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Explainable Artificial Intelligent as a solution approach to the Duck Curve problem

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Abstract

This paper presents a new approach for solving the electrical load sharing problem generally known in energy circles as the Duck Curve problem. The Duck Curve problem is a curve showing the difference between the total electrical load a utility serves to its consumers (energy from thermal power plants), and what that load looks like after wind and solar generation (or local generation) has served a portion of that load (renewable resources or green energy). This approach based on unsupervised learning Long Short Term Memory (LSTM), with the attention mechanism, aims to give a clear interpretation of the Duck Curve prediction, and to understand the clear reasons for this discrepancy which can help decision makers to better interpret the curve and solve the problem efficiently. Information and Communication Technology (ICT) and Internet of Things (IoT)are necessary for the deployment of green energies. Therefore, the data from the different sensors can be used as a support to validate the information at the local production level and contribute in an effective and targeted way to solve the problem of the ”Duck Curve”.

Keywords: XAI, LSTM, Attention mechanism, Duck Curve problem, IOT, Smart grid, Renewable energies

1. Introduction

The advent of renewable energies, IOT and ICT contributed to achieve the Smart Grid that become a key component in the world energy strategy. Smart Grid optimizes the use of energy by intelligently and dynamically managing the production of energy generated from various existing and new sources (fossil and green energies) according to consumers' needs. To address the challenges of climate change, we are increasingly investing in renewable energy sources, which emit low levels of carbon dioxide (CO2). However, these renewable energies are subject to weather conditions and therefore not always available. Consequently, energy storage will be necessary to ensure a constant

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supply of energy. To successfully manage this energy storage, it is important to have a correct understanding of the issues related to energy production and consumption in order to avoid the production of excessive energy.

Renewable energy refers to all energies that, at least on a human scale, are inexhaustible and available in large quantities. There are five main types of renewable energy: solar energy, wind energy, hydraulic energy, biomass and geothermal energy [6]. Photovoltaic solar energy describes the electricity produced by photovoltaic (PV) cells. These cells receive sunlight and can convert part of it into electricity. Solar photovoltaic energy has been growing very rapidly in the state of California, where the Independent System Operator Corporation (California International Organization for Standardization (ISO)), responsible for the majority of California's electric grid, published a graph of the net load and its potential future appearance [2]. This graph shows the difference between the load forecasted by the grid operators and the variable electricity production entering the grid from solar panels.

With solar PV, California's ISO grid operator is looking at a future with 33% renewable energy, which raises many challenges. The most important of these challenges addresses the Duck Curve problem, illustrated by a popular graphic in the energy communities. The graph in Figure 1 shows the difference between the total load served by a public utility versus how this load looks after the wind and solar generation has served a part of this load. The graphical interpretation of this scenario looks like a sitting duck [2]. From this graph, utilities face a dual challenge of *(i)* assessing the risk of overproduction in the afternoon, and *(ii)* anticipating an increased need for power ramping when solar energy declines in the late afternoon. This leads several utilities to question the long-term adequacy of renewable energy resources. They argue that the ideal solution is to flatten the Duck Curve to reduce the need for conventional production. Most existing solutions focus on flattening the load curve and solving minimum system load problems, by tariff reform, new ancillary services, storage and energy productivity, improve inverter functionality and control systems, etc. While several solutions have been proposed, the influence of the sensor network that constitutes the environment in which these photovoltaic panels are located has not yet been addressed. Our work belongs within this context, and address this issue. In this paper, we propose a new approach based on LSTM neural network paired with attention mechanisms for the prediction to understand all the environmental factors that influence the solar PV production. The proposed approach is applied to photovoltaic or solar sensor and to smart grids sensors. By studying the influences of these data from IOT sensors, we use the eXplainable Artificial Intelligence (XAI) to interpret the Duck Curve prediction in order to find a better way to solve the problem. This paper is organized as follows. Section 2 presents the Duck Curve problem. Then we browse in section 3 several related work to solve the duck problem. Section 4 describes the architecture of our proposed approach. Section 5 presents an application of our proposed approach to the Power PV sensors. Finally, Section 6 concludes the paper.

