Computers and Electronics in Agriculture 127 (2016) 221–235

Contents lists available at ScienceDirect

Computers and Electronics in Agriculture

journal homepage: www.elsevier.com/locate/compag

Original papers

Application of wireless sensor networks for beehive monitoring and in-hive thermal patterns detection

Douglas S. Kridi [a], Carlos Giovanni N. de Carvalho [b], Danielo G. Gomes [a,*]

[a] Universidade Federal do Ceará (UFC), Departamento de Engenharia de Teleinformática, Grupo de Redes de Computadores, Engenharia de Software e Sistemas (GREat), Fortaleza – CE, Brazil

[b] Universidade Estadual do Piauí (UESPI), Laboratório de Sistemas Onipresentes e Pervasivos (OPALA), Teresina – PI, Brazil

ARTICLE INFO

Article history:
Received 2 November 2015
Received in revised form 20 May 2016
Accepted 29 May 2016
Available online 24 June 2016

Keywords:
Sensor networks
Absconding
Thermal patterns recognition
Precision beekeeping

ABSTRACT

As cold-blooded animals, bees seek to control the environment thermal variation to live and work in their hives. In semi-arid regions, such as in Northeast Brazil, bees lead a natural thermoregulation mechanism inside their hives so that they can deal with high temperatures. However, when thermoregulation is not fully accomplished, all bees can leave the nest in a process known as *colony absconding*. In such a process, absconding is due to a thermal stress stimulus. In this context, here we propose a proactive monitoring of hives using a wireless sensor network which detects atypical heating. Through thermal patterns obtained on a daily basis, we developed a mechanism for detecting the temperature rise inside the hive (microclimate). Our results show various thermal patterns related to hive conditions, and highlight the temperature as a key factor to detect potential absconding conditions.

1. Introduction

Over the last few years, beekeepers in semiarid Northeastern Brazil have faced severe losses in their honey production due to a biological process known as *colony absconding*. In such a process, all bees leave the established nest to seek another and suitable new one Freitas et al. (2007). This natural phenomenon can be still considered an open issue because there are few environmental monitoring data of both hive external and hive internal temperatures (microclimate). By instinct, bees strive to keep the microclimate *homeostasis*, which is comprised of an in-hive temperature range between 33 °C and 36 °C Kridi et al. (2014) and Human et al. (2006). This control is known as thermoregulation.

According to ABEMEL[1] and IBGE,[2] between 2009 and 2013, Brazil had fallen from 4th to 11th place in the ranking of the world's honey exporters (Fig. 1a). This heavy drop happened in 2012 when the long drought affected the production of Brazilian Northeast region, which accounts for much of the honey produced in the country (Fig. 1b). Among the northeastern states most notably in the production of honey and beekeeping supplies, Piauíranked first between the Northeastern producers in 2010 and 2011 but was affected by the excessive heat in 2012 (Fig. 1c).

In the Northeast of Brazil, where high temperatures are common for most of the year, a large number of hives is lost due to the colony absconding. As a result, the prolonged drought in 2012 led 70% of the hives bees leave their nest, which caused a drop of 66% in honey production compared to 2011 in the state of Piauí Kridi et al. (2014).

With respect to monitoring solutions that can give some support or even control the in-hive thermal conditions, Wireless Sensor Networks (WSN) are a well-known alternative for distributed sensing and environmental monitoring Naumowicz et al. (2010), Alippi et al. (2011), Díaz et al. (2011), Kviesis and Zacepins (2015) and Edwards-murphy et al. (2016). This type of network meets two basic requirements for hive monitoring: (i) autonomy, because the sensor nodes can remain operational even in apiaries located in remote areas, and (ii) a low-invasive method, due to the small size of sensor nodes and the use of wireless communications Naumowicz et al. (2010), Bromenshenk et al. (2015) and Edwards-murphy et al. (2016). Moreover, as the entire abandonment of hives occurs gradually, proactive monitoring actions may indicate alerts between instability situations in microclimate.

Here we aim to use thermal patterns as a parameter to alert about overheating problems inside the hives. Our main concern is to monitor overheating itself, and this is important because high temperatures can cause a lot of apiculture damages, such as absconding (see Section 2), malformation and offspring death, and even the poor quality of honey. We highlight three goals of this paper: (i) obtaining sufficient data to both external and internal

* Corresponding author.
E-mail address: danielo@ufc.br (D.G. Gomes).

1 Brazilian Association of Honey Exporters (http://brazilletsbee.com.br/).

2 Brazilian Institute of Geography and Statistics (http://www.ibge.gov.br/).

http://dx.doi.org/10.1016/j.compag.2016.05.013
0168-1699/

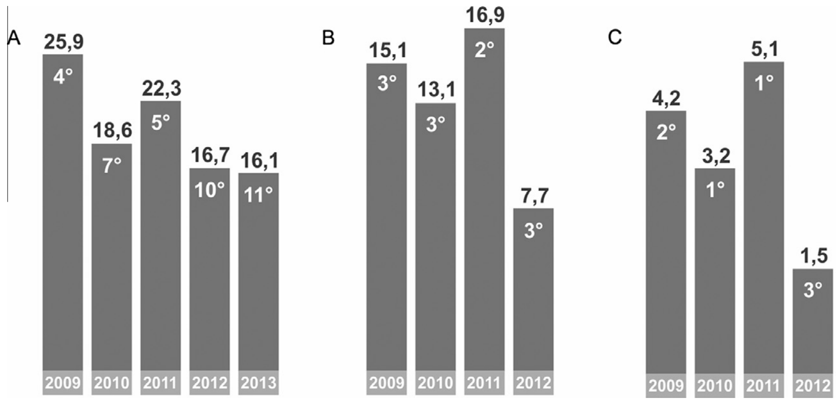

Fig. 1. Production of honey. Export and production of honey in thousands of tonnes (out of scale), (a) in Brazil/World, (b) in the Northeast/Brazil and (c) in Piauí/Northeast.

hive temperature; (ii) using similarity clustering techniques for discovering patterns in the mentioned datasets; and (iii) applying and testing patterns obtained in relation to the readings using a WSN, in normal and heating scenarios.

2. Related work

Absconding and swarming are bees behaviors that have been frequently used as synonyms Kridi et al. (2014), even though they mean distinct processes. Swarming is when a colony becomes two separate colonies, one staying behind in the original nest with a new queen, the other one leaving with the older queen and seeking a new nest somewhere else. Absconding is when all bees leave the nest as a consequence of some generalized stress factors, such as high temperature, variations in relative humidity, predators attack, lack of water Almeida et al. (2006) and Ferrari et al. (2008).

Both thermoregulation and absconding impact on beehives *homeostasis* Rangel and Seeley (2008), Ferrari et al. (2008), Bencsik et al. (2011), Meikle and Holst (2014) and Edwards-murphy et al. (2016). Microclimate thermoregulation in beehives is made by joint actions that can gather from hundreds to thousands of bees. In the cold season, the "worker" bees warm the nest by agglomeration and by muscle contraction, which increases metabolic heat (Fig. 2a). In the hot season, bees vibrate their wings by the beehive entrance bringing the external airstream and ventilating the nest (Fig. 2b). In instances of remain high temperatures, the bees spread water droplets, which due to evaporation entails a decrease of the internal temperature Kridi et al. (2014) and Zacepins and Karasha (2013). In the last case, when the temperature regulation has no effect, the entire colony leave the nest (absconding).

Zacepins and Karasha (2013) collected internal and external information of hives during the winter period in the northern hemisphere using wired sensor networks, and air-conditioned greenhouses to accommodate the hives. In a later version Kviesis et al. (2015), the authors collected some metrics using a Wireless Sensor Network, and sent them to a remote server.

Almeida et al. (2006) studied how the temperature rise leads to the abandonment of *Apis* colonies. The authors noted that the absconding process triggers when microclimate reaches around 41 °C. The time necessary to the nest complete abandonment depends on the colony strength which, in turn, depends on the hive population size.

Edwards-murphy et al. (2016) used a heterogeneous wireless sensor network to monitor hives and keep track of events related to the colonies. The authors used classifiers to handle sensor inputs and establish a correlation with events that are verified by on-site observations.

Rangel and Seeley (2008) used cameras and microphones to detect movement and audio of bees within the hive. In three separate colonies where bees had swarmed, similar patterns were observed in both buzz and movement of bees. In this way, Ferrari et al. (2008) used audio, temperature and humidity sensors to correlate these measures during the absconding process.

Freitas et al. (2007) concluded that, in the dry season, Apis bees flock to the coast and make their way around during the rainy season, which indicates that temperature variations impacts on colony absconding.

Eskov and Toboev (2011) have used infrared radiation to examine the beehive temperature during the passage of winter, and also to differentiate the temperature of individual bees. Human et al. (2006) have used data loggers to measure changes in temperature and mainly moisture in different parts of the hive.

Stalidzans and Berzonis (2013) have noted periods of increased labor activity of individual colonies by sensing the temperature values at the beehives top.

Kridi et al. (2014) used a wireless sensor network to monitor beehives temperatures to meet internal and external thermal patterns that indicates the colony agitation.

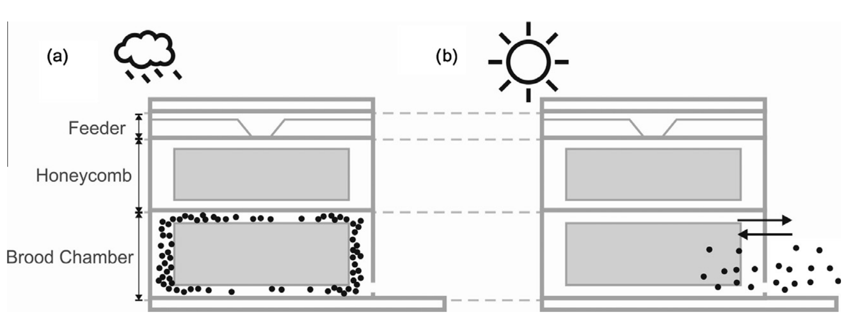

Fig. 2. In-hives thermoregulation going towards (a) heating and (b) cooling.

Table 1
Techniques for monitoring hives summed up by its main features.

