

Displacements prediction of an arch dam: LSTM versus HST models

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ABSTRACT: The readings of the upper and lower pendulums of the central block of an arch dam have been analysed for the 2000-2012 period in order to predict the deflections which occurred in the following years 2013-2017. Data-based models using Machine Learning methods have been preferred to structural analyses for this prediction because all conditions were optimal for their use (large experimental period, few non-cyclic delayed effects, no major non-linear behaviour expected).

Preliminary models for both time series based on the Hydrostatic-Seasonal-Time (HST) statistical method were prepared with CONDOR-C software, developed by Tractebel. These models showed that the deflections readings had no time drift. Then the model for the deflections measured by the upper pendulum between the crest and the toe has been enhanced by taking into account the air temperature using the Hydrostatic-Seasonal-Time-Temperature (HST-T) statistical method. Logically the model for the deflections measured by the lower pendulum between the toe and the foundation was not significantly enhanced.

Both time series have then been analyzed with models based on Machine Learning methods on a web platform developed by Tractebel. Whereas the models based on the Support Vector Regression and the Random Forest methods could not accurately follow the readings over the validation period, the models based on the Long Short Term Memory method (Recurrent Neural Network) proved more efficient. They provided a prediction with an expected average accuracy of ± 2.5 mm for the readings of the upper pendulum and of ± 0.5 mm for the readings of the lower pendulum. The results compared well with HST/HSST models and were deemed more realistic when an extrapolation was needed.

1 INTRODUCTION

The objective of the present exercise is to predict the movements of an arch dam measured by pendulums CB2 and CB3 in the central block from 2013 to 2017, starting from observations accumulated during 2000-2012. For such purpose, two main methods are applicable: the structural, so-called 'deterministic' method, and the data-based one. Conditions prevailing for the subject are especially favourable to data-based analyses, since delayed effects are likely to be small. For this reason, the Authors decided to support their contribution upon data-based analyses.

Preliminary models for both time series based on the Hydrostatic-Seasonal-Time (HST) statistical method were prepared with CONDOR-C software, developed by Tractebel. These models showed that the deflections readings had no time drift. Then the model for the deflections of the upper pendulum (measured between the crest and the toe) has been enhanced by considering the air temperature. The model has been prepared with the Hydrostatic-Seasonal-Time-Temperature (HST-T) statistical method. Logically the model for the deflections measured by the lower pendulum (displacement between the toe and the foundation) was not significantly enhanced using the HST-T method.

The time series have then been analyzed with models based on Machine Learning methods on a web platform developed by Tractebel based on Support Vector Regression methods, Random Forest methods and Recurrent Neural Network methods whose results have been compared with those of HST/HST-T models.

2 PREPARATION OF THE DATA-BASED ANALYSIS

2.1 *Preparation of Databases*

Two databases have been prepared:

- One dedicated to Condor-C has been prepared including the main characteristics of the dam (crest level, height, date of impoundment) and with the readings extracted from the file ThemeA_data_fmt03.xlsx provided by the Formulator for the pendulums CB2 and CB3 in the central block of the dam.
- One dedicated to Tractebel Machine Learning Web Platform with the readings extracted from the file ThemeA_data_fmt03.xlsx provided by the Formulator with the special formatting required by the platform (cleaning of dates without water level or readings, time series for training and prediction on the last column of the Excel file). The characteristics of the dam have not been specified.

Statistical models have then been prepared with Condor-C for temperatures and water levels.

The attention has been called upon two special aspects which are discussed below. No abnormal reading or interpolated value (Tb temperatures) has been detected on these variables for the period 1995-2017.

2.2 *Seasonal variations of the reservoir level*

The reservoir level follows rather well a cyclic yearly variation (Figure 1), however the coupling with the season is imperfect with an explanation coefficient of only 0.25.

A rather good independence of hydrostatic ("H") and seasonal ("S") functions is therefore expected which is a favourable factor for the use of HST/HST-T models.

From 1995 to 2012 the reservoir has been operated between the normal water level and the minimum operating level, i.e. within the range 237 m – 174 m in the reference system given by the Formulator, and more precisely between 235.145 m and 181.89 m. This range is still valid from 2000 to 2012, a period when the deflections of the dam are known.

From 2013 to 2015 the reservoir levels have stayed within this range with yearly variations rather close to the ones known from 1995 to 2012.

The reservoir levels have been quite different in 2016 and 2017 as the reservoir was totally emptied in the first quarter of 2016 (down to 164 m) and as the yearly maximum reservoir levels stayed below those known before the full drawdown.

