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Wireless Sensor Networks, Actuation, and Signal Processing for Apiculture

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A thesis submitted to the National University of Ireland, Cork in fulfilment of the Requirements for the degree of Doctor of Philosophy

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Declaration

I hereby state that all of the work undertaken in this thesis is original in content and was carried out by the author. Work carried out by others has been duly acknowledged in the thesis. The work presented has not been accepted in any previous application for a degree.

Signed:____________________

Date:_____________________

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Abstract

Recent United Nations reports have stressed the growing constraint of food supply for Earth's growing human population. Honey bees are a vital part of the food chain as the most important pollinator for a wide range of crops. Protecting the honey bee population worldwide, and enabling them to maximise productivity, are important concerns. This research proposes a framework for addressing these issues by considering an inter-disciplinary approach, combining recent developments in engineering and honey bee science. The primary motivation of the work outlined in this thesis was to use embedded systems technology to improve honey bee health by developing state of the art in-hive monitoring systems to classify the colony status and mechanisms to influence hive conditions. Specific objectives were identified as steps to achieve this goal: to use Wireless Sensor networks (WSN) technology to monitor a honey bee colony in the hive and collect key information; to use collected data and resulting insights to propose mechanisms to influence hive conditions; to use the collected data to inform the design of signal processing and machine learning techniques to characterise and classify the colony status; and to investigate the use of high volume data sensors in understanding specific conditions of the hive, and methods for integration of these sensors into the low-power and low-data rate WSN framework.

It was found that automated, unobtrusive measurement of the in-hive conditions could provide valuable insight into the activities and conditions of honey bee colonies. A heterogeneous sensor network was deployed that monitored the conditions within hives. Data were collected periodically, showing changes in colony behaviour over time. The key parameters measured were: CO_2, O_2, temperature, relative humidity, and acceleration. Weather data (sunshine, rain, and temperature) were collected to provide an additional analysis dimension. Extensive energy improvements reduced the node’s current draw to 150 μA. Combined with an external solar panel, self-sustainable operation was achieved. 3,435 unique data sets were collected from five test-bed hives over 513 days during all four seasons.

Temperature was identified as a vital parameter influencing the productivity and health of the colony. It was proposed to develop a method of maintaining the hive temperature in the ideal range through effective ventilation and airflow control which allow the bees involved in the activities above to engage in other tasks. An actuator was designed as part of the hive monitoring WSN to control the airflow within the hive. Using this mechanism, an effective Wireless Sensor and Actuator Network (WSAN) with Proportional Integral Derivative (PID) based temperature control was implemented. This system reached an effective set point temperature within 7 minutes of initialisation, and with steady state being reached by minute 18. There was negligible steady state error (0.0047%) and overshoot of <0.25 °C.

It was proposed to develop and evaluate machine learning solutions to use the collected data to classify and describe the hive. The results of these classifications would be far more meaningful to the end user (beekeeper). Using a data set from a field deployed beehive, a biological analysis was undertaken to classify ten important hive states. This classification led to the development of a decision tree based classification algorithm which could describe the beehive using sensor network data with 95.38% accuracy. A correlation between meteorological conditions and beehive data was also observed. This led to the development of an algorithm for predicting short term rain (within 6 hours) based on the parameters within the hive (95.4% accuracy). A Random Forest based classifier was also developed using the entire collected in-hive dataset. This algorithm did not need access to data from outside the network, memory of previous measured data, and used only four inputs, while achieving an accuracy of 93.5%.

Sound, weight, and visual inspection were identified as key methods of identifying the health and condition of the colony. Applications of advanced sensor methods in these areas for beekeeping were investigated. A low energy acoustic wake up sensor node for detecting the signs of an imminent swarming event was designed. Over 60 GB of sound data were collected from the test-bed hives, and analysed to provide a sound profile for development of a more advanced acoustic wake up and classification circuit. A weight measuring node was designed using a high precision (24-bit) analogue to digital converter with high sensitivity load cells to measure the weight of a hive to an accuracy of 10g over a 50 kg range. A preliminary investigation of applications for thermal and infrared imaging sensors in beekeeping was also undertaken.

List of Publications

Publications on Topic

Peer reviewed journal publications

F Edwards-Murphy, D Morgan, D O'Brien, G Hao, WMD Wright, PM Whelan, and E M Popovici. "Sensing and Actuation for Airflow and Temperature Control in Beehives". *IEEE Sensors Journal*, (Under Review), 2017.

F Edwards-Murphy, M Magno, PM Whelan, J O'Halloran, and EM Popovici. "b+ WSN: Smart beehive with preliminary decision tree analysis for agriculture and honey bee health monitoring". *Computers and Electronics in Agriculture*, vol. 124, pp. 211-219, 2016.

B Srbinovski, M Magno, F Edwards-Murphy, V Pakrashi, and E Popovici. "An Energy Aware Adaptive Sampling Algorithm for Energy Harvesting WSN with Energy Hungry Sensors". *Sensors*, vol. 16, no. 4, pp. 448, 2016.

F Edwards-Murphy. "To bee, or not to bee? Honey bees, Boolean logic, bits and information". *The Boolean: Snapshots of Doctoral Research at University College Cork*, vol. 5, pp. 117-122, 2015.

Conference proceedings

F Edwards-Murphy, E Popovici, P Whelan, and M Magno. "Development of an heterogeneous wireless sensor network for instrumentation and analysis of beehives". *IEEE International Instrumentation and Measurement Technology Conference (I2MTC)*, 2015, pp. 346-351.

F Edwards-Murphy, M Magno, P Whelan, and EM Popovici. "b+WSN: Smart beehive for agriculture, environmental, and honey bee health monitoring—Preliminary results and analysis". *IEEE Sensors Applications Symposium (SAS)*, 2015, pp. 1-6.

F Edwards-Murphy, M Magno, L O'Leary, K Troy, P Whelan, and EM Popovici. "Big brother for bees (3B)—Energy neutral platform for remote monitoring of beehive imagery and sound". *6th IEEE International Workshop on Advances in Sensors and Interfaces (IWASI),* 2015, pp. 106-111.

F Edwards-Murphy, B Srbinovski, M Magno, EM Popovici, and PM Whelan. "An automatic, wireless audio recording node for analysis of beehives". *26th IEEE Irish Signals and Systems Conference (ISSC),* 2015, pp. 1-6.

DW Fitzgerald, F Edwards-Murphy, W Wright, PM Whelan, and EM Popovici. "Design and development of a smart weighing scale for beehive monitoring". *26th IEEE Irish Signals and Systems Conference (ISSC)*, 2015, pp. 1-6.

Other Related Publications

Peer reviewed journal publications

D O'Donnell, R Wright , M O'Byrne, A Sadhu, F Edwards-Murphy, P Cahill, D Kelliher, B Ghosh, F Schoefs, A Mathewson, E Popovici, and V Pakrashi. "Modelling and testing of a historic steel suspension footbridge in Ireland". *Proceedings of the Institution of Civil Engineers-Bridge Engineering*, 2017, pp 1-17.

Conference proceedings

F Edwards-Murphy, M Donovan, J Cunningham, T Jezequel, E García, A Jaeger, J McCarthy, and E M Popovici. "i4Toys: Video technology in toys for improved access to play, entertainment, and education". *IEEE International Symposium on Technology and Society (ISTAS),* 2015, pp 1-6.

F Edwards-Murphy, M Magno, and E Popovici. "Design and Implementation of a Heterogeneous, Power Efficient Wireless Sensor Network for Smart Toys". *International Workshop on Robotic Sensor Networks, Cyber-Physical Systems Week,* 2014.

F Edwards-Murphy, M Magno, A Frost, A Long, N Corbett, and E Popovici. "Demo abstract: SmartSync; when toys meet wireless sensor networks". *Proceedings of the 5th International Workshop on Real-World Wireless Sensor Networks (REALWSN),* 2014, pp. 91-96.

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List of Abbreviations

3G – Third Generation wireless mobile telecommunications technologies

ADC – Analogue to Digital Converter

ASA – Adaptive Sampling Algorithm

CFD – Computational Fluid Dynamics

CSV – Comma Separated Values

DWV – Deformed Wing Virus

EASA – Energy-aware Adaptive Sampling Algorithm

FSR – Fixed Sampling Rate

FTP – File Transfer Protocol

GPS – Global Positioning System

GPRS – General Packet Radio Service

GSM – Global System for Mobile Communications

IoT – Internet of Things

IR – Infra Red

MEMS – Micro Electro Mechanical System

PID – Proportional, Integral, Derivative

PPM – Parts Per Million

PSD – Power Spectral Density

RH – Relative Humidity

RFID - Radio-frequency identification

RMS – Root Mean Square

RTC – Real Time Clock

SD card – Secure Digital non-volatile memory card

SMS – Short Message Service

SPIC – Single Point Impact Cell

SPI – Serial Peripheral Interface

UART - Universal Asynchronous Receiver/Transmitter

WSAN – Wireless Sensor and Actuator Network

WSN – Wireless Sensor Network

1 Introduction

1.1 Motivation

Humans and honey bees have had an important relationship from the beginning of civilisation, with records of honey bee agriculture (apiculture) dating as far back as 2400 BC [1] . In modern times, the Western honey bee (*Apis mellifera*) plays a role in a range of human activities, including nutrition, medicine, and agriculture. The most vital activity of the honey bee for humans is pollination. The EU parliament noted in 2008 (resolution T6-0579/2008) that 79% of human food depends on honey bee pollination. As the global human population grows, to secure food supplies, the amount of pollinator dependant crops will increase dramatically.

Aizen *et al.* [2] found that the volume of pollination dependant crops has grown 300% in the last 50 years. It is also noted in the same work that wild/feral honey bees are increasingly subsidising the pollination requirements of commercial agriculture. As pests such as Varroa spread [3], wild native or feral honey colonies have virtually disappeared in several countries. To protect food supply, and agriculture-dependant economies, honey bee populations need to be maintained in an optimal state of health and afforded opportunities to grow. A bee colony costs approximately €250 in Ireland and improved monitoring would be significant for beekeepers worldwide. The global value of pollination is estimated at €153 billion and improved pollination by healthy bees, through hive monitoring, could increase the performance of agriculture dependant economies [4].

Wireless Sensor Networks (WSN) consist of embedded sensing, computing, and communication devices, and are a key technology of the Internet of Things (IoT) concept. WSN have found many applications, including healthcare, environmental monitoring and medicine [5, 6]. One of the main challenges of WSN is enabling them to perceive and understand the world in a similar way to humans. Perceptive low-power sensor devices should be able to interpret the world around them using intelligent algorithms. Machine learning technologies have been used with great success in many WSN application areas, solving real-world problems in in transport, health care, and surveillance [7, 8]. Another important feature of WSN is the potential to achieve long life time or, even better, self-sustaining operation through energy harvesting [6].

Agriculture has been identified as one of the key application areas of Wireless Sensor Network technologies. Examples include the use of WSN to monitor cattle fertility, growth of crops, and irrigation effectiveness [9]. The most useful aspect of WSN technology in such applications is the ability to collect data from a wide area for feeding into decision support systems. This has value because agriculture typically involves labour-intensive actions spread over a wide area. Increased information leading to more effective planning, and more efficient use of resources has a dramatic impact on both the productivity levels and profitability of almost all agricultural activities.

Traditional beekeeping, or apiculture, is an example of a labour-intensive agricultural activity. Beekeeping involves planning, in terms of locating apiaries, managing reproduction, inspecting hive health, and harvesting honey. All of these actions involve a visit with specialised equipment to hives, which can be located many kilometres from each other. As commercial beekeepers can have several hundred hives the required resources and time rise exponentially for large scale operations.

Many bee monitoring systems have been reported and described in the literature [10]. Automated, precision beehive monitoring has been identified by many as an important and feasible goal [11]. It is clear, however, that truly ubiquitous monitoring of colonies (monitoring of hives located in apiaries far from access to power or established networks and without affecting the colony or beekeepers' activities) has not been achieved, and that the interdisciplinary analysis of beehive data is in its infancy. Hive monitoring systems in the literature use observation hives (hives designed to expose the colony for research), wired networks connected to data-loggers or PCs, or require mainline power supplies. These requirements make these systems effective research techniques, but are not feasible for monitoring real-world hives maintained by the average beekeeper, or for large scale monitoring of many hives simultaneously.

The primary motivation of the work described in this thesis was to use embedded systems technology to improve honey bee health by developing in-hive monitoring systems to classify colony status and mechanisms to influence hive conditions. In this research, the subspecies of honey bee which was investigated was the European dark honey bee (*Apis mellifera mellifera*), and the beekeeping practices and hive conditions were typical of North Western Europe. To demonstrate the usefulness of in-hive monitoring systems, such as those described in this work, Table 1.1 shows the most important hive conditions for the keeper to know about, how soon they need this knowledge, and if they can be detected by the solutions presented in this work.

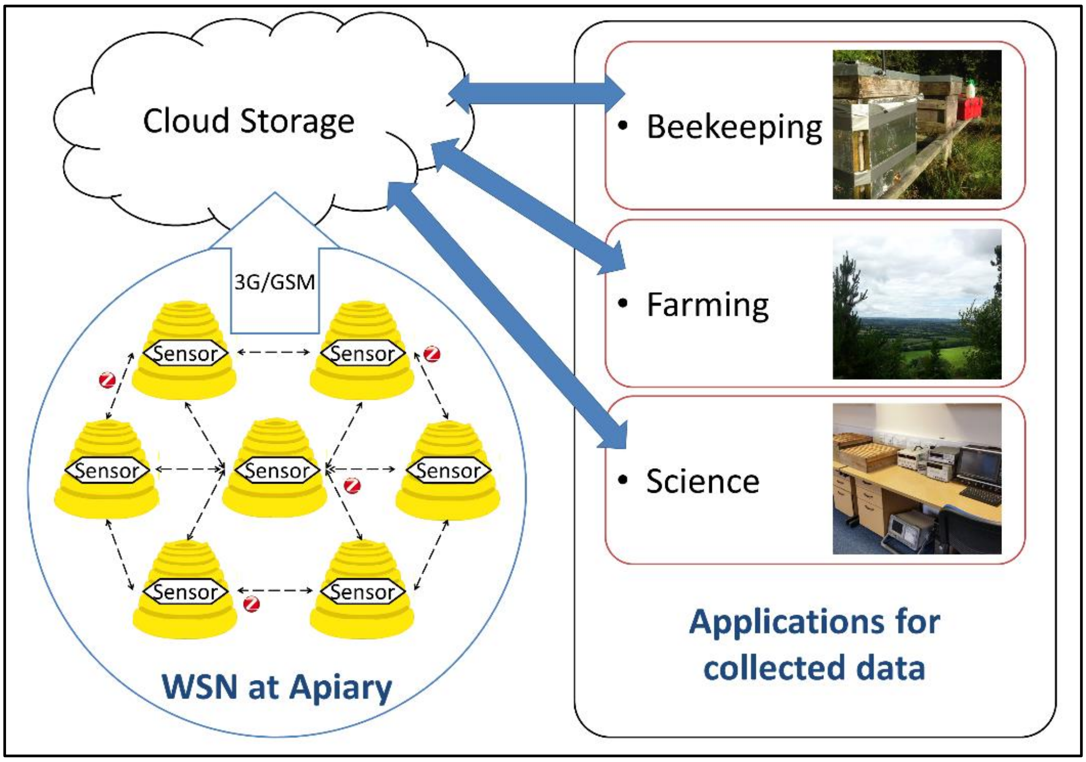

Figure 1.1 – Envisioned application of WSN in apiculture [12]

Specific objectives were identified as steps to achieve this goal: to use Wireless Sensor networks (WSN) technology to monitor a honey bee colony in the hive and collect key information about its activity and environment (Figure 1.1); to use these data and resulting insights to propose mechanisms to influence the hive conditions; to use the collected data to inform the design of signal processing and machine learning techniques to characterise and classify the colony status; and to investigate the use of high volume data sensors in understanding specific conditions of the hive, and methods for integration of these sensors into the low-power and low-data rate WSN framework.

Table 1.1 – Examples of typical hive conditions and the response required

Hive condition	**Speed of response required**	**Detected using the described systems?**
Swarm	Immediate	Yes
Queenlessness	Immediate	Yes
Fallen hive	Immediate	Yes
Declining population (due to disease or starvation)	Within a few days	Yes
Colony Collapse Disorder	Immediately	No
Overcooling	Within a few days	Yes
Overheating	Within a few days	Yes
Peak honey production	Within a few days	Yes
Is honey production happening?	Ongoing condition – Summer	Yes
Is the brood temperature in the ideal range?	Ongoing condition – Summer	No – but can be inferred from above brood temperature
Is a Winter cluster forming?	Ongoing condition – Winter	Yes
What are the mite levels in the hive?	Ongoing condition – Year round	No

1.2 Thesis Contributions

The work outlined in this thesis comprises of four main sections: the automated collection of data from hives in the field; research improving the airflow and temperature control of the National beehive; development of machine learning based classification algorithms for the colony; and applications of specialised sensors to the beehive.

To provide a solution in this space it was necessary to gain an understanding of the honey bee hive. To design a system which could monitor the colony and its environment, an understanding of the hive structure, typical behaviour of the colony inside the hive, and typical beekeeper activities were required. It was also necessary to understand the typical conditions of: the healthy hive; the hive undergoing important events (swarming, clustering, converting nectar to honey); and the unhealthy hive to design systems for maintaining ideal conditions and to detect and classify important events for the keeper. The outcome of this investigation is described to provide the background and context for the contributions.

The first contribution of this work is the design and implementation of a non-invasive, self-sustaining Wireless Sensor Network which collected data from inside the hive. The mechanical design allowed the in-hive sensors to sample the hive conditions effectively, without impeding the beekeeper or bees' activities. The most effective selection of sensors was identified as temperature, humidity, carbon dioxide, oxygen, and acceleration. Each of these sensors contributed to an accurate understanding of the colony's condition as identified in the literature review, while contributing as little as possible to the overall energy budget of the system. Oher gases were also monitored but found not to provide a significantly increased understanding of the colony condition. The selected network and energy harvesting methods allowed six samples of the hive condition to be collected per day, with one upload of each 24-hour period's aggregated data, while maintaining self-sustaining energy performance. A large database (3,435 sets) was collected from in-field beehives for validation and further research.

It can be seen from the literature that temperature in the hive is one of the most important parameters for honey bee health [13-15]. During brood rearing, very precise temperature control is necessary, and throughout the year temperature is key for influencing the spread of pests and disease. In this research, a modification to the traditional design of the National Hive's "crown board" for improved airflow and temperature control was proposed based on numerical modelling and simulation of hive airflow. The improved airflow in the proposed design was experimentally validated. To use this alternative layout to maximum effect, a novel airflow control mechanism was proposed. The final contribution in the space of airflow was the design and implementation of a Wireless Sensor and Actuator Network, using this mechanism together with the sensor network described above. Experiments validated that this mechanism could control the temperature effectively inside the hive to a suitable level of accuracy for improving colony health.

As described above, the natural progression of Wireless Sensor Networks in agriculture is towards machine learning and decision support systems for more effective management. This feature is particularly important for management of beehives. In this research, an initial ID3 decision tree based classification algorithm was proposed and developed. The algorithm was trained and tested using the data collected from the first deployment of the in-hive sensor network. This algorithm can identify ten important hive states with a high level of accuracy. Further work was carried out on machine learning using Random Forests to achieve similar levels of accuracy with reduced network traffic, memory use, and reduced sensitivity to noise. A 95.3% accuracy was achieved by using the entire dataset collected over all five deployments for training.

Some important features of the hive which beekeepers use to understand the conditions of their colony could not be determined using the simple sensors utilised above. These conditions are: sound, weight, and visual inspection. In this thesis the use of microphones, load cells, and cameras to monitor each of these parameters respectively is proposed. A focus is maintained on using these high-volume data sensors in a low power and resource constrained system. Analysis of sound recorded from in-hive microphones led to an audio based wake-up sensor to alert the system to important events. A WSN load cell based weighing system was proposed to provide accurate high-resolution weight measurement over a large range, as is required to measure honey production accurately. A preliminary investigation of infrared and thermal imaging of hives to estimate in-hive activity levels and cold weather clustering patterns unobtrusively was also described.

1.3 Thesis Structure

The structure of this thesis is as follows: in Chapter 2 a review of the literature is presented, in order to describe the expected conditions in the hive, the conditions associated with particular changes in the hive such as reproduction, disease, pests, and hibernation, and to describe the previous work in the area of automated hive monitoring; in Chapter 3 the design, methods, and implementation of an in-hive wireless sensor network for automated sampling of the colony's conditions is presented, along with the results collected from five deployments of such networks; Chapter 4 presents a study and model of the airflow within a standard National beehive, the design and test of a proposed new geometry for the crown board, a compound mechanism with this new geometry to adjust airflow in the hive, and the design and test of a WSAN to automatically control the in-hive temperature; Chapter 5 presents the development of machine learning algorithms to classify the condition of the colony automatically using the data collected from the deployments described in Chapter 2 to train and test decision tree algorithms; Chapter 6 describes investigations into using less generic sensors in the hive to monitor important hive features including microphones, weight, and infrared and thermal imaging; Chapter 7 concludes the research and outlines proposed future work.

2 Honey Bees & their Environment

2.1 Introduction

Honey bees and humans have had an important relationship from the dawn of civilisation [1]. In Ireland, the historic role of apiculture in society is shown in “An Bechbretha” – “bee judgements”, the oldest surviving Irish legal manuscript, which outlines early laws related to beekeeping from the 7th century [16]. In modern times, the most important role of the honey bee is pollination. Along with this, honey bees produce several important by-products including honey, wax, venom, and propolis which are important for nutrition, medicine, and as a sealant [17]. As the human population continues to grow, and the pressure on food supply increases proportionally, it is vital that bee populations are protected, and the number of colonies is provided with opportunities to grow. To achieve this, it is necessary to develop technologies to support beekeeping, reducing the workload of the beekeeper and maximising the productivity of each hive.

From the advent of sensor technology, monitoring of honey bee hives has been undertaken. This has been driven by the desire to understand and observe honey bee behaviour and activity inside the hive; to estimate the productivity of commercial beehives; to detect and understand hive problems, diseases, and pests; and to predict future behaviour of the colony. Meikle *et al.* found weight, temperature, humidity, respiratory gases, vibration, sound, and forager traffic as suitable parameters for continuous monitoring in hives [18].

To inform the design flow of this research, an investigation of the state of the art in precision apiculture was also required. This provided a base on which the methods and experimentation in future chapters were developed. The key areas of precision apiculture were identified as: instrumentation of hive interiors, analysis of airflow within the hive space, monitoring of hive entrances, and sound monitoring of honey bee colonies. The objective of reviewing the literature in the space of hive monitoring was to: understand previous work in the field; identify methods for use in the research and experimentation to be undertaken; and identify avenues of research which have not been thoroughly investigated. In this research, the subspecies of honey bee which was investigated was the European dark honey bee (*Apis mellifera mellifera*), and the beekeeping practices and hive conditions were typical of North Western Europe.

To gain an understanding of both honey bees and apicultural activities several literature sources were considered, including:

- Databases of academic papers outlining studies of the honey bee and beehive, as well as engineering databases – Scopus®, Science Direct®, Web of Science®, and IEEE Xplore®;
- Manuals of beekeeping recommended by experienced beekeepers and beekeeping organisations - [19-21];
- Online resources provided for beekeepers by groups such as government research groups, beekeeping federations, and expert beekeepers [22-26].

2.2 Beehive Temperature and Humidity

2.2.1 Influence of temperature and humidity of the hive interior

2.2.1.1 Temperature and humidity inside and outside the hived colony

Maintaining the colony at a suitable temperature is vital to the health and productivity of the hive. The activities and behaviour of the hive change throughout the year, in response to changing external conditions, availability of forage, and the number of young bees which are required to be reared. The ideal temperature and humidity for the colony changes in response to these.

Immediately before the Winter months, when the external temperature is too low for individual bees to fly, and very little forage is available, the colony prepares to survive by building up large stores of honey, and ceasing brood production. Once the external temperature starts dropping below 10°C, the bees in the colony begin to "cluster" together, forming a ball in the hive interior to conserve heat. The cluster will be formed completely as the external temperature reaches 6-8 °C. The minimum temperature of the surface of the cluster is 8 °C, and the average temperature of the core is 21.3 °C [27]. During this time, the size of the colony will be at its lowest point (15,000 bees at minimum). When possible, the bees will leave the hive to collect water to dilute honey for consumption. They will also occasionally leave the hive to defecate or collect winter pollen if the temperature is suitable [22]. The optimal internal humidity for a broodless hive is 40 % relative humidity as described by Human *et al.* [28].

In early Spring, the colony uses the external temperature and weather to estimate when to begin foraging. The new honey bees begin to emerge and the foraging activities begin to resume as soon as the weather is clear and the temperature rises to 10 °C [23]. This time is a period of intense growth for the colony, as the brood is rapidly reared to establish the colony to produce the main honey flow effectively. The colony is susceptible at this time to fluctuations in the weather, a sudden drop in temperature can easily kill many of the young foragers around the hive [19]. It was found by Gebremedhn *et al.* that flight intensity (number of bees entering and leaving the hive) is negatively influenced by increased relative humidity [29]. The flight intensity level of foragers directly impacts the amount of honey produced.

The ideal temperature for the brood is 33 °C – 36 °C. A deviation of more than 1 °C in either direction will lead to deformities in the developing larvae, which can have a significant impact on the productivity of the hive [30]. When the colony is broodless then a significantly cooler core temperature (29 °C – 32 °C) is acceptable [31]. Doull found that the optimal humidity range for hatching larvae was 90-95 % relative humidity (RH) [32]. Outside of this range the number of healthy larvae which hatched without abnormalities decreased from 98.8 % - 92.4 % (90 – 95 % RH) to 65.4 % healthy hatches at 100 % RH, and 59.5 % healthy hatches at 80 % RH. During brood rearing the worker bees bring water droplets into the hive to evaporate for temperature control [33]. This evaporation also increases the humidity of the hive to suit the hatching of healthy larvae.

2.2.1.2 Heating and Cooling

Honey bees have a variety of physiological processes in which they can engage to cool or heat the hive as needed. When the hive is in danger of overheating (in warmer climates such as during summer months in Mediterranean countries (subspecies *Apis mellifera ligustica*)), the bees will spread out and move to the outside of the hive to create more space for ventilation in the hive. They also have a process known as “fanning”, where the individual bees stand at the entrance of the hive and on the comb, then move their wings in a repeated motion to force air throughout the hive for cooling, and for removal of humid air from the hive during honey production [34]. Fanning is a highly energy intensive activity for the bees, which takes away workers from other activities such as rearing brood or foraging. They also can bring extra water droplets into the hive and place them on cells and the hive interior to encourage cooling through evaporation [35]. If the hive temperature drops too low (external temperatures of <10 °C) then the bees begin to cluster together as described above. The lower temperature limit for a honey bee is 7 °C, at which they are unable to move their wing muscles for flight [30]. They can warm the brood by “shivering” and pressing their bodies against the brood cells. “Shivering” involves rapidly moving their wing muscles to dramatically increase their core body temperature. Engaging in shivering during winter months is energy intensive and therefore will cause the colony to use its food stores faster [36]. If the external weather varies between 7-14 °C during the Winter months the colony can run out of food stores quickly, as the colony will not cluster effectively.

2.2.1.3 Diseases and pests

Nosema is recognised as the most widespread bee disease globally [37]. It consists of two species – *Nosema apis* and *Nosema ceranae* which are microsporidian organisms. The former is a parasite of the western European honey bee, while the latter parasitizes the Asian honey bee (*A. cerana*). However, *N. ceranae* has also been found recently in the European honey bee where it is considerably more virulent that in its typical host *A. cerana*. Nosema affects the gut of the bee, impacting its ability to digest pollen and thereby reducing the lifetime of the bee [38]. This disease causes the colony to fail to build up well in the spring, and in extreme cases can cause the colony to dwindle and die. The only current method of identification of Nosema is through microscopic examination. Nosema is spread quickly through hives also infected with dysentery, as bees carry many infected spores in their gut cells [39]. Woyciechowski *et al.* found that the rate of infection of honey bees with *N. apis* maintained at 25 °C was much higher than those maintained at 30 °C and 35 °C [40]. Chen *et al.* found that the *N. ceranae* pathogen load was also inversely related to temperature, with the highest spore count at 15 °C and infection levels matching the average hive at 23.8 °C [13]. No relationship between *N. ceranae* and humidity levels has been reported.

Acarapis woodi, also known as Tracheal mite, or Acarine, is a small mite which reproduces in the trachea of the honey bee. An infestation of Acarine slows the growth of the colony and reduces the lifespan of individual bees. This disease causes bees to cluster outside the hive, and become disoriented/confused [41]. The most effective identification method for Acarine is through microscopic examination. Acarine can cause colony losses during winter, where the infestation grows during the winter, and there are not sufficient bees available to raise the brood in early Spring [42]. Acarine is killed by the same treatments which are effective on the Varroa mite so products based on Thymol paste work well, as do synthetic miticides. Keepers often also re-queen colonies which show a susceptibility, as there is evidence that some bees have a genetic resistance to Acarine [43]. Mc Mullan *et al.* found that honey bees raised from brood maintained at 30 °C were more susceptible to Tracheal mite than those raised at 34 °C by a factor of two [44].

Varroa destructor is a parasitic mite of the honey bee which has emerged as the most serious pest of the honey bee globally. Australia is the only continent to which Varroa has not spread. The female Varroa mite lives on the adult honey bee, where it feeds on its haemolymph, and has a flat, brown, oval, body, typically 1.6 by 1.1 mm long [45]. To reproduce, a mite enters a brood cell and lays one male and up to seven female larvae. The female larvae mate with the male and feed on the bee pupae. Usually two to three mites successfully emerge attached to the abdomen of the newly hatched honey bee where they can live for up to six months. As the mite larvae feed on the bee pupae they stunt its growth and lifespan, leading to deformed bees as well as weakened colonies.

Varroa also spread several viruses throughout hive populations, including

Deformed Wing Virus (DWV) which can lead to colony loss [3]. Control of Varroa levels is achieved by monitoring the number of mites in the hive, to apply treatments at the most effective time. No available treatment completely eradicates Varroa, so limiting the mite count in the hive is the best possible outcome for these treatments [19].

There are several widely-accepted methods of Varroa control: chemical varroacides which generally use thymol and other essential oils, these cannot be applied until after honey has been harvested and before winter feeding; synthetic miticides such as Bayvarol (active ingredient: Flumethrin) in some regions this method is now restricted because Varroa have developed resistance to such miticides; and other chemical methods using organic acids (formic acid, oxalic acid, etc.) which can only be applied to hives during the winter phase, as the damage brood and contaminate honey stores; and biotechnical controls which can be used during the honey flow season as they do not use chemicals [46, 47].

Hou *et al.* monitored temperature and humidity of hived colonies with and without *V. destructor* infestation and found that infected hives had a higher temperature of on average 1.69 °C and a lower humidity of as much as two percentage points [15]. Annoscia *et al.* found that bees infested with *V. destructor* exposed to a lower humidity environment had an increased mortality rate [48]. As well as this, it was found by Kraus *et al.* that 2 % of Varroa produced offspring successfully when present in brood maintained at 79-85 % RH compared to 53 % of mites in brood maintained in the 59-68 % RH range [49].

Another pest of the honey bee is the Small Hive Beetle (*Aethina tumida*) that originated in Africa, but has spread to cause major problems Australia and the USA, and has recently been detected in Europe in Italy posing a major threat to European apiculture. This beetle reproduces inside the hive, and scavenges for the eggs, brood, honey, and pollen inside. They defecate in the hive causing the honey to ferment and destroying comb. Chemical controls are of limited use in controlling Small Hive Beetle, and prevention is identified as the most effective means of control. Small Hive Beetle can be identified through visual inspection of the hive interior [50]. Guzman *et al.* found that the Small Hive Beetle eggs hatched faster, and hatched beetles were significantly larger when maintained at a higher temperature (34 °C) than in a cooler environment (24-28 °C) [51].

Chalkbrood (*Ascosphaera apis*), a minor infection of the brood, is a fungal infection which kills sealed brood and mummifies the larvae. Regularly replacing brood combs reduces incidence [52]. Flores *et al.* studied effects of temperature and humidity on the development of chalkbrood, and low brood temperatures (25 °C) and high humidity (87 % RH) were identified as producing maximum infestation [53]. Chilled Brood is the name given when the brood becomes too cool (10 °C, or lower), this can be caused by the bees not covering the brood sufficiently due to starvation, poisoning, late frosts in Spring, or mishandling by the keeper, and this can be prevented through careful attention of the keeper [25].

2.2.1.4 Swarming

Swarming is the natural method by which honey bee colonies reproduce. It is described in detail in Section 2.5.2. It is an event normally associated by beekeepers with distinct sound patterns, but Ferrari *et al.* found that temperature and humidity drop by 2 °C and 5 percentage points respectively before a swarm [54]. This was identified as due to the increased fanning and activity of the bees as they prepare to leave the hive.

2.2.1.5 Summary of temperature's influence on colony

The typical temperatures for a healthy colony, together with the typical external conditions, and the temperatures associated with overheating and cooling are summarised in Table 2.1.

Table 2.1 – Influence of temperature on colony

Situation	**External Temperature**	**Internal temperature**
Winter Cluster	<10 °C	21.3 °C
Brood Rearing	Summer Temperatures	33 – 36 °C
Spring – Foraging	>10 °C	Rising
Broodless	End of Summer	29 – 32 °C
Swarming	Summer Temperatures	> 36°C
Overcooling	Hot Summer	< 10 °C
Overheating	Cold Winter	> 46 °C

2.2.2 Instrumentation of hive interiors for temperature and humidity

The conditions within the hive interior are not typically measured as part of traditional beekeeping practices, as they can be difficult parameters to measure without specialised equipment. These conditions provide vital information about the colony and reflect its health, activities, condition, and brood size. When a beekeeper inspects a hive (often using smoke to calm the bees), the act of removing the roof changes the in-hive conditions (temperature, humidity, gases, and airflow) within the hive, as well as interrupting the activities of the bees within and around the hive. This has led to the use of automated monitoring of hive interiors to evaluate the colony condition without disturbing it. Several studies have focused on the monitoring of hive interiors. This involves the use of sensors inside the hive interior, to monitor one or more parameters which can describe the activities of the colony inside.

Van Nerum *et al.* described the automatic collection of temperature data from demonstration hives using wired temperature probes connected to a PC. Humidity, CO_2, and O_2 levels were also recorded manually during this study [55]. Vornicu *et al.* described a wired network of temperature and humidity sensors embedded in three demonstration hives [56]. Human *et al.* used humidity and temperature sensors interfaced with dataloggers to study the humidity changes in a hive resulting from the colony activity (brood development, fanning/cooling the hive, ripening honey) [28]. Bacher *et al.* described a wired temperature sensor array for monitoring the temperatures of individual brood cells [57]. Zacepins *et al.* proposed a method of detecting brood rearing in the hive using a single temperature sensor in each hive on a wired network [58]. This was proposed as a solution to detect and alert the beekeeper to early brood rearing in late Winter/early Spring, allowing them to act to save the colony. Stalidzans *et al.* also used a single wired temperature sensor in 14 hives, placed directly above the brood to create a model for the expected hive temperature throughout different beekeeping seasons [59]. Recently, Marković *et al.* implemented a decision support system for beekeeping using an array of temperature sensors in each of three beehives which provided an alarm based on any region of the hive falling below a defined minimum temperature, or the centre of the cluster rising above 36 °C [60].

2.2.3 Influence of temperature and humidity in 5 km foraging range

Foraging is a vitally important activity for the survival of the colony – worker bees need to be able to leave the hive to collect the nectar for honey production, pollen, resins for propolis, and water. As described previously, honey bees begin to die as their temperature falls below 7 °C due to being unable to move [30]. Heinrich highlighted that honey bees are capable of flight in a temperature range of 10 °C to 46 °C, though with difficulty and for extremely short periods at each extreme of this range [61]. It was noted by Joshi *et al.* that atmospheric humidity had very little effect on the flight capabilities of the honey bee, however it influenced the amount of nectar available in crops, directly influencing the productivity levels of foraging [62]. Traditional methods of collecting temperature and humidity include the use of weather stations and commercially available sensors. Highly accurate records of temperature, humidity, and other factors affecting these parameters such as sunshine hours and rainfall levels are available from meteorological services such as Met Éireann in Ireland [63].

2.3 Oxygen (O_2) and Carbon Dioxide (CO_2) within the Hive

2.3.1 Respiratory gases within the hived honey bee colony

Respiratory gas levels have long been used as a measure of the activity and status of the honey bee colony. The amount of CO_2 produced by the colony can be used to estimate the number of bees inside the hive, and to determine whether the colony is dead or alive. Honey bees adjust their behaviour, including fanning to maintain suitable temperature and oxygen concentration in the hive. Carbon dioxide, however, is a far more variable parameter. Nagy *et al.* noted the changing CO_2 concentration in the hive in proportion to the recorded brood temperature, as a result of the colony's thermoregulation activities [64]. Seely observed that the colony was able to distinguish the CO_2 concentration in the hive, and that the bees took actions to regulate it [65]. The bees increased fanning (described in Section 2.2.1.2) to ventilate the hive when the CO_2 concentration rose above 3%.

2.3.1.1 Relationship of in-hive CO_2 with disease and pests

Infection rate of Nosema (see Section 2.2.1.3) was associated with carbon dioxide in [66]. It was found that both the infection rate of *N. apis* and the mortality rate of infected bees were increased in high CO_2 environments. This was suggested as a possible cause of the higher Nosema infection rates during the Winter, when CO_2 levels in the hive are higher.

Carbon dioxide has been suggested as a non-invasive method of control for Varroa (see Section 2.2.1.3). Bahreini found that increasing the CO_2 concentration in the hive to 200 % of typical winter values through restriction of the ventilation holes in the hive increased Winter Varroa mortality rates from 23 % to 37 %, without increasing mortality of the bees themselves [67].To maintain the necessary average temperature of 21.3 °C in the Winter cluster, the exchange of air with the outside environment often needs to be reduced to almost zero. This considerably increases the carbon dioxide in the cluster, and to survive in these conditions honey bees are not susceptible to hypoxia. Eskov *et al.* found that the minimum concentration of CO_2 needed to increase the mortality rate of honey bees was two orders of magnitude higher than ambient levels [68]. Excessive CO_2 was found to lead to deformities in the brood in terms of body symmetry and wing size (brood rearing does not take place in the Winter cluster).

Chalkbrood (see Section 2.2.1.3) infection rates are directly influenced by carbon dioxide levels. Heath *et al.* found that the almost all of the chalkbrood fungal spores were activated at 12.5 % CO_2 concentration, compared to just 50 % at 5 % CO_2 [69].

2.3.2 Instrumentation of hive interiors for CO_2 and O_2

Automated monitoring of oxygen (O_2) and carbon dioxide (CO_2) is a topic that has not been widely explored, due to the sensor technologies in this space not advancing at the same pace or with the same price reduction as the other sensor technologies described in this chapter. However, several studies have used other manual methods to observe the gas levels in colonies. In 1921 Milner *et al.* used a respiration calorimeter to measure the carbon dioxide and oxygen percentage in air extracted from a beehive every 30 minutes for 12 days to measure the energy consumed and work done by the colony [70]. Seely used a CO_2 analyser attached to a tube with flowing air extracted from the hive for continuous monitoring in an experiment demonstrating the fanning response of a colony to an introduced stream of CO_2 [65]. This experiment demonstrated that honey bees can detect the CO_2 level in the hive and take actions to control it. Nerum *et al.*used preinstalled syringes to extract defined volumes of air from the hive without disturbing the colony in a study to evaluate the use of hypoxia (oxygen deficiency) to control the metabolic rate of the colony in winter [55]. It was found that honey bees use hypoxia to control the colony metabolism during the winter months. A study by Ohashi *et al.* used automated CO_2 monitoring to compare in-hive values to the ambient climate, where three sensors were integrated into a two frame observation hive as part of a multi-sensor wired network designed to enable high quality data collection [71].

2.4 Airflow in Hived Colonies

2.4.1 Airflow in the National beehive

2.4.1.1 Airflow, and its effect on the hived colony

The normal method of ventilation for the hive is natural ventilation driven by the differing temperatures between the colony and the air outside the hive [72]. Ventilation holes at the top and bottom of the National hive [73] allow both thermal buoyancy and external wind to act on the hive. During mild weather, this natural ventilation is sufficient to keep the hive's temperature, respiratory gas, and water vapour levels within a suitable range for a healthy colony. Poor temperature control has been linked with several diseases including chalkbrood and Nosema [74].