Reference	Monitored metrics	SN	S/A	Interface
Kviesis et al. (2015)	Temperature, humidity	Yes	n/a	Wireless
Zacepins and Karasha (2013)	Temperature	Yes	S	Wireline
Almeida et al. (2006)	Temperature, humidity	No	A	Wireline
Rangel and Seeley (2008)	Audio, video	No	S	Wireline
Ferrari et al. (2008)	Audio, temperature, humidity	No	S	Wireline
Bencsik et al. (2011)	Vibration	No	S	Wireline
Freitas et al. (2007)	Visual inspection	n/a	n/a	n/a
Eskov and Toboev (2011)	Temperature	No	n/a	Wireline
Human et al. (2006)	Temperature, humidity	No	n/a	Wireline
Stalidzans and Berzonis (2013)	Temperature	No	S	Wireline
Bencsik et al. (2015)	Vibration	No	S	Wireline
Kridi et al. (2014)	Temperature	Yes	A	Wireless
Edwards-murphy et al. (2016)	Temperature, humidity, gases	Yes	S	Wireless

Note: SN = Sensors Networks; S/A = Swarming or Absconding.

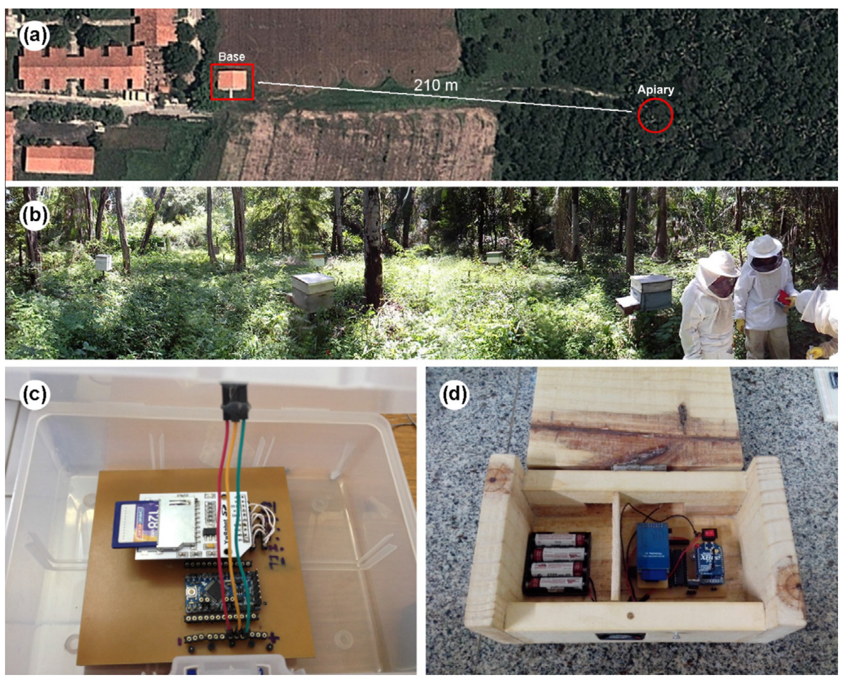

Fig. 3. Implementation in the Apiary. In (a) and (b) the experimental apiary located in Teresina – PI. In (c) and (d) the prototype with protections in plastic and wood, respectively.

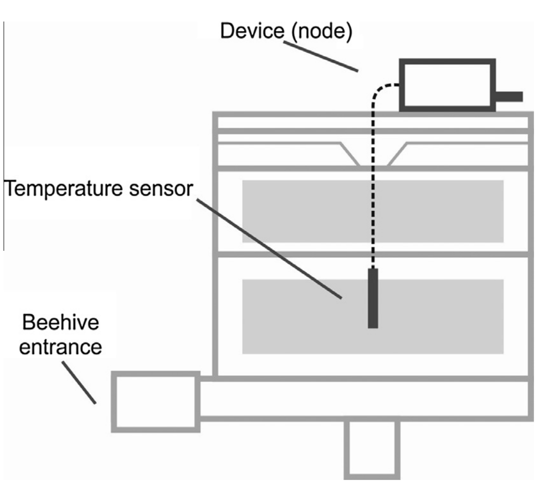

Fig. 4. Prototype disposition in/into a monitored hive.

By using accelerometers, Bencsik et al. (2015) found a strong correlation between measured vibrational amplitude and phase of the brood cycle in hives. Their solution reduces the need for visual inspections in hives, reducing too the stress caused to the colony.

Because of in-hive thermal patterns recognition, our proposal could also be applied to other such as brood cycles monitoring Bencsik et al. (2011, 2015). According to Stalidzans and Berzonis (2013), temperature may also represent different stages of the brood cycle.

Table 1 shows a comparison between each work described in this section, whose only one does not use a wired communication interface. In addition, cameras and microphones increased the energy consumption.

3. Materials and methods

3.1. Experimentation scenario

We used two different hives containing the same number of boards brood and average population (above 30 thousand bees).

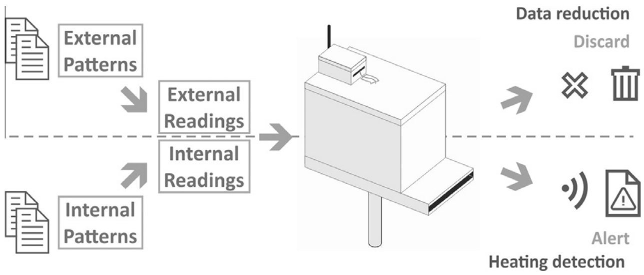

Fig. 5. Mechanism overview. Simplified steps of the proposed mechanism.

These two hives are from the same apiary, and each one has had monitoring device implanted. Fig. 3a shows the distance between apiary where the experiments were conducted and the local where the base node (sink) receive the readings sent. Fig. 3b reveals the interior of the apiary where especially during the first half of the year, vegetation is mostly green and benefits from excess moisture, as these are hot and rainy months, and for being a region near to the river. This climate combination requires attention for ensuring the proper functioning of the electronics that make up the sensor device.

In the first version, the sensing prototype was protected by a plastic casing and was not sealed (Fig. 3c), which quickly proved inadequate to environmental weather. In the following versions, the case became made of wood and sides sealed with gaps, with only one protected passage of air (Fig. 3d).

Another issue which required particular attention during the adaptation of the sensing device to the reality of hives concerns the natural reaction of bees to cover with *propolis* the elements they consider strange. Because of this, the sensor (the only part of the monitoring equipment in contact with bees) was encapsulated and coated with the wax produced by bees themselves. In this way, the sensor remained unnoticed inside the hive and its measurement capability was not compromised.

The main reason for thermoregulation in hives is the preservation of offspring Kridi et al. (2014) and Edwards-murphy et al. (2016) because high temperatures can lead to death or malformation of the offspring, which would affect the future of the colony.

There are secondary reasons as described in Section 1. As a result, the nest area is where bees concentrate the greatest efforts in maintaining the microclimate, and where the sensor was positioned. Fig. 4 shows the sensor deployment in the hive.

The device implanted in the hive sends its data to the sink node located 210 m away from the apiary. The sink mote is attached via USB interface with the base station desktop PC which is connected to the Internet.

3.2. Prototype design

The prototype developed for data collection in the field was based on the Arduino platform, which was used as microcontroller with the ATmega328 model, with a CPU clock frequency of 8 MHz and 32 KB of flash memory for storage instructions. The prototype radio is a module XBee – PRO 900HP with an operating frequency of 900 MHz and 24 dBm of signal intensity.

According to datasheet, its range varies between 610 m and 14 km, depending on the amount of obstacles and the antenna, and can reach up to 45 km, however, in the field experiments such values could not be achieved, because even using the equipment indicated with a distance of 210 m, communication could not be established between the sensor node and the base. Thus, a high-gain antenna (grid type) was used to improve the data transmission. Also, this device has very limited computational resources, which makes imperative a lightweight solution and energy economical.

Energy supply is composed of four AA batteries (with 2500 mA h and 1.5 V). The prototype also has a recording SD card, which stores all the collected readings, even those not sent over the radio.

The temperature sensor using (LM-35) was a popular and cost effective model. Before the collections in the field, each sensor has to be calibrated for consistent readings. The engine that implements our proposal was encoded in C for being the native language of Arduino platform, and its total size was approximately 8.6 KB when embedded in the prototype.

3.3. Study strategy

The graphic of the daily temperatures presents a sinusoidal pattern which could suffer small variations according to the predominant climate. We therefore propose a proactive monitoring able to identify the pattern of temperatures measured by sensors inside and outside of the hive is in accordance with expectations. Our suggested solution is to detect instabilities in the microclimate and, at the same time, saving energy by reducing data sent to the sink node, which receives all data in the nodes and sent over through the network.

Our solution was coded in C, embedded and subjected to tests using actual measurements collected by a prototype in the field. To obtain the temperature patterns of each month, we have used *Simple K-Means* to be a popular method Xu and Wunsch (2005). Most of the parameters for the algorithm execution were maintained in accordance with the software pre-configuration [WEKA software Hall et al. (2009)]. Ten *seeds of randomness*; maximum number of iterations at 500; and similarity measure *Euclidean*

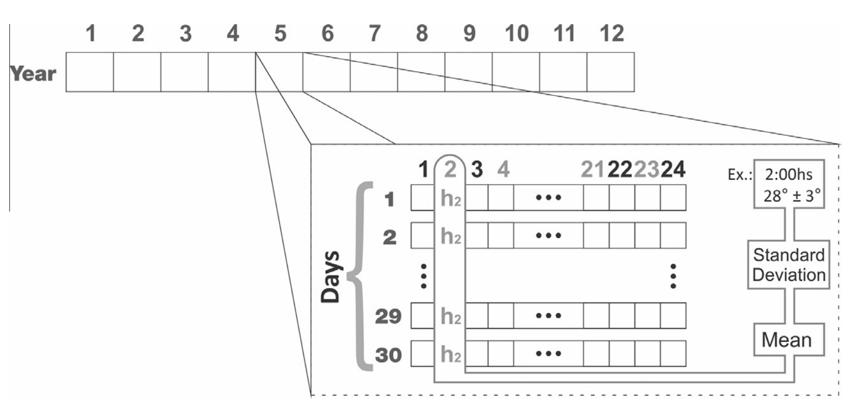

Fig. 6. Data processing. The mean and standard deviation for each hour everyday of a given month.

Fig. 7. Obtaining the thermal patterns. A limited number of patterns will represent the major thermal variation of the month.