2. The Duck Curve problem

In 2013, the California Independent System Operator (CAISO), the organization that oversees California's electricity generation and transmission system, published a now-famous graph. As illustrated in Figure 1, this graph displays the energy demand over time on a spring day, and how it is expected to change in the future. The graph also predicts energy demand over time on a typical California spring day. It was only after conducting studies on green grid deployment that researchers noticed that as small-scale solar generation increased during the day, the demand for electricity from the grid decreased (the duck belly). This is due to the excess energy of photovoltaic energy. Then, once the sun begins to set and people return home in the evening, demand on the network begins to peak (the duck's neck). Therefore, they conclude that the grid demand drops in the daytime and then increases again in the evening, as we see in the Figure 1. In this figure, the line of the graph, especially the increasingly pronounced shape of the predictions over the years looks like the silhouette of a duck. This phenomenon was nicknamed the Duck Curve, and the name stuck.

3. Related work

The state of the art about solutions around the Duck Curve has been well established. The first guidelines were developed by Jim Lazar, in his report "Teaching the duck to fly" [5] in which he proposes ten strategies to solve the problem without resorting to an entirely new technology. In his first approach, he proposes to target energy efficiency

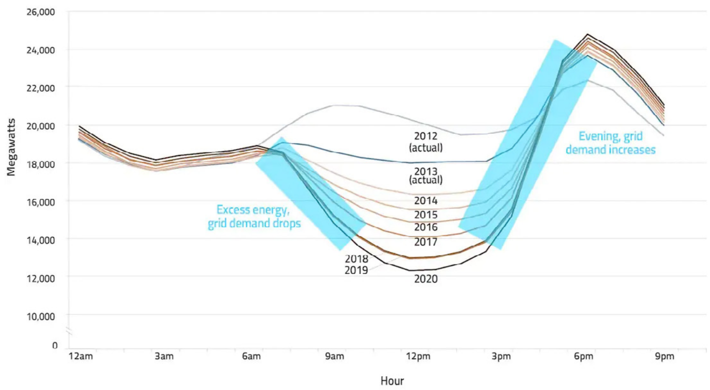

Fig. 1. Presentation of the Duck Curve problem [3].

at times when the electrical load of the panels increases significantly. One example is to encourage the use of Light-Emitting Diodes (LED) in households and businesses. From the same perspective, Thiede S. et al. [10] proposed a guided method for creating an energy portfolio to classify and prioritize energy consumers in companies. This method is intended to provide action plans for improving energy and resource efficiency in manufacturing companies. The second approach consists of acquiring and deploying renewable resources according to peak hours, for example, by swapping them. Vahid Amir and Mahdi Azimian [11] proposed a dynamic planning tool for the various green energy production resources using a two-stage stochastic programming method that combines the MATLAB genetic algorithm and the non-linear mixed integer programming model of the GAMS software. The third strategy focuses on managing water and wastewater pumping loads. It involves controlling water and wastewater pumps to operate during periods of low existing load or high solar generation, and reducing pumping load during peak hours. Anginé Zohrabian et al. [12] mainly focused on the demand & response measures through simulations implementing the benefits of the water-energy nexus for the power grid. The fourth approach consists in controlling electric water heaters to reduce peak demand and increase load at strategic times. This increases electricity consumption at night and in the middle of a sunny day, and therefore redirect its use during the morning and evening peak periods. S. Ali Pourmousavi et al. [13] proved the effectiveness of this approach through computer simulations in real time. Due to the fact that 20% of commercial air conditioning systems are converted to ice or chilled water storage systems; and that compressors and chillers operate during day and night, and are downsized during peak hours, Jim Lazar [5] recommends a fifth approach focusing on the conversion of commercial air conditioning to ice or chilled water storage. Uys et al. [14] use this approach to convert an ice storage facility to a chilled water system in a deep gold mine.