During extreme weather (cold or heat), or when a very specific temperature is required (during brood rearing: 33 °C – 36 °C) honey bees have a variety of physiological processes in which they can engage to change the airflow within the hive, which are described above in Section 2.2.1.2. The process of fanning is used by the colony both to cool the hive through forced convection and to remove water vapour or waste gases by significantly increasing the exchange of air between the hive and the outside environment [75]. When the hive temperature is too low, the bees work to reduce the size of the ventilation holes by blocking them with wax and propolis to restrict the air exchange, and they can engage in shivering to increase the heat energy in the colony and directly on the surface of the brood [20].

A recent trend in hive floor design is known as an "open mesh floor", where the floor of the hive is made of a mesh together with a removable board. This gives the beekeeper extra control over the airflow in the hive to reduce the need for the colony to engage in the intense airflow control mechanisms described above. The board's position can be adjusted to dramatically increase or reduce the airflow in the hive. This removable board has another important use, it can be used to monitor the level of Varroa infestation by counting the number of mites falling to the bottom of the hive [76].

2.4.1.2 The National Hive

The hive structure design selected for use in this work was the National hive [73] (Figure 2.1). The national hive is the most common hive style used in the Republic of Ireland and the United Kingdom. The hive is made of several individual pieces which are stacked together [77]. The national hive is typically made out of wood (originally cedar) but in recent years polystyrene National hives have also become widely available as they are considered to be warmer in NW European climates and they can be manufactured in such a way that their components form an almost air-tight seal.

The floor, which supports the rest of the hive. It has three raised sides and one open (forming an entrance to the hive) the open side can be reduced to adjust the size of the entrance to facilitate defence of the hive by guard bees, reduce airflow, or close the hive.

The brood box is the main area of the hive, including eleven large removable frames, which contains the queen bee and the developing larvae. Frames are removable sheets of comb in which brood rearing is undertaken (in the brood box) and honey is stored (in the supers).

The Queen excluder is a mesh which prevents the larger queen from moving from the brood box to the supers and laying eggs in the frames intended for honey, but does not restrict the other, smaller bees from access to the supers.

The supers are boxes of smaller frames than the brood box, which are placed above the queen excluder. These boxes are where the bees store honey in ten frames that are shallower than those in the brood box, up to seven supers can be required per hive depending on the amount of honey being stored by the honey bees in a season.

The crownboard, is the inner cover of the hive. It seals the top of the hive, and traditionally has either one or two holes for feeding and ventilation. The roof, is an additional cover which creates a waterproof shield for the hive.

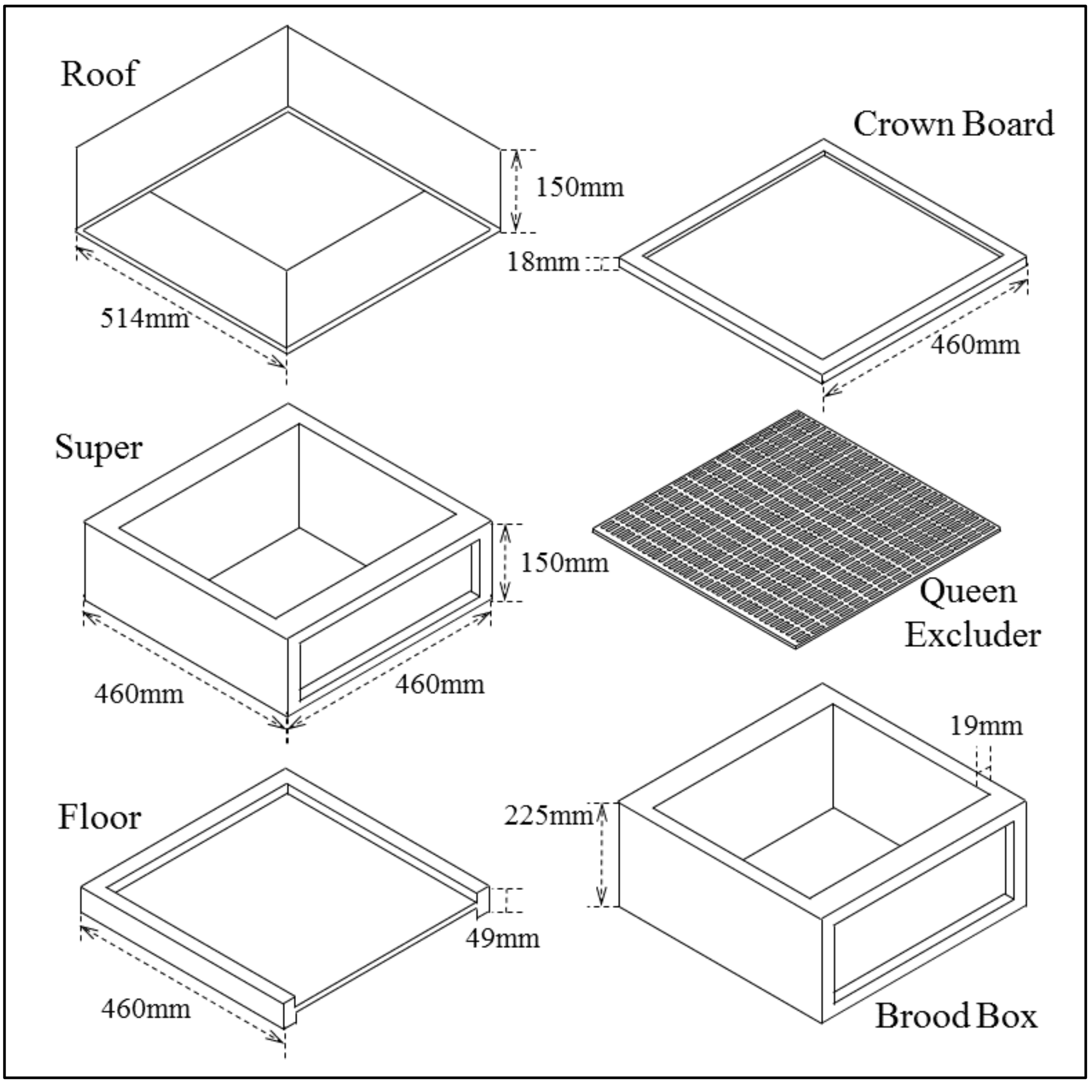

Figure 2.1 – Dimensions of the National beehive

2.4.2 Analysis of hive airflow

Evaluating the airflow within the hive has been a major focus throughout the literature. The hive is a complex thermodynamic system with several air inlets and outlets, varying density, and with several heat sources. As temperature is widely acknowledged as one of the most influential parameters within the hive, many studies have attempted to model the temperature and airflow accurately within the hive.

One of the most complex aspects of modelling the beehive is that throughout the different seasons the colony exhibits different shapes, densities, and behaviours, requiring several different models to reflect each scenario. Lemke *et al.* proposed a thermal model for bees in the winter cluster [78]. Basak *et al.* proposed a thermal model for a recently escaped swarm of bees [72]. Fehler *et al.* proposed a model for the summer hive, which considered the brood as well as the colony, as the winter and recently swarmed colonies would not have any brood to consider [79]. Sudarsan *et al.* [80] performed a computer aided simulation of the airflow and thermal regulation in a Langstroth beehive [81], and described a comprehensive overview of the equations and techniques used.

In recent years advances in sensor technology have enabled more in-depth analysis of hive airflow and temperature. Stalidzans *et al.* placed a wired temperature sensor in the roof cavity of each of 14 colonies to develop a model for the above-brood temperature of the colony throughout its daily and yearly cycles [59]. Meikle *et al.* collected temperature data using thermocouples interfaced with data loggers from eight hives [82]. They proposed a model for calculating brood mass using average measured temperature. Most recently, Kridi *et al.* used a wireless sensor network to measure the hive core temperature, and proposed a model based on collected data for generating alerts when the temperature deviated from the typical range [83].

Following this review, it was found that extensive work has focused on modelling the thermodynamics of the Langstroth hive, but not the National hive which is used in this work. Also, that all of the studies found focused on modelling the existing structure of the hive, but had not considered the possibility of changing the hive geometry to improve air and heat transfer from or to the hive.

2.5 Sounds in Hived Colonies

2.5.1 Hive activities

2.5.1.1 Alarm sounds of the colony

Honey bees use sounds to spread information rapidly throughout the hive. Lefebvre *et al.* exposed honey bees to two chemicals which are produced by honey bees when alarmed [84]. It was found that these chemicals caused one, two, and three week old bees to produce an alarm response centred at 140 Hz, 152 Hz, and 166 Hz respectively. The normal spectrum of honey bee noises is in the 190-250 Hz range.

Poisoning can occasionally present a problem for colonies, usually due to agricultural activity in the local area. Bees can pick up agricultural sprays that are used on the plants which they forage from, or as they pass through agricultural land on their way to or from other forage [85]. They can be found dead at the entrance to the hive having being repelled by the guard bees, and poisoning can be confirmed through toxicological analysis [26]. In extreme cases, up to 30,000 bees have been found dead at the entrance of the hive [86]. Pérez *et al.* proposed under “future work” to monitor the alarm sound of honey bees to detect the use of pesticides in the area local to the hive (5 km radius) [87].

2.5.2 Colony reproduction

Swarming is the natural method by which honey bee colonies reproduce. During high levels of productivity in-hive an additional queen bee (or several queens) may be reared [88]. The old queen will then leave the hive to form a new colony elsewhere, taking half of the existing colony with her, and two newly emerged queens will fight for control of the remaining colony. Successful swarming will result in the establishment of two or more colonies, which successfully survive the following winter. If unchecked, swarming is allowed to happen and many new queens may be reared sequentially, leading to successively smaller swarms, or casts [89].

Newly formed queens produce specific sounds known as “piping” at and just prior to their hatching which allows them to find each other within the beehive. Emerging virgin queens can also kill other emerged as well as developing (unhatched) queens which are sometimes used to form new colonies. Piping has two components – “tooting” and “quacking” which are described in Table 2.2. When the swarming process is in its early stages, the existing free queen toots. In response to tooting, worker bees will confine other queens to their cell. If the hive is not preparing to swarm, the free queen will find the other queen cells and kill the occupants [90].

Tooting also helps the emerged queen prepare for future fights. Workers become still when they hear tooting, and engage in less aggressive actions towards the newly hatched free queen [91]. When confined queens hear other confined queens quacking, they will join in and synchronise their quacking, and eventually many queens will join to form a “Quacking chorus” or “concert”. Confined queens, upon hearing tooting (from a free queen) will slow its efforts to cut the cap of its cell (i.e. open the entrance to its cell in order to escape). It will delay its emergence from the cell until another stimulus occurs, for example a swarm [92].

If swarming is not managed effectively by a beekeeper it can lead to large scale losses of both colonies and honey stocks. If several swarms occur in one season unchecked, then the beekeeper can be left with a significantly diminished colony size. If this occurs at the end of the Summer then the remaining colony has little chance to rebuild before Winter. Allen found a colony to be reduced from 10,500 bees to 1,500 as a result of a prime swarm and two subsequent casts [93].

The value of a honey bee colony is in the order of several hundred euro (~€200 in Ireland) and the reduced population in a post-swarm beehive loses much of its honey producing capacity. A colony will prepare to swarm zero, once, or several times per season, and there is no reliable, widely-available method to predict in advance which colonies will swarm or not without opening the hive and examining the frames for queen cells [20]. This means that the keeper must manage all colonies with the assumption that they will swarm. This is a contributor to the keeper’s labour load during the Spring and Summer seasons.

Table 2.2 – Sound components of swarming

Piping Component	*Tooting*	*Quacking*
Type of queen	New queen has emerged from her cell	New queen is confined to her cell
Temporal description of signal	One long (~1 s) syllable, followed by a series of increasingly shorter syllables	Short, similar (but not identical), length syllables of approximately 0.1 s duration
Occurs	When hive is preparing to swarm	In response to tooting. Can also be spontaneous
Frequency (Hz)	~350-500Hz, Rising with age of queen	~200-400Hz, slightly rising with age of queen
Frequency (instance)	Twice per minute	N/A

2.5.3 Instrumentation of hive interiors for sound

Despite the large amount of information it can provide, very few beekeepers monitor the sound of their hive. Sound analysis can be one of the most useful ways to identify the condition of a hive. Listening to the hive can help to identify and evaluate several important features of the colony without disturbing the hive by opening it. By listening carefully to the hive, the beekeeper can identify: if the colony is surviving well during the winter; if queen cells are being produced; if swarming is an immediate concern; and if the bees are fanning for honey production or to cool the hive effectively. It is not surprising that the first automated applications of sensors and electronics to honey bee colonies were in the space of sound monitoring. The very first recorded example of hive monitoring through electronics is a patent filed in 1957 [94]. The device used microphones and band pass filters to detect the changing frequencies in a hive in the weeks leading up to a swarm.

Using microphones to monitor the sound and vibrations produced by the colony was the earliest documented example of using electronics in research to monitor the typical behaviour of honey bees. Wenner manually recorded [95] the sound produced by honey bees during the waggle dance using the von Frisch experiment (the classic experiment designed by von Frisch to demonstrate the waggle dance [96]). A Magnemite 610-E high-fidelity tape recorder (15 inches per second) and American Microphone Company D33A microphone were used to record bees performing the waggle dance in a demonstration hive. The recordings were used to confirm the findings of von Frisch and calculate the frequencies of the various stages of the waggle dance. Fanning was noted as a source of interference in his recordings. A microphone and a laser vibrometer were used by Michelsen *et al.* to record the "tooting" and "quacking" of an observation hive [90] which allowed for an in-depth analysis of the specific sounds produced by the colony before swarming. In further research into sound in honey bee colonies, an experiment is described by Eren *et al.* where a frequency analysis of both worker honey bees and a large group of queen bees was performed [97]. The results were then used to generate audio files, which could be played to the hive during honey harvesting. The generated sound caused the bees to expect a swarming event and group together outside the hive entrance, allowing the keeper reduce bee loss during harvest.

More recently, since 2008, continuous, automatic monitoring of honey bee sounds has become possible through improved technology, including wireless sensor networks, smaller microphones, and increased storage capacity. A wired network of microphones, humidity, and temperature sensors to monitor hives automatically during the swarming phase were used by Ferrari *et al.* [54]. In 2009, an experiment was described by Mezquida *et al.* where a wired network of microphones and temperature sensors were used to monitor the daily sound activities of 15 hives in a Spanish apiary [98]. The RMS (root mean square) power of the waveform, and the frequency components in five identified important frequency bands were collected to compare patterns over time. Further, the continuous collection of sound data from in-field hives in Uruguay on an SD card for analysis was described by Pérez *et al.* [87].

Following the investigation into the state of the art in this space, it was clear that monitoring the sounds of the hive as a tool for detecting its activities and conditions would be of value for beekeeping. Both the everyday sounds produced by the colony, and the specific sounds related to swarming should be considered. The main area for improvement in this space would be to use signal processing techniques to improve both the data size and processing performance to the point where sound monitoring is viable as part of a wireless sensor network. This would allow truly ubiquitous remote monitoring of hive sounds.

2.6 Honey Production, Winter Stores, and Hive Weight

2.6.1 Honey production and weight changes in the hive

2.6.1.1 Weight changes in the hive

Throughout the year the weight of the hive changes dramatically, as the number of bees in the hive and amount of brood changes, as foraged pollen and nectar are stored in the hive, and as stored nectar is converted into honey. The total hive weight, as well as the individual weights of honey, brood etc. from May – September were recorded for hived colonies in the south of Scotland by McLellan [99]. It was found that the max weight (mean 23.1 kg) was reached in June, when the colony population was at its largest and peak foraging had been reached. The lowest mean weight (12.5 kg) was in May, as the hive was repopulating and beginning to replenish food stores following overwintering.

Many commercial and private beehives throughout the world are kept primarily for honey production. Honey is a valuable commodity, with global annual consumption predicted to reach 2.4 million tons by 2022 [100]. The most accurate way for keepers to estimate the productivity of their hives is through weight measurement. The weight of honey produced by each colony varies dramatically in relation to weather, hive size, and colony health. Chauzat *et al.* described the variation in honey production throughout Europe in 2010 [101]. Europe wide, there was an average production of 1.6 tons/100 colonies, with extremes in the Netherlands (0.5 tons/100 colonies), and Finland (4 tons/100 colonies).

2.6.1.2 Foraging and honey production

To maintain the hive and build up food stores, honey bees collect four substances from the area local to their hive: pollen, propolis, water, and nectar [102]. These are important to have available to the colony to ensure good health and condition.

Pollen is collected from plants and stored in cells to be used as a food source for young bees. Its high protein, lipids, and vitamin content help newly emerged worker bees develop and grow effectively [103]. Each larva requires 125 mg of pollen, and the average colony will require 20 kg of pollen over a year [21].

Propolis is generally pine resin (or resin from other conifers), or a sticky substance which is collected from tree buds. It is used for a variety of applications in the maintenance of the hive, including: reinforcing the hive structure; blocking gaps to make the hive water and air tight; providing an antiseptic layer in brood cells for improved brood health; and to mummify large intruders which die in the hive such as slugs, moths, or mice [104].

Nectar is the key substance collected by the honey bees. It is the primary ingredient in honey production as well as a direct source of food for the bees. Raw nectar is converted into honey as it has a long lifetime to provide nourishment during the winter and poor weather. Collected nectar has a high water content (up to 70%) as well as bacteria which would lead to mould and decay if stored as is. To create honey, the bees first evaporate water from the nectar to reduce the water content to between 17 and 18 % by exposing it to the flow of air in the colony, which can be increased by “fanning” (2.4.1.1) [21]. Two enzymes are then added from the bees’ digestive systems: Invertase and Glucose Oxidase which break the sucrose in the nectar down into simple sugars (glucose and fructose) and produce hydrogen peroxide to kill bacteria. The final product is stored in sealed cells as a readily available source of easily digestible food for the colony [105].

Water is collected and used to dilute honey for consumption, particularly during brood rearing as larvae need highly diluted food, as well as for cooling the hive.

2.6.1.3 Winter honey stores

At the start of the winter season, the beekeeper must prepare the colony to survive the winter. This involves ensuring the colony is free from disease and pests, has a healthy laying queen, and has sufficient food stores to survive the winter [21]. The beekeeper will typically ensure that the queen is less than two years old, that there are plenty of bees in the colony, and provide additional food stores to the colony in the form of sugar syrup to supplement the remaining honey. Depending on the size of the colony it requires between 18 and 27 kg of honey to survive an average winter season. Honey can be supplemented with a 2:1 mixture of sugar to water which can then be supplied to the colonies through various types of feeder [106]. Once the Spring weather begins, and external temperatures begin to rise, the activity level in the hive increases. The queen begins to lay brood, increasing the activity levels and core temperature of the hive. This new brood increases the number of bees in the hive dramatically, and the extra activity increases the honey consumption of the colony by up to 400% [21].

Ensuring that there are sufficient stores left over after the winter for the colony to survive this rapid growth is a key concern for the beekeeper and emergency feeding may be necessary. Traditionally keepers “heft” their hives by lifting them on one side to estimate the weight of the honey stores inside [19]. Many beekeepers will keep beds of early-flowering plants which flower at this crucial time nearby their apiary so that the bees have extra access to pollen and nectar.

2.6.2 Instrumentation for weight measurement

Accurate measurement of the changing weight of a hive (recorded manually) was used by Gates in 1914 to estimate the health of honey bee colonies throughout a winter season [107]. Several studies have focused on using weight sensors to measure honey bee colonies automatically and accurately. The first example of automation was an industrial scale interfaced with a PC to achieve continuous monitoring of hive weight in in 1990 [108]. Lecocq *et al.* used an SMS enabled scale (range of 200 kg with a resolution of 100 g) to compare the productivity of 31 hives across Denmark [109]. They found that beehives in urban areas were able to build up greater stores than those in mainly rural areas.

Meikle *et al.* monitored four hives for 17 months using weighing scales connected to data loggers, with a 100 kg range and ±30 g resolution [110]. They observed the weight changes during several swarms of 3.77 kg of bees and estimated the honey loss of 0.94 kg. A wireless sensor network-based hive weighing system was described Gil-Lebrero *et al.* [111], they used a load cell with an 150 kg range and a resolution of 100 g to estimate the ideal time for honey harvesting by observing the end of the main honey flow.

This investigation led to the conclusion that automated hive monitoring is a valuable resource for both beekeepers and for research. It was noted that the weighing scales with a suitable range for monitoring hive (variations of greater than 100 kg) do not generally have a sufficient resolution to measure the small changes which can occur during foraging, honey production, and colony growth (as little as 10’s of grams).

2.7 Monitoring of Hive Entrances

Monitoring the entrance of the hive is an important consideration for beekeepers to estimate foraging levels and honey production, as well as the overall health and size of the colony. Important features to note are: the number of bees entering and leaving the hive, as well as the timing of their movement; the number of bees gathering outside the hive in clumps; and the appearance and condition of the bees entering and leaving of the hive. Several studies have focused on automating this process using a variety of technologies. The earliest example of automated bee counting was by Spangler [112], where photocells and a digital counter were placed at the hive entrance to count bees entering and leaving the hive as they blocked the light entering the photocell. Throughout the following years several other studies focused on using photocells and phototransistors to count bees entering and leaving the hive [113-115]. This method of bee counting can produce a lot of error due to dirt/debris on the surface of the sensor; or bees clustering around sensors or moving around at the entrance without leaving to forage, as was shown in 2007 by Danka *et al*. following the comparison of a photocell based counter with manually recorded bee activity [116].

In more recent years, focus has moved to more accurate methods of automated bee counting. Streit *et al.* first proposed the use of RFID tags attached to honey bees for detecting the entry/exit of individual bees. This method, though invasive, expensive, and time consuming, had the additional benefit of identifying specific entry and exit events for individual bees [117]. Campbell *et al.* proposed the use of a capacitive sensor to detect bees at the hive entrance, which avoided the error which occurred in optical based counters when the photosensitive surface became dirty or obstructed [118].

Video and computer vision based systems have become the most widely investigated methods of honey bee counting. Automatic detection of bees entering and leaving the hive through processing of video data was first proposed by Campbell *et al.* [119]. Computer vision together with symbols attached to the dorsum of the bees were used by Chen *et al.* to track 100 bees successfully, as well as measure the length of time each bee spent outside the hive [120]. Computer vision for honey bee monitoring has now matured to the stage that enter/exit activity, total number of bees, as well as inter-bee social interaction can be identified, detected, and counted on beehives in the field, as described by Tu *et al.* [121].

The outcome of the bee counting review was that the technology in this space is quite mature. Current trends point to the use of computer vision and automatic image processing for estimating the activities of the colony. All studies focused on image processing at the hive entrance. A potential avenue for further work would be in applying camera or video technology to other regions of the hive.

2.8 Other Conditions of Note in the Honey Bee Colony

Other important conditions of the colony, which are not known to be detectable with the sensor technology explored in this work, are outlined in Table 2.3. It is important to understand these problems, and to be able to understand them for future work. The in-hive monitoring systems developed in this work will be deployed on hives with these conditions to investigate if they can be detected using such sensors.

Table 2.3 – Other hive conditions of note

Hive Condition	*Brief Description*	*Reference*
Drone Laying Queen	Queen has insufficient sperm. This leads to the production of unfertilised eggs, which become drone bees. No new bees are produced, and without intervention the colony will weaken and die	[122, 123]
Queenlessness	Queen is either lost or dead. The colony will respond within 24 hours by starting construction of new queen cells. If no worker eggs or larvae are present the colony will not be able to produce a new queen.	[124, 125]
Starvation	Colony does not have sufficient food stores. Can be recognised by bees staggering and lying outside the hive, and very still or dead bees sitting with their heads inside the cells of the comb within the hive	[106]
Colony Collapse Disorder (CCD)	Decimated honey bee populations in North America during 2006 and 2007, and continues to be responsible for approximately 30% of reported annual wintering losses in the region. Not a well understood phenomenon, but its symptoms are well documented as a sudden loss of the worker bees of a hive without many dead bees remaining.	[126, 127]
Chronic Bee Paralysis Virus (CBPV)	Virus of *Apis mellifera* which lies dormant in colonies throughout the year though asymptomatic bees. CBPV can cause the death of colonies due to lost worker bees	[128, 129]
American Foul Brood (AFB)	Caused by the bacterium *Paenibacillus larvae*, which releases spores which infect larvae when ingested. The bacteria reproduce rapidly, eventually killing it and reducing the remains to a sticky mass.	[130]
European Foul Brood (EFB)	Caused by the bacterium *Melissococcus plutonius*, which also enter the brood as spores are ingested by larvae. These bacteria remain in the gut of the larvae, where they multiply and compete with the larvae for food. This starves the larvae to death.	[131]

2.9 Summary

In this chapter, the existing literature on the changing conditions inside the hive, and the state of the art in beehive monitoring were presented and analysed. The first topic explored was hive temperature and humidity, which was found to be a key indicator of the hive status. These parameters influence the health, reproduction, and disease levels of the hive. The state of the art in monitoring temperature and humidity uses arrays of wired and wireless sensors to study demonstration hives.

Respiratory gasses (CO_2 and O_2) can be used to estimate the productivity and size of the colony, as well as being a factor in the development of several diseases. Very little work has been undertaken in utilising such gas sensors in hive instrumentation. Airflow is also a key factor in heating and cooling the hive throughout the year. Previously extensive work has aimed to model the hive at various stages of the year, but not on modifying hive structures to improve the thermodynamics of the hive.

Sound is a key indicator of the colony activity and status, but has not been utilised very well by beekeepers to manage their hives. Recent developments have focused on detecting hive events such as swarming and alarms from the colony using data loggers and microphones. Hive weight and activity at the hive entrance are parameters which beekeepers use to estimate honey stores, activity/foraging levels, and colony health. Several examples of hive weight measurement and hive entrance monitoring were identified.

3 Wireless Sensor Networks for Instrumentation of Beehives

3.1 Introduction

Recently, technological advances have caused embedded sensing, computing and communication devices to become an integral part of daily life. WSN have been recognised as a critical component of the emerging internet of things (IoT) concept. WSN have found applications in nearly every aspect of human life in developed countries, including smart homes, security, and personal healthcare [6, 132-134]. This versatility has greatly increased its popularity in industrial and academic research [135, 136]. New WSN products from leading technology companies are fuelling the next wave of exponential growth in the consumer market [137]. For this reason there is an increasing quantity of off-the-shelf WSN devices which can be bought as *ad hoc* solutions to act as specific or generic wireless sensor nodes for a wide range of applications [138]. From the review of the literature described in Chapter 2 it was understood that automated, unobtrusive measurement of the in-hive conditions (temperature, humidity, carbon dioxide, oxygen) could provide valuable insight into the activities and conditions of honey bee colonies. It was also clear that in-hive sensing was a suitable application for WSN technology, fitting many of the ideal characteristics for a WSN deployment.

This chapter discusses the instrumentation of honey beehives in the field. Heterogeneous sensors were deployed, monitoring the conditions within a hive (temperature, CO_2, pollutants). Data were collected periodically, showing how the colony behaviour changed over time. This posed a range of challenges, including multi-radio communications, low energy performance, and novel combinations of sensors. The key research questions during development were:

- What combination of sensors will provide an accurate understanding of the hive conditions?
- How can the system be integrated into the hive for minimal impact on the colony?
- How to effectively transmit data from remote locations to a beekeeper?
- How to provide sufficient energy to collect and transfer these data?

3.2 Sensor Selection for the Hive Environment

3.2.1 Requirements

As identified in Chapter 2, sensing inside the beehive is a complex challenge for several reasons. Firstly, the interior of a beehive is not a suitable environment for electronics to operate. The internal temperature of the beehive can vary greatly throughout the season from as low as 10°C up to 50°C. When combined with damp external weather and a poorly insulated sheet metal roof, these temperature fluctuations can cause condensation in the hive interior. During honey production, the bees intentionally “fan” the honey combs to remove water from nectar they have collected and this further increases the amount of water vapour in the hive interior. Secondly, honey bees cover many parts of the hive interior with wax and/or propolis. This is part of the bees’ natural activities, in some cases related to draught-proofing and cannot be prevented. These would prevent most sensors from operating, particularly gas detection sensors that require air flow, and could damage circuitry.

Another barrier to the instrumentation of beehives is the fact that beehives are often placed in remote locations and in a variety of environments. This limits the networking and connectivity options for the system of in-hive sensors. Additionally, this property makes energy harvesting and low energy operation a high priority, as power sources are unavailable and replacing battery packs etc. may cause increase in beekeeping costs due to the need to visit hives more frequently.

One of the most important considerations in the design of a beehive monitoring solution is that of the beekeeper. As part of their normal activities the beekeeper needs to be able to regularly disassemble the beehive to undertake inspections, feed the bees, apply treatments, etc. Speed can be an important factor for some of these activities, as during cold or wet weather, leaving the interior of the hive exposed can be detrimental to the colony.

Therefore, the beehive monitoring system should not prevent these inspections, or make the beehive more time consuming to disassemble. In the peak beekeeping season, keepers typically visit their hives once per week, and during the winter hives may not be inspected for up to four months. The system needs to send data more often than visits during the summer to be useful to the keeper, and have a suitable lifetime to survive overwintering. Several necessary properties were identified for the system:

- Non-invasive, minimum impact on hive and honey bee colony.
- No impediment or disruption to beekeeper activities.
- Robust and resistant to hive conditions.
- Energy harvesting for self-sustainable operation.
- Suitable for remote deployment.

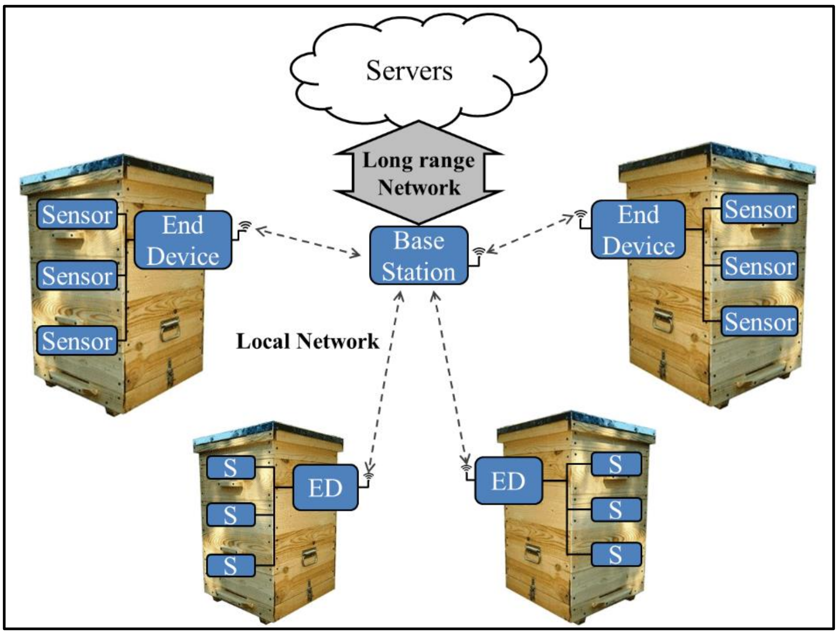

Figure 3.1 – Envisioned layout of hive monitoring sensor network

To satisfy all of these requirements, an unobtrusive in-hive wireless sensor node was envisioned, working as part of a multi-radio network, with a low-power network for local aggregation of data, and a long-range network for remote data collection. From Chapter 2 the minimum sensor range was identified as temperature, humidity, CO_2, and O_2. The sampling rate would need to accurately reflect the well documented diurnal behaviour of the honey bee [139]. The envisioned in-hive monitoring system is shown in Figure 3.1.

3.2.2 Sampling schedule

Honey bees live by a diurnal cycle. When the weather is suitable for pollen collection for feeding young bees and nectar gathering for honey production, the worker bees typically leave the hive during the warmest and brightest parts of the day to make repeated foraging visits to habitats within about 5km radius of the hive. Foraging visits cease at dusk or when it rains. During the night, the honey bees remain inside the hive. This cyclical behaviour informed the design of the desired sampling schedule for an in-hive sensor system.

Six samples/day were collected from the sensors, to minimise use of power hungry sensors while giving a clear picture of the changing parameters throughout the day. This sampling rate was the minimum sampling interval required to monitor conditions in the hive at key moments during the 24-hour cycle during the honey production season, (pre-nectar/pollen honey collection in the morning, peak of nectar/pollen collection at noon/early afternoon, end of nectar/pollen collection period, night time when all the bees are in the hive). It was important to sample at these times each day, particularly given the changeable Irish climate, with the weather changing almost hourly, which could affect colony behaviour.

To upload all of the data generated in the multi-node network, all data was aggregated on a single "base node" which compiled a single file for upload. To minimise packet loss due to collisions, and the resulting energy waste, each end device was given a dedicated 5-Minute time slot within the 12:00 – 12:55 period to join the local network and transfer its data to the base station. The base station therefore was only awake from 12:00 – 13:00, to listen to the available data, then after listening, aggregate and upload. An illustration of the nodes' daily software schedule can be seen in Table 3.1 and Table 3.2.

Table 3.1 – Firmware Schedule for end devices

TIME	*ACTION*
02:00 – 02:04	Wake, sample sensors, store data, sleep
06:00 – 06:04	Wake, sample sensors, store data, sleep
10:00 – 10:04	Wake, sample sensors, store data, sleep
12:XX – 12:XX	Wake at designated staggered timeslot, send data via local network to base station, sleep
14:00 – 14:04	Wake, sample sensors, store data, sleep
18:00 – 18:04	Wake, sample sensors, store data, sleep
22:00 – 22:04	Wake, sample sensors, store data, sleep

Table 3.2 – Firmware Schedule for base station

TIME	*ACTION*
12:00 – 13:00	Wake, receive data from local network during staggered timeslots, compile file with all data, upload to servers via long-range network, sleep

3.2.3 Sensor selection

The critical in-hive parameters which may indicate the status of the colony have been identified in the literature as: temperature, humidity, Carbon Dioxide (CO_2) levels, and Oxygen (O_2) levels [69, 140]. These are known to vary in response to one or more of these scenarios: the number of honey bees in the hive, the health of the colony, and the weather. These observations motivated the sensor choice. In order to eliminate noise from the sensors, for each sample the average of 10 sensor readings was selected.

The gas monitoring node had five sensors measuring the composition of the air in the prototype hive. These sensors were: molecular oxygen (O_2) sensor SK-25 from Figaro; carbon dioxide (CO_2) sensor TGS4161 from Figaro; nitrogen dioxide (NO_2) sensor MiCS-2710 from E2V Technologies; and two air contaminants sensors

TGS2600 and TGS2602 from Figaro which sensed a range of contaminant gases the most significant of which are ethanol (CH_3CH_2OH), hydrogen sulphide (H_2S), ammonia (NH_3), carbon monoxide (CO), and methane (CH_4).

The general hive conditions node utilised three external sensors: particle dust (GP2Y1010AU0F) from Sharp; humidity (808H5V5) from Sencera Co; and temperature (MCP9700A) from Microchip Technology. This node also utilised the Waspmote platform's built in 3-axis accelerometer (LIS331DLH) from STMicroelectronics. The NO_2, contaminant, and dust sensors were not identified in the literature review (Chapter 2), but were included in Deployment I(a) and I(b) to investigate if they had a response to the hive airflow. All sensors were calibrated and tested in University College Cork, Ireland before deployment.

Following the results of deployments I(a) and I(b) (described in Section 0) the sensor selection was reduced to 5 of the previously used sensors which were identified as important to describe the in-hive environment, and the hive's position: oxygen, carbon dioxide, humidity, temperature, and acceleration. The dust sensor was not found to provide any useful response to the hive environment, and the gasses detected by the NO_2 and air contaminant sensors were not present at detectable levels in deployment I(a) or I(b), possibly due to the rural location of the apiary used for the study. These sensors may be useful in a deployment on a beehive in a city environment, where particle matter and pollutant gasses are more prevalent.

3.3 System Design

3.3.1 Platform

To achieve the goals outlined above a preliminary WSN system was envisioned, with two types of low power in-hive node supporting a variety of sensors (network architecture is shown in Figure 3.7). The system also included a single base station which collected data from the local network of in-hive nodes, then used a long-range radio to relay results to a cloud based server. The two developed end device nodes were: a gas detection node, which measured the concentration of various gases within the hive; and a general hive conditions node, which measured other important parameters, including temperature and humidity.

The platform used to develop the system utilised an 8-bit ATmega1281 microcontroller. Low power sleep modes (0.7 µA @ 3.7 V) with duty cycling and energy harvesting were used to permit an extended lifetime. The platform had a modular architecture allowing a combination of over 70 sensors and 11 radio technologies, a built-in SD card slot, real time clock, and accelerometer. It had sleep and hibernate modes, and an energy harvester adapter. The radio solutions utilised were ZigBee® and 3G/GPRS, the selection criteria and properties for the networking solution are described in detail in Section 3.4. An encapsulated version of the platform was available with an IP65 enclosure. An outline of all node architectures are shown in Figure 3.2.

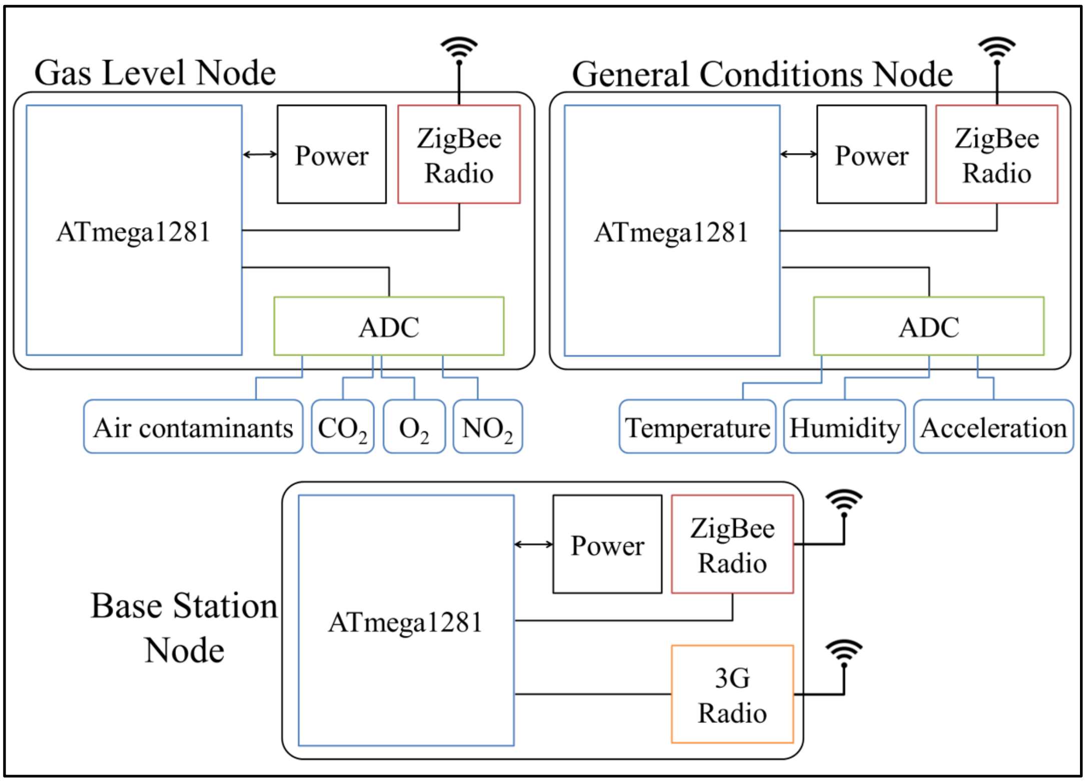

Figure 3.2 – Node architecture version 1[141]

Following the results of deployments I(a) and I(b) (described in Section 0) the system was redesigned to include a single in-hive node with the above identified key sensors. This allowed for a greater number of future deployments by reducing the amount of materials required per hive. The revised system included improved firmware with lower energy requirements, better sensor calibration, and more data backups for redundancy. The revised system also included an external solar panel instead of the previous integrated solar panels (described in Section 3.5). An outline of the revised system can be found in Figure 3.3.