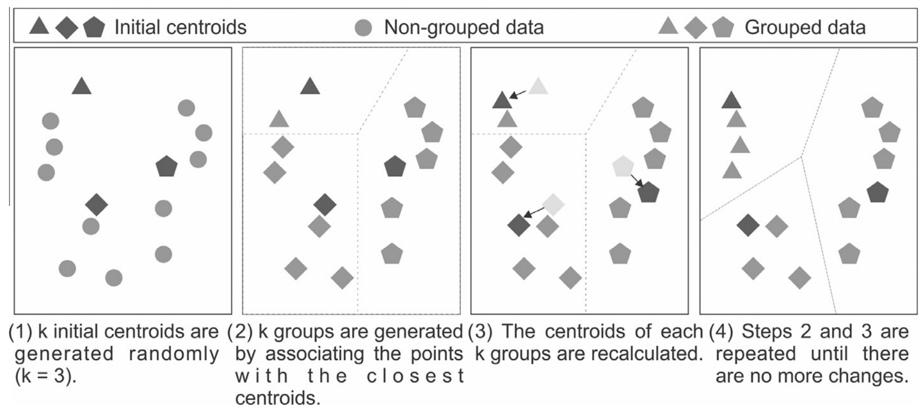

Fig. 8. *K*-means in steps. If the problem has attributes with scalar values, the similarity will be detected by the distance between them, thus, the smaller the distance between a pair of elements, the greater the similarity between them.

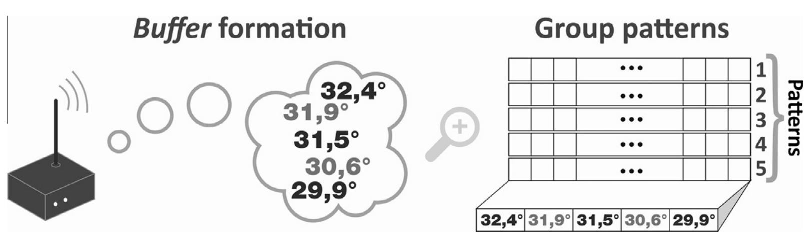

Fig. 9. Comparisons. Comparisons between patterns and sensor readings.

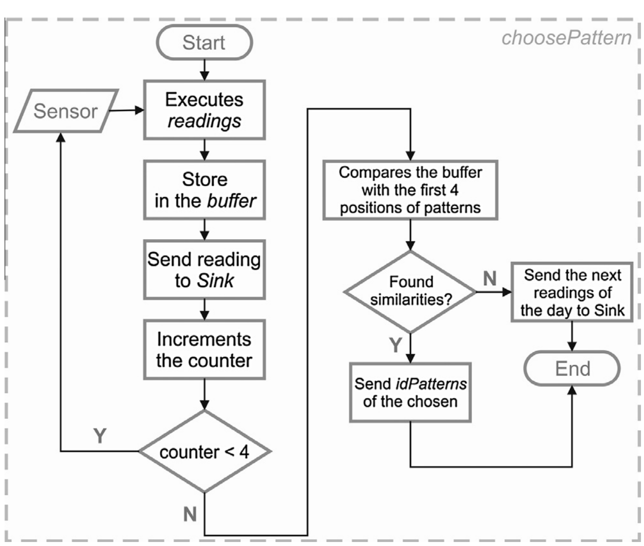

Fig. 10. Flowchart *choosePattern*. Creates the buffer with readings of the initial hours of the day that will be compared with the group of predetermined patterns.

Distance. While the parameter *numClusters* has been changed from according to the number of groups we intended to extract from each month.

With this configuration, it was generated five or more patterns which represent the thermal variation of each month. At this stage verified that less than 5 patterns per group were not sufficient to cover all possible thermal variations of a month. Therefore, each group has at least 5 patterns.

According to Kridi et al. (2014), when the inside a beehive overheats, and if there is no success in controlling the microclimate, the bees can leave the hive. In this paper, we consider that the main cause of absconding are high temperatures, so it is crucial to get a fair amount of internal readings, so we extract thermal patterns that represent the *homeostasis* of the colony, and from there identify atypical situations, as overheating.

Then, the proposed technique makes use of a automatic mechanism to determine, based on thermal patterns, when the microclimate of a hive is heating above the limits considered healthy. The same strategy also allows the detection of redundant readings while monitoring. Fig. 5 shows in a simplified way the process involving external data allowing the disposal of redundant

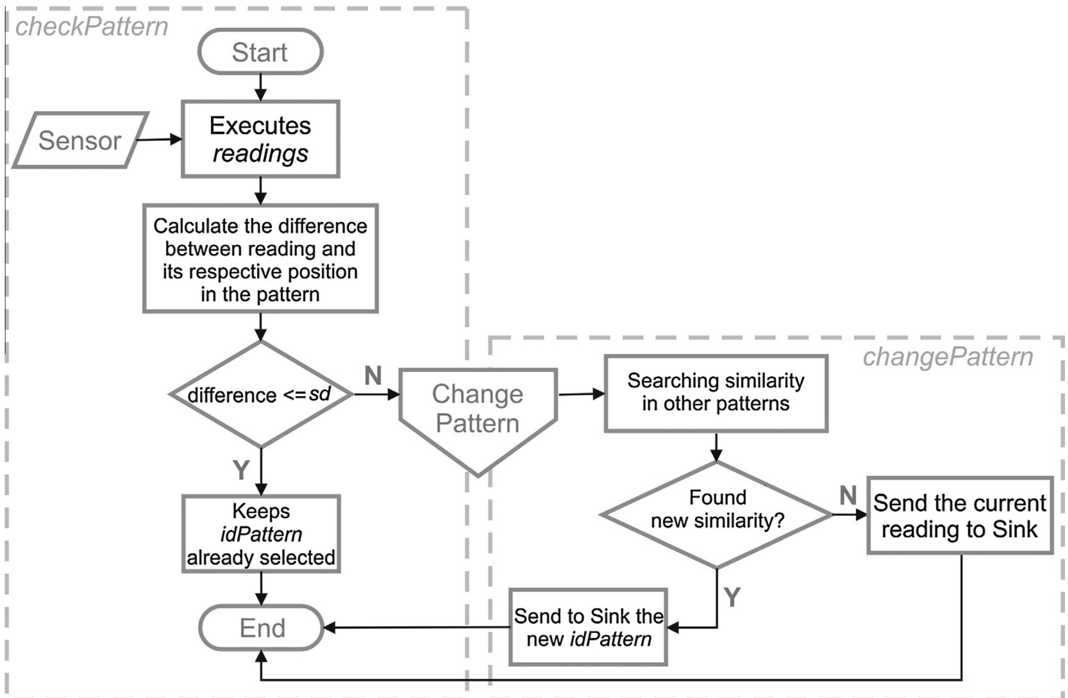

Fig. 11. Flowcharts *checkPattern* and *changePattern*. Seek proactive verification of the integrity of the chosen pattern.

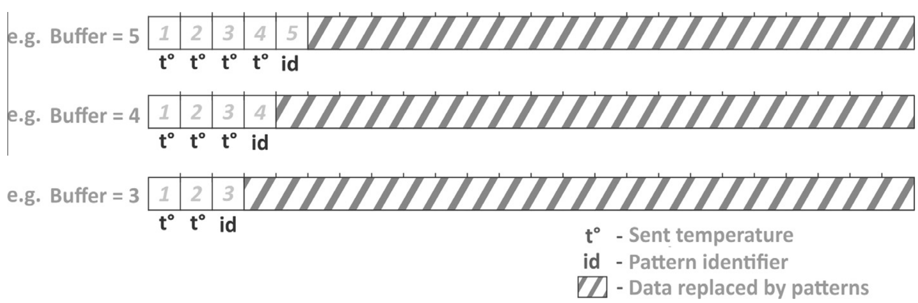

Fig. 12. Buffer size. Buffer capacity in relation to messages sent directly to the sink.

information. For internal data, what matters is sending alerts for possible overheating.

Sensor makes regular hourly external and internal readings of the hive while the automatic engine embedded compares them to predetermined patterns. There are two comparisons being made. The first checks whether the data are internally within the expected (according to the internal thermal pattern) trend. If the results are as expected, no further action is taken and the monitoring continues, but if these are not, a heating alert message will be reported to sink node.

Next, the second comparison examines whether the external sensor readings differ from weather features within that month patterns (external thermal patterns) which would lead to the sending of the respective readings. In spite of that, if there is compliance in comparison, that reading will be removed, because that is an information we already know from thermal patterns (redundant).

3.4. Obtaining thermal patterns

We used some reading datasets as a training database. These are necessary to discover the thermal patterns (aforementioned) and make comparisons with data collected by field sensors. These sets contain daily temperatures around the year 2012 and 2013 of Teresina city (Piauí), which is the place of our case study, and they were provided by INMET.

Each set contains the external temperatures and these were divided into other 12 sub-datasets, with temperatures of each month. From this information, we obtained the average temperature in degrees for each hour ($h_1, h_2, \ldots, h_{24}$ in Fig. 6) every day, as well as its standard deviation. Such metrics is useful for comparisons between readings in the field, through the sensor with the patterns obtained by an clustering algorithm.

The comparison between the readings of the sensors and the thermal patterns must have a tolerance. Outside the hive, tolerance is the aforementioned standard deviation, while inside the hive the tolerance follows a fixed limit of 1 °C.

Our goal here was to detect thermal patterns groups formed from the clustering similarity about temperature datasets obtained inside and outside of the hives in Teresina. Each pattern represents a daily temperature variation in a given month. As shown in Fig. 7, which $h_1, h_2, \ldots, h_{24}$ represent the 24 h of every day.

At the end of the process, we have 12 sets of external patterns (each one representing the thermal variations of a month) and a group with only internal patterns to the hive.

In general, the similarity clustering composes automatic grouping of data according to their degree of similarity.