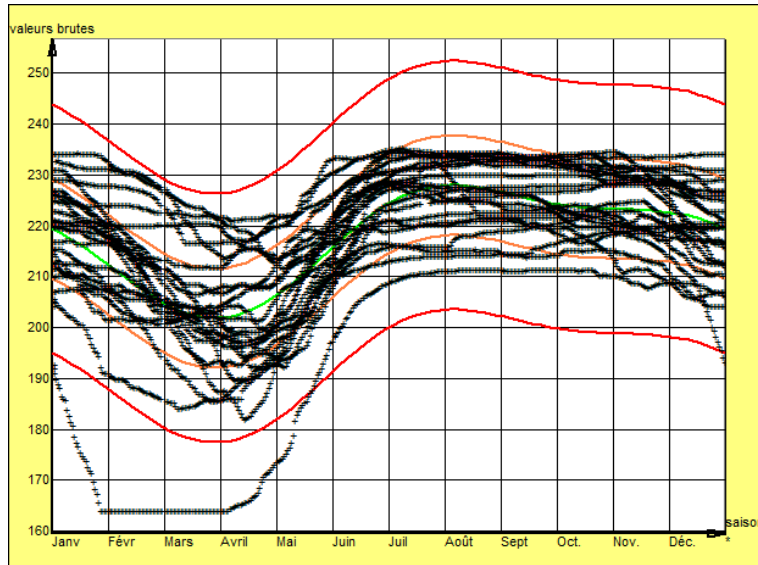


Figure 1. Yearly variations of reservoir level – 1995-2017.

2.3 Seasonal variations of temperature values and selection of temperature time series

The Formulator provided two time series of daily air temperatures from 1995 to 2017: Ta measured within 50 km from the dam but at a different altitude and Tb interpolated from several stations and reflecting the altitude of the dam.

Both time series show as expected similar seasonal variations with no time drift between them.

The standard deviation is roughly the same for both time series (respectively 6.24°C and 6.14°C) but the median value is lower for Tb (4.45°C for Tb compared to 12.60°C for Ta) as well as the minimum value (-15.5°C for Tb compared to -8.3°C for Ta) and the maximum value (20.5°C for Ta compared to 29.55°C for Tb). Tb values have been assumed to be more representative of the air temperature at the dam location and thus more likely to influence the pendulum readings variations and particularly the upper one.

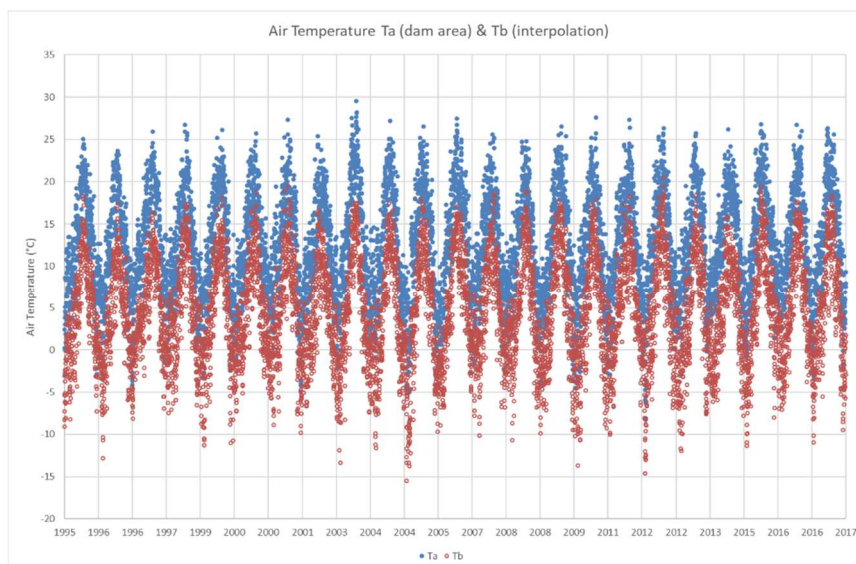


Figure 2. Variations of Air Temperature versus time – 1995-2017.

3 PREPARATION OF THE DATA-BASED MODELS

3.1 *HST and HST-T Models*

The HST models, classically used for the analysis of the monitoring data of dams, are multiple linear regression models which assume that the response of the dam is a sum of the responses to hydrostatic (“H”) and thermal loadings (“S”) (reversible effects) and in addition to time (“T”) (irreversible effects). The HST method has been improved by considering the deviations of observed temperatures to seasonal variations with a time lag is called HST-T (Penot, 2009).

$$\text{Reading} = \text{constant} + f(Z) + f(S) + f(T) + f(\theta) + \varepsilon$$

The coefficients of the functions of Z, S, T and θ are determined by multiple linear regression.