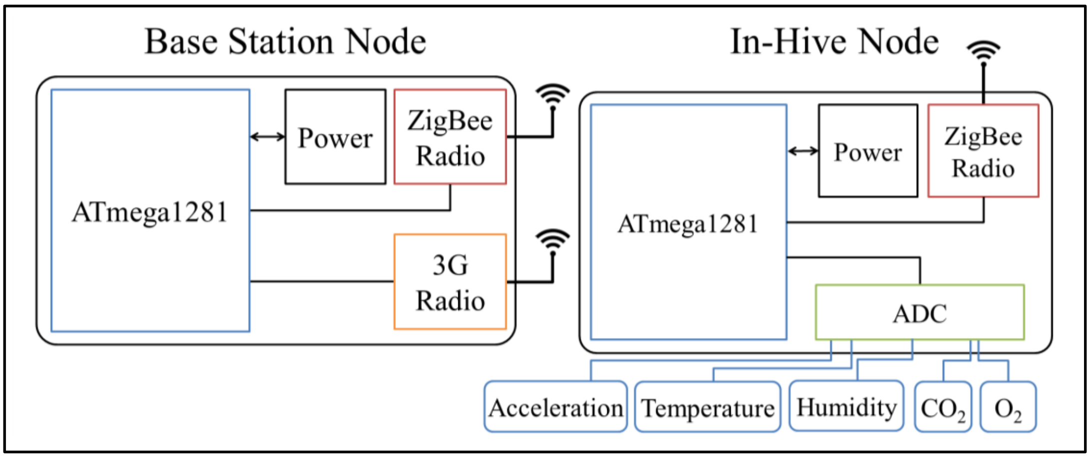

Figure 3.3 – Node architecture version 2

3.3.2 Hive roof design

To satisfy the above-described system requirements a prototype system was proposed (Figure 3.4) and developed.

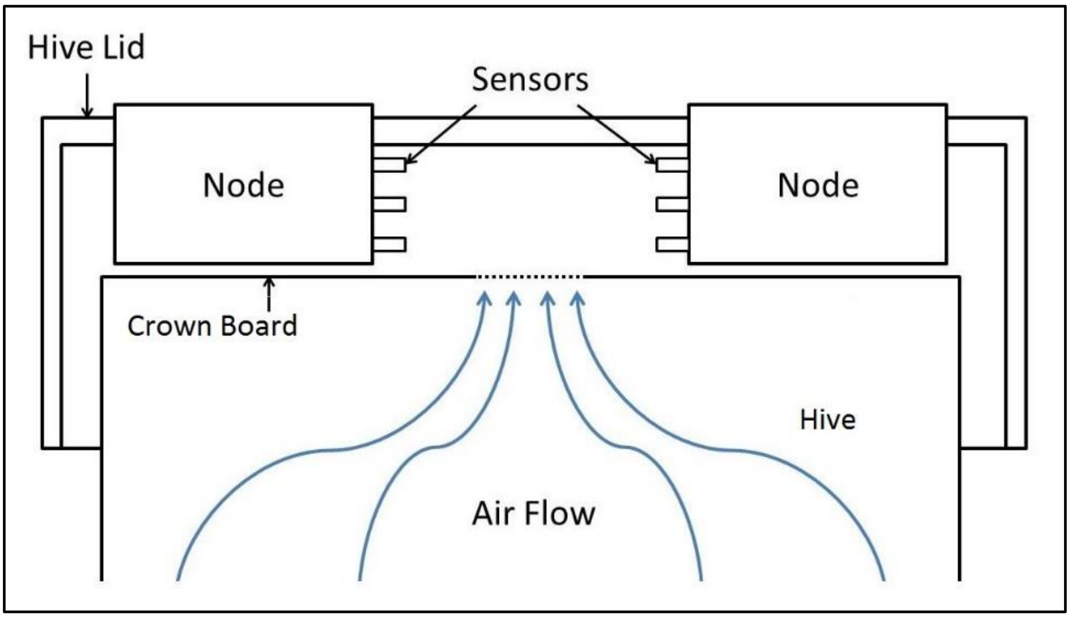

Figure 3.4 – Proposed layout for prototype

These nodes were integrated into the existing hive roof as shown in Figure 3.5. The barrier (crown board) between the roof and main hive allowed the sensors to monitor the hive conditions without allowing the honey bees to access the sensors. Air flowed through the hive naturally through a mesh covered hole in the crown board, allowing the gas sensors to collect accurate data about the respiration in the hive. This hole is a typical feature of the crown board, and the addition of a mesh prevents the bees from crawling into the roof cavity to reach the electronics to place wax, honey, or propolis on them. It was initially necessary to occasionally check the mesh for build-up of wax, pollen, or dust and clear it out with a wire brush.

An improved solution for sealing the hole in the crown board was found, a perforated plastic sheet placed over the hole, which the honey bees were found not to interfere with, and therefore did not need to be cleaned. This layout did not change the beekeeper's typical activities in any way, as the system was entirely integrated into a single section of the hive. Inspections, treatments, and feedings could be performed as normal by removing the roof and placing it to one side. The only addition to the beekeeper's routine was a quick inspection of the mesh as described above. The developed prototype can be seen in Figure 3.5.

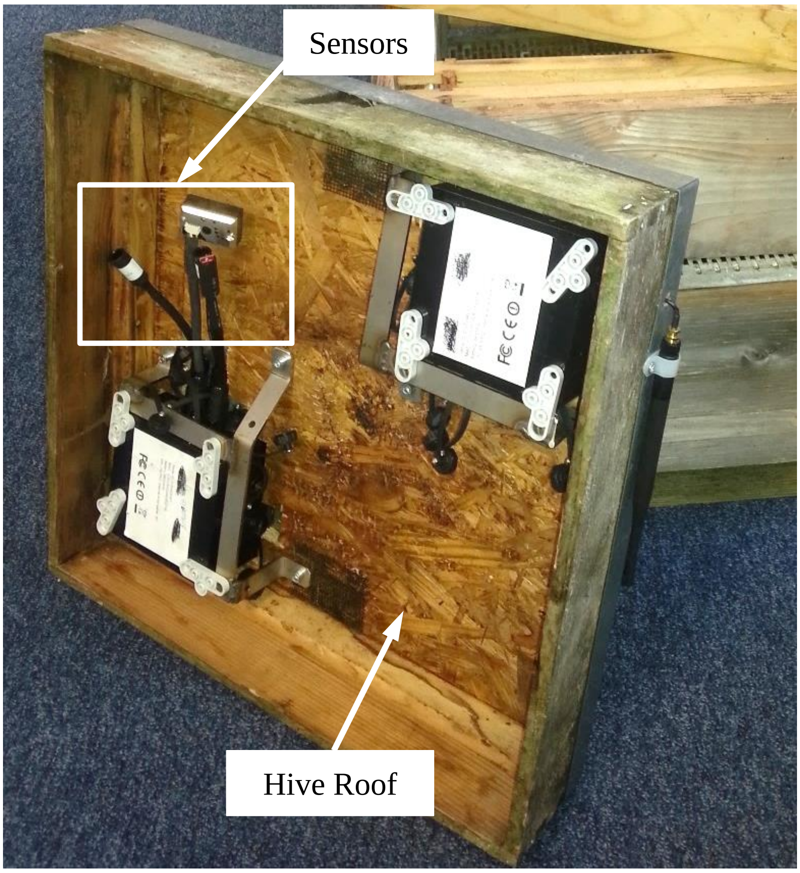

Figure 3.5 – Prototype of sensor system version 1 installed in a hive roof

After deployments I(a) and I(b) (described in Section 0) the system was redesigned to improve performance, and 5 prototypes were developed (Figure 3.6). The key features of the design remained the same, with the entire system integrated into the hive roof. However, several important improvements were made:

1. The entire sensor node was placed within the hive roof rather than extruded through. This change was made because in deployment I(a) and I(b) the temperature gradient across the node led to condensation within the node enclosure.

2. A custom hive roof was manufactured with an extended depth (7" (17.78 cm) rather than the traditional 4.5" (11.43 cm)). This improved the design by increasing the space available for electronics and sensors, and increasing the weight and stability of the system, thereby reducing the likelihood of the hive being blown or knocked over. Greater depth also reduced the possibility of condensation in the roof cavity due to rain or mist entering the roof space.

3. A fully waterproof external solar panel was utilised, and mounted on the hive roof at an optimal angle for improved energy harvesting (further details in Section 3.5).

4. Other general design improvements included better cable layout to maximise waterproofing, and improved mounting of the antenna.

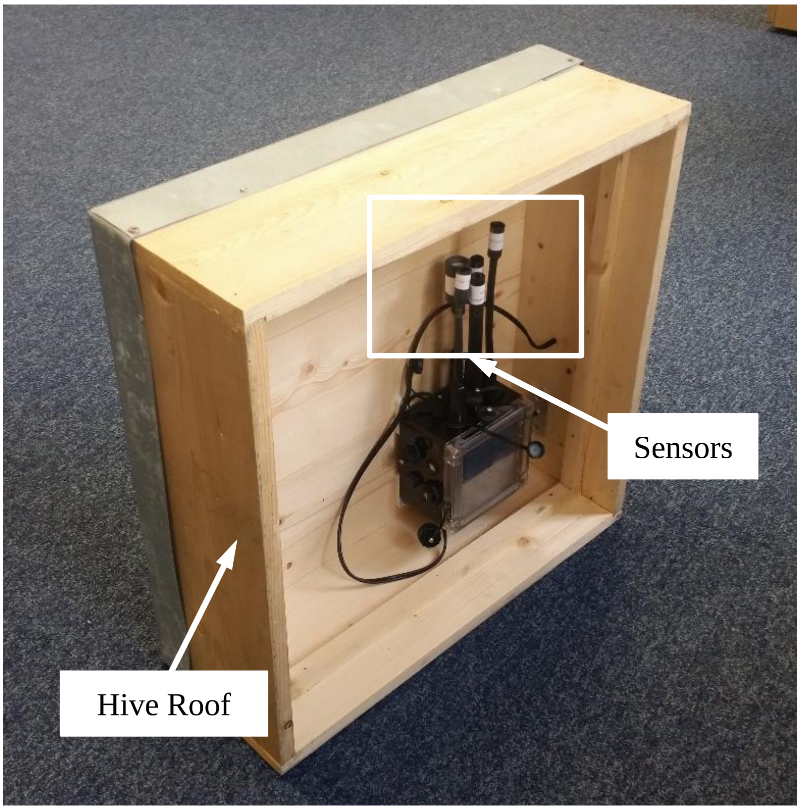

Figure 3.6 – Prototype of sensor system version 2 installed in a hive roof

3.4 Network Topology and Connectivity

3.4.1 Multi-network solution

To satisfy the design requirements outlined in Section 3.2.1 a multi radio system was envisioned. A single network solution has not been developed that satisfies the various requirements of a beehive monitoring solution. The necessary properties identified for each network are described below:

3.4.2 Local (apiary level) network:

1. Low power – The apiary level radio had to be integrated into the hive with the sensor node. Therefore, the radio should not significantly increase the energy requirements of the system.

2. Data rate – The data rate requirements for the network were low. Single data points from each sensor were collected several times per day, creating data in the 10s of kB per day.

3. Flexible – Flexibility should be an important feature of the apiary level network. The network needed to be able to adapt when the hives are moved and as various hives are removed and introduced.

4. Range – The apiary level network needed to be able to communicate over a short distance. The width of the typical Irish apiary which the network needed to cover was approximately 25 metres.

3.4.3 Wide (data aggregation) network

1. Range – As apiaries are often located in remote and rural areas, it was important for the wide network to use an ultra-long range radio.

2. Ubiquitous – As beekeepers often have hives in a variety of locations, and regularly move hives between sites, it was important that a ubiquitous networking solution was selected.

3. Interface with servers – The data collected from the hives was aggregated in an FTP server (detailed description Section 3.4.5) so it could be accessed remotely for processing. It was therefore important for the networking solution to be able to access such a server.

4. High data rate – Long range networking solutions are typically energy hungry. Therefore, it was important to select a solution with a sufficient data rate that allows the radio to be off for most of the system cycle for improved system life.

3.4.4 Radio selection

The communication protocol selected for the local (in-hive) network was ZigBee®, as energy performance was a critical parameter for in-hive nodes which cannot be accessed easily post-deployment. The XBee-ZB-PRO module from Digi International was selected to achieve this. The XBee-ZB-PRO was a low power full Zigbee enabled radio which can be reprogrammed easily into gateway, router, or end-device mode.

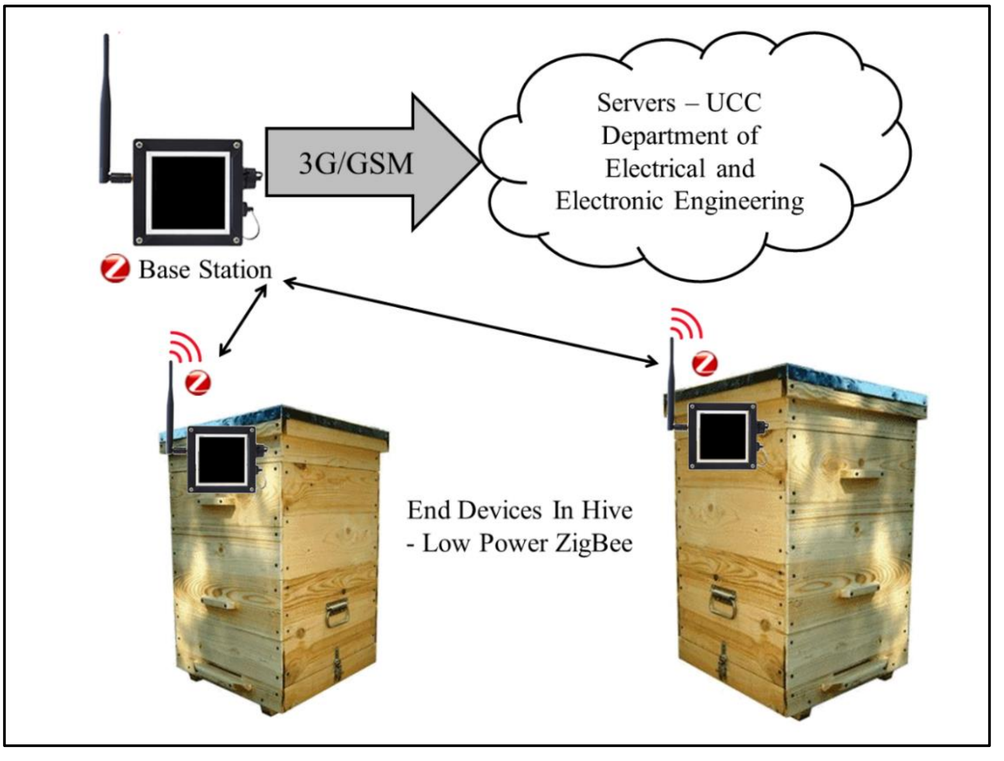

Figure 3.7 – Network structure

For the long-range communication in the base station node, 3G was selected for its widespread availability, including rural areas where beehives, in Ireland, are typically kept. The SIM900 (SIMCom) GSM/GPRS module was selected for networking. This module had ultra-low power operation (30µA) and provided phone call, SMS and FTP upload/download operations. GSM/GPRS networking was selected to suit the remote deployments of many beehives. Other possible solutions such as WiFi and High-Power ZigBee were considered, but did not satisfy the long range and ubiquitous requirements as well as GSM.

The Zigbee network synchronised and end devices sent collected data to the base. Data were transmitted by a 3G radio to a server (cloud storage). This combination of networks allows the smart hive to be a fully IoT enabled system, relaying data from the beehive to the laboratory. The network structure can be seen in Figure 3.7.

3.4.5 Data storage

Each data point was time stamped as it was sampled, and as it was transferred through each stage of each network. This ensured an accurate record of the changing beehive conditions was obtained. It also allowed for reconstruction of data in the case of jumbled packets.

Each of the nodes in the network were enabled with a 4 GB SD card. A record of each data point passing through every node was stored on this SD card in a CSV file. This guaranteed maximum recovery of data in the case of any network or device failure.

The primary location for data storage in the system was a 1.11 TB LINUX Debian server based in the Department of Electrical and Electronic Engineering at University College Cork. The base station of the apiary level network connected to this server once per day (at 12pm) and uploaded the newest CSV data to the server via FTP. Two backups of this server were maintained on external hard drives stored in a locked laboratory in the Department of Electrical and Electronic Engineering, in case of server failure or accidental deletion. The total size of data transferred per day to the server was approximately 6 datasets (42 datapoints) 4 KB per active hive. This allowed a large amount of insight into each hive while remaining low cost and without excessive bandwidth usage.

3.5 Energy Efficient Design

3.5.1 Prototype design

The first design of the system featured an internal solar panel integrated into each of the two end-device’s waterproof casing (size 111 mm x 91 mm, maximum output 6.5V at 205mA). The nodes were extruded through the roof of the beehive in order to expose the panel to sunlight. The nodes were mounted at an angle of 11° from horizontal to prevent rain from accumulating on its surface and to allow the panels to be oriented facing a southerly direction to increase performance (Figure 3.8)

For the more power-hungry base station of the network a larger, external solar panel was utilised to provide more energy (234 mm x 160 mm, maximum output 7 V at 500 mA). This solar panel was mounted on a bracket with a 30° angle from horizontal, and always oriented due south. This angle was selected as it is the average of the yearly ideal solar panel angles for maximum solar energy collection in Ireland as advised by the Irish Solar Energy Association [142]. The final solar panel brackets for the in-hive nodes can be seen in Figure 3.10.

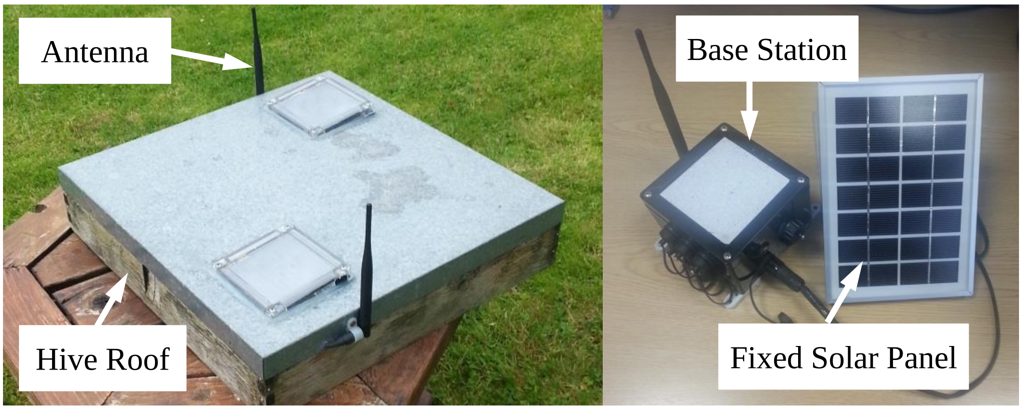

Figure 3.8 – Solar panel orientation version 1

3.5.2 Preliminary energy challenges

The performance of the solar energy harvesting throughout the deployments I(a) and I(b) was observed by monitoring the recorded battery level. The energy harvester did not provide enough energy for the gas sensing node, due to the power-hungry gas sensors which need to be powered for an extended time before they provided an accurate result.

The options for improving this node’s energy performance were explored, including reducing the rate of sampling from 6 samples per day to 3 or 2 samples per day (labelled A), maximising solar panel efficiency at each of these sampling rates (η) by deploying it at on a customised mount which moves the panel to an angle optimised for the deployment location (labelled B) (38° from vertical for Ireland, latitude ~50°), and then, additionally improving the power consumption of node operation by 30% through reducing the node's idling time and changing the order of sensor readings so they used energy more effectively (labelled C) (Figure 3.9). It can be seen in graph C that these three techniques combined lead to a self-sustaining node [143].

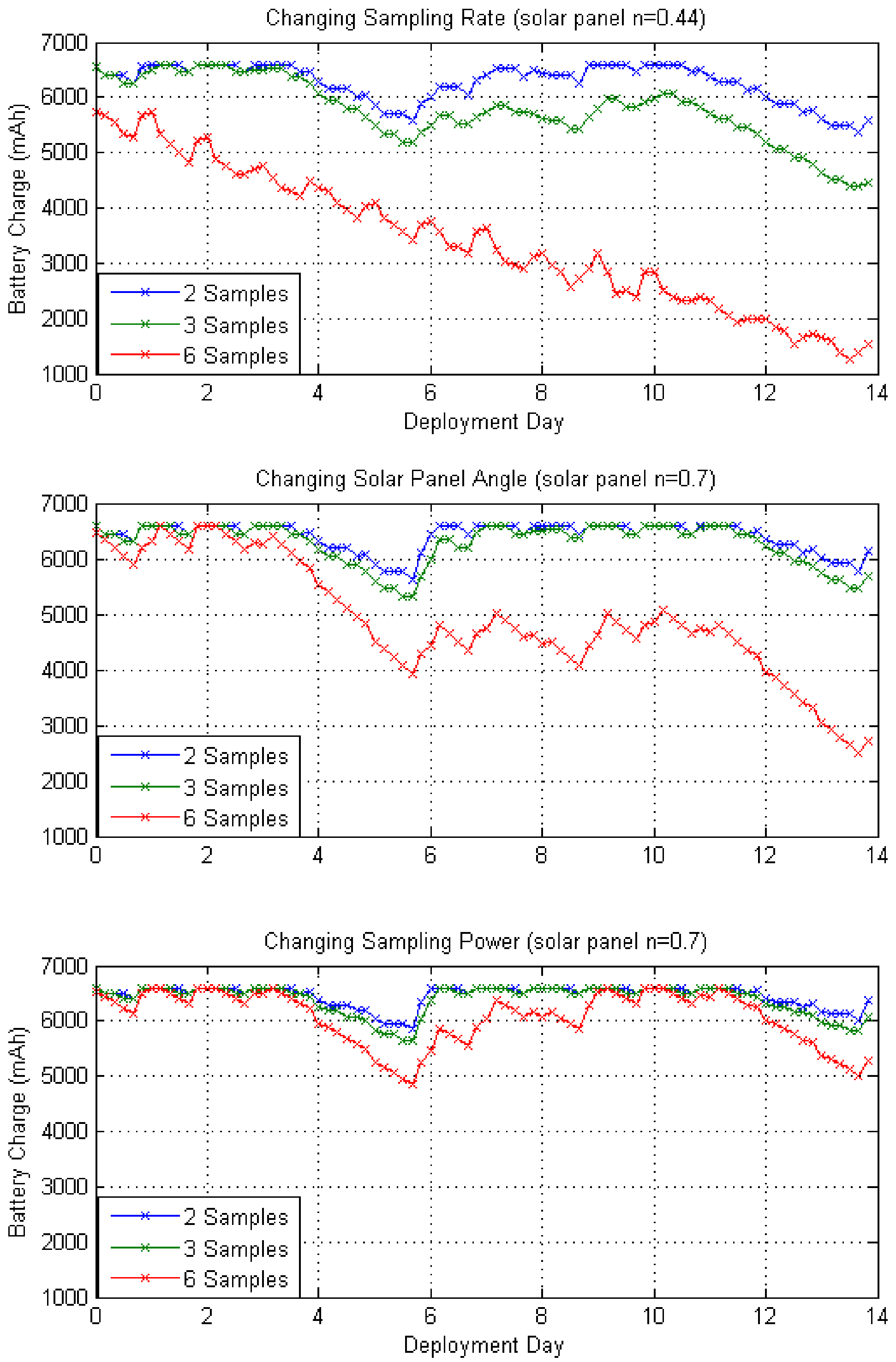

Figure 3.9 – Simulated energy performance

It was estimated that by using one or more of these techniques it would be possible to improve energy performance to achieve self-sustainable operation. The hardware and software were redesigned to achieve this for subsequent deployments.

3.5.3 Hardware improvements

The primary improvement in hardware which could be implemented was improved energy harvesting. This was achieved by replacing the integrated solar panels used in deployments I(a) and I(b) with dedicated solar panels external to the hive (Figure 3.10). The dimensions were 234 mm X 160 mm with a maximum output 7 V at 500 mA compared to the 111 mm X 91 mm 6.5 V at 205 mA solar panel used in deployments I(a) and I(b). These solar panels provided far more energy to the sensor nodes than the previous panels, even during winter deployments at high latitudes.

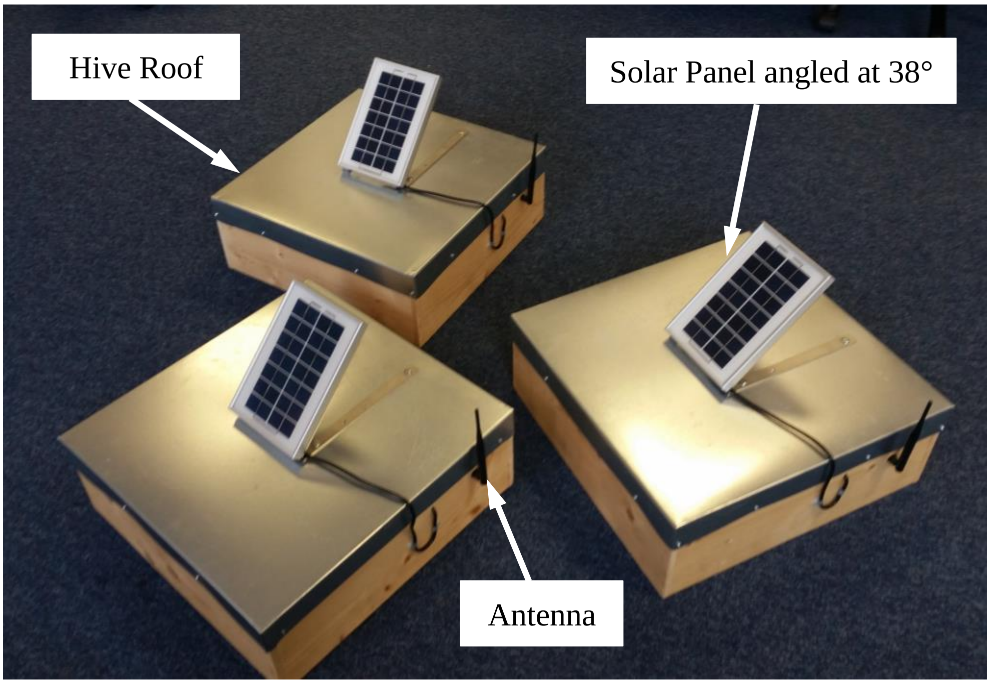

Figure 3.10 – Hive roofs with fixed solar panels

These improved solar panels were mounted on the roof of the hive to increase the amount of exposure to sunlight, as optimal beehive placement in colder climates involves placing the hives facing in a southerly direction in areas exposed to sunlight. The solar panels were mounted on brackets with a 38° angle from vertical to maximise energy harvesting as outlined in Section 3.5.2 (Figure 3.10). An adjustable mounting was designed, which allowed the angle of the solar panel to be changed to match the seasonal changes in the sun's position. This mounting was used in all subsequent deployments for the solar panel of the base station, but it was not necessary for the in-hive nodes as the fixed bracket described above combined with other energy improvements as discussed below in Section 3.5.4 provided excess energy in all seasons.

Another hardware change designed to improve energy performance was the identification of the most important sensors following deployments I(a) and I(b). Several sensors, including three power hungry gas sensors, were removed. Namely: nitrogen dioxide (NO_2) sensor MiCS-2710; two air contaminants sensors TGS2600 and TGS2602, and the particle dust sensor (GP2Y1010AU0F).

3.5.4 Software energy improvements

Several improvements were made in the firmware of the nodes which significantly improved their energy performance. A power analysis of the gas sensing node used in deployments I(a) and I(b) found that when the device was in sleep mode it consumed an average current of 10.2 mA. This is an unsustainable current for the device to operate on using a 6600 mAh battery for long term deployments. It was also several orders of magnitude higher than the 55 µA sleep current expected based on the platform datasheets. Problems in the platform libraries for the SD card, radios, and sleep modes were identified:

- An error with the function designed to switch off the SD card. The SD card and the Xbee ZigBee radio shared an SPI line. This error in the SD library led to random behaviour on the SPI line and increased current consumption when using the Xbee radio's sleep modes once the SD card was initialised. This problem was overcome by using low level code to put the Xbee module to sleep and close the connection, rather than the library functions provided.

- There was a problem with the library code for the sockets of the sensor expansion board, where current was constantly leaking as long as the board was initialised, even when in deep sleep mode (the board should disconnect when the deep sleep function is called). This issue was resolved by disconnecting the expansion socket using low level code when the sensors were not in use.

- The length of time when the power-hungry sensors were drawing current was reduced. This was achieved by rearranging the order in which the sensors were sampled to allow non-energy hungry sensor readings to overlap with the gas sensors heating. The gas sensors which required heating were initialised before the other sensors were sampled, allowing the sensor board to be turned off earlier.

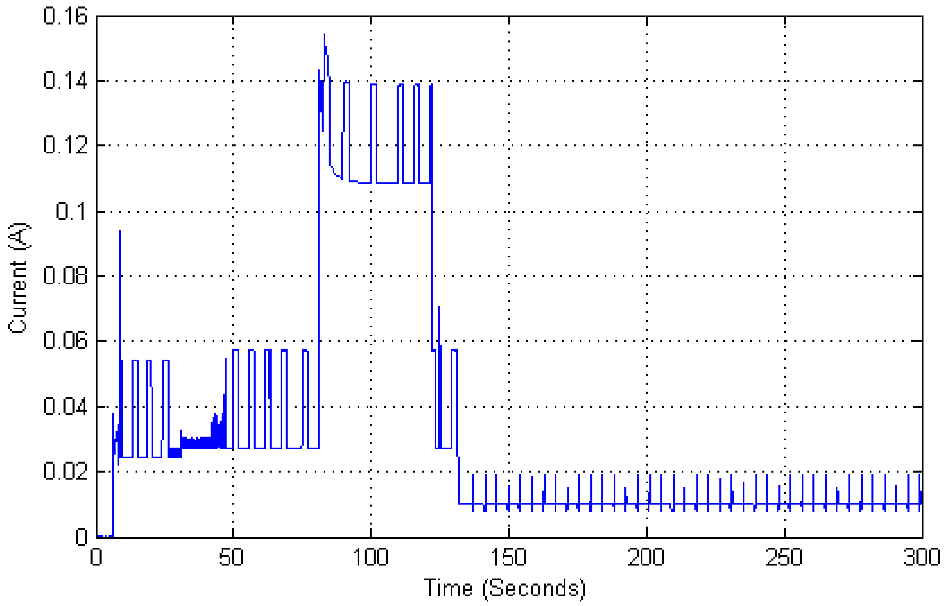

Figure 3.11 – Current profile - software version 0.17

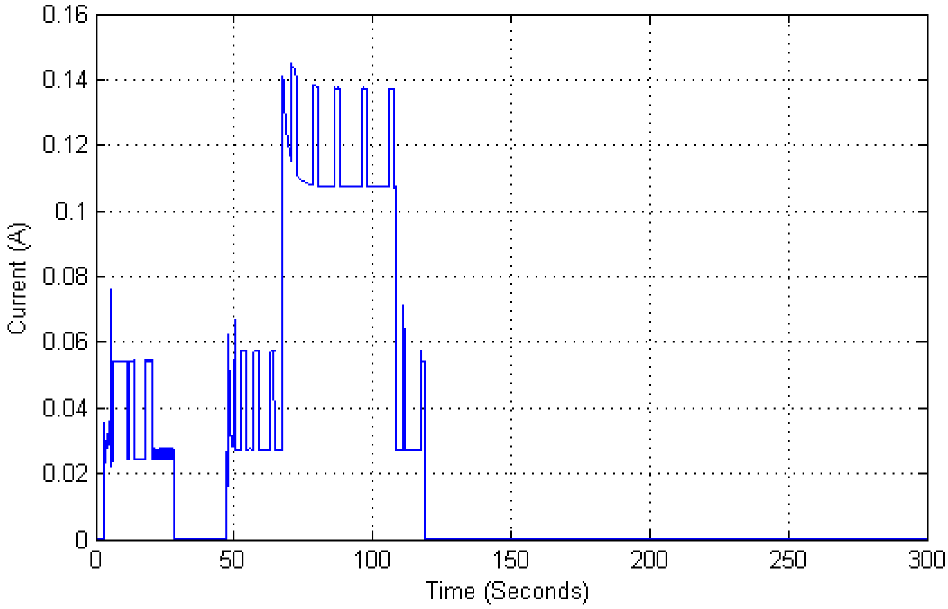

Figure 3.12 – Current profile - software version 0.22

The improvements described above were implemented, and found to markedly improve the energy performance of the system. The current draw in the deep sleep mode was improved from 10.2 mA to 150 µA. This represents a reduction by a factor of 66. The estimated lifetime of the node in deep sleep mode while utilising a 6,600 mAhour battery was extended from 18.8 days to 1,233 days. This leads to the conclusion that a significantly smaller battery could be used in future versions of the system. During the Winter months, a hive may not be visited by the keeper is approximately 4 months. This suggests that a 700 mAhour battery would be suitable to supply the system, reducing the cost of the node.

The improved energy performance made it unnecessary to reduce the sampling frequency as suggested in Section 3.5.2. A plot of the current profile of the gas sensing node before (Software version 0.17) and after (version 0.22) the software revision can be seen in Figure 3.11 and Figure 3.12.

3.5.5 Energy performance in-field

To evaluate the effectiveness of the energy improvements above, the battery level throughout Deployments III – V was monitored. The in-hive nodes were found to be self-sustaining. i.e. they used less energy in their operation than they collected from their energy source. Figure 3.13 shows the battery level of four nodes over the 66 days of Deployment V.

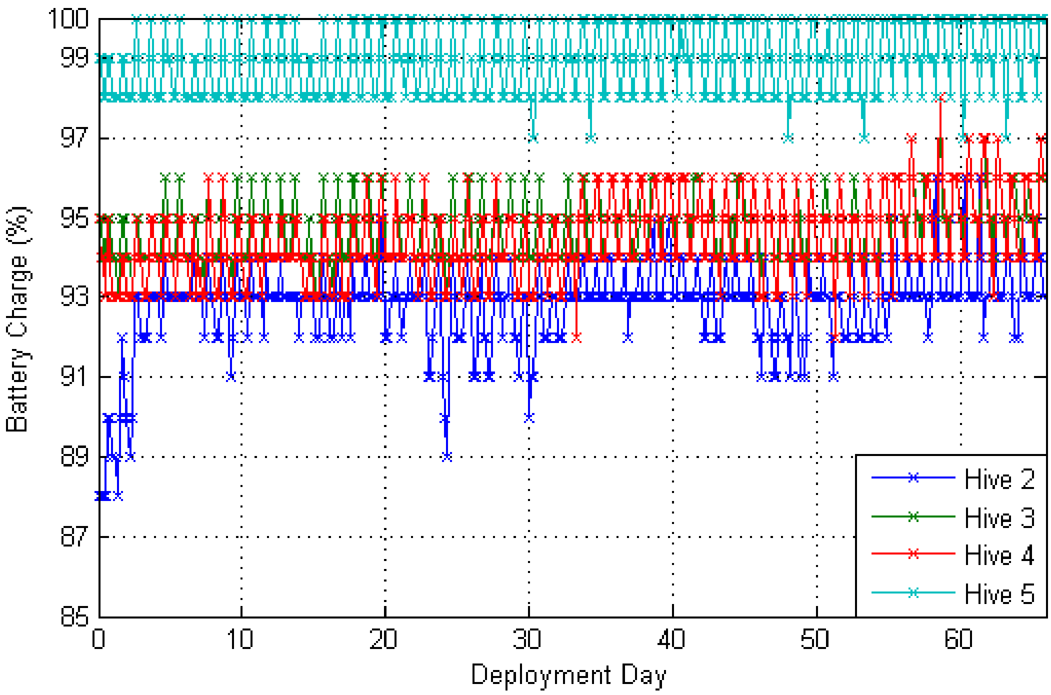

Figure 3.13 – Battery level for deployment V

It is worth noting that this deployment took place during Winter months, which is the worst-case scenario for solar based harvesting in Ireland. Other possible energy sources were considered and identified as suitable for future deployments of the in-hive monitoring system, including wind power from a small turbine (due to the rural and often exposed positioning of apiaries), and thermoelectric charging (utilising the often-large temperature differential between the core of the hive and the external weather).

3.5.6 Energy aware adaptive sampling algorithms

A major obstacle for WSN in harsh applications is energy availability. Battery life is limited, and improvements have not matched the rate of advancements in other WSN technologies, such as memory, networking and processing. Energy harvesting provides a partial solution by recharging the battery. However, this energy is unpredictable which can lead to node failure. This is particularly true for the application of WSN nodes to beehives. The energy harvesting method used was solar panels which are unreliable in overcast regions. As well as this, the gas sensors required to evaluate the colony were extremely power hungry, and needed to be powered for extended periods of time (up to 40 seconds each) to provide an accurate reading.

The most demanding gas sensor was the CO2 TGS4161, which needed to be powered for 40 seconds to reach a suitable level of accuracy. This caused the sensors to be the most energy demanding component of the sensor nodes, compared to other WSN examples, where the radio was the most demanding component. These properties identified the beehive sensor network as an ideal application to demonstrate adaptive sampling algorithms.

The approach used was a novel energy-aware adaptive sampling algorithm (EASA) designed by Bruno Srbinovski, a PhD candidate in the Department of Electrical and Electronic Engineering at University College Cork. This combines adaptive sampling techniques with an energy harvesting management technique to increase the node lifetime, achieving self-sustainability. The design and development of the EASA are outlined by Srbinovski *et al.* [144]. The EASA had a generic design for calculating the desired sampling frequency as outlined in equations 1 and 2, and could easily be implemented on the existing WSN platform.

$$f_{EASA} = f_{Sampling}K \tag{1}$$

$$\begin{cases} K = 1\ ,\ if\ E_{batt} \geq X \\ K = 1 - \left(\dfrac{X_{level} - E_{batt}}{100}\right)^{m},\ if\ E_{batt} < X \end{cases} \tag{2}$$

Where f_{EASA} was the new sampling frequency, $f_{sampling}$ was the previous sampling frequency, K was the energy cost function, E_{batt} was the measured percentage level of the battery, X_{level} was the selected fixed critical battery level in percentage, and m was a parameter used to tune the rate of frequency change. A MATLAB simulation of the EASA algorithm applied to the beehive gas sensing node used in deployment I(a) and I(b) was run using the actual solar energy harvested and energy requirements of the node.

The frequency changes throughout the EASA simulation for different values of m (1/3, 0.5, and 1) and the frequency changes for a traditional ASA (no energy harvesting management) were recorded. Each of the EASA simulations responded faster to the dropping battery level than the ASA, with m=1/3 having the fastest response time. This response makes the EASA more effective at preserving battery, but results in less data being collected during a given period. The frequency changes throughout the simulation are shown in Figure 3.14.

The measured battery level throughout the deployment was compared with the simulated battery level. It was found that the EASA was more effective than the ASA at preserving battery life (Figure 3.15). The EASA with m=1/3 leading to a battery level of 40% in the same time a node with no adaptive sampling would completely deplete.

The battery levels throughout the simulations compared to the measured values (E_{FSR} – “Fixed Sampling Rate”) are shown in Figure 3.15. Based on this, it was identified that Energy Aware Adaptive Sampling Algorithms are an effective method of energy conservation for in-hive sensor network. This could help greatly extend the lifetime of each node, particularly as the times when energy harvesting is less effective (e.g. winter and night in the case of solar harvesting) are also times when less frequent collection of hive data is likely to be more acceptable.