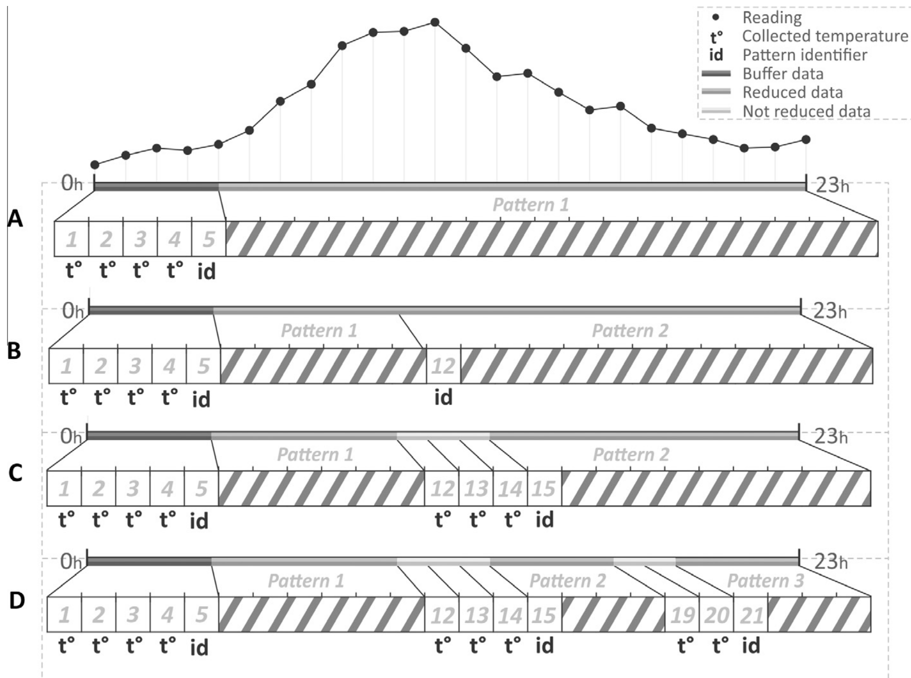

Fig. 13. Composition of information. Information obtained by (a) a pattern, (b) an exchange pattern, (c) an exchange plus data sent and (d) more than one exchange and data sent.

Formally, given a set of n elements, $X = \{X_1, X_2, \ldots, X_n, \}$, the clustering consists in obtaining a set of k clusters, $C = \{C_1, C_2, \ldots, C_k\}$, such that the elements contained in one cluster C_i have greater similarity to each other than elements of any other clusters of C ensemble.

In this context, to determine the internal and external thermal patterns of hives, we used a partitional clustering technique based on square error, called "k-means". The k-means partitions the data set into k clusters, which should provide the value of k. These clusters are formed according to some similarity measure, in this case as the distance between its elements (euclidean distance).

Each group starts from a set of k centroids (group elements that serve as a reference for the calculation of similarity). This initialization can be done in different ways, of which the most common is the random choice of k objects of the data set to represent the initial centroids. Then, each point in the dataset is associated to the closest cluster. After that, the centroids are recalculated in each iteration, and this process is repeated until there are no further changes (Fig. 8).

As stated, the grouping criteria of *k-means* is the squared error defined by Eq. (1):

$$E = \sum_{j=1}^{k} \sum_{x_i \in C_j} d(x_i, \bar{x}^{(j)})^2, \tag{1}$$

Knowing that $i = \{1, 2, \ldots, n\}$ and $j = \{1, 2, \ldots, k\}, \bar{x}^{(j)}$ is the cluster centroid C_j, and $d(x_i, \bar{x}^{(j)})^2$ is the euclidean distance between an object x_i and the centroid $\bar{x}^{(j)}$. In other words, *k-means* minimizes the distance between each object and cluster centroid to which it belongs.

According to Meratnia and Havinga (2010), calculating the distances that define the similarity between the elements of the groups requires a large computational effort for the limited nodes in a WSN. Therefore, this step should happen outside the network, and it can also be understood as part of data preparation.

3.5. Detection mechanism of atypical temperature patterns

The first readings of the day, collected by the sensor node, are stored in a variable called *buffer* and are compared to the group of thermal patterns, obtained in the previous step.

As seen in Fig. 9, the readings of the buffer are compared to the thermal patterns data. The pattern to present more similarities with the data collected by the sensor and stored in the *buffer*, is admitted as the appropriate pattern to replace the readings of the day. Then the next readings made by sensor nodes are considered normal and no longer need to be sent because they will be consistent with the selected pattern.

In Fig. 10, we see the flowchart of the procedure *choosePattern*, which is responsible for determining the closest pattern of readings stored in the variable *buffer*. First, the readings are stored in the *buffer* (with size 4), then compares these readings with the respective positions in a pattern.

The pattern to obtain a closest comparison with the readings of the buffer will be chosen to replace the next readings throughout the day. This pattern chosen will be identified by the variable *idPattern*.

However, when the comparison does not find similarities between the *buffer* and the patterns, it means that the readings made by the sensor node are atypical which should result in sending the following readings in addition to heating alerts.

When a comparison does not find similarities, it is indicative of an unusual phenomenon, such as an isolated rain on a hot month or overheating in a beehive due to failures in thermoregulation.

Flowchart in Fig. 11 aims to check the integrity of the chosen pattern proactively, preventing the use of a pattern that may become inconsistent throughout the day, identifying atypical readings. When this procedure (check Patterns) find inconsistencies between the patterns and thermal readings from the hives, readings and heating alerts will be sent to the sink node.

Even after choosing a pattern, the device will continue collecting readings for proactive verification of the consistency of this pattern, as shown in Fig. 11. The inconsistency is verified when the result of comparison between the readings and the pattern is greater than a preset tolerance (see Section 3.4).

As seen in Fig. 11, the *changePattern* procedure can determine the choice of a new pattern or send directly to *Sink* readings and alerts. This will depend on if there is a new pattern that can be associated with the readings or if they are really atypical, enough not to be represented by another pattern.

As the initial search for a compatible pattern may result in negative (Fig. 10), the readings stored in the *buffer* will always be sent, even before the comparison, so the *buffer* size influences the consumption. For example, if a *buffer* has size four, readings 1–3 (first three hours) will be sent directly to the sink, and in the fourth reading, the buffer is confronted with the patterns to know if we continue sending data or not thereafter (Fig. 12).

Buffer size also impacts on the initial accuracy of the flowchart Fig. 10. Therefore if the buffer size equals three, it means there are only three readings compatible with any pattern, so that it is selected, which affects the engine's ability to choose a pattern representing all day. Hence, the buffer size is directly proportional to the accuracy of the proposal and the energy consumption.

3.6. Information composition

As can be seen in Section 3.5, even when a predetermined pattern is selected by the mechanism to represent the day readings, atypical thermal variations, as an unexpected rain in the afternoon, can lead to readings that do not correspond to the variation represented by the initial pattern. This makes the current pattern be not suitable anymore.

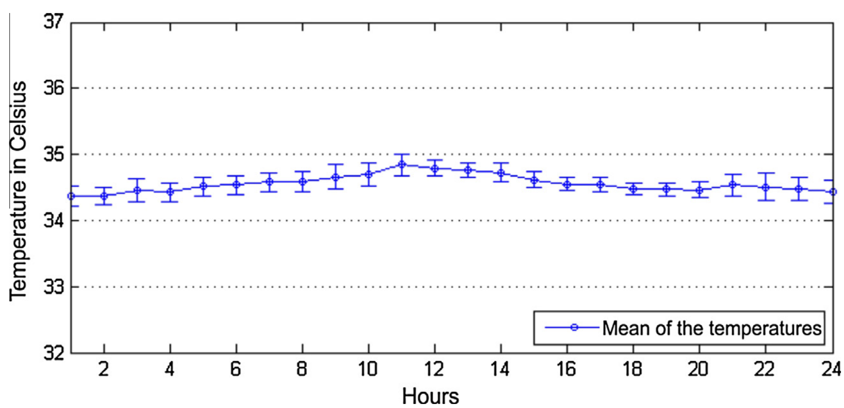

Fig. 14. Average temperatures. Average record (95% reliable) of temperatures of 24 h during 40 consecutive days.

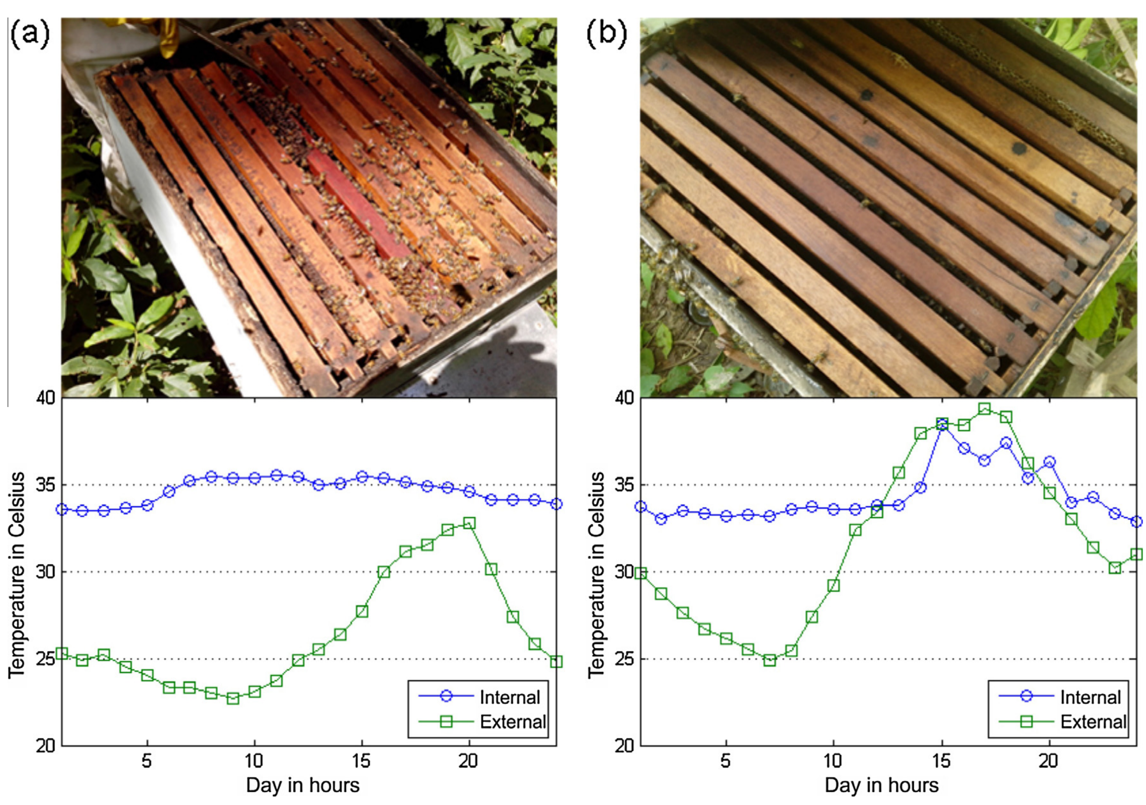

Fig. 15. Thermoregulation. Different hives in situations (a) healthy and (b) in heating situation.

In such case, a new comparison seeks another thermal pattern that can match the new climatic variation detected by the sensors. Attempts occurring after a first choice can find a new pattern immediately, or directly send the readings taken by the sensor to a new choice. This mix between sent and already known data (patterns) make up a complete information about the monitored day.

