Prediction of Water Consumption Using Machine Learning Algorithms*

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Abstract

The objective of this study is to propose solutions for predicting drinking water consumption over a period of 5 days. To achieve this, machine learning methods such as neural network algorithms are used to confront different results in order to obtain a model that optimizes daily water consumption the most. The algorithms used include Multi-Layer Perceptron (MLP), Simple Recurrent Neural Network, Long Short-Term Memory (LSTM) recurrent neural network, and Gated Recurrent Unit (GRU) recurrent neural network. Since the data comes from multiple sources, the algorithms are used to train models on each dataset. At the end of this study, the model that optimizes the best is selected for each dataset after comparing the results of different algorithms. Based on the various results obtained, the performance of the algorithms varies depending on the periods and the data. For example, the best performance in predicting consumption in the KUA area on the J+5 day period is attributed to the MLP algorithm based on mean absolute errors (MAE).

Keywords

Machine learning, data analysis, prediction

I INTRODUCTION

Agencies responsible for managing water consumption are increasingly encountering challenges related to water distribution. One of the primary causes of these challenges lies in the high demand stemming from the significant growth of the population, both in urban and rural areas. Given the increasing complexity of water management, new and innovative solutions must be considered to effectively address these issues. In this context, it is essential to explore the opportunities provided by emerging technologies in order to identify a solution capable of efficiently responding to the current situation. A particularly relevant approach involves leveraging modern technologies to forecast water consumption volumes. To enable such forecasting, it is necessary to rely on historical consumption data. Indeed, whether it concerns coagulant dosage modeling in treatment plants [7], water monitoring through sensors [5], or addressing broader water management challenges [10]—particularly those related to consumption—having a sufficient volume of historical data is crucial to facilitate accurate predictions. By implementing such a solution, the National Office for Water and Sanitation (ONEA) can address these challenges while also modernizing its operational practices. Current approaches, which are based on conventional methods (such as the statistical estimation method employed by ONEA in 2019), exhibit significant limitations in terms of efficiency and reliability. There is a pressing need

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to adopt modern technological methods to improve the management of water distribution systems. The methods proposed in this study are based on neural networks. The performance of traditional methods is negligible when compared to that of neural networks. These networks offer substantial predictive capabilities thanks to their complex structure, which enables them to process and model highly nonlinear and intricate problems. Their architecture consists of multiple successive layers, granting them strong analytical power in data processing. Each layer is composed of interconnected neurons that handle incoming information. The complexity of a neural network is directly related to the number of neurons it contains: the greater the number of neurons, the more complex and powerful the network becomes, with its strength lying in the interactions between neurons [20]. Within the scope of neural networks, various predictive methods exist. Among these, this study focuses on those based on quantitative data, a choice that is justified by the nature of the data collected from ONEA. This paper is structured into four main sections: (1) a detailed description of the methods employed, (2) an explanation of the data collection process, (3) data preprocessing and preparation, and finally, (4) a presentation and discussion of the results, followed by a conclusion.

II METHOD DESCRIPTION

In the scope of our study, given that the available data are quantitative, the choice was made to utilize four (4) methods, namely Multi-Layer Perceptron (MLP), simple recurrent neural network, Long Short-Term Memory (LSTM) recurrent neural network, and Gated Recurrent Unit (GRU) recurrent neural network.

2.1 The Multi-Layer Perceptron (MLP)

The MLP (Multilayer Perceptron) is a neural network comprised of layers, wherein the activation functions within each layer are identical [20]. The MLP network typically consists of three layers: the input layer, the hidden layer, and the output layer (refer to figure 1). Each layer employs an activation function to process the incoming information. This information processing is facilitated by the backpropagation method ([17]), enabling the flow of information from the input layer to the output layer and vice versa.

2.2 Simple recurrent neural networks

Recurrent Neural Networks (RNNs) are a class of neural networks characterized by cyclic connections, making them particularly well-suited for processing sequential data such as time series, video streams, or audio signals.

Simple RNNs represent the most basic form of recurrent networks. Similar to Multi-Layer Perceptrons (MLPs), they rely on the backpropagation algorithm [22], specifically a variant known as Backpropagation Through Time (BPTT), to learn temporal patterns from sequential data. Their architecture resembles that of MLPs, with one crucial distinction: they incorporate recurrent connections that allow information to persist across time steps. Fully Recurrent Neural Networks (FRNNs) go a step further by introducing complete connectivity between all neuron outputs and all inputs. This structure represents the most generalized form of neural network topology, capable of simulating any other configuration by appropriately adjusting the connection weights (for instance, by setting certain weights to zero to simulate the absence of connections).

It is important to note that, in visual representations, these networks are often “unrolled” in time to resemble layered structures. This can be misleading: what appears to be multiple dis-

tinct layers is, in fact, the same network repeated across time steps. In illustrations (Figure 2), the recurrent connections—typically represented by arcs labeled 'v'—are unfolded over time, creating the illusion of several layers, when in reality it is the same set of neurons processing input data at different temporal intervals.

2.3 Long Short-Term Memory (LSTM)

Long Short-Term Memory (LSTM) is a type of neural network known for its high complexity, characterized by the integration of two forms of memory: long-term memory and short-term memory. Its architecture consists of four interacting components that enable the selective addition and removal of information. These components, referred to as gates, correspond to the functional layers of the network:

- the Input Gate,
- the Forget Gate,
- the Memory Cell,
- and the Output Gate.

The core strength of LSTM networks lies in their ability to capture and manage long-term dependencies, which makes them particularly suitable for processing long or complex sequences.

The equations of the LSTM model are defined by the set of the following equations ([25]):

$$
\begin{aligned}
F_t &= \sigma\left(b^F + x_t U^F + h_{t-1} W^F\right) \\
I_t &= \sigma\left(b^I + x_t U^I + h_{t-1} W^I\right) \\
O_t &= \sigma\left(b^O + x_t U^O + h_{t-1} W^O\right) \\
F_t &= \sigma\left(b^F + x_t U^F + h_{t-1} W^F\right) \\
c_t &= F_t c_{t-1} + I_t tanh\left(b + x_t U + h_{t-1} W\right) \\
ht &= tanh\left(c_t\right) O_t \\
\hat{y} &= g\left(b^{\hat{y}} + h_t W^{\hat{y}}\right)
\end{aligned}
$$

Where F corresponds to the "forget gate," the gate responsible for updating the memory cell c. I and O correspond to the "input" and "output" gates, allowing the input and output of information in the LSTM based on the input data x and ht-1, which represents the hidden state, the output vector of the LSTM at time step t-1. The vectors U and W correspond to the weights associated with the input data and recurrent weights associated with the hidden layer at time step t-1. g represents an activation function used to obtain ŷt, the LSTM's prediction or classification at time step t.

2.4 Gated Recurrent Unit (GRU)

The Gated Recurrent Unit (GRU) model is a simplified version of the LSTM network. Like LSTM, it is capable of capturing long-term temporal dependencies, but its architecture is based on only two gates:

- the Reset Gate,
- and the Update Gate.

A key advantage of the GRU lies in its reduced training time, making it computationally more efficient. Figure 4 illustrates the structure of a GRU network.

III DATA COLLECTION

The data used in this study originate from daily potable water consumption, collected from the National Office for Water and Sanitation (ONEA) in Bobo-Dioulasso. The city of Bobo-Dioulasso and its surrounding areas are supplied with drinking water by ONEA. To improve water management, the agency has divided the city and its outskirts into eight (8) water distribution zones. The data related to the volume of water distributed in each of these zones constitute the dataset for this study, covering the period from November 2018 to November 2021. In addition to consumption data, temperature data were also of particular interest in this study. To obtain them, temperature records for the Bobo-Dioulasso region, covering the same period (November 2018 to November 2021), were collected from the official platform of the national meteorological agency of Burkina Faso.

The data provided to us has undergone a cleaning process to ensure the acquisition of reliable and consistent data. Following this cleaning process, nine variables were selected for further analysis in the study, including data on:

- The distribution of KUA
- The distribution of LOW SARFALAO,
- The distribution of HIGH SARFALAO,
- The distribution of BAMA,
- The distribution of BELLE VILLE,
- The distribution of LAFIABOUGOU,
- The distribution of BOLO VERS VILLE,
- The distribution of BELLE VILLE PIQUAGE,
- Maximum temperature.

After statistical analysis, we obtain the results (summaries) in the table 1.

IV DATA PROCESSING

Data processing involves model training, encompassing data cleaning and normalization to ensure high-quality inputs. Data cleaning—which accounts for more than half of the total processing time—ensures that the dataset is reliable, consistent, and meaningful. Normalization, in turn, standardizes the data onto a common scale while preserving the original range and informational content. In this study, Z-score normalization is applied, which involves subtracting the mean from each raw value and dividing the result by the standard deviation (see Equation 1).

Before normalization, the dataset is partitioned into training and testing subsets. Although there is no universally fixed ratio for this split, previous studies commonly recommend proportions such as 75% training and 25% testing, or 80% and 20%, respectively [10]. In the present work, data from each zone and corresponding temperature records underwent the full preprocessing pipeline: cleaning, normalization, and partitioning according to the selected ratio.

$$X_{norm} = \frac{X_i - \bar{X}}{\sigma_x} \tag{1}$$

where:

- X_{norm} : normalized value
- X_i : gross value
- $\bar{X}$: average of the data
- σ_x : standard deviation

V RESULTS

The data obtained from each zone after processing was used to train models over multiple periods using the selected algorithms. The results obtained after training on the different zones are presented in the following sections.

5.1 Prediction results of Belle ville

The water consumption data from the Belle Ville zone were preprocessed to ensure data reliability, alongside daily temperature records from the city of Bobo. The resulting dataset was then used to train the algorithms and develop predictive models for days J+2, J+3, J+4, and J+5. Model evaluation was conducted based on the corresponding Mean Absolute Error (MAE) values, which are reported for each forecast horizon in Table 2.

5.2 Prediction results of Lafiabougou

Regarding the Lafiabougou zone, the models obtained based on the water consumption data of the area and the temperature were evaluated using the error values recorded in Table 3.

5.3 Prediction results of Bolo Vers Ville

The error values obtained from the training models of the Bolo Vers Ville zone are thus presented in Table 4.

5.4 Prediction results of Bama

After the training and evaluation phase of the models using data from the Bama zone, their errors, on which the models were evaluated over multiple periods, are listed in Table 5.

5.5 Prediction results of Kua

The data collected in Table 6 represents the outcomes of various training models using consumption data from the Kua zone.

5.6 Prediction results of High Sarfalaho

The mean absolute errors in Table 7 are the evaluation results of the various models obtained with the data from the High Sarfalaho zone.

5.7 Prediction results of Low Sarfalaho

For each period, models were established for water consumption prediction. The performance of these models was measured based on mean absolute errors. Table 8 presents the different errors for the periods.

5.8 Prediction results of Belle Ville Piquage

The consumption data from the Belle Ville Piquage zone allowed the development of various models across the four forecast horizons. Model performance was evaluated based on the Mean Absolute Error (MAE), with the corresponding error values presented in Table 9.

VI TABLES AND FIGURES

6.1 Tables

	Mean	Standard deviation	Min	Max
KUA	8044.157	1320.111	360.0	10000.0
LOW SARFALAO	5326.553	744.506	528.0	6000.0
HIGH SARFALAO	1804.199	553.291	8.0	2500.0
BAMA	18543.119	2903.644	225.0	21000.0
BELLE VILLE	1730.155	899.705	70.0	3000.0
LAFIABOUGOU	6313.376	1195.902	2.0	7000.0
BOLO VERS VILLE	5065.460	1059.768	195.0	6000.0
BELLE VILLE QUILTING	2445.469	230.131	135.0	3000.0

Table 1: Statistics on the parameters used.

	MLP	RNN Simple	LSTM	GRU
J+2	0,2255	0,0793	0,2289	0,0763
J+3	0,2225	0,0908	0,2287	0,0863
J+4	0,2242	0,0921	0,2274	0,0939
J+5	0,225	0,0974	0,2305	0,0927

Table 2: Table summarizing the errors of the different algorithms after evaluation of the Belle Ville zone

	MLP	RNN Simple	LSTM	GRU
J+2	0,0738	0,0281	0,0934	0,0311
J+3	0,0813	0,0309	0,0888	0,0339
J+4	0,083	0,0351	0,0791	0,0383
J+5	0,072	0,034	0,097	0,0296

Table 3: Table summarizing the errors of the different algorithms after evaluation of the Lafiabougou zone.

	MLP	RNN Simple	LSTM	GRU
J+2	0,0946	0,0971	0,0918	0,0975
J+3	0,0937	0,1007	0,0908	0,1013
J+4	0,0888	0,0935	0,0887	0,0929
J+5	0,0895	0,0956	0,0887	0,0947

Table 4: Table summarizing the errors of the different algorithms after evaluation of the Bolo Vers Ville zone.

	MLP	RNN Simple	LSTM	GRU
J+2	0,0741	0,0839	0,0828	0,081
J+3	0,0766	0,0805	0,0797	0,0859
J+4	0,072	0,0821	0,0787	0,0782
J+5	0,0767	0,083	0,0832	0,0822

Table 5: Table summarizing the errors of the different algorithms after evaluation of the Bama zone.

	MLP	RNN Simple	LSTM	GRU
J+2	0,0845	0,0834	0,0864	0,0833
J+3	0,0842	0,0854	0,0865	0,0865
J+4	0,0845	0,0836	0,0847	0,0835
J+5	0,0842	0,0868	0,0874	0,0863

Table 6: Table summarizing the errors of the different algorithms after evaluation of the Kua zone.

	MLP	RNN Simple	LSTM	GRU
J+2	0,1581	0,1268	0,1629	0,1296
J+3	0,1561	0,1466	0,1582	0,1444
J+4	0,1579	0,1265	0,1565	0,1248
J+5	0,1547	0,1414	0,1596	0,1403

Table 7: Table summarizing the errors of the different algorithms after evaluation of the High Sarfalaho zone.

	MLP	RNN Simple	LSTM	GRU
J+2	0,0543	0,0855	0,09	0,0884
J+3	0,0883	0,0828	0,0885	0,0897
J+4	0,0803	0,0838	0,0919	0,0896
J+5	0,0821	0,0934	0,089	0,0901

Table 8: Table summarizing the errors of the different algorithms after evaluation of the Low Sarfalaho zone.

	MLP	RNN Simple	LSTM	GRU
J+2	0,4234	0,0039	0,4419	0,0088
J+3	0,3945	0,0069	0,4442	0,0051
J+4	0,418	0,0057	0,431	0,008
J+5	0,4339	0,0025	0,4482	0,0045

Table 9: Table summarizing the errors of the different algorithms after evaluation of the Belle Ville Piquage zone.

6.2 Figures

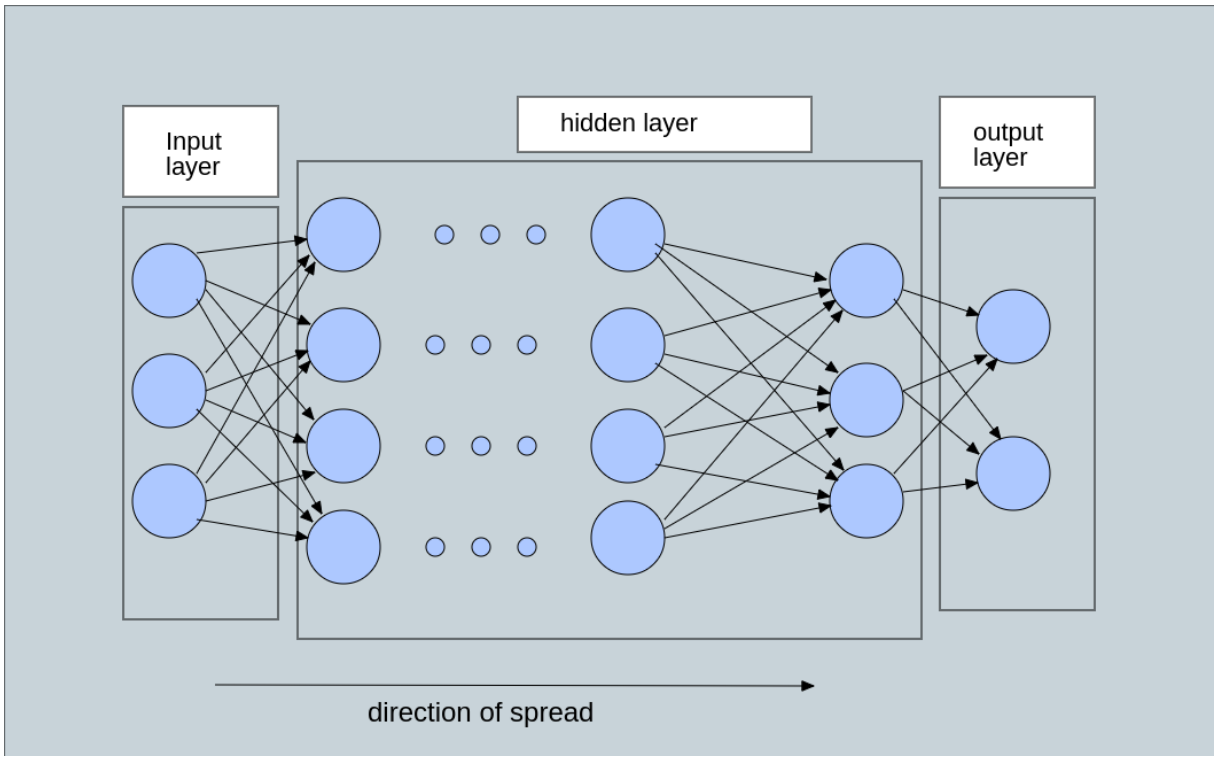

Figure 1: The architecture of a multi-layer perceptron. [33]

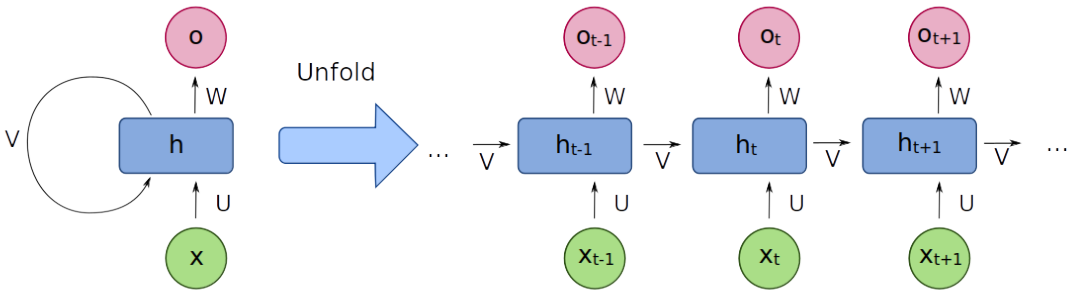

Figure 2: Schema of a RNN. [32]

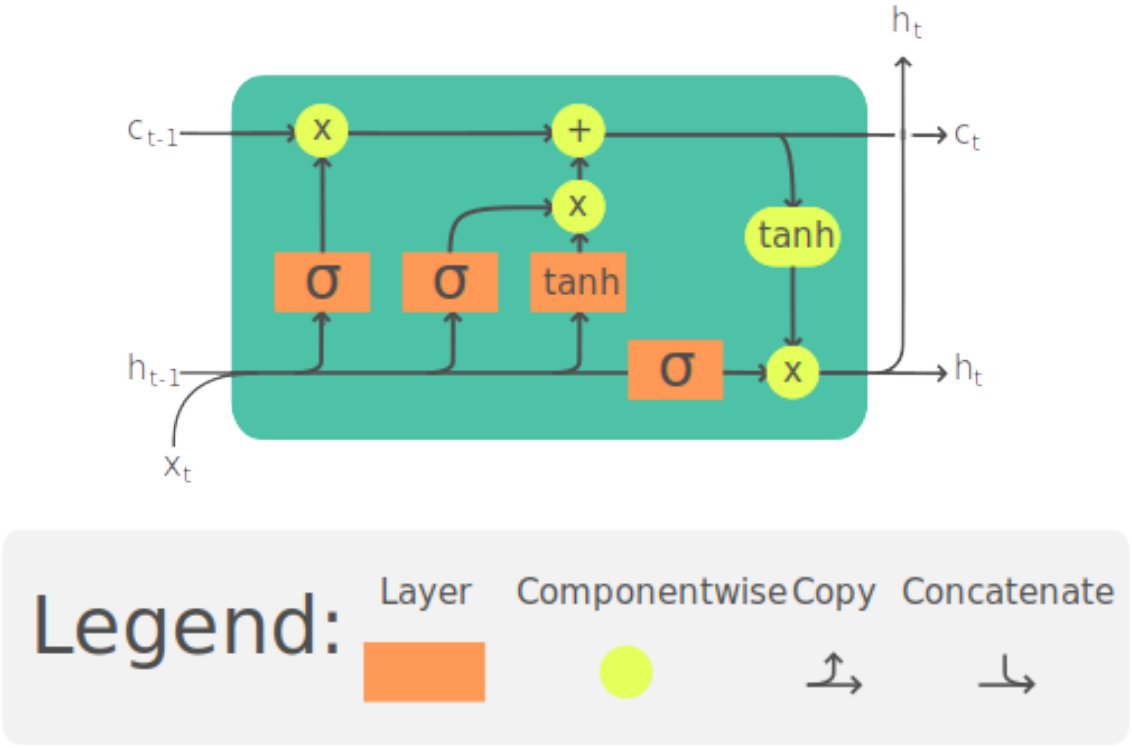

Figure 3: Schema of a LSTM. [32]

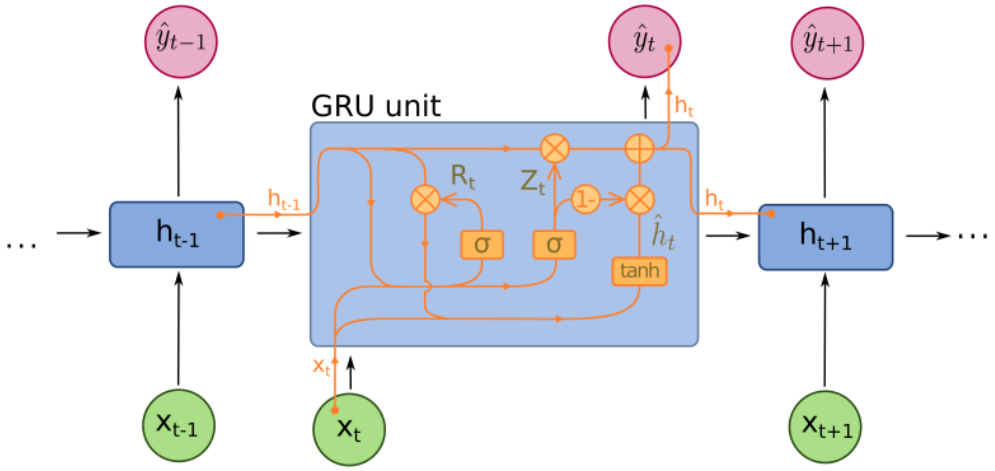

Figure 4: Schema of a GRU. [25]

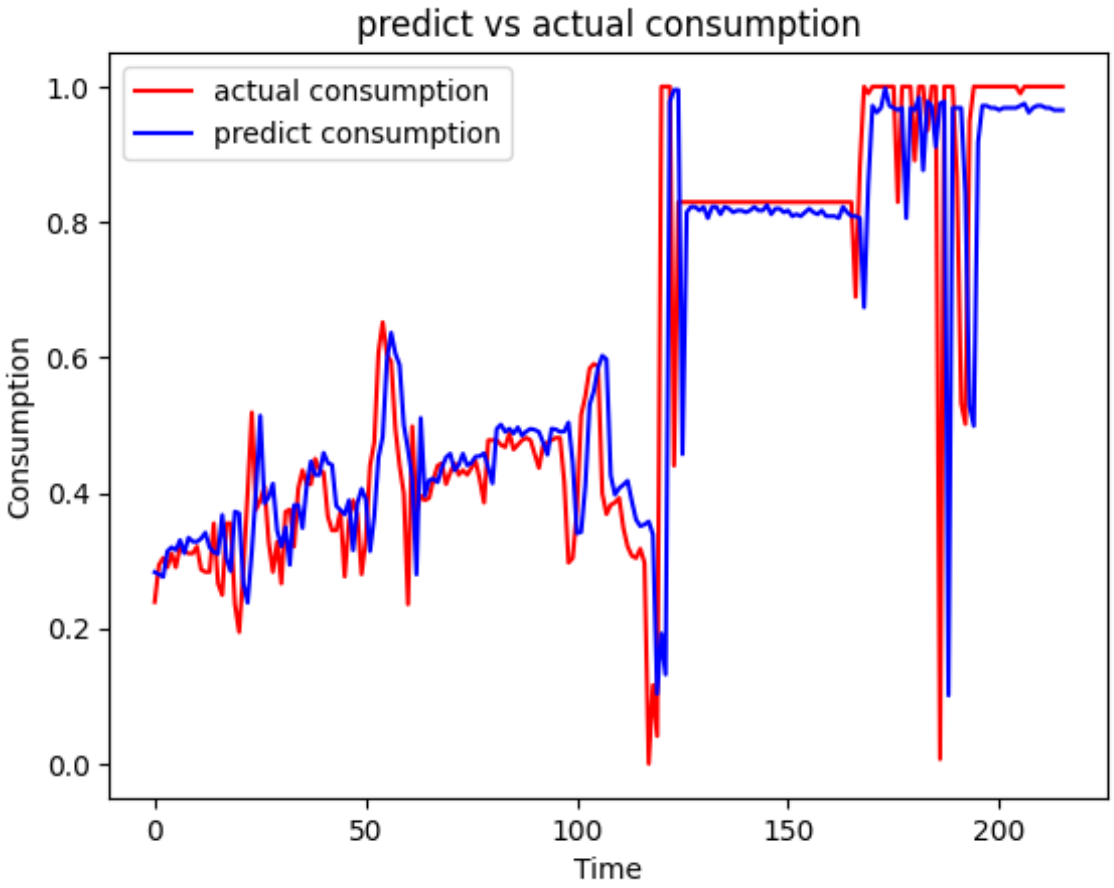

Figure 5: Variation des valeurs observées et celles prédites de la zone Lafiabougou par l'algorithme GRU.

