulation. If $\theta(t) \geq \tilde{\theta}$ not only is there rainfall but also the accumulated snow (if any) starts to melt,
2. The rainfalls and the melted snow are then processed into the soil moisture module to evaluate which proportion of it contributes to the surface runoff and which contributes to the soil moisture storage.
3. Then, the soil moisture can be evaporated through the evapotranspiration module.
4. Finally the output of the model is the water runoff, which itself comprises of:

- The surface runoff $a_0(t)$ the fastest runoff
- The interflow $a_1(t)$, which is the near surface flow
- The baseflow $a_2(t)$, which is the groundwater flow, the slowest runoff

Now follows an explanation of each module.

1.2.1 Snow melting and accumulation module

Snow melting and accumulation are assumed to be proportional to temperatures. We can distinguish the following cases:

- If $\theta(t) \geq \tilde{\theta}$, the snow melts and precipitations contribute as rainfalls
- else $\theta(t) \leq \tilde{\theta}$, precipitations accumulate as snow

The snow melting rate as water is given by the following equation

$$S_m(t) = F\dot{(}\theta(t) - \tilde{\theta})$$

with F the degree-day factor which represents the decrease of water in the snow caused by a rise of 1 degree above the threshold $\tilde{\theta}$. It can be assumed constant or varying: as rainfall increases, so does the snow melting as additional thermal energy is available in the warmer rainwater.

NB: A reasonable value for $\tilde{\theta}$ is 0°C.

NB 2: For the sake of simplicity we will assume F to be constant in the rest of this paper.

1.2.2 Soil moisture

From the rainfalls and snow melt there is water contributing to the surface runoff while the remaining contributes to the soil moisture $SM(t)$. We define the Field Capacity FC as the maximum soil moisture that the subsurface zone can store. The higher the amount of soil moisture, the more the precipitation contributes to the runoff. As the soil moisture amount tends to FC, the infiltration reduces and the runoff contribution increases.

$$P_{\text{eff}}(t) = \left(\frac{SM(t)}{FC}\right)^{\beta} (P(t) + S_m(t))$$

with:

- $S_m(t)$ the melted snow
- $P_{\text{eff}}(t)$ the effective precipitation
- $SM(t)$ the actual soil moisture
- FC the Field Capacity, ie the maximum soil storage
- $P(t)$ the volume of rainfall water
- $\beta \geq 0$ the shape coefficient

The ratio $\frac{SM}{FC}$ represents the soil moisture deficit and $\frac{P_eff}{P+S_m}$ the runoff coefficient.
And for a given soil moisture deficit, β controls the proportion of the water amount $(P(t) + S_m(t))$ that contributes to the runoff $P_{\text{eff}}(t)$, the higher the β, the lower the runoff coefficient $\frac{P_eff}{P+S_m}$.

1.2.3 Evapotranspiration

Using the inputed long-term monthly mean potential evapotranspiration, we can compute for each day the adjusted potential evapotranspiration. It is computed by reducing the long term monthly potential value based on the difference between the daily mean temperature and the long term monthly mean temperature:

$$PE_a(t) = (1 + C(\bar{\theta}(t) - \theta_m)).PE_m$$

where

- $PE_a(t)$ is the daily adjusted potential evapostranspiration
- $\bar{\theta}(t)$ is the mean daily temperature
- θ_m is the long term monthly mean temperature
- PE_m is the long-term monthly mean potential evapotranspiration
- C is a model parameter

Parameter C helps to improve the performance when the deviation between $\bar{\theta}(t)$ and θ_m is too big. The relation between the daily evapotranspiration $E_a(t)$ and the soil moisture $SM(t)$ is given by the following equations:

$$E_a(t) = PE_a(t)\frac{SM(t)}{PWP} \text{ if } SM(t) \leq PWP$$

$$E_a(t) = PE_a(t) \text{ if } SM(t) \geq PWP$$

where PWP is the Soil Permanent Wilting Point, ie the minimal amount of soil moisture for plants not to wilt. This equation adjusts the evapotranspiration to the lack of soil moisture availability below PWP.

