Department of Information Engineering and Computer Science

Bachelor's Degree in
Information and Communications Engineering

Final Dissertation

Thesis Title

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Academic year 2019/2020

Acknowledgments

. . . thanks to my family, my girlfriend, my supervisors and all the U-Hopper team . . .

Contents

Abstract

Sentence that describes the problem ...

The abstract is a short summary of the work describing the target, the subject of the thesis, the methodology and the techniques, the data collection and elaboration, the explanation of the reached results and the conclusion. The abstract of the dissertation must have a maximum length of 3 pages and must include the following information:

- context and motivation
- short summary of the main problem you have dealt with
- developed and /or used techniques
- reached results, the personal contribution of the student has to be highlighted

1 Introduction

Brief introduction of the internship and the project done at U-Hopper.[1]

1.1 Problem statement

In managing a company that provides services to physical customers, the most important aspect is how to manage the flow of customers to guarantee them optimal service. Overcrowding and long waiting times are serious problems caused by poor demand management. These problems spoil the service experience of the users and especially during this pandemic period due to COVID-19, it is important to avoid generating crowds and queues to avoid new contagions. The repetition of these events leads to the loss of customers and therefore to the loss of revenue for the company. This fact is increasingly relevant in this period of crisis with very low liquidity.

Offering an efficient and fast service is the key to increasing the number of customers in their own business. The solution is not to use all the available resources to try to meet these requirements, as excessive use of these leads to an increase in costs without leading to an increase in revenues. Of course, in order to calibrate the correct amount of service to offer, it would be necessary to know the demand. In particular it is necessary to know every time how many people require the service. Having this information is not trivial as it is highly variable over time and depends on several factors.

The purpose of this thesis is to create a system capable of providing useful information to a company's organizational departments to manage its resources more effectively and efficiently. In particular, the proposed system will provide estimates of the number of customers in real-time through the use of machine learning techniques. From this information, it will be possible to understand how the demand is distributed over time and what the peak hours are. This will clarify in which time slots it is necessary to increase the capacity of the service in order to be able to provide it to a greater number of people. In a dual way, this information is also useful for understanding when there is less demand and it is possible to reduce the capacity of the service, with the aim of saving resources.

The idea can also be extended to provide the same crowding data to its customers. With this data, they can plan better when to use the service offered, avoiding being in crowded situations or situations that require long waiting times.

1.2 Approach to the problem

This is the approach ...

1.3 Outline

In chapter 2 the state of the art is analyzed. In chapter 3 the methodology and the choices in the system design are presented. Chapter 4 presents how the system is implemented. In chapter 5 the proposed system is validated and the results are evaluated. In the end, chapter 6 reports the conclusions and suggests some ideas for future work.

[1] website: https://www.u-hopper.com/

2 State of the Art

In this chapter, the current state of the art is analyzed in the context of counting people in a particular place of interest. The various technologies presented in the literature for this purpose are discussed. Furthermore, the reasons why counting people through the sniffing of the Wi-Fi probe request frames is the solution with the best trade-offs are explained. In addition, several implementations and some use cases are presented. At the end of this chapter, it will be clear the choice to develop this type of system with the U-Hopper team to find a solution to estimate the number of people. Unlike other solutions, our system achieves high accuracy, has a low-cost implementation, allows the transmission of data in real-time and ensures user privacy.

2.1 People counting methods

Let us start by thinking about before the popularity of mobile devices and the development of all these new communication technologies that are making this world increasingly interconnected. Therefore, before it becomes possible to exploit the signals of people's devices to identify and count them.

In 2010, Pinna et al. compared some of the technologies of the time (e.g. infrared sensors, treadle switch-based systems, weigh in motion systems using load cells) to avoid the manual collection of the occupation information and promote automatic counting [18]. All of these methods presented in the paper have good accuracy (95% in optimal conditions of use for treadle mats and approximately 90% for the infrared sensors, 97% for load cells) but have high costs and need the installation and the maintenance of the sensors.

Other studies have been carried out to improve the performance of infrared sensor systems. Jia and Zhang described a system with subordinate nodes for collecting information from pyroelectric infrared sensors and a master node that when it receives information from a sensor has to determine whether a person is entering or leaving [9]. Such systems require sensors for each entry point, in the case of overcrowding or continuous flows of people, some sensors may not work properly and can lead to a wrong estimation. In these solutions, errors accumulate over time.

Mikkelsen et al. compared a a light sensor estimator based method with a Wi-Fi-based method to estimate the number of people present [13]. This simple Wi-Fi implementation uses a probability distribution of the number of Wi-Fi enabled devices that a person is carrying. They concluded that the Wi-Fi estimator is better at recovering after errors, while errors in light sensor estimator accumulate over time. These presented methods, in which errors accumulate over time, are not acceptable in a continuous monitoring system and this does not happen with the Wi-Fi solution and other solutions.

Many methods are proposed in the literature for processing images and videos captured by a camera device. Recognition and tracking of people by a stereo vision system to increase or decrease a people counter [2], a separated-aggregated framework based on deep learning to estimate the number of people from still images [28], a deep learning-based method for estimating crowd density and the total number of people in high-density crowd images [27], estimation of the people flows and then summing them to obtain people densities [11], a locate size and count CNN (Convolutional Neural Network) model is proposed to to resolve people in dense crowds [20]. These methods rely on the use of cameras to get the data to analyze and therefore have the problems related to these devices. Images can be noisy in dim light conditions and, due to the presence of obstructions or overlaps, people may not be detectable. Moreover, the implementation of these methods entails high costs due to video camera devices. However, taking photos or videos of unknown people is always a privacy issue as decreed by the GDPR (General Data Protection Regulation) in the rights of the data subject. Therefore, these types of solutions cannot be used to solve our problem.

A not very popular but interesting method of counting the number of people is to analyze the audio

of a place with a microphone and count the different audio tones [10]. Afterward, Valle proposed a more sophisticated prediction model to estimate the occupancy of a room which borrows speech recognition tradition and is based on Gaussian mixtures and hidden Markov models [25]. These methods can be inaccurate due to high ambient noise and the limitations on the quality of the microphones must be considered during the analysis. In addition, other sounds from smartphones or radios must be filtered to avoid being counted as people. However, as in the case of video methods, the analysis of the voice of unknown people is always a privacy issue as decreed by the GDPR. Therefore, these types of solutions cannot be used to solve our problem.

As reported by wearesocial.com in the Digital 2020 report [2], 67% of the world population is a mobile phone user. In Europe, Internet users are equal to 84% of the population and 92% of total Internet users is a mobile phone user. In this new era dominated by smartphones, radio-frequency solutions to exploit the signals of these devices to count people are increasing. In recent years Wi-Fi, Bluetooth, Bluetooth Low Energy, LTE (Long Term Evolution) approaches have been developed.

Many researchers have investigated the possibility of estimating the number of people using the two most popular standards for wireless communication, i.e. Wi-Fi and Bluetooth. In 2014 Schauer et al. performed this type of comparison with the aim of creating a pedestrian flow estimation system. They stated that only a fraction of surrounding devices could have been tracked by periodical Bluetooth scans. Therefore Bluetooth-based estimations were less accurate, showing an average correlation to the ground truth of only 0.53 in the best case. In contrast to Bluetooth, Wi-Fi tracking provided a good approximation of crowd densities and pedestrian flows with an average correlation of 0.75 [21].

