Precision Beekeeping Systems

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Precision beekeeping (PB) systems have promising strength points and represent great opportunities for the development of beekeeping; however, they have some weaknesses, represented especially by the high purchasing costs and the low preparedness of the addressed operators, and imply some possible threats for beekeeping in terms of unrealistic perception of the apiary status if they applied to some hives only and a possible adverse impact on the honeybees' colony itself.

sensors and systems | beekeepers | precision beekeeping | honey bee | precision livestock farming | hive management | environmental monitoring

1. Introduction

One of the most important challenges of this and, probably, the next century is to safeguard biodiversity around the world. In this regard, great attention has been focused on insects, whose decline on the local and global scales has been reported [1]. Insects are responsible for a wide range of functional roles [2][3][4][5], one of which is pollination; in fact, the pollinators can improve the production of 70% of the globally most important crop species and influence 35% of the global human food supply [6]. Medium- and long-term strategies can be studied to control the decline of wild pollinators [7], but, in the short-term, one of the possible strategies is to increase the number of farmed pollinators, in particular honeybees (*Apis mellifera* L.). In this context, honeybees and beekeepers are two important resources for the Earth: insects for their pivotal role in pollination, and humans for their ability to protect and preserve the health and survival of the honeybees. However, the famed honeybee is also exposed to several risks, such as the use of pesticides for intensive crops [8][9][10][11], climate change, and the impact of pathogens (parasites, bacteria, and viruses) responsible for a wide range of illnesses. Beekeepers try to contrast these risks by using appropriate farming techniques, different kinds of chemicals, and/or drugs; however, the results are not always satisfactory [12][13], and the health and production of the honeybee are often negatively affected. To obtain better production (and better insect health) from a hive, it is important to have proper management, as it is well known that regular inspections of the colonies can improve honey production and thus the remuneration of the farming activity. However, it is important to underline that, in some circumstances, manual visits to the hive can have negative impacts on the colony [14]. In addition, very often the beekeepers could not check their hives with regularity, for example, due to climate conditions or low time availability. In this context, modern technology can be a valuable help for beekeepers. The term "Precision Beekeeping" (PB) has been defined for the first time by Zacepins et al. [15] as a strategy for the management of an apiary based on monitoring individual honeybee colonies to minimize resource consumption and maximize productivity. This new approach can be considered a new evolutionary phase of beekeeping, as indicated by Zogovic et al. [16]: from “traditional beekeeping”, through “rational beekeeping”, up to “Precision Beekeeping”. The PB is organized into three key points: data collection, data processing, and the data output phase [17]. As recently reported by Alleri et al. [18], data can be captured by different kinds of sensors for monitoring, for example, weight, temperature, humidity, sounds, etc. The sensors can be placed inside or outside the hive; in this way, the hive becomes “smart”. In this way, the data is checked in real-time through specific applications on different devices (personal computers, tablets, and smartphones) and processed thanks to algorithms. Beekeepers can thus consult and download the data obtained from their archives. The data processing is important to define if a condition measured at a specific time falls or is not within a “normal” range. In addition, the processing data system can produce signal alarms if some parameter is out of the “normal” standard. From a practical perspective, PB is not only the application of intelligent technologies to hive bee farming but also an in-depth knowledge of the various genetical, nutritional, physiological, and physio-pathological aspects linked to the world of bees. Precision beekeeping is at the beekeeper’s service, but the beekeeper must be able to properly read the indications that the digital system provides him, including the alarm signals. Technology is a very important aid, but it is not infallible; therefore, it can support the beekeeper but not replace him, because obviously, it is up to him to make the final decision on any corrective measures to be taken in the presence of anomalous situations. All in all, it seems clear that talking about a multifaceted topic such as precision beekeeping is not easy.