NB: C and PWP can be estimated by model calibration.

1.2.4 Runoff Discharge

As illustrated on figure 1.2.4 we model the water flows using theoretical reservoirs. An upper reservoir models the surface and near surface flows while a lower one models the groundwater flow. They are connected to each other as water from the upper one percolates to the lower reservoir at a constant percolation quantity $Perc$. Finally the water runoff is comprised of three different sub-runoffs:

- The surface runoff $a_0(t)$ is the fastest runoff and runs only if the water level is higher than a threshold L
- The interflow $a_1(t)$, which is the near surface flow
- The baseflow $a_2(t)$, which is the groundwater flow, the slowest one

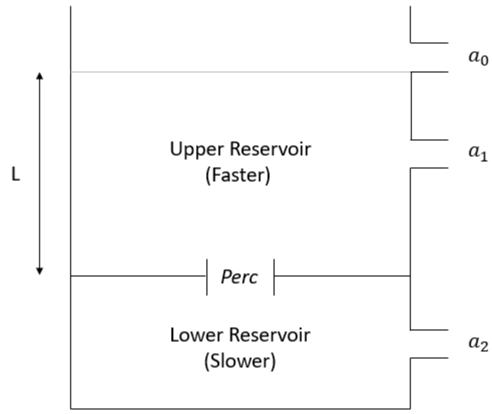

Figure 2: Theoretical reservoirs representation

We define by rl and ru the quantity of water in the upper and the lower reservoirs respectively. They have the following inflow dynamics:

$$ru(t) = (ru(t-1) + P_{\text{eff}}(t) - Perc)^{+}$$

$$rl(t) = rl(t-1) + \min\left(Perc, ru(t-1) + P_{\text{eff}}(t)\right)$$

Then the runoffs are given by:

$$a_0(t) = K_0\left(ru(t) - L\right)$$

$$a_1(t) = K_1\left(ru(t) - a_0(t)\right)$$

$$a_2(t) = K_2 rl(t)$$

With K_0, K_1 and K_2 the recession coefficients such that $K_0 \geq K_1 \geq K_2$ to respect the flowing speed orders.

The total water runoff obtained is the sum of the three water runoffs:

$$a_{\text{total}}(t) = a_0(t) + a_1(t) + a_2(t)$$

The final water in the reservoir is given by:

$$ru(t) = ru(t) - (a_0(t) + a_1(t))^{+}$$

$$rl(t) = rl(t) - a_2(t)$$

2 Hydro Power Plant modeling

We are now introducing the hydro power plant model. First we will briefly explain how a hydro power plant works. Then, we will describe the several constraints imposed by the regulators that we need to account for in our model. Finally we will introduce the objective function of the model.

2.1 Notation

The following notations will be used throughout this paper:

- $a(t)$ the inflow of water to the reservoir in m^3
- $\delta(t)$ the spilling, i.e. the water that leaves the reservoir if the production is at its maximum in m^3

- $e(t)$ the energy produced on day t in MWH
- $q(t)$ the flow that is ran in m^3
- $q_{\text{min}}(t)$ and $q_{\text{max}}(t)$ the daily bounds on flown quantities in m^3
- $S(t)$ the power spot price in $/MWH$
- $X(t)$ the level of the reservoir in m^3
- $X_{\text{min}}(t)$ the daily minimum of water in the reservoir in m^3 imposed by the regulator
- $X_{\text{max}}(t)$ the maximum reservoir capacity in m^3
- X_{end} the final water level minimum in reservoir in m^3

2.2 Operating a hydro power plant

Hydro power plant converts the energy of falling water into electricity. Water falling from reservoir through a dam turns a turbine that is connected to an energy generator. The used water is channeled to the river to continue the cycle of power generation. The main specification of the electricity is that it is non-storable commodity. That makes the pricing and optimization of Hydro power plant an issue that requires sophisticated methods. To optimize the profit of the hydropower plant we need to determine when and how much water to flow through a dam. This quantity in its turn depends on several parameters such as the water level in reservoir, the inflows to the reservoir, the regulatory and operational constraints on flow bounds and the spot price of electricity.

