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Data preparation for prediction and anomaly detection in precision beekeeping

Sid Ahmed Metidji^a, Jean-Charles Huet^{a,*}, Lamine Bougueroua^a

^aUniversité Paris-Panthéon-Assas, Efrei Research Lab, Paris, France

Abstract

Faced with a major decline in the population of a variety of pollinators essential to our food security, it is essential to study their behavior and their evolution. The proposed approach is illustrated as an example of application in the beekeeping sector. Indeed, this sector is affected by a crisis due to the disappearance of bees and the different actors need support to make their decisions. We hope to offer new tools to help beekeepers predict the evolution of their hives, as well as tools to detect any anomalies. To meet these challenges, we have been looking for usable hive data. We have found data on line over a long period, but it needs to be completed and resampled. The dataset covers weight, internal humidity and internal temperature. In this article, we describe how these data have been prepared for prediction and anomaly detection by adding the external data like external temperature. Time-series resampling and interpolation techniques were used to help in this process. At the end of this process, the datasets are structured, cleaned and completed: they are ready to use in intelligent models.

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Keywords: precision beekeeping ; precision agriculture ; prediction ; anomaly detection ; data preparation

1. Introduction

Over the past twenty years, the beekeeping industry has been faced with a sharp drop in honey yields per colony, which has had a serious impact on productivity and sustainability. For instance in France, After an excellent production of 31,791 tonnes in 2020, honey production in 2021 is expected to fall sharply to 19,802 tonnes (-37.7%). Honey production in 2021 is one of the lowest recorded since the Observatory was set up, reaching the level of 2017 [9]. National honey consumption is said to be stable at 40,000 tonnes per year. French honey production is not sufficient to cover national consumption. The trade balance is in deficit, averaging over 80 million euros per year between 2014 and 2020 [9]. Yield for 2021 is estimated at 14 kg/hive, 39.6% lower than in 2020. This is the lowest level recorded

* Jean-Charles Huet. Tel.: +33-188-289-000.

E-mail address: jean-charles.huet@efrei.fr

since the beginning of the FranceAgrimer observatory [9]. As well as producing honey, beekeeping also plays an important role in preserving nature's biodiversity, by ensuring that bees pollinate crops under optimum conditions.

Today, beekeepers benefit from significant technological advances to assist them in the technical management of their livestock, notably with the widespread use of automatic scales. However, despite the emergence of computerized data recording systems, the computerization of data by beekeepers themselves remains a marginal practice. To date, the apiary notebook remains the most widespread tool, to which is added the inscription of the most essential data on the roof of the hives. The history of a colony is therefore difficult to consult, and beekeepers' references are empirical.

In this context, our long-term goal is to propose a complete real-time hive monitoring system. In addition to collecting data in real time from the hive's sensors, the aim of the system is to visualize the data collected in a Web Dashboard, forecast future data and highlight anomalies detected in the data collected by generating real-time alerts and notifications.

Humidity is one of the most important parameters in honey. Humidity has a major influence on fluidity, crystallization speed and, above all, on the risk of fermentation. Honey that exceeds 20% humidity can no longer be labelled as honey. Such honey should be consumed very quickly, as it will begin to ferment within a few weeks.

The more intense the honeyflow, the less time the bees will have to dry the honey as soon as it arrives in the hive. While one or two days are sufficient for a low-intensity honeyflow (about 1 kg per day), it will take at least four days for the bees to dry the honey properly in the hive. What's more, the efficiency of the drying process is adversely affected by atmospheric humidity and outside temperature. So obtaining honey with an acceptable moisture content is never a simple operation.

The normal temperature range in a honeybee colony is between 33 and 36°C [2]. Honey bees try to keep the internal temperature within this range, as the bee brood is very sensitive to changes in hive temperatures. When the temperature is above 36°C, honey bee workers mimic the fan's behavior by rapidly vibrating their wings and taking specific positions during ventilation to be more efficient [2]. During hot periods (especially in summer), ventilation is not sufficient to bring the hive temperature down to the desired range. In fact, they use another mechanism: water evaporation, where the bees bring water back into the hive to evaporate it and bring down the temperature. This affects the humidity of honeys, including capped honeys. In fact, capped honey is a sign that the bees have produced good honey, but this does not mean that it is of good quality (i.e. with the right moisture content).

