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TIME SERIES MACHINE LEARNING AUGMENTED WITH SOCIAL NETWORK EVENTS TO IMPROVE NATIONAL ELECTRICITY CONSUMPTION PROFILE ESTIMATION

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ABSTRACT

Assessing the electricity demand is essential for the grid stability, as energy production must always meet energy demand. It is also important for the electricity market settlement. Depending on that, energy load investigation is fundamental in enhancing the reliability, efficiency and fairness of the electrical grid. In general, two main factors impact the energy load. The first one is the meteorological conditions. The second one is human activities. Nevertheless, human activities are hard to anticipate and evaluate. Yet this work focuses on identifying and quantifying important human events (regarding their impact on the energy consumption) from social media. In order to achieve that, this work proposes a complete method to detect when an event might have occurred. It develops a mechanism to collect data from social media, more particularly from Twitter. Then it presents how different events can be picked and labeled. It shows how those events can be quantified and integrated into different models to enhance the load profile estimation. Eventually, it validates the whole process with real data from the French electrical grid. It also demonstrates how the proposed approach can minimize the error of the profile load estimation up to 60% the root means square error. In addition, it does illustrate how artificial intelligence techniques like transfer learning can be helpful in extracting knowledge from a standard energy profile like a residential profile and project it on another one like an industrial profile, especially when there is a lack of historical data.

INTRODUCTION

One way to manage the stability of the grid is to use demand forecasting. The electrical demand varies throughout the day and is affected by many factors, such as the weather or human activities. Inaccurate demand forecasting can lead to an imbalance between the supply and demand, which can result in a power outage or other disruptions.

Human activities can significantly impact the amount of electricity that is being consumed. For example, heating system are starting at the morning when inhabitants wake up. And when they are engaging in various activities, such

as using lights, appliances, and electronic devices, the demand for electricity tends to be higher. Similarly, in the evenings when people are returning home from work and engaging in activities such as cooking dinner, watching television, or using computers, the demand for electricity increases. Additionally, events such as sporting events or concerts can also significantly impact the load on the grid [21].

In the past, measuring half-hourly load curves for the mass market was costly, and models were calibrated using a small dataset and used to predict future load curves for several years. However, this method was not very accurate as it did not account for changes in behavior, renovations, or specific events. In 2018 [15], a new method called the dynamic load profiling was introduced. This method uses a complex weighted average of the half-hourly load curves of a representative sample of 10,000 users [16], which are collected daily from Linky smart meters. To control the quality of these calculations, a confidence interval reference is needed to validate the profiles and provide emergency profiles when load curves are not available. The reference was first created using basic calculations, but there is a need to improve this forecasting.

There has been extensive research on methods to accurately predict electricity load on different timeframes using various techniques [19]. Researchers have proposed solutions ranging from those based on knowledge to those utilizing machine learning [17][18]. However, most studies have primarily relied on utilizing weather data and have overlooked incorporating events data in their predictions. The reason for this is the challenges in acquiring such data and determining which events are significant enough to impact the load, as well as how to quantify their effect on the prediction to minimize errors when similar events occur in the future.

This study presents a method for using social media data, specifically tweets, to improve energy load profile estimates. The method involves collecting tweets, identifying events mentioned in the tweets, determining the impact of those events on energy consumption, and incorporating this information into load profile models. The goal of the research is to reduce the error of the load profile estimated by up to 60% using root mean square error. The researchers also explore the use of artificial intelligence techniques, such as transfer learning, to apply

knowledge from one type of energy profile (e.g. residential) to another type (e.g. industrial) when historical data is limited. The results of the analysis are validated using real data from the French electrical grid.

MODELING WITH ANOMALY DETECTION

In previous research works, researchers did try to model the demand with the changes in meteorological data. Yet when load curves are analyzed; they contain changes that cannot be related to the weather changes. For example, in figure 1 it can be remarked that on the left for the 20th of March 2017 where the consumption reached 6.4 GW at 7.30 pm while in the right for the previous day (March 19th, 2017) with the same meteorological conditions the consumption stayed around 5.5 GW at 7.30 pm of consumed energy.



