Analysing the Foraging Behaviour of Bees using Process Mining: A Case Study*

Zahra Ahmadi[1][0000−0002−2313−5392], Yannis Bertrand[2][0000−0002−6407−7221], María Isabel Pozo Romero[3][0000−0003−1135−1327], and Estefanía Serral[2][0000−0001−7579−910X]

[1] LIRIS, KU Leuven, Brussels,
Belgium {zahra.ahmadi, yannis.bertrand, estefania.serralasensio}@kuleuven.be
[2] ETSIAA, Universidad de Valladolid, Valladolid, Spain
mariaisabel.pozo@uva.es

Abstract. In this paper, we present a novel case study for the application of process mining on data captured by Internet of Things (IoT) devices. In this case study, IoT sensors in robotic flowers are employed to gather a comprehensive dataset on bee colony behaviour through a series of experiments conducted under various conditions. The primary objective of this paper is to investigate the applicability of process mining to analyse the collected sensor data, map bee colony behaviour, and uncover the learning patterns exhibited by the bees during these experiments. Encouraging results have emerged from this research, demonstrating the feasibility of converting the collected sensor data into event logs that can produce insights on bees foraging behaviour using a process mining tool. This case study serves as a solid foundation for future research endeavours on the application of process mining to similar processes that can be monitored using IoT devices.

Keywords: Internet of Things · IoT · Process mining · Process Discovery · Bees · Foraging behaviour · Case study.

1 Introduction

Bees being one of the most important insect pollinators for our ecosystem [13], numerous authors have extensively studied their behaviour. The observation of bees has traditionally relied on manual and time-intensive methods. Researchers were required to be physically present for live observations or meticulously review recorded video footage within a specific time frame to track bee behaviour. This approach yielded a restricted amount of data and was prone to errors stemming from the human element [5].

The latest innovations of the Internet of Things (IoT) have made it possible to create robotic flowers that can collect detailed information about bees' actions [14]. These flowers record very precisely and at second-level frequency the visits of the bees on such flowers. This fine-granular and rich data can be translated into a higher-level event log usable for process mining (PM) [7, 17].

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PM has shown to be a very powerful tool to enable the automatic discovery and visualisation of actual process flows based on event data. It provides a detailed understanding of how processes are executed, revealing the actual paths and their variations. The application of PM to sensor data is challenging, although it has been increased recently, however, most of the existing literature focusing on deriving process models of human behaviour from sensor logs in smart spaces [3].

In this paper, we present a very novel case study where we apply PM to obtain new insights on the foraging behaviour of bees. We ran 4 experiments to capture data on 8 bees' colonies using 16 robotic flowers per experiment. Using these data, we use PM to compare the behaviour and the learning capabilities of healthy bees versus sick bees. Understanding this behaviour could reveal insights on the pollination process which could be used to increase bees survival chances and maximise honey production.

The rest of the paper is structured as follows. Section 2 summarizes the related literature focusing on 1) PM with IoT data and 2) previous methods used to understand foraging behaviour. Section 3 describes the case study. In Section 4, we apply PM to the case study, dealing with the challenges that sensor data analysis pose for PM. The results of the analysis are discussed in Section 5. Finally, Section 6 concludes the paper and proposes directions for future work.

2 Related Work

2.1 Process mining using sensor data

Although PM has never been applied to understand the foraging behaviour of bees, it has been used to investigate sensor logs (see [7, 9, 16, 4, 19] for some representative examples). One of the most frequent domains where PM was applied to sensor data is smart spaces, namely to perform habit mining. Habit mining consists of analysing and modelling human routines and activities of daily living using IoT data collected in smart spaces [18]. Various approaches exist to create models of human behaviour based on IoT data collected smart spaces; see [2] for an overview of these approaches.

To apply PM to sensor data, different challenges need to be addressed [2], among others:

1. The low-level nature of sensor data compared to process data, requiring event abstraction. A typical sensor log contains measurements of sensors that do not necessarily match with activities, e.g., a contact sensor merely indicates whether contact with the sensor is detected.
2. The definition of cases and the log segmentation following the case definition. A sensor log contains sensor measurements that may not match with one process execution.