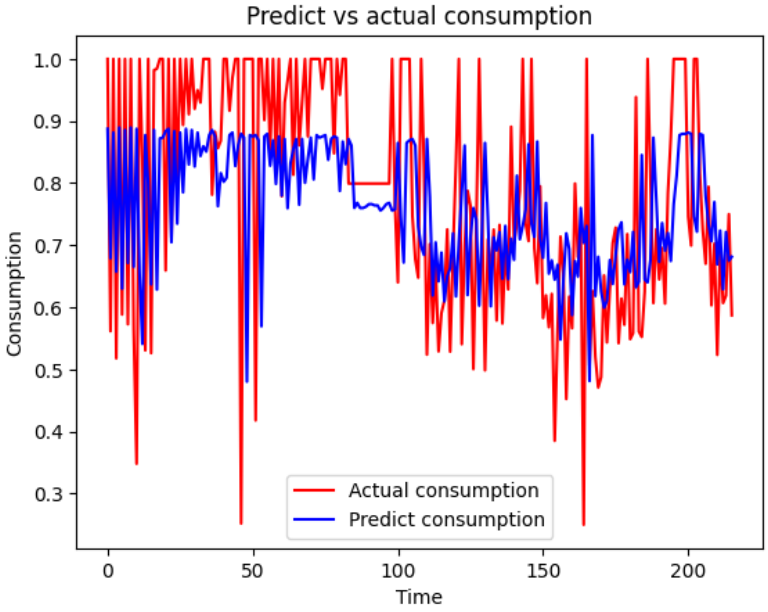

Figure 6: Variation des valeurs observées et celles prédites de la zone Sarfalaho haute par l'algorithme GRU.

VII CONCLUSION AND REFERENCES

7.1 Discussion

This study builds upon the work of [33], which focused on forecasting water consumption for a given day based on previous consumption data. The dataset used in that prior research is the same as the one employed in the present study, which aims to predict water consumption for days J+2 through J+5. The algorithms used are those previously described, and their performance is evaluated based on the Mean Absolute Error (MAE) metric.

Following the training and evaluation phases, the best MAE values vary depending on the algorithm, dataset, and prediction horizon. For day J+2, the GRU algorithm yielded the best results for the Belle Ville and KUA datasets. The simple RNN performed best on the Lafiabougou and High Sarfalaho datasets, while the MLP model achieved the highest accuracy for Bama and Low Sarfalaho.

For day J+3, the results shift slightly, with some algorithms maintaining their performance across the same datasets, while others change. For instance, the datasets corresponding to Lafiabougou, Belle Ville, and Bama continue to yield optimal performance with the same algorithms used for J+2. In contrast, for KUA, High Sarfalaho, and Low Sarfalaho, the best-performing algorithms are MLP, GRU, and simple RNN, respectively.

For the J+5 forecast horizon, the zones that produced the best models using the MLP algorithm are KUA, Low Sarfalaho, and Bama. The GRU algorithm demonstrated superior performance on the High Sarfalaho, Belle Ville, and Lafiabougou datasets.

Across all the analyzed prediction horizons, the LSTM algorithm never emerged as the top-performing model in the various cases studied. However, it consistently produced the best-performing model for all forecast horizons when applied to data from the Bolo Vers Ville zone. No other algorithm managed to produce satisfactory models for this zone, as indicated by the MAE values.

Compared to the study conducted in [33], the GRU algorithm consistently stands out in terms of performance. This result can be attributed to its strong ability to solve complex problems, particularly in the context of time series processing.

Figures 5 and 6 illustrate the variation between observed and predicted values for the Belle Ville and High Sarfalaho datasets, respectively, using the different algorithms.

7.2 Conclusion

This study highlights the effectiveness of machine learning algorithms in predicting water consumption data. Comparative analysis revealed that no single algorithm consistently outperformed the others across all datasets and time periods. Instead, performance varied depending on the specific characteristics of the dataset and the prediction horizon. These results underscore the importance of selecting appropriate algorithms and considering contextual factors when developing predictive models for water consumption. Future research could focus on refining model architectures and incorporating additional features to further enhance prediction accuracy.

Overall, the insights gleaned from this study can inform water management practices, enabling water management agencies to make informed decisions to optimize water distribution and ensure sustainability in the face of increasing demand and environmental challenges.

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