4. Proposed approach

From the literature, as presented in the previous section, it is clear that none of these approaches pay particular attention to the grid sensor network that equip these renewable energy production sites. While such sensors are essential elements to better understand what is happening locally on the network. Applying artificial intelligence tools, especially, LSTM-based Attention mechanism, to smart data provided by these sensors can help to understand what is happening at the production sites, and other reasons not necessarily related to the availability of solar energy for PV power generation for which we are not able to straighten the duck's back. This amounts to an interpretation of the prediction at the output of the Duck Curve, and this interpretation can help us to solve the problem effectively (control and save energy). To address this, we propose an original approach consisting of a Long Short-Term Memory-based neural network with attention mechanisms for the prediction and understanding the influence of smart grid sensors in solar PV production. Figure 2 presents our proposed approach. With this approach, it is possible to understand clearly the output of the prediction model about the Duck Curve in order to know what this prediction does not tell us and to understand the clear reasons for this discrepancy, which can help decision makers to better interpret the curve and solve the problem efficiently.

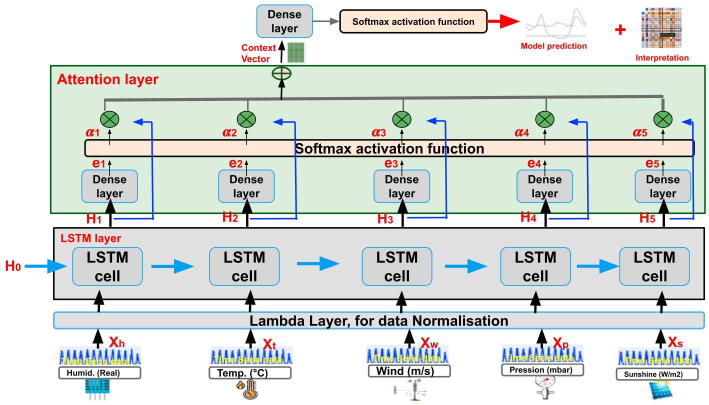

Fig. 2. Global architecture of the proposed LSTM-based model with attention mechanism.

4.1. Long Short-Term Memory neural networks

Long Short-Term Memory (LSTM), are networks that contain both short and long term information. Such networks address the problem of sequential data. LSTM cells can generate a context vector that is used to make predictions about the data. As presented by Figure 3, in its external structure, the LSTM network is presented as a cell of two types of state vectors. The first one called the Hidden State and denotes by *H1* contains important information about the short term. While, the second one called the Cell State and denoted by *C1* contains the important information on the long term. With such a structure, the LSTM can process the data more efficiently by focusing on the short and long term.

In Figure 3, LSTM internal structure is composed of three main gates. The first gate, *Forget Gate*, is used to save important information from the cell state in the long term. It consists of a Dense layer and a Sigmoid function, which are represented at the output in the form of a vector $f1$ with values between 0 and 1, which is used to filter the cell state information. The second input gate, plays a similar role but with a Tanh function. This function adds the long term information from the input information $X1$, and the hidden state $H1$ (which contains the short term information) to give a new vector called *candidate vector* and denoted by $K1$, which is added to the internal cell state vector being created. Before being added, the vector $K1$ is filtered from another vector $i1$ (constructed in the same way as $f1$, i.e. from a Dense layer and a Sigmoid function). The new obtained cell state contains the values of the candidate vector filtered by $i1$. The third gate called *Output Gate* allows reconstructing a new hidden state $H2$, from the old hidden state $H1$, by recovering among the information contained in the previously created cell State and which contains the long-term information, important information for the short-term. To achieve this, the first step consists of create a $Q1$ filter from the hidden state $H1$ and the input $X1$. This filter is then used to filter the values previously processed by the Tanh function. The preprocessing by Tanh allows updating the values of the cell state previously created in the interval $]-1, 1[$. Thus, after filtering by $Q1$, the new Hidden State $H2$, which is updated with the output of the cell state values, has values between 0 and 1, and contains information on the short term. The architecture also shows that the cell state $C1$ is updated by addition at each calculation time.