Several models have been prepared successively for CB2 and CB3 readings, until reaching a prediction considered optimal. Results have been evaluated on the basis of the residual variation coefficient, which quantifies the average difference between the predicted values and the readings. All models are based on the observations available between 01/01/2000 and 31/12/2012, that is 689 observations for CB2 and 682 observations for CB3.

- For both CB2 and CB3 models the default model automatically calculated by the software has discarded insignificant functions and the time effect functions: time step function, time-drift function T and drift reduction function Exp.(-T).
- For CB2 model the software has kept three “H” functions (Z, Z², Z³) and all four seasonal “S” functions (SinS, 1-CosS, Sin²S and SinS × CosS). The residual standard deviation is 2.5 mm which corresponds to an explanation coefficient as high as 73.5 percent.
- For CB3 model the software has kept three “H” functions (Z, Z³, Z⁴) and all four seasonal “S” functions (SinS, CosS, Sin²S and SinS × CosS). The residual standard deviation is 0.5 mm which corresponds to an explanation coefficient as high as 80.7 percent.
- Since H functions are used to simulate the effect of hydrostatic pressure on the upstream face of the dam, we capped the water levels below the dam foundation to 194.

A second model has been prepared for CB2 and CB3 with the influence of the air temperature Tb with a thermal inertia. The “H” and “S” functions are the same (and the “T” functions are still discarded). The CB2 model shows a better adjustment with a higher explanation coefficient (78.4 percent). The influence of the hydrostatic effect is slightly lower and the seasonal effect is slightly higher. The CB3 model does not show any better adjustment as the displacements of the toe of the dam are not significantly influenced by the short-term variations of the air temperature.

The main features of the CB2 model with Tb influence and CB3 model without Tb influence are provided below and illustrated by Figure 3 and Figure 4:

- The residual standard deviation is reduced to 2.0 mm for CB2 and is 0.5 mm for CB3,
- The corresponding explanation coefficients are higher than 70 percent, which is a good result: 78.4 percent for CB2 and 80.7 percent for CB3 (determination coefficients are respectively 95.3 percent and 96.3 percent),
- The influence of the seasonal effect is 20.7 mm for CB2, with the maximum at mid-August and the minimum at mid-January, and 2.6 mm for CB3, with the maximum at mid-August and the minimum at the end of February,
- The thermal inertia towards the air temperature calculated by Condor-C for CB2 model is 8.4 days,
- The influence of the hydrostatic effect when the water level varies from el. 235 to el. 194 (the correction function is no more valid below) is 27 mm for CB2 model and 9.1 mm for CB3 model.

Any attempt to obtain better adjustment of the models on readings over the 2000-2012 period have failed, which means that the models described above are the optimal ones for their kind. It has therefore been selected to carry out the prediction for the 2012-2017 period as a basis for comparison with the models based on Machine Learning methods.

CB2	CB3		
Prediction (mm) =	+19.6777	+5.4456	Constant
- 76.0574	- 21.48961	* Z	Hydrostatic functions Z = (237-water level) / 45
+47.1672	+11.4479	* Z ²	
		* Z ³	
		* Z ⁴	
- 8.4186	-0.7334	* [1-Cos(S)]	Seasonal functions S = 0 to 360 from 01/01 to 31/12
+ 5.4527	+1.0514	* Sin(S)	
- 1.0006	+0.2413	* Sin ² (S)	
- 3.5081	+0.3117	* Sin(S)*Cos(S)	
+0.6493		*f(T°C)	Thermal correction, thermal inertia = 8.2 days (defined by software)

Figure 3. Formulation of the statistical HST/HST-T models for CB2 and CB3 pendulums