The extracted beehive data is clearly grouped according to the type and associated labels are placed [8]. The supervised learning is applied. Several specific types of supervised learning can be considered: (1) Classification - When the data is used to predict given category; (2) Regression - When a value is predicted; (3) Anomaly detection - Identification of abnormal data; Better knowledge of the data essence and well-formulated goals play an important role of the overall process for determining the required type of the supervised learning algorithm [8].

The data used in these types of algorithms have to be correctly organised and prepared. In this paper, we present this important and capital step: the preparation of the data.

The paper is structured as follows: Section 2 presents all the concepts used and a review about the monitoring and the anomaly detection in precision beekeeping, Section 3 describes the target architecture, Section 4 presents the dataset used and explained how the data have been prepared. Finally, Section 5 presents conclusions and perspectives for future works.

2. Related Work

Traditional beekeeping involves physically inspecting the hive, taking qualitative notes on the various parts of the hive. Precision Apiculture or Precision Beekeeping can be defined by "an apiary management strategy based on the monitoring of individual bee colonies to minimize resource consumption and maximize the productivity of bees" [20]. These modern concepts come from the field of the Internet of Things (IoT) and are based on a management strategy of individual colony monitoring using electronic equipment installed in the hives [15, 10]. What these strategies have in common is that they should not be taken as a substitute for beekeeping work [14]. Indeed, activities such as manually checking the hive to determine the queen's state of health, the number of provisions, the lack of space in the hive and rearing are still activities that no beekeeper should stop doing as this would involve various associated risks.

2.1. Precision beekeeping techniques

These techniques can be divided into two areas depending on the electronic equipment and analysis techniques used: the computer vision and based on sensors. The data generated by these electronic equipment will be used by AI to make predictions on various hive parameters.

The computer vision monitoring approaches are mainly based on the installation of a surveillance camera in front of or at the top of the hives, opposite the hive flight boards, possibly with an integrated microphone. Existing works in the literature have used video recordings differently to extract relevant information. The authors in [18] or [13] have designed systems to detect and analyse the incoming/outgoing bees, while other works distinguished Varroa mites¹ with several techniques [3, 11]. Due to their parasitic nature, varroa mites can weaken, cause physical damage and transmit a variety of pathogens to bees, particularly viruses.

Time-series approaches are based on sensors of several types. Most of the work based on this type of monitoring uses sensors to measure humidity, internal temperature and external temperature of the hive, sensors to measure weight and others to measure CO2 emissions inside the hive. These sensors are all connected to a Raspberry Pi board. For example, the authors of [5] have developed an IoT platform based on all these types of sensors for sending data to a remote server that will analyze the data to extract relevant information. The main measurements used are the hive weight [15], the internal temperature [15], and the humidity [12].

The approach can be also a combination between computer vision and sensors [17].

2.2. detecting anomalies in beekeeping

Detecting anomalies can be explained that “Anomaly detection refers to the problem of finding patterns in data that do not conform to expected behavior.” [6].

In the precision beekeeping field, five kinds of anomalies in the data linked by the hive sensors are generally mentioned [7, 16]:

- **Swarming:** this phenomenon is an important behavioral anomaly for beekeepers, as it can lead to the complete exhaustion of a colony, described by a sudden drop in hive weight. It leads to a reduction in honey production and requires immediate action to gather new colonies.
- **Sensor malfunctions:** it's an anomaly that's not directly linked to bees. However, it is important to detect them so that urgent repairs can be made to restore a hive's full functionality.
- **Opening the hive:** the beekeeper's physical interactions with the hive lead to the recording of abnormal data by the sensors (temperature and weight).
- **Attacks on hives by predators:** during winter, mice sometimes try to enter the hive, disturbing the bees, which are tightly grouped to keep their temperature stable.
- **Physical damage to the beehive:** stormy conditions or the intrusion of ants or wasps can cause damage to the hive, possibly leading to unwanted water infiltration, which will be reflected in the data by increased weight and internal humidity.

To detect anomalies, time series are widely used, for example the authors in [7] evaluated several common non-regressive models for anomaly detection, namely deep recurrent AutoEncoder (AE), Elliptic Envelope, Isolation Forest, Local Outlier Factor and One-Class SVMs, a rule based algorithm are presented in [19] and regressive approaches to detect anomalies in the hive are used in [16].