Fig. 13a shows an example of information formed by forced transmission of buffer readings (size 5) with data of a chosen pattern. Readings of 1–4 issued by buffer contain measured temperature (t°) at that time while the fifth reading maintains the pattern identifier choice (id). This identification points out what information already known (patterns) should be considered. It means the last informed id by the buffer reading allows us to learn from the group of climatic patterns, the ones that corresponds to the readings that will be made thereafter.

In the case presented by Fig. 13b, after submissions through buffer readings, a pattern is chosen, nonetheless, in the eleventh reading this same pattern becomes outdated, which motivates a new comparison. At this moment, to face a new pattern, the twelfth reading will be sent containing only the id of the second pattern chosen for that day. The temperature does not compose the package of the latter message because it is already inserted in the new pattern chosen.

Fig. 13c shows a case similar to the previous one, however, readings 12, 13 e 14 could not be fitted in any of the known patterns and are sent to their respective t°. The fifteenth reading reaches a positive comparison and is sent with the id of the new pattern. In Fig. 13d the readings 12 and 19 shows that two different lags occur on the same day which led to the choice of three patterns.

4. Results

Our results show the nature of the collected data in hives and the potential of temperature to determine the stress that can trigger a colony absconding process. These indicate the performance of the proposed solution in relation to energy consumption, precision and reducing data. The tests were conducted in 2013 and 2014.

4.1. Homeostasis, thermoregulation and heating detection

When we group the average of the temperature readings of each 24 h inside a beehive in sequence, for a period of 40 days (between July and August of 2014), we noted that all measures (Fig. 14) coincided with the "expected" track (*homeostasis*) of 33 °C, 36 °C.

The activity (or the lack of it) inside the hive is associated to temperature variations, that may indicate as Fig. 15a maintaining a microclimate properly thermoregulated the default external temperature, while in Fig. 15b, we see that in a virtually empty hive,

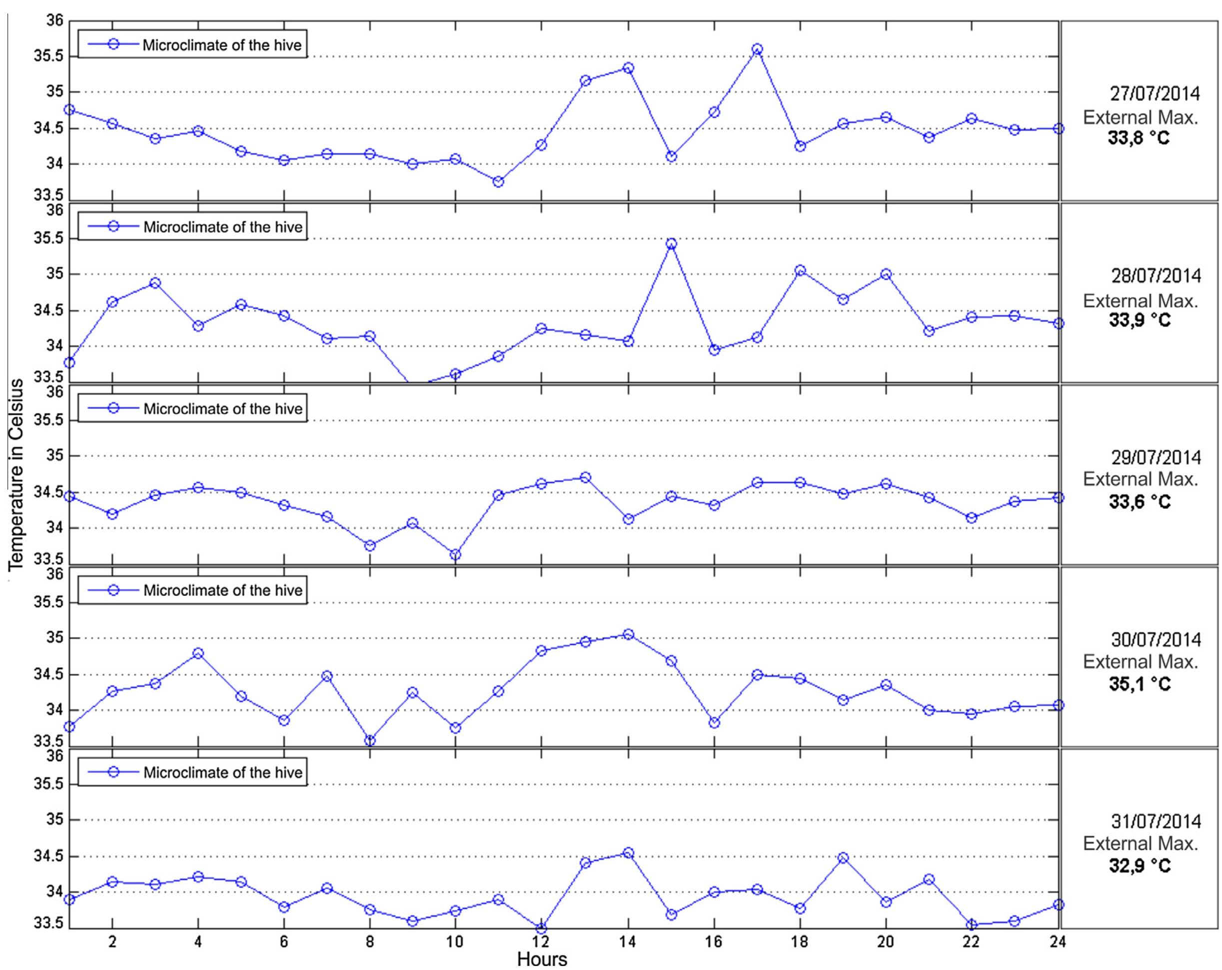

Fig. 16. Healthy internal temperatures. With the mild external environment, thermoregulation of the microclimate is maintained successfully by bees. This figure shows the in-hive thermal variation for five consecutive days of July 2014.

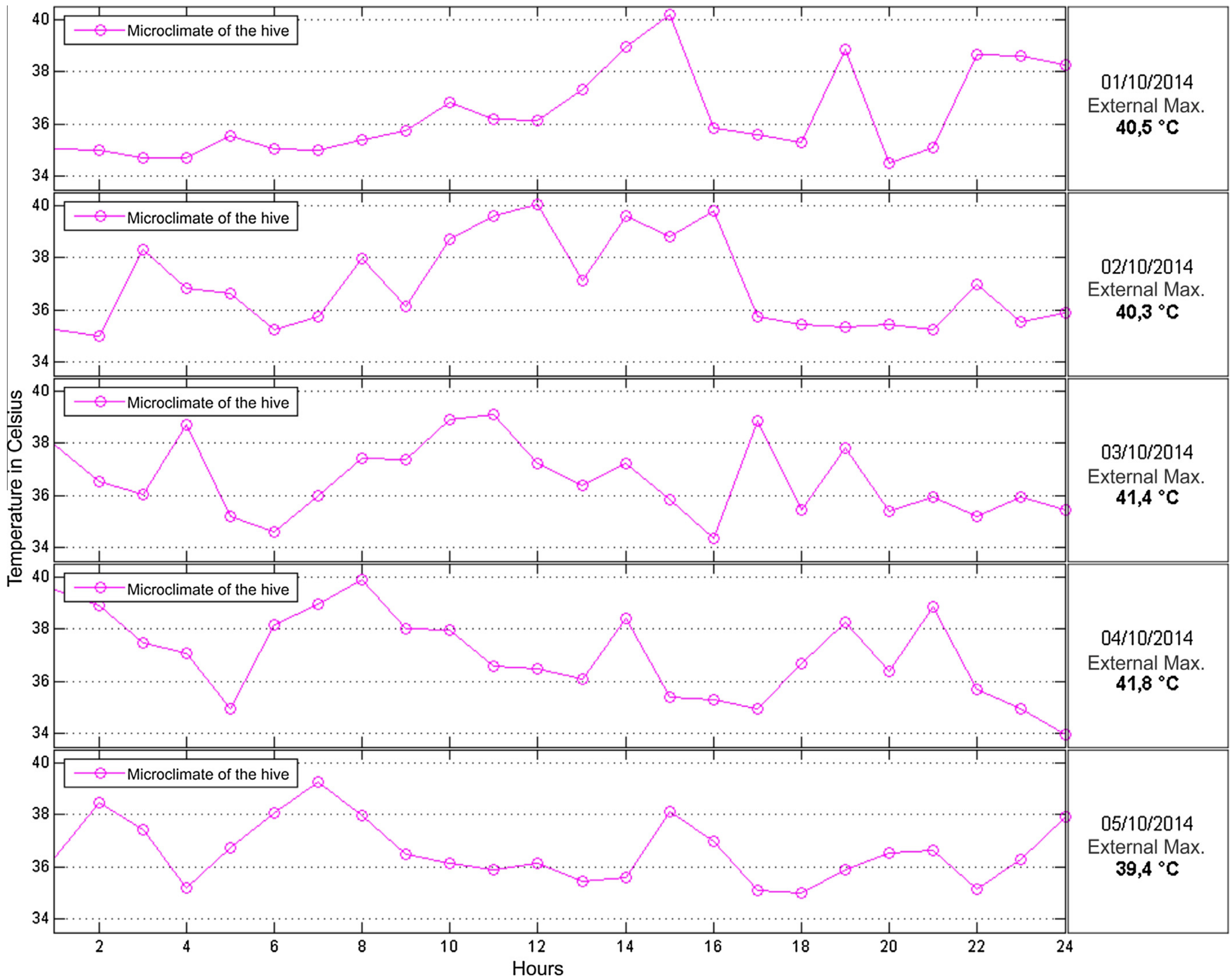

Fig. 17. Atypical internal temperatures. In unfavorable temperature conditions, thermoregulation microclimate is impaired, destabilizing the *homeostasis* of bees. This figure shows the in-hive thermal variation for five consecutive days of October 2014.

the thermoregulatory work of bees is not enough to prevent internal heating in a hot day.

In Fig. 16, we have a time series (5 days) of internal measures of July 2014. The ambient climate is mild and does not exceed 35.1 °C, while domestic conditions are maintained within the homeostatic range.

In Fig. 17, we have another sequence of five days, in October 2014, when the region temperatures are higher. We realized that the bees suffer to keep the microclimate thermoregulated. The presence of very high internal temperatures is noticed, close to 40 °C on October 01, 02 and 04.