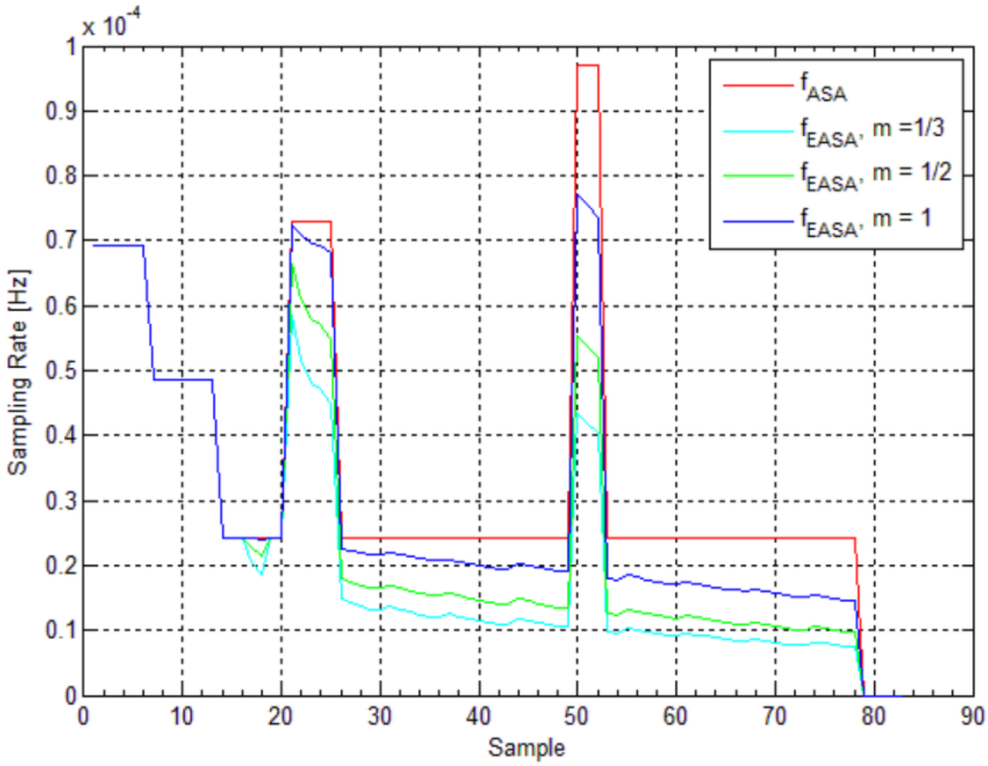

Figure 3.14 – Simulated sampling rate for ASA and EASA[144]

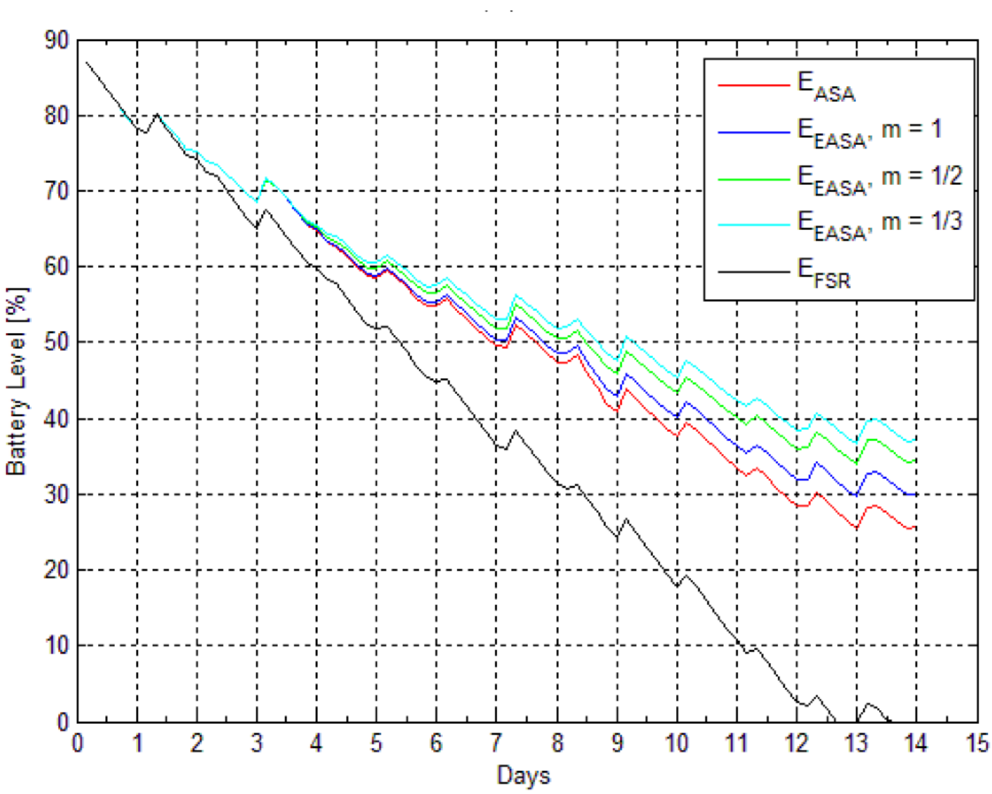

Figure 3.15 – Simulated battery level for fixed rate, ASA, and EASA[144]

3.6 In-field Deployments

Throughout the research described in this thesis, five deployments of the in-hive sensor network were performed over 513 days on up to five hives simultaneously. This facilitated the collection of 3435 datasets, where one “dataset” is defined as a set of seven values describing: temperature, humidity, CO_2, O_2, acceleration, timestamp, and node battery level; for a single node collected within the same 3-minute window. The primary sampling frequency for these deployments was three times per day (4 hour intervals, 0.694 µHz), with one deployment (deployment I (b)), which sampled the gas sensors three times per day (8 hour intervals, 0.347 µHz) to evaluate the impact on energy performance.

To validate that the sensor nodes were not influencing the colonies they were monitoring, several hives in the apiary were intentionally not monitored using the sensor nodes. Throughout the various deployments the condition and productivity levels of the monitored and non-monitored hives were compared by an experienced beekeeper, and no differences between the groups were identified.

3.6.1 Deployment I, (a) & (b)

The first deployment, termed Deployment I(a), of the prototype beehive monitoring system took place on a single beehive with a healthy bee colony near Banteer, Co. Cork, Ireland on 29/06/2014 and continued until 13/07/2014. The prototype was adjusted and redeployed (termed Deployment I(b)) from 11/08/2014 onwards on the same hive until 27/08/2014. Weather conditions were recorded throughout the deployment for analysis (Figure 3.25). Weather data were obtained from the Irish national meteorological service Met Éireann. The temperature, wind speed, atmospheric pressure, and rainfall were recorded from the nearest automatic station at Moorepark, Co. Cork, Ireland (39 km from deployment) and the sunlight data were recorded from Cork Airport, Co. Cork (40 km from deployment), Ireland (Figure 3.16).

Daily rainfall data were also collected manually at the apiary. Both nodes were sampled 6 times per day during Deployment I(a). The sampling rate was adjusted to sample general conditions six times per day (4 hour intervals, 0.694 µHz), and gas levels three times per day (8 hour intervals, 0.347 µHz) during Deployment I(b). These sampling frequencies were selected to provide a picture of the hive at the critical times (i.e. at night when bees are in the hive, during the morning when foraging is taking place, and in the evening when foraging has ended).

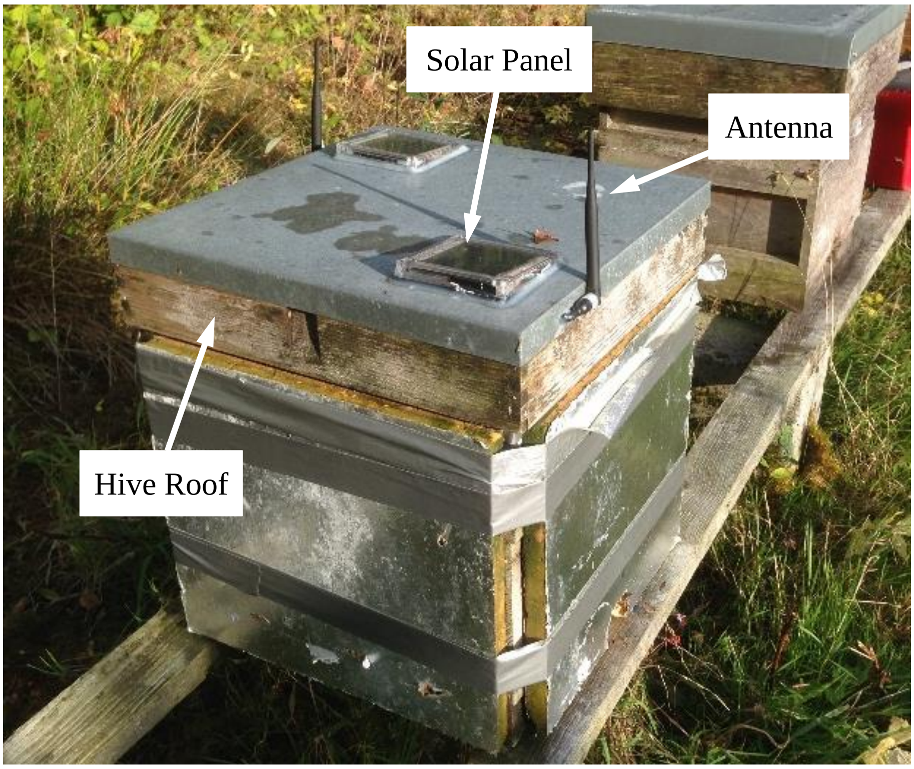

Figure 3.16 – First assembled prototype deployed in-field

The data collected during deployment I(a) show large fluctuations in temperature from 12 °C to 42 °C and CO_2 from 370 ppm to 445 ppm initially, with both parameters stabilising, with temperature fluctuating around 18 °C by ±~5 °C and rising towards 470 ppm for CO_2, towards the end of the deployment. Over the first deployment O_2 was found to remain steady between 20% and 21.5%, while humidity varied between 65% and 95%. In deployment I(b) the CO_2, temperature, and O_2 readings were quite constant over the duration of the readings with values of approximately 472 ppm, 12 °C ± ~ 7 °C and 21.5% respectively, with humidity fluctuating between 80% and 100%. These data are summarised as graphs, with time on the X-axis, the vertical gridlines marking the 2 pm point in each 24-hour period, allowing the diurnal pattern in almost every dataset to be seen clearly. Figure 3.17, Figure 3.18, Figure 3.19, and Figure 3.20 show the results collected from deployment I(a), Figure 3.21, Figure 3.22, Figure 3.23, and Figure 3.24 show the results collected from deployment I(b), and Figure 3.25 shows the related weather data.

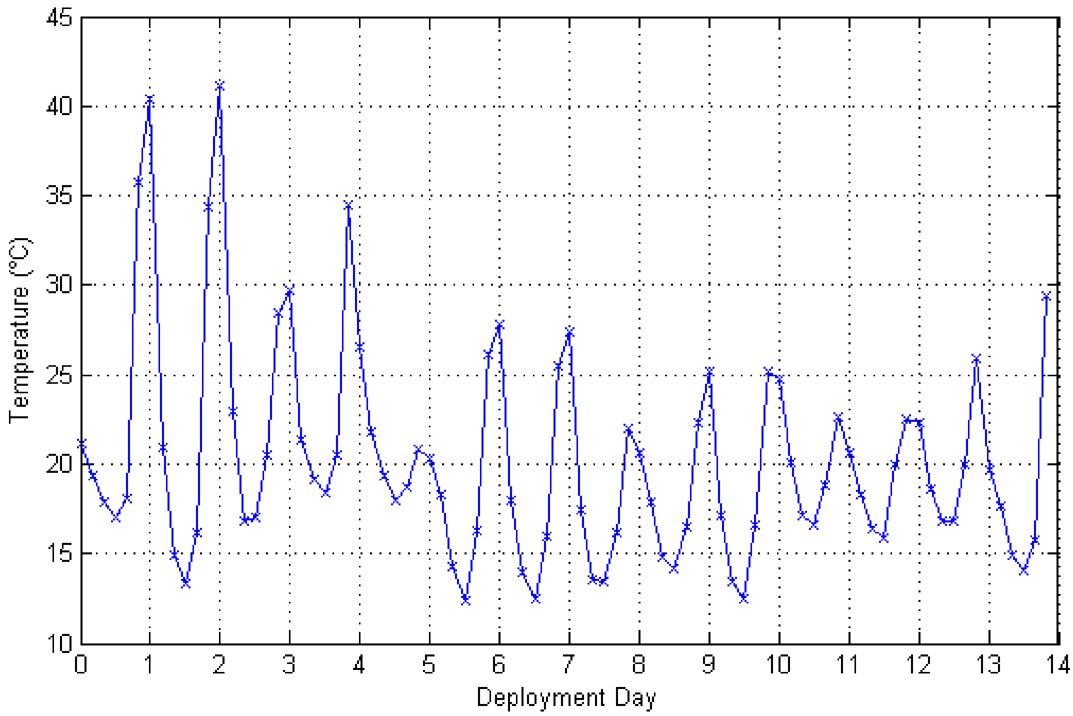

Figure 3.17 – Temperature Deployment I(a)

Figure 3.18 – Humidity Deployment I(a)

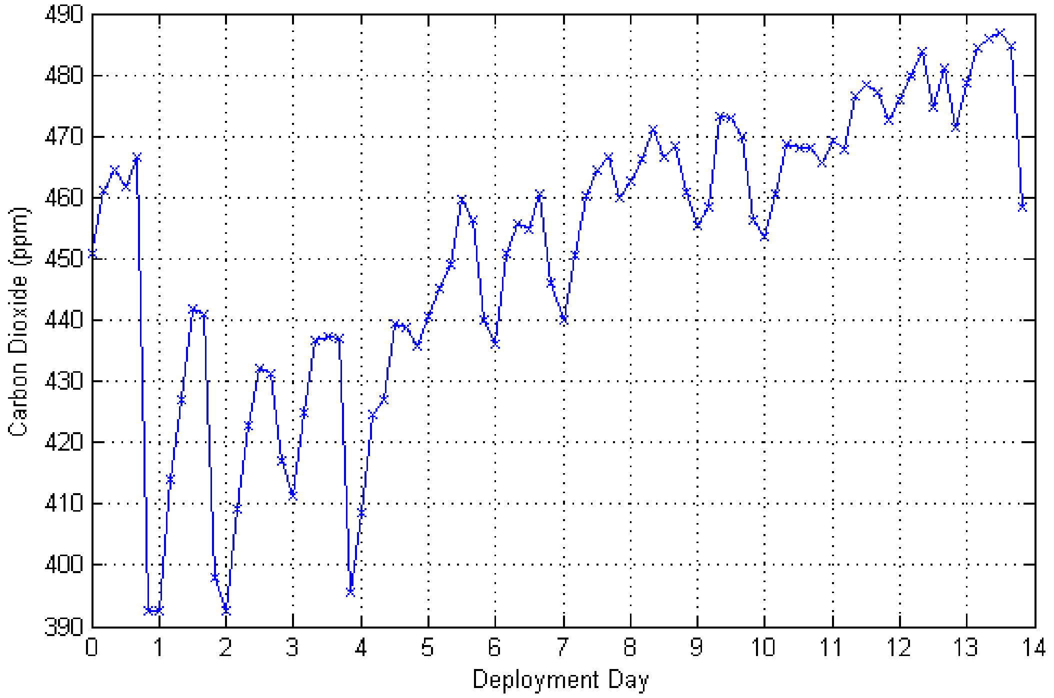

Figure 3.19 – Carbon dioxide Deployment I(a)

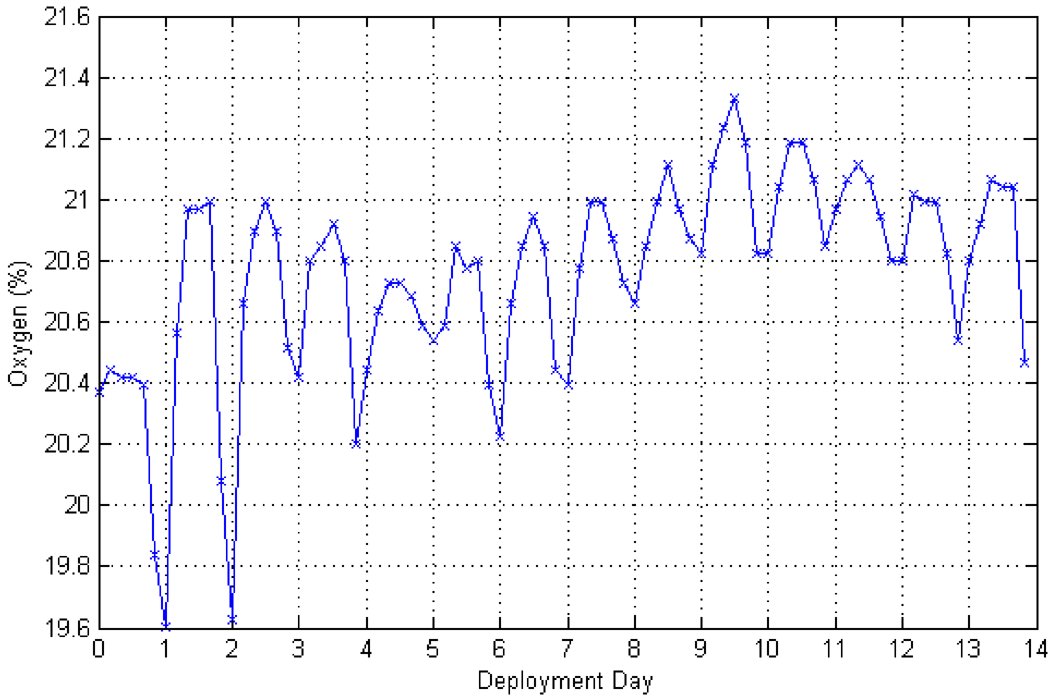

Figure 3.20 – Oxygen Deployment I(a)

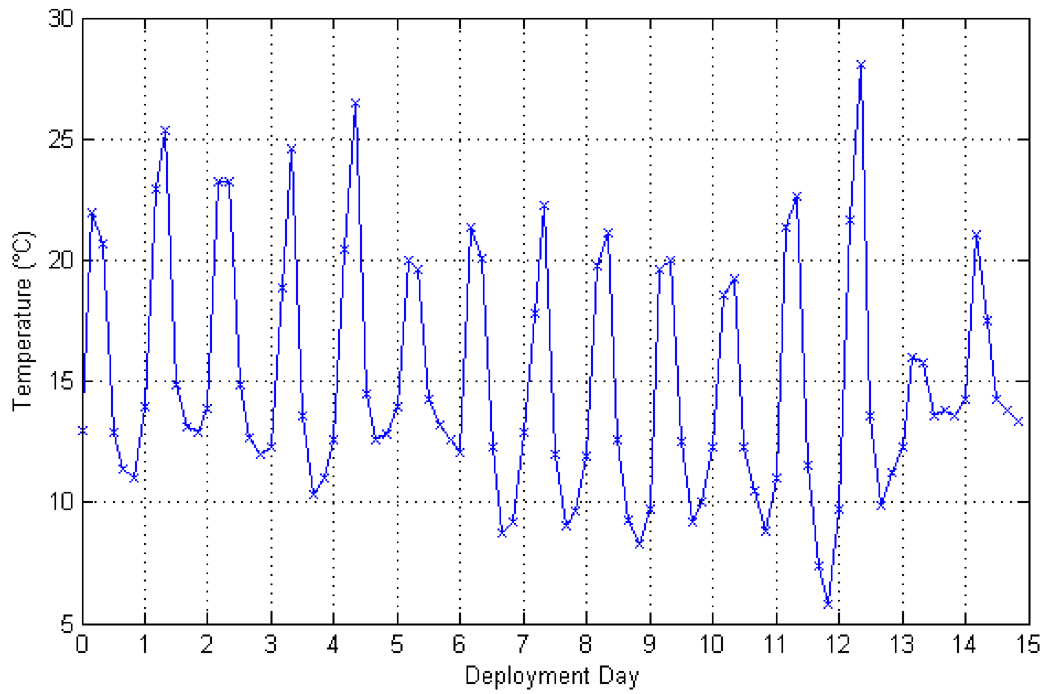

Figure 3.21 – Temperature Deployment I(b)

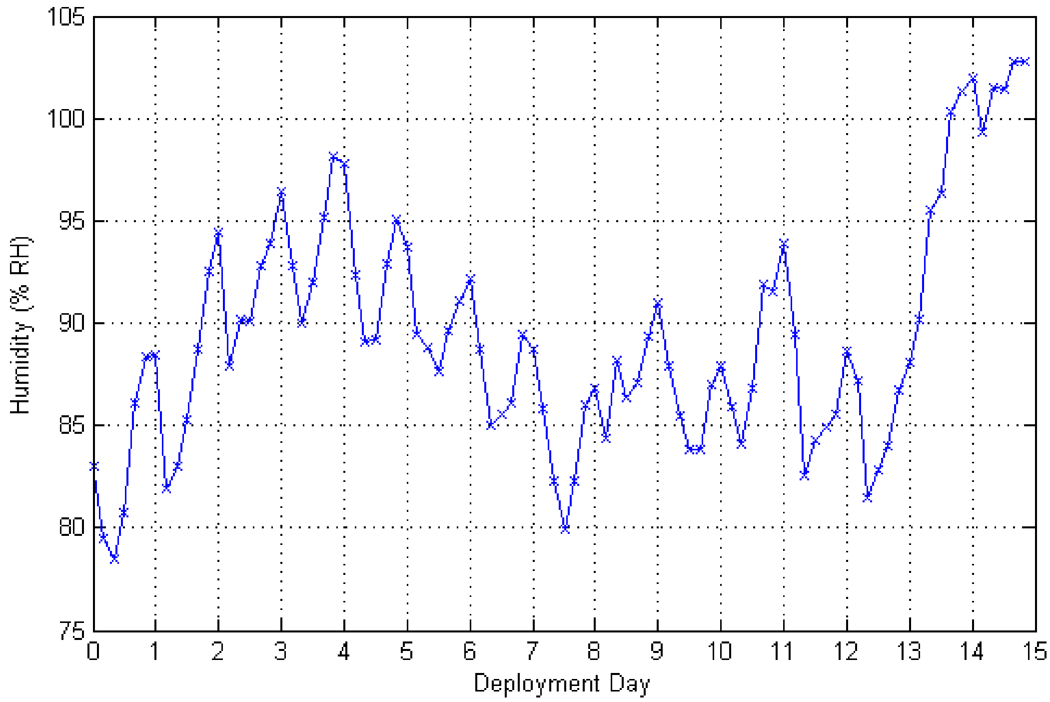

Figure 3.22 – Humidity Deployment I(b)

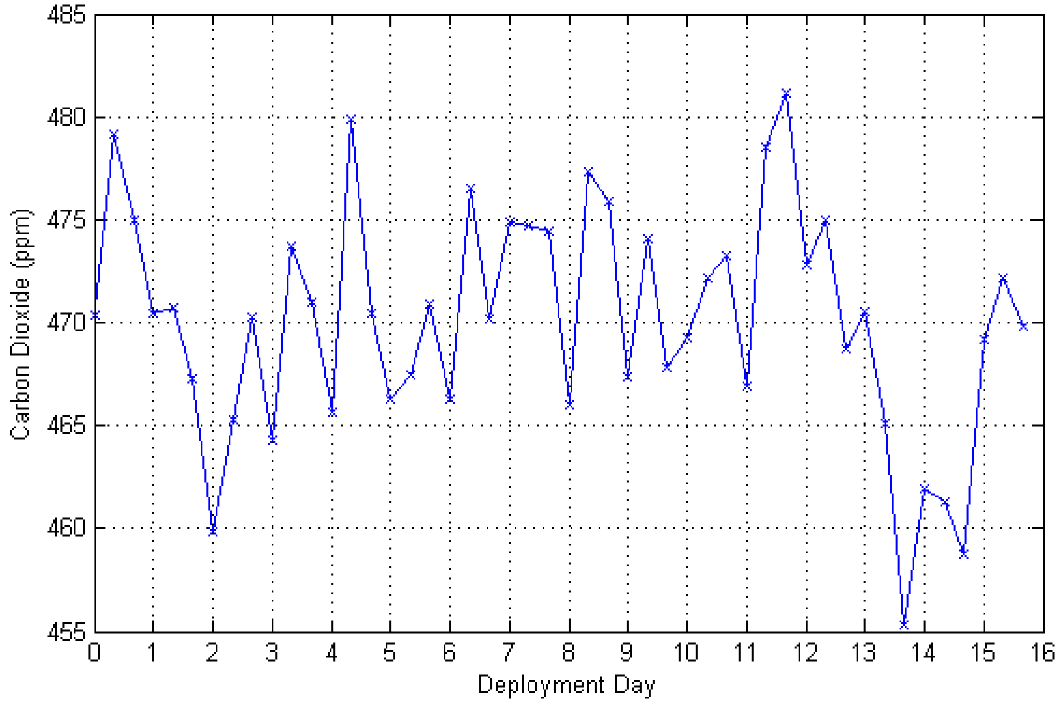

Figure 3.23 – Carbon dioxide Deployment I(b)

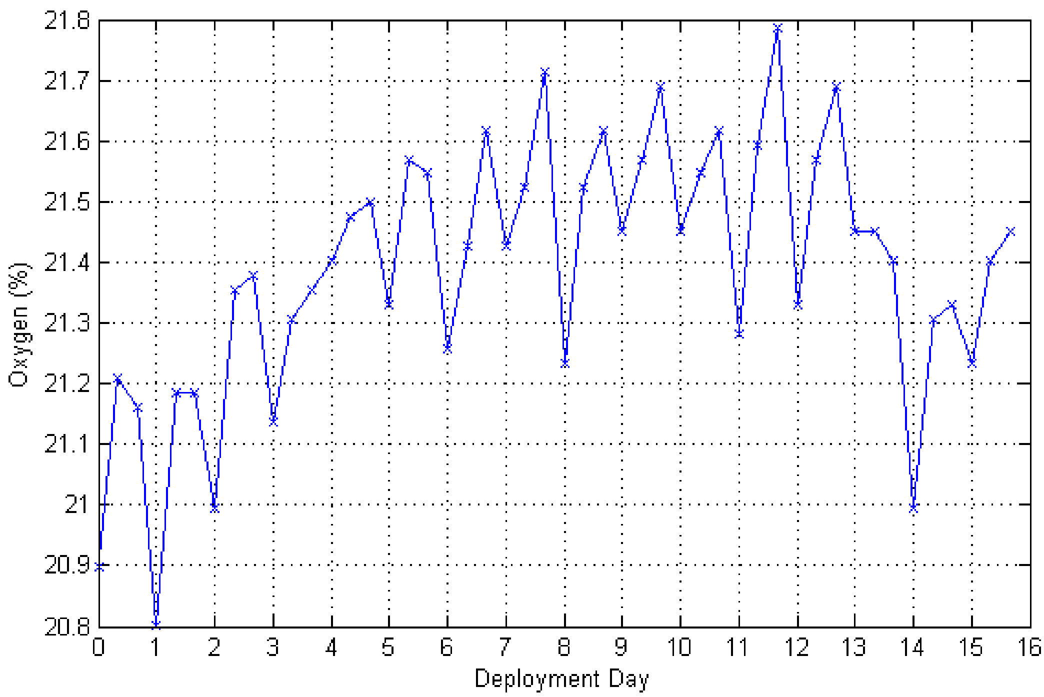

Figure 3.24 – Oxygen Deployment I(b)

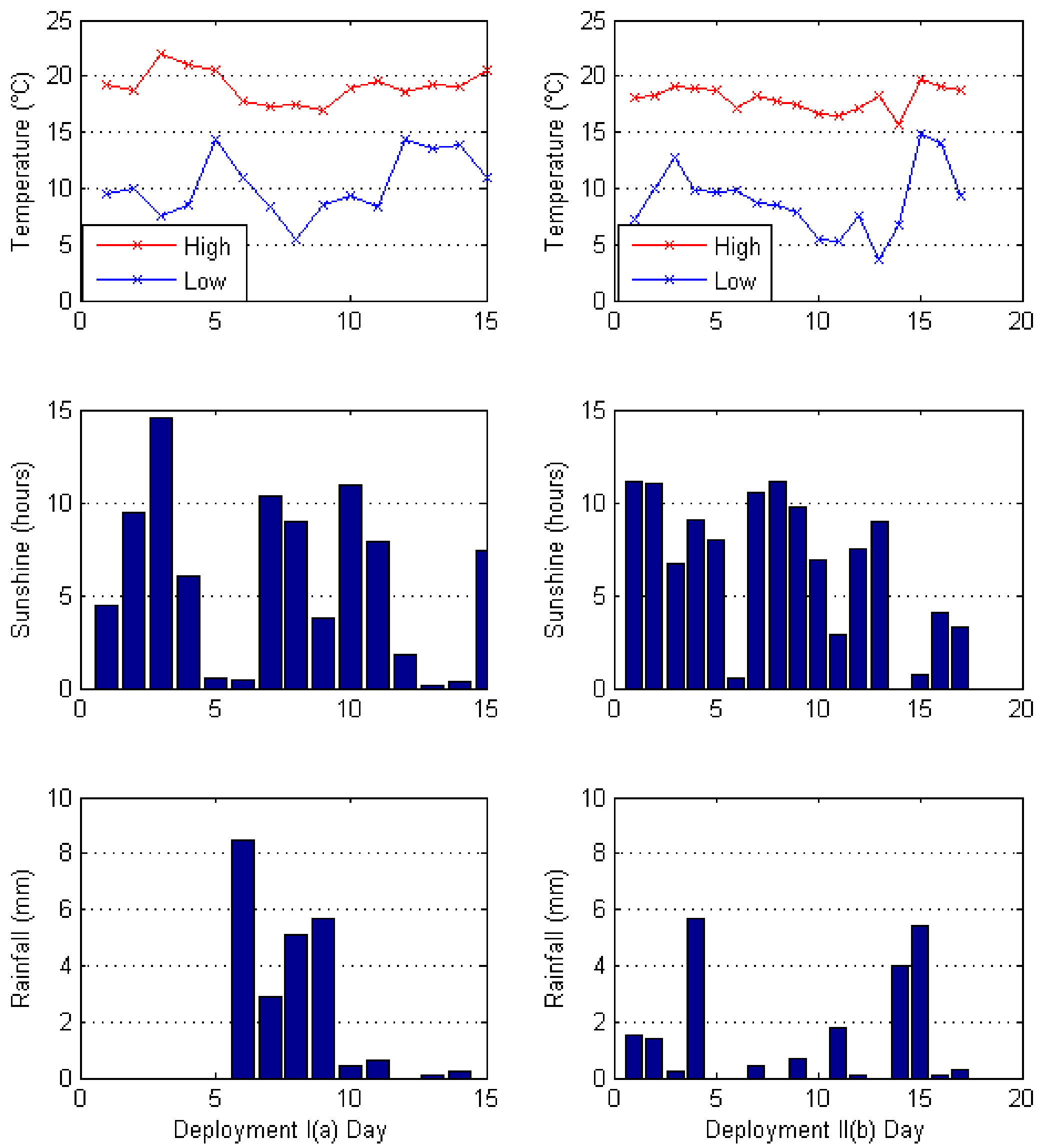

Figure 3.25 – Weather data Deployments I(a) and I(b)

3.6.2 Deployment II - Empty beehive deployment

In order to perform accurate observations on the data collected from the beehive, and to correctly validate future data/signal processing and machine learning, a deployment on an empty beehive was undertaken. This deployment took place on an empty beehive near Wilton, Co. Cork from 13/03/2016 to 20/03/2016 the collected data can be seen in Figure 3.26, Figure 3.27, Figure 3.28, and Figure 3.29. It was necessary in this case to deploy the hive much nearer a weather station, rather than at the existing apiary, to accurately observe the effect of the weather on the hive structure. This was required to identify that the changes observed in hives with colonies were a result of the colony behaviour, rather than changing weather patterns.

The relevant weather data were collected from the nearest Met Éireann automatic weather station at Cork Airport, 3km from the instrumented hive This provided accurate temperature, and sunshine readings for the area, which can be seen in Figure 3.30. The small difference between the temperatures at the weather station and at the hive can be seen in Figure 3.30 on day six, where the hive reached 0 °C, but the minimum recorded at the weather station was 1 °C. No rainfall was recorded at the weather station throughout this deployment.

The first step was to compare the external weather with the conditions recorded inside the hive. The measured internal and external temperatures had a linear correlation coefficient of $r = 0.65$, which is considered a strong correlation. The remaining temperature relationship is explained by the effect of sunshine on the metal roof of the hive. Sunshine, external temperature, and internal temperature are graphed in Figure 3.30. A proportional spike in hive temperature can clearly be seen on days with high levels of sunshine. The correlation coefficients between internal temperature and measured CO_2, humidity, and O_2 levels were $r = -0.59$, $r = -0.64$, and $r = -0.94$.

When compared with the data collected from a hive with live bees (Sections 0, 3.6.3, 3.6.4, and 3.6.5) a clear difference can be seen. The empty beehive's temperature, humidity, and gas levels varied based on the effect of the external weather. The carbon dioxide and oxygen levels were at relatively constant levels of ~416 ppm and 24.76% respectively, with the average carbon dioxide level being significantly lower than measured inside a healthy beehive. The spikes in temperature and humidity were seen to reflect the changes in the external environment including the ambient external heat and humidity, as well as changing due to the sun shining on the hive exterior and rainfall.

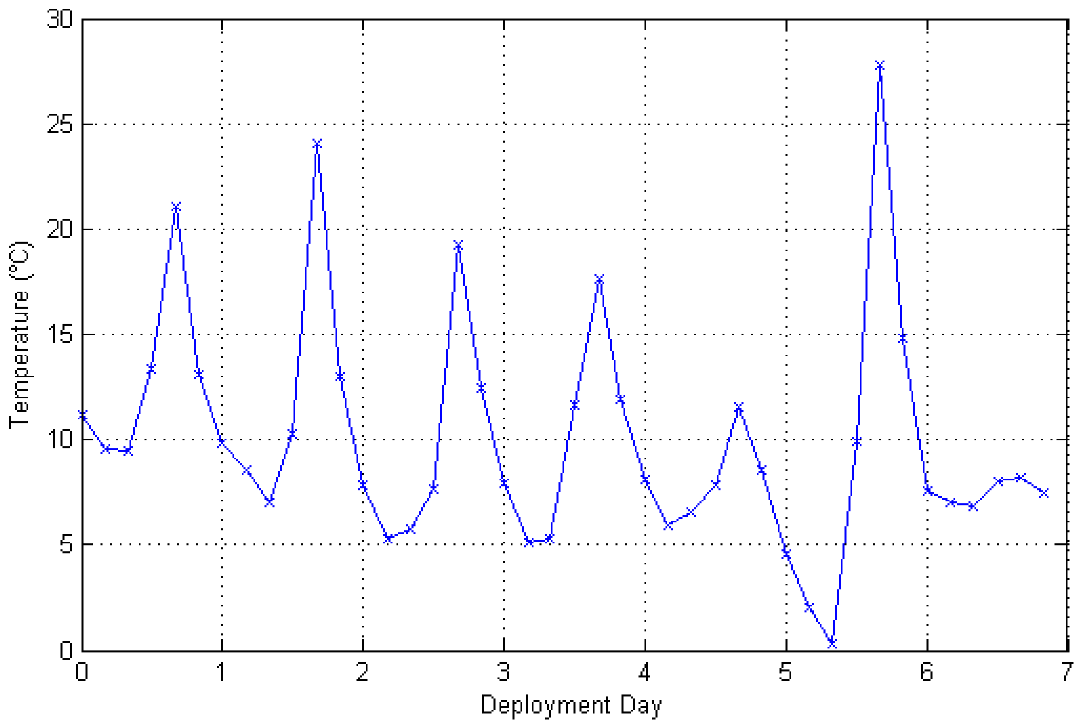

Figure 3.26 – Temperature Deployment II

Figure 3.27 – Humidity Deployment II

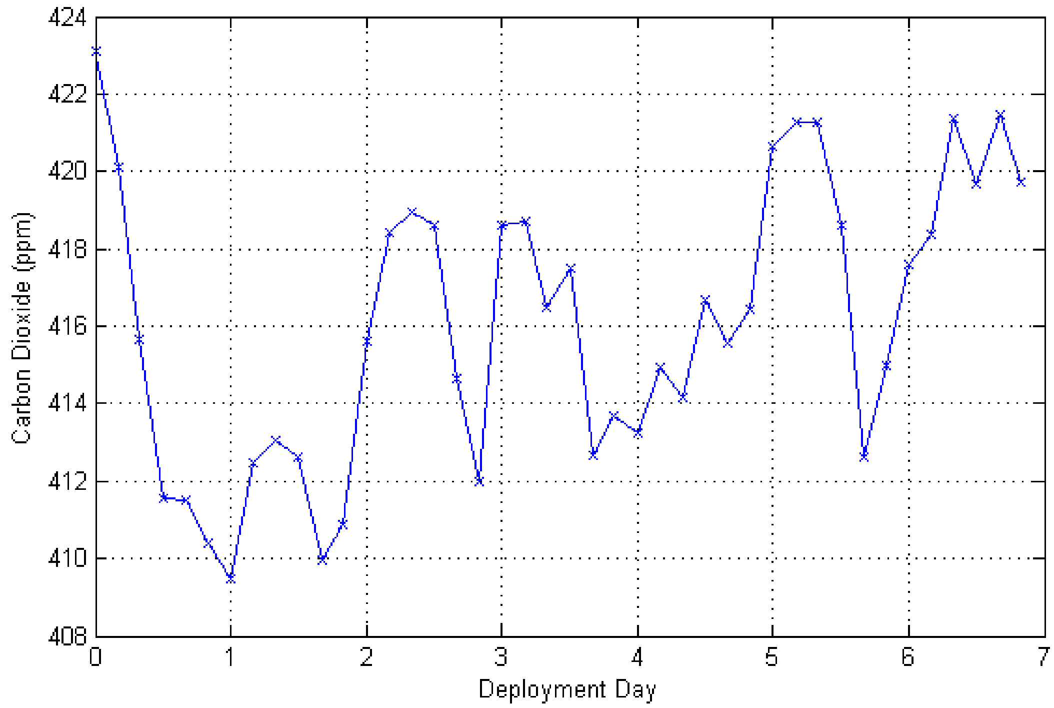

Figure 3.28 – Carbon dioxide Deployment II

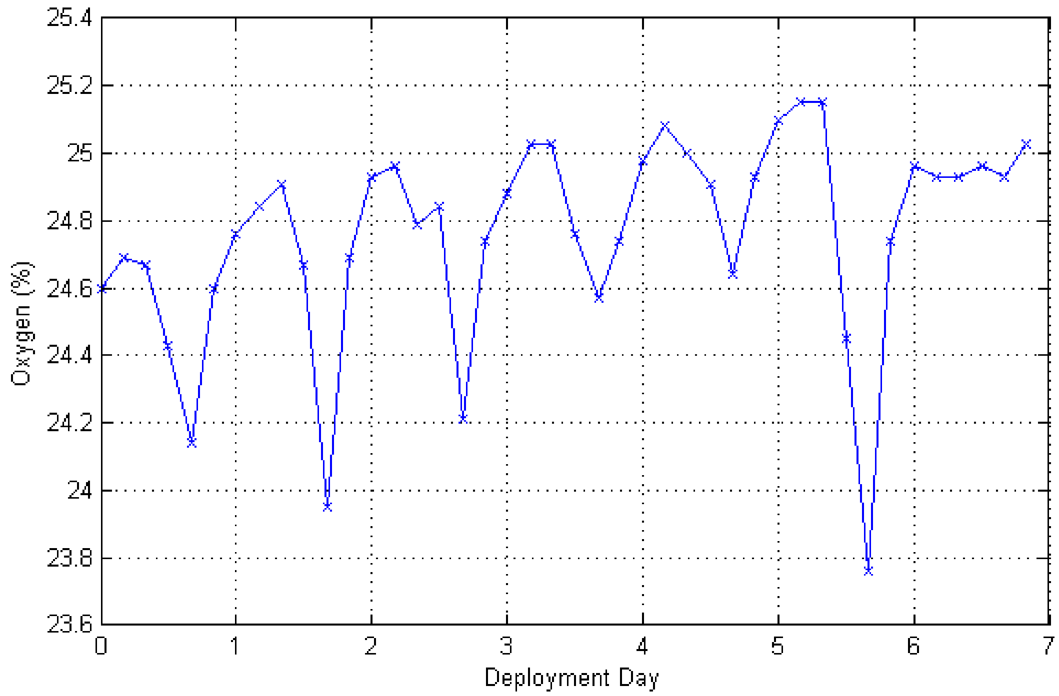

Figure 3.29 – Oxygen Deployment II

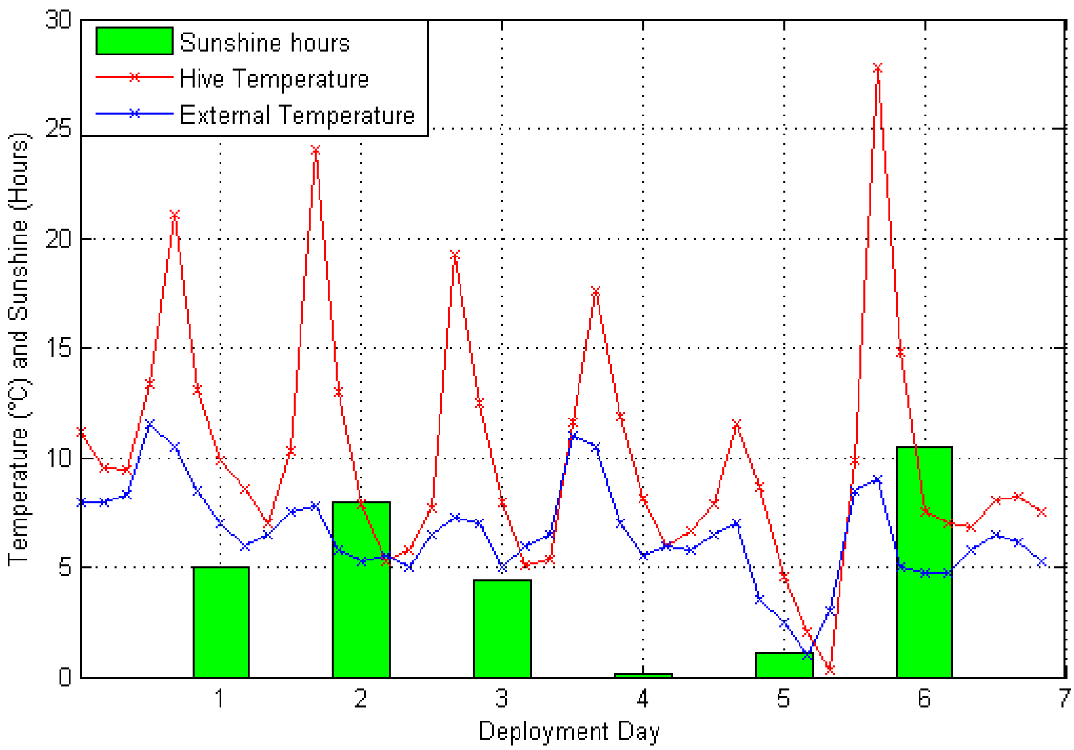

Figure 3.30 – Weather and hive temperature Deployment II

3.6.3 Deployment III - Summer deployment

Following the initial deployments I and II described above, the in-hive sensor system was revised extensively (as described in Sections 3.3 through 3.5). A further deployment of the technology was undertaken during Summer months to gather more data about the activity and conditions of colonies at this time. This deployment was undertaken on three hives at the apiary near Banteer, Co. Cork from 24/07/2016 to 05/08/2016. The same five hives were used for deployments III through IV, to compare and contrast the changes in the same colonies throughout the different datasets. To facilitate this the hives were given numerical identifiers 1 to 5, which were physically written on the hive exteriors, and included in the data packets transmitted from each sensor node.