2. Data Collection and Storage: Sensors and Systems

In PB, data collection is the first and probably one of the most important steps. It is typically performed using sensors integrated into beehives and connected to the main processing system [19]. A sensor (or node) is a device sensitive to a specific physical–chemical cue and, if solicited, can generate an electrical signal [20]. These advanced sensors are equipped with a microprocessor powered by batteries; the microprocessor records the data and, thanks to a Wireless Sensor Network (WSN) system [21], sends it to a remote server for processing [18]. Sensors, microprocessor, battery, and remote server are part of the “system” that is completed by the device of the beekeeper (personal computer, smartphone, or tablet) in which a specific application shows the data to the user on demand and sends signals of alarm if a parameter, for example, the temperature, the weight, the relative humidity, the buzz sounds, the gases, as well as the honeybee activity and the location of the hive, are outside the normal range [18][22]. Thus, the type of sensor (and thus its accuracy) is very important. It is possible to use very simple and low-cost systems. The problem is whether these systems can achieve useful control over the hive. For example, Romanov [23] used an on-site bee colony approach to evaluate the hive temperature, in which a small digital sensor is placed inside the hive and connected to an external display where the temperature is reported. This very simple system is not able to send the data via the web, and the temperature can be observed remotely only by placing a camera near the digital display. This system may seem functional, but the main problem is that the data cannot be stored [19], and it is possible to only do on-site or on-time observation without an alarm signal available for beekeepers. The progress of these technologies allows for different and more flexible systems to record, store, and process data. For example, the data recorded by sensors can be transmitted by wired or wireless connection to a PC on the apiary [15][24]. This kind of solution allows for more information to be given to the beekeeper, but to record and send the data, the PC must be turned on (energy expenditure). Another possibility is double-data sending. The sensors recorded the data and transmitted them to the apiary PC, which is connected to a remote service or a cloud device [25]. In this case, the local PC is only an intermediary, and the data storage and processing are from the remote service. The remote service will send the data to the beekeeping devices. When the apiary's PC is turned off, it is possible to store the data on the remote server, but they cannot be processed. Another approach relies on micro-controller platforms to collect and send the data to the remote controller. The micro-controller platforms need less energy and thus are more stable than a PC, but if the system is turned off, the data processing is interrupted, and no data or alarms are sent to the beekeeper's devices. However, more modern technologies are producing sensors able to connect to the web using 4G or 5G connections. In this way, recorded data is sent directly to the remote server for storage and processing, and only the interruption of the network or the breakage of the sensors can interfere with the monitoring of the hives. All this is possible where the apiary is reached by a 4G or 5G connection (even 3G in some sensors). Though networks are by now fairly spread in rural areas, it is possible that some areas are not completely covered by the service. In addition, with this kind of approach, each sensor point needs a battery as a source of energy and a SIM for the connection to the network. It means that each hive beekeeper must provide these resources.

2.1. Weight

The weight of a beehive fluctuates according to the season (the lowest during winter, the highest during the productive period) and can be a valuable predictor of honey production and, in general, of the activity of the hive. The weight is probably the easiest parameter to measure by using, in general, non-invasive sensors. The different systems available on the market use a scale consisting of load cells, which rely on mechanics and resistive theory, integrated with amplifier modules that are linked to the microcontroller [26]. The load cells are made of a material that moves back when pressure (weight) is applied. One used technology is a "resistive strain gauge" in the load cell, which makes it possible to measure the resistance (Ohm) of the cell [27]. An important aspect when working with load cells is the temperature and humidity around the cell, which will make the value change for the same load, resulting in different measurement values [27]. The load cells can be converted into dedicated electronic circuits (Analog to Digital Conversion, ADC). The ADC circuits are standardized, and one interesting characteristic of ADC converters is the resolution, defining how detailed values the ADC will provide as output. For accurate, reliable measurements and ease of use, the weight sensor or weighing scale is placed under a hive, where each hive can comprise multiple supers/chambers. A single honey chamber can weigh up to 30 kg, which means that a hive with three honey chambers and a brood chamber can weigh up to 120 kg. The weighing scale needs to have an appropriate range of measurements and must be sensitive enough to detect daily changes in the weight of the hive with a resolution of a few grams (in general, less than 100 g) [28]. The choice of hive type also plays a role in this variation.

2.2. Temperature

Temperature was one of the first parameters recorded in a hive. Almost a century ago, in 1926, Dunham [29] conducted one of the first experiments by using eight thermocouples placed in different sites of the hive and manually recording the temperature each hour [30]. The temperature is a very important parameter for bee colonies, as its detection can be used to identify different conditions in the hive, such as brood development, the pre-swarming condition, and, in general, the health status of the hive. The temperature of the hive can be monitored by using different systems. Cook et al. [31] equipped the experimental hives with four temperature sensors located in the middle of the frames, from the central one to the outskirts of the hives. In hives with active bee colonies, there was an average gradient of 0.03 °C/cm in the observed temperature range ($p < 0.001$). In hives with no bees, this slope was reduced from 0.025 °C/cm ($p < 0.001$) to 0.005 °C/cm [31]. However, based on a total of 776,872 observations, the authors concluded that the variation in the time to reach the peak temperature at different sensor points was not significant [31].