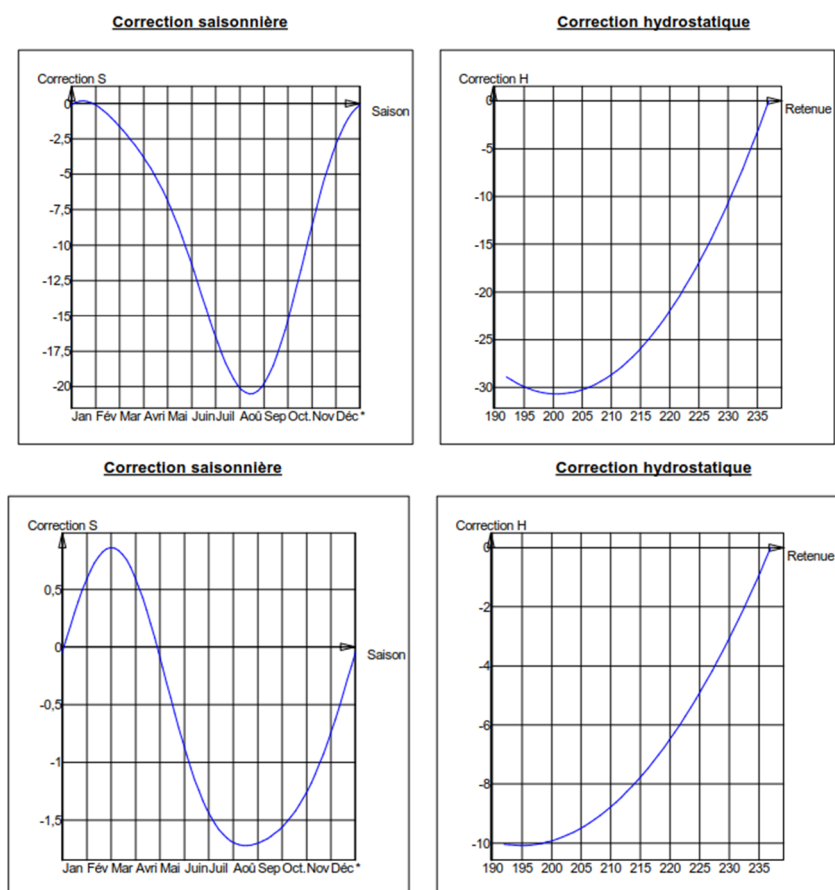


Figure 4. Left: Seasonal effect function; Right: hydrostatic effect function for CB2 model (Top) and CB3 model (Bottom)

3.2 Models based on Machine Learning Models

The Tractebel Machine Learning Web Platform has been developed to prepare and to run Support Vector Regression (SVR) models, Random Forest (RF) models and Recurrent Neural Networks (RNN) models. Scikit Learn, Tensor Flow, Keras and Plotly Python libraries have been used.

SVR methods (Vapnik, 1995) derive from Support Vector Machine (SVM) methods used for classification problems. RF methods (Breiman, 2001) are based on decision trees and segmentation functions. The reader will find a description of SVR and RF methods in (Veylon, 2021).

The Recurrent Neural Network method implemented in the platform is the Long Short Term Memory (LSTM) method well fitted for time series (Hochreiter, Schmidhuber, 1997). As the other RNNs, LSTM has a chain-like structure with repeating modules of neural network but the repeating module is more complex. The core idea is to control the memory with gates letting or no information through as illustrated by Figure 5.

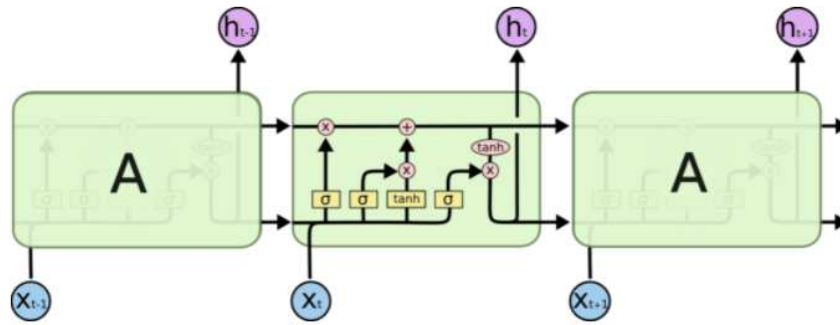


Figure 5. repeating module of LSTM (source: <https://colah.github.io/posts/2015-08-Understanding-LSTMs>)

The values given to the hyperparameters of the models have been chosen in the ranges generally proposed in the literature with a view to avoid over-fitting for the training period and to fit as much as possible the readings for the validation period. These values were as follows:

- SVR (Gaussian Kernel): C, regularization parameter penalizing the errors = 0.1; ϵ , tolerance margin on the regression error = 10.
- RF: number of trees = 100, number of variables randomly drawn at each branch = 2,
- LSTM: number of epochs, iterations during training = 30; batch-size, number of samples from the training dataset to work through before updating the internal model = 30; dropout percentage to avoid over-fitting = 30%. It has been checked that the number of epochs was sufficient to reach convergence.