Throughout this deployment the average temperature in all three hives remained constant, at 17-19 °C with the typical diurnal fluctuation seen in previous deployments, in this case the fluctuation was ±~4 °C. The humidity in all three hives remained quite constant in the 65 – 80% range, despite one extremely rainy day with 21 mm of rain, which can be seen reflected in the humidity data of all three hives.

The carbon dioxide (CO_2) in all three hives fluctuated between ambient levels (400 ppm) and 500 ppm for the first 4 days of the deployment, before reaching a steady value in the 450 – 500 ppm range. This reflects the previous observation that a healthy, normal sized colony regulates it's carbon dioxide levels, and works to maintain it at a constant level, which is slightly higher than the ambient level found outside the hive.

As in previous experiments the oxygen levels remained constant around 23%, with diurnal fluctuations. A possible explanation for this fluctuation would be airflow changes as a result of fanning, which would be expected at this time of year. In particular, a dramatic drop in O_2 can be observed on day eight, which was the day with high rainfall. On such a day, most of the bees would have not left the hive to forage, is it would be unsafe for them to fly, extra fanning would be expected to prevent the hive from overheating due to the warm weather. The data collected can be seen in Figure 3.31, Figure 3.32, Figure 3.33, and Figure 3.34. Weather data was collected from the weather stations at Moorepark, Co. Cork and Cork Airport, and can be found in Figure 3.35.

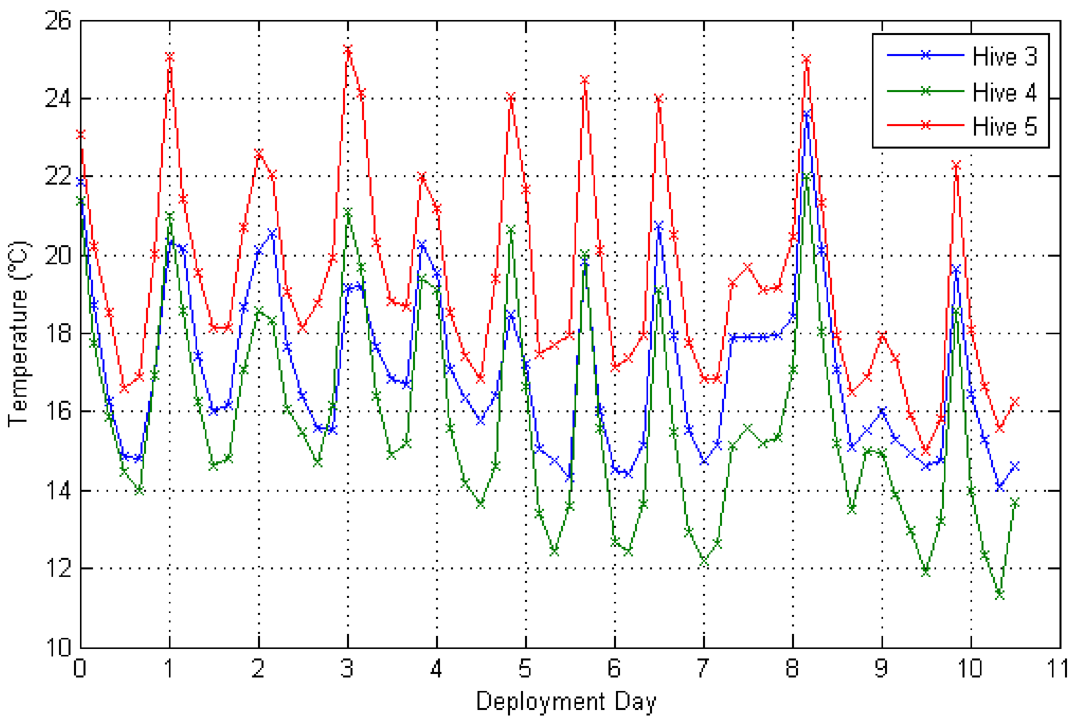

Figure 3.31 – Temperature Deployment III

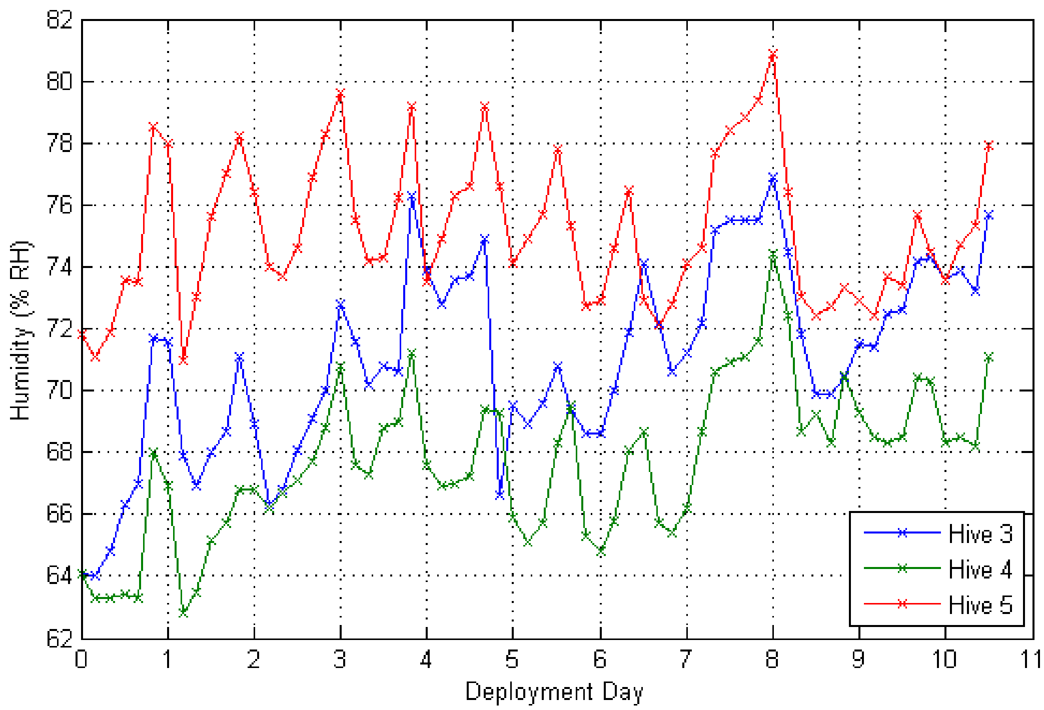

Figure 3.32 – Humidity Deployment III

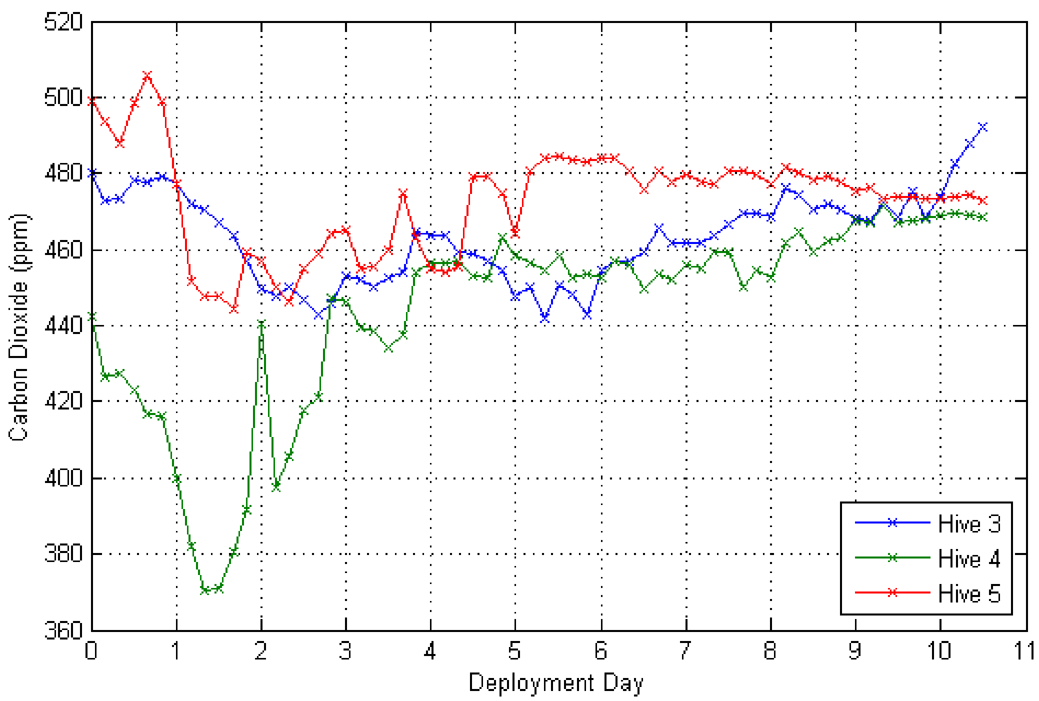

Figure 3.33 – Carbon dioxide Deployment III

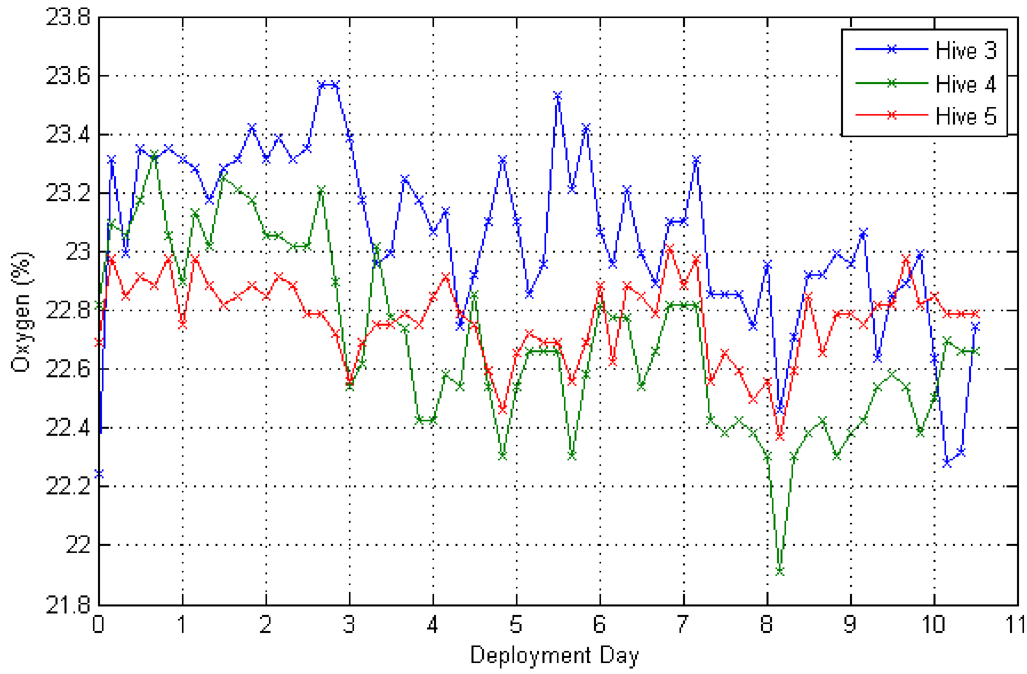

Figure 3.34 – Oxygen Deployment III

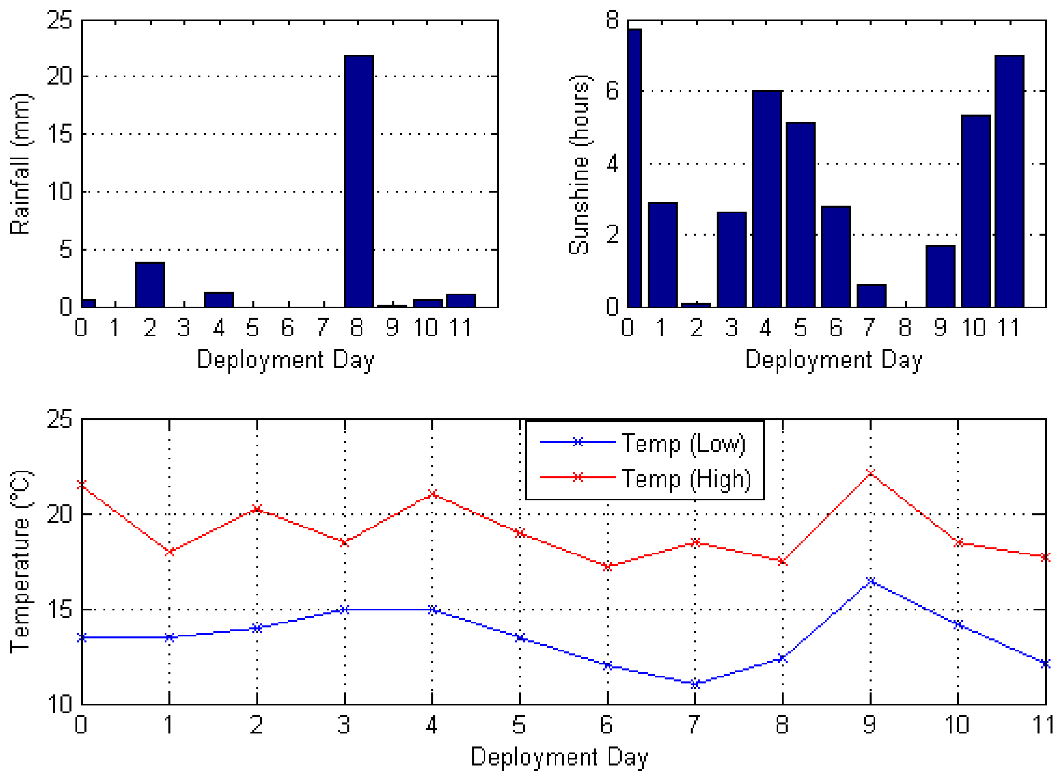

Figure 3.35 – Weather Deployment III

3.6.4 Deployment IV - Autumn/Winter deployment

For deployment IV, the late autumn/early winter season was selected for observation of a hive preparing for the winter season. Three in-hive sensor systems were deployed on the same three hives near Banteer, Co. Cork as in Deployment III, from 12/10/2016 to 18/11/2016. Again, relevant weather data was collected from the Moorepark, Fermoy, Co. Cork and Cork Airport automatic Met Éireann weather stations for comparison with the in-hive recordings.

The temperature in all three hives was constant for the first 13 days, at approximately 14 °C ±~4 °C. Following this the average temperature drops off to an average of 6 °C, peaking once more to 15 °C on day 32, and falling back to ~3 °C by the end of the deployment. The humidity remained in the 60 – 85 °C range for all three hives throughout the deployment. The carbon dioxide levels fluctuated over a very wide range from 350 ppm (minimum sensor reading, sensors saturated at this point multiple times) to peaks of >2500 ppm. Again, the oxygen levels were constant with fluctuations throughout around 23%. The collected temperature, humidity, carbon dioxide, and oxygen data is plotted in Figure 3.36, Figure 3.37, Figure 3.38, and Figure 3.39, and the weather data is shown in Figure 3.40.

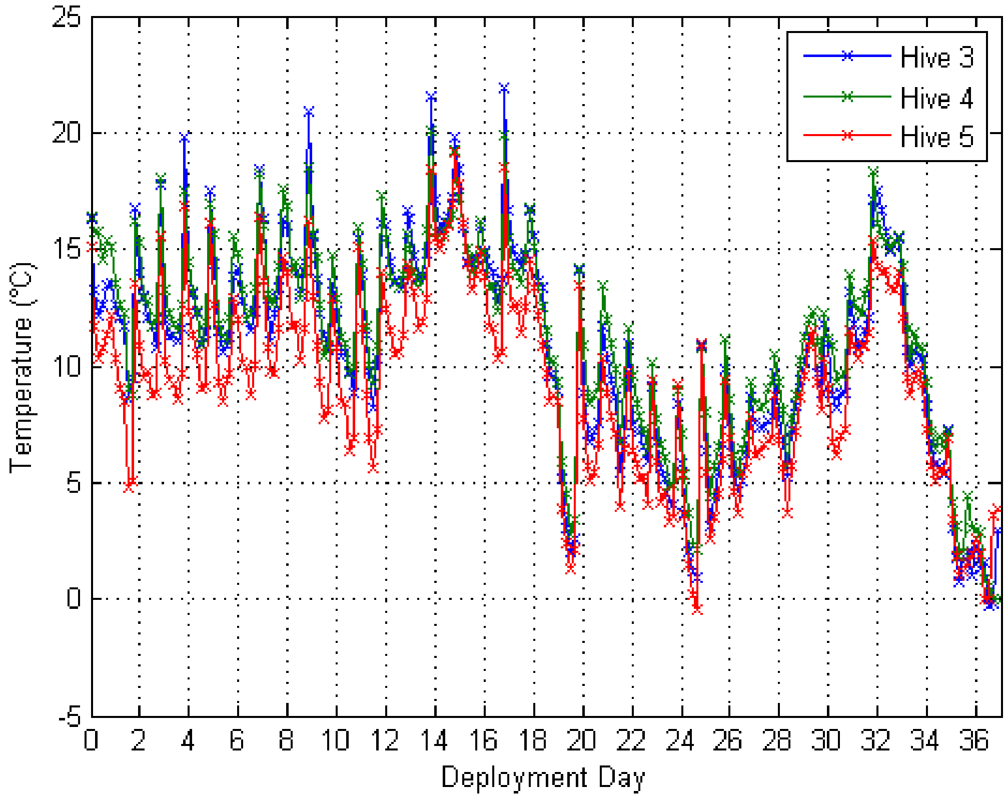

Figure 3.36 – Temperature Deployment IV

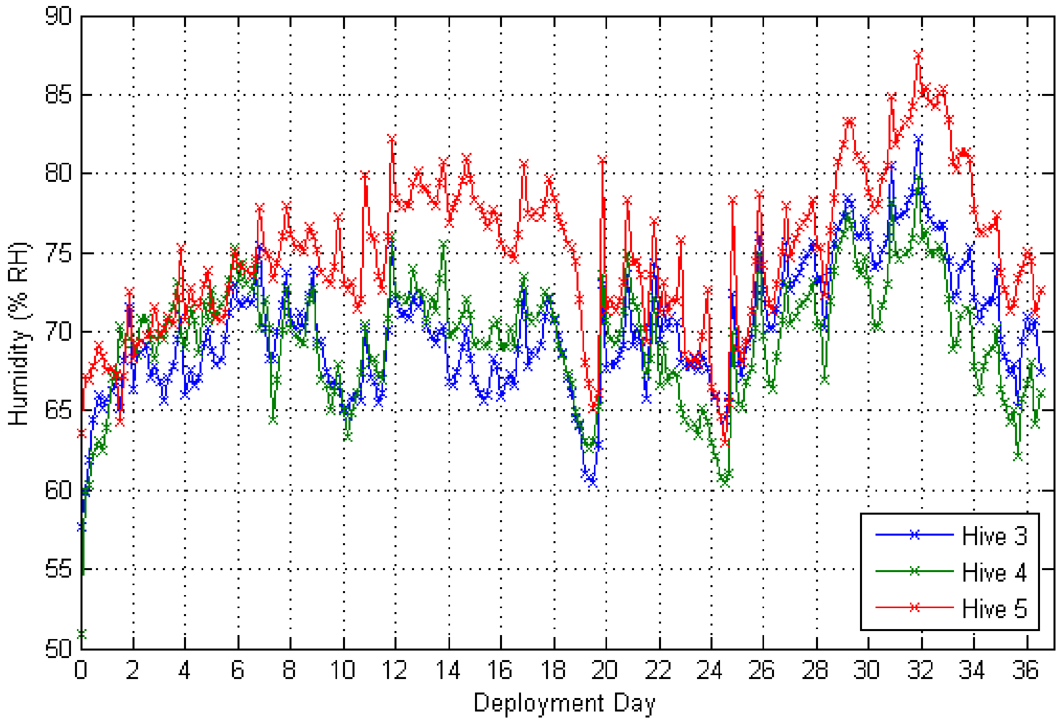

Figure 3.37 – Humidity Deployment IV

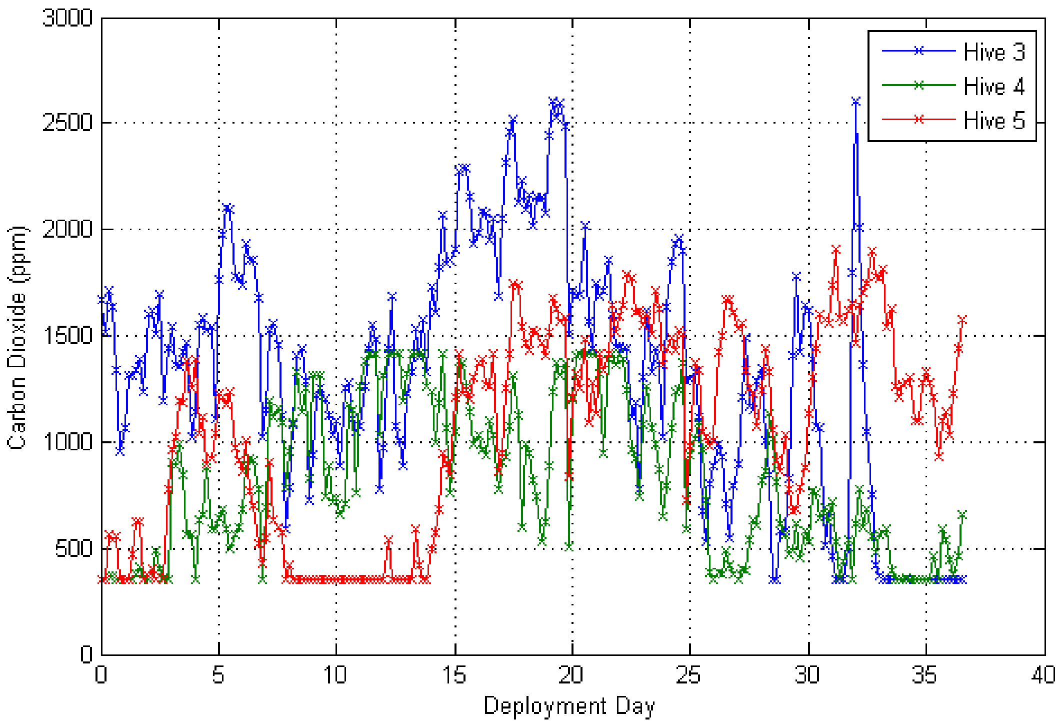

Figure 3.38 – Carbon dioxide Deployment IV

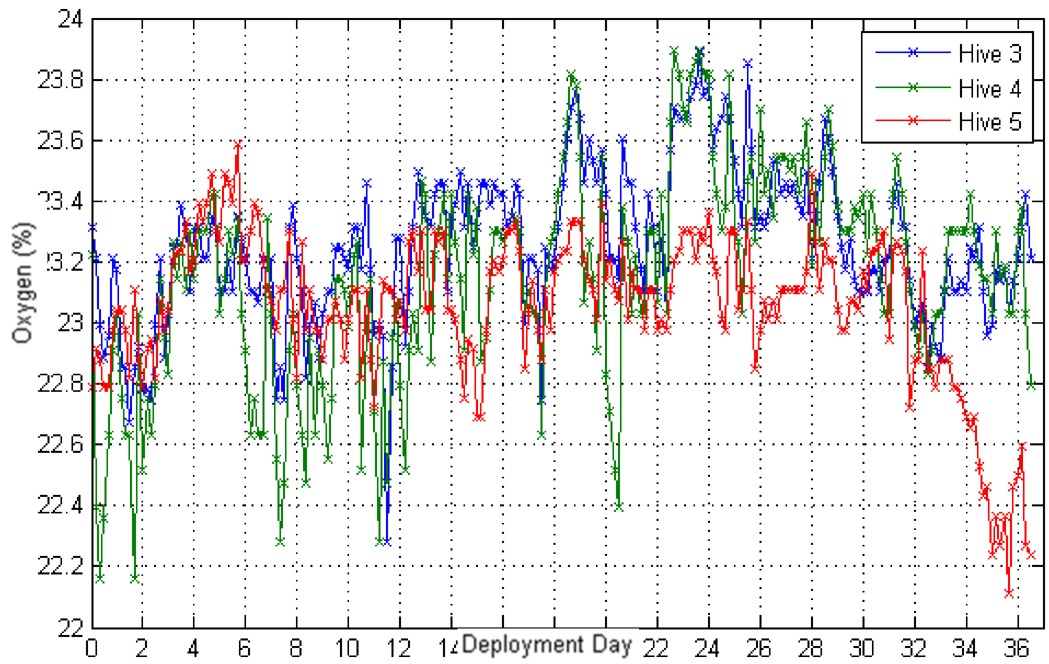

Figure 3.39 – Oxygen Deployment IV

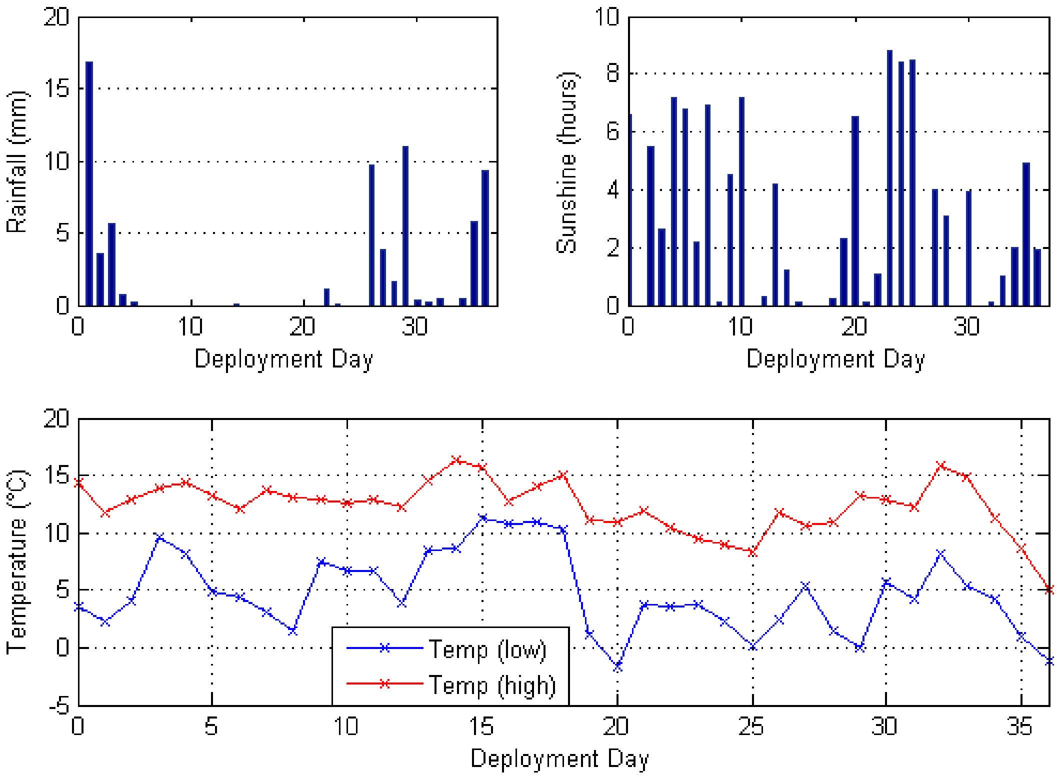

Figure 3.40 – Weather Deployment IV

3.6.5 Deployment V – Late Winter/Early Spring

The final deployment was during late Winter and early Spring, to measure the parameters within the hive as the colony prepared to restock the hive population and begin foraging. This deployment took place on 5 hives at the apiary near Banteer, Co. Cork, over 66 days from 12/01/2017 to 18/03/2017. The colony in Hive 4 during this deployment was very weak, and died shortly after the deployment ended. The internal temperatures recorded was consistent across all five hives, fluctuating around 5 °C until day 30 of the deployment. Following this the average temperature of all hives rose to ~10 °C for 8 days, dropped to ~5 °C again for 12 more days, and rose to ~10 °C for the remainder of the deployment. All hives maintained a humidity of 70 – 90%, except Hive 1, which showed a humidity of >90%. The carbon dioxide levels in Hives 3 and 5 started at high constant levels (3,100 and 2700 ppm respectively) before dropping rapidly to the 350 – 1500 ppm range, this is expected to be as a result of the formation of a Winter cluster (Section 2.3.1). The CO_2 in Hive 1 remained constant at high levels (500 – 700 ppm) throughout the deployment. In Hive 2, the measured CO_2 remained in the 450 – 550 ppm range. In Hive 4 the CO_2 remained in the rural ambient range (350 – 410 ppm). The oxygen levels in all hives remained between 21 – 23% throughout the deployment. The hive data, and the data collected from the Met Éireann weather stations at Moorepark and Cork Airport are shown in Figure 3.41, Figure 3.42, Figure 3.43, Figure 3.44, and Figure 3.45.

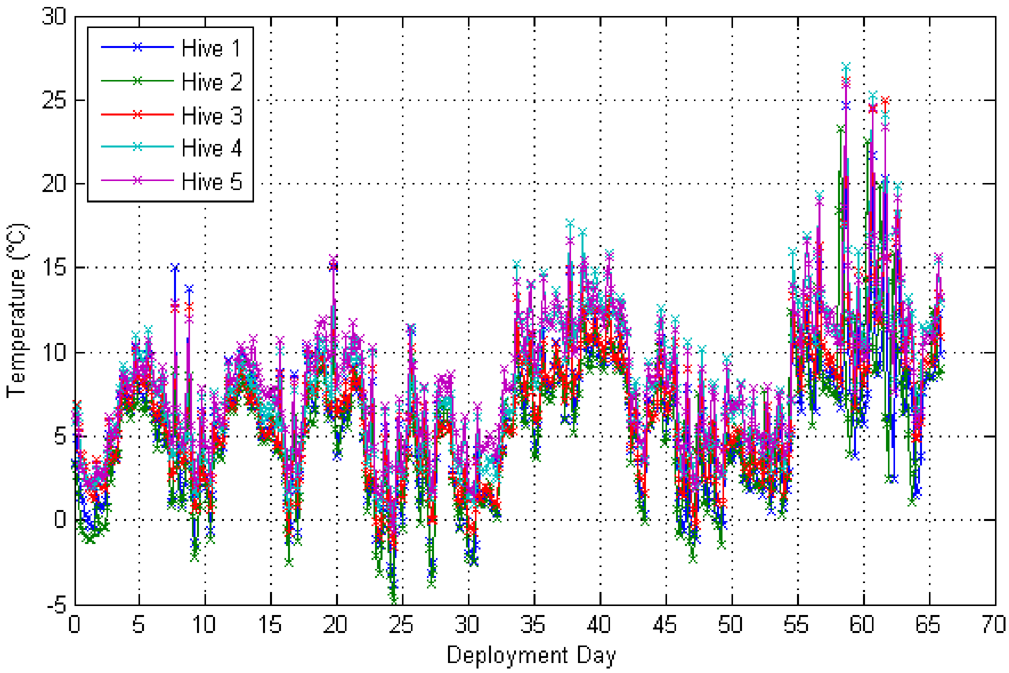

Figure 3.41 – Temperature Deployment V

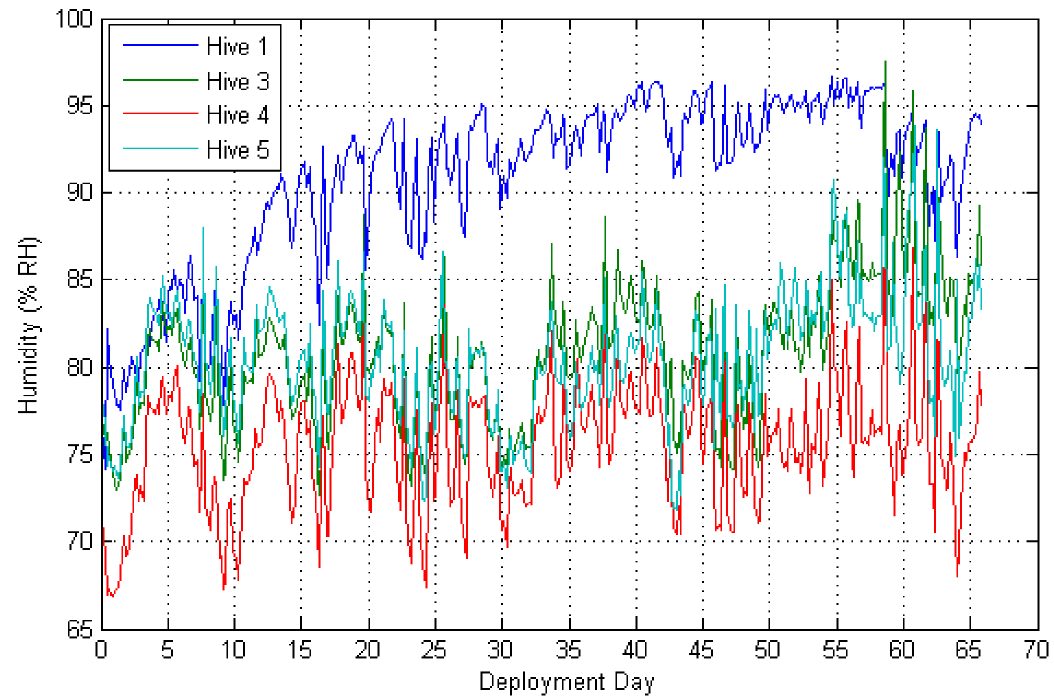

Figure 3.42 – Humidity Deployment V

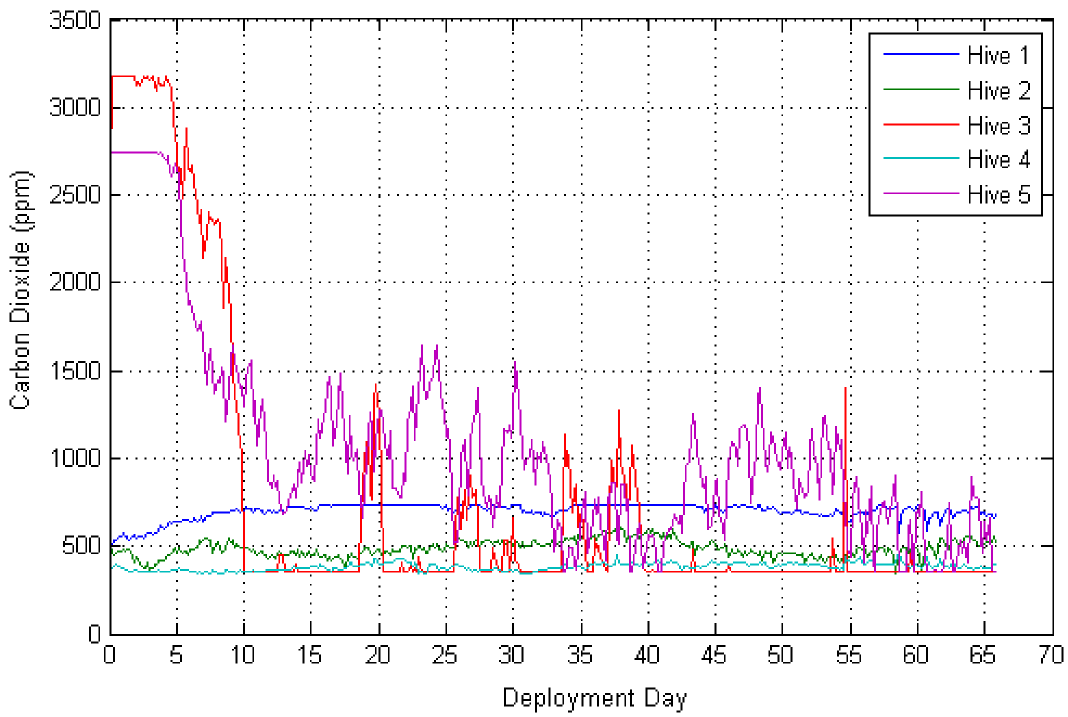

Figure 3.43 – Carbon dioxide Deployment V

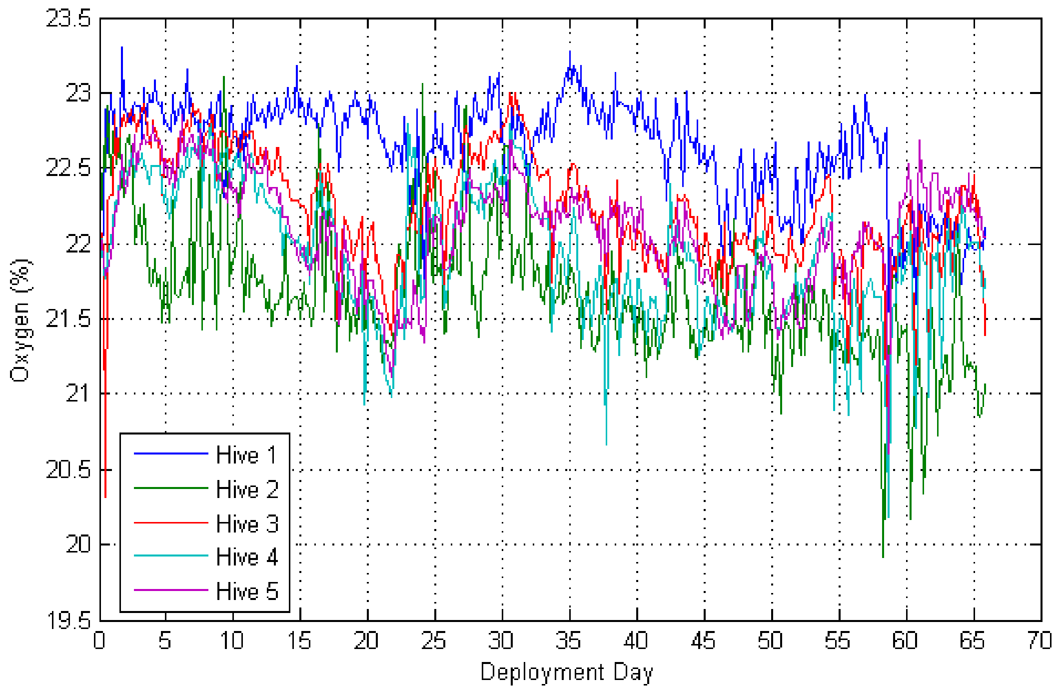

Figure 3.44 – Oxygen Deployment V

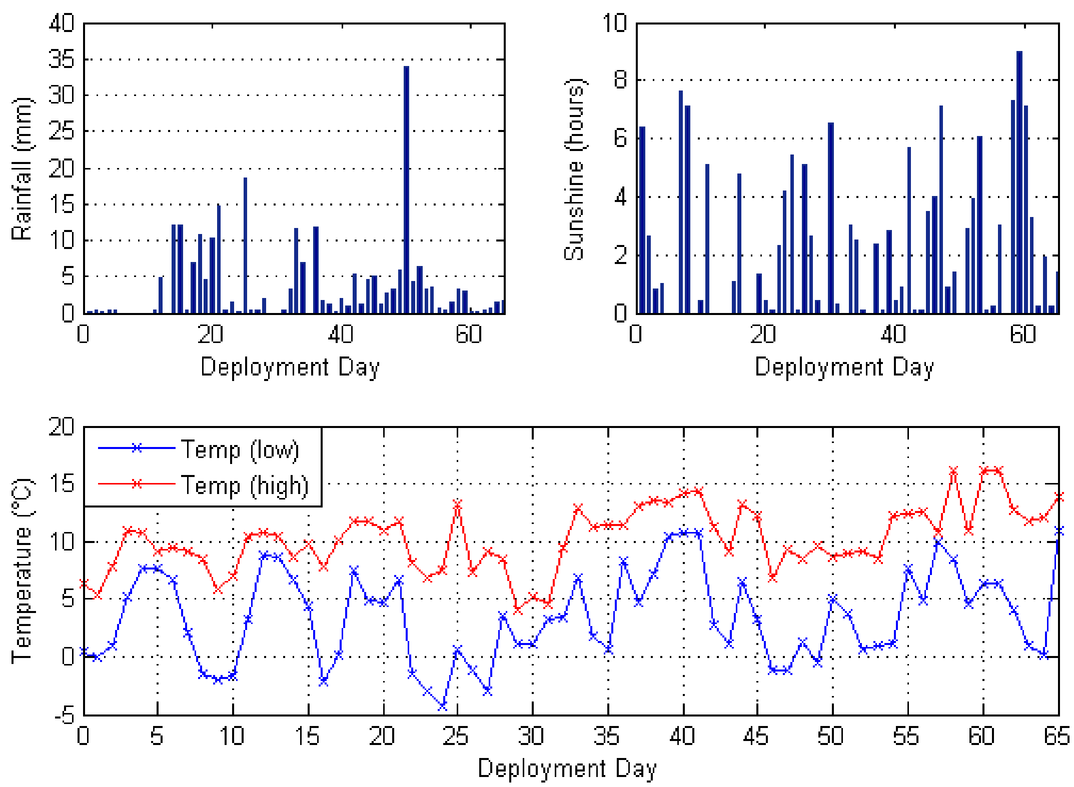

Figure 3.45 – Weather Deployment V

3.7 Discussion

This chapter discussed the successful design, test, and in-field deployment of a Wireless Sensor Network system for in-hive monitoring of honey bee colonies.