2.3. Data Preparation

We saw earlier the importance of detecting anomalies and making predictions in helping beekeepers with IoT and computer vision. Before data can be analyzed, they must be organized into an appropriate form. Data preparation is the process of manipulating and organizing data prior to analysis [1]. According to [4], data preparation may be the

¹ Varroa mites : <https://www.ontario.ca/page/varroa-mites> (available June, 2024)

most important part of a machine learning project. Data preparation is the act of transforming raw data into a form that is appropriate for modeling. As mentioned in [4], there are common or standard tasks to explore during the data preparation step in a machine learning project. One of these tasks is Data Cleaning. It consists to involve fixing outliers and missing data. In this article, we propose to focus on this task.

3. Target Architecture

The monitoring of connected beehives represents a significant challenge. It can provide crucial assistance in detecting anomalies and predicting issues that may affect the health of the hives. The monitoring system must be equipped with an anomaly detection system that generates notifications to alert the user about the state of the hives in real time. A monitoring system should allow the user to (fig. 1):

1. View real-time data received from hive sensors for the three metrics : internal temperature, internal relative humidity and weight.
2. Select the hive to view its data: received data and alerts.
3. View short-term forecasts for the selected hive for the three metrics.
4. Disable/enable data reception and anomaly detection to avoid storing false information or generating false alerts during certain specific events such as hive inspection or honey harvesting.
5. Control the sensitivity level for generating alerts for the three metrics.

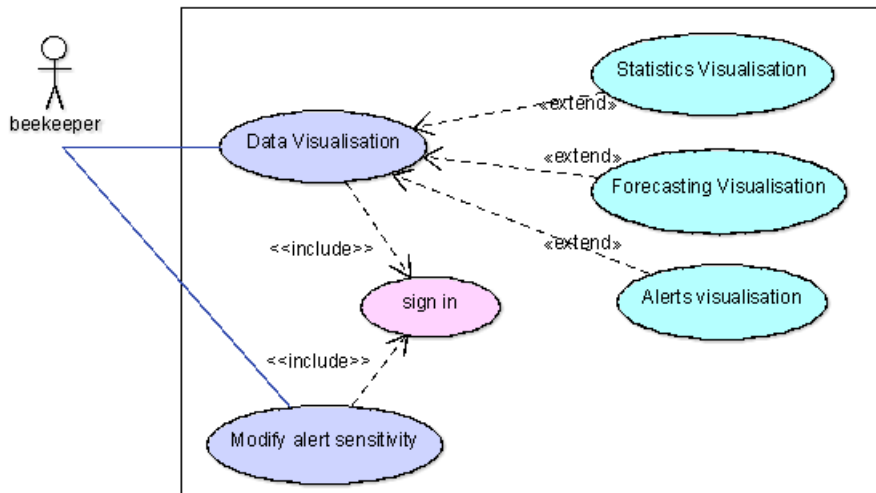


Fig. 1. Requirements of the target architecture represented by a use case diagram

Our solution is based on six groups of components (fig. 2):

1. Connected hives: these are the hives owned by our user, and will send their internal data (temperature, humidity and weight) in real time thanks to their built-in sensors.
2. Cloud database : cloud storage is crucial in our system for storing data broadcast in real time by connected hives.
3. Intelligent systems for time-series processing: these systems mainly handle all the tasks involved in processing the data received from our connected hives, in order to detect anomalies and forecast the future for the three metrics.
4. Learning DB: this represents all the already acquired data we need to train, validate and test our intelligent systems.

5. Web application (Dashboard): the Dashboard to be developed will enable beekeepers to view real-time data from their connected hives, together with forecasts and alerts generated by our intelligent systems.
6. APIs : these APIs act as a gateway by providing an HTTP portal to communicate with intelligent systems and our DBMS. In addition, they will ensure real-time communication with the sensors of the connected hives to provide real-time visualization in the dashboard.