From the samples taken, a group was extracted with 6 thermal patterns representing healthy microclimate (*homeostasis*) and will be the base of the mechanism proposed. Fig. 18, daily collection of excerpts show the operation of the mechanism in different situations.

Fig. 18 shows the messages issued by the mechanism, that may indicate heating readings (black dots) and warnings of overheating (black triangles), characterized like these because it is not an isolated heating reading, but a sequence of at least three readings outside the internal patterns (*homeostasis*).

We can see in Fig. 18e and f that overheating alerts were issued at two different times, but these alerts were preceded by a sequence of heating readings. In Fig. 18c and d these readings are isolated (in time), so this are not sufficient to alert. In Fig. 18a and b, readings were maintained within the range *homeostasis*, which is represented by the patterns and they're upper and lower limits of 1 °C (highlighted area).

4.2. Energy consumption

Fig. 19, shows the power consumption of data sent (the ones that could not be reduced) in the odd months of 2013. In January, it was observed the lowest energy expenditure and March had the highest consumption recorded.

To get the consumption, we used the energy model (Eq. (2)) proposed by Jurdak et al. (2008). This power model was chosen for its comprehensive implementation and for being used in other WSN work of the research group to which this work is linked Carvalho et al. (2011), Hermeto et al. (2014) and Kridi et al. (2014):

$$E_t = P_{send} * P_{size} * T_B * I_t * V, \tag{2}$$

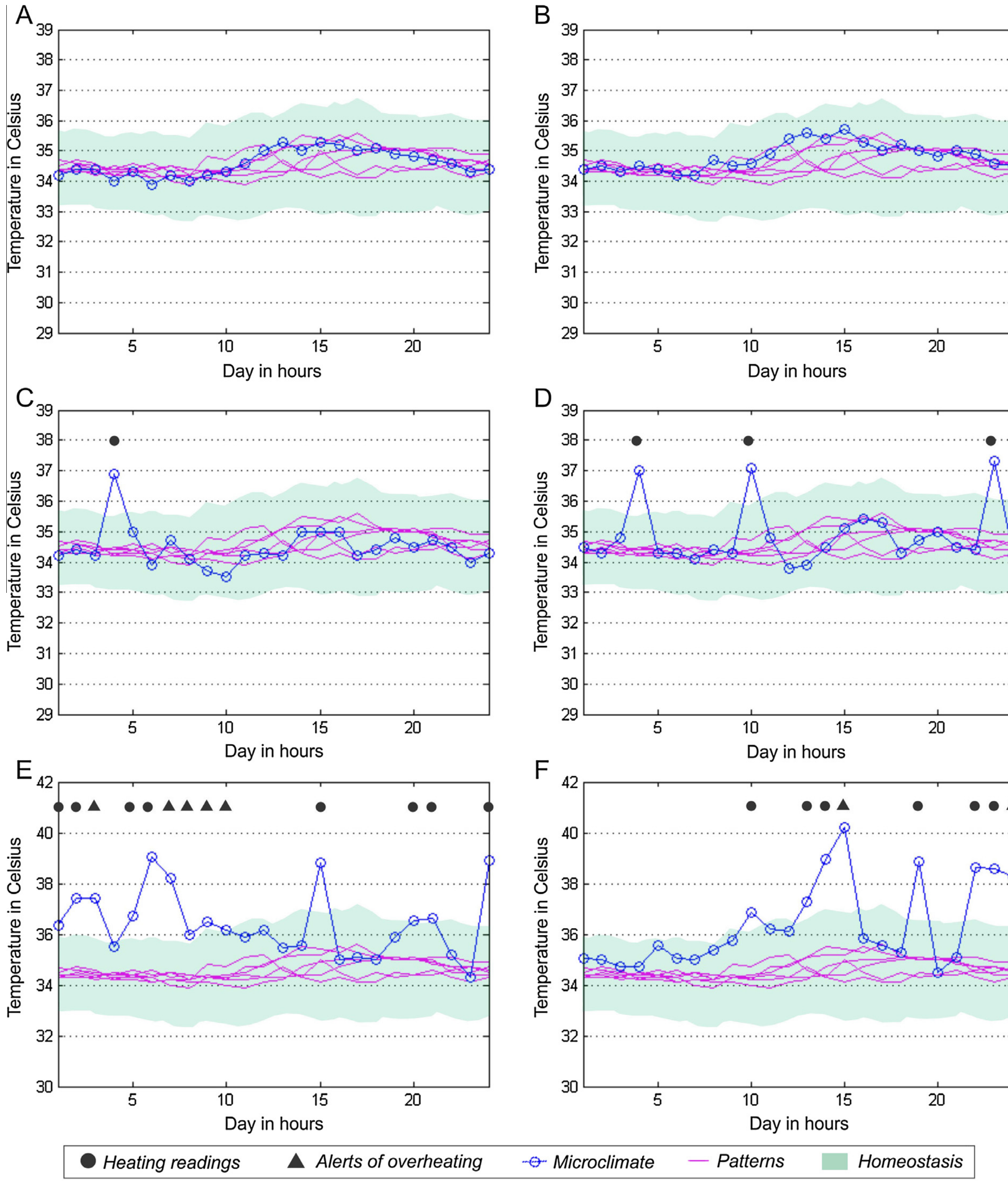

Fig. 18. Heating detection. Operation of the automatic mechanism for detection heating inside hives. In (A) and (B) readings within normal limits (homeostasis), in (C) and (D) heating isolated readings, and (E) and (F) overheating alerts.

where E_t represents the energy cost in millijoules (mJ) for packet transmissions; P_{send} is the quantity of packets sent; P_{size} is the size in bytes of each packet (4 bytes referring to a float number that represents the temperature sent), considering *payload* only; T_B represents the time required for the XBee module to send 1 byte (32); I_t is the electrical current value in the wireless module in transmit mode (45 mA) and V is the voltage supplied to the device. Note that we do not analyze packet receive costs, since we are interested to see how much of these will be saved by reducing the node to send data. All the values listed above have as reference the XBee module datasheet.

4.3. Data reduction

To determine the reduction in sending data, Figs. 20 and 21 show the average number of reduced packets in a day and the total number of sent packets in a monthly basis. We can see in Fig. 20 that March

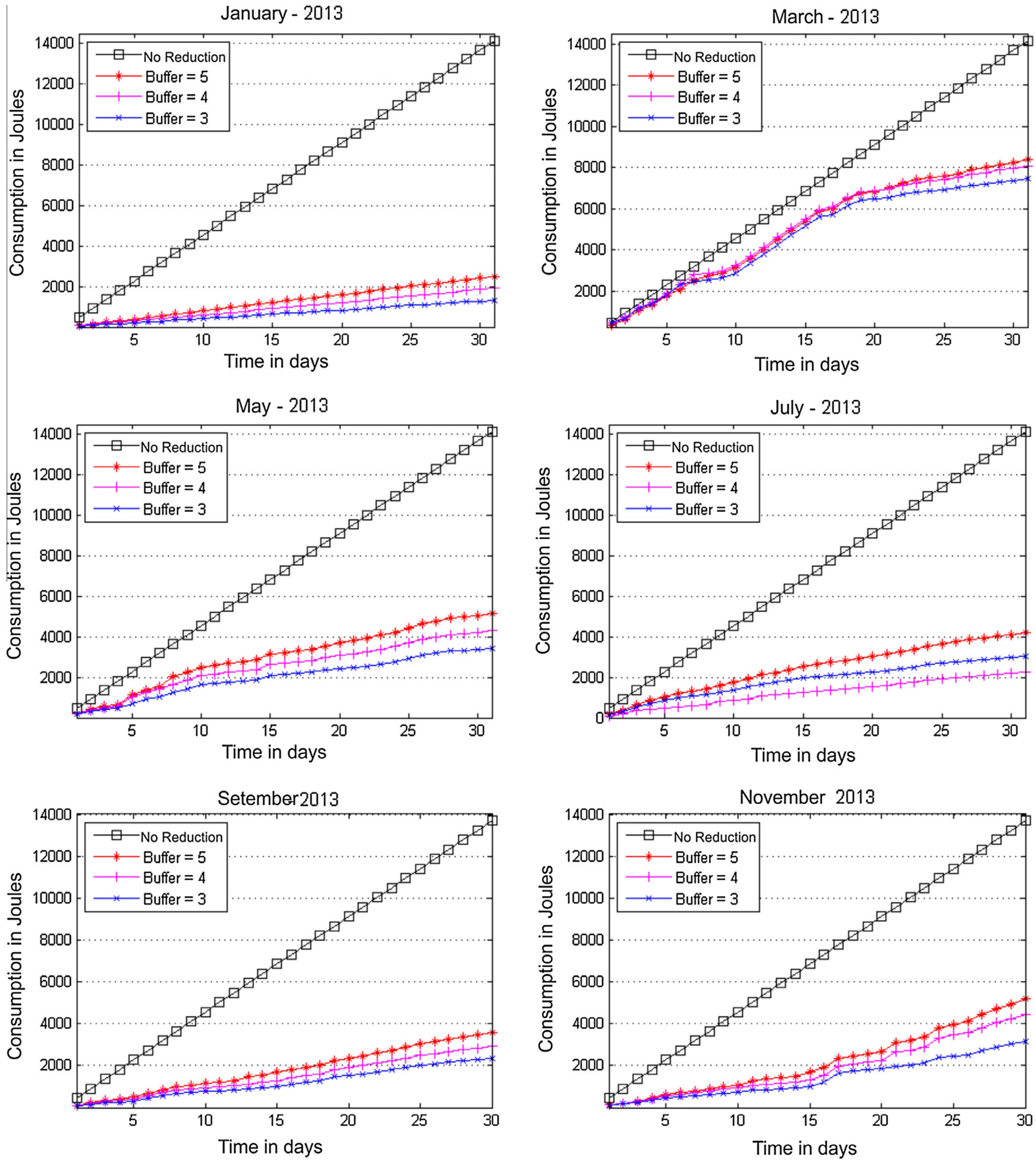

Fig. 19. Energy expenditure. Power consumption (J) of the odd months of 2013.

has the lowest average reduction recorded per day, which explains the higher observed energy consumption (Fig. 19 – March-2013).

4.4. Engine accuracy

Table 2 shows the number of patterns changes per month. In most cases, buffer size 5 is more accurate as it generates fewer exchanges. The cumulative error generated by the mechanism can be seen in Fig. 22. We evaluated the error generated by the engine when using different amounts of patterns ($k = 4$, $k = 5$, and $k = 6$), and with a buffer = 4 for the odd months of 2013.