Bai et al. tried to detect devices with different approaches. The number of the sensed Bluetooth Low Energy devices was about $\frac{1}{3}$ of the sensed Wi-Fi devices. Bluetooth Low Energy data were sparse, and most of the sensed devices only appeared for a few seconds. The number of unique Bluetooth MAC addresses was less than $\frac{1}{10}$ of the unique Wi-Fi MAC addresses, so they gave up the possibility of using Bluetooth Low Energy and Bluetooth data. They concentrated on filtering the Wi-Fi data and obtained a correlation with the ground truth of 0.839 [1]. These papers show us the feasibility of using methods based on Wi-Fi, unlike the methods based on Bluetooth and Bluetooth Low Energy which do not provide satisfactory results in terms of accuracy.

Di Domenico et al. were the first to propose to use LTE signals of opportunity for applications different from location/tracking, i.e. to estimate crowd density within an environment relying on the analysis of variations of the LTE reference signal received power [5]. This approach is affected by the changing of positions that lead to a different superimposition of multipath components and, hence, to a different received power. The same number of people at different times can generate totally different values, thus leading to significant errors during the estimation process. They achieved an average accuracy ranging of 82%, but they tested this system only with a maximum of 5 people. As the number of people increases, the accuracy of the classification decreases. Therefore this approach cannot be used in overcrowded areas.

Shibata and Yamamoto used a sensor node to obtain time-series data of signal strength on a frequency band used for cellular communications. Then they analyzed them using several machine learning techniques to estimate the crowd density around the sensor node installation site [23]. This method did not provide the number of people but only the stages of occupancy, with three stages (Low, Normal and Crowd) the precision is 78% but with five (Low, Little_Normal, Normal, Little_Crowd and Crowd) is only 53%. From this type of information, it is not very clear how many people are in the place and listening to a reserved part of the spectrum is illegal.

Another set of solutions developed exploits the attenuation of signals, which could be made by an IR-UWB (Impulse Radio Ultra Wideband) radar, Bluetooth Low Energy devices or RFID (Radio Frequency Identification) readers with antennas.

Choi et al. presented an approach using an IR-UWB radar which requires a preliminary detection of the clusters of people in the environment to set the parameter values for the algorithm. After collecting the data, through the use of statistical models they found the number of people that have the maximum likelihood from the minimum of 0 people to the maximum of Np people [4]. This type of approach needs to know the maximum number of people and works only in a restricted area depending

[2] https://wearesocial.com/digital-2020

on the antenna. In this case with an angle of 80° and a maximum distance of 5 meters, therefore it cannot be used for applications like ours that need to cover a wide space.

Brockmann et al. presented a method to count people in a queue using the attenuation of Bluetooth Low Energy signals [3]. Almost 98% accuracy, but a lot of devices are needed and it can be used only in situations where there is a queue with a predefined path where the sensors are located.

Gupta et al. proposed an algorithm to estimate the number of people that are crossing the RFID installation in both the directions, achieving 90% accuracy by real-time experiments for continuous movement up to 75 persons [6]. For realize a system like this a lot of RFID readers, antennas and tags are needed. An optimum distance is required between the readers, and with the tags. It works only assuming that people do not reverse directions while walking in the passage. However, if the density of the crowd increases beyond an extent, it tends to completely block the reading of the tag and therefore cannot be used in environments where there are large flows of people entering and leaving.

2.2 Wi-Fi probe request frames implementations

From the previous section, it is clear that the Wi-Fi solution is a step further compared to other solutions in the literature. By analyzing the Wi-Fi probe request frames, it is possible to better estimate the number of people in a certain place with lower costs. This method does not accumulate errors over time, does not require a predefined path where users must be and can cover a large area. Moreover, it is possible to anonymize the MAC address to ensure user privacy.

Handte et al. presented one of the first approaches to estimate crowd density by monitoring Wi-Fi probe request frames. They modified the firmware of some existing access points and created a Web service that allows the upload of the latest crowd density measurements [8]. The system was able to continuously detect around 20% of the people on average because in 2014 there were far fewer mobile devices than nowadays (only 49% of the population had a smartphone in Span in 2014) and they didn't have the advanced techniques of nowadays.

Mikkelsen and Madsen presented a system to anonymize the MAC address of the sniffed probe request frames, to sent them to a server and to analyze them putting two thresholds: minimum value of the RSSI (Received Signal Strength Indicator) and minimum detection time [12]. The ratio between the estimated number of devices, obtained by setting the two thresholds, and the number of people is around 50%. They said that the use of machine learning techniques could have ensured greater accuracy of estimates.

Oliveira et al. designed a specific device to monitor the presence of people by analyzing the Wi-Fi probe request frames [15]. Subsequently, they proposed a method for estimating the number of devices with a very strong correlation with the ground truth of the number of people in the environment, with a Pearson,Äôs correlation coefficient of 0.896 [16]. They said that the experiment should be replicated in other scenarios to test the versatility of the method. Moreover, they believed that one of the answers to get estimates closer to the ground truth values may be in the use of machine learning techniques.

Nishide filtered the collected data using a combination of RSSI, packet frequency, and the total time duration which the nearby device is detected. Filtering is performed individually for each parameter, and then the linear regression and correlation coefficients are calculated in different places [14]. He said that there may be other ways to accurately estimate the number of people using machine learning.

These papers show us the possibility of sending data in real-time and that there is a correlation between the devices obtained from the collected data and the presence of people. Furthermore, they suggest that the use of advanced techniques, such as machine learning, could have a positive impact on accuracy in solving the occupancy problem.

Wang et al. employed the Random Forest method to infer occupant counts using the Wi-Fi connection counts data [26]. The method was tested in a real office building with an average occupancy of 22-27 people and a peak occupancy of 48-74 people, the RMSE (Root Mean Square Error) is four people on the test set. For more than 70% of estimations, the errors are within two people counts, and for more than 90% of estimations, the errors are within six people counts. This paper confirms that the use of machine learning techniques has a good impact on estimating the number of people but this method does not have a communication system for the transmission of data and results in real-time.

2.3 Use cases of the Wi-Fi method

The Wi-Fi method has several use cases. A strength of this method is in fact the versatility of use for many application contexts.

Prasertsung and Horanont used the Wi-Fi probe request frames monitoring technique to identify the number of the customers visiting a coffee shop. They showed that the number of customers tends to increase on the average of 30% on a promotion day [19]. This can be used to explore how a promotion can drive customers into stores. Shen et al. proposed a shopping group detection system using Wi-Fi. Experimental results indicated that this method could is capable of detecting over 90% of the groups with an accuracy of 91% [22].

Using real-world data collected in a large social event by a network of passive Wi-Fi sensors Zhou et al. extracted patterns related to crowd behaviors [29]. Singh et al. proposed a first-hand application of Wi-Fi sensors and LSTM (Long Short Term Memory) neural network for crowd forecasting and large-scale public event monitoring [24].

The particular case of people estimation on public transport such as buses is a complex application because, unlike the estimation in a static place such as a shop, it is necessary to consider that the vehicle is in motion. Therefore, the presence of people waiting at the stops, people in the traffic, pedestrians and other things should be considered during the data cleaning phase. The esteem of people in public transport is a really interesting challenge that is dealt with in literature. This can provide some useful information to public transport managers, from which they can better manage the routes and reorganize the distribution of their vehicles.