The input variables used by the models are globally the same as those used for Condor-C models: “Z” functions: Z, Z^2, Z^3, Z^4 ; “S” functions: $\cos S, \sin S, \cos 2S, \sin 2S, 1 - \cos S, \sin S, \sin S \times \cos S$; “T” functions: $\exp(-T), T, T^2$. As no time function has been used in the HST/HST-T models, some models including time functions have been tested but proved to be less fitted for the validation period than the models without time functions. The input variables used by the models have then been all the “Z” functions and all the “S” functions.

For the training and the validation process, 70% of the readings of CB2 (respectively CB3) from 2000 to 2010 are used for training. The 30% left are used for testing. The data are selected by random draw for each run of the model.

As the values calculated by the model differ for each random draw, the model has been run ten times successively to give ten (independent) series of calculated values which have been averaged to reduce the variance of the predictions.

The concept of correcting the data by subtracting the reversible hydrostatic and seasonal effects does not exist for these methods, contrary to the HST and HST-T methods, as the formulation is non-linear. The residual variation coefficients can thus not be assessed. The selection of the best-fitted model has been based on the determination coefficient on the validation period. The data predicted from the model have been compared to the readings for the period 2011-2012, i.e. two full year of operation.

The SVR and RF models were not well fitted to the readings of the validation period. The determination coefficients for the validation period were around 60 percent. The LSTM models proved to be better fitted with determination coefficients on average 93.8 percent for CB2 model and 97 percent for CB3 model for the test period (30% of the readings from 2000 to 2010) and 82.9 percent for CB2 and 95.3 percent for CB3 for the validation period.

Figure 6 and Figure 7 show the main results of LSTM models for CB2 and CB3. The sign convention is: positive for downstream displacements of the upper part of pendulum (dam crest for CB2 and dam toe for CB3), negative for upstream displacements.

As LSTM models are not linear, the curves showing the influence of water level and season are drawn with the other parameters fixed at their median values (around 224 for reservoir level and July 1st for season).

The general trends are those expected: upstream displacement with increasing temperature and decreasing reservoir level with higher thermal and hydrostatic influence for the upper pendulum.

The influence of water level for and the influence of season has roughly the same shape for LSTM and HST/HST-T models for CB2 and CB3. The amplitude for seasonal influence is very similar for LSTM and HST/HST-T models. A smaller amplitude of the influence of water level is noted for LSTM models compared to HST/HST-T models: 21 mm compared to 27 mm for CB2 and 8.5 mm compared to 9.1 mm for CB3. The influence of the reservoir level for LSTM models is slightly smaller above 228.5 m for CB2 and 227.5 m for CB3 as shown by the small inflexion on the curves of Figure 6 and Figure 7.