Key design considerations were used to ensure that the sensor nodes did not impact the activities of the colony, or the beekeeper’s typical hive maintenance and inspections. This included: selecting a platform with an IP65 rated waterproof enclosure to reduce node replacement, installing the node inside the hive roof to allow the keeper to remove it easily during hive visits, and including a mesh to prevent the bees from accessing the sensors.

Nine sensors were initially tested in deployments I and II, before being reduced to five (temperature, humidity, carbon dioxide, oxygen, and acceleration). These five identified sensors provided an accurate reflection of the hive conditions and position using only one node per hive.

A multi-radio solution utilising a local ZigBee network for in-hive data collection and aggregation on a base station, with a 3G radio for remote upload of aggregated data, was selected. This allowed the in-hive sensor nodes to achieve low power communication for extended lifetime, while also enabling rural deployment through long range 3G communication.

Extended system lifetime, and self-sustainable operation was achieved through energy harvesting (solar panels), low energy operation, and restricted use of long range radios. An Energy-Aware Adaptive Sampling Algorithm (EASA) was proposed and explored as an option for increased node lifetime in future studies. Alternative solutions for energy harvesting sources were proposed for future deployments.

The comprehensive dataset collected from five separate deployments of these sensors, throughout the different key beekeeping seasons were presented, together with the local weather conditions for each deployment. The recorded data from the hives was analysed with consideration for the observations from Chapter 2, and many of the expected behaviours such as fanning, swarming, clustering, foraging, and overwintering were observed.

These results were used to develop, train, and test the proposed hive geometry changes, signal processing techniques, and machine learning algorithms described throughout Chapters 4 through 5 of this thesis. Parts of this chapter were published in peer reviewed conference proceedings [143] and a peer reviewed journal paper [144]

4 Actuation for Airflow & Temperature Control in Beehives

4.1 Introduction

The temperature of a honey bee hive is identified in Chapter 2 a key parameter influencing almost every aspect of the colony's behaviour and conditions. Unsuitable temperature conditions can lead to: proliferation of disease or infestation; chilling of the brood (bee larvae); comb instability; delayed/reduced honey production; or in extreme cases, bees dying from overheating or cooling. Throughout the year, a significant portion of the colony's activities are dedicated to controlling the hive temperature. Honey bees have a variety of physiological processes they can engage in to either increase or decrease the temperature or airflow within the hive [140].

A method of maintaining the hive temperature in the ideal range through effective ventilation and airflow control would allow the bees involved in the activities above to engage in other tasks. This could improve the productivity and condition of the beehive considerably throughout the year. This work outlined in this chapter proposed to design an energy efficient actuator system as part of the hive monitoring WSN described in Chapter 3 to control the airflow within the hive in response to the recorded temperature changes. Parts of the work described in this chapter were undertaken in conjunction with MEngSc students in the Department of Electrical and Electronic Engineering at University College Cork [145, 146], and one journal paper based on this chapter is currently in the peer review process [147].

To achieve effective control of beehive airflow an accurate model of beehive airflow and geometry was required. To achieve this a comprehensive study of beehive ventilation was undertaken [146]. Finite Element Analysis was used to develop a model for simulating the flow of air inside a beehive. A 3D geometric model of a National hive was created and Computational Fluid Dynamics (CFD) modelling software was used for analysis. The airflow in a real hive was tested using heating elements to represent the internal temperature conditions of an actual colony. Using these studies, the potential impact of changing hive geometry to improve the colony conditions and improve colony productivity was explored. A compound mechanism was designed to control the ventilation of the hive through multiple inlets. A lead screw based mechanism was selected for its simplicity, efficiency and accuracy [145]. A prototype was designed and fabricated for test and calibration on a deployment beehive.

This prototype mechanism, and the improved beehive geometry, were used together with a Wireless Sensor Network (WSN) to implement a temperature control system for beehives. The control algorithm utilised was based on the classic Proportional Integral Derivative (PID) controller. An experimental prototype of the control system was deployed and tested in the laboratory on a cedar wood National beehive. The response of the system to the hive temperatures recorded during the WSN deployments described in Chapter 3 were also simulated. The control system was found to be effective for controlling the in-hive temperature detected by the WSN to a high accuracy, and reducing the temperature control actions required from the colony.

The key research questions in this chapter were:

- How can the ventilation and thermoregulation behaviours of the hive structure be modelled?
- Are there alternative hive geometries for the typical beehive which would provide more effective airflow?
- Can a mechanism be designed to control the hive environment effectively and remotely, to reduce the amount of regulation activities required from the bees?

- Can this mechanism be designed with a suitably low energy profile to be deployed in an energy aware constrained system?

4.2 Thermoregulation Within the Beehive

The temperature of a beehive is a vitally important parameter, influencing almost every activity and process undertaken inside the beehive. During honey production the temperature and airflow within the hive are controlled by the worker bees to evaporate water, a key step in turning nectar into honey [148]. During reproduction, in order for larvae to develop correctly the brood must be maintained at a temperature of 33 °C – 36 °C [30]. Variations from this temperature range can lead to reduced numbers of brood surviving the season, as well as developmental issues in the young bees including poor foraging behaviours and poor sensory reception [14, 149].

Overheating within the hive can cause the wax frames to lose quality, weaken, and collapse, beeswax has a melting point of 61 °C [150]. Several diseases and pests can infest the hive as a result of poor temperature control, including: chilled brood, chalkbrood, and dysentery [139]. Temperature has been identified as a predicting factor in over-winter colony losses by Switanek *et al.* [151]. Several studies have investigated the use of temperature sensors within the hive to evaluate and predict the status of a colony [82, 83, 152].

Honey bees have developed several physiological processes which they engage in to control the temperature and airflow within the hive. When the ambient temperature is high, the bees will move their wings in a "fanning" motion to force air throughout the hive for cooling [75]. In cool ambient temperatures, the bees can vibrate the muscles of their wings to increase their body heat dramatically to as high as 43 °C [75]. This is known as “shivering”, the bees then press their bodies against the brood cell to increase the temperature of the larvae inside. Bees also use their bodies to reduce the temperature of the hive in warm conditions by pressing themselves against the overheating surfaces to absorb heat energy. They can also carry water droplets into the hive to reduce the temperature of cells through evaporation [30]. During cold winter months, when the external temperature drops below 7 °C, the bees engage in an activity called “clustering”. When clustering, the bees move to the centre of the hive and form a well-insulated ball, using their body heat to increase the likelihood of survival until spring [153].

Ventilation in the hive has two main purposes for the colony: removal of waste gases and moisture, and thermal regulation of the hive [30]. The primary method of ventilation within the beehive is natural ventilation through the ventilation holes at the top and bottom of the hive, due to thermal buoyancy and the effect of external wind. These holes can be opened and closed by the bees using wax and propolis in order to increase and decrease the flow rate. This method of ventilation is key, as it doesn't require the bees to actively expend energy to move air through the hive, freeing them to work on other activities required.

4.3 Simulation of Beehive Airflow

4.3.1 Requirements

To simulate the heat and mass transfer within the beehive accurately, a suitable model for the colony within the hive was required. Several varieties of model were found in the literature, including a cluster of bees inside the hive [154], and a cluster outside the beehive [72]. The most useful model of a honey bee colony was described by Fehler *et al.* [79]. In this model, the colony is treated as a porous medium made up of honeybees and air with a fixed shape. For the simulations described in this chapter the colony was considered to be evenly distributed over the face of each beehive frame. This colony layout is a preliminary assumption as the positioning and density of the bees are known to vary throughout the hive, but have not been thoroughly investigated or modelled previously.

Another consideration for accurate simulation of beehive airflow is the dimensions of the hive used in the model. The dimensions of a National beehive are outlined in Figure 2.1 in Chapter 2. This was the design of all the beehives on which the hive monitoring WSN described in Chapter 3 was deployed. The simulations considered a typical National beehive consisting of one brood chamber, one honey super, an open mesh floor, and a roof.

4.3.2 Numerical modelling

The model of the beehive used for numerical modelling was developed based on the dimensions shown in Figure 2.1 in the SolidWorks® computer aided design software [146]. To create a full 3D beehive model, the individual components of the beehive were developed and combined. SolidWorks is an ideal environment to accurately draw the model, but not to run the flow simulations. Therefore, the model was exported from SolidWorks to ANSYS Fluent 12.0, a dedicated CFD solution suite. The model build and CFD simulation work was undertaken by Donal O'Brien, a MEngSc student in the Department of Electrical and Electronic Engineering at University College Cork [146]. The parameters of the CFD simulation are outlined below:

- Humidity, swarm volume, base mesh, and queen excluder were not considered in the model.
- Internal hive surface temperature of 35 °C.
- Temperature of inlet air was varied between 12-25 °C with a velocity of 1 m/s.
- Activities of the bees to control the temperature were not considered.

Figure 4.1 is a graphical representation of the air flow with the Velocity Path lines indicating how the air flows through the hive from the entrance through to the outlets. The results indicated that the air flow velocities increase rapidly near the hive outlets due to the pressure difference in the external air.

From the ANSYS simulation results, it was clear that ambient air temperature affects fluid flow in a beehive. At low ambient air temperature (12 °C), the beehive was passively ventilated by the temperature difference between the external environment and the internal surface of the hive (35 °C). This temperature gradient creates buoyancy forces and free convection currents that push the warm air out of the hive through the vents in the hive roof and pull ambient external air into the hive through the entrances, thereby cooling the internal surfaces. The greater the temperature gradient, the more the hive is ventilated. As the internal temperature of the hive remains constant with very little variation (35 °C), this factor is therefore mainly dependent on the temperature of the external air.

From the simulation results, it was found that when the ambient air temperature rose from 15 °C to 25 °C, the air flow from the hive reduced by 35%. In such conditions, bees must engage in fanning to increase the air flow through the hive by forced convection. This activity is energy intensive, potentially reducing the productivity of the colony in terms of foraging and brood rearing, may use honey stores, and may affect the ability of the bees to maintain stability and the health of the colony.

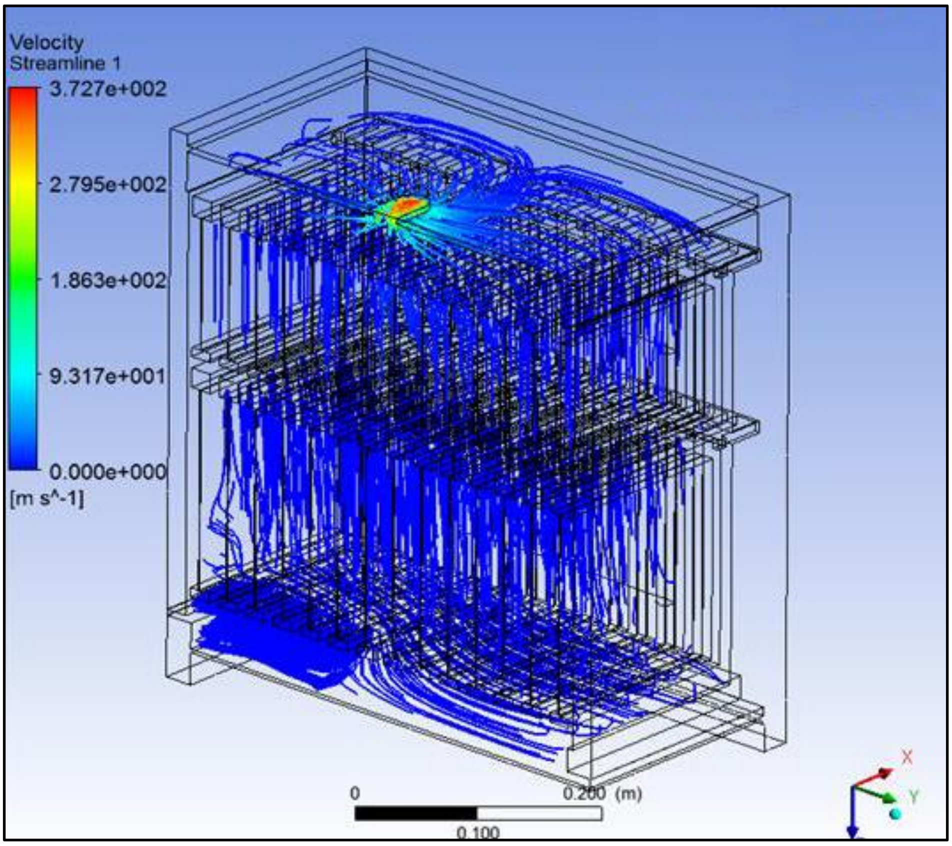

Figure 4.1 – Air flow in the National hive [146]

4.3.3 Experimental modelling

The next stage of the study was to perform experimental work on an actual beehive. The objective of this stage was to perform experiments on a beehive in a laboratory and compare the recorded data with the theoretical results achieved in ANSYS Fluent simulations. The air flowing inside and outside the beehive was measured using a testo 435 vane anemometer. The external air temperature was varied between 12-25 °C, and the internal temperature of the hive was maintained at 35 °C using heating elements. These results agreed with the results from ANSYS simulations to within a margin of 10%. This allowed the developed model to be used as a preliminary model of a National beehive for future work.

4.4 Hive Geometry

An alternative geometry for parts of the hive was proposed based on the results of the 3D model. The internal cover of the hive is known as a “crown board”. It typically contains one or two outlets which allow the keeper to place buckets of syrup with sugar solution to feed the bees; they also allow hot air and pollutants to exit the hive.

An alternative model of this part with five outlets was proposed and tested in simulations and laboratory experiment This, if effective, would be an easily implemented change that could be made by beekeepers of all skill levels to their National hives to improve airflow. The prototype of the proposed crown board change can be seen below in Figure 4.2, the classic National hive model is labelled “Model A”, and the proposed alternative geometry is labelled “Model B”.

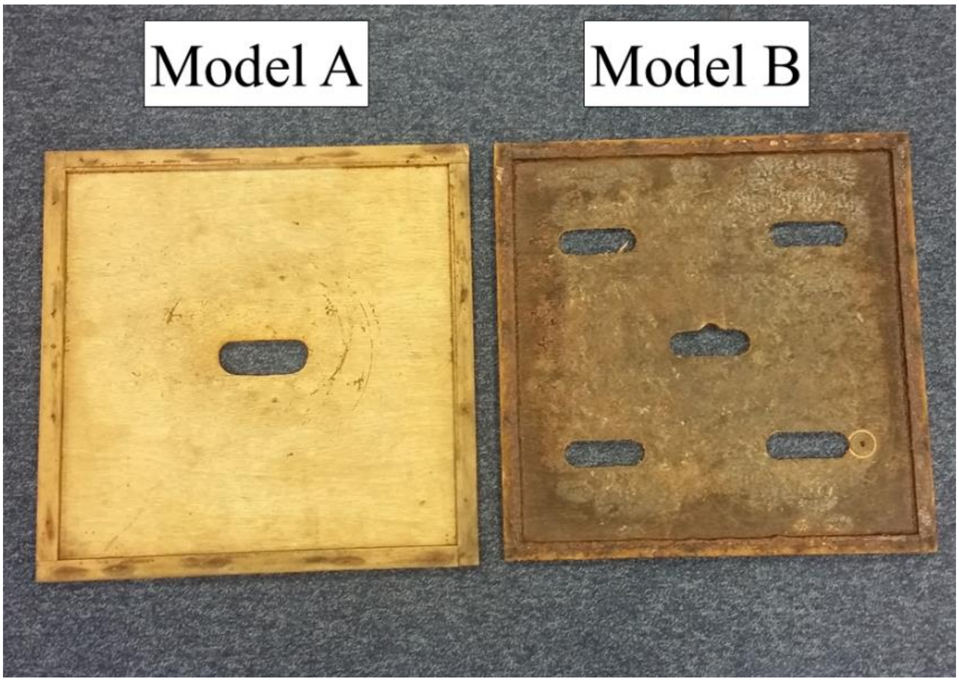

Figure 4.2 – Crown board geometries

Model B was simulated in ANSYS using the same parameters as the simulation of Model A described above in Section 4.3.2. Results from the ANSYS simulations illustrated in Figure 4.1 and Figure 4.3 indicate the effect of altering the beehive geometry. The additional outlets from the beehive increased the overall volumetric flow rate of the air exiting the hive, with the air velocity at each outlet remaining constant, thereby allowing for easier removal of waste gases and excess heat. The ambient temperature of the outside air was found to have a much smaller impact on the internal temperature of model B than on model A. This improved ventilation suggests that model B is better in terms of effective air transfer from the beehive to the environment.

A crown board matching the design of Model B was fabricated in order to perform an in-laboratory experiment on the new model. The volume of air exiting the hive (in total) in model B was found to be greater than that of model A. This agreed with the simulation in showing that the overall transfer of air from the hive was more effective for model B.

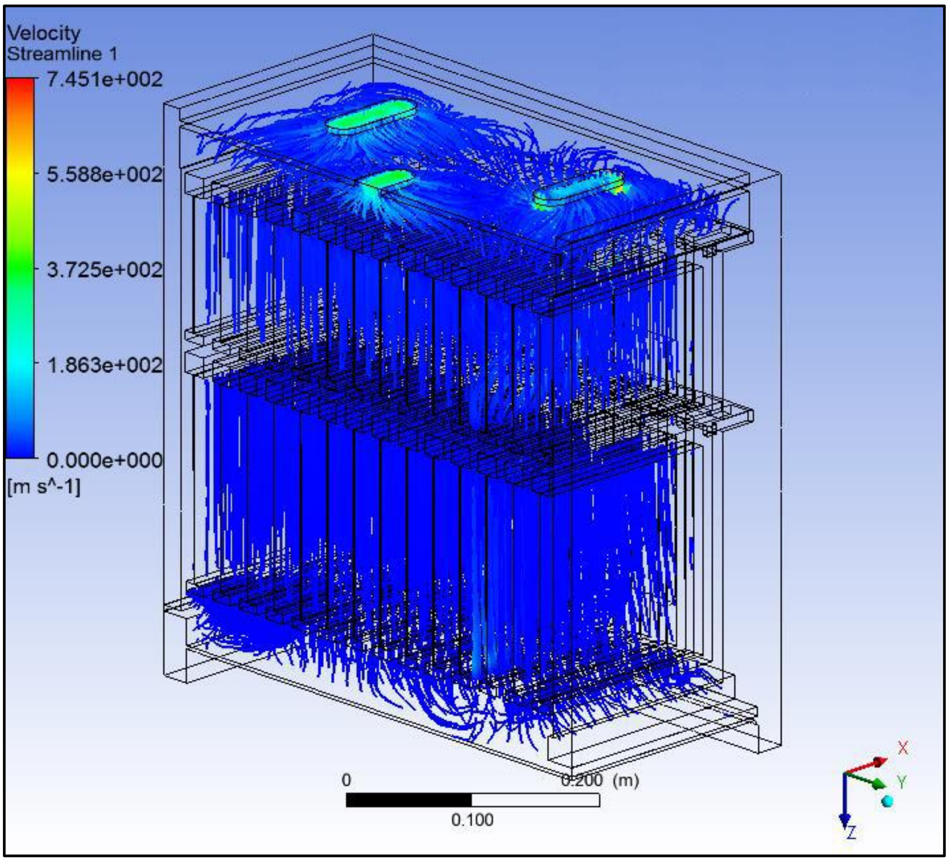

Figure 4.3 – Air flow in the modified National hive [146]

4.5 Mechanical design for Beehive Ventilation

Based on the simulations and experimentation on the airflow in the hive, it was proposed that a ventilation mechanism could be designed based on these insights. This mechanism would provide a higher level of control over the airflow within the hive. This mechanism, based on the proposed five outlet design above, could adjust the airflow and ventilation within the hive in order to optimise the conditions within the hive, thereby reducing the amount of temperature control actions required by the colony. This mechanism could be integrated with the WSN outlined in Chapter 3 to create a Wireless Sensor and Actuator Network (WSAN), using the sensor data to achieve real time control of the colony conditions.

4.5.1 Lead screw mechanism design

A lead screw design was proposed for the design of the ventilation mechanism. Other mechanisms were considered (namely, the iris mechanism [155] and slider crank mechanism [156]), but the lead screw design was selected as it provided a high level of accuracy while maintaining a low complexity design with a low number of parts which were easy to fabricate. This is a simple mechanism design which can translate rotary motion from a motor to linear motion. The mechanical design of the mechanism was undertaken by Danny Morgan, a MEngSc student in the Department of Electrical and Electronic Engineering at University College Cork [145].

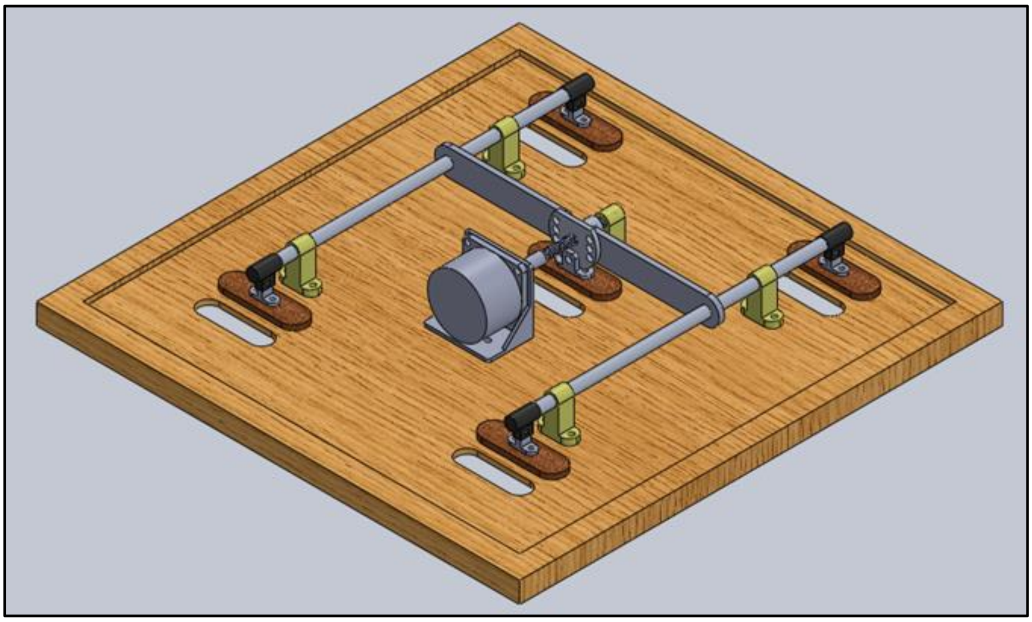

Figure 4.4 – Mechanism design [145]

The lead screw design utilises a single motor, and by using a stepper motor it would be possible to achieve a high level of precision in the width of the outlet. An 8mm diameter, 75mm lead, 10 turn per inch, 2.5 mm pitch, single start, ACME thread was selected for the core lead screw part of the mechanism [145]. An orthographic projection of the final mechanism design can be seen in Figure 4.4.

These design considerations guaranteed the core design requirements of the mechanism for this application, which were:

- High torque, to overcome friction between the mechanism and the crown board of the hive.
- High precision and repeatability, to guarantee the size of the openings, even after many cycles.
- Quiet and low speed operation, to not disturb the colony or crush bees.

4.5.2 Motor selection

The motor selected to drive the designed mechanism was selected based on the following initial considerations:

- High torque to overcome friction between the mechanism and crown board. The minimum torque required to rotate the screw was calculated to be 0.0111 Nm. This torque must be provided at a low speed to reduce noise and avoid damaging the bees passing between the hive and the roof cavity.

- Suitable physical dimensions to both fit inside the hive roof cavity, and match the mechanism design.

- Drive interface which can receive commands from the Waspmote platform, for integration into the existing WSN.

- Extremely high accuracy and resolution to adjust the ventilation openings with a high level of precision.

- Robust design, to survive in the harsh conditions within a beehive, including exposure to moisture and wax, being glued to the crown board by the bees with propolis and temperature variations of up to 45 °C.

A stepper motor was selected as a suitable motor design for such an application, as it can provide high torque at a low speed, and provide a high level of precision, accuracy, and repeatability. One disadvantage with stepper motors which would need to be overcome is that they continuously draw a large amount of current, even in static mode. This feature is particularly bad for use with energy harvesting systems. The issue was resolved for the hive ventilation system by disconnecting the motor when not in use using a technique known as power gating as described Magno *et al.* [157], and heavily duty cycling the use of the motor.

The Radionics Pro Hybrid Stepper Motor (1.8°, 260mNm, 5 V dc, 1 A, 8 Wires) [158] was selected as a stepper motor which suited the physical dimensions of the mechanism design. It provided a minimum holding torque of 0.26 Nm which far outreached the identified torque requirements. In future iterations of the mechanism a lower torque motor could be used to drastically reduce the energy consumption of the system.

A drive card was required to interface this motor with the WSN node for control applications. The drive card selected was the DRV8825 [159]. This drive card was designed for use on bipolar stepping motors capable of driving the motor with an accuracy of 1/32 of a step. It also had a current limiter to protect the stepper motor from damage.

4.5.3 Calibration, precision, and accuracy

In order to design an effective control system for ventilating beehives it was vital to test and calibrate the mechanism. It was necessary to test the system in both the open loop and closed loop configurations to collect a comprehensive result of the system. A photograph of the fabricated prototype used to perform the tests can be found below in Figure 4.5.

An experiment was undertaken to evaluate the accuracy and precision of the mechanism. In this experiment, the mechanism was controlled by a Waspmote device (described in Section 3.3.1) via the motor driver card. The original position of the motor was marked on the crown board, so that any displacement from this position could be measured by use of a Vernier calliper. In the procedure of the experiment, the software implemented on the Waspmote instructed the motor to step 4000 times right (50 mm displacement), then 4000 times left, to return the mechanism to its original position. This cycle was allowed to repeat 50 times. The position of the mechanism in relation to its initial state was measured at the end of each cycle. The distance from the original position was found to drift by 0.3 mm over 50 cycles.

This displacement was small compared to the size of the outlets, and the probable cause was identified as "backlash". Backlash describes the error in threaded systems due to the gap between the inner and outer threads of the system, and the lag it causes in the system during direction changes. It is a common source of error for lead screw mechanisms and other threaded systems. This error however, does have a limited impact on the system (defined by the size of the selected thread) that is more than compensated for by the fact that the mechanism's inlet covers were designed to be 10% larger than the holes on the crown board.

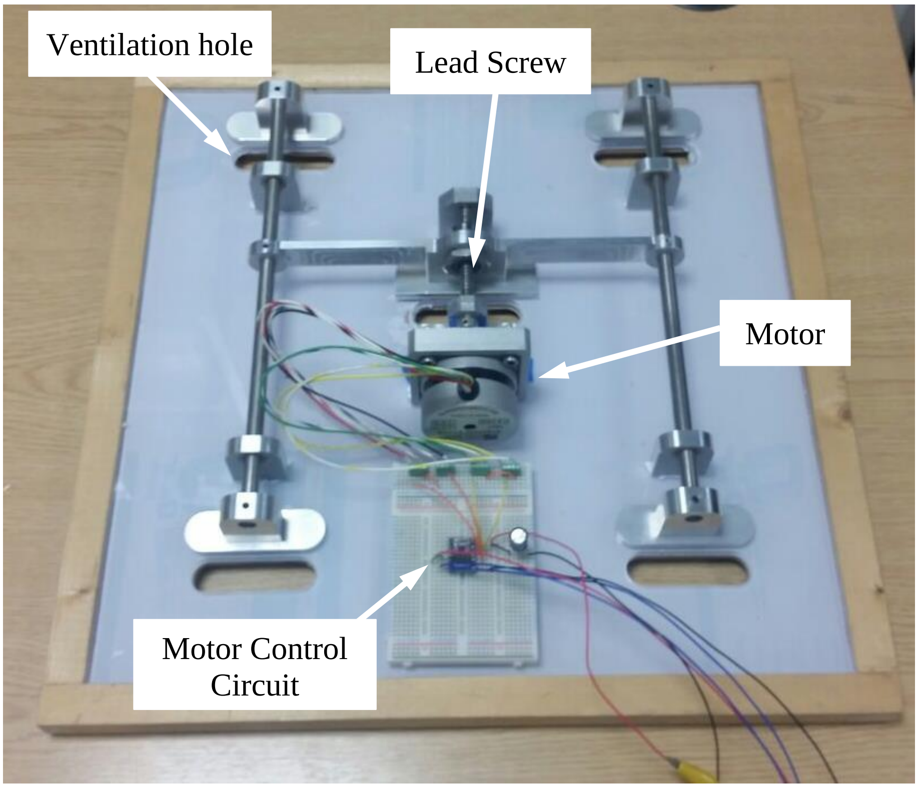

Figure 4.5 – Mechanism prototype

4.6 Control of Beehive Temperature

As described above in Sections 2.2 and 2.4, a suitable uniform temperature is one of the most vital properties of the hive. Temperature influences almost every feature of the hive including the health and activity of the bees, the condition of the brood, and the stability of the hive structure itself. Temperature was a parameter directly measured by the WSN described above. It was proposed to implement the mechanism described in this paper as part of the WSN together with a control loop, with the aim of maintaining an ideal temperature within the hive, thereby, implementing a WSAN which could identify temperature problems in the hive and taking steps to remedy them with no input form the beekeeper.

4.6.1 Design of control loop

The control loop design selected for use in the system was the classic PID controller. The classic Proportional, Integral, Derivative (PID) controller, originally developed in the 19th Century by Maxwell [160], is one of the most common control loop designs used throughout the world due to its flexibility and effectiveness. The taxonomy of a PID control loop is outlined below in Figure 4.6 and the fundamental equations describing a PID controller are shown in (3) and (4). In the beehive WSAN system the controller was to be implemented on the microcontroller of the node operating the ventilation mechanism.

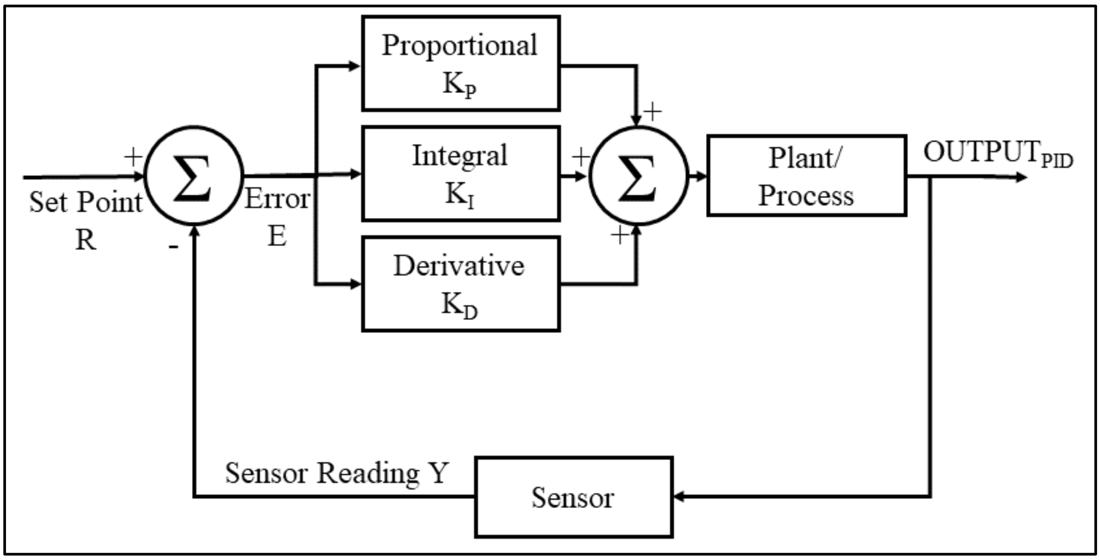

Figure 4.6 – PID control loop

$$OUTPUT_{PID} = K_P E + K_I \sum (E \times \Delta t) + K_D \left[\frac{\Delta E}{\Delta t}\right] \quad (3)$$

$$E = R - Y \quad (4)$$

Where R is the set point, Y is the sensor reading, K_P is the proportional gain constant, K_I is the integral gain constant, Δt is the time step, and K_D is the derivative gain constant. It can be seen form the above formulae that the design and operation of a PID controller is based purely on the changes in the measured process variable, not on any underlying knowledge of the system operation. This was ideal for the application of controlling beehive temperature, as no suitably comprehensive knowledge of the thermodynamics of the beehive interior was available. For the PID loop implemented in this work the process variable to be measured was the temperature of the hive interior.

The Error (2), measured in °C, was taken to be the set point temperature (R) minus the current temperature measured by the sensor network (Y). The output was set to be the position of the mechanism (width 25mm) in relation to the hive ventilation holes (width 20mm). To achieve this the maximum distance to be moved (completely opened to completely closed) was divided into 10 discrete positions of 2.5mm. The output of the PID controller would then vary between 0 and 10. This reduced the energy requirements of the system by only switching on the motor when a movement of 2.5mm or greater was required.

4.6.2 Simulation

The behaviour of the proposed system (PID controller, mechanism, and sensor node) was simulated in Matlab® to understand the performance of the system. The outputs of the simulation when applied to the temperature datasets of deployment I(b) and deployment IV were used to evaluate the behaviour of the mechanism in such environments. The results are shown in Figure 4.7 and Figure 4.8.

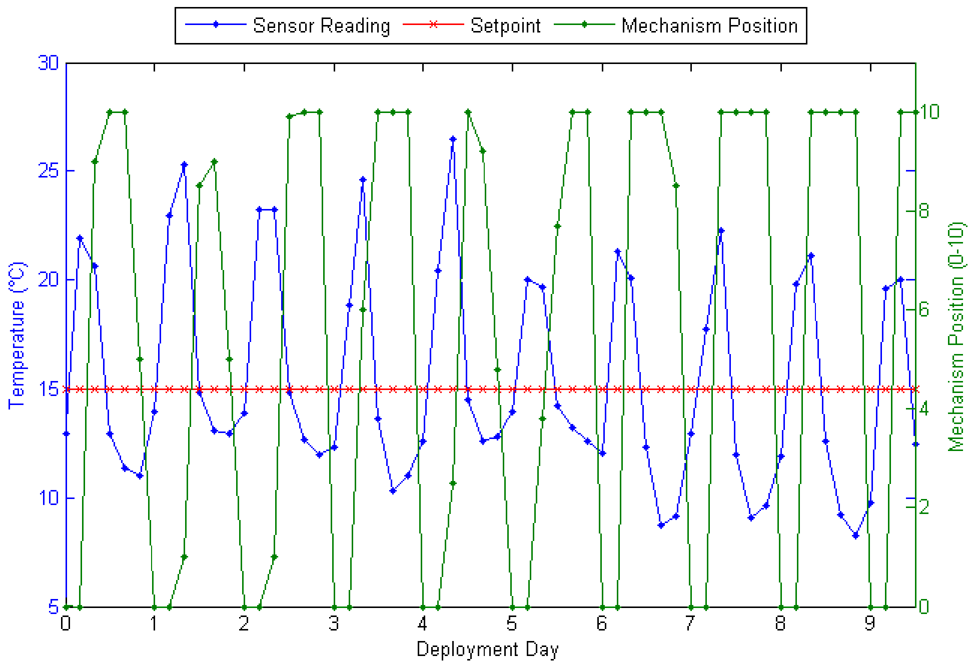

Figure 4.7 – Simulated PID response to Deployment I(b)

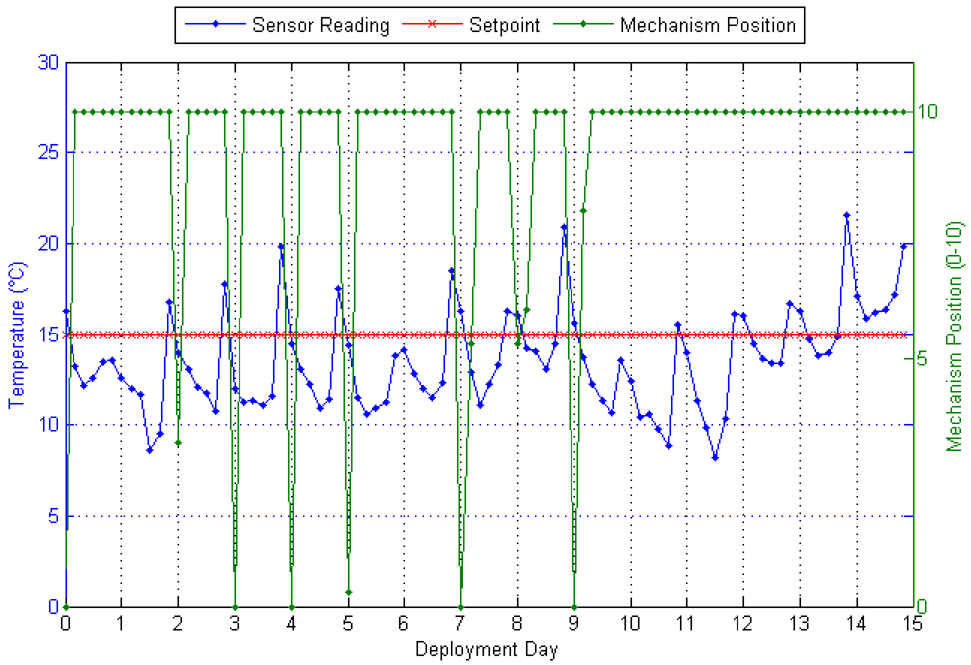

Figure 4.8 – Simulated PID response to Deployment IV

4.6.3 Implementation

The PID controller described above was implemented in software on a single Waspmote device for an experimental evaluation of the WSAN system. The controller, and the motor driver code were implemented in embedded C and added to the existing WSN node code for sampling the temperature of the hive. The assumptions included in the code were:

- A regular sample time, defined in the code, to simplify the calculations performed on-node
- A fixed maximum and minimum output of 0 and 10 respectively, to match the mechanism's limits. This was required to prevent the classic PID error of "integral windup" where the integral component attempts to push the output of the system further than is possible. In the case of this system this would cause major problems by moving the mechanism out of the effective range of the ventilation holes.
- At the start time, the position of the mechanism was assumed to be "position 0" i.e. the vents were completely open.
- The PID constants and set point were stored as variables which could be changed for tuning.

- When moving to a new position the motor applied multiples of 200 steps to the mechanism which resulted in displacements of 2.5mm.