Handte et al. presented a navigation system for bus passengers that has the ability to seamlessly interconnect bus passengers with the real-world public bus infrastructure. Using the occupancy classes to classify the prediction (low, medium, and high occupancy), they got an exact match accuracy of 61.9% [7]. This work provides an indication of the feasibility of real-time information but accuracy can certainly be improved with the use of machine learning techniques.

Oransirikul and Takada presented a method to predict the number of passengers at the bus stop by capturing Wi-Fi activity. They used a polynomial regression method with six independent variables with a degree of 2 [17]. It works well with an average MAE (Mean Absolute Error) of the prediction of 6, but they did not deal with transmission and analysis of data in real-time. Our approach is similar but used machine learning to determine the best polynomial approximation, i.e. the degree and the coefficients, using two variables: trend and seasonality of the number of devices detected.

3 System Design

In this chapter, the methodology and the choices in the system design are presented. Starting by describing the components of the system with their functionalities (the blocks in the system architecture) and then explaining the working logic of the developed system. After this section, it will be clear which are the main parts of this system and how they cooperate to achieve the project goal.

3.1 System architecture

In a place of interest, there are people/users with their devices that are sending Wi-Fi packets, if they have the Wi-Fi device turned on. The purpose of our system is to exploit these packets to infer the number of people present. The system architecture of the developed system is shown in figure 3.1. This is a distributed architecture, in fact, there are three main components on different platforms that cooperate over a communication network in order to achieve this goal.

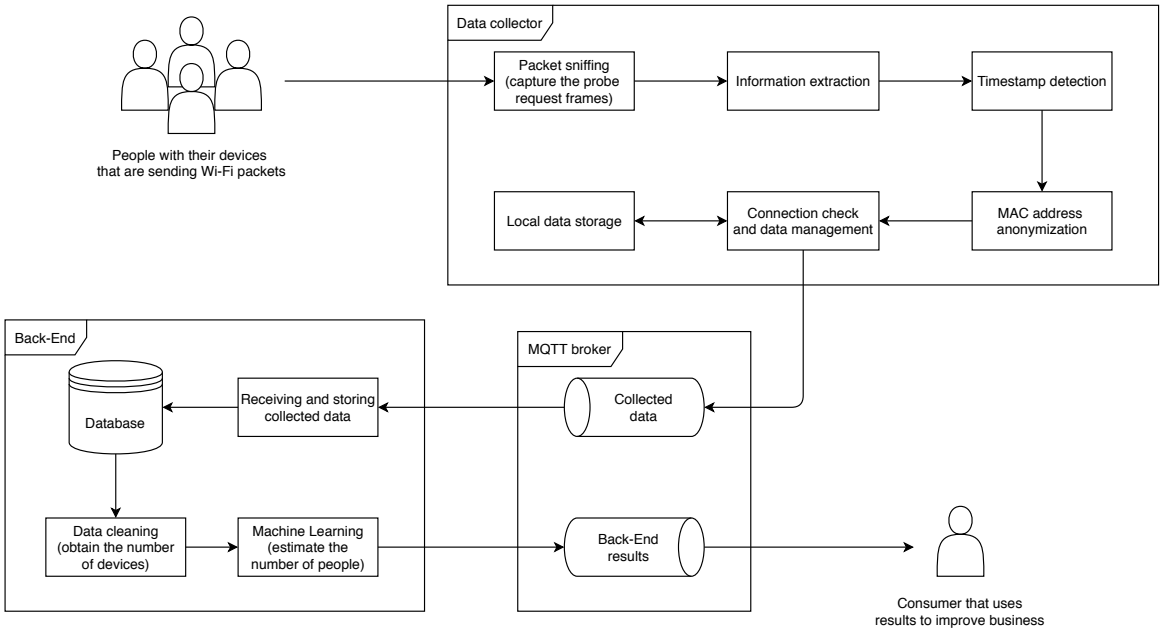

Figure 3.1: Architecture of the proposed system.

The first block of the system is a data collector (implemented on a Raspberry Pi 2B) which is located in the place of interest. It performs a preprocessing of the data (distributed work) with its functionalities: sniffing of Wi-Fi packets, capture the probe request frames; extract the useful information from these; detect the current timestamp; anonymize the MAC address using a hash function (no more privacy issues); check the internet connection; if there is no connection, save the data in the local storage; if there is a connection, publish the collected data to the dedicated queue (Collected data).

The system uses the MQTT protocol for data forwarding, an MQTT broker (situated TBD, it must have a static IP address to be accessible, implemented using Mosquitto MQTT broker) with 2 dedicated queues: one for the collected data (published by the data collector and received by the subscribed Back-End) and the other one for the Back-End results (published by the Back-End and received by the subscribed consumer).

The Back-End (situated TBD, implemented on a pc/server or running on Google Colaboratory)

deals with collected data cleaning – (to be decided based on the use case/case study: RSSI thresholding) remove random encounters (and randomized addresses are removed with this), make a blacklist to remove the ever-present devices or devices revealed too many times during the day and then get the number of devices present in the place of interest –, data analysis using Machine Learning – fit the degree and the coefficients of the polynomial approximation using the trend and the seasonality of the number of devices detected to obtain the number of people present – and publication of the results to the dedicated queue (Back-End results).

At the end of this processing, there is the consumer who receives the results of the Back-End, the number of people/users in the place of interest, and could use this information to improve his business.

This architecture is scalable, it could admit many sensors physically distributed in different environments for data collection, to provide a practical example some use cases are shown in figure 3.2. It is important to locate them properly in the environments to cover all the areas of interest. All sensors publish data to the same MQTT broker and then all data is forwarded to the same Back-End. Cleaning and analysis will be performed according to the data source, each sensor will publish data in its own reserved queue and will be analyzed adequately to the characteristics of the use case for which it was used. (in the end, they are sent to the respective consumer through an appropriate queue)