Figure 1 The national energy demand for the 19 and 20 of March 2017

So, the important question to answer is what is the origin for this difference? As it is not related to weather changes. And how it can be identified, quantified and validated?

For the 20th of March 2017, after checking with social media the most popular event at that moment was the French presidential debate at that moment with more than 9.8 million spectators in direct [20].

The solution proposed in this paper explain those changes or anomalies in the load curves is to first detect those anomalies not related to weather changes. Second step is to look for what happened at those moments with the help of social media to identify the events causing those anomalies. Third step is to quantify the impact of those events and integrate them in the future models.

The social media that was chosen for this is twitter, because of its popularity and as an example to what can be done.

SOCIAL MEDIA DATA

Twitter

Twitter is a social media platform that enables users to post short messages, known as "tweets," that are limited to 140 characters [6]. Unlike other social networks, the accounts on Twitter are publicly visible by default and it is common

for users to follow well-known individuals such as politicians and celebrities. Twitter users can also use hashtags, which are words or phrases preceded by the "#" symbol [2], to categorize their tweets and improve their discoverability. According to a study, there are approximately 12 million Twitter users in France and around 50 million tweets are sent per day [5].

Collecting the data

Obtaining data from Twitter can be difficult due to regulatory considerations, such as the General Data Protection Regulation (GDPR). In addition, the sheer volume of data on Twitter can be overwhelming, with approximately 500 million tweets per day [3] and a total size of 280 GB daily. It means in the period between 2014 and 2019 (our data set) we need to collect more than 608 TB of data which is a lot.

One potential solution to these challenges is to use web scraping tools to extract data from Twitter, although this can be a resource-intensive process.

Web scraping refers to the process of collecting and compiling information from the internet in an organized manner [7]. This is done by using a program, called a web robot or "bot", that mimics the actions a person would take while browsing the web, such as accessing a website and extracting specific data. The bot then structures the collected data in the desired format. In this case, the bot is accessing the Twitter website, extracting data of interest, and structuring it accordingly.

To determine which data to collect and when to collect it, one approach is to use anomaly detection algorithms, which can help identify patterns in data that do not conform to expected behavior. These anomalies may indicate the occurrence of important events or trends that could be relevant for electricity load estimation.

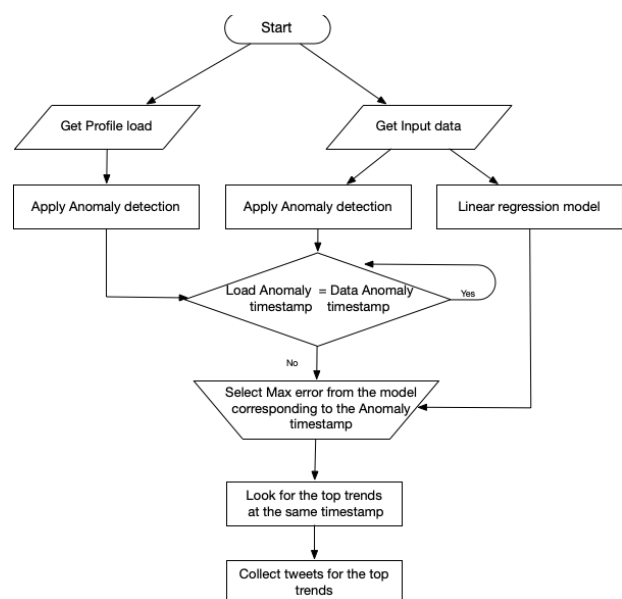


Figure 2 Which data to look for and how to get it.