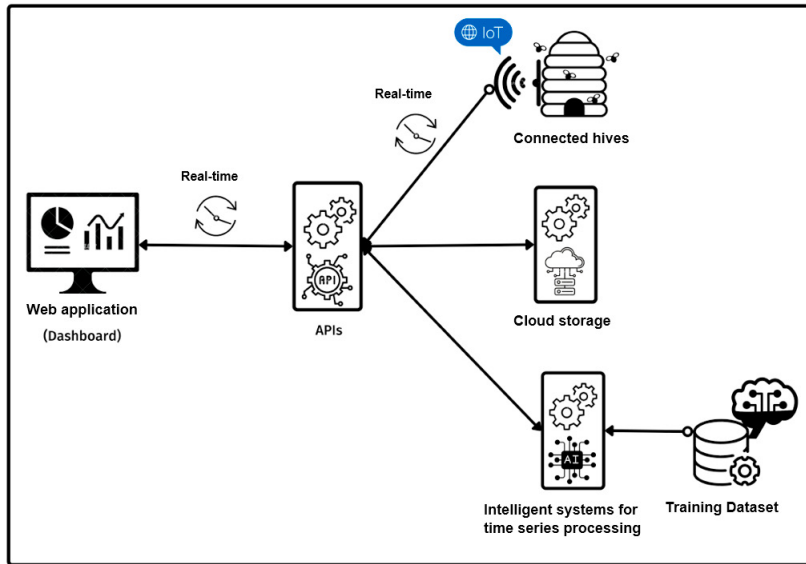


Fig. 2. Target architecture

In this paper, we focus on data preparation. In the following section, we detail the selection, analysis and formatting of the training dataset.

4. Resampling and completing the dataset

Several research projects have used open source data to develop their own version of the monitoring system. In this section, we will present the research tools used, the datasets found and the comparison between them. Our goal is to have a dataset without outliers and missing data. This dataset must correspond to uninterrupted data over many several years, covering the three most important parameters (temperature, humidity and weight). We focused on the Kaggle platform, as well as the Google Dataset Search engine. This gave us access to a vast collection of publicly available datasets. These datasets cover a wide range of topics and domains, making them valuable resources for data science, machine learning and research projects. Users can browse, search and download datasets in a variety of fields. We found 4 databases used in the field of beekeeping, we describe these databases in the next subsections. A comparative summary is presented in the Table 3.

4.1. HOBOS (HoneyBee Online Studies)

HOBOS² is a research and education project using the honeybee as a model organism operated by Jürgen Tautz and Hartmut Vierle from 2006 to 2019 at the University of Würzburg in Germany. HOBOS presents data collected between January 2017 and April 2019 from two German hives: a hive located in the city of Würzburg and a hive located in the city of Bad Schwartau. For each hive, four types of data were collected: internal temperature, internal

² HOBOS : <https://hobos.de/> (available April, 2024)

humidity, weight and flow (the number of departures/arrivals from/to the hive). Table 1 summarizes the frequency and quantity of data available for each hive. Data collection from the Würzburg hive was not functioning during one period. We noted the lack of data for the period between May 2018 and October 2018.

City	Humidity		Weight		Temperature	
	Frequency	Quantity	Frequency	Quantity	Frequency	Quantity
Würzburg	/1hr	20846	/1min	1035862	/5min	958832
Schwartau	/12hr	1762	/12hr	1762	/5min	253431

Table 1. HOBOS data overview

4.2. Beehives (Temperature and Relative Humidity Data of Beehives)

The dataset Beehives³ is part of a data collection work carried out on beehives in Turkey. Data were collected from 3 hives in an apiary located in the city of Çanakkale in 2021. Table 2 summarizes the frequency and quantity of data available for each hive.

Beehive	Humidity		Weight		Temperature	
	Frequency	Quantity	Frequency	Quantity	Frequency	Quantity
Beehive 17	/1hr	1847	/1hr	1847	/5min	1847
Beehive 36	/1hr	4227	/12hr	4227	/5min	4227
Beehive 85	/1hr	6037	/12hr	6037	/5min	6037

Table 2. Beehives data overview

4.3. Smart Bee Colony Monitor (Clips of Beehive Sounds)

Smart Bee Colony Monitor⁴ is the largest set of bee audio data, as well as multidimensional data presenting several internal (temperature, humidity and atmospheric pressure) and external (humidity, pressure, wind speed, rain, etc.) weather conditions captured on a single hive. For each metric, 1,275 data points were collected at an hourly frequency (/1hr).

4.4. We4bee

The We4bee project⁵, initially funded by the Audi Environmental Foundation (funding from December 2018 to November 2019), is a non-profit environmental project that started in 2019 with the provision of 100 connected beehives (mainly in Germany) to set up a global data collection and analysis network. The types of data available: Internal (Temperature, Humidity and weight) and External (Precipitation, wind speed, atmospheric pressure, luminosity).