2.2 Analyses of Foraging Behaviour

Within the bio-engineering domain, it is frequent to use several insects as study subjects in dual-choice experiments, where two conditions are offered simultaneously in a cage or enclosure. Typical tests on such experiments collect two sets of variables: number of visits to a given group (one or more flowers), and the duration of the visit.

Number of visits is recalculated as a proportion of visits to each group. Two options are often used to compare the proportions of visits to each condition (see [14] for a representative example). On the one hand, a two-sample test for equality of proportions with a continuity correction (Pearson's chi-squared test) compares the proportion of visits to each category, already calculated by a contingency table. On the other hand, a generalised linear model can be used to determine preferences, e.g., coding one group as success and the other as failure, thus setting the response variable as binomial.

The second variable, visit duration, may indicate preference to stay (e.g., odour, colour, warmth) or a higher intake. To investigate whether visit time differed significantly between treatments, generalised linear models are often used to compute the model-adjusted average of that time and the model-adjusted error for each experimental group. Significance arises when averages plus/minus error do not overlap. The main problem in analysing this variable is to get the right distribution of the response variable. When the number of observations is high, it is assumed the data will approach a Gaussian distribution, but data collected with IoT technologies already showed otherwise.

Note that these analyses are not focusing on foraging behaviour as a process but as individual variables: number of visits and their duration. PM can therefore bring a new perspective into play and provide an alternative or complementary way to analyse behavioural aspects.

3 Case Study Description

We focus our analysis on better understanding the foraging behaviour of bumblebees (from now on referred to as bees or foragers). Normally, bee foraging behaviour comprises flower visits of different lengths, and this length correlates with different biological activities: probing, eating (ingesting pollen/nectar provided by flowers), resting, and sleeping. Foragers are attracted to the flowers because they often provide nectar and pollen, used to fuel their flight activities and to rear their offspring. As such, foragers try to maximise their energy intake while spending the least amount of energy to forage [15]. The biggest cost to a forager is the amount of time and energy spent on landing on, entering, and probing flowers [11]. Hence, in theory, foragers will focus their efforts on nectar-rich flowers [11]. The flower colour may play a role as well in attracting a bee.

According to the optimal foraging theory, pollinators are expected to discriminate high-quality nectar resources from less valuable resources [8, 10]. However, floral nectar is often rich in plant secondary compounds [1]. About 1/3 of these compounds have a medicinal influence on the colony. They have a different taste, color and odour than floral nectar, and as such they are typically avoided by most pollinators. This case study focuses on investigating if such avoidance still applies when the colony status changes, i.e. when colonies become sick. In such cases, sick bees may focus their foraging efforts on flowers that contain a medicine capable to cure them. We are interested in understanding and comparing the foraging behaviour of sick bees vs. healthy bees. We will focus on understanding the collective behaviour, i.e., behaviour for each colony, rather than the behaviour for each individual bee, as foragers mostly collect the sugar water to feed the offspring, and not to satisfy their own nutritional demands.

4 Process Mining Application: Gathering Insights on Foraging Behaviour

In order to understand bees' foraging behaviour, we follow a typical PM methodology [20] and adapt it for IoT data. First, we identify the hypotheses to be studied. Second, we collect the necessary data to test those hypotheses using IoT sensors. Third, we preprocess the collected data to deal with quality issues. Fourth, we convert the IoT data into event logs ready to be used by PM tools. Fifth, we perform an iterative analysis to confirm or reject the hypotheses by applying PM and evaluating the results.

4.1 Hypothesis Formulation

Previous research having demonstrated that bees learn and adapt their foraging behaviour , the case study focuses on investigating whether bees adapt their foraging behaviour when they are sick. It was expected that the bees would explore and thus probe from all types of flowers equally at first, and progressively learn and increase their eating activities on flowers offering a more rewarding diet: sick colonies would prefer treated sugar water containing a medicinal compound (treatment); while healthy colonies would naturally show deterrence towards the medicinal compound and prefer untreated sugar water (control) . Based on this prior research and expert knowledge, the following hypotheses were formulated:

H1: Foragers will learn and adapt their foraging behaviour over time. This is further subdivided in two hypotheses:

H1a: Sick colonies will eat more and more from flowers that contain medicine.