2.3. Sounds

Sounds, produced through body vibrations, are one of the methods used by honeybees for on-colony communication [32]. The detection of specific sound signals produced by honeybees can be useful in assessing physiological or pathological conditions in the hive. The honeybees can produce sound with frequencies ranging from about 0 up to a few thousand hertz [22]. Thus, the first requirement for an acoustic sensor to be included in the hive is to work in this frequency range. Another very important point is to choose the most appropriate acoustic sensor, as the technology supplies different kinds of microphones: electret microphones, a type of electrostatic capacitor-based microphone that eliminates the need for a polarizing power supply by using a permanently charged material, used by Qandour et al. [33] and Anand et al. [34]; and microelectromechanical system (MEMS) microphone, a micro-scale device used, for example, for smartphones, that provide high-fidelity acoustic sensing and is small enough to be included in a tightly integrated electronic product [35][36]. In the past, another system has been studied to measure the vibration in the hive: the laser Doppler vibrometer proposed by Michelsen et al. [32]. The laser Doppler vibrometer (LDV) is a tool that measures such vibrations by directing a laser at a surface and comparing the frequency of the returning light to an internal reference beam [37]. This system is very precise and has several applications in different kinds of industries, but it is also too expensive. In fact, no other research is available in the literature on the application of this system for vibration detection in the hive.

2.4. Images

The collection of images is an interesting and very useful approach. By acquiring videos of pictures, the beekeeper can directly see the honeybees and, in some cases, detect a problem without the necessity of data processing. Optical cameras have, in general, been placed at the entrance of the hive to monitor the honeybee “traffic”, including foraging, surveillance, and fan activities. Edwards-Murphy et al. [27] tried to use an infrared camera inside the hive to monitor the activity of the family, but this system had no further applications, probably due to technical problems. To control the honeybee traffic, the external camera must be placed at an adequate distance from the hive entrance. Crawford et al. [38] placed the cameras 27.4 cm from the hive entrance; Yang and Collins [39] placed the camera 30 cm above the hive entrance; and, to permit better vision of the animals, the platform was painted green; and Sledevic [40] placed the cameras 40 cm above the hive. Kulyukin and Mukherjee [36] placed the cameras on top of supers (one or two with a distance camera-landing platform of 35 and 60 cm, respectively) and showed no problems with computer vision and the consequent algorithm application. Shimasaki et al. [41][42] placed the cameras in front of the beehives. All those approaches have proven to be effective for monitoring honeybee activity, but their efficacy depends on the resolution of the camera used. As a specific type of camera, thermal cameras can also be used to monitor the temperatures of the honeybees or the hives, with the aim of detecting temperature changes in pre-swarming conditions [43][44]. To date, no thermal camera has been used to count the incoming and outgoing activity at a hive entrance [45] due to its high cost, low resolution, and low frame rate in comparison to optical cameras. Probably, this kind of system can have future development as the technology recently produced low-cost thermal cameras for medical applications [46].

2.5. Gases

The air inside the hive is a complex mixture of many different volatile compounds released by the honeybees (e.g., pheromones, other chemicals released to repel pests and predators, metabolites, etc.), within the hive (from honey, nectar, larvae, beeswax, pollen, and propolis, or materials out of which hives are constructed), and external sources (from vehicles, farms, industries, and households in the vicinity of hives) [47]. Each hive has an individual gas profile. Considering that the other gas producers are, in general, constant, changes in gas composition inside the hive are tied to changes in gas emissions by honeybee adults or larvae. The simplest gas to detect is carbon dioxide, whose increasing concentrations can indicate, for example, an increase in workers' population in the hive and, over a certain limit, can indicate an inappropriate environment for honeybees [48]. Metal oxide semiconductors (MOx) are gas sensors whose small size allows their placement in the hive [49]. One family of these MOx sensors responds to give an estimate for CO_2. These sensors have a low power consumption [50], but the cost is still high, so a practical application in beekeeping is difficult at this stage. In addition, MOx sensors can detect a wide range of gases, so a specific calibration is mandatory to understand what kind of gas the sensor is measuring at a specific time [51][52].