4.2. Attention mechanism

Originally, the attention mechanism was applied to text translation problems, especially the translation of English sentences to French [15]. This mechanism has overcome the difficulties of LSTM networks in retaining all the information required to process a long sequence of data (difficulties in memorizing the sequential sequence of events). Its architecture consists of an *encoder*, an *attention layer*, and a *decoder* [16]. We denote the input vectors of the encoder by x_1, x_2, x_3, x_4 and the output vectors by h_1, h_2, h_3, h_4. The attention mechanism is located between the encoder and the decoder, its input is composed of the output vectors h_1, h_2, h_3, h_4 of the encoder and the states of the decoder s_0, s_1, s_2, s_3. The output of the attention layer is a sequence of vectors called *context vectors*. This context vectors allow the decoder to focus on certain parts of the input when predicting its output.

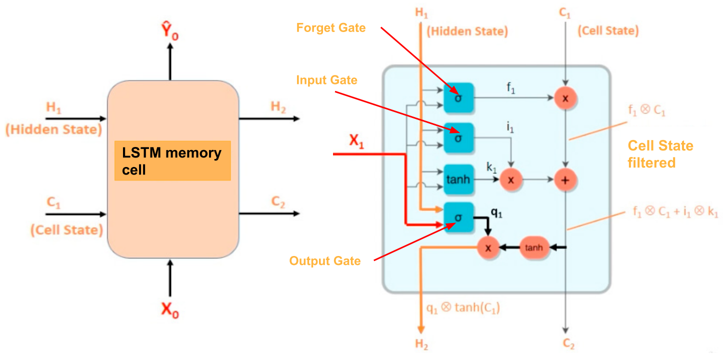

Fig. 3. External and internal architecture of an LSTM cell.

4.3. LSTM-Based Method with Attention Mechanism

The input of the network after the normalization of the input data is an encoder consisting of LSTM cells. This encoder receives the data in the form of univariate time series with a time step equal to the length of the input vector data. This process is done for each observation. Subsequently, this encoder passes its output result, a set of vectors representative of the data taken in input called hidden states, to the attention layer as input. Then, in the attention layer, we use the attention algorithm to create a new context vector called attention vector from the attention weights a_i corresponding to the input variables. After this step, the context vector to be sent to the decoder depends on these attention weights.

The decoder applies a non-linear function on the context or the attention vector. Instead, the generator applies a linear function to the output of the decoder and the attention vector to produce the prediction. After that, we use the context vectors, attention weight and input variable to show the interpretation of this prediction.

Figure 4 shows us an architecture that summarizes the pseudocode of this approach.

5. Experiment

5.1. Dataset

In order to validate our approach, we chose to work on a set of power IOT sensors data. The dataset describes the evolution of the environmental sensors of a location where a solar panel was installed between July 2018 and April 2019. It contains a total of six variables describing the weather conditions of the area where the solar panel is installed, and its produced energy produced, namely: The *temperature* denoted by *Temp.* (C) which is the temperature of the place where the solar panel is installed. The *relative humidity* denoted by *Humid. Rel.* (%) which represents the evolution of the relative humidity. The *wind speed* denoted by *Vent* (m/s), which represents the wind speed in this environment. The *atmospheric pressure* denoted by *Pressure* ($mbar$), which describes the atmospheric pressure of the environment. The *sunshine* denoted by *Ensoleillement* (W/m^2), which provides information on the level of sunshine in the environment. The *power* denoted by *Watts* (W) refers to the power delivered by the photovoltaic panel. The dataset contains also 27553 observations taken every 15 minutes. For the purposes of our study, we have separated these data sets into 80% and 20% representing the training and test data, respectively. Table 1 gives us an overview of these data. The power PV dataset is freely available on Github[1].