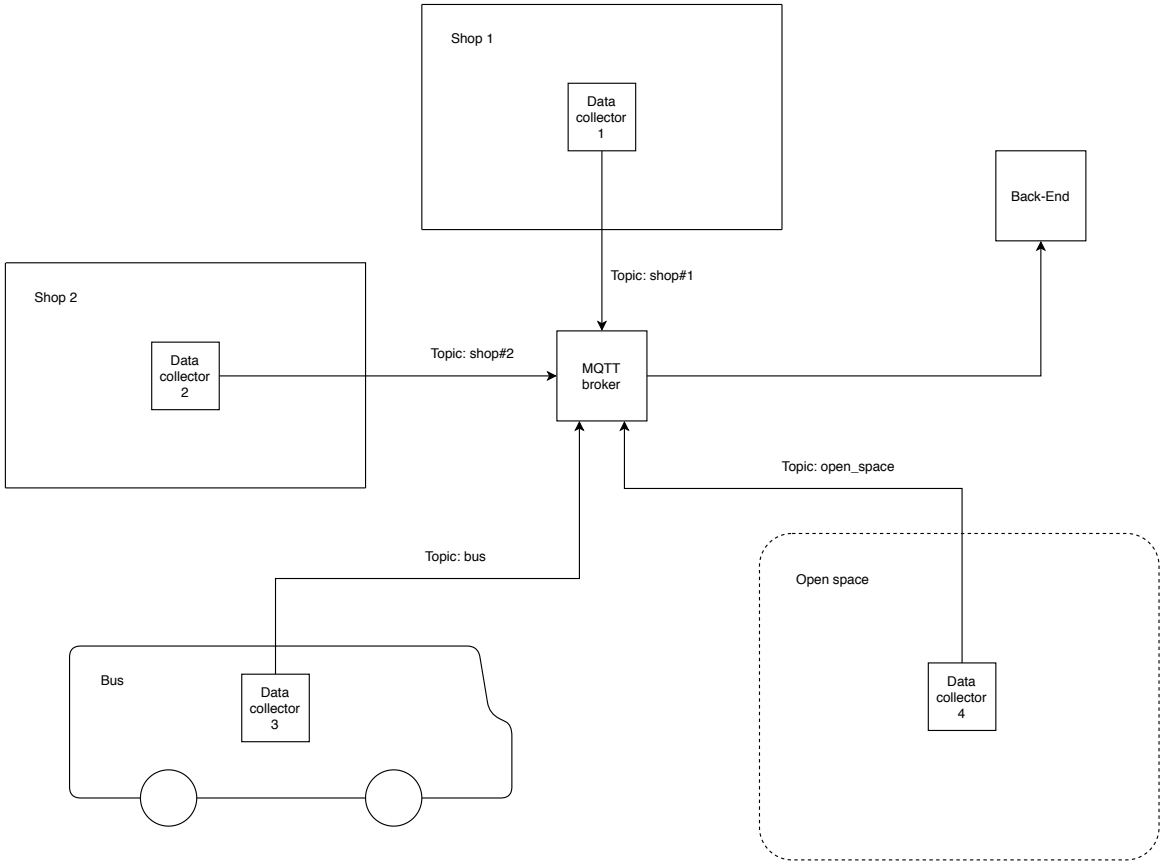

Figure 3.2: Presentation of a possible implementation with different use cases.

3.2 Data collection

The main block I worked on is the data collector. I developed the logic behind this block, with particular attention in the research of the connection and in the management of the data collected.

The flowchart representing the data collector logic is shown in figure 3.3. When the data collector is turned on, the system searches for the connected Wi-Fi dongle and puts it in monitor mode to perform the packet sniffing. Initially, a packet counter is set = 0 and the actual time is saved. When a packet is received, it checks if it is a probe request frame and if it is not, it is thrown away (using Scapy). When a probe request frame is captured, the following information are extracted: RSSI,

SSID (Service Set Identifier), MAC address, sequence counter. The timestamp when the packet was revealed is given by an RTC (Real Time Clock) board and together with the other information are saved and the packet counter increases by one.

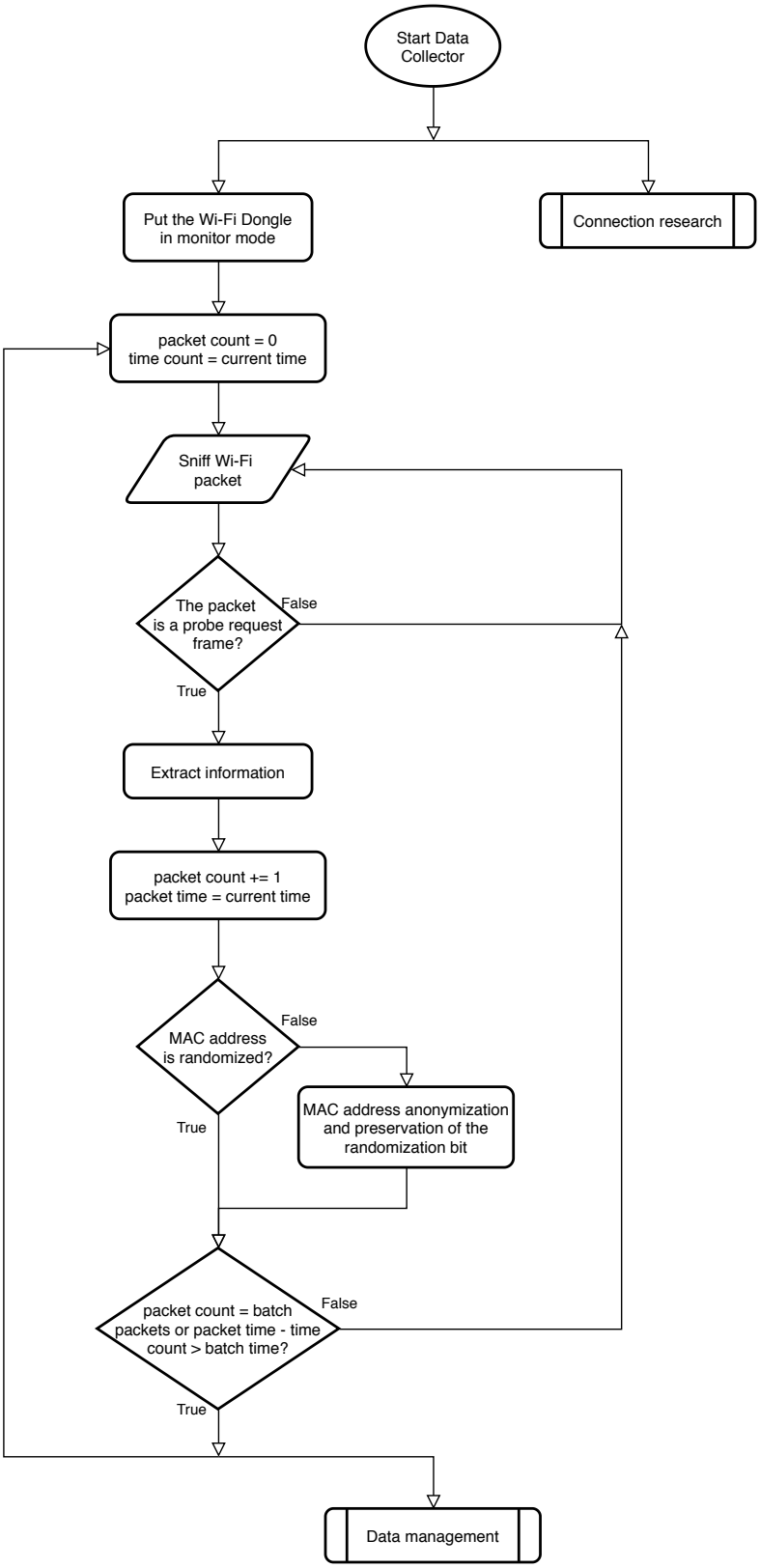

Figure 3.3: Flowchart representing the data collector logic.

Among the information that can be extracted from the MAC address before performing the anonymization there are the OUI (Organizationally Unique Identifier), from which the manufacturer

of the device can be identified, and the local bit, the 7^{th} bit of the MAC address, from which it can be seen whether the MAC address is randomized or not.

After extracting the information, there is the anonymization of the MAC address to preserve the privacy of the users and comply with the GDPR. This is made only for the MAC addresses that are not randomized, i.e. the real MAC addresses of the devices present. Anonymization is performed at this point in the architecture because then there are no more privacy problems, this work does not have to be done from the Back-End and for reasons of data security in case of a data breach during transmission. This process consists of hashing the MAC address using BLAKE2s, an implementation of the BLAKE2 cryptographic hash function based on BLAKE [3] (BLAKE3 is faster but still under development). BLAKE2 is faster than MD5, SHA-1, SHA-2 and SHA-3, and provides security superior to SHA-2 and similar to that of SHA-3. BLAKE2 supports keying and salting, and can output digests from 1 up to 32 bytes for BLAKE2s. This hash function is the ideal for changing hash results every 24 hours or predefined time, simply modifying the key or adding a different value of salt. This is made for privacy reasons and to avoid tracing the MAC address although it is not the real one but always the same after hashing. If the anonymization changes the state of the local bit, the previous state is forced/imposed to preserve this information on randomization, which can be used in the cleaning phase.