H1b: Foragers from healthy colonies will eat more and more from flowers that do not contain medicine.

H2: Foragers visit more flowers that are closer to their nest to minimise energy expenditure (i.e., collect more nectar using less energy).

4.2 Data Collection

Four experiments were performed to collect data on the behaviour of bees. Two experiments, namely E1 and E2, were run with healthy bees, and two experiments, namely E3 and E4, were run with sick bees.

In each experiment, two identical greenhouse tents (namely left cage -L- and right cage -R-) were used. In each tent, a colony of around 30 workers and one queen was placed and 8 robotic flowers were deployed. The robotic flowers were presented in [6] with the purpose of measuring flower visit rates and duration per visit (in seconds) using a wireless transmission. The flowers are equipped with an infrared sensor located in the feeding hole that records when a bee visits it and the duration of the visit. In addition, sugar water is offered by the flowers in discrete amounts to simulate the natural availability of nectar and stimulate foraging in floral patches.

Half of the flowers provided regular sugar water, while the other half contained sugar water that was treated with a plant secondary compound, being able to act as a medicine to cure the disease from which the sick bees suffered.

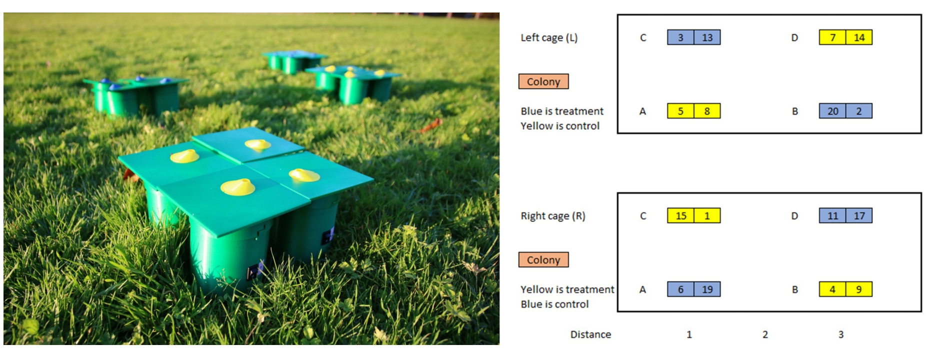
See Figure 1.(a) for a picture of the flowers and Figure 1.(b) for a schematic representation of the experiments' setting. As Figure 1.(b) shows, flowers were distributed in 4 groups of 2 inside the tent, with 2 groups of each colour located in diagonal to minimise influences of external variables. This setting was replicated for all four experiments. Each experiment ran for 96 hours (from the noon of the first day to the noon of the fifth day), a duration that is considered by experts enough time to learn behaviour patterns.

4.3 Data Preprocessing

We assumed that only one bee can sit on each flower at a time and we focused on studying the behaviour of each bee colony as a single entity (not behaviour of individual bees).

Given that bees usually only leave their nest during the day, visits logged after 12PM and before 6AM were considered as noise and dropped. Data quality issues due to logging, such as missing data, duplicate visits and truncated visit duration, were also solved during preprocessing.

The sensor logs are not segmented in traces of execution of the process. However, identifying a case is a prerequisite to apply process mining. Since our intention is to study the collective behaviour of the bees, we considered each colony as an individual case, i.e., experiment + left/right cage. For certain analyses, to segment the sensor data further, we use a time window approach of 24 and 6 hours. The timestamps of each day are separated into 4 quarters, namely Quarter1 (morning), Quarter2 (afternoon), Quarter3 (evening) and Quarter4 (night) in the intervals [6:00 - 12:00[, [12:00 - 18:00[, [18:00



(a) (b)

Fig. 1: (a) The robotic flowers used to collect data on the bee foraging process (picture taken outside of experiments) (b) Schema of the experimental setup to collect data on bee foraging behaviour.

- 0:00[and [0:00 - 6:00[respectively. Quarter4 records are ignored After that, data were split into 24-hour time-based windows, as follows (i represents the window number):

$$window(i) = Quarter2(i) + Quarter3(i) + Quarter1(i+1)$$

In the end, for each colony from each experiment, we have data distributed within four 24-hour windows and three-quarters per window. This step yielded a sensor log containing 35092 events: 13062 from the first experiment (E1), 11120 from the second one (E2), 5046 from the third one (E3), and 5864 from the last one (E4).