4.7 Experimental Design

To evaluate the performance of the WSAN system, a controlled experiment was implemented. A demonstration hive, including brood box, super, base, queen excluder, and frames with wax were set up. The prototype crown board with the mechanism placed on top, and the WSN node with temperature sensor was placed inside the hive space. Heating elements were used to simulate the effect of the honey bee colony providing heat energy to the hive space in a constant and controlled manner. The temperature of the laboratory space was controlled to simulate changing external conditions, and to maintain a constant temperature for testing and tuning the system. The experimental setup can be seen in Figure 4.9, the hive is suspended over a space as they are typically deployed in the field to allow air intake for ventilation.

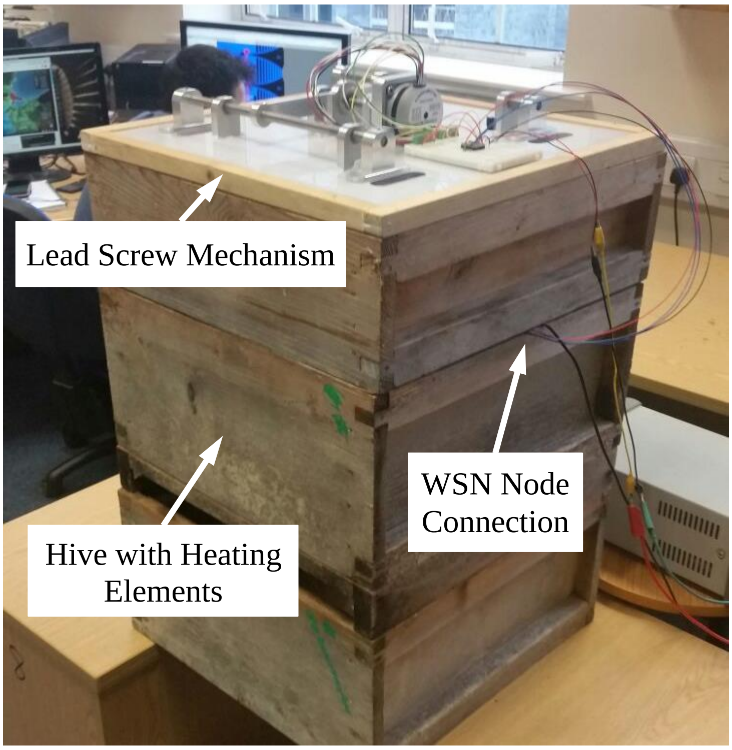

Figure 4.9 – Experimental setup

To implement the PID controller effectively, a suitable value for the three gain constants (K_P – proportional gain, K_I – integral gain, and K_D – derivative gain) needed to be selected and applied through tuning. This is a difficult step in the implementation of a PID controller, as these gains are difficult to determine when the transfer function of the system is unavailable. The Ziegler-Nichols tuning method is a practical experimental method for finding a suitable set of constants for a PID controller [161]. This method was applied to the system to get the preliminary constants. The K_I and K_D constants were set to zero and the K_P value was adjusted until the output of the system was found to oscillate. This K value was then selected as K_U (ultimate gain), and the oscillation period was measured (T_U), which allowed an effective set of gain parameters to be calculated using the following formulae:

$$K_P = K_U \times 0.6 \tag{5}$$

$$K_I = \frac{1.2 \times T_U}{K_U} \tag{6}$$

$$K_D = \frac{3K_U T_U}{40} \tag{7}$$

Application of this method to the experiment resulted in $K_U = 5.5$ and $T_U = 1$ which resulted in calculated gains of $K_P = 3.3$, $K_I = 1.5$, and $K_D = 1.375$. Further manual tuning of the system during experimentation led to gain parameters of: $K_P = 4$, $K_I = 0.1$, and $K_D = 0.075$. These parameters were found to give faster response to temperature changes in the hive, with less overshoot and oscillation, as well as responding well to external changes in temperature. To demonstrate the effectiveness of the system, experiments were run using the hive setup described above (Figure 4.9). These experiments simulated real life scenarios which the beehive would encounter and tested the response of the WSAN to them. The parameters which were varied included the ambient temperature in the laboratory, the temperature of the heating elements simulating the colony, and the set point temperature which the controller worked to achieve.

4.8 Results

The experiment described in Section 4.7 was an in-laboratory simulation of a real-world application of the temperature WSAN. This real-world scenario was a typical Irish summer hive, with a warm external temperature, and honey bees active inside the hive. The key requirement in such a scenario would be maintaining the brood at a suitable temperature for optimal development (33 °C – 36 °C [30]). The experiment had the following parameters:

- Ambient external temperature 18.7 °C,
- temperature of the heating elements 33.87 °C (based on the typical temperature of a honey bee colony in the hive),
- set point temperature 35.5 °C (suitable temperature for healthy brood),
- mechanism starting position 0 (vents open),
- fixed time step of 60 seconds.

The mechanism moved immediately to the closed position and raised the core temperature of the hive to the suitable range within 7 minutes. The temperature peaked at 35.75 °C at Minute 7 of the run. After 15 minutes, the system reached a steady state, with an average value of 35.483 °C. This temperature was achieved while using minimum energy, as the motor remained switched off for 18 out of 30 cycles, due to the output signal changing by less than 1 (not reaching the 2.55 mm step requirement). The output position of the PID controller and the core temperature of the hive detected by the sensor are plotted in Figure 4.10.

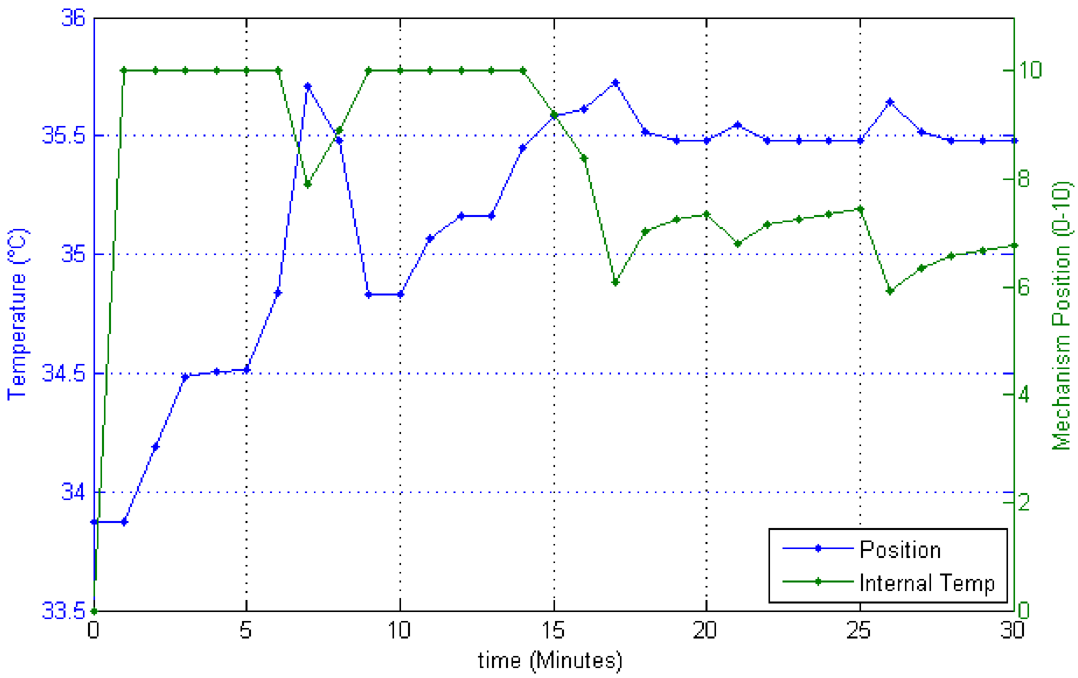

Figure 4.10 – Experimental results: hive temperature and mechanism position

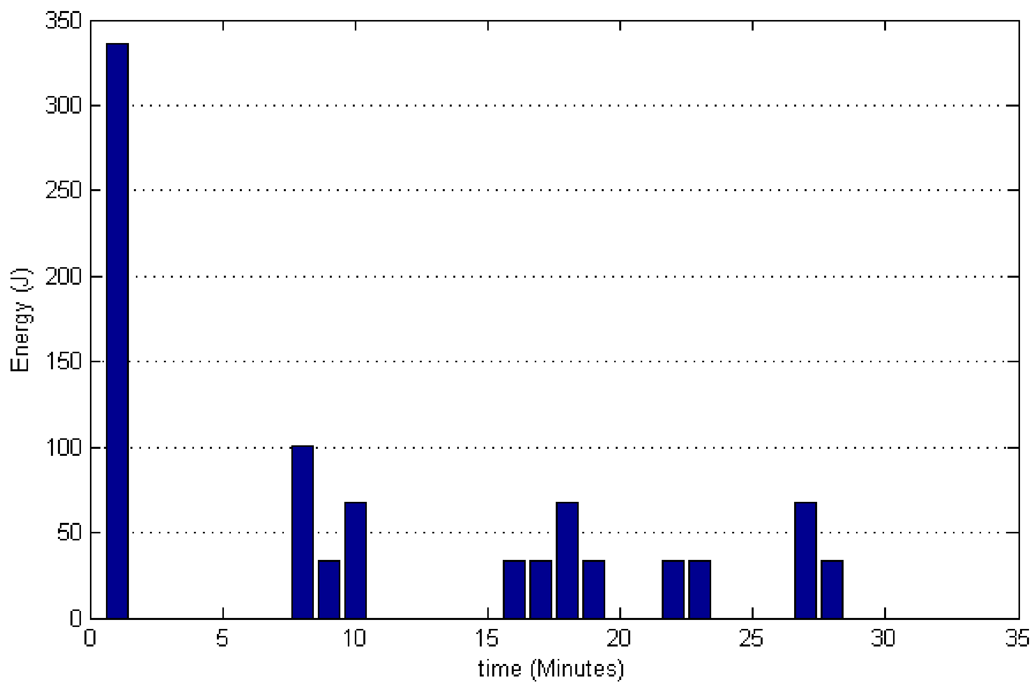

Figure 4.11 – Energy draw over experiment

The energy required for the motor to move the mechanism one step of 2.5 mm was measured to be 33.6 J. The total energy draw of the motor for each movement throughout the experiment above is shown in Figure 4.11.

4.9 Applications for In-Field Beehives

The results of the experiment indicated that the designed WSAN system was a suitable method of temperature control in beehives. An appropriate temperature for brood development was achieved within 7 minutes of initialisation, and with steady state being reached by minute 18. There was negligible steady state error (0.0047%) and overshoot of <0.25 °C. These results indicate that PID is an appropriate control mechanism for this system, and that the gain parameters used in the experiment are suitable.

Application of this WSAN system to a real-world beehive would have several benefits for the colony. Firstly, the hive automatically maintaining a suitable temperature throughout the year would free up a large portion of worker bees, who would typically be involved in heating or cooling activities. These bees would then be free to engage in other useful hive activities, such as foraging, rearing brood, or maintenance of the hive. This would improve the health of the hive by freeing bees for maintenance and grooming, as well as significantly increasing the productivity of the colony from the beekeeper's perspective in terms of honey production and pollination. Maintaining the hive at a constant temperature within the suitable range has been shown to lead to a healthier brood and more productive bees [44, 139, 149]. The WSAN system could facilitate this level of temperature control.

The energy draw of the system was 33.6 J per movement of the mechanism (Figure 4.11). Providing this level of energy to the hive in a real-world application is achievable, with a 1.2 Ah battery being a sufficient source for the experiment above. However, for long term, energy harvesting powered deployments of the technology this draw would need to be reduced as much as possible. It has been identified that the motor used in this experiment could be replaced with one providing 1/10th of the torque without impacting the performance of the mechanism. This motor change could be used to select a motor with properties which would dramatically reduce the current draw of the system. The stepping time of the system could also be reduced compared to this experiment. To move one 2.5 mm step, the system required the motor to be powered for 4 seconds, this time could be reduced further through careful motor selection. Increased power gating [157] and duty cycling could be utilised to improve energy performance. Finally, a larger solar panel setup could be utilised to provide a large surplus of energy, which could be utilised by the motor.

Other future steps for improving the performance and applications of the WSAN system have also been identified. Studies refining the understanding of the wattage and energy profile of the honey bees would inform a further improved geometry of the crown board. The shape and size of the outlets may not be optimal for effective heat transfer and ventilation of the hive interior. As well as this, the ideal temperature of the hive can be different depending on the season, the external conditions, and the current activities of the hive. A method of identifying and classifying the status of the hive would allow the required set point for the control system to be selected and applied.

4.10 Discussion

Considering the importance of thermoregulation and airflow to the condition and health of honey bee hives, a first step towards air conditioning systems for smart bee hives was investigated. The temperature of the hive is a crucial factor for the overall health of the colony and brood. The aim was to mimic natural processes where temperature is regulated through collaboration of airflow control and biological activity within the hive. Although the results and deployments use laboratory idealised conditions, this is the first step towards an in-field deployment where behaviours and impact could be further assessed.

To investigate and develop methods of controlling temperature and airflow within the hive, a model of simulated airflow within the hive was developed using SolidWorks CAD software and ANSYS Fluent CFD suite. This simulation model was compared with the results of experimental airflow analyses and found to conform to within a margin of 10%. This allowed the software model to be used as a preliminary model for the airflow within a National hive structure. Using the airflow models, an alternative geometry for the “crown board” of the hive was proposed, which provided improved overall air transfer from the hive, with a reduced air velocity at each individual outlet.

A mechanism to control the airflow in the hive, based on the alternative crown board geometry was designed. The purpose of this mechanism was to control the airflow rate from the vents to change the in-hive environment. A single motor, lead screw design was selected for this mechanism for its high accuracy and low design complexity. The mechanism was fabricated and tested for accuracy, precision and repeatability.

A control system was proposed to utilise the above mechanism together with the existing hive monitoring WSN (described in Chapter 3) to maintain a suitable temperature within the hive by adjusting the airflow. The combination of actuators and the WSN created a temperature control WSAN for the hive. A PID controller design was selected for the controller system. This controller was implemented on one of the network nodes which provided the input to the mechanism. The controller was experimentally tested in a controlled environment on a demonstration beehive and found to be highly effective when suitable PID gain parameters were selected. The design of the WSAN was identified as suitable for real world control of beehive conditions. Several methods of reducing the energy requirements of the system, to make it more suitable for remote, energy harvesting driven deployments were identified.

A machine learning algorithm using the in-hive sensor data to classify the state of the hive was identified as an ideal method of selecting such set points and is described in Chapter 5. Parts of this chapter have been submitted for publication in the IEEE Sensors Journal. Some of the presented work is a result of collaboration with MEngSc (Mechanical Engineering) students [145, 146]. Parts of this chapter are currently undergoing peer review for journal publication [147].

5 Machine Learning for Honey Bee Health

5.1 Introduction

In Chapter 3 several deployments of an in-hive WSN were described, and the resulting datasets were presented. Over five node deployments on five hives a significant number of data were collected. In real-world, year-round deployments with many hives (up to several hundred hives per beekeeper), the volume of data generated would be too large for any individual person to comprehend and extract value from. It was proposed to develop and evaluate machine learning solutions to use the collected data to classify and describe the hive. The results of these classifications would be far more meaningful to the end user (beekeeper). Classification was also identified as an ideal enabling technology for the hive temperature control WSAN described in Chapter 4. The classifications can be associated with individual ideal colony temperatures, and the set point of the PID controller could be adjusted to suit the current hive state.

WSN have been applied in many information rich environments, including healthcare, environmental monitoring, and medicine [5, 6]. One of main challenges of WSN is enabling them to perceive and understand the world in a similar way to humans. Perceptive low-power sensor devices should be able to interpret the world around them using intelligent algorithms. Machine learning technologies have been used with great success in many WSN application areas, solving real-world problems in entertainment systems, robotics, health care, and surveillance. Another important feature of WSN is the potential to achieve long life time, or even better, self-sustaining operation through energy harvesting [6].

A system which used threshold-based algorithms in a WSN was described Gutierrez *et al.* [162]. The objective was to optimise water use in an agricultural irrigation system. In this paper threshold-based algorithms were utilised to generate interrupts describing the beehive status. For improved performance in the in-hive monitoring system, a machine learning algorithm known as a “decision tree” was utilised as well as threshold-based algorithms, and the results of both methods were compared. An example of a system designed to use decision trees for agricultural decision support was described by Tang *et al.* [163].

The classification tree developed for the in-hive monitoring system has been deployed in a real system and the performance has been analysed. A unified and efficient model of decision trees was described by Criminisi *et al.* [164]. Machine learning algorithms are used in a variety of areas to solve problems through making decisions and predictions. One subdivision of machine learning is called, “supervised learning” which uses previous examples of inputs and outputs of a system to train an algorithm which can effectively estimate or “classify” future outputs of the system based on known inputs.

The key parameters which describe a given machine learning technique are: training speed; memory usage; predictive accuracy; and transparency. Decision trees were initially selected for this work due to their very small memory requirements, and high transparency. Subsequently, Random Forests were used for their greater levels of accuracy in return for increased memory usage and reduced transparency [165]. Training speed was also greatly increased for Random Forests compared to individual decision trees, but this was not a major concern as in both cases training took place outside of the WSN system.

Many bee monitoring systems can be found in literature [10]. Automated, precision beehive monitoring has been identified by many as an important and feasible goal [11]. It is clear, however, that the interdisciplinary analysis of beehive data is in its infancy. In this chapter, data have been analysed from biological, meteorological, and engineering perspectives. This analysis informed the design of three classification algorithms, two for classifying the condition of the hive, and one preliminary algorithm which attempts to predict the weather local to the hive. These algorithms can be used with the data collected from the in-field hive to provide information on the status of the bee colony and external conditions in real time through network alerts.

The system described can be used to provide feedback and prediction for beekeepers, as well as the general agriculture sector local to the hive (covering an area of up to 113 sq. km - the typical home range of bees in a hive is 6 km [166]), which relies on accurate short term weather prediction. This would be important to economies such as Ireland where agriculture is primarily grass-based (beef and dairy production) [167].

Such agricultural activities can be strongly influenced by weather, making accurate forecasting vital. There are strict environmental protection requirements relating to weather and farming practices, including spreading of slurry and fertiliser. Identifying incoming weather is also crucial for other farming activities, including optimising silage harvest and preventing spread of diseases such as potato blight.

The key research questions explored in this chapter were:

- How do the collected data described in Chapter 3 reflect biological and beekeeping knowledge?
- Can simple threshold algorithms provide a suitable level of accuracy for understanding the conditions of the hive?
- Can machine learning techniques be applied to the data collected from the hive, and if so do they provide a higher level of accuracy than threshold algorithms?
- Can the in-hive data be used to understand and classify the conditions outside the hive?
- Can the developed algorithms be integrated into the in-hive WSN system without significantly impacting its energy performance?

5.2 Analysis of Hive Data

The results gathered from the first two deployments I(a), I(b), and II (Section 3.6) were analysed, firstly from a biological and beekeeping perspective. Secondly, they were analysed with a view to exploring meteorological implications.

5.2.1 Biological and beekeeping analysis

The first observation from the collected data was that the temperature of the hive roof cavity typically remained in a steady range of min 9 -12 °C, max. 20 - 30 °C, with a diurnal fluctuation. These temperatures were achieved regardless of external weather, which indicates that the activities of the bees, during day and night, maintained a desired internal temperature within this range. Temperatures varied more during the day than at night. It is suggested that this is due to the majority of the adult honey bees leaving during the day to forage, thus reducing the number of bees available to maintain stable and higher temperatures.

Cyclical temperature fluctuations throughout the day of about 8 – 15 °C were seen to be typical of a normal, healthy hive. Departure from this behaviour should indicate decreased honey bee numbers. The humidity within the hive appeared to respond to the external meteorological conditions. During both deployments, the humidity rose on days when high levels of rainfall were recorded (> 95 % RH). At the end of the second dataset, with rainfall of <17 mm per day, extreme humidity to the point of condensation within the roof space was recorded (100 % RH).

At the surface of Earth, atmospheric concentrations of CO_2 are normally measured at approximately 400 ppm and respiration by the bees in the hive raised the CO_2 concentration to levels of between 400 and 500 ppm with a diurnal cycle of lower levels during daytime, though these differences tended to become reduced as the time increased. In deployment I(a) the CO_2 levels were initially similar to ambient conditions (recorded as ~400 ppm in an empty adjacent hive) with a diurnal pattern. They rose until they were consistently measured at 460 – 480 ppm and in deployment I(b) they were remarkably constant at this 460 – 500 ppm level. It is noteworthy that while oxygen levels continuously matched those of the external environment (~ 20-21 %), CO_2 built up in the hive. This suggests that the hive activity ensured equal to ambient O_2 levels while permitting CO_2 to build up almost 20% above ambient (460 – 480 ppm).

A swarming event (half of the colony's population left to form a new colony which is a typical biological phenomenon) was observed prior to deployment one. It is suggested that the low and fluctuating CO_2 levels (350 -450 ppm) at the start of the June-July deployment was due to having insufficient adult bees to maintain stable airflow conditions within the hive as a result of this swarm. In this way, observing the CO_2 levels within the hive can provide the beekeeper with an indication of whether or not the colony has a sufficient number of bees.

The pattern observed in the pollutant sensors (nitrogen dioxide, and raw pollutant sensor data) was that initially low levels were detected, with the volume growing over time from that point. This suggests that removal of the roof ventilated the beehive of some pollutants, and the same gases then built up within the hive when the roof is in place.

5.2.2 Meteorological and environmental analysis

When the local meteorological data were analysed, it was observed that in-hive CO_2 levels of a healthy hive varied in a similar manner to weather patterns. A healthy colony (consistent number of bees) would be expected to produce stable CO_2 levels. The variation in CO_2 levels recorded was expected to be caused by local air pressure changes influencing the airflow of the hive. This is a very early observation, and data from more hives will need to be collected for validation.

5.3 Algorithms and Classification

5.3.1 Threshold-based algorithms

Initially, a threshold-based algorithm was proposed to automatically detect the factors described above in the beekeeping and biological analyses. These algorithms are shown in Figure 5.1 and Figure 5.2. In Figure 5.1 C_0, C_1, C_2, C_3, and C_4 are the current and previous four CO_2 readings, and T_{EXT} is the external temperature. In Figure 5.2 T_0, T_1, T_2, T_3, T_4, T_5, and T_6 are the current and previous six in-hive temperature readings. These algorithms were validated using deployment data and produced accurate alarms, warning of possible poor colony health. Another proposed alarm was triggered when the Z-axis (vertical) of the hive, as measured by the accelerometer, varies from the typical value expected due to gravity (1 G). These algorithms provided a simple description of the hive, based on a single parameter. A beehive, however, is a complex system where a change in one parameter could signal different scenarios when placed in context of other parameters. This prompted the implementation of machine learning algorithms capable of utilising different datasets simultaneously.

```
procedure CO2(inputs:C_0,C_1,C_2,C_3,C_4,T_EXT; outputs:alarm_type)
    C_avg ← average(C_0,C_1,C_2,C_3,C_4)
    C_max ← max(C_0,C_1,C_2,C_3,C_4)
    C_min ← min(C_0,C_1,C_2,C_3,C_4)
    deltaC ← C_max - C_min
    if C_avg < 450 AND T_EXT > 7        then
            alarm_type ← alarm1 .    ► Potential illness or swarm
    else if C_avg < 450 AND T_EXT < 7   then
            alarm_type ← alarm2 .    ► Colony may be hibernating
    end if
    if deltaC > 20                      then
            alarm_type ← alarm3 .    ► CO2 is fluctuating - check hive
    end if
end procedure. Wait for another sample
```

Figure 5.1 – Threshold based CO_2 algorithm

```
procedure CO2(inputs:T_0,T_1,T_2,T_3,T_4,T_5,T_6; outputs:alarm_type)
    T_max ← max(T_0,T_1,T_2,T_3,T_4,T_5,T_6)
    T_min ← min(T_0,T_1,T_2,T_3,T_4,T_5,T_6)
    deltaT ← T_max - T_min
    if T_min < 7                        then
            alarm_type ← alarm4 .    ► Hive is Too Cold
    else if T_max > 7                   then
            alarm_type ← alarm 5 .   ► Hive is Too Hot
    end if
    if deltaT > 20                      then
            alarm_type ← alarm6 .    ► Temperature is fluctuating, check hive
    end if
end procedure. Wait for another sample
```

Figure 5.2 – Threshold based temperature algorithm

5.3.2 Decision tree algorithms

To provide a more comprehensive and accurate reflection of the in-hive conditions, the use of a decision tree algorithm was proposed to "classify" the condition of the hive. Decision tree algorithms were selected for use as they are an effective method of modelling in resource-constrained systems, as discussed by Rokach *et al.* [168] and Zia *et al.* [169]. The objective was to implement the final algorithm on the on-board 8-bit ATmega1281 microcontroller and for the system to remain self-sustaining. As well as this, decision tree algorithms are more effective when large datasets are available for training, as was the case here.

The hive states of highest priority for detection were identified in conjunction with the beekeeper, using established apicultural knowledge about the optimum parameters within the hive, and parameters associated with disease or ill health [140, 162]. The results of the biological analysis in section 5 above were also used to inform the specific values used in the class descriptions. The classes were selected to maximise identification of crucial colony activities, including healthy and unhealthy conditions, to provide a clear description at all times. The following classes of hive status were identified:

1. Normal hive with typical humidity, temperature, and CO_2 characteristics as observed in Chapter 3.
2. Hibernating hive, during the winter the colony will hibernate by forming “clusters” to preserve heat and food.
3. Fanning bees working to generate evaporation and ripen nectar, to make honey.
4. Low humidity hive, ideal for pest and mite treatment application during winter.
5. A hive with no diurnal temperature fluctuation, which would indicate the colony has absconded, or is dead.
6. A hive with an extremely large (> 20 °C) diurnal temperature fluctuation, which would indicate that the colony is diminished or ill, and cannot engage in important ventilation and temperature control activities. This hive is likely to suffer large losses if not addressed
7. A hive with an extremely large (> 15 ppm) diurnal CO_2 fluctuation, which also indicates a diminished or ill colony.

8. A hive which does not have the expected average CO_2 levels which would indicate that the population of the hive is reduced (reduced respiration)

9. A hive with an unusually high internal temperature which requires attention from the keeper to improve ventilation.

10. A damp hive due to high humidity which can damage the colony if not addressed

The 10 possible classes were split into two groups: conditions which do not require a response from the beekeeper, and conditions which do require action from the keeper. This grouping allows the algorithm to trigger alarms, as well as providing an in-depth picture of the hive status. The expected hive parameters (provided by biological analysis) associated with the above classifications were used as the decision tree attributes and inserted into the training table shown in Table 5.1.

The decision tree shown in Figure 5.3 was generated using the 10 examples in Table 5.1, together with 40 of the raw hive datasets collected during deployments I(a), I(b), and II, which provided a number of examples of the various classes. A preliminary decision tree training algorithm developed in Matlab was used, which was based on the ID3 decision tree algorithm described by Quinlan [170].

This is a simple decision tree algorithm, which does not utilise pruning measures, or handle missing data. Due to deployment restrictions (time of year of the deployments, and the hive did not experience every possible condition), some classes had an extremely limited number of dataset examples (including hibernating hive, and overheating hive). Compounding this, all data were collected from a single beehive.

The decision tree was generated by calculating the information gain of each attribute (i.e. the amount of information provided by that attribute), as given in (8), and selecting the attribute which maximises the result. This allowed the more important attributes to always be tested first. In (8) “I(Y;X)” is information gain, “H(A)” in (9) is the entropy of A, “EH(B)” in (10) is the is the expected remaining entropy remaining after decision B.

Table 5.1 – Training table for classification decision tree

	Attributes							Goal	
	H_{AVG} (%RH)	T_{EXT} (°C)	> 5 mm of Rain in last 24 h	ΔT_{INT24} (°C)	T_{INT} (°C)	$\Delta CO_{2\,24}$ (ppm)	CO_2 (ppm)	Requires hive visit?	Classes
X1	70 - 95	9 -35	N	5 -20	10 - 37	< 15	440 - 500	N	Normal Hive
X2	70 - 95	< 9	N	5 -20	< 10	< 15	440 - 500	N	Hibernating Hive
X3	> 95	9 -35	N	5 -20	10 - 37	< 15	440 - 500	N	Evaporating Nectar
X4	< 70	9 -35	N	5 -20	10 - 37	< 15	440 - 500	N	Ideal humidity to treat for pests
X5	70 - 95	9 -35	N	< 5	10 - 37	< 15	440 - 500	Y	Colony no longer in hive
X6	70 - 95	9 -35	N	>20	10 - 37	< 15	440 - 500	Y	Diminished population – Poor temperature control
X7	70 - 95	9 -35	N	5 -20	10 - 37	> 15	440 - 500	Y	Diminished population – Fluctuating CO_2
X8	70 - 95	9 -35	N	5 -20	10 - 37	< 15	< 440	Y	Diminished population – Reduced CO_2 production
X9	70 - 95	9 -35	N	5 -20	> 37	< 15	440 - 500	Y	Hive is too hot
X10	> 95	9 - 35	Y	5 -20	10 - 37	< 15	440 - 500	Y	Hive is too damp

$$I(Y;X) = H(Y) - EH(X) \tag{8}$$

$$H(A) = -\sum_{i=1}^{K} P_i \log_2 P_i \tag{9}$$

$$EH(B) = \sum_{i=1}^{K} \frac{P_i}{P} H(P_i) \tag{10}$$

By maximising the information gain of each step as described above, the number of steps to reach a conclusion is minimised. The hypothesis generated the final hive classification decision tree as shown in Figure 5.3. The T_{EXT} attribute was found to provide no additional information about the classification of the hive and was eliminated from the tree.

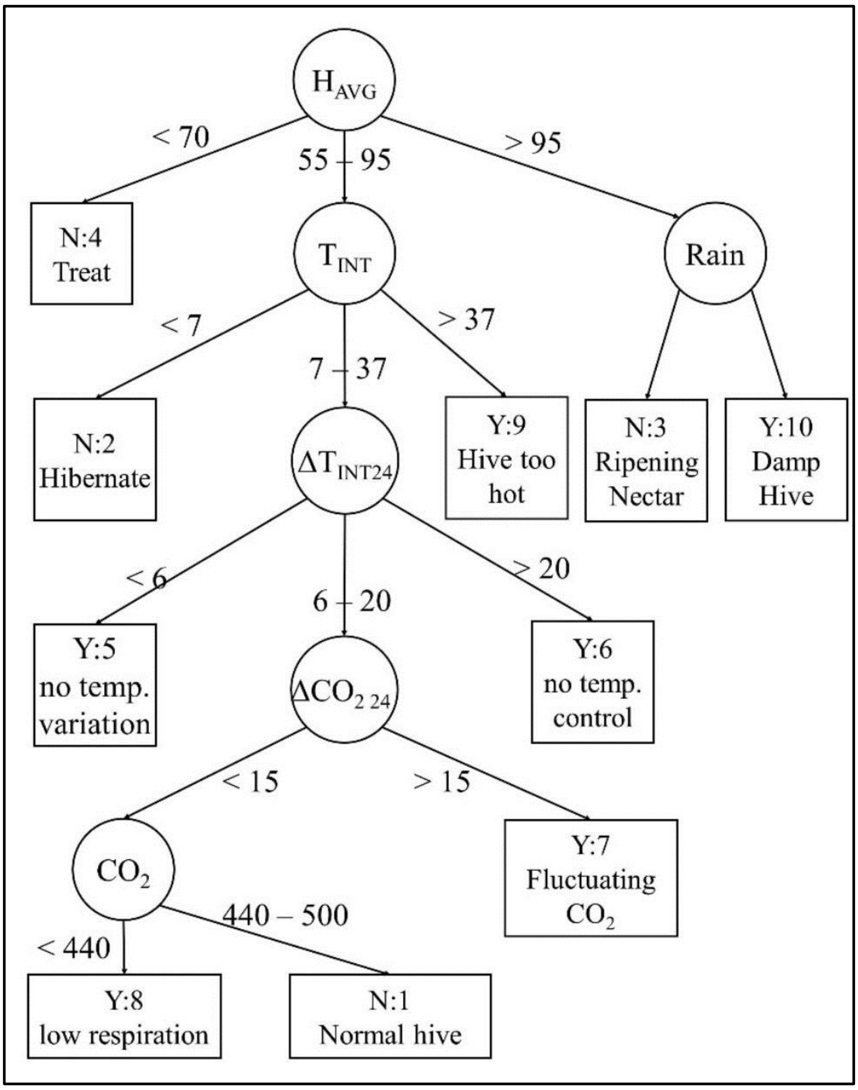

Figure 5.3 – Hive classification decision tree

When implemented in the network, the decision tree analysis was performed in real time, re-evaluating the classification each time data were collected from the sensors (every 4 hours). This allowed alerts to be sent to the beekeeper within 4 hours of a change in hive conditions in the worst-case scenario.

A second decision tree was developed using the CO_2 levels of a healthy hive to predict external weather. This decision tree was developed based on the preliminary observation (from the demonstration hive) that changing external pressure influences hive ventilation, which can be measured through changes in CO_2 from the sensor inside the hive roof. Monitoring pressure changes over time to predict local rainfall is one of the oldest methods of weather prediction. Three classifications describing future rain patterns:

1. An unhealthy hive which cannot be used to predict rain.

2. CO2 levels indicate rain in the next 6 hours

3. CO2 levels indicate no rain in the next 6 hours

Table 5.2 – Training table for weather decision tree

Example	Are C_0, C_1, or $C_2 < 440$?	$C_1 > C_0$?	$C_2 > C_0$?	$C_2 < C_1$?	Classification
X1	Y	~	~	~	Can't Predict
X2	N	Y	Y	~	Clear
X3	N	N	~	N	Clear
X4	N	Y	N	~	Rain
X5	N	N	~	Y	Rain

Table 5.2 describes the training set used to generate the decision tree shown in Figure 5.4, 5 of the 15 available raw CO_2 datasets from were also used in training using the same decision tree training algorithm described above. This tree compares the changing CO_2 levels measured over the previous 16 hours to provide a prediction on whether or not rain is expected local to the hive over the next 6 hours. Unlike the first decision tree, this algorithm provided one result per day at 6am. This decision tree was not trained with a suitable amount of data to create a reliable algorithm, and all data were collected from a single site, but it can be taken as an indicator that future work in this space is worthwhile.

5.4 Experimental Results and Analysis

5.4.1 Analysis of classification algorithm

The final step in the development of the decision tree classification algorithm was to select a test set, apply the decision tree to them, and evaluate the performance of the tree. The data collected during deployments I(b), I(b), and II were used as part of the test set. In Figure 5.5, the output of the decision tree when applied to these results is shown. The results of the decision tree, provided an in-depth picture of the colony condition. An overview of the beekeeper's observations of the hive during the deployments are overlaid in Figure 5.5. It was clear in the classification results from Deployment I(a) that the colony had a diminished population up to day 11, and that the colony was failing to control its environment. This was due to the swarming event which was observed by the beekeeper. In Deployment I(b), the hive was performing as expected up to day 12, with several instances of "fanning" observed (a typical honey production activity in a healthy hive). After day 12, increased humidity was detected, triggering an alarm. This was expected as the weather data showed heavy rainfall.

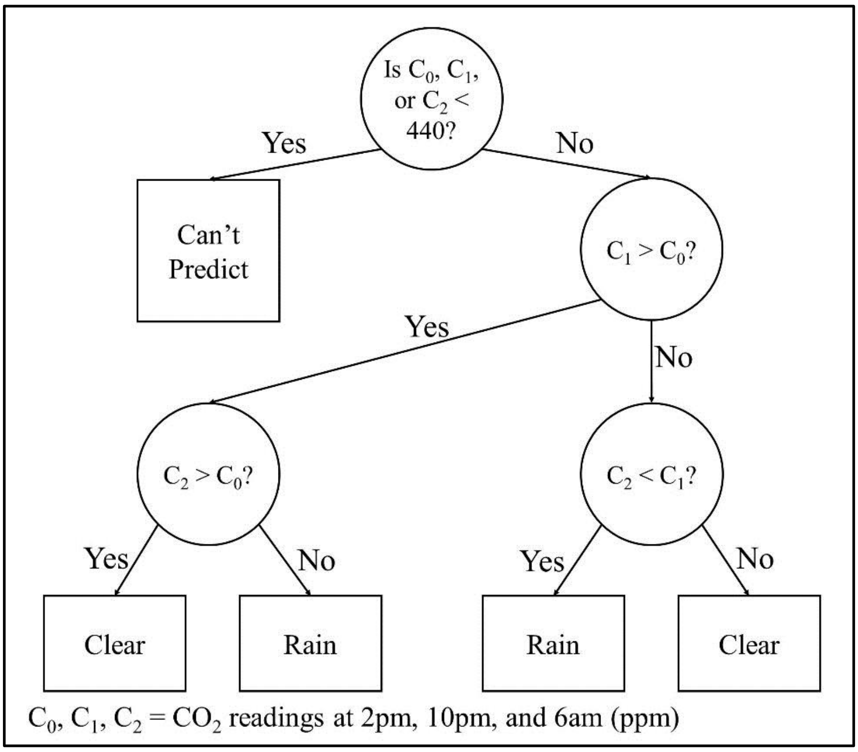

Figure 5.4 – Weather classification decision tree

The final total test set included 262 dataset examples; an effective test set size for evaluating this decision tree's performance. To evaluate the performance of the classification algorithm, a confusion matrix was compiled; shown in Table 5.3. In this matrix, the "Actual Class" of the hive throughout the various deployments is compared with the "Predicted Class" selected by the algorithm. As there was a lack of access to hives matching classes 2, 3, and 9 (i.e. hibernating, fanning, and overheating hives) throughout the deployments it was not possible to verify the accuracy of these predictions. These classes were therefore omitted form the confusion matrix and performance calculations. Future deployments to collect data from a variety of hives in such states will be required to verify these classifications.

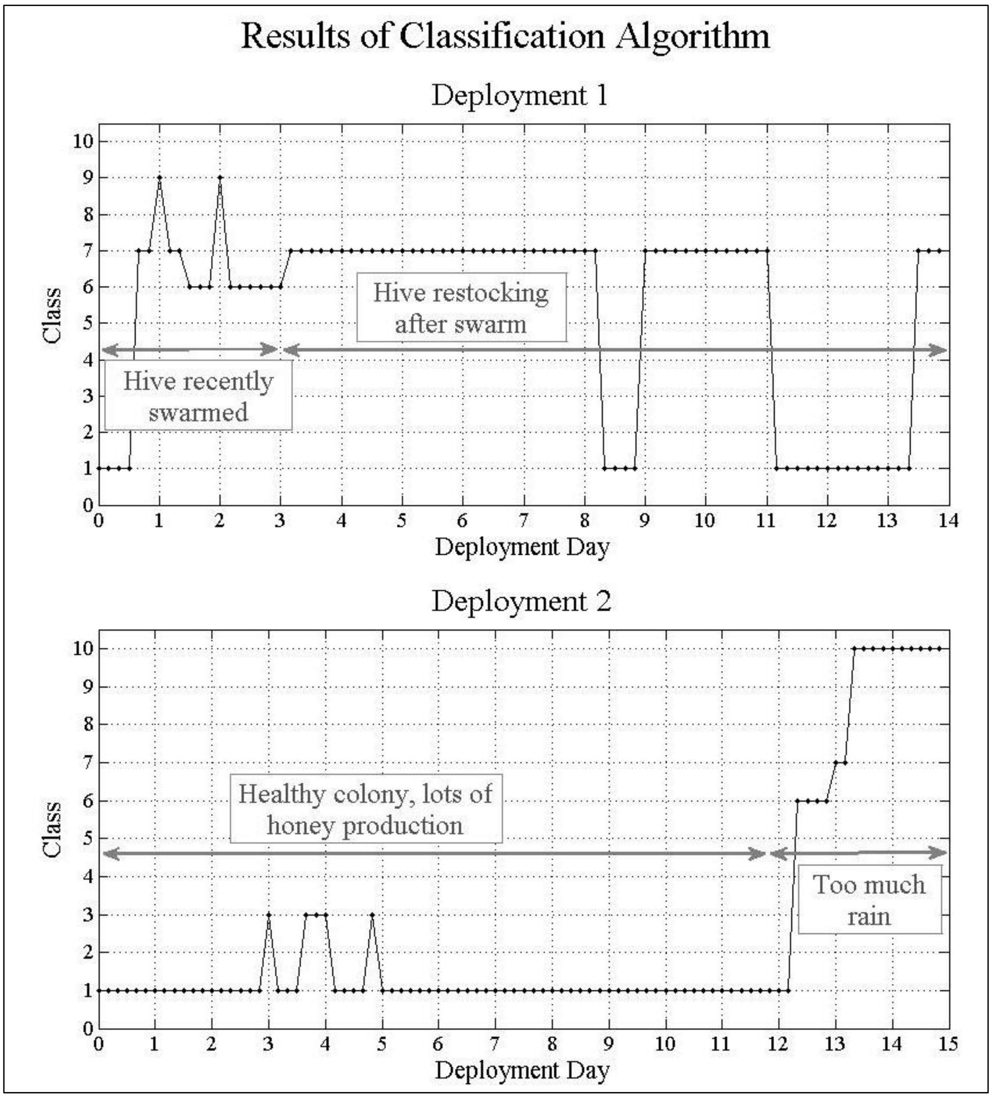

Figure 5.5 – Hive classification results Deployment I(a) and I(b)

When compiling the confusion matrix, the "Actual Class" was found by selecting the class which most closely matched the beekeeper's recorded description of the hive status at that point, without knowledge of the algorithm's results. In Table 5.3 the accuracy of identifying each class is found at the bottom of each column; overall, the hive condition was successfully identified in 95.38% of cases. For an increased understanding of classification performance, the "Sensitivity", "Specificity", and "Precision" was found for the algorithm's ability to correctly identify that the hive required beekeeper intervention.