[1] https://github.com/main/Series_Temporelles/Seq2Seq/Data/Power$_P V.csv$

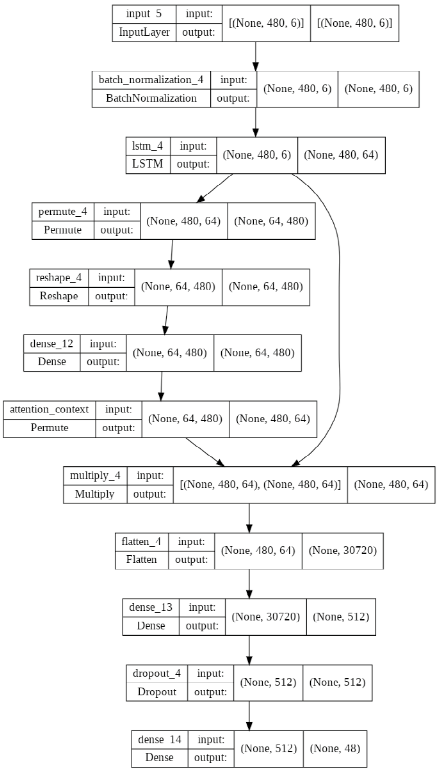

Fig. 4. Pseudocode of the proposed approach.

Table 1. An overview of the Power PV dataset.

Number of variables	Number of observations	Train size	Test size	Type
06	27553	22042 = 80%	5511 = 20%	Float_32

Figures 5 and figure 6 show us some important results after analysis on the created time series. Figure 5 (a) and 5 (b) are respectively the auto correlation and partial correlation graph after analysis over 500 lags. They show us the presence of a series even after 400 lags, and also tell us that the majority of lags are around the value 100.

Figure 5 (c) shows the total distribution of the dataset into training data (80% of the total dataset on the left), and test data (20% of the total dataset on the right).

Figure 6 (d) gives us an overview of the series corresponding to the variable Watt that will be used and how it has been distributed in the total dataset under an offset of 1, and figure 6 (e), this same overview for all input variables with an offset of 1 as well.

5.2. Parameters setting

A manual step-by-step selection of hyperparameters for this study was to refer to some basic parameter sets existing in the literature. Table 2 show the parameters that we found important for this study.

5.3. Result and Analysis

For a good analysis of the predictions in the time series domain, we considered several techniques from different domains, in order to evaluate both the quality and the reliability of the result for a good accuracy that correlates with reality. There are many performance measures available, but we have used the following: MAE, MSE, RMSE.

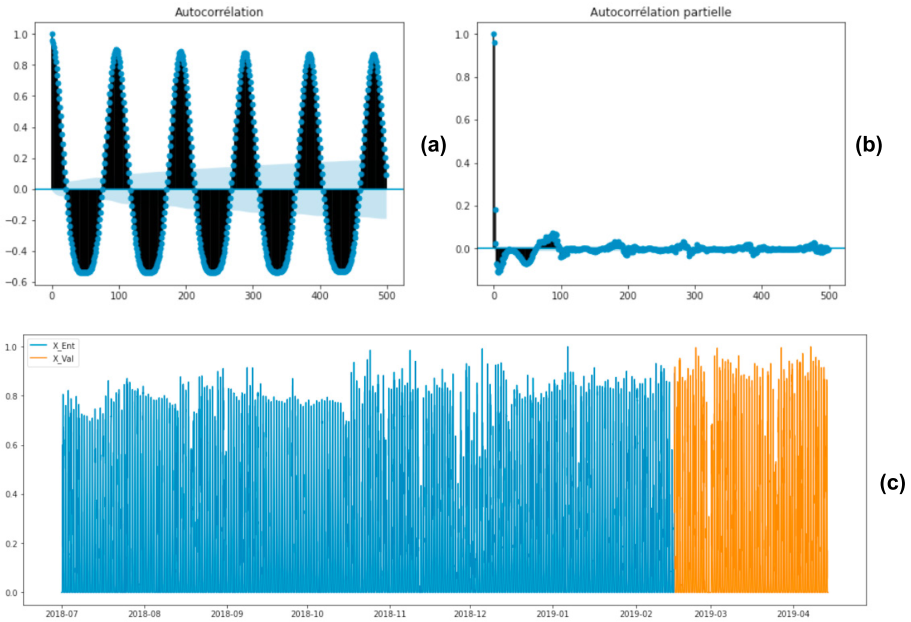

Fig. 5. (a) Auto-correlation plot. (b) Partial correlation plot. (c) Dataset distribution plot.