2.6. Humidity

The measurement of humidity is readily available in low-cost, small capacitive sensors that provide a high level of accuracy both in analog and digital formats [53]. Digital devices usually include temperature measurements in the same package and reduce measurement errors by undertaking Analog to Digital Conversion on the sensor chip rather than introducing possible noise in the measurements [54][55]. Easily deployable breakout boards start for as little as EUR 8, with the raw chips costing even less. Many manufacturers produce these with inter–integrated circuit (i2c) interfaces, each with different addresses, allowing some spatial variation over a hive to be monitored with relatively simple and inexpensive hardware [49].

3. Internet of Bees and Data Management

The term "Internet of Bees" (IoB) is reported to indicate the application of IoT to beekeeping. The data collected with the different kinds of sensors applied to the hive must be stored in a system (from a local PC to a cloud). As more data are collected, the more precise will be any sort of prediction of hive behavior or activity. From this point of view, a great role plays in the possibility of creating archives of big data and the possibility of sharing the data collected from different apiaries. Different datasets can be available in the libraries of the companies producing PB systems, where data is protected from other web users. The working process of data can be described by using the OODA loop as described by Brehmer [56] and Atwood [57]: Observe, Orient, Decide, Act. Also, in traditional and rational beekeeping, the same loop is used, but with manual or semi/automated inspection instead of using electronics, like IoB devices. All IoB devices need internet connectivity. There are multiple techniques used, including Wi-Fi, Bluetooth, Mobile Internet (5G, 4G, or 3G), Fibre Broadband, etc. The development of embedded electronics like Arduino® and Raspberry Pi™ has created new opportunities to have a low-cost, standardized device to use as an IoT device. The processing phase of bee colony data is typically limited to basic statistical analysis [58] to determine such bee colony states as queenlessness, bloodlessness, pre-swarming, swarming, and after-swarming. The data output phase includes methods to provide processed data—information—to the end user in the form of a graphical or tabular representation. As recently underlined by [59], the use of wireless network technologies in PB has some limitations, represented by data imperfections, granularity, or inconsistency, but also technical problems such as internet or mobile network coverage. To reduce mistakes that can generate false alarms, it is possible to use multi-sensors with additional data sources. However, this solution poses another challenge: processing data from different sources as a singular unit. This kind of advanced approach is defined as data fusion. Data fusion is the process of integrating multiple data sources to produce more consistent, accurate, and useful information than that provided by any individual data source. In the OODA approach, orienting and deciding acts are possible with the application of specific mathematical models (algorithms) able to analyze data and predict possible evolutions or consequences of a specific situation. Machine Learning (ML) integrates statistics and computer science to build algorithms that are more efficient when they are subject to relevant data rather than being given specific instructions [60]. Different mathematical models can be used to process the data, and the precision of the output depends on the quantity and quality of the data as well as the accuracy of the prediction model. Brini et al. [61] used different tree methods: Random Forest [62], Extreme Gradient Boosting (XGB) [63], and a regression tree [64] to analyze data on hive weight and concluded that the first two methods outperformed linear models when predicting the hive weight variation. Andrijevi et al. [65] applied mathematical models based on recurrent neural networks to the data obtained from a bee counter at the hive entrance and showed a very high accuracy of the prediction. Pham et al. [66] tested different algorithms to process data on the foraging behavior of honeybees and observed that all were highly competitive in terms of learning accuracy and speed. Dimitrios et al. [67] tested three different classification algorithms: the k-Nearest Neighbors algorithm (k-NN) and Support Vector Machine (SVM), and a newly proposed by the authors, U-Net Convolutional Neural Network (CNN), developed for biomedical image segmentation. The results show that k-NN and SVM, which are already used for bee sound analysis processes, provide the most accurate results for late and early detection of swarming, respectively. Focusing on early detection, which can alleviate or prevent the event, our experiment showed that SVM is the most appropriate method, while k-NN fails to detect it accurately. For early detection of swarming events, U-Net CNN performs almost as well as SVM and has the potential to perform even better with frequency-targeted data input and model parameter fine-tuning. The authors set, as future work, the extensive evaluation of the proposed U-Net CNN algorithm fine-tuning towards swarming events and the extension of their experiments to other deep learning algorithms.

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