Once the pre-processing of the data is completed, we decided to process the collected data in batches and therefore there are to check 2 batch criteria, based on a maximum number of packets and a maximum time since the last batch transmission. These parameters have to be set according to the use case/case study, once one of these is reached it is possible to decide what to do with this data by running the data management flowchart (shown in figure 3.4).

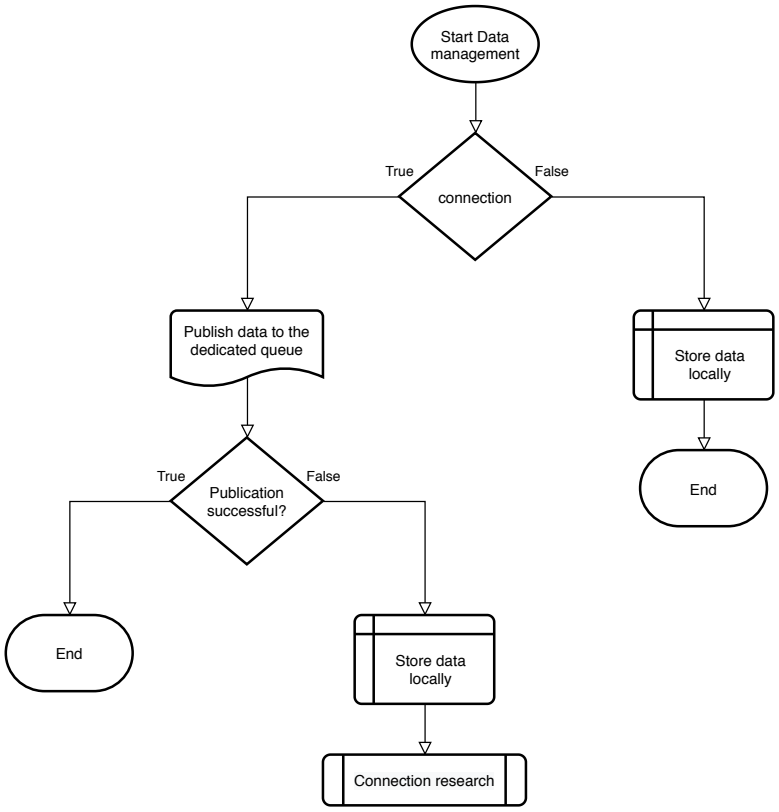

Figure 3.4: Flowchart representing the data management logic.

Higher values of the parameters allow us to avoid a continuous transmission of data and to fill the queue on the broker or in the lack of a connection, to open the file to save the data every time a packet is detected. On the other hand, choosing smaller values of the parameters reduces estimation delay, making the system more responsive. In our experiments, we used intermediate values with a maximum

[3] website: https://blake2.net/

number of packets of 50 and a maximum time since the last batch transmission of 60 seconds, which is a good trade-off between congestion and transmission delay.

When the batch is ready, the algorithm for managing what to do with the data starts. If there is no connection, the collected data is stored locally (using json.dump()) to be sent later when a connection is found. Instead, if there is a connection with the MQTT broker, the collected data is published to the dedicated queue (Collected data, converted in a string using json.dumps() to be published). If the publication is successful, the flowchart ends. Otherwise, it is stored locally (using json.dump()), subsequently the system searches again for a connection.

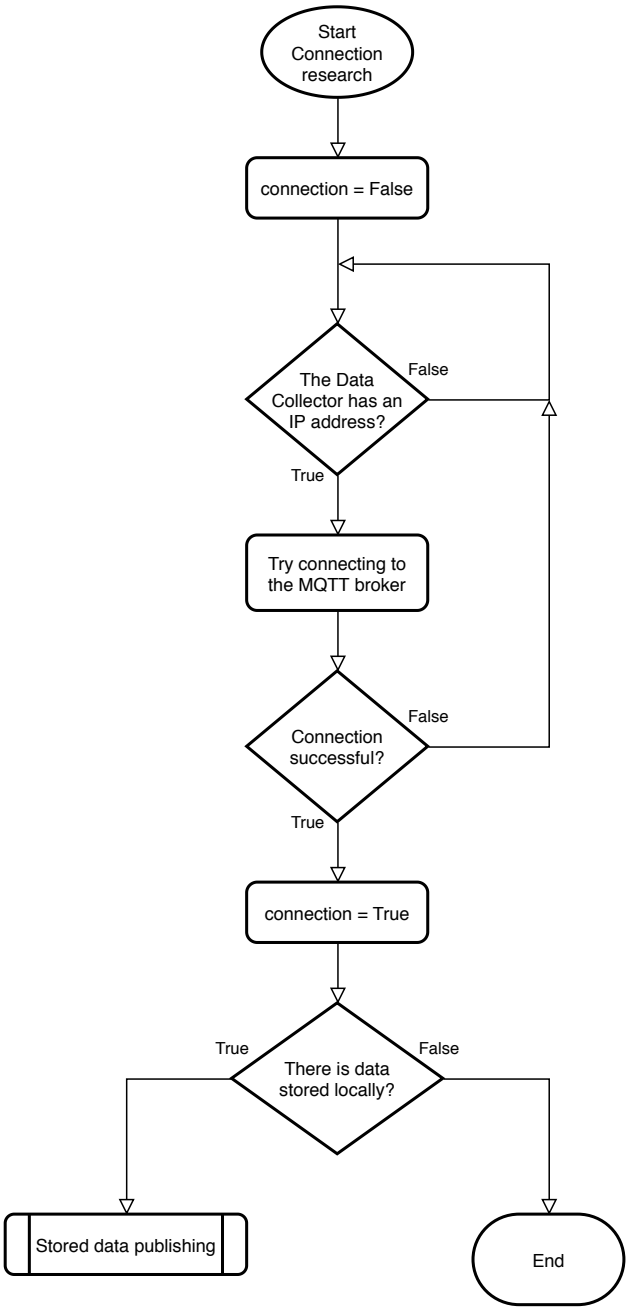

Figure 3.5: Flowchart representing the connection research logic.

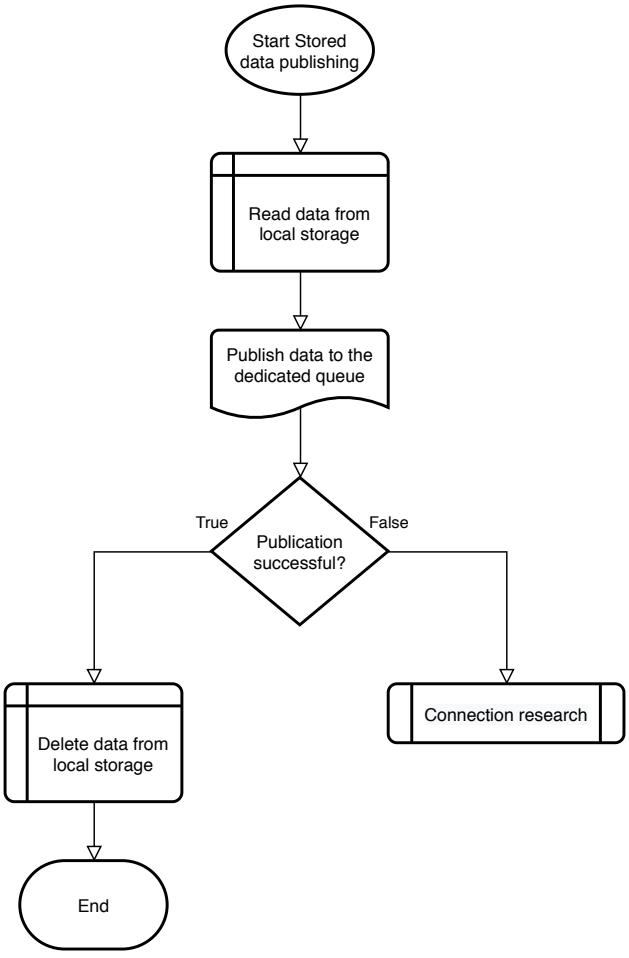

Figure 3.6: Flowchart representing the stored data publishing logic.

