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Spillage Forecast in Hydroelectric Power Plants via *Machine Learning* ⋆

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Abstract: Brazilian hydroelectric power plants often use telemetry stations to extract information about the environment. These equipment are usually installed in several strategic spots of rivers that “feed” the reservoir, and are capable of providing important information such as precipitation, river level, and water flow. This paper presents an analysis of Machine Learning applied to the forecasting of spillage occurrences over a set amount of time in a Brazilian power plant. To achieve this goal, telemetry stations’ data were utilized together with the plant’s operations historical, which provides information about previous spillages, turbines’ flows, among others. The Machine Learning approach has shown to be promising in this problem, and the developed model presented the potential to effectively support decisions by helping the operators prepare for significant incoming water flows.

Keywords: Telemetry; Hydroelectric Power; Machine Learning; Forecasting; Resources Managing.

1. INTRODUCTION

In the Brazilian energy grid, 67.6% of the total generation capacity is related to hydroelectric power, with 85.6% being related to renewable energy sources in general (ONS, 2020b). However, when observing actual generation values, around 80% of the energy is provided by hydroelectric power plants (HPPs) (ONS, 2020a). Therefore, managing water resources properly is advised so that water shortages or excessive increase in the reservoir level are avoided as often as possible during dry or wet periods, respectively. An effort to prevent the former scenario, i.e., low availability of resources, is done by optimizing the operation of the HPP, as in Arce et al. (2002), Bortoni et al. (2007), and Finardi et al. (2016), which minimizes costs, maximize efficiency, and minimizes resources usage, respectively. This paper, however, focuses on preventing the latter scenario, i.e., avoiding that unexpected and expressive incoming water flows reach the reservoir and increase its level up to unsafe values.

Researching such a subject is very important since excessive reservoir level values may put life in danger and cause massive damage in case of a dam rupture. For instance, on the 14th of December, 2005, a break in Missouri Power Plant’s dam destroyed homes and vehicles, critically injured children, and severely damaged the nearby area (CBS News, 2005). The property damage was estimated at more than $1 billion, and the cause was connected to an excessively high reservoir level (Association of State Dam Safety Officials, 2005).

To achieve the proposed goal, a total of ten telemetry stations (TSs) had their data extracted and treated. This equipment, which register the river water flow, precipitation, and level, among other information not relevant to this work, are spread over the bay around the HPP Luís Eduardo Magalhães, also known as HPP Lajeado, which is the HPP studied in this paper. The historical information was then subjected to an approach based on Artificial Neural Networks (ANNs) so that a Spillage Forecasting Model (SFM) could be implemented. Given the presented problem, the model’s output was designed as the spillage status over the following five hours, i.e., starting from the simulation moment, the model will “say” if there should or there should not be spillage during the five hours ahead, hence acting as a decision support tool. The following paragraphs briefly describe the ANN-based methods utilized in the development of the SFM.

As stated in Goodfellow et al. (2016), people, in general, expect Artificial Intelligence (AI) “to automate routine labor, understand speech or images, make diagnoses in medicine, and support scientific research”. AI has proved its effectiveness in solving problems that can be written by straight-forward mathematical rules. However, situations that are easy for humans to perform, although difficult to formally describe, such as recognizing a specific person’s voice, can be really challenging. The concept of Deep Learning (DL) is based on the application of many layers, which allow the network to gather knowledge and learn complex notions from experience by extracting patterns from data. Many domains of science had their state-of-

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the-art improved via the utilization of DL (LeCun et al., 2015), in particular the time-series problems as in (Yao et al., 2017), (Bao et al., 2017), and (Chen et al., 2018). A rich summary of DL can be consulted in Schmidhuber (2015), and, more specifically for time-series classification, in (Fawaz et al., 2019).

The Multilayer Perceptron (MLP) is a feed-forward ANN with one or more hidden layers. The Back-Propagation algorithm is often used in these nets' learning process when applied to forecast problems (Dibike and Solomatine, 2001). According to Bastarache et al. (1997) and Wen and Lee (1998), this architecture is powerful for solving problems involving water resources. In Dibike and Solomatine (2001), the MLP methodology was applied to the forecasting of the Apure River, Venezuela, downstream water flow. In Shamseldin et al. (2002), it was combined with several rain-forecasting models to provide general flow forecasts of several rivers. In Phitakwinai et al. (2016), it was combined with the Cuckoo Search Algorithm, proposed in Yang and Deb (2009), to forecast the level of Ping river, Thailand, with 7 hours in advance.