5. Discussion

5.1. Heating detection

From the monitoring prototype, it was possible to collect thermoregulated temperature readings internally by bees and relate them to external temperatures (from the environment). The information collected show that regardless of the temperature outside, the microclimate of the hives is mostly close to the interval between 33 °C and 36 °C, except where the bees can no longer do thermoregulation.

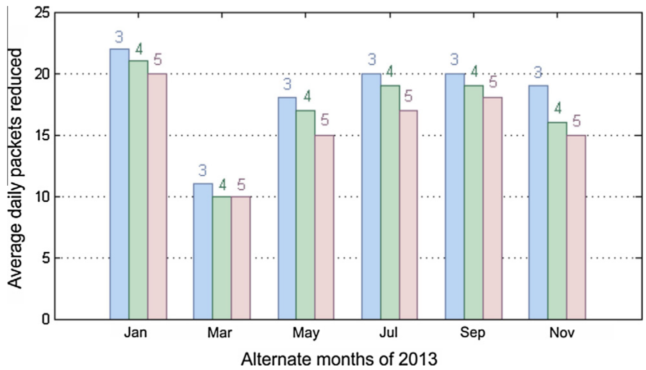

Fig. 20. Data reduction. Average of reduced package daily.

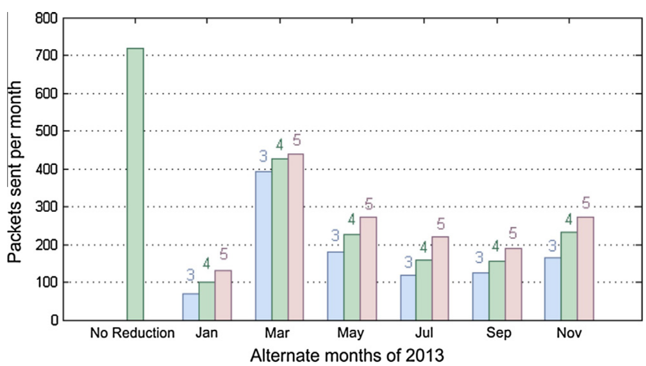

Fig. 21. Data sent. Total number of packets sent per month.

Table 2
Number of patterns exchanges per odd months/2013.

Buffer size	January	March	May	July	September	November
Buffer = 5	53	92	119	117	123	84
Buffer = 4	57	88	130	84	137	92
Buffer = 3	58	96	140	120	139	106

Figs. 14, 15a and 16 show a thermal pattern that corresponds to the colony *homeostasis* Kridi et al. (2014) and Human et al. (2006). This pattern recognition supports our automated method proposal by using thermal patterns as a input parameter to alert for in-hive atypical heating.

In this context, we can see in Figs. 15 and 17 that high temperatures outside the hive affect *homeostasis* and can lead to the abandonment of these Kridi et al. (2014), Zacepins and Karasha (2013), Zacepins et al. (2015) and Human et al. (2006). Therefore, the temperature changes in the microclimate causing discomfort that can lead between 3 and 4 days until absconding Almeida et al. (2006). This time can be used by beekeepers to take proactive actions that may avoid a potential absconding. For this reason, here we propose a mechanism to monitor and alert for in-hive overheating situations so that the beekeeper can handle it and avoid worse problems, such as absconding.

The warnings issued by the proposed mechanism and the one in Fig. 18 follow the above logic, both warning of isolated heating, as reinforcing warnings by heating alerts that indicate longer status, that are more stressful for bees. Fig. 23 exemplifies this logic.

As seen in Fig. 18e and f, the amount of heating alerts must vary according to the duration of heating. In other words, while the internal measurements are above normality patterns, the sensor node will continue to send alerts.

We can also observe through Fig. 18c and d, that the existence of one or two heating readings can characterize a false positive if they pose isolated measurements.

5.2. Representation of data and energy saving

Matlab software package was used to carry out simulations that aims to evaluate some metrics such as energy consumption, number of packets sent and cumulative error. These metrics are important to demonstrate the viability of the proposal.

By comparing the direct sending of data with our solution using three different sizes of buffer (Fig. 19), the option full size sends all 24 daily readings and energy consumption ends up being bigger. On the other hand, the other three options (with different buffer sizes) using our mechanism, reduce the number of packets significantly and, consequently, energy consumption by up to 90.7% (Fig. 19 – January, buffer = 3).

As seen in Section 3.4 *Materials and methods*, buffer size affects consumption, which explains the different values shown in Fig. 19 for three size options using our mechanism. If we used a buffer with capacity for 5 readings, at least 4 will be sent independently of a pattern or may not be associated with these readings.

When used with smaller buffers (for example, size = 3) consumption further decreases, because it results in a less restrictive initial comparison, and the number of packets sent independently of a positive comparison is less. This also affects the number of reduced packages, as seen in Fig. 20, where the option with size 3 reduces more than the other options with sizes 4 and 5.

Balancing the cost for the benefit, the option with size 4 is the most interesting, because it does not affect drastically initial accuracy of mechanism, since the initial comparison will have at least four readings compatible, and has a relatively low consumption (Fig. 19), in comparison with the option with size 3.

In January, July and September (when the best results are recorded), with buffer size 4, the decrease in consumption was 86.6%, 83.9% and 83.4%, respectively (Fig. 19 – January, July, and September). Confronting Figs. 19 and 20, we also noted that March/2013 was the month with the highest spending due to the low range, recording a drop in consumption of 48% (Fig. 19 – March, buffer = 3).

In Table 2 it is noted that, for most months, the size of the initial buffer of comparisons are inversely associated with the number of changes of patterns. As seen previously, a change in the buffer size also influences the initial accuracy of the mechanism, therefore, changes the amount of readings required for an initial comparison to patterns, so, the lower the buffer, greater the chances of initially choose a pattern not very durable, leading to additional exchanges throughout the day.

Another aspect associated with the accuracy of the mechanism is how good is the patterns reliability in relation to the collected data. We can note that in Fig. 22 the three options of k have a very similar cumulative error in every month, nonetheless, we choose $k = 6$ as the better option because it has the lowest error compared to other options in most cases.

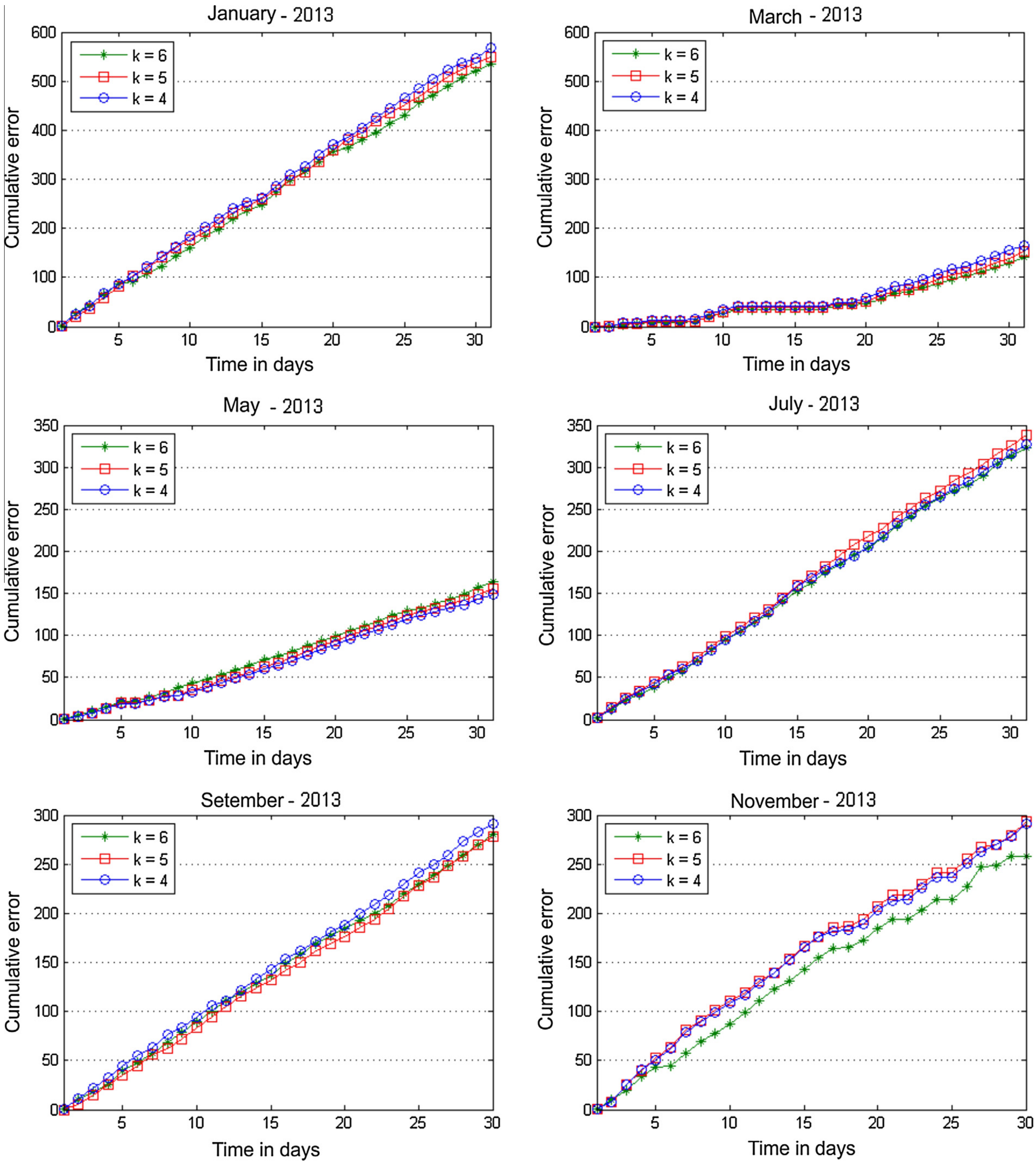

Fig. 22. Accuracy of comparisons. Cumulative error for three values of k.

6. Conclusion

Here we propose a beehive monitoring able of detecting specific information about the behavior of the bees in adverse temperature conditions, analyzing the microclimate and alert of overheating that can cause absconding process. To do this, we developed a clustering-based mechanism consisting of (i) a regulated approach from a set of thermal patterns that identifies readings outside the expected range, and (ii) a proactive and continuous monitoring via WSN to assess the integrity of the history of thermal patterns and temperature data from a hive collected by sensors in the field.