When the data collector is turned on, the system searches also for a connection with the MQTT broker. Figure 3.5 shows the flowchart explaining the logic behind this. Initially, the connection is set = False and the system checks whether the data collector has a peripheral with an IP address for Internet access. When it has an IP address, a Paho MQTT Client with its credentials tries connecting to the MQTT broker. When the broker is reachable and accepts the client connection, the connection

is set = True and if there is data stored locally, it can be published by running the flowchart for the publication of the stored data (shown in figure 3.6).

The data is read from the local storage (using json.loads()) and is published to the dedicated queue (Collected data, converted in a string using json.dumps() to be published). If the publication is successful, the data is deleted from the local storage. Otherwise, it remains stored locally and the system searches again for a connection.

3.3 Data forwarding

MQTT [4] stands for Message Queuing Telemetry Transport. It is a publish/subscribe, extremely simple and lightweight messaging protocol. It is designed to be bandwidth-efficient and to use little battery power. It is efficient in distributing information to one or many receivers. Information is organized in topics. Topics are treated as a hierarchy, using a slash (/) as a separator. These principles make it the ideal protocol for the emerging world of machine-to-machine/Internet of Things and for mobile applications where bandwidth and battery power are limited. It is useful for connections with remote locations, as in our case to send a huge amount of data to the Back-End. Moreover, it can easily scale from a single device to thousands.

The MQTT protocol defines two types of network entities: a message broker and clients. An MQTT broker is a software (in our case we used Mosquitto) running on a computer that receives all messages from the clients and then routes them to the appropriate destination clients. An MQTT client is any device that runs an MQTT library (in our case we used paho-mqtt for Python) and connects to an MQTT broker over a network. For security reasons, the MQTT broker can be configured to require clients to use a username and password when connecting. If they match allowed credentials, clients can publish/subscribe to the topics. Otherwise, the connection is refused. When a publisher has new data to distribute, it publishes this data to the broker. Any client that wants a copy of that message will subscribe to that topic. The broker then distributes the data to any clients that have subscribed to that topic. Multiple clients can receive the message from a single broker. Similarly, multiple publishers can publish topics to a single subscriber.

The protocol uses a publish/subscribe architecture in contrast to HTTP with its request/response paradigm. The main difference to HTTP is that a client does not have to pull the information it needs, but the broker pushes the information to the subscribed client, in case something new has been published. The broker also keeps track of all session information as clients connect and disconnect. If this connection is interrupted by any circumstances, the MQTT broker can buffer all messages and send them to the client when it is back online, setting the clean session bit = False. If clean session bit is true, then all subscriptions will be removed for the client when it disconnects.

Each subscription/publication to the broker can specify a quality of service measure. These are classified in increasing order of overheads:

- 0: At most once - the message is sent only once and the publisher and broker take no additional steps to acknowledge delivery to the subscribers (fire and forget, with no confirmation).
- 1: At least once - the message is re-tried by the sender (publisher or broker) multiple times until acknowledgment is received (by the broker or the subscribers) (acknowledged delivery).
- 2: Exactly once - the sender (publisher or broker) and receiver (broker or the subscribers) engage in a two-level handshake to ensure only one copy of the message is received (assured delivery).

For these illustrated features, the MQTT protocol is used in the system for data forwarding. A broker (situated TBD, it must have a static IP address to be accessible, implemented using Mosquitto MQTT broker) with two dedicated queues is used, one for the collected data (published by the data collector and received by the subscribed Back-End) and the other one for the Back-End results (published by the Back-End and received by the subscribed consumer). The broker is set up to allow only connections from the data collector, the Back-End and the consumer. They have their own credentials for authentication.

[4] website: http://mqtt.org/

Client(client_id="name", clean_session=False), connect("broker_address", port=1883)
username_pw_set("username", password="password")
publish("topic", payload=json.dumps(data), qos=2)
subscribe("topic", qos=2)

The clean_session is set = False. If this connection is interrupted by any circumstances, the MQTT broker can buffer all messages and send them to the client when it is back online. The QoS is set = 2 both in publish and subscribe. To ensure exactly one copy of the data, no loss, no duplicates to clean. Data is converted in string using json.dumps() to be published and forwarded.

3.4 Data cleaning and analysis

The two main Back-End functionalities are data cleaning and data analysis. (situated TBD, implemented on a pc or running on Google Colaboratory)

The flowchart representing the data Back-End logic is shown in figure 3.7. Initially, the Back-End subscribes to the collected data queue to receive the data when published by the data collector. Input data is managed by adding corollary information for future analysis and is stored in the database (in our case we used MongoDB for its simplicity in handling json files).

When a time slot is over, the data of the current time slot is read from the database. An RSSI-based threshold is applied to delete data from devices too far from the data collector (to be decided based on the use case/case study, the position of the data collector has to be taken into consideration, as well the environment in which they are located, for cleaning and analysis). Random encounters are removed, as shown in the flowchart in figure 3.8. Unique devices are extracted with their occurrence timestamps. If there are devices that appear only once or for a short time, they are removed. These parameters have to be adapted at the use case/case study (and randomized addresses are removed with this).

Then a blacklist is made to remove the ever-present devices or devices revealed too many times during the day, as shown in the flowchart in figure 3.9. A list of occurrences is created with a maximum interrupt time of delta_t. If there are devices that appears many times or for a long time, they are blacklisted. These parameters have to be adapted at the use case/case study. At this point, it is possible to get the number of devices present in the place of interest for each timestamp based on the occurrences of the devices not in the blacklist.

Finally, data analysis is performed, as shown in the flowchart in figure 3.10. Trend (raising/lowering) and seasonality (repetition of the components) of the number of devices are extracted using a decomposition of the corresponding temporal series. Once these two variables are known, it is possible to apply to them the correct polynomial approximation relating to the current time slot to get the forecast of the people present in the place of interest. The best degree and coefficients of the polynomial approximation are calculated during the training phase/preparation of the model for each time slot of each day of the week, using manually-collected ground truth. Figure 3.11 shows the flowchart of the logic used in that phase.

I did not develop the part of machine learning, but I integrated an existing one into this project to get the final results, i.e. the number of people/users in the place of interest for each timestamp. Then the results, when available, are published to the dedicated queue (Back-End results) to be received by the subscribed consumer who could use this information to improve his business.