The contributions of this paper are:

- A report is given regarding the Spillage Forecast Problem (SFP) based on TSs, which, to the best of the authors' knowledge, has no exploration in the literature;
- A guide on how to treat TSs' data together with the HPP's data is provided.
- The presented model, i.e., the SFM, may inspire deeper researches on the subject, and contribute to the safety of HPPs' reservoirs.

2. PROBLEM DATA

This paper reports a study whose goal is to assist HPP Lajeado operators regarding the decisions of when part of the reservoir water should be spilled, i.e., to inform/forecast about the necessity of spilling water hours ahead. To achieve such goal, information from the HPP's data set (historicals of turbines' water flows, spillages and reservoir levels) and from its TSs (historicals of rivers' levels and precipitations) were utilized. Figure 1 shows the HPP's region and its TSs' locations. Table 1 lists the names of the TSs.

Table 1. TSs' names.

Number	TS
I	Jacinto
II	Jerônimo
III	Ipueiras
IV	Jurupary
V	Areias
VI	Mangues
VII	Barramento
VIII	Jusante
IX	Lucena
X	Tocantínia

The information obtained from the TSs were measured during the period of 08/13/2018 to 11/10/2019 and are presented with a discretization of 15 minutes. The ones extracted from the HPP's operations historical are presented with a discretization of 1 hour. Considering the difference observed in the discretizations, part of the TSs' data could not be utilized since each data point must contain information of the same moment in time. Furthermore, all data from the operations historical that are related to dates outside of the TSs' data range could not be used either.

Since the TSs are installed in open environments, they are vulnerable to weather changes, hence requiring corrective maintenance from time to time, apart from predictive maintenance routines. I.e., the equipment is occasionally unavailable, and, therefore, there are gaps in the data sets. Given the significant importance of data quality, it is crucial that no incoherence, error, or inconsistency is present in the data sets since these compromise the performance of the network training process. Therefore, a treatment consisted of linear interpolations was applied to the TSs' data via Equation 1 so that empty intervals could be filled. It is important to emphasize that there were no gaps in the data extracted from the HPP's operations historical.

$$y = y_0 + (y_1 - y_0)\frac{x - x_0}{x_1 - x_0} \tag{1}$$

In which (x_0, y_0) and (x_1, y_1) are data points.