This process, as presented in figure 2, involves using an algorithm based on a decision tree technique to identify anomalies in the electricity load curve and input data. If an anomaly is detected in the load curve but not in the input data, it is assumed to be caused by an event rather than a change in weather conditions. In this case, the scraper searches for popular hashtags at the time of the anomaly and uses them to identify the most relevant events [8]. The tweets associated with these hashtags are collected and processed, and the resulting data is integrated into models. The algorithm first looks for the top three hashtags and collects all tweets associated with them over the entire data collection period. These tweets are then processed and incorporated into the models.

Explore the data

Each tweet record consists of 40 key-value pairs including the tweet text and the language of the tweet. In this study, only French language tweets will be used. However, the data cannot be directly incorporated into models as is.

Many of the keys are not useful for our purposes, and the data must be transformed to accurately reflect people's interests in a subject. To do this, the number of tweets about each event is aggregated on an hourly basis to create an indicator of the level of interest in the event. This indicator should capture both the peak period for an event and the number of people interested in it. The process of preparing the tweet data for use in models is illustrated in figure 3 and involves identifying relevant tweets, aggregating the data on an hourly basis, and processing the resulting data. Some events can be directly identified from hashtags, while others are more difficult to identify.

Table 1 shows the top hashtags for April 29, 2019, between 9 am and 10 am. The first hashtag, "marathonnantes," represents a sporting event in France. The second hashtag, "giletsjaunes," represents a political social movement in France. The third hashtag, "srfcpgs," represents a football match in France's League 1 after analysis of the associated tweets and hashtags.

| Event | Number of occurrences |
|------------------|-----------------------|
| Marathonnantes | 99 |
| Giletsjaunes | 90 |
| srfcpgs | 84 |
| journeedelafemme | 75 |

Table 1 Hashtags count in 29 of April 2019 between 9 am and 10 am.

The fourth hashtag, "journeedelafemme," represents a social event for women's rights. Currently, the process of determining which hashtags represent events and which do not is done manually using human expertise. This study aims to assess the value of social data before automating the process.

In some cases, different hashtags may refer to the same event, such as "gameofthrones" and "got." When collecting tweets for each hashtag, it is possible to end up with duplicated tweets that use both hashtags. To address

this issue, the hashtags are merged, and the duplicated tweets are removed. The process of identifying whether two hashtags refer to the same event is performed manually. This helps ensure that the data is accurate and avoids double-counting tweets.

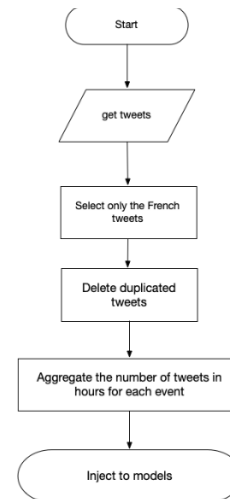


Figure 3 Schema of the different steps to treat the tweets data

VALIDATION

This research validates and evaluate the proposed approach using electricity data from France as a test case. The data was collected over a period of five years (2014-2019) from 32 weather stations across France. It includes 313 variables related to temperature, humidity, solar irradiance, and wind, and contains approximately 49,178 measurements for each variable at various times. These data were collected from Enedis.

Enedis and RTE, the French electricity distribution and transmission operators respectively, are responsible for maintaining the stability of the electrical grid [22]. As part of this responsibility, they divide their customers into different energy profiles based on their usage levels and subscription limits. For example, the RES1 profile is for residential customers with a subscription limit of 6 KVA, and the PRO1 profile is for industrial customers with a maximum subscription of 36 KVA [22]. This system helps to accurately estimate and allocate energy resources and can assist in maintaining equilibrium on the network.

The data from 2014 to 2018 was used to train a model, while the data from 2019 was used to test and verify the model's accuracy. Before the data could be used for analysis, it had to be cleaned and prepared.