4.4 Event log creation

A necessary phase to transform the sensor log into an event log is to derive higher-level events from lower-level sensor data, i.e., aggregating events to represent more meaningful activities [2].

The logged data includes the colony, flower ID, cage (L/R), treatment/control and colour (Yellow/Blue) values for each visit to a robotic flower, in association with a start timestamp and duration. In the preprocessing, various information such as greenhouse and cage numbers, flower identifier, flower type (whether it has nectar or medicine), color, and time of day are automatically extracted from the raw data. Figure 2.a and Figure 2.b show the raw and preprocessed event log of our dataset, respectively.

Then, for each captured sensor data, we created a record in the event log containing the information mentioned in the sensor reading such as timestamp, colony, cage and treatment and added some other processed information like group and distance. We determined the group (A/B/C/D) identifier and a distance attribute by grouping the flowers based on their distance from the nest in each cage. More specifically, we consider flowers located in groups A and C as distance 1 and flowers in groups B and D as distance 3 (see Figure 1.(b)).

colony	hour	prob	Flower	date	trt	cage	color	disease
R2	13:51:58	6	flower6	20220404	D1	R	YELLOW	Healthy
R2	13:52:49	3	flower6	20220404	D1	R	YELLOW	Healthy
R2	13:53:10	4	flower6	20220404	D1	R	YELLOW	Healthy
R2	13:54:01	4	flower6	20220404	D1	R	YELLOW	Healthy
R2	13:53:29	5	flower6	20220404	D1	R	YELLOW	Healthy

(a)

Colony	Day	Window	EventNumber	FlowerNumber	StartTime	Hour	Activity	Prob	Cage	Color	Disease	Date	Treatment	Group	Distance
R2	Day1	Window1	1058	Flower6	4/4/2022 18:04	18	Probing	2	R	BLUE	Healthy	4/4/2022	CONTROL	A	1
R2	Day1	Window1	1059	Flower6	4/4/2022 18:05	18	Probing	2	R	BLUE	Healthy	4/4/2022	CONTROL	A	1
R2	Day3	Window3	1060	Flower6	4/6/2022 15:59	15	Probing	1	R	BLUE	Healthy	4/6/2022	CONTROL	A	1
R2	Day3	Window3	1061	Flower6	4/6/2022 16:03	16	Probing	3	R	BLUE	Healthy	4/6/2022	CONTROL	A	1
R2	Day3	Window3	1062	Flower6	4/6/2022 17:47	17	Eating	17	R	BLUE	Healthy	4/6/2022	CONTROL	A	1

(b)

Fig. 2: A snapshot of the event logs (a) raw data and (b) preprocessed data

In addition, we labelled the activities based on the duration of the visit of a bee on a flower. The used cutoffs were chosen based on previous research on bee behaviour [12] and expert knowledge. Events with a duration between 0 to 4 seconds are labelled as *Probing*, 4 to 30 as *Eating*, 30 to 200 as *Resting*, and 200 to 600 as *Sleeping*.

4.5 Applying Process Mining

Process mining tools such as Celonis[3], Disco[4] and ProM[5] can help identify inefficiencies, bottlenecks, and opportunities for process optimization. Among the available commercial and research PM tools, we chose Disco as it is a powerful tool with a user-friendly interface and it provides the necessary functionalities to analyse the hypotheses. Using Disco, we have studied the events in the experiments and analysed the frequency, performance, and statistics of processes to confirm or reject the hypotheses. The results are next described in detail per hypothesis. Note that the activity and path parameters in Disco are set to 100% in all analyses, and that the conclusions of the analyses are drawn only for the experiments at hand.

H1: Foragers will learn and adapt their foraging behaviour over time. We analysed the behaviour of bees for each colony focusing on the content provided by the flower, i.e. containing treated (D1) or untreated sugar water (CONTROL), over different time windows. In this way, we have considered colony as case in order to see in one single process model the behaviour evolution over the windows. In addition, the window, the bees' activity type and the flower content are considered all together as the activity feature in Disco. We then evaluated their eating activity on each flower content over time (the activity types are filtered and only data for *Eating* and *Probing* are used). In general, we observed for all colonies that the number of probing and eating activities on both flower contents increases over the time windows, decreasing a bit in the last window.