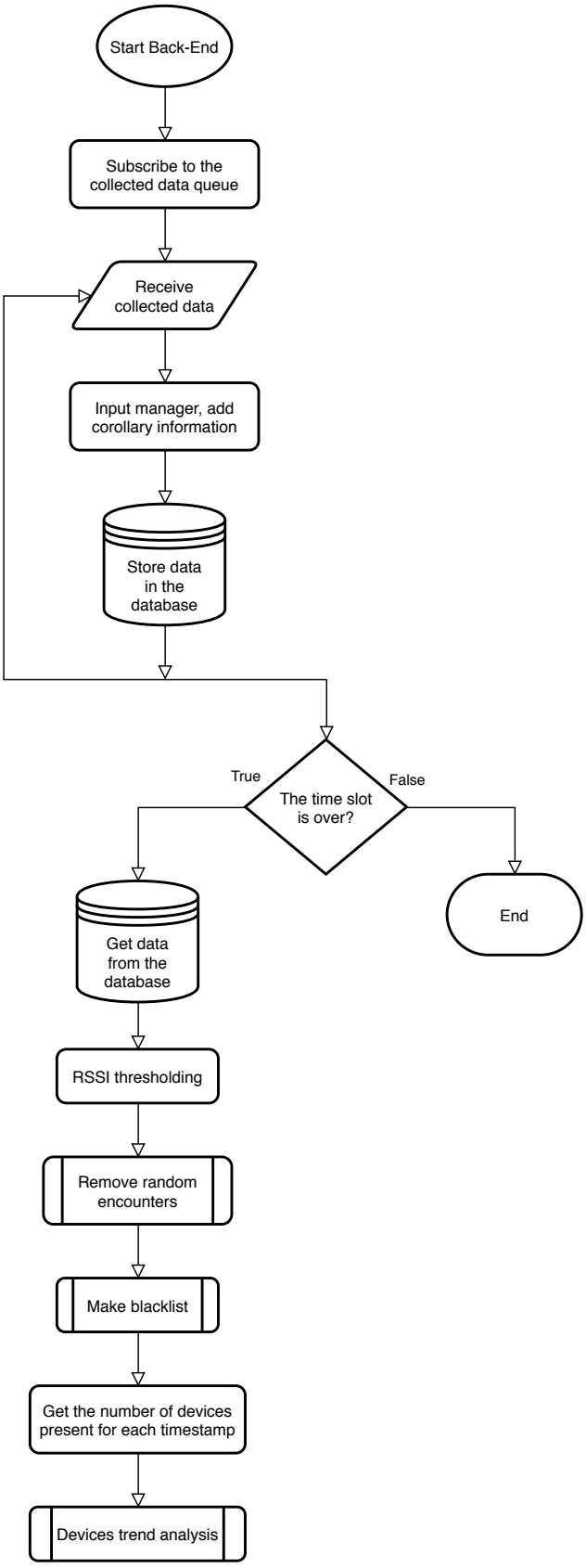

Figure 3.7: Flowchart representing the Back-End and the cleaning logic.

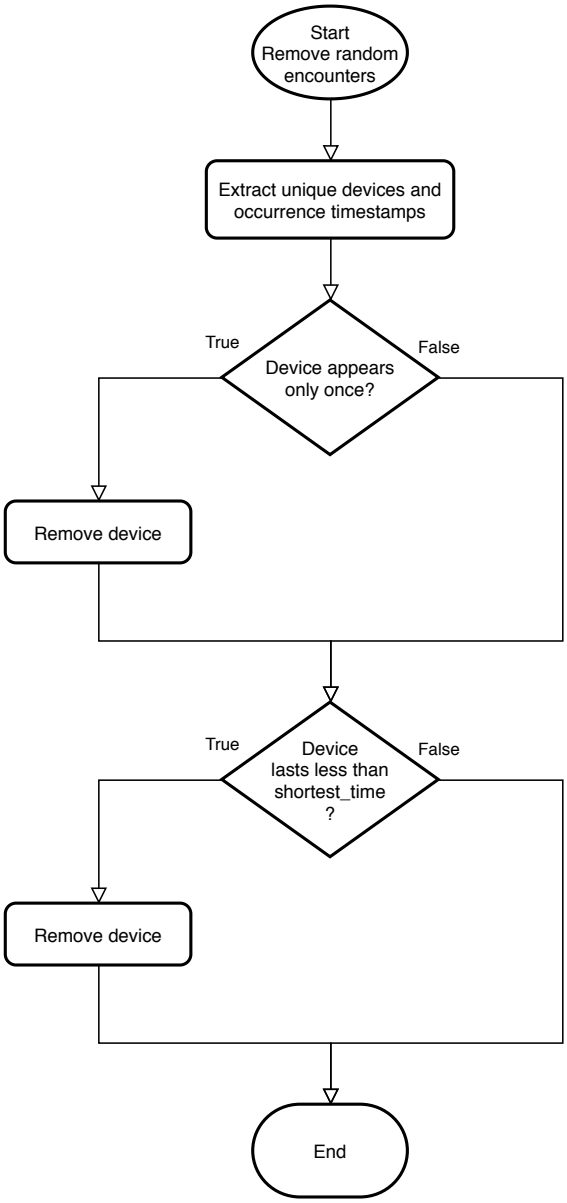

Figure 3.8: Flowchart representing the logic of removing casual encounters.

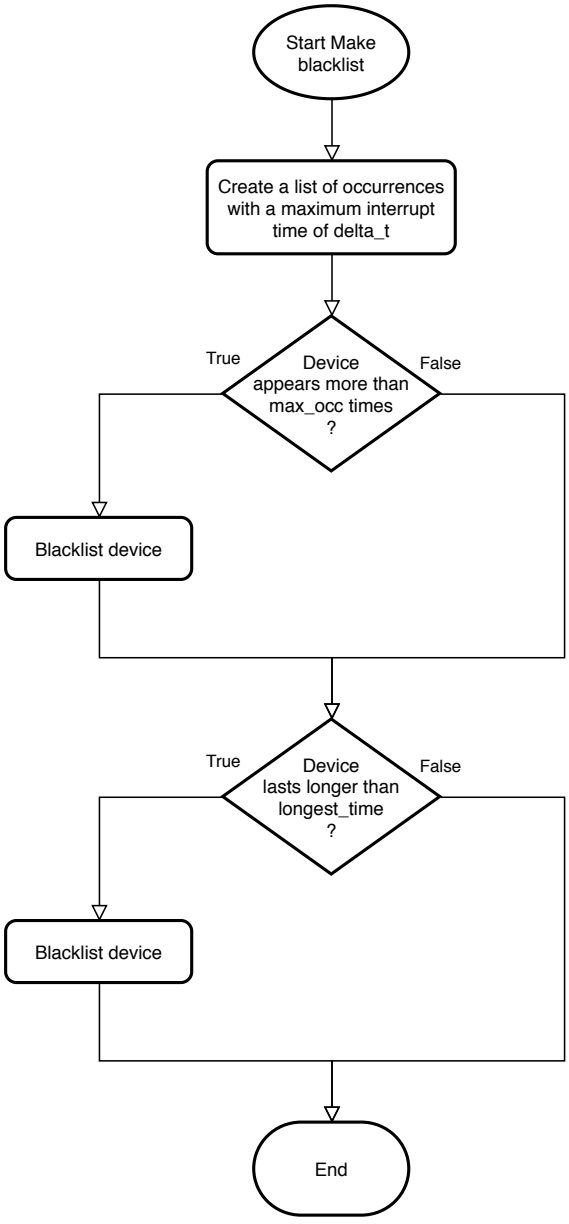

Figure 3.9: Flowchart representing the logic of making the blacklist.