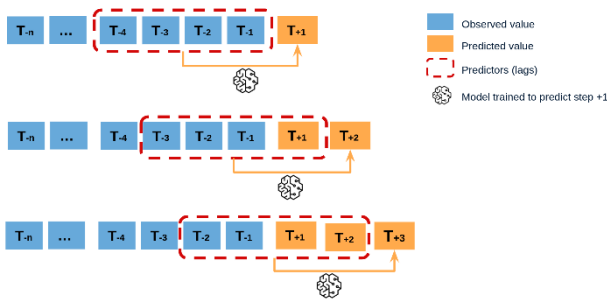


Figure 4 Continuous cross validation

One method that can be used to cross-validate time-series data is continuous cross-validation. This involves starting with a small subset of data for training, using it to predict subsequent data points, and then evaluating the accuracy of the predictions. The predicted data points are then included in the training set for the next iteration, and the process is repeated until all the data has been used for prediction and evaluation. This process is illustrated in Figure 4.

The prediction horizon was one week, or 168 hours. After making predictions, the results were incorporated into the training data and the process was repeated. In order to evaluate the performance of the model, two metrics were used: max error and root mean square error (RMSE). These evaluation metrics were used to compare the precision of different models before and after integrating social data, in order to determine the impact of the social data on the accuracy of load profile estimates. Three types of models were considered in this study: linear regression, XGboost, and deep learning.

- Linear regression is a statistical method used to model the linear relationship between a dependent variable and one or more independent variables [11].
- XGboost is a package that includes efficient implementations of gradient boosting algorithms and linear model solvers [13], and can be used for tasks such as regression, classification, and ranking [12].
- Deep learning is a type of machine learning that involves training artificial neural networks on large datasets [9]. One type of deep learning model used in this study was long short-term memory (LSTM), which is a type of recurrent neural network that is particularly well-suited for processing sequences of data such as time series data [10].

| | MAX ERROR | RMSE |
|---------------------|-----------|--------|
| LINEAR MODEL | 0.403 | 0.0947 |
| XGBOOST | 0.374 | 0.0918 |
| LSTM | 0.310 | 0.0441 |

Table 2 Accuracy scores for residential profile without social data

The evaluation metrics for the three models, as they were

applied solely to weather data, are provided in Table 2.

Through the research we collected a large amount of data, including over 182 events and more than 100 million tweets, which took a significant amount of time and computing power. The events covered a wide range of topics, including sports, politics, culture, history, TV shows, festivals, and more, spanning various time periods. To give an example, figure 5 presents a graph that shows the number of tweets for a TV show named “Top Chef” in France. Tweets are aggregated by hour and covering the period between 2014-2019. This graph first shows a periodic pattern that corresponds to the regular broadcast of the TV show, but also how the French people are losing interest through time as they tweet less through the years. It does also indicate that people are in general more interested in the first and the last episode of each season, which can be very helpful when trying to quantify the impact of this event.

Now they are ready to be used along with weather information, to run our models and obtained the accuracy results presented in Table 3.

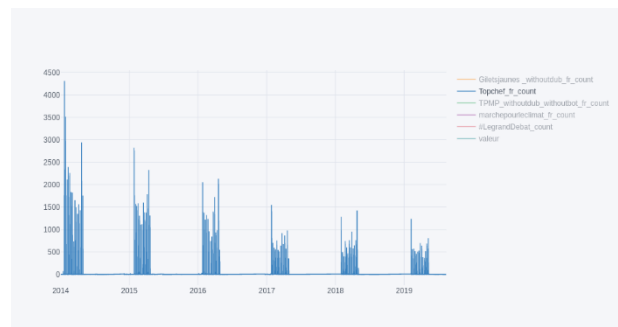


Figure 5 Aggregated tweets a Tv show called “Top chef” in France for 6 years

When comparing the results from Table 2 and Table 3, it is clear that incorporating events data from Twitter in addition to weather data improves the performance of the linear regression model. Specifically, the maximum error is reduced by 12% and the RMSE is decreased by 1.4%. This improvement is largely due to the reduction of the maximum error, which allows for correction of calendar effects caused by events that the model is not aware of. While there are not yet any structural improvements in the model, such as trend capture, the overall performance of the model is improved by drastically reducing the error for certain instances of data, which removes the negative impact of data with a very different variance from the rest of the data. This is particularly beneficial for linear regression-based algorithms, which is why this model saw such a significant improvement. Overall, the reduction of the max error and improvement in the RMSE for all three

models demonstrates the importance of incorporating social data and supports the proposed approach of utilizing it to improve the model's performance.