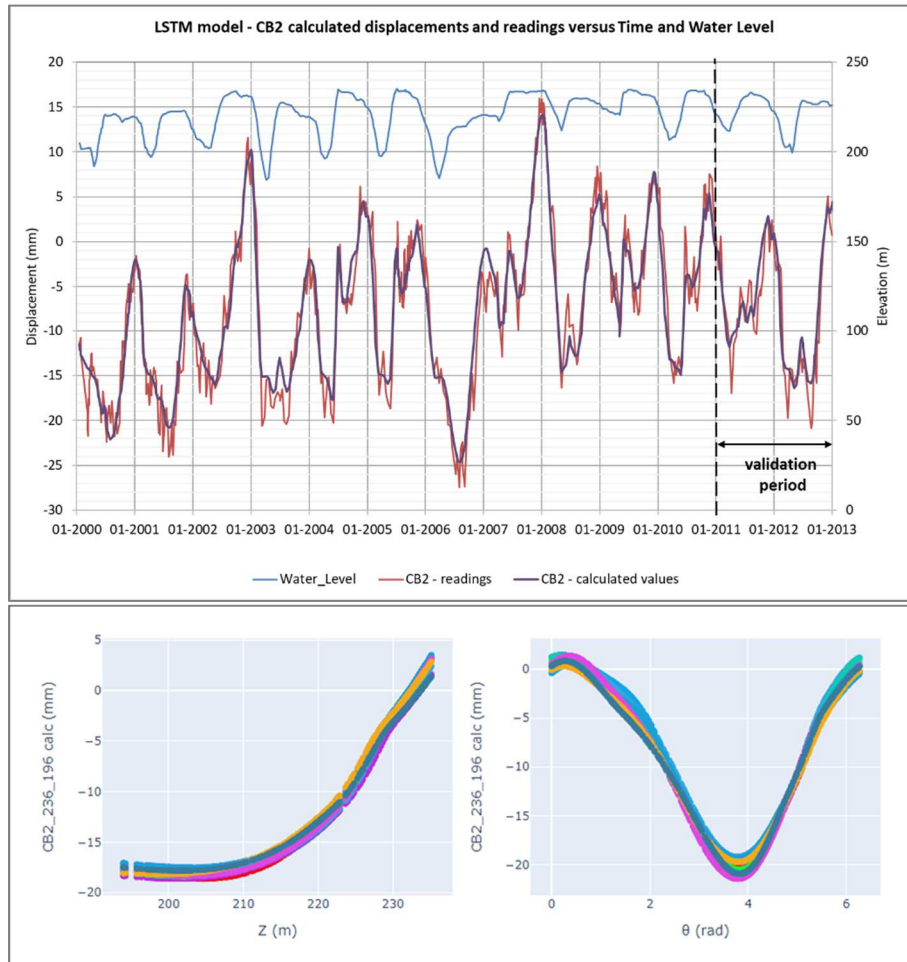


Figure 6. CB2 LSTM model –Top: calculated values versus Time and Water Level; Bottom: hydrostatic and seasonal effect function (θ : season angle)

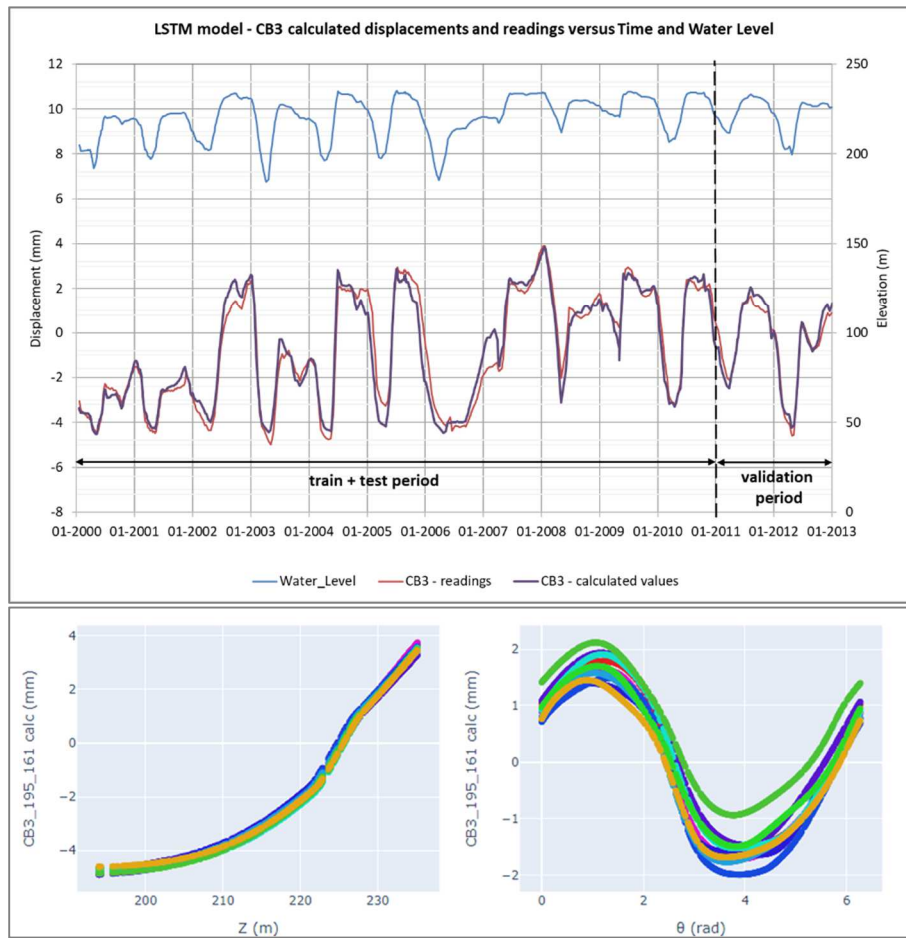


Figure 7. CB3 LSTM model – Top: calculated values versus Time and Water Level; Bottom: hydrostatic and seasonal effect function (θ : season angle)

4 RESULTS

The results for the LSTM models are provided under the shape of the predictive values for the first half-year of 2013 (short term prediction) and from beginning of July 2013 to end of December 2017 (long term prediction) as an Excel files provided to the Formulator for CB2 and CB3 LSTM models (average of 10 runs). The results for HST/HST-T models are provided for comparison.