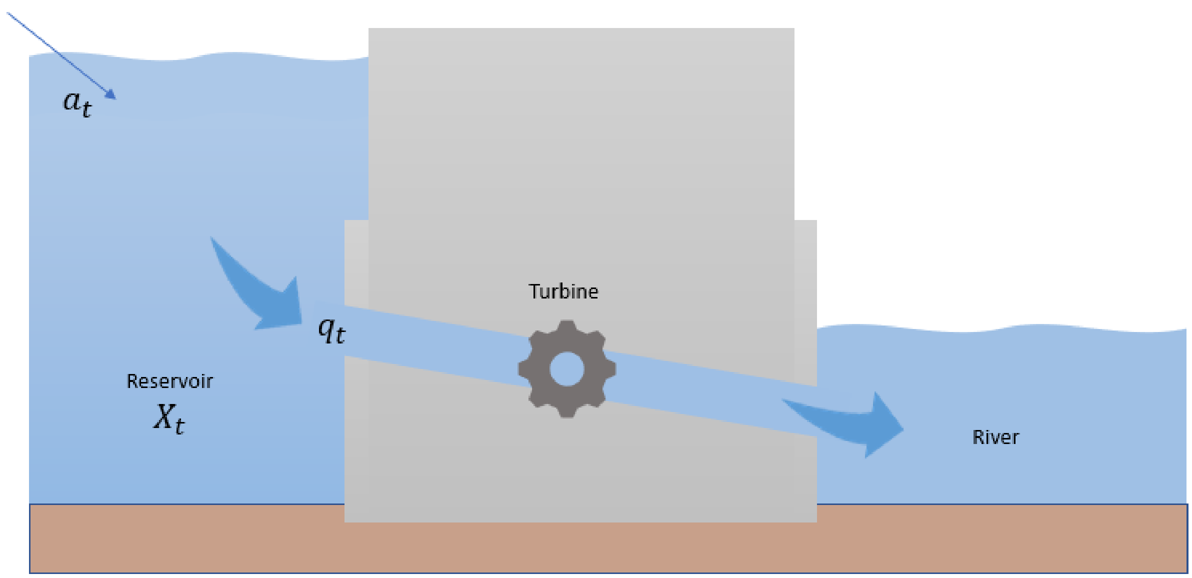

Figure 3: An Hydro Power Plant

Though in reality hydro power plants comprise of several hydro units to optimize at the same time, here we are using a simple unique power plant. The generalization of the model would not change much except for the computational time and the model complexity.

The water level $X(t)$ in the reservoir is defined by the following dynamic:

$$X(t) = X(t-1) + a(t) - q(t) - \delta(t)$$

In this paper we use the HBV modeling for the variable $a(t)$ in order to improve the model inputs.

2.3 Constraints

The operator of the dam needs to respect constraints imposed by the regulator. There are three types of constraints:

1. Constraints on daily flows
2. Constraints on the periodic flow
3. Constraints on the daily minimum reservoir volume
4. Constraint on the final minimum reservoir volume

2.3.1 Constraints on daily flows

The daily flow of water that is used on day t to produce power must satisfy the following condition:

$$q_{\text{min}}(t) \leq q(t) \leq q_{\text{max}}(t) \forall t \in [0, T]$$

2.3.2 Constraints on periodic flow

Over the running period of the hydro power plant, the total amount of water used to produce power must satisfy the following condition:

$$q_{\text{min [0,T]}} \leq \sum_{t=0}^{T} q(t) \leq q_{\text{max [0,T]}}$$

2.3.3 Daily constraints on minimum reservoir volume

The total volume of water that is left in the reservoir on day t must be higher than a certain amount imposed by the regulator:

$$X(t) + a(t) - q(t) - \delta(t) > X_{\text{min}}(t) \ \forall t \in [0, T]$$

2.3.4 Daily constraints on the maximum reservoir volume

On everyday the water volume in the reservoir $X(t)$ must be less than the capacity of the reservoir X_{max}. If it is not the case, the reservoir spills over the dam and flows to the river.

$$X(t) + a(t) - q(t) - \delta(t) < X_{\text{max}} \ \forall t \in [0, T]$$

2.3.5 Constraint on the final minimum reservoir volume

The volume that is left in the reservoir at the end of the running period, ie on day T, must satisfy the following constraint:

$$X(T) + a(T) - q(T) - \delta(T) > X_{\text{end}}$$

NB: Practically this constraint is actually included in the daily constraint on minimum reservoir volume.