To meet the autonomy requirements of the environmental monitoring, our mechanism reduces sending redundant information from the source. Consequently, it allows energy saving on the sensor nodes by reducing data transmission costs.

As future perspectives, we plan to extend and improve our proposal as follows:

1. Sensing other variables such as humidity, light, vibration, and beehive weight;
2. Since we have monitored only two colonies, we plan to generalize the results by monitoring a larger number of colonies;
3. We also plan to describe the in-hive behavior of pollinating bees through a real-time and non-intrusive monitoring for at least two successive years;

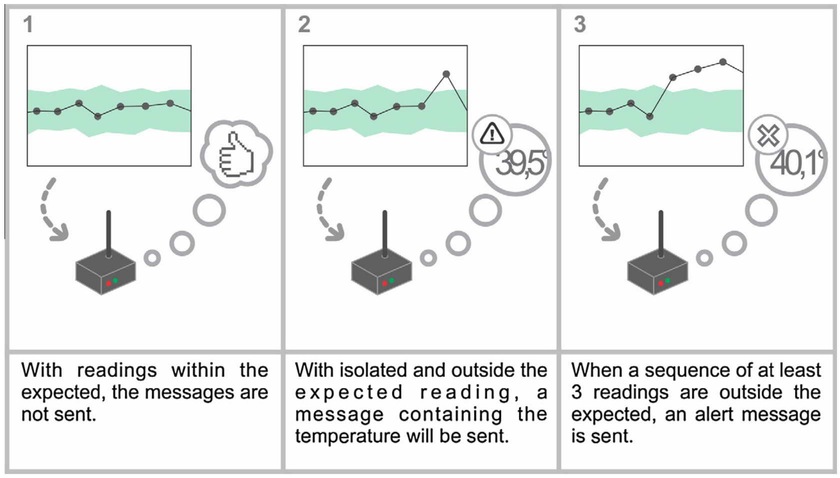

Fig. 23. Sending messages. Normal situations, isolated and prolonged heating.

4. Beehives data could be remotely accessed from any Internet enabled device in any web browser. We estimate the development of a MVP (Minimum Viable Product) will cost between $150 and $200.

Acknowledgements

We thank the financial support of CNPq – Brazil (#480872/2012-0, #482271/2013-2) and NUPA (Embrapa Meio-Norte). We also thank M.Sc. Michelle Cacais for proofreading the manuscript.

References

Alippi, C., Camplani, R., Galperti, C., Roveri, M., 2011. A robust, adaptive, solar-powered WSN framework for aquatic environmental monitoring. IEEE Sens. J. 11, 45–55. http://dx.doi.org/10.1109/JSEN.2010.2051539 http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=5483130.

Almeida, G.F., Grassi, M.L., Gramacho, K.P., Gonçalves, L.S., 2006. Comportamento enxameatório em abelhas africanizadas induzido por temperatura com auxílio de câmara de controle de temperatura, sensores e apidômetros. XVI Congresso Brasileiro de Apicultura e II Congresso Brasileiro de Meliponicultura Aracaju, 2006 (in Portuguese).

Bencsik, M., Bencsik, J., Baxter, M., Lucian, A., Romieu, J., Millet, M., 2011. Identification of the honey bee swarming process by analysing the time course of hive vibrations. Comput. Electron. Agric. 76, 44–50. http://dx.doi.org/10.1016/j.compag.2011.01.004 http://linkinghub.elsevier.com/retrieve/pii/S0168169911000068.

Bencsik, M., Le Conte, Y., Reyes, M., Pioz, M., Whittaker, D., Crauser, D., Simon Delso, N., Newton, M.I., 2015. Honeybee colony vibrational measurements to highlight the brood cycle. Plos One 10, e0141926. http://dx.doi.org/10.1371/journal.pone.0141926 http://dx.plos.org/10.1371/journal.pone.0141926.

Bromenshenk, J.J., Henderson, C.B., Seccomb, R.A., Welch, P.M., Debnam, S.E., Firth, D.R., 2015. Bees as biosensors: chemosensory ability, honey bee monitoring systems, and emergent sensor technologies derived from the pollinator syndrome. Biosensors 5, 678–711. http://dx.doi.org/10.3390/bios5040678.

Carvalho, C., Gomes, D.G., Agoulmine, N., de Souza, J.N., 2011. Improving prediction accuracy for WSN data reduction by applying multivariate spatio-temporal correlation. Sens. (Basel, Switzerland) 11, 10010–10037. http://dx.doi.org/10.3390/s111110010 http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=3274268&tool=pmcentrez&rendertype=abstract.

Díaz, S.E., Pérez, J.C., Mateos, A.C., Marinescu, M.C., Guerra, B.B., 2011. A novel methodology for the monitoring of the agricultural production process based on wireless sensor networks. Comput. Electron. Agric. 76, 252–265. http://dx.doi.org/10.1016/j.compag.2011.02.004 http://dx.doi.org/10.1016/j.compag.2011.02.004.

Edwards-murphy, F., Magno, M., Whelan, P.M., Halloran, J.O., Popovici, E.M., 2016. b + WSN: smart beehive with preliminary decision tree analysis for agriculture and honey bee health monitoring q. Comput. Electron. Agric. 124, 211–219. http://dx.doi.org/10.1016/j.compag.2016.04.008 http://dx.doi.org/10.1016/j.compag.2016.04.008.

Eskov, E.K., Toboev, V.A., 2011. Seasonal dynamics of thermal processes in aggregations of wintering honey bees (Apis mellifera, Hymenoptera, Apidae). Entomol. Rev. 91, 354–359. http://dx.doi.org/10.1134/S0013873811030109 http://link.springer.com/10.1134/S0013873811030109.

Ferrari, S., Silva, M., Guarino, M., Berckmans, D., 2008. Monitoring of swarming sounds in bee hives for early detection of the swarming period. Comput. Electron. Agric. 64, 72–77. http://dx.doi.org/10.1016/j.compag.2008.05.010 http://linkinghub.elsevier.com/retrieve/pii/S0168169908001385.

Freitas, B.M., Sousa, R.M., Bomfim, I.G.A., 2007. Absconding and and migratory behaviors of feral Africanized honey bee (*Apis mellifera* L.) colonies in NE Brazil. Acta Scient. Biol. Sci. 29, 381–385.

Hall, M., Frank, E., Holmes, G., Pfahringer, B., Reutemann, P., Witten, I.H., 2009. The WEKA data mining software. ACM SIGKDD Explorat. Newslett. 11, 10. http://dx.doi.org/10.1145/1656274.1656278 http://portal.acm.org/citation.cfm?doid=1656274.1656278.

Hermeto, R.T., Kridi, D.S., Da Rocha, A.R., Gomes, D.G., 2014. A distributed algorithm for semantic collectors election in wireless sensors networks. J. Appl. Comput. Res. 3, 1–10. http://dx.doi.org/10.4013/jacr.2013.31.01 http://www.revistas.unisinos.br/index.php/jacr/article/view/5830.

Human, H., Nicolson, S.W., Dietemann, V., 2006. Do honeybees, Apis mellifera scutellata, regulate humidity in their nest? Naturwissenschaften 93, 397–401. http://dx.doi.org/10.1007/s00114-006-0117-y.

Jurdak, R., Ruzzelli, A.G., O'Hare, G.M.P., 2008. Adaptive radio modes in sensor networks: how deep to sleep? 2008 5th Annual IEEE Communications Society Conference on Sensor, Mesh and Ad Hoc Communications and Networks, 386–394. http://dx.doi.org/10.1109/SAHCN.2008.54 http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=4557777.

Kridi, D.S., Carvalho, C.G.N.D., Gomes, D.G., 2014. A predictive algorithm for mitigate swarming bees through proactive monitoring via wireless sensor networks. In: Proceedings of the 11th ACM symposium on Performance evaluation of wireless ad hoc, sensor, & ubiquitous networks – PE-WASUN'14. ACM Press, New York, New York, USA, pp. 41–47. http://dx.doi.org/10.1145/2653481.2653482 http://dl.acm.org/citation.cfm?doid=2653481.2653482.

Kviesis, A., Zacepins, A., 2015. System architectures for real-time bee colony temperature monitoring. Proc. – Proc. Comput. Sci. 43, 86–94 http://dx.doi.org/10.1016/j.procs.2014.12.012.

Kviesis, A., Zacepins, A., Durgun, M., Tekin, S., 2015. Application of wireless sensor networks in precision apiculture. In: 14th International Scientific Conference Engineering for Rural Development, pp. 440–445.

Meikle, W., Holst, N., 2014. Application of continuous monitoring of honeybee colonies. Apidologie, 1–13. http://dx.doi.org/10.1007/s13592-014-0298-x.

Meratnia, N., Havinga, P., 2010. Outlier detection techniques for wireless sensor networks: a survey. IEEE Commun. Surv. Tutor. 12, 159–170. http://dx.doi.org/10.1109/SURV.2010.021510.00088 http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=5451757.

Naumowicz, T., Freeman, R., Kirk, H., Dean, B., Calsyn, M., Liers, A., Braendle, A., Guilford, T., Schiller, J., 2010. Wireless sensor network for habitat monitoring on Skomer Island. In: IEEE Local Computer Network Conference. IEEE, Denver, pp. 882–889. http://dx.doi.org/10.1109/LCN.2010.5735827 http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=5735827.

Rangel, J., Seeley, T.D., 2008. The signals initiating the mass exodus of a honeybee swarm from its nest. Anim. Behav. 76, 1943–1952 http://linkinghub.elsevier.com/retrieve/pii/S0003347208004041.

Stalidzans, E., Berzonis, A., 2013. Temperature changes above the upper hive body reveal the annual development periods of honey bee colonies. Comput. Electron. Agric. 90, 1–6. http://dx.doi.org/10.1016/j.compag.2012.10.003 http://linkinghub.elsevier.com/retrieve/pii/S0168169912002542.

Xu II, R., Wunsch, D., 2005. Survey of clustering algorithms. IEEE Trans. Neural Networks 16, 645–678.

Zacepins, A., Brusbardis, V., Meitalovs, J., Stalidzans, E., 2015. Challenges in the development of Precision Beekeeping. Biosyst. Eng. 130, 60–71. http://dx.doi.org/10.1016/j.biosystemseng.2014.12.001 http://dx.doi.org/10.1016/j.biosystemseng.2014.12.001.

Zacepins, A., Karasha, T., 2013. Application of Temperature Measurements for Bee Colony. Engineering for Rural Development, Jelgava (pp. 126–131).