Based on the standard deviation of the difference between readings and calculated values 2.35 mm for CB2 and 0.47 mm for CB3 the prediction with LSTM models is expected to have an average accuracy of ± 2.5 mm for CB2 and ± 0.5 mm for CB3. These values are very close to the values of the residual standard deviation obtained by HST/HST-T models: 2.05 mm for CB2 and 0.52 mm for CB3.

As shown on Figure 8 and Figure 9 the values predicted with LSTM models compare well to those predicted with HST/HST-T models from 2013 to 2015 when the reservoir level variations are within the range of 2000-2012 variations. This gives confidence in both models to provide good quality interpolation.

The main differences are found from 2016 to 2017 that is a period when the models need to extrapolate: the reservoir level has reached its historical minimum and remained below the dam toe from January to April 2016 and the yearly maximum levels for 2016 and 2017 are below those known for the 2000-2012 period, respectively around -10 m and -5 m to the lowest yearly maximum level of 2000.

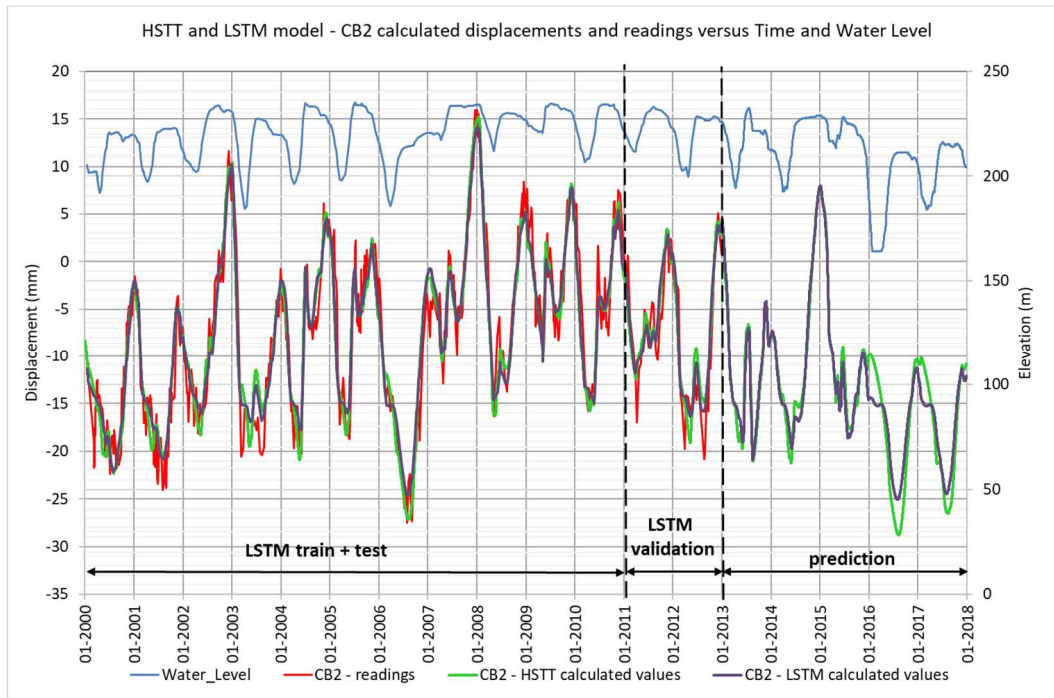


Figure 8. CB2 calculated values versus Time and Water Level (2000-2017)