4.5. Discussion

Table 3 presents a comparative summary of the four DBs found, focusing on the advantages and disadvantages of each DB.

After analyzing the four DBs and considering the advantages and disadvantages of each database presented in the table 3, we decided to use the HOBOS DB as a training DB for our intelligent systems. We chose HOBOS because it's a large database, with data covering several years. HOBOS is also the most referenced database in beekeeping articles. Nevertheless, we have analyzed, structured and cleaned the database before designing the intelligent models that will use it.

³ Beehives : Temperature and Relative Humidity Data of Beehives : <https://www.kaggle.com/datasets/vivovinco/beehives> (available April, 2024)

⁴ Smart Bee Colony Monitor : Clips of Beehive Sounds - <https://www.kaggle.com/datasets/annajyang/beehive-sounds> (available April, 2024)

⁵ We4bee : <https://analytics.we4bee.org> (available April, 2024)

DB	Advantages	Disadvantages
Hobos	<ul style="list-style-type: none"> - The most popular DB in Kaggle and the most referenced in research papers in the field of beekeeping. - Data availability for two different different hives. - Availability of large quantities of data. 	<ul style="list-style-type: none"> - Lack of data on external conditions. - Missing data between October 2018 and May 2018 for one hive.
Beehives : Temperature and Relative Humidity Data of Beehives	Data availability for three different hives.	DB used particularly for anomaly detection (not prediction)
Smart Bee Colony Monitor : Clips of Beehive Sounds	/	<ul style="list-style-type: none"> - The absence of the weight metric. - DB is particularly useful for the detection of sound anomalies.
We4bee	Data availability from several hives.	<ul style="list-style-type: none"> - The difficulty of using data directly. - Most of the data available is short term (a few days or a few weeks).

Table 3. DB comparison

4.6. Learning DB analysis

In this subsection, we will present the various manipulations we performed on the training DB before arriving at the final version of the DB to be used to feed our prediction and anomaly detection models. In fact, we observed a few problems: missing data from the Wurzburg hive over a long interval (between May 2018 and October 2018), data from only 2 hives and very short data recording frequencies leading to a risk of corrupted data.

So how can we reduce the impact of missing data on learning? How can we generalize prediction and anomaly detection from 2-hive data? How can we reduce overfitting problem? How can we manage small-scale variations that are useless to detect?

Time series resampling is a technique used to adjust the frequency or time intervals of a given time series. This adjustment can be made using two methods. The first is to increase the frequency in order to have more data points during a specific period (oversampling). This is done by inserting new data points to fill gaps using interpolation functions. The second method is to reduce the frequency to have fewer data points (sub-sampling) by aggregating several data points within a specific period into a single data point. Resampling is particularly useful when dealing with time series with irregular time intervals, or when comparing data collected at different temporal frequencies. It enables us to transform the data into a consistent format, making it easier to analyze, model and interpret trends in the time series data.

In the context of resampling, time step units refer to the new time intervals or frequency at which the time series data is adjusted. These units determine the level of granularity of the resulting time series and are essential for its interpretation and analysis at different temporal resolutions.

For our solution, the possible time step units were defined according to three criteria:

- The nature and characteristics of the metric to be resampled: For example, temperature may vary significantly from hour to hour, while hive weight may have no significant variation from hour to hour, but may be significant from day to day.
- Data frequency: Temperature data is more frequent (e.g. every 5 minutes) compared to weight or humidity data, which may be less frequent (e.g. every 12 hours).