- H1a: Foragers from sick colonies will eat more and more from flowers that contain medicine (treated sugar water).
  To study this hypothesis, we created process maps for each sick colony (i.e., experiments E3 and E4, left and right cages). As a representative example, Figures 3.(a) and 3.(b) illustrate the process maps for E3, Left colony (i.e., the experiment and cage values are filtered to E3 and left respectively, and eating and probing activity). For each window except Window1, the number of eating activities on the medicine flowers (represented by nodes which have D1 in their labels) is higher than the flowers with untreated sugar water (nodes with control in the label). The same happens for E4 left. For the right cages, bees eat more from the control flowers in all windows, but there is a higher increase in eating activities in the treated flowers over time. This shows the sick bees' tendency to eat more and more treated sugar water, which follows our hypothesis.
- H1b: Foragers from healthy colonies will eat more and more from flowers that do not contain medicine (untreated sugar water).
  To study this hypothesis, we created process maps for each healthy colony (i.e., experiments E1 and E2, left and right cages). The discovered maps for the eating and probing behaviour of healthy bees for experiments E1, and E2 right cage,

[3] https://www.celonis.com/
[4] https://fluxicon.com/disco/
[5] https://promtools.org/

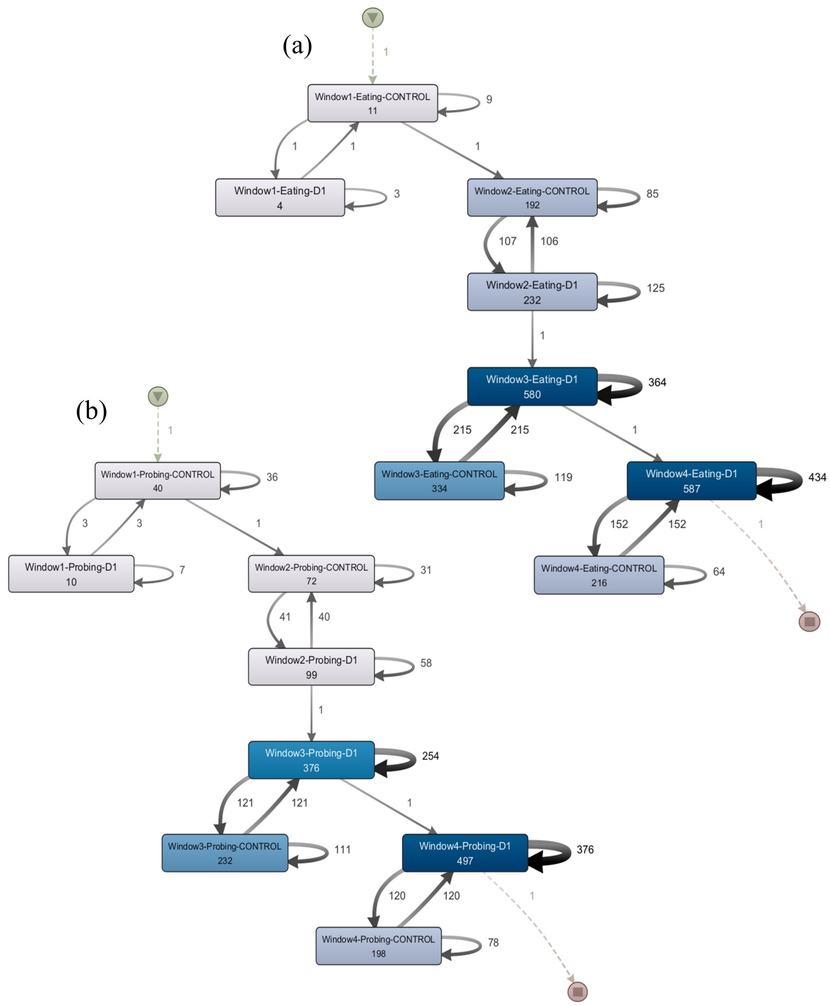


Fig. 3: (a) Eating and (b)Probing Behaviour of sick left colony in E3 (treated (D1) and untreated (control) sugar water)

show that from the beginning to the end bees ate and probed more treated sugar water than not treated, however, both types of activities increased more in proportion over time for not treated sugar water than for treated sugar water. For E2, Left colony, bees started from Window 1 eating and probing more non-treated sugar water and kept that trend until the end (see Figure 4.(a) and Figure 4.(b)).