Classes 1-4 do not require a hive visit, while classes 5-10 do. This allowed the confusion matrix to be broken down into four regions (true positive, true negative, false negative, and false positive) and the classic performance evaluation formulas to be applied. The final result was that the necessity of a hive visit was correctly diagnosed with: a Sensitivity of 97.33%, a Specificity of 95.45%, and a Precision of 96.68%.

Table 5.3 – Hive classification confusion matrix

Predicted Class								
1	**4**	**5**	**6**	**7**	**8**	**10**		
87	0	0	0	4	0	0	**1**	**Actual Class**
0	18	0	0	0	0	0	**4**	
0	0	28	0	0	1	0	**5**	
0	0	0	11	0	0	0	**6**	
4	0	0	2	47	0	0	**7**	
0	1	0	0	0	42	0	**8**	
0	0	0	0	0	0	15	**10**	
95.6	94.7	100	84.6	92.1	97.7	100	Accuracy %	

The performance of the decision tree algorithm was compared with that of the threshold-based algorithms, using both result sets from deployment I(a) (14 days). Both algorithms identified the poor conditions within the hive, due to the previously mentioned swarm. The classification tree provided equal detail of the issues (overheating, poor temperature control, and fluctuating CO_2 levels) in a single algorithm. For the threshold based algorithms to achieve the same level of detail, two algorithms were required. The decision tree also responded faster to changes in the hive environment, particularly in response to CO_2 variations. This was a result of the threshold based CO_2 algorithm using an averaged 24-hour value for CO_2 levels in-hive, making its response to sudden changes comparatively slow when compared to the more complex decision tree.

The decision tree responded more quickly to the improved hive conditions as the hive restocked (days 8-11), identifying that the hive was normal at some points in the day. It also detected the sudden drop in CO_2 levels on day 13, which the threshold based algorithm failed to identify. The results of the threshold based algorithm were compared with the "Actual Class" results, using the same process which was used to evaluate the decision tree performance. It was found that the threshold based algorithm accurately described the hive in 89.28% of cases. The decision tree accuracy found above was 95.38%, which represents a considerable improvement.

5.4.2 Analysis of weather prediction algorithm

The CO2 data collected during the two deployments were used to validate the rainfall decision tree. These data provided a test set of 31 examples. This test set was enough to show that this algorithm is accurate for the specific hive used for the deployments. A reliable test set will be required from future deployments (in various locations) to further validate this decision tree, and create a general model applicable to any hive. A general rule of thumb for decision trees is a minimum of 20 cases per predictor, making the minimum effective test set 100 examples.

The performance of this decision tree was evaluated by comparing the output of the decision tree when applied to the dataset above with the hourly rainfall records from Met Éireann [63]. The decision tree was found to predict incoming rain correctly, or identify that the hive population was too low to predict weather, in 96.87% of cases. Excluding low colony population cases, the tree could predict rain with 95.4% accuracy.

The same CO_2 sensor is used to assess the status of the colony and predict local rain. This is a first step in optimising the number of sensors within the hive. This minimisation will lead to reduced cost and improved energy performance by using single sensor providing several different kinds of information – bee health, productivity, weather prediction.

5.4.3 Energy performance analysis

The decision trees were implemented on the base station of the sensor network as described in Section 3.3. This allowed the algorithm to access data from all sensor nodes, as well as the necessary weather data from cloud storage. Deploying the algorithms on the base station also allowed text alerts to be sent to the beekeeper using the 3G radio. The energy consumption of the node was found to increase by 5.35% (from 360.3 J per cycle to 379.57 J for the base station node) when the decision tree algorithms were implemented, allowing the network to remain self-sustaining.

5.5 Applications in Apiculture

Following the validation and analysis of the classification tree, the results were presented to the beekeeper to assess the value of these predictions to beekeeping. A summary of the value of identifying each class in a timely and accurate manner is below. In the case of the hive requiring immediate attention from the beekeeper (classes 5-10), the beekeeper identified the typical hive issues associated with the detected state.

It was noted that by dividing the unhealthy hive status into 5 classes and presenting the current class in the alarm, the beekeeper could prepare more appropriately for the hive visit. The alarms would also vastly increase the response time, especially during winter months, when opening the hive for inspection is usually avoided.

1. Normal Hive/2. Hibernation: Identifying which hives are behaving normally (as expected based on season) will allow the beekeeper to prioritise resources and hive visits far more effectively.

3. Evaporating Nectar: Traditionally, louder sounds from the colony due to fanning are noted be beekeepers as a sign of high nectar input, that is being fanned by a full hive of bees, to produce honey. Automatic detection of when fanning occurred will allow for more accurate predictions of nectar flow from several hives at once.

4. Ideal humidity to treat for pests: Humidity levels can have a strong influence on many hive treatments including some organic acids and Thymol dust. Identification and notification of good conditions will lead to more effective treatment.

5. Colony no longer in the hive: Though there is little that a beekeeper can do in this case, it does, however, alert that missing stock in the apiary should be replaced. The alert may be an indication of theft of the entire internal contents of a hive, which is a concern for many beekeepers who have apiaries far from their homes.

6. Diminished population – Poor temperature control: Temperature control is crucial for laying and the development of brood. In summer, honey bees have only a

6-week lifespan, it is crucial that optimal conditions (principally temperature) be maintained to ensure continuous birth of young bees. Lower hive temperatures in winter are also known to promote higher infestations of diseases and pests, particularly the Tracheal mite pest [44].

7. Diminished population – fluctuation in CO_2/8. Low CO_2 levels: This could indicate losses of bees due to pests, disease, poisoning, attack by predatory animals, or a failing queen. Such diminished populations are a serious problem which require immediate action by the beekeeper in terms of: disease/pest control, replacement of the queen, and/or combining the weak hive with another to give a single viable hive which is more likely to survive.

9. Hive is too hot: In extreme cases, the wax can melt and spill honey on the brood frames that are situated below them, and impede access by bees to frames with uncapped brood. When temperatures are very high the honey bees divert their activities from foraging to cooling by fanning and by collecting water. This re-orientation of activities decreases foraging for nectar and decreases honey productivity.

10. Hive is too damp: Damp leads to the proliferation of fungi in the hive as well as the presence of slugs neither of which are acceptable for honey production. Fungal honey bee diseases that kill developing bee larvae, such as chalkbrood and Stonebrood, proliferate in damp conditions. Damp also leads to pollen, which has been gathered by bees, becoming mouldy inside in the hive and ignored as a food source for developing larvae.

5.6 Random Forests for Hive Classification

5.6.1 Motivation

The single decision tree hive classification algorithm described above in Section 5.3.2 achieved an acceptable level of accuracy (95.38%). However, it required external weather data to make accurate predictions, and could not be considered reliable for other honey bee colonies, as it was trained using a limited dataset from a single hive. As well as this, it needed both past and present measurements to monitor changes in hive conditions.

Following Deployments II – V (Section 3.6) a large database of hive information had been collected (3,435 unique datasets) from five different hives. These datasets had been collected over a variety of different seasons and hive conditions (see Section 3.6 for details).

It was proposed to train a new algorithm for classifying the hive status using only the most recent set of measured conditions from the in-hive sensor systems described in Chapter 3. Classification using the in-hive data only would pose an improvement in network and node performance by eliminating the need for a downstream flow of data, and using only the current dataset would reduce the memory requirements of the system. To achieve effective classification within these constraints it was proposed to use a more accurate classification algorithm known as Random Forest [164].

5.6.2 Method

Random Forest [171] is an ensemble method which uses a large group of decision trees (a forest) which are trained using a random selection of features. These individual decision trees are grown in the same way described above in Section 5.3.2. To perform a classification, the output of each tree for the current input is calculated, and the class with the most "votes" is selected as the result.

Random Forest is a very accurate classification method, designed to run efficiently even when processing large amounts of data. It also has various techniques for improving the accuracy when developing a specific forest, including feature importance and error calculations. Forests can also be trained, tested, and stored for implementation in a different environment, which is ideal for application in WSN, as training is often too complex for in-network implementation.

Six classes were identified for the Random Forest to be able to identify. The number of classes was reduced from the ten used in the single decision tree in Section 5.3.2. The concept of a "normal hive" was removed, as the ideal conditions for the hive are different during the varying seasons and activities throughout the year (described in Chapter 2). There is no single ideal condition for any colony that can be expected throughout the year.

The three "diminished population" classes were replaced with an "unhealthy colony" and "shrinking colony" class, to differentiate between when the colony is declining because of problems or disease, and when it is shrinking because it is preparing for overwintering which is a normal annual behaviour. The high humidity, high heat, and damp (condensation in the hive) classes were removed. These alerts could be implemented as equally accurate threshold based alarms based on a single sensor reading rather than increasing the complexity of the classification algorithm. The goal of this work is to create algorithms which can be implemented locally on the in-hive node, so reducing complexity is a key concern. The classes to be identified were:

1. Unhealthy colony – An unproductive colony which has a reduced population, as a result of swarming, disease, or pest infestation.
2. Growing colony – Colony is rapidly rearing brood to increase size
3. Productive colony – A colony which is behaving as expected during the main honey flow, including foraging, brood rearing, and fanning to evaporate nectar to produce honey
4. Dead colony/empty hive – A colony with no live bees; they have died or left the hive entirely
5. Shrinking colony – A colony which is not rearing any brood and is shrinking, typically to prepare for overwintering
6. Hibernating colony – A colony which has formed a cluster in the centre of the hive in response to cold external conditions

The features for each class which were used for training were five of the values (temperature, humidity, CO_2, O_2, time of day) captured by the in-hive sensor nodes described in Chapter 3. No other values were used to train, allowing the decision tree to be stored in-node and applied to data as it is collected for maximum efficiency and speed for alarms. The features used were:

1. Time of dataset collection (hour: minute)
2. Temperature (°C)
3. Relative humidity (%)

4. Carbon dioxide level (ppm)

5. Oxygen level (ppm)

The 3,435 unique datasets collected during Deployments I – V (Section 3.6) were used to train and test the Random Forest classifier. These data were randomly sorted into a 70:30 ratio to create the training and test data respectively. Sound data was identified as a suitable sixth feature, but was not included due to the limited availability of sound data to match the large dataset described above.

5.6.3 Results

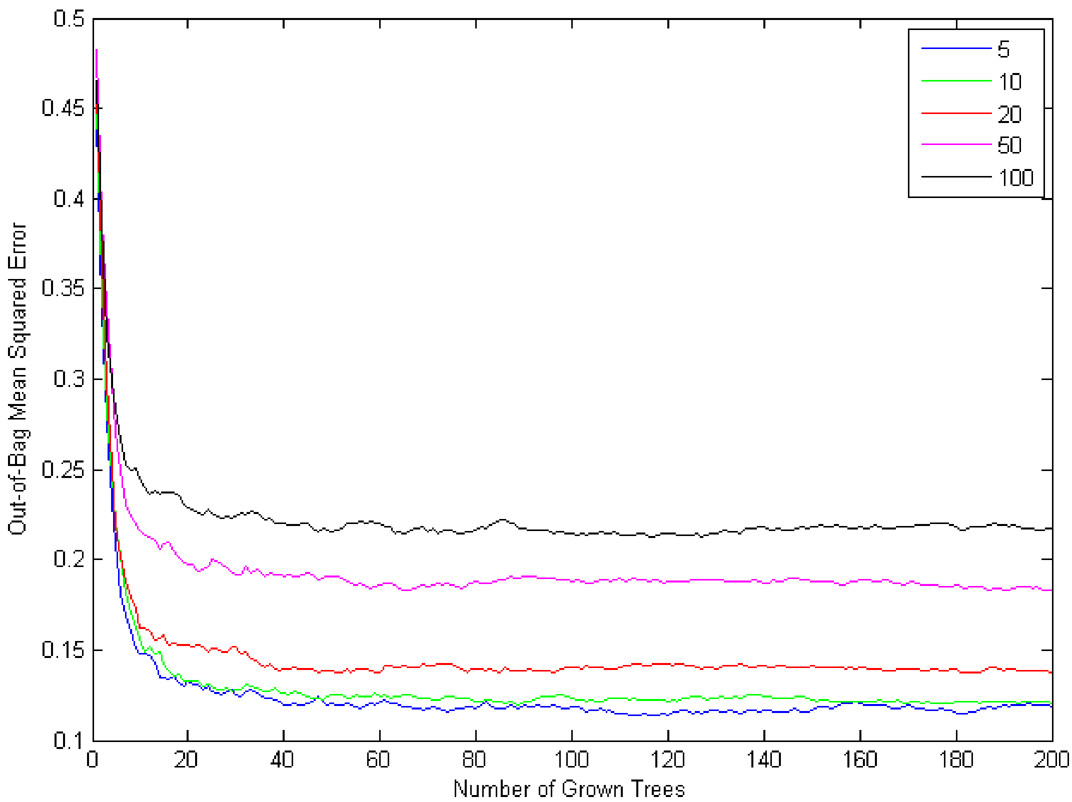

Figure 5.6 – Testing number of leaves from 5 to 100

Initially, six Random Forest algorithms were trained with a large number of trees (200) and with varying minimum leaf sizes (5 to 100 leaves). The results are shown in Figure 5.6. A leaf size of 5 was found to have the lowest steady state error. In Random Forest, small minimum leaf sizes are known to create algorithms susceptible to noise. Extensive testing of the final algorithm was required for such a low leaf size. The error was found to level out at approximately 70 trees, which was selected as the size of the final forest. The error curve for the final parameters (minimum leaf size of 5, and tree count of 70) is shown in Figure 5.7. The mean squared error was found to be 0.115 at the maximum forest size of 70 trees.

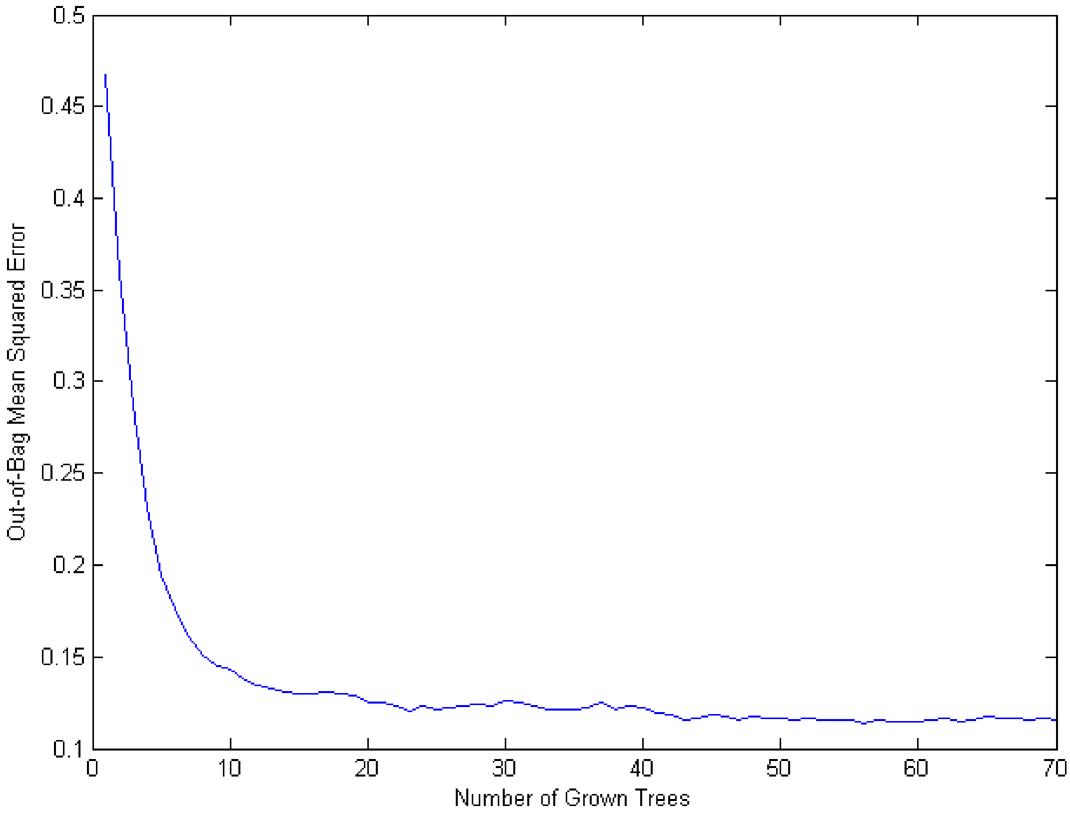

Figure 5.7 – Error of decision trees for 5 leaves, 70 trees

5.6.4 Analysis

The key aspect of Random Forests is the removal of features which do not provide strong predictions. The randomly selected feature used for generating each tree will then be guaranteed to provide an accurate prediction. The importance of each of the 5 features were calculated, and 1 (time of day – feature importance 0.65) was found to be significantly less important than the other 5 features (importance 4.3 – 5.79) as shown in Figure 5.9.

The "Time of Day" feature was removed, and the random forest was trained again with a minimum leaf size of 5, and using 70 trees. The error for the revised Random Forest increase marginally to 0.121. This increase in error was acceptable when compared to the increase in noise resistance.

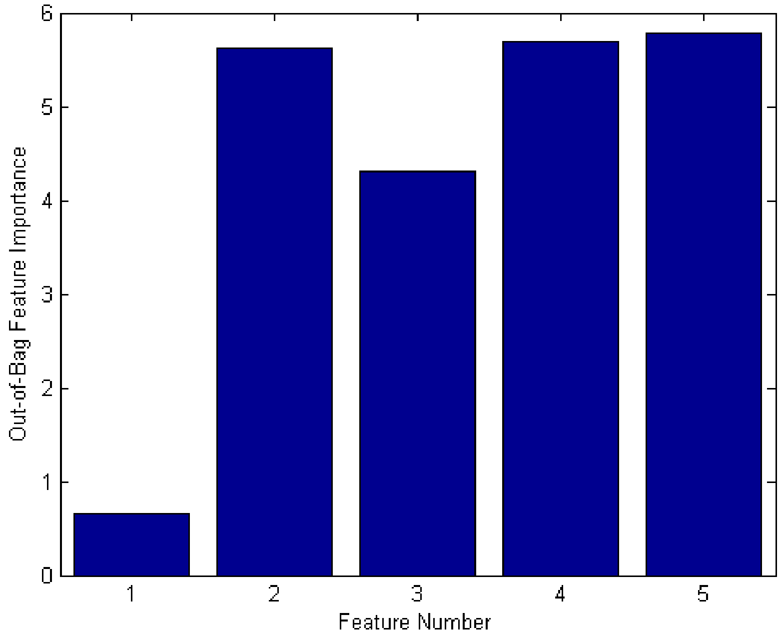

Figure 5.8 – Feature importance

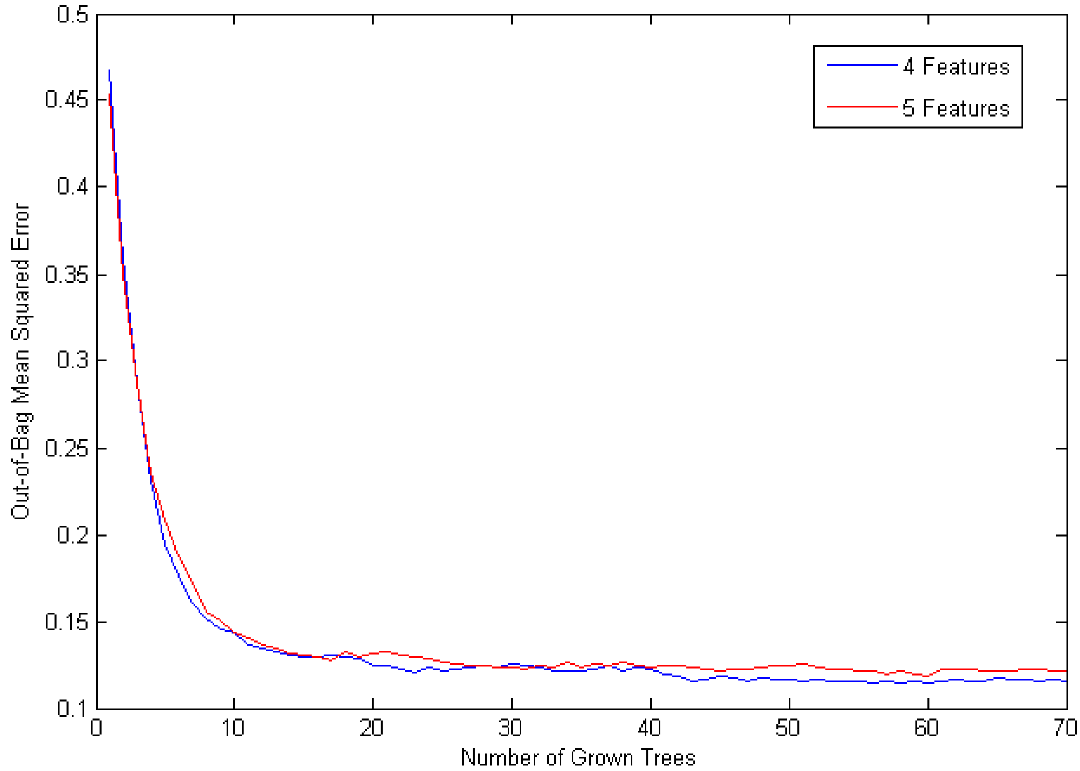

Figure 5.9 – Increase in error without time of day as a feature

To test the performance of the decision tree, it was applied to the test dataset (30% of collected hive data). A confusion matrix of the results is shown below in

Table 5.4 and Table 5.5 in both absolute results and percentage format respectively. Class 4 (no colony/dead colony) was found to have the highest accurate prediction rate (100%) and Class 6 (hibernating colony) was found to have the least accurate prediction rate (74%). The most common error was a hibernating hive misclassified as a growing hive (Class 2). The total accuracy of the classifier on the test data was 88.1%. This was an acceptable accuracy rate for identifying the state of the hive.

Table 5.4 – Confusion matrix – test data

Predicted Class							
1	**2**	**3**	**4**	**5**	**6**		
104	12	1	0	0	0	**1**	**Actual Class**
6	330	8	0	1	6	**2**	
0	34	222	0	7	0	**3**	
0	0	0	13	0	0	**4**	
0	0	19	0	77	0	**5**	
0	19	1	0	0	58	**6**	

Table 5.5 – Percentage matrix – test data

Predicted Class							
1	**2**	**3**	**4**	**5**	**6**		
0.89	0.1	0.01	0	0	0	**1**	**Actual Class**
0.02	0.94	0.02	0	0	0.02	**2**	
0	0.13	0.84	0	0.03	0	**3**	
0	0	0	1	0	0	**4**	
0	0	0.2	0	0.8	0	**5**	
0	0.24	0.01	0	0	0.74	**6**	

The fully trained Random Forest based classifier was then applied to the entire collected in-hive dataset. The confusion matrix for total results and percentages are shown in Table 5.6 and Table 5.7. Class 4 (no colony/dead colony) again had an accuracy of 100%, and Class 6 (hibernating colony) had the lowest prediction rate (86%). The overall accuracy of the classifier was found to be 93.5%.

Table 5.6 – Confusion matrix – all data

Predicted Class							
1	**2**	**3**	**4**	**5**	**6**		
393	19	3	0	0	0	**1**	**Actual Class**
8	1144	15	0	1	11	**2**	
2	73	797	0	10	0	**3**	
0	0	0	42	0	0	**4**	
0	0	27	0	299	0	**5**	
0	27	2	0	0	184	**6**	

Table 5.7 – Percentage matrix – all data

Predicted Class							
1	**2**	**3**	**4**	**5**	**6**		
0.95	0.05	0.01	0	0	0	**1**	**Actual Class**
0.01	0.97	0.01	0	0	0.01	**2**	
0	0.08	0.9	0	0.01	0	**3**	
0	0	0	1	0	0	**4**	
0	0	0.08	0	0.92	0	**5**	
0	0.13	0.01	0	0	0.86	**6**	

Class 4 (no colony/dead) had an accuracy of 100%, which was a far more accurate rate than the other classes. This was expected, as the conditions measured inside the hive with and without the colony are quite different, even at a casual glance. However, as it was also the class with the fewest training and testing datasets (42), more examples to further train the algorithm, and validate the high level of accuracy are necessary.

Class 6 (hibernating colony) had the lowest overall accuracy (86%). This lower accuracy was a result of the low number of example datasets (184) available for training. The hibernating colony did not have as much of a dramatic change in conditions as was seen in the case of the dead colony, leading to the low number of datasets causing a dramatic drop in accuracy. The accuracy of this classifier could be significantly improved with the inclusion of more examples of hibernating hives.

The Random Forest classifier had a total accuracy of 93.5%. This represented a small drop when compared the 95.38% accuracy of the single decision tree described above in Section 5.4.1. However, the Random Forest did not require external data (weather), thus reducing network traffic; did not need to be aware of any previous datasets, thus reducing memory and node complexity requirements; and the algorithm required only 4 inputs (compared to 7 for the decision tree classifier), which made it more resistant to noise. These three improvements, together with the small decrease in accuracy, make the Random Forest algorithm a more appropriate classifier for use in resource constrained in-hive WSN nodes.

The Random Forest classifier algorithm was too large to be implemented on the microcontroller used in the in-hive WSN node described in Chapter 3 (122 kB max binary file size). However, it would be very suitable for implementation in future nodes which are suggested in Section 7.3.

5.7 Discussion

The results of two deployments from Chapter 3 were analysed from biological, meteorological and engineering perspectives. A threshold-based algorithm was first proposed to detect important hive changes and alert the beekeeper. The algorithms were verified by comparing the outputs from the deployments to observations from the beekeeper and official weather records.

Using the analysis, a decision tree was developed which classified the hive as being in one of ten possible states. The algorithm was found to classify the hive accurately in 95.38% of cases. From the meteorological analysis a short term, local, weather prediction decision tree was proposed using in-hive CO_2 levels (95.4% accuracy, to be validated in future studies). This algorithm predicted rain patterns local to the specific hive monitored. These algorithms were deployed on the 3G/GSM enabled node and increased energy requirements by just 5.35%. Machine learning is used to automatically apply established beekeeping knowledge to the collected data, allowing early identification of poor health for improved colony health, as well as analysis of behaviour.

A second hive classification algorithm was developed using Random Forest techniques. This algorithm did not need access to data from outside the networks, memory of previous measured data, and used only four inputs, while achieving an accuracy of 93.5%. While it was not possible to implement this algorithm on the existing node described in Chapter 3 due to code size restrictions on the 8-bit ATmega1281 microcontroller. It is proposed to expand the processing capabilities to allow for implementation in future work (Section 7.3).

A summary of the value of these classifiers for beekeepers was also presented. It was noted that by presenting the current class in the alarm, the beekeeper could prepare more appropriately for the hive visit. The alarms would also vastly increase the beekeeper's response time to hive problems, especially during winter months, when opening the hive for inspection is usually avoided. Parts of this chapter were published in a peer reviewed journal paper [172].

6 Big Brother for Bees – Advanced Monitoring in the Hive

6.1 Introduction

There are several important hive parameters which were identified in Chapter 2, namely sound, weight, and visual inspection, which were not addressed by the in-hive WSN described on Chapter 3. In the case of sound and visual inspection, the signal processing and networking requirements of such sensors are far higher than can be achieved in a low energy system for long term deployments. In the case of weight monitoring, this was not included in the system firstly because load cells with the range (200 kg), resolution (10’s of grams), and low energy performance was not available, and secondly because adding load cells to the system would make it much harder to deploy on hives in the field, by requiring them to be moved.

These parameters however, provide valuable information about the conditions of the colony which may not be detected by the existing in-hive sensor node. In this chapter the preliminary use of microphones, load cells, and cameras to monitor each of these parameters is proposed. A focus is maintained on using these high-volume data sensors in a low power and resource constrained system. Techniques for integrating these high-volume data sensors together with the in-hive WSN described in Chapter 3 without excessively reducing node performance or lifetime have been explored.

The key research questions addressed in this chapter are:

- How can the knowledge relating colony conditions, productivity, and activity with sound, weight, and visible changes be captured through the use of sensor technology?
- Can the processing power of an in-hive WSN node be sufficient to extract valuable information for such sensors?
- Is there a way to implement the relevant sensors in an unobtrusive way that follow the identified design requirements in Section 3.2.1?
- Can this information be extracted from the hive in an energy efficient way, that does not significantly reduce the lifetime of the in-hive WSN node described in Chapter 3?
- Can the information and alerts created be conveyed to the end user (beekeeper) using the existing ZigBee and 3G networks described in Section 3.4?

6.2 Sound Recording in Hives

6.2.1 Introduction

It is possible to gain a large amount of information from monitoring the varying sounds occurring within a beehive. In this chapter, the first section of work describes the expansion of the in-hive WSN node described in Chapter 3 to monitor amplitude of the sound within the hive and generate an alert for large changes in volume. A sudden rise in noise levels from the honey bees could reflect a variety of events which may result in loss of profit to the bee keeper, such as alarm sounds around invasion by a pest or swarming. Following this, the design was further developed into an in-hive WSN node for detecting the signs of an imminent swarming event by observing the sounds coming from the honey bee colony. This node detects both the specific "piping" noise emitted by queens, as well as the louder sounds produced by the rest of the colony prior to swarming. When an imminent swarming event is suspected the node made a short, high quality recording of the hive sound as well as sending an alert to the beekeeper through the network. This node was designed to work together with the larger sensor network designed for monitoring the health and conditions of the beehive described in Chapter 3.

Finally, to enable development of a generic in-hive WSN node for monitoring and detection of other events in the hive using sound a long-term experiment was undertaken to record the sounds of hives in the field. Audio based data loggers were installed in hives for long term deployments to generate a large database of colony sounds throughout the varying colony events and seasonal changes. An analysis of these data is presented with identification of the key frequency ranges and magnitude for future classification work. Throughout this work, conventional electret and MEMS microphones were used for collection of sound data, due to their ease of deployment, ability to be mounted inside or outside the hive if necessary, and as they do not need to be fixed to the comb of the hive. Accelerometers were also explored as a potential solution, as described by Bencsik *et al.* [173], but were not used due to the requirement to fix them on the comb. A radar based microphone has also recently been explored by Aumann *et al.* [174], which offers another effective method for hive sound monitoring.

6.2.1.1 Swarming

An important part of a beekeeper's activities during the reproductive season is to monitor for "swarming", which is the method by which a natural colony of *Apis mellifera* reproduces. The process of swarming is described in detail in Section 2.5.2. Sequential hatching of new queens can lead to secondary or further swarming events with progressively fewer numbers of bees in each swarm and the original colony which are unlikely to survive winters. All such swarming events, if not managed, represent considerable losses to beekeepers in terms of lost colonies, reduced numbers of bees in remaining colonies and reduced honey production. Newly formed queens produce specific sounds known as "piping" at or just prior to their hatching. Traditional beekeeping methods involve managing swarming (prime or secondary swarms) to avoid losses of bees from an apiary. Such management requires close monitoring of the formation of virgin queens by the colony with frequent (weekly) visits by the beekeeper. Emerging virgin queens can also kill other emerged as well as developing (unhatched) queens which are sometimes used to form new colonies. This makes swarm management a labour intensive and time critical activity for the beekeeper.

6.2.2 Colony volume alerts

One of the most important aspects of the sound emitted from the hive it its volume. A sudden increase in volume from the hive may not only indicate swarming, but that the bees were showing aggression towards an intruder in the hive, for example a mouse creating a nest in the hive, or a larger animal or human approaching the hive. In the first step of this research, a microphone was used to identify an increase of the sound levels within the hive. This microphone was implemented as part of a dedicated sound monitoring WSN node external to the hive, in the same network as that described in Section 3.4.

6.2.2.1 Implementation

The microphone used was the SparkFun Electret Microphone Breakout. Accompanying the microphone was an amplification circuit with an op amp (OPA344). Using this microphone circuit, together with the ADC input of the microcontroller as part of the in-hive WSN node, the volume of the colony sound could be measured. As the volume of the sound was required, rather than frequency detection, the microphone circuit was sampled at 100Hz, which is far below quality sound recording, or even the ideal range for monitoring honey bees. A more suitable sampling frequency would be greater than 700 Hz. As a major aim of the project was to provide a low power platform suitable for remote deployment, this low sampling rate reduced the energy requirements of the solution.

6.2.2.2 Signal Processing

The objective of the sound detection node was to pick up major sound disturbances within the hive. Once a disturbance occurred, and was found to be sustained over several seconds, an alert would be generated and sent via the network to the user. To design an algorithm to detect this, several recordings of calm, aggravated and swarming hives were analysed and compared. Tests were carried out in relation to distance of microphone from the sound source to give the best results and to reduce clipping false positives. An optimum distance of 0.75 m was reached, which was used throughout the rest of the experiment.

In the software implemented on the WSN node microprocessor, the magnitude of the sound detected by the microphone was first calculated, and then a threshold was applied to each resulting data point where the value was kept if it met the threshold, or forced to zero if it did not. The remaining points were put through a moving average filter. If the output of this filter confirmed that the increased noise levels were in fact sustained over time (rather than say one bee flying near the microphone), it was confirmed that the colony was indeed increasing its volume and a network alert was generated.

6.2.2.3 Results

The response of the sound detection node to a high-quality recording of a "piping" beehive is shown in Figure 6.1. In Figure 6.1 the elevated noise levels during the piping can be clearly seen, as well as the response of the filter which triggered an alert.

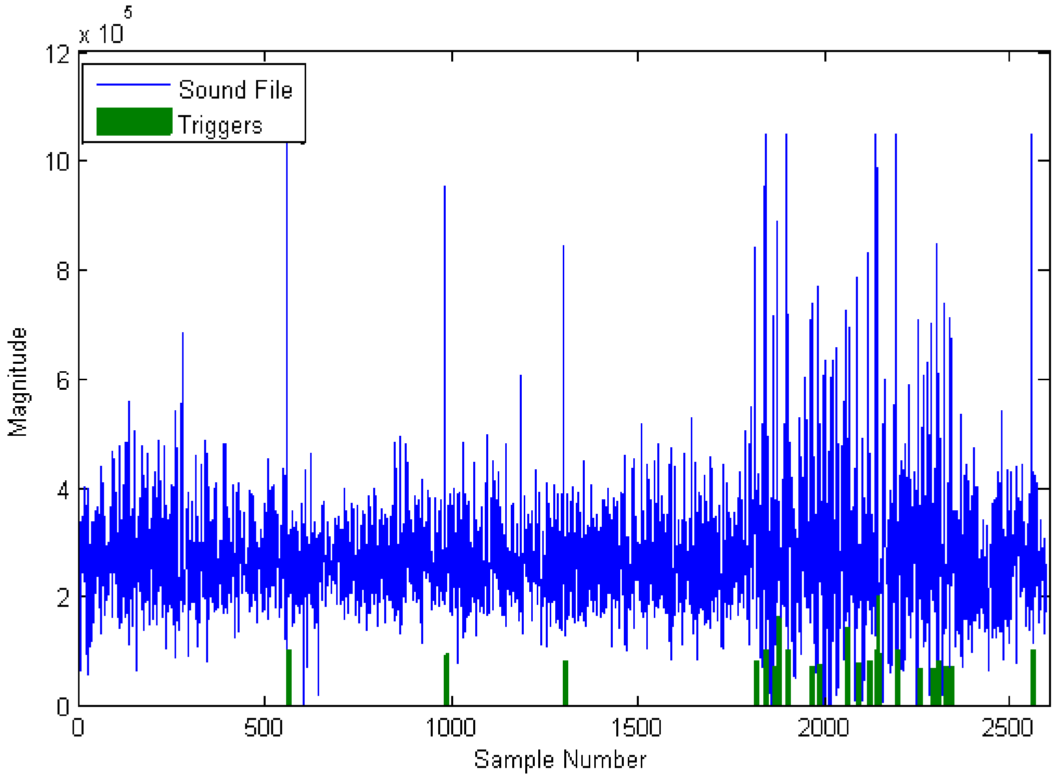

Figure 6.1 – Response of sound detection node to "piping"

6.2.3 Frequency Based Acoustic Interrupt Node

Simple volume alerts as described above are of limited use to the end user, as they do not capture any data describing the sound which triggered the alarm. As well as this, there are specific frequencies (piping) which are key indicators of swarming. These sounds are not detected by the volume alert circuit, as reducing the volume level to trigger an alarm when they occur would cause a dramatic increase in false alarms.

It was proposed to resolve these problems by increasing the complexity of the sound detection WSN node in three ways. Firstly, to implement the volume alarm in hardware as an acoustic wake-up signal using a low power comparator. Secondly, to add a second feature to the acoustic wake-up – a lower threshold volume alert, limited to the key piping frequencies by a band pass filter. And finally, to add a dedicated sound recording circuit with a dedicated processor which can be woken up to create a short high-quality recording when the acoustic wake-up circuit is triggered. A block diagram of the revised acoustic interrupt node is shown in Figure 6.2, and a schematic overview of the wake-up circuit is shown in Figure 6.3.

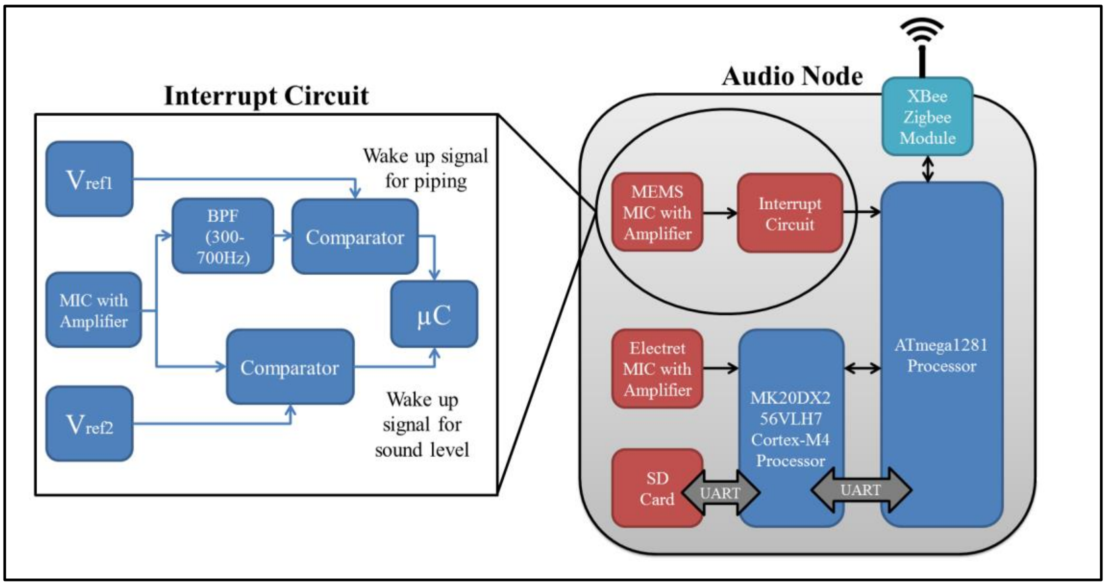

Figure 6.2 – Acoustic wake-up WSN node

6.2.3.1 Design

Eren *et al.* showed that the majority of sounds produced by honey bees (workers and queen) lie in the <3 kHz range [97]. Based on these findings a high sampling was required to get a high-quality representation of the in-hive activity (6.3 kHz). Due to this required sampling rate, the files generated are relatively large and not suitable for transmission though the low-power, low data rate ZigBee network utilised by the existing sensor network in Chapter 3. Local storage of the sound data on an SD card (secure digital non-volatile memory card) was selected instead, an alarm message was also sent though the network to the beekeeper, notifying them that an event was detected. When the beekeeper receives this alarm he/she