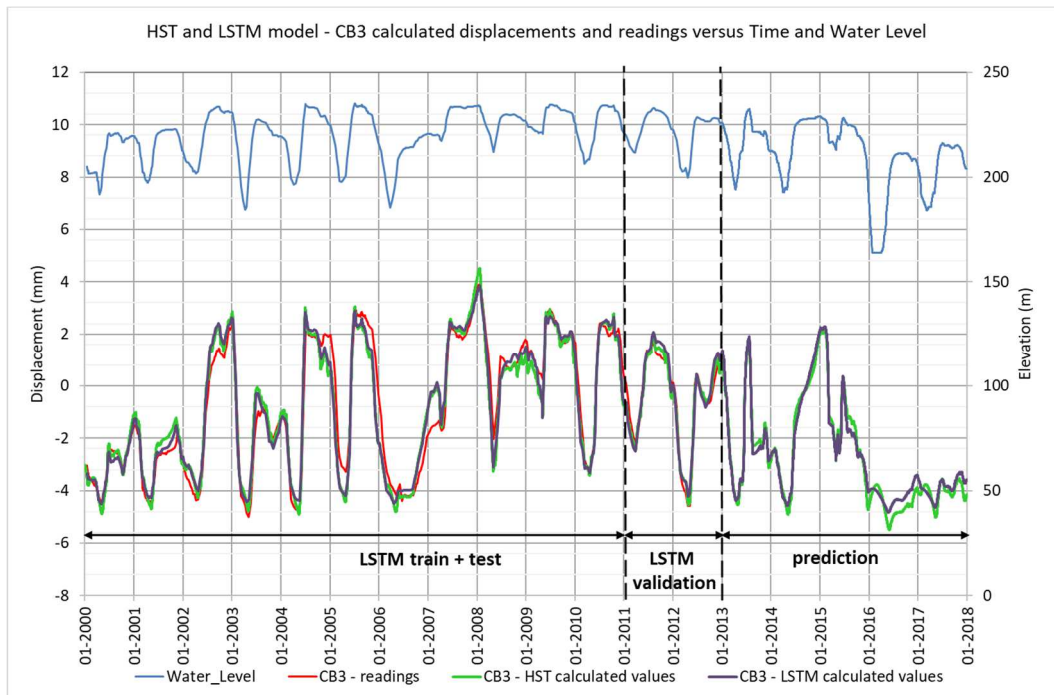


Figure 9. CB3 calculated values versus Time and Water Level (2000-2017)

- When the reservoir level remains below the dam toe in 2016 (winter):
 - CB2 HST-T model foresees a millimetric reversible downstream displacement and a position some 2.5 mm downstream the one reached in 2003 and 2006 with drawdown below the dam toe whereas the LSTM model levels off with a position similar to those reached in 2003 and 2006 which is more in line with expected behaviour.
 - CB3 HST model foresees a 1 mm reversible downstream displacement from the position reached in 2003 and 2006 whereas the LSTM model foresees almost no displacement and

a position slightly downstream the ones predicted in the past which is more in line with expected behaviour.

- When the reservoir level reaches its 2016 and 2017 yearly maximum (summer):
 - Both CB2 models foresee an upstream displacement consistent with the predominance of thermal effects over hydrostatic effects. The most upstream position is reached in 2016 which seems rather consistent as the water level has been lower though the air temperature has been lower.
The position is the historical most upstream one with the HST-T model, more upstream than the one reached in 2006 with a reservoir 3 m higher with similar temperatures, whereas the LSTM model foresees an upstream position very similar to 2006 which is less realistic.
 - Both CB3 models foresee a 2016 downstream position below (upstream) the one reached in 2006 with lower reservoir level and a 2017 downstream position intermediate between the 2006 one and the 2000 one with higher reservoir level (+2 m) – which seems rather realistic.
- When the reservoir level reaches its 2017 yearly minimum (winter), CB3 HST predictions level off before showing an upstream displacement and a position similar to the one reached in 2003 with roughly the similar reservoir and thermal conditions whereas CB3 LSTM model foresees a smoother upstream displacement similar to the one calculated for 2003 - which seems more realistic.

The predictions for CB2 and CB3 pendulums displacements with LSTM models seem globally more realistic than those with HST/HST-T models for the 2016-2017 period where an extrapolation is required.

Warning levels could be defined by analogy with the definition of warning levels of HST/HST-T models and assuming the readings follow a normal distribution as the calculated value $\pm 2.5 \times$ standard deviation of the difference between calculated values and readings for the period 2000-2012. This corresponds to ± 5.9 mm around CB2 calculated values and ± 1.2 mm around CB3 calculated values. These values compared well with the warning levels which could be defined for HST/HST-T models that is ± 5.2 mm around CB2 calculated values and ± 1.3 mm around CB3 calculated values.

In the opinion of the authors, these warning levels are not direct indicators of the safety of the dam. They only alert on the fact that the readings are out of a normality range. A reading exceeding the alert level should raise the attention of the person in charge of the monitoring data analysis. The reading should be repeated. If it is confirmed, following questions should be answered: is a change occurring in the behaviour of the dam? does this change affect the dam safety?

5 CONCLUSION

The exercise presented above showed that data-based models based on LSTM methods could be used for the prediction of monitoring data measurement.

For the case studied – displacements of an arch dam mainly influenced by the hydrostatic loading and the seasonal thermal condition – the results obtained with less input variables are very similar to those obtained with HST and even HST-T models and seem more realistic when an extrapolation is needed.

This conclusion needs however to be confirmed by the comparison of the prediction with the actual readings of 2013-2017 and by similar exercises with other time series.

Next steps considered for the development of the Machine Learning Web Platform are focused on improving the selection of hyperparameters of the models and including temperature time series in the input variables.

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