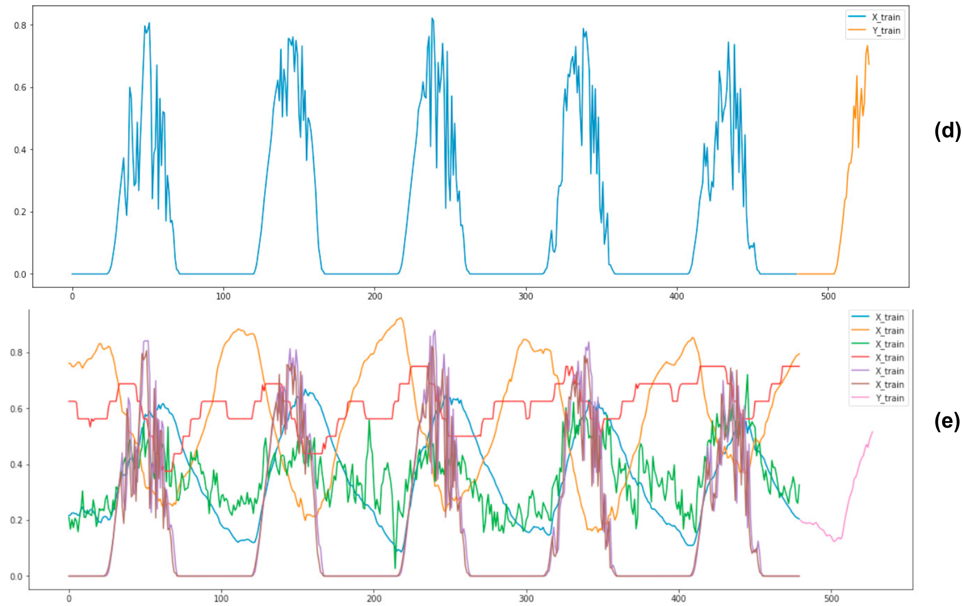

Fig. 6. (d) Time series corresponding to power (in Watt). (e) Time series of all study variables.

Figure 7 shows us the result of the prediction obtained. In this figure, the capture in figure 7 (g) shows us the matrix of real values in the field, and the one in figure 7 (f) the predicted values which at first sight seem very close to the observed values over the taken data period.

The average MAE, MSE and RMSE values obtained after evaluation of the test are summarised in Table 3

Table 2. Parameter tuning details for our LSTM-based attention mechanism approach.

Parameters	**Attention mechanism + LSTM method**
Input Layer	[(None, 480, 6)]
Output Layer	(None, 48)
Batch size	128
Normalisation	Batch normalisation
Learning rate	$\alpha = 0.003$
Optimizer	Adam ($\beta_1 = 0.5, \beta_2 = 0.999$)
Loss	Mean squared error
Epochs	100