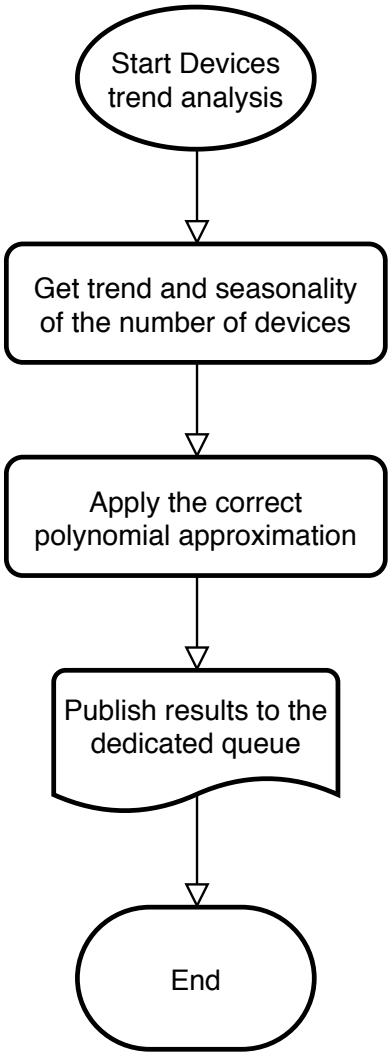

Figure 3.10: Flowchart representing the data analysis logic.

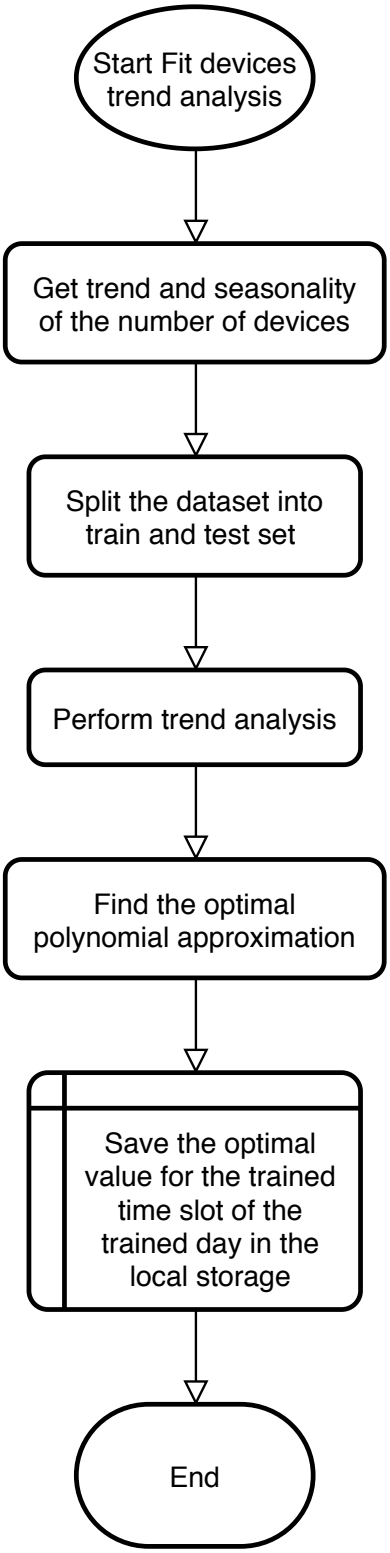

Figure 3.11: Flowchart representing the ML training logic.

4 Implementation

Write about the implementation of the system ...

This chapter presents how the components of the system have been implemented. Starting by describing the implementation of the data collector on a Raspberry Pi and then explaining how the Mosquitto MQTT Broker, the MongoDB database and the two Back-End parts, one for receiving and storing the data and the other one for analyzing the data, has been implemented on Docker containers. After this section, it will be clear how the system was implemented for the testing and validation, that are discussed in the next section.

4.1 Data collector implementation

Write how the sniffer has been implemented on the Raspberry Pi ...

Data collector on a Raspberry Pi model 2B

EDUP 802.11n Wi-Fi Dongle (Range 10 meters) + Scapy for Wi-Fi packets sniffing

RTC Board for timestamp detection

BLAKE2s for MAC address anonymization

Netifaces for managing the connection

Paho-MQTT for the MQTT transmission

4.2 Server implementation

Write how the Back-End for analysis has been implemented ...

Docker Containers:

MQTT broker: Mosquitto [5]

Database: MongoDB [6]

Receiver with MQTT client using paho-MQTT for receiving the data and Mongo client using pymongo for storing data on MongoDB

Analyzer with Mongo client using pymongo and pandas to read and manage the data

Sklearn is used to analyze this data and to implement the machine learning part

[5] website: https://hub.docker.com/_/eclipse-mosquitto

[6] website: https://hub.docker.com/_/mongo

5 Evaluation

Write about the evaluation case study ...

In chapter 5 the proposed system is validated and the results are evaluated. Starting by describing where and how the system is tested for the experimental validation and then presenting an evaluation of the achieved results. The data collector on a Raspberry Pi has been placed in a place of social interest. In this place of social interest, I manually collected the ground truth for training and evaluating the model. The Mosquitto MQTT Broker, the MongoDB database and the Back-End part for receiving and storing the data in the database have been executed on the U-Hopper server. The final Back-End part for analyzing the data has been executed on my computer to adapt the parameters and train the Machine Learning model. After this section, it will be clear how the system has been validated and what the results achieved by the proposed system are. Overall conclusions are discussed in the next section.

5.1 Experimental validation

Write about the experiments ...

Experimental environment considerations.

Management of the different time-series + drawings about that: GT: random point process Probe revelations: random point process Presence of devices: temporal range based on revelations

Data collector on a Raspberry Pi model 2B has been placed in a place of social interest.

In this place of social interest, I manually collected the ground truth on my computer.

Mosquitto MQTT Broker, the MongoDB database and the Back-End part for receiving and storing the data in the database have been executed on the U-Hopper server.

Final Back-End part for analyzing the data has been executed on my computer. Setting of the cleaning parameters. Training and preparation of the ML model with the ground truth.

In the end, we store the results in the database instead of sending them to a hypothetical consumer of this type of system.

5.2 Evaluation of the results

Write the evaluation ...

We calculated the following parameters for evaluating the KPIs, taking as the ground truth the number of people that I have manually annotated, with a random look strategy of some hours per day in different time slots:

Error mean = mean(abs(people_present - people_estimated))

scaled_MSE_trend += $\left(\frac{people\_present - people\_estimated}{people\_present}\right)^2$

Scaled_MSE_trend/count = $\frac{scaled\_MSE\_trend}{rivelations}$

scaled_MAE_trend += abs$\left(\frac{people_present - people_estimated}{people_present}\right)$

Scaled_MAE_trend/count = $\frac{scaled\_MAE\_trend}{rivelations}$

R2 score = r2_score(people_present , people_estimated)

Correlation with revealed devices:

Spearman's rank correlation coefficient = spearmanr(people_present, devices)

Pearson correlation coefficient = pearsonr(people_present, devices)

Correlation with estimated people:

Spearman's rank correlation coefficient = spearmanr(people_present, people_estimated)

Pearson correlation coefficient = pearsonr(people_present, people_estimated)

6 Conclusions

Write conclusions about the work done ...

6.1 Future work

Write about future work ...

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