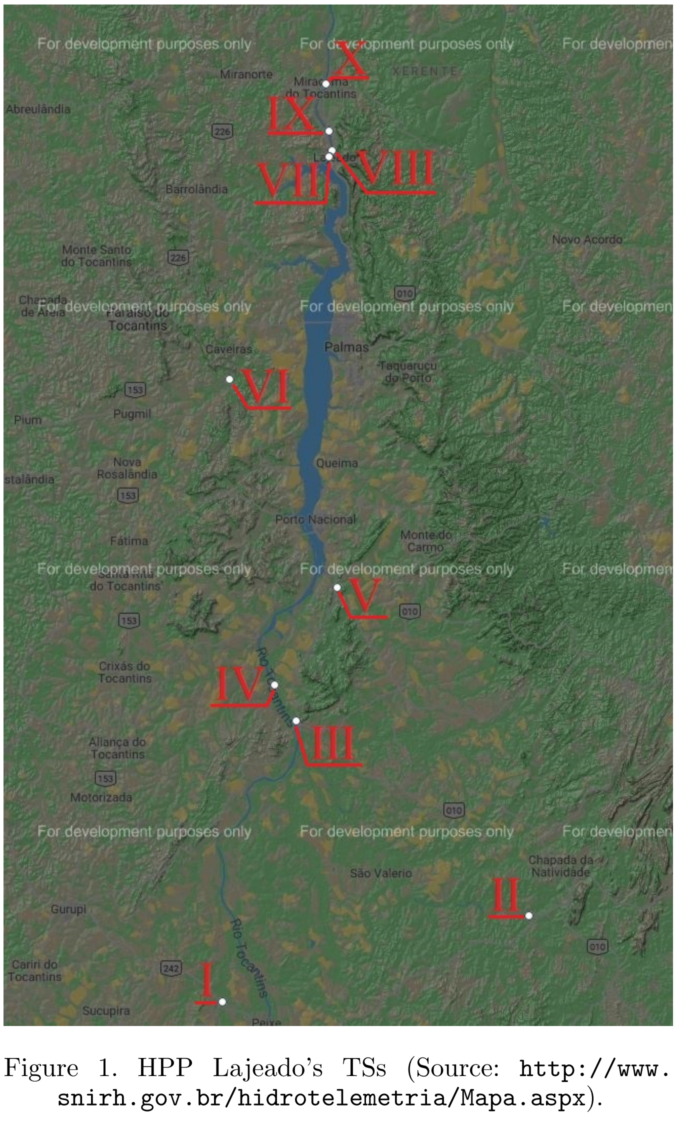


Figure 1. HPP Lajeado's TSs (Source: `http://www.snirh.gov.br/hidrotelemetria/Mapa.aspx`).

3. METHODOLOGY

The development of the SFM was divided in three main steps: (1) the correlation analysis of the data set, (2) adjusting the data imbalance, and (3) the training via MLP.

3.1 Data Correlation

The first step to establish the SFM consists of verifying the correlations of the TSs' level measurements regarding the reservoir's historical of level, spillage, and turbines' water flow values registered in HPP Lajeado. By doing so, it is possible to reduce the model's number of inputs since part of the TSs' data may present negligible correlation with the model's output.

Following this line of thinking, the calculation of Pearson's correlation coefficient (ρ), which determines the correlation between two scale variables via Equation 2, was applied to the data.

$$\rho = \frac{\sum_{i=1}^{N} (x_i - \bar{x}) . (y_i - \bar{y})}{\sqrt{\sum_{i=1}^{N} (x_i - \bar{x})^2} . \sqrt{\sum_{i=1}^{N} (y_i - \bar{y})^2}} \tag{2}$$

In which x_i and y_i are the variables' measured values, $\bar{x}$ and $\bar{y}$ are the variables' mean values, and N is the discretization interval. Values between -1 and 1 are assigned to the ρ coefficient, which represent:

- $\rho = 1$ - perfect positive correlation between two variables;
- $\rho =$ - 1 - perfect negative correlation between two variables, i.e., if one is increased, the other is decreased;
- $\rho = 0$ - variables do not linearly relate to each other.

3.2 Data Adjustment

As part of the training stage, sensitivity analysis were carried out focusing on the possible treatments to the available database. The first treatment is related to the format of the values of future spillages, i.e., the target spillage values for the network to learn, these either being considered normalized values between 0 and 1, or binary, i.e., an assignment of 1 if there is any spillage, or 0 if there is none.

As observed in the HPP's historical data, most of the time the operation does not present spillage occurrences. Therefore, considering the splitting of the data in vectors to be used as inputs, the assembled spillage database presents an imbalance among the amount of data in which there is spillage, in which there is no spillage, or in cases with at least one change in the spillage status. Thus, the second treatment of this database refers to the adjustment of the training data, seeking the balance of information.

The adjustment made to balance the database consists of repeating the parts with fewer data until it is greater than or equal to the part with the most massive volume of information. Figure 2 illustrates the unbalance observed in the original database, and the adjustment implemented to improve the training of the proposed model. The database originally contain 10905 data points, of which 86.7% present no spillage, 11.6% present it, and only 1.7% correspond to moments with at least one change in the spillage status.

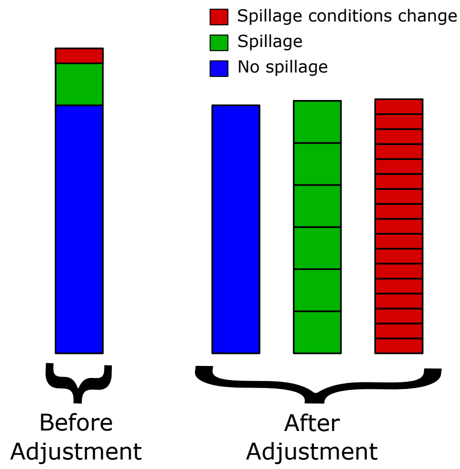


Figure 2. Adjustment performed on the training bench.

3.3 Multilayer Perceptron

There is a wide range of supervised or unsupervised machine learning models. In this paper, the model is a Multilayer Perceptron (MLP), which can be presented with an input layer, an output layer, and one or more inner layers, also known as hidden layers. Figure 3 shows an MLP structure in which its layers are densely linked, i.e., each neuron of an anterior layer is attached to all neurons of the next layer.

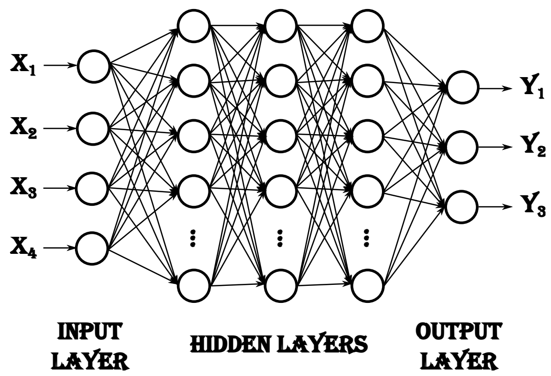


Figure 3. MLPs structure.

Regarding the forecasting approach chosen in this work, it was decided to predict whether there will or there will not be spillage over the next 5 hours instead of predicting if such an event will occur or not at each of the next 5 hours, which, at first, may seem to make more sense. However, although the latter alternative was first implemented, analysis led to the conclusion that some particular events were causing errors to be very expressive, and the results to be unreliable. Figures 4(a), 4(b), and 4(c) exemplify situations where the spillage status change during the observed 5 hours. Such occurrences represent 9% of the training data, i.e., few samples are available for the SFM to absorb these situations' information, hence making it very difficult for it to provide accurate predictions. Furthermore, since the decisions of spilling depend on the

HPP operators, i.e., some subjectivity may be involved, it is possible and likely that different employees take distinct decisions in very similar scenarios.

When forecasting spillage status over the next 5 hours, situations like the ones shown in Figures 4(a), 4(b), and 4(c) represent the same output for the network, which is the occurrence of spillage. Thus, detecting such events properly becomes a less difficult task, and, therefore, the model's accuracy is increased.

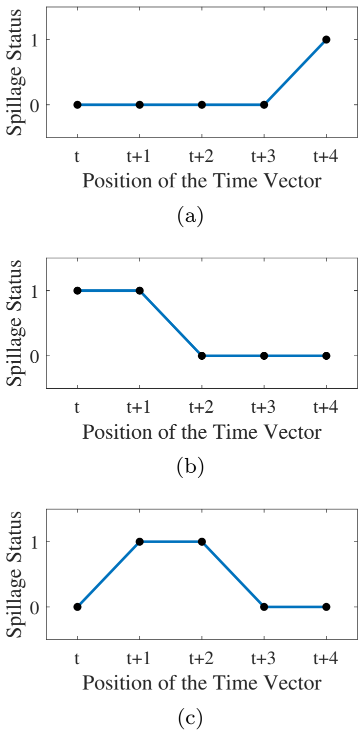


Figure 4. Examples of behaviors in the spillage data set, in which 1 indicates its occurrence, whereas 0 indicates the opposite.

An interesting aspect of this approach is worth mentioning. Assuming that the model is executed hourly at the HPP, if in a particular simulation the model indicates spillage, it is very unlikely that it is supposed to happen in the first hours since, if this was the case, the model would have indicated spillage at a prior simulation. At this point, the operators should be attentive to possible significant incoming flows. Then, if in the next simulation the model indicates spillage again, it is more likely that it is a correct prediction, and so on. However, if the next simulation indicates no spillage, the previous indication is likely to have been a mistake since, as any forecasting mechanism, the proposed model is prone to errors.

4. RESULTS AND DISCUSSION

In order to evaluate the SFM, the TSs' data set was initially subjected to a correlation analysis regarding HPP Lajeado reservoir level, turbines' water flow, and spillage data so that the model's inputs could be determined. Since the TSs Barramento and Jusante correspond to the stations that measure information about the HPP itself, and such information is the target to establish correlation, calculating their correlation would be redundant. The TSs Lucena and Tocantínia were completely excluded from the study due to the fact that they are located at the HPP downstream basin.

From Pearson's correlation, it was observed that the TSs Jurupary and Areias presented the strongest correlations with the reservoir level and spillage. However, concerning turbines' water flows, the strongest correlations were presented by the TSs Jacinto, Jerônimo, and Mangues, although Jurupary and Areias also provided significant correlation values. Since the TSs Jacinto, Jerônimo, and Mangues presented weak correlations with the reservoir level and spillage, Jurupary's and Areias' data were used to train the SFM. Tables 2, 3, and 4 expose the TSs' level data's correlations with the HPP's reservoir level, spillage, and turbines' water flows data, respectively.

Table 2. Pearson's correlations with reservoir level.

Jacinto	**Jerônimo**	**Ipueiras**	**Jurupary**
0,335764	0,35442	0,260321	0,879909
Areias	**Mangues**	**Turbine's Flow**	**Spillage**
0,79423	0,37688	0,211556	0,243282

Table 3. Pearson's correlations with spillage.

Jacinto	**Jerônimo**	**Ipueiras**	**Jurupary**
0,172506	0,195892	0,075992	0,346746
Areias	**Mangues**	**Reservoir Level**	**Turbine's Flow**
0,284422	0,198355	0,243282	0,033022

Table 4. Pearson's correlations with turbines' water flows.

Jacinto	**Jerônimo**	**Ipueiras**	**Jurupary**
0,620352	0,590626	0,298244	0,458023
Areias	**Mangues**	**Reservoir Level**	**Spillage**
0,461375	0,598686	0,211556	0,033022

Pearson's correlation technique investigates the linear relationship between the data. Therefore, for a better analysis of the data correlations, the polynomial regression technique was applied to verify if there is any non-linear correlation in the data. The regression was performed for second-degree to twentieth-degree polynomials. The best values of non-linear correlation coefficient (R^2) are presented in Tables 5, 6, and 7. Thus, analyzing Pearson's correlation values and R^2 coefficients, it was defined that only Jurupary's and Areias' data would remain as entries for the SFM.

Table 5. Best R^2 value with reservoir level.

Jacinto	**Jerônimo**	**Ipueiras**	**Jurupary**
0,308803	0,163124	0,400753	0,807284
Areias	**Mangues**	**Turbine's Flow**	**Spillage**
0,772773	0,267777	0,055882	0,109415

Table 6. Best R^2 value with spillage.

Jacinto	**Jerônimo**	**Ipueiras**	**Jurupary**
0,260555	0,117192	0,297040	0,383564
Areias	**Mangues**	**Reservoir Level**	**Turbine's Flow**
0,125329	0,191937	0,187039	0,132359

With the correlation study executed and the model's inputs determined, the next step consists of the network

Table 7. Best R^2 value with turbines' water flows.

Jacinto	**Jerônimo**	**Ipueiras**	**Jurupary**
0,395672	0,422390	0,419171	0,240786
Areias	**Mangues**	**Reservoir Level**	**Spillage**
0,268703	0,381825	0,185544	0,039001

training stage. The development was carried out in Python since it is an open-source programming language with great support for machine learning. Keras, an open-source neural-network library written in Python, was used.

The SFM's structure is exhibited in Figure 5. The inputs are vectors composed of 10 samples, i.e., of information concerning 10 previous time discretizations for each input type, except for the turbine flow input vector, which not only is composed of 10 samples about the past but also of 5 more samples containing information about the expected turbines' water flow during the next 5 hours starting one hour ahead of the simulation time. These expected values are provided by an optimization model that grants the operation schedule for the next 24 hours based on generation goals assigned to the HPP. The SFM's output is the spillage classification over the 5 hours ahead, i.e., the model predicts if there should or there should not be spillage at any point during the next 5 hours.

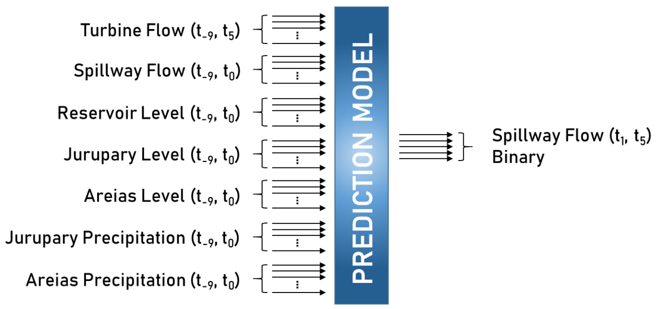


Figure 5. SFM's structure.

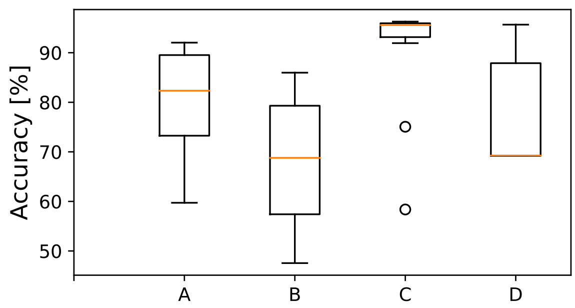
The MLP training was performed and the testing groups A, B, C, and D were formed in order to carry out a sensitivity analysis focusing on the treatments of the database. Groups A and C present the values of future spillages in binary format, whereas the other groups present normalized values between 0 and 1. Groups A and B present the treatment described in subsection 3.2 seeking a better data balance, whereas groups C and D do not. Table 8 shows the groups and their characteristics.

Table 8. Description of sensitivity groups.

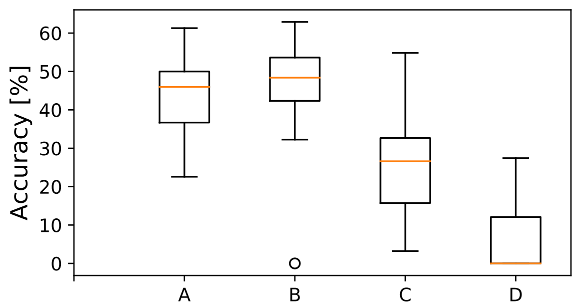
Group	Description
A	· Binary future spillage. · Database compensation.
B	· Normalized future spillage. · Database compensation.
C	· Binary future spillage. · No database compensation.
D	· Normalized future spillage. · No database compensation

Simulations led to the conclusion that the most challenging situations for the SFM to properly predict are the ones where there are changes in the spillage status within the 5 hours data vector, i.e., situations like the ones exposed in Figure 4, as explained in subsection 3.3. Thus, not only analysis of the accuracy during the test stage concerning the entire database was performed, but also concerning exclusively the data with at least one change in the spillage status.

For each of the groups presented in Table 8, 20 different training simulations of the SFM were carried out. Figure 6 (a) presents the accuracy concerning a scenario where the whole test data was considered, whereas Figure 6 (b) shows the accuracy in a second scenario where only specific moments where there are changes in the spillage status were considered, both presented as boxplots. The prediction model, based on an MLP, was configured with 2 hidden layers containing 64 neurons each, ReLU activation function, Adam optimizer, 20 training epochs, 20% validation, and 10 batch size. The database is formed of 10905 data points, from which 8760 were used in the training processes, i.e., an amount equivalent to one year of information. Such choice is based on the fact that a training data set containing information about all seasons is of great importance for the generalization capacity of the SFM. Consequently, 2145 data points were used in the test processes.



(a)



(b)

Figure 6. Boxplots of the precisions obtained from the 20 trained models: (a) Accuracy concerning all test samples. (b) Accuracy concerning samples that show a change in the spillage status.

Analyzing Figure 6, it can be seen that Group C provided high accuracy in general, granting values greater than 95%. However, it presented low accuracy in moments with changes in the spillage status. It can also be observed in the second scenario that the median is between 20% and 30%. Group D provided very poor predictions, often not being able to predict any of the moments that presented changes in the spillage status. Regarding groups A and

B, the former presented better results concerning general accuracy, whereas the latter provided a lesser dispersion of results when analyzing the accuracy in moments of change in the spillage status. Table 9 shows the accuracy, precision, recall, and F1 score values for the best-trained models in groups A, B, C, and D. Accuracy values are presented considering the 1st scenario (1st S) and the 2nd scenario (2nd S), the other values refer only to the 1st scenario. So, considering the importance of both scenarios studied and the goal of obtaining good results in both, the model trained with the configurations of Group A showed the best overall performance, i.e., the SFM benefited from the database compensation shown in Figure 2 and performed better with binary values for future spillages.

Table 9. Accuracy, Precision, Recall, and F-score of the best networks in each group.

Metrics	A	B	C	D
Accuracy 1st S	0.91	0.86	0.94	0.93
Accuracy 2nd S	0.60	0.48	0.35	0.27
Precision	0.95	0.89	0.92	0.92
Recall	0.80	0.72	0.90	0.87
F1 Score	0.87	0.80	0.91	0.90

Figure 7 shows the ROC curve (Receiver Operating Characteristic Curve) and the AUC (Area Under Curve) value for the best result in Group A. In this image, the broken line (also called reference line) represents random choices. Its AUC value is 0.5. The blue line, referring to the ROC curve, is located above the reference curve, which states better performance than random choices. The AUC value for the ROC curve is 0.91, which is very close to 1, which would represent perfection in the classifications.

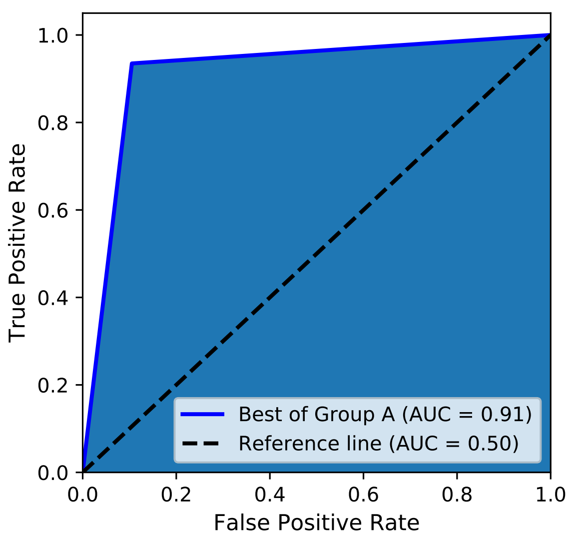


Figure 7. SFM's structure.

As explained in subsection 3.3, the predictions provided by the proposed SFM considers spillage occurrences during the next 5 hours. To illustrate such approach, Figure 8 (a) shows a range of information extracted from the test data, in which the black curve represents raw spillage data plotted hourly, and the blue curve represents treated spillage data, i.e., a particular data point has a value of 1 if there is spillage in any of the next 5 hours, and a value of 0 if there is none. For instance, in the blue curve, the value assigned to hour 5 is 0 since there is no spillage from hours 6 to 10, whereas the value assigned to hour 6 is 1 since there is spillage between hours 7 and 11, more specifically in hour 11. In Figure 8 (b), the prediction of the spillage status associated with the best result of Group A, shown in Table 9, is exhibited. In this short period, the model managed to forecast the changes in spillage status properly. However, a wrong prediction occurred at hour 29, which would indicate to the HPP operator a possibility of spillage at some point during the next 5 hours. However, the next predictions correct the mistake since they do not inform spillage occurrences, hence not causing the operator to make an inadequate choice. It is worth emphasizing that more than one forecast should be taken into account before the decision making.

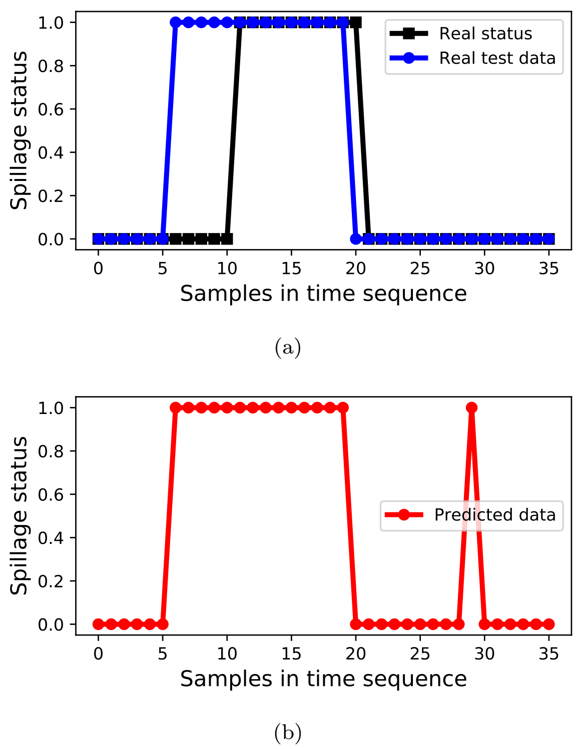


Figure 8. Time sequence of part of the test bench: (a) Modeling the forecast format. (b) Prediction of spillage performed by the trained model.

5. CONCLUSION

This paper has presented a simple yet effective approach to the forecasting of spillage occurrences in hydroelectric power plants. The developed model granted very high accuracy in a general context. Concerning the moments of change in the spillage status, the model presented promising results considering the complexity of forecasting with high accuracy at these scenarios. Though not explored in the literature, such a tool may help operators decide when to allow water spillage, and, therefore, secure safe reservoir levels. A successful and vastly utilized network-based technique was applied to the problem and analyzed. The applying of MLP to the problem has shown to be suitable.

As possible further works, it is intended to test different well-known forecasting tools, such as ANFIS and Extreme Learning Machine, in the spillage forecasting problem. It is also intended to execute hybridizations of two or more of the aforementioned methods, seek possible improvements in the compensation of the database by applying synthetic minority over-sampling technique (SMOT) and other techniques, and develop a more complex model capable of "saying" not only when, but how much water must be spilled.

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REFERENCES

Arce, A., Ohishi, T., and Soares, S. (2002). Optimal dispatch of generating units of the itaipú hydroelectric plant. *IEEE Transactions on power systems*, 17(1), 154–158.

Association of State Dam Safety Officials (2005). *Case Study: Taum Sauk Dam (Missouri, 2005).* [online] Available at: `https://damfailures.org/case-study/taum-sauk-dam-missouri-2005/`. [Accessed 9 Jan. 2020].

Bao, W., Yue, J., and Rao, Y. (2017). A deep learning framework for financial time series using stacked autoencoders and long-short term memory. *PloS one*, 12(7).

Bastarache, D., El-Jabi, N., Turkkan, N., and Clair, T.A. (1997). Predicting conductivity and acidity for small streams using neural networks. *Canadian Journal of Civil Engineering*, 24(6), 1030.

Bortoni, E.C., Bastos, G.S., and Souza, L.E. (2007). Optimal load distribution between units in a power plant. *ISA transactions*, 46(4), 533–539.

CBS News (2005). *Dam Breaks At Missouri Power Plant.* [online] Available at: `https://www.cbsnews.com/news/dam-breaks-at-missouri-power-plant/`. [Accessed 9 Jan. 2020].

Chen, J., Zeng, G.Q., Zhou, W., Du, W., and Lu, K.D. (2018). Wind speed forecasting using nonlinear-learning ensemble of deep learning time series prediction and extremal optimization. *Energy conversion and management*, 165, 681–695.

Dibike, Y.B. and Solomatine, D.P. (2001). River flow forecasting using artificial neural networks. *Physics and Chemistry of the Earth, Part B: Hydrology, Oceans and Atmosphere*, 26(1), 1–7.

Fawaz, H.I., Forestier, G., Weber, J., Idoumghar, L., and Muller, P.A. (2019). Deep learning for time series classification: a review. *Data Mining and Knowledge Discovery*, 33(4), 917–963.

Finardi, E.C., Takigawa, F.Y.K., and Brito, B.H. (2016). Assessing solution quality and computational performance in the hydro unit commitment problem considering different mathematical programming approaches. *Electric Power Systems Research*, 136, 212–222.

Goodfellow, I., Bengio, Y., and Courville, A. (2016). *Deep learning.* MIT press.

LeCun, Y., Bengio, Y., and Hinton, G. (2015). Deep learning. *nature*, 521(7553), 436–444.

ONS (2020a). *Carga e Geração.* [online] Available at: `http://www.ons.org.br/paginas/energia-agora/carga-e-geracao`. [Accessed 4 Jan. 2020].

ONS (2020b). *Sistema em Números.* [online] Available at: `http://www.ons.org.br/paginas/sobre-o-sin/o-sistema-em-numeros`. [Accessed 4 Jan. 2020].

Phitakwinai, S., Auephanwiriyakul, S., and Theera-Umpon, N. (2016). Multilayer perceptron with cuckoo search in water level prediction for flood forecasting. In *2016 International Joint Conference on Neural Networks (IJCNN)*, 519–524. IEEE.

Schmidhuber, J. (2015). Deep learning in neural networks: An overview. *Neural networks*, 61, 85–117.

Shamseldin, A.Y., Nasr, A.E., and O'Connor, K.M. (2002). Comparison of different forms of the multi-layer feed-forward neural network method used for river flow forecast combination. *hydrology and earth system sciences*, 6(4), 671–684.

Wen, C.G. and Lee, C.S. (1998). A neural network approach to multiobjective optimization for water quality management in a river basin. *Water Resources Research*, 34(3), 427–436.

Yang, X.S. and Deb, S. (2009). Cuckoo search via lévy flights. In *2009 World Congress on Nature & Biologically Inspired Computing (NaBIC)*, 210–214. IEEE.

Yao, S., Hu, S., Zhao, Y., Zhang, A., and Abdelzaher, T. (2017). Deepsense: A unified deep learning framework for time-series mobile sensing data processing. In *Proceedings of the 26th International Conference on World Wide Web*, 351–360.