H2: Foragers visit more the flowers that are closer to their nest to minimise energy expenditure. To explore this hypothesis, we considered the distance from the nest to the flowers as an attribute of the data in Disco. Then, we measured the

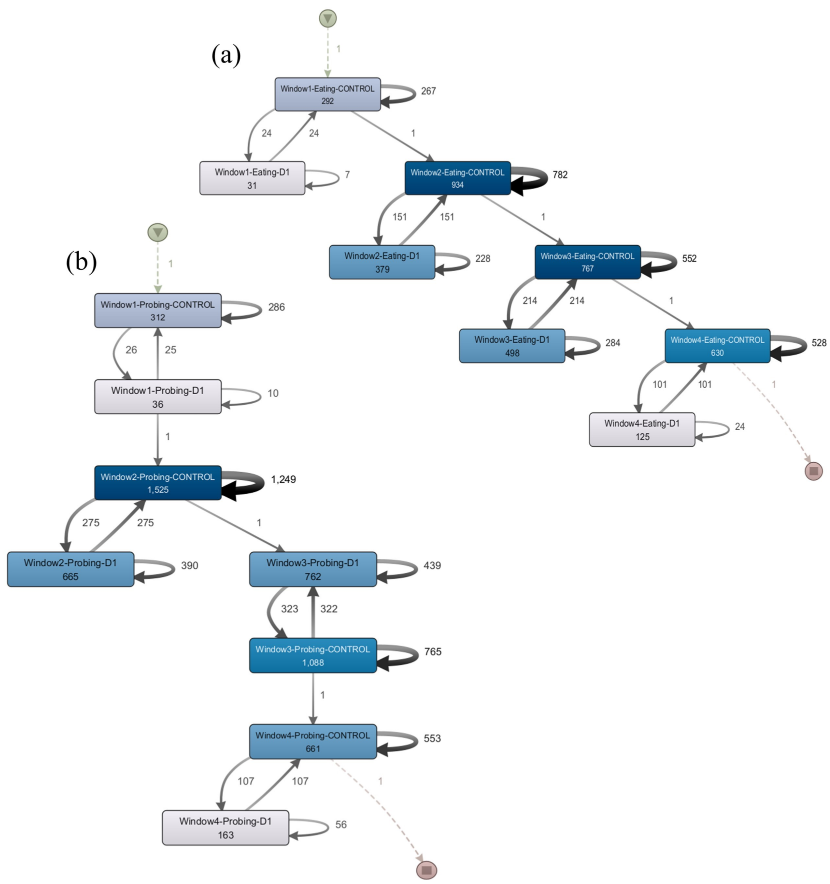


Fig. 4: (a)Eating and (b)Probing Behaviour of healthy left colony in E2 (treated (D1) and untreated (control) sugar water)

percentage of all activities (eating, probing, resting and sleeping) for all experiments according to the distances that flowers were located at, Distance 1, and Distance 3, as shown in Table 1. We considered all the activities during different windows for each colony, to see if they change their selection of flowers based on their distance. Again, the colonies are considered as our cases in order to see in one single process model the behaviour evolution over the windows. The bees' activity type, window and distance are considered all together as the activity feature in Disco.

The discovered process maps indicate a similar pattern for the left colonies of sick bees: bees visit more remote flowers than close ones in all windows. Also, the sick bees in the right colonies started by visiting farther flowers in Window1 and changed their behaviour to visit the closer flowers afterwards. However, the behaviour of healthy bees do not follow any clearly identifiable pattern. Thus, the results do not show that bees prefer to visit closer flowers.

Table 1: Percentage of events based on the distance of flowers.