2.4 Objective

We want to maximize the payoff of running the hydro power plant, our objective function is thus:

$$\max_q \sum_{t=0}^{T} e(t)S(t)$$

where $e(t)$ is the energy produced on day t in MWH.

with the following dynamic for the reservoir water level:

$$X(t) = X(t-1) + a(t) - q(t) - \delta(t)$$

and the previously defined constraints $\forall t \in [0, T]$:

$$q_{\text{min}}(t) \leq q(t) \leq q_{\text{max}}(t)$$

$$q_{\text{min [0,T]}} \leq \sum_{t=0}^{T} q(t) \leq q_{\text{max [0,T]}}$$

$$X(t) + a(t) - q(t) - \delta(t) > X_{\text{min}}(t)$$

$$X(t) + a(t) - q(t) - \delta(t) < X_{\text{max}}$$

$$X(T) + a(T) - q(T) - \delta(T) > X_{\text{end}}$$

To get the energy produced by the hydro power plant we use the following formula:

$$e(t) = \rho \times q(t) \times g \times h \times cf$$

where:

- $e(t)$ is the energy produced on day t in MWH
- ρ is the water density, ie $\rho = 1000kg/m^3$
- g is the acceleration of gravity, ie $g = 9.81m/s^2$
- h the head in m, ie the altitude from which the water fall to the turbine
- $q(t)$ the quantity of water flown on day t in m^3
- cf factor of conversion from J to MWH, $cf = 2.78e-7$

The endogenous variables are

- $q(t)$ the optimal flown water trajectory over time
- $X(t)$ the reservoir water level that depends on $q(t)$

The other variables are exogenous. Particularly $a(t)$ is derived using the predefined HBV model (see Section 1).

NB: For implementation purposes we rewrite the dynamic of the reservoir water level as follows:

$$\begin{aligned} X(t) &= X(t-1) + a(t) - q(t) - \delta(t) \\ &= X(0) + \sum_{k=0}^{t} (a(k) - \delta(k) - q(k)) \end{aligned}$$

3 Implementation and Results

We implemented the HBV model and the hydro power plant optimization in Python.
Our code can be found here (`http://github.com/Arthurim`).

We tested our model for the optimization of the french ”Grand’Maison dam”. Its characteristics are the following:

- Water reservoir capacity $X_{\text{max}} = 137e06\, m^3$
- Installed capacity of 1820 MW, ie the plant produces at most 43680 MWH per day.
- Head $h = 0.85m$
- Flow capacity of 216.3 m^3/s ie 216.3 * 86400 = 18688.3 m^3/day

For the water flows predictions we used data from the French Ministry of Ecology, Sustainable Development and Energy’s water database.

To calibrate the HBV we used data from local government agencies and cities that do gather data for the region (Isere). Data is scarce and very hard to find. There are very few data available. We had to make large assumptions regarding the quality and precision of those data.

Spot prices were publicly available on Epexspot website.

The goal was to look at the power plant optimization using the HBV model versus the power plant optimization using only water level that the TSO provides.

NB: We only used daily base prices as we optimize on a daily basis, but optimizing on a hourly basis would require to take into account both peak and base prices.

First let us look at the plot of actual water flow versus the predicted flow using the HBV.