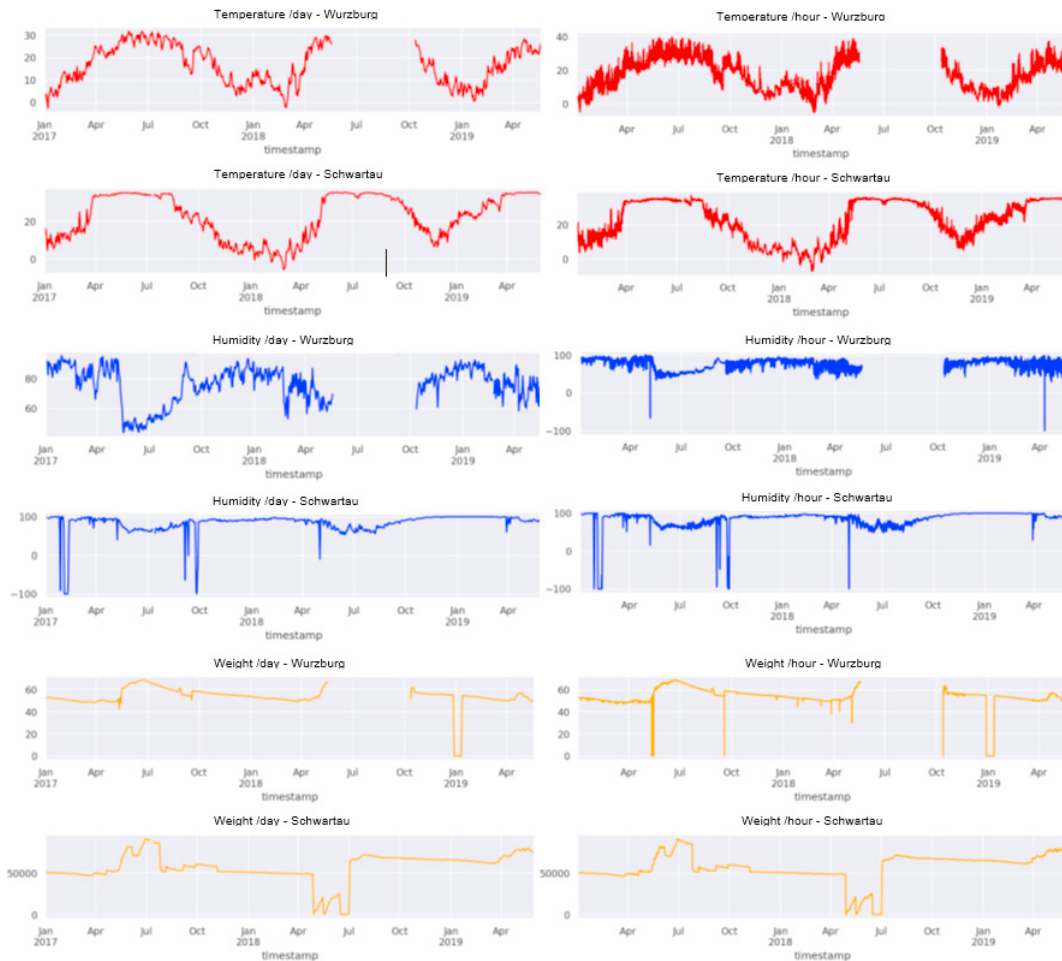


Fig. 3. Resampled time series visualization (a) /Day - (b) /Hour

- Forecast horizon: This is the length of time over which a predictive model projects the future values of the time series. The resampling time step unit is highly dependent on this forecast horizon. Based on these criteria, two useful time step units have been defined for the three metrics:
- Hourly time-step: Each hour is represented by a dot.
- Daily time-step: Each day is represented by a dot.

These time-step units make it possible to adjust the time-series data at different levels, according to specific analysis and forecasting needs.

Figure 3 show resampled versions of the three metrics :

- Temperature: we can see that the two versions have the same behavior and layout. Nevertheless, we can see that hour-by-hour monitoring of hive temperature is essential for real-time monitoring of hives, and this is why we opted for hourly resampling for temperature.
- Humidity: we note the presence of several data outliers in the hourly version. Moreover, the daily variation seems more significant than the hourly variation for the internal humidity of the hive, and having a long-term predictive model for humidity (for several days, instead of several hours) is more interesting. Consequently, we opted for daily resampling.

- **Weights:** we note the similarity of scheme for both versions. However, we note the presence of data outliers in the hourly version, which can have a negative impact on the training procedure. In addition, long-term prediction of weight is important, as hive weight does not change significantly from one hour to the next.

We used the interpolation method to impute missing data in the training dataset. Indeed, the impossibility of carrying forward the last observed value or carrying forward the next observed value because we have a horizontal line presenting a constant value of the metric over four months (missing data between May 2018 and October 2018), which contradicts the time-varying nature of these metrics. We tested three interpolation method and chose the one with the best results to replace our missing data (figure 4): (a) Linear interpolation, (b) Cubic interpolation and (c) Piecewise Cubic Hermite Interpolating Polynomial (PCHIP).