Distance	E1	E2	E3	E4
1	56.03	43.54	50.32	40.81
3	43.97	56.46	49.68	59.19

5 Discussion

Using behaviour data from 8 colonies, 4 sick and 4 healthy, we have explored the use of process mining to understand the bees' behaviour and its evolution, in particular, their foraging activities and to which extent colonies learn and adapt their behaviour.

Following the successful implementations of PM in the literature mentioned in Section 2, we have demonstrated in our analyses that the use of a PM tool like Disco is a very suitable option to study the stated hypotheses and as such a very valid alternative or complementary tool for the current methods used by domain experts (see Section 2.2), specially to deal with the increasing amount of data that can be collected using IoT sensors.

After preprocessing the data, their conversion into event logs by 1) abstracting the log into activities and 2) determining traces by focusing on collective behaviour (colonies) has proved capable to derive the necessary insights by applying PM. Different process models focusing on different aspects (treatment vs control, closer or farther flowers, different activities, etc.) could easily be generated using Disco, and different analyses based on the discovered models could be performed (e.g., average or total time spent per activity). Once explained, the results are easily interpretable by domain experts, and specially the models provide very helpful visuals to draw conclusions (when possible) or provide insights for further experiments.

In particular, the results allow us to draw the following insights:

- H1: while H1a is confirmed (sick bees have a tendency to eat more and more from treated sugar water), H1b is rejected: healthy bees tend to keep their eating behaviour over time regarding the choice between treated or untreated sugar water. More experiments should therefore be carried out to reach conclusive results for confirming or rejecting H1.
- H2 can be rejected. We can conclude that the distances in our experiments did not seriously affect the preference of the bees for certain flowers. However, this may be due to the relative small distances between flowers (considering the greenhouse space limitations) compared to the areas that bees can cover for foraging in the nature.

The above insights on the behavioural differences between sick and healthy bee colonies can be used in real scenarios to test in vivo the efficacy of drugs against bee pathogens. Also, by monitoring the activity level of the bees at real-time, it may be possible to identify the discovered differences between sick and healthy colonies to determine the existence of a disease in the hive and treat the bees on time.

It is important to note that the rejection of the hypotheses in some aspects or the need to perform further experiments could be attributed to the complexity of the processes representing the behaviour of living beings, together with the involvement of multiple interacting variables that may not fully be captured by the initial setup. Next to this, we think that illumination may have caused differences in the bees' behaviour as well. The analyses enabled by PM allowed us to determine that colonies monitored in the right cages were in general less active than in the left cages. Although the experiments having mirrored cages tried to be performed under the same environmental conditions, after getting this insight from the PM analysis, the experts realised that the right cage was a bit further from the external light. The domain experts will try to minimise this difference in the next experiments. Furthermore, it is important to note that our findings only apply to the collected data. In order to obtain a more accurate understanding of bee behaviour and generalize our findings, it is necessary to collect data over extended periods of time, under diverse environmental conditions, and with a wider range of flowers and nectars.

Finally, although the chosen cut-offs to derive the high-level activities are based on previous research and expert knowledge, they should be investigated further as a difference in a few seconds could output very different process maps and as such different conclusions, especially for H1. Another approach that could be followed to be certain on the cut-offs is to install a weight scale in the flowers that monitors at real time the exact amount of sugar water that is eaten in each visit.

6 Conclusions and Future Work

In this paper, we have presented a novel case study where a process mining analysis has been successfully applied to study the foraging behaviour of bees. We showed that PM, and Disco in particular, is a powerful and relatively easy-to-use tool to discover and visualise the colonies' process flows and the behaviour evolution in time, and as such it showed to be suitable to evaluate the stated hypotheses on bees' foraging behaviour. This shows the potential to use PM to study insects behaviour that can be monitored using IoT technology. It is very important however that all relevant variables are carefully determined and monitored at the right frequency in order to get insights that reflect the reality as close as possible.

As further work, we plan to use NFC or RFID tags to track the behaviour of individual bees. These data may allow us to get a better understanding on the individual behaviour and preferences of bees and their individual foraging patterns. In addition, we are going to conduct further analyses and experiments to study the behaviour of the bees for longer periods of data collection and larger distances between flowers and hives, more in line with what happens in reality. Within these experiments, contextual data such as illumination will also be captured as the difference behavioural difference between the cages (left/right) may be attributed to that factor.

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