| | Without events | | With events | | Improvement | |
|--------------|----------------|--------|-------------|-------|-------------|--------|
| | Max error | RMSE | Max error | RMSE | Max error % | RMSE % |
| Linear model | 0.403 | 0.0947 | 0.279 | 0.080 | 12.4 | 1.4 |
| XGboost | 0.374 | 0.0918 | 0.342 | 0.079 | 3.2 | 1.2 |
| LSTM | 0.310 | 0.0441 | 0.271 | 0.041 | 3.9 | 0.3 |

Table 3 Precision for residential profile with social data

TRANSFER LEARNING

For this research transfer learning can be very helpful to apply for the different consumer profiles where there is limit in the available data to train a complete model; less than 2 years of data are available.

The reason for this is that the model has a high number of parameters that need to be adjusted, which is greater than 17 million. Additionally, the model must process a significant amount of input data spanning four years (with more than 100 million tweets), including more than 500 columns. Transfer learning is a machine learning technique that involves using a pre-trained model as a starting point to solve a new task [1]. In the context of neural networks, transfer learning can be used to save time and resources by leveraging the knowledge and features learned by a model on a different task, rather than training a new model from scratch. This can be especially useful when there is a limited amount of data available for the new task, as the pre-trained model can provide a good initial set of features that can be fine-tuned on the new data. Figure 6 shows how transfer learning is applied for different consumption profiles.

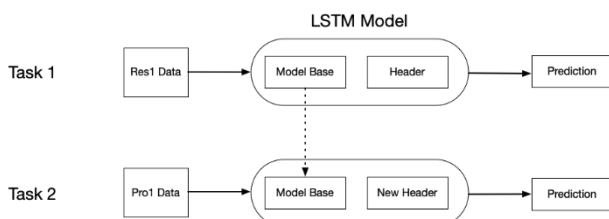


Figure 6 Transfer learning technique for different consumption profiles

To apply the transfer learning in this work will two main steps need to be executed:

- 1 - Use a pre-trained model as a fixed feature extractor: This approach involves using a pre-trained model to extract features from the input data, and here the model which is trained on the residential profile will be used.
- 2 - Fine-tune the pre-trained model: This approach involves unfreezing some of the layers of a pre-trained model and training them on the target task dataset like the small data we have from an industrial profile or others.

Table 4 show the results obtained for the industrial profile after transfer learning, while before the transfer learning the algorithm didn't converge.

| | MAX ERROR | RMSE |
|---------------------|-----------|-------|
| LINEAR MODEL | 0.390 | 0.088 |
| XGBOOST | 0.35 | 0.088 |
| LSTM | 0.292 | 0.030 |

Table 4 Accuracy scores for industrial profiles with social media and transfer learning

This method addresses the issue of limited data for different profiles. This eliminates the need for waiting for an extended period of time to collect a significant amount of data. Instead, by using pre-trained models, it is possible to leverage knowledge learned from a different profile model to improve performance on the target profile, even with limited data.

CONCLUSION

This study aims to improve the accuracy of profile load energy estimates for the electrical grid by incorporating information from social media, specifically Twitter. The proposed method involves identifying events that are likely to impact energy consumption for each profile and using this information to optimize the load estimation. The study presents a comprehensive approach for collecting, processing, and analyzing tweets in order to improve the accuracy of the estimates. The proposed approach was validated using electricity consumption data from France, and the results showed that the linear regression model improved by 12% in terms of max error, and all three models showed improvements in terms of accuracy metrics.

The article also describes how to address the issue of limited data for certain profiles by utilizing transfer learning techniques. This is crucial as it eliminates the need for waiting for an extended period to collect a substantial amount of data.

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