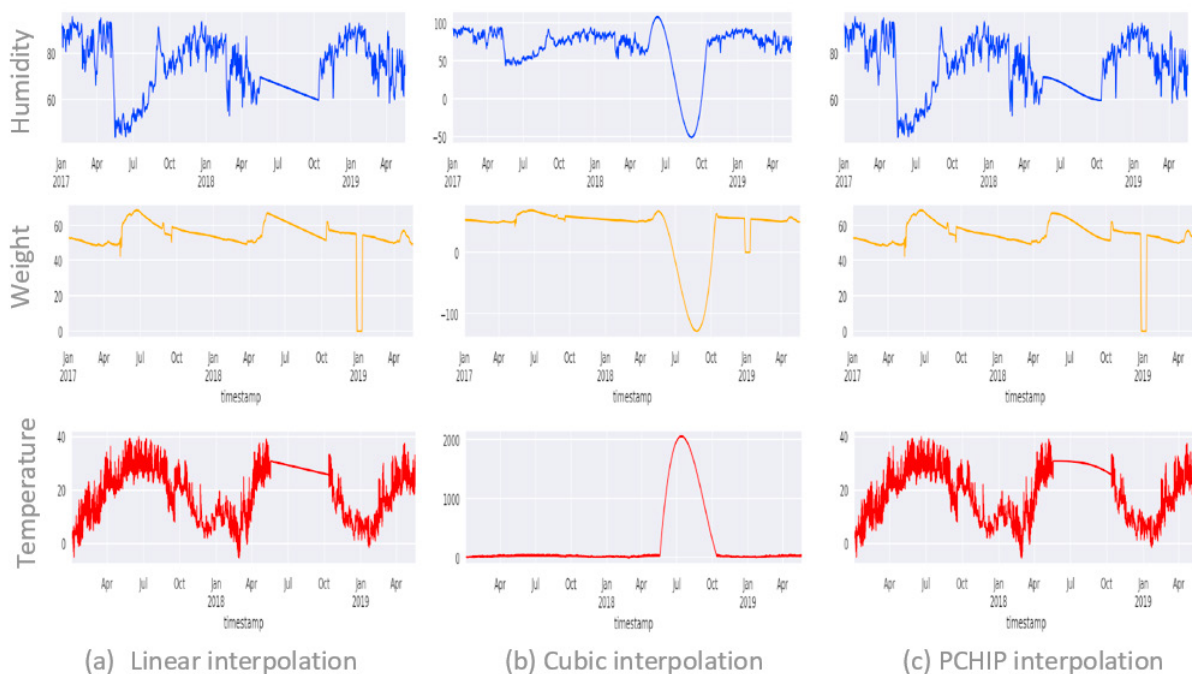


Fig. 4. Missing data interpolation

Figure 4 shows that the PCHIP method gives the best results for imputing missing data for all three metrics.

For anomaly detection, we have no information on the anomalies observed on the two hives. We will therefore learning on the Würzburg hive dataset.

For prediction, we decided to use the data from one hive (Würzburg) for training and validation, and to use the data from the other hive (Schwartau) to evaluate the performance of the trained models. This choice will enable us to study whether our models are capable of generalizing the events in the hive, and how well they can handle data from another hive. We used the last five months of the Würzburg dataset (non modified data) to validate the training and then, our data cleaning of this dataset.

5. Conclusion and futur work

We presented in this paper the preparation of data from the monitoring of precision beehives. Our goal will be to explore the possibility of visualizing, predicting and detecting anomalies in other crucial metrics related to bee activities, such as CO₂ emissions, which are essential for assessing the metabolic state of the colony. Similarly, the monitoring of inflow/outflow, which reflects colony activity, and external temperature, which clearly correlates with internal temperature, could also be interesting aspects to integrate into the platform. The developed platform

will intelligently detect anomalies and generate short-term forecasts thanks to our intelligent time series processing systems. This enables the beekeeper to receive real-time alerts and anticipate future abnormal variations. We exposed the target architecture with an analysis of the system's requirements and of the different components.

We explained why we selected the HOBOS dataset for training and what is missing in. HOBOS is an open dataset for two hives equipped by sensors. We detailed an approach to format and complete this dataset. The Time series resampling and Interpolation technique have been used to tackle this challenge.

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