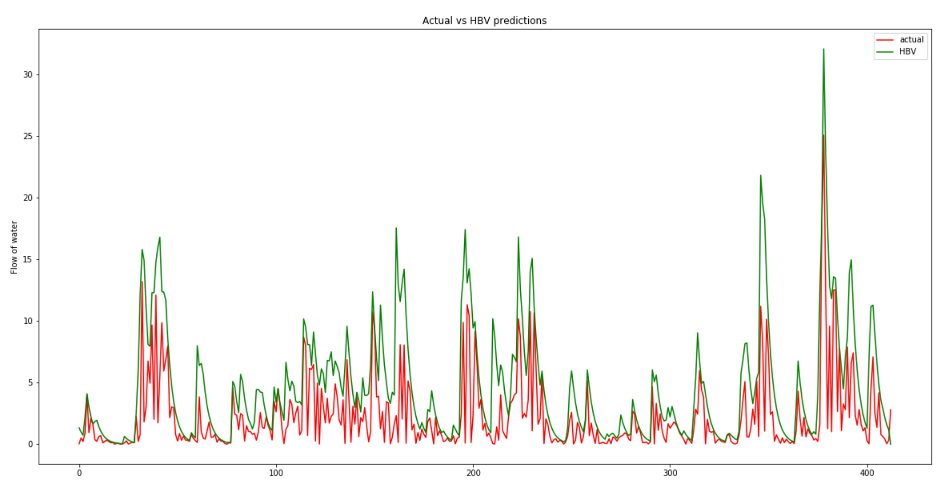

Figure 3: Actual flow vs HBV predicted flow

And now of the actual water flow versus the flow predicted by the TSO:

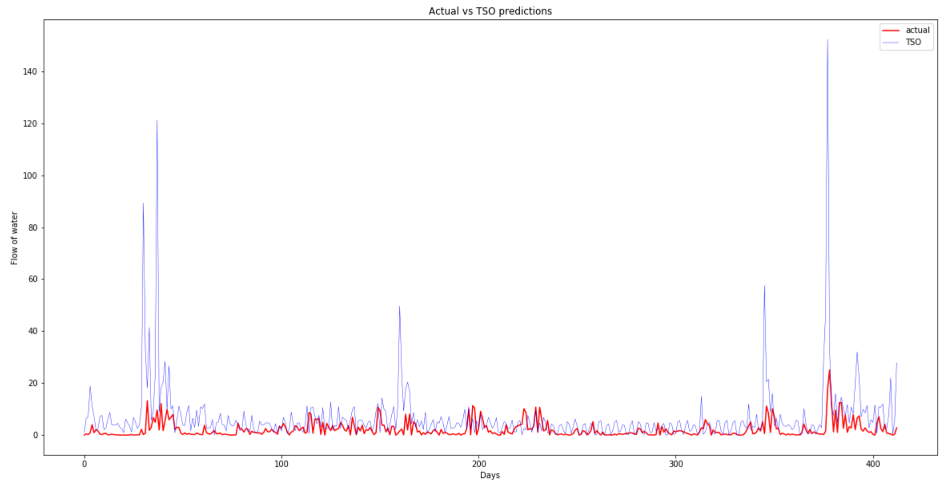

Figure 4: Actual flow vs TSO predicted flow

We can see that the TSO seemed to overestimate the actual water during the period while the HBV model predictions were better.
Using the HBV definitely improves the predicted flow of water, we have a correlation coefficient of 0.74 using it versus a correlation coefficient of 0.37 using the prediction from the TSO.
However that does not mean that it changes significantly the optimization of the hydro power plant. We need to have really different paths and P&Ls for the HBV model to truly add value.
First we conducted an optimization without daily constraints on the flows (ie $q_{\text{min}}(t) = 0$, $q_{\text{max}}(t) = X_{\text{max}}, q_{\text{min}}(t) = 0 \ \forall t \in [0, T]$) and with a minimum of 25% of the reservoir filled each day.
Let us look at the quantity flown paths we get for each case:

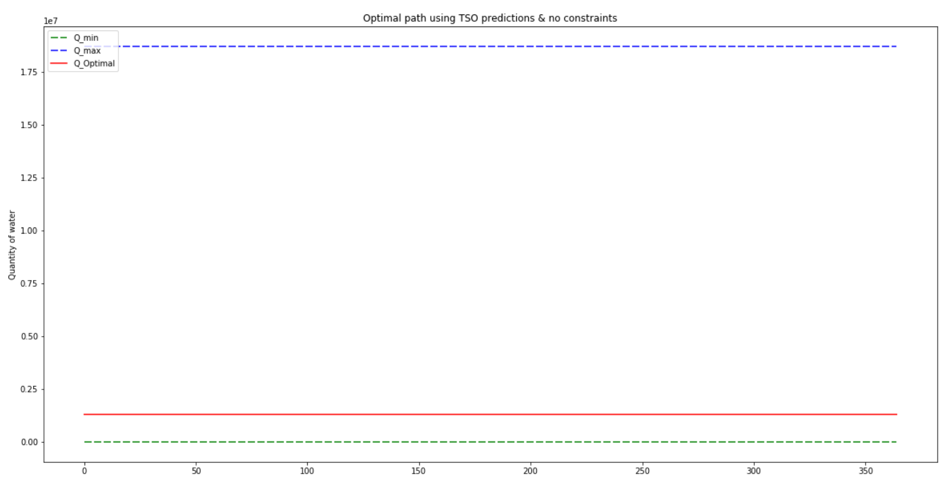

Figure 5: Optimal path using TSO predictions and no constraints

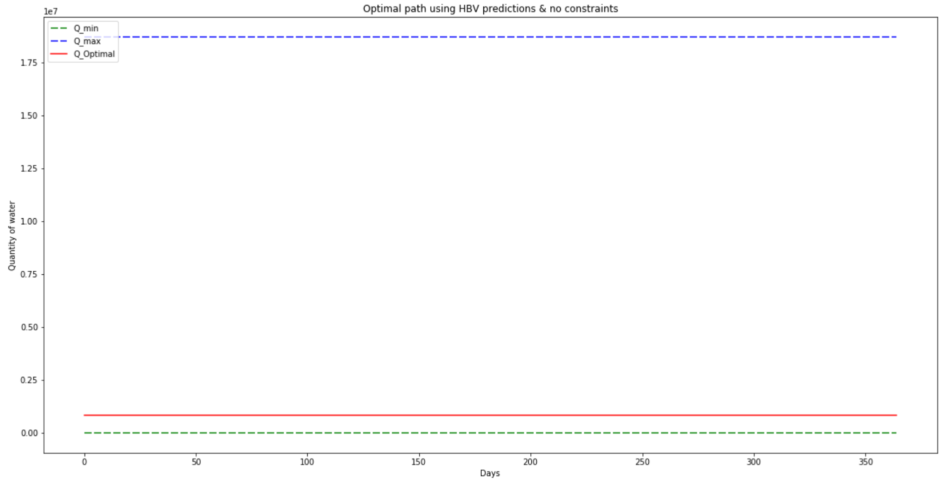

Figure 6: Optimal path using HBV predictions and no constraints

Using the TSO predictions we flow much more water than using the HBV predictions, this is easily explained by the fact that the TSO overestimates the water flows for each day. Flowing more water implies getting a higher P&L, it is 110 980 955 € using the TSO predictions, versus 71 585 888 € using the HBV predictions.
In this case using the HBV predictions instead of the one from the TSO does not seem very much beneficial.
Let us add constraints on the daily flows for the optimization, it yields the following paths:

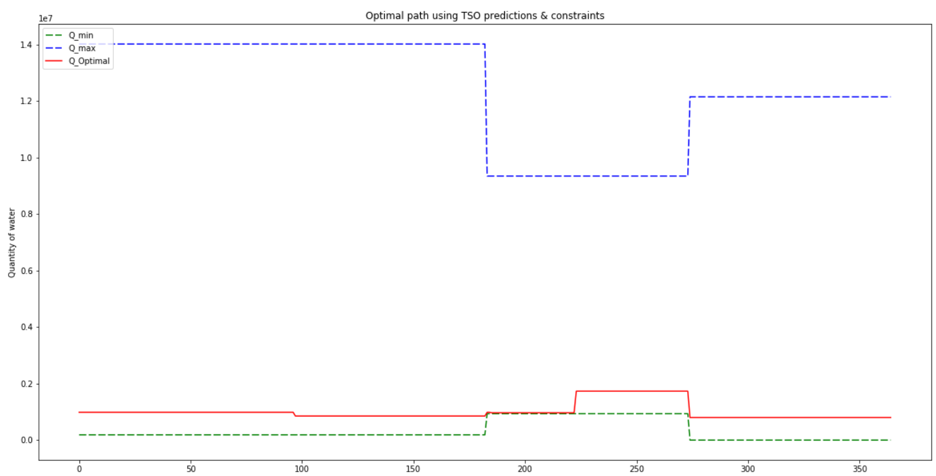

Figure 7: Optimal path using TSO predictions and constraints

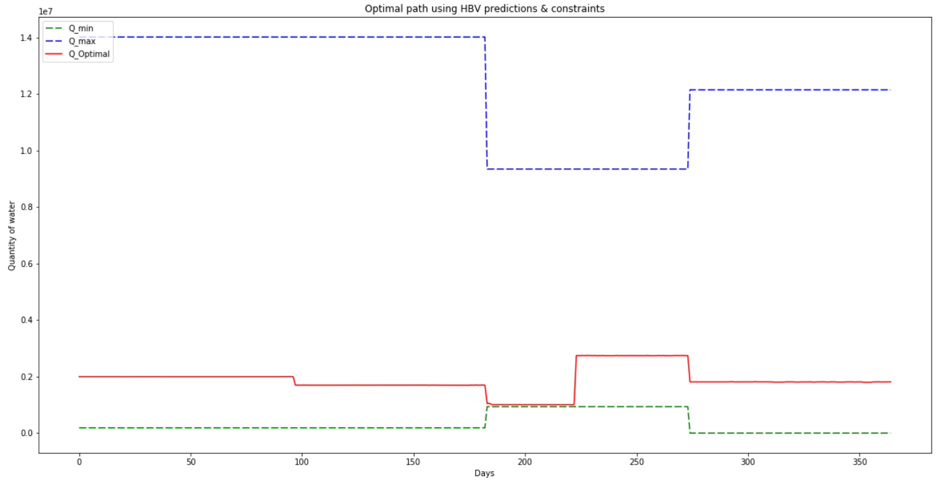

Figure 8: Optimal path using HBV predictions and constraints

This time the gap in P&Ls is on the other side: 85 433 467 € using the TSO predictions and 158 790 211 € using the HBV predictions, which is almost a 100% difference.
We can explain the first difference in P&Ls and optimization by the fact that the TSO overestimates the flows from the river, thus yielding to run more water for the hydro power plant and to sell more power. This is not a problem for the current period we looked at. However, looking at what is happening after, if prices were to go up and the available water to drop the power plant manager would miss an import profit. Thus we should always look for the most accurate predictions if the differences in P&Ls can be of such an importance.

The reader should however notice that this optimization might not be representative and other tests should be done on longer periods of optimization and on a larger sample of power plants.

4 Conclusion

In this paper we aimed at giving a better representation of the water flows that arrives at the hydro power plant reservoir in order to improve both the physical optimization of the asset by the power producer and the power trader that aims at representing the market to predict prices.

Our results are for this precise case of power plant optimization is that one should always look for the most accurate inputs if he desires to optimize the payoff of its hydro power plants. This would avoid him to miss opportunities in the future by using overestimated/underestimated water flow inputs. We should also remember that this study has been done in one precise case as data are very difficult to gather and that further tests should be conducted over other hydro power plants for the results of this study to generalize. It is also to be noted that the costs to access meteorological data of such a precision is very high and if it seems legitimate in our case it might not be in others.

For further work it is necessary to extend this study to a larger sample of hydro power plants. It could also be interesting to look at a dynamic programming implementation of the hydro power plant optimization. This would give us the exact right decision to take depending on the state in which we are and would therefore be very well suited for scenarios testing. Some hydro power plants have the capacity to pump the water during the night, then buying power at a lower price to sell it at higher price during the day. This could easily be implemented to improve our modeling. It would also be interesting to look at the use of the HBV model for more complex hydro power plants structures (with different plants on the same river to optimize) to see how the scale of differences would change.

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