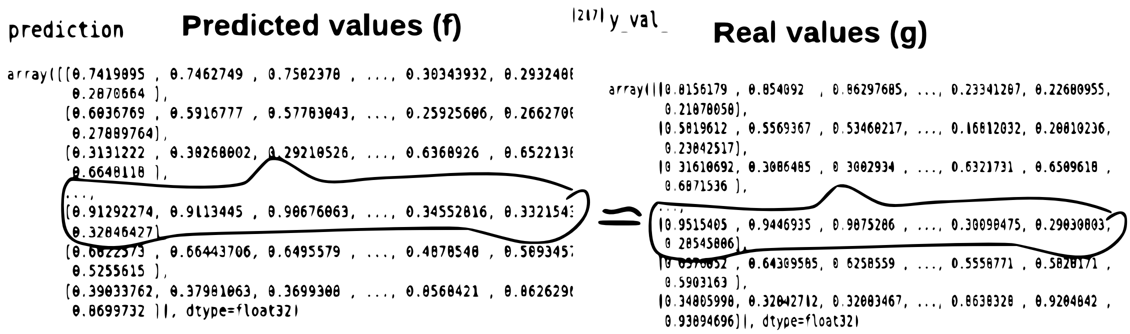

Fig. 7. Duck Curve prediction.

Table 3. Summary table of Comparison of MSE, MAE, RMSE tests for LSTM based approach with attention mechanism.

Test Scores	MAE	MSE	RMSE
LSTM + Attention mechanism	Test Score: 0.08 MAE	Test Score: 0.01 MSE	Test Score: 0.11 RMSE

According to this table, the model has learned well with a margin of error of 0.01, and that [MAE] is less than [RMSE] so all the errors made by the model have the same amplitude. As for the RMSE, it indicates that the model gives a prediction with respect to the ground truths with a margin of error of 10%.

5.4. *Interpretation of the model output*

Like all other prediction models detailed in the section 3, our approach only provides a more or less perceptible prediction as an output. Hence, the urgent need to look at other areas that can speak to us better. These new approaches are part of XAI, and by following this approach we want to find out why the model has provided such a prediction exactly why the model has provided such a prediction. This allow us to broaden our view of the problem to be solved, as so far most of the conclusions are against PV collectors, while the site contains other collectors that can also contribute to the solution of the problem efficiently. Figures 8 and 9 allow us to understand the nature of the prediction.

The first figure 8 shows us the different variables that the model has to pay attention to in order to make the prediction during one hour of the day. We notice for example that wind speed, and atmospheric pressure have a great impact on solar production even in the presence of the sun. This should be a challenge for policymakers to include such variables in their decision-making. According to the same figure, panels placed in very humid regions (e.g. tropical zone) have not the same production as those installed where the air is warm, which should challenge engineers to take environmental factors into account when installing or designing PV.

Figure 9 gives a much better interpretation by specifying, for each hour, the value and the sensor on which the model has focused to give the prediction.

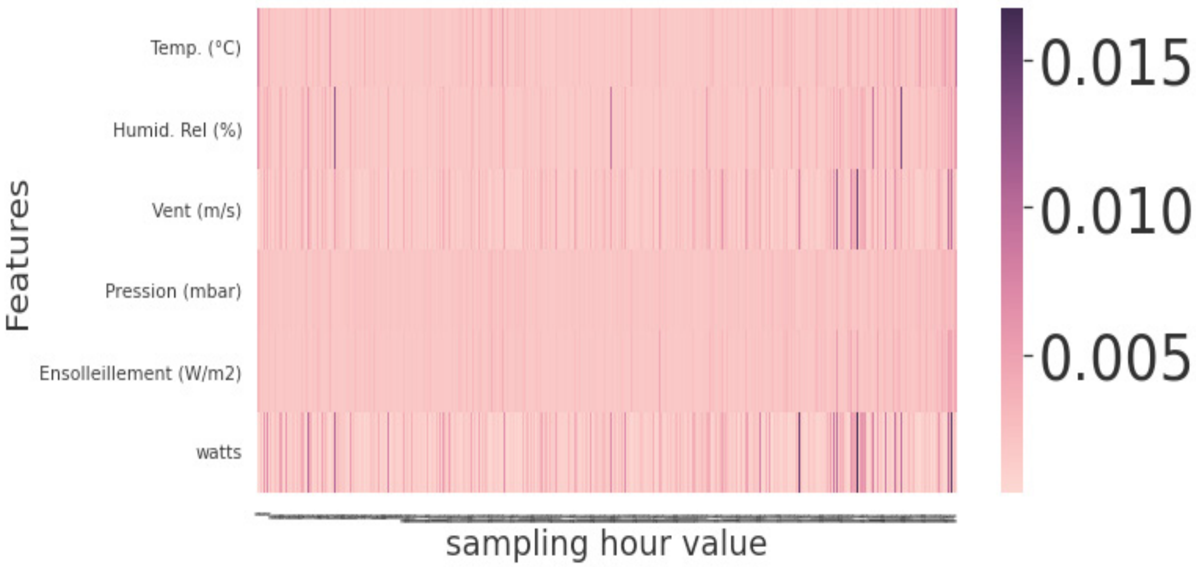

Fig. 8. Explanations provided by the attention mechanism showing the sensors contributing the most to the PV production.

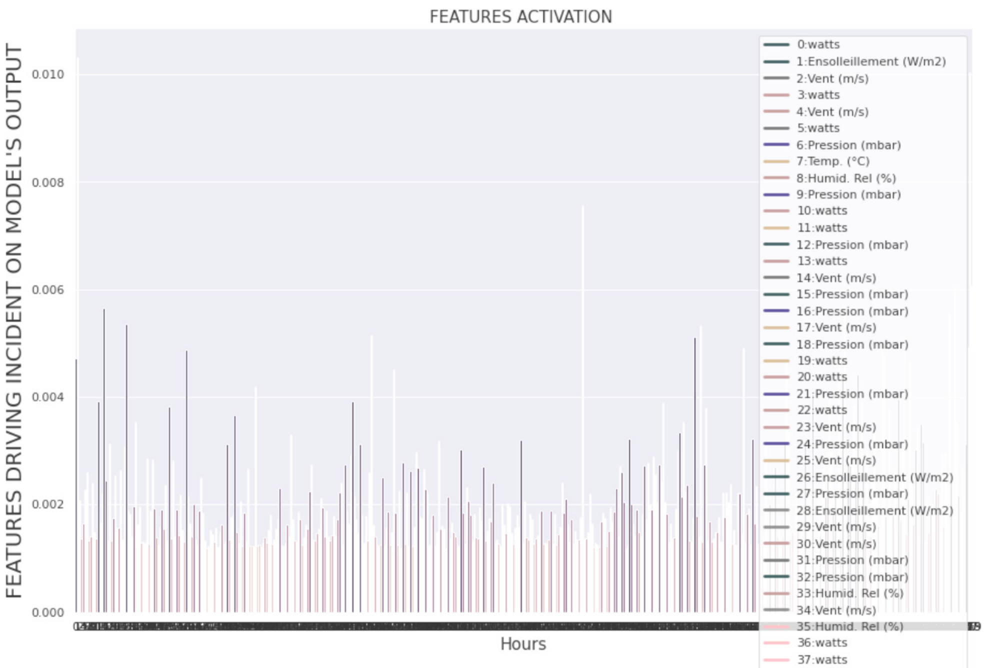

Fig. 9. Explanation of the influence of the different sensors on the PV production during the day.

The limits of this solution are found in the visualization on the x-axis of the different hours on which the model has been trained. Thus, by reducing these hours in order to have a better visualization of the interpretation, we lose a lot of precision because the model does not have enough data to train itself properly. The challenge remains to be met at this level.

6. Conclusion and future work

The aim of this study was to give another vision of the solution of the Duck Curve problem, which has become famous in the field of renewable energies. For this purpose, we proposed an XAI approach based on the attention mechanism and the LSTM model. We obtained satisfactory results with a model that is able to tell why it made any prediction at a given time. With this interpretation given automatically by the model, we open the way to other solutions around the Duck Curve. The first is environmental, one must take into account climate factors when installing PV and if possible counteract some of these factors to be able to straighten the Duck Curve. However, this study of the sensor data in the PV environment is also necessary to perform predictive maintenance so that the panel does not suddenly fail. This opens the door to the study of anomalies in the PV sensor data that may contain information that can guide researchers in finding a solution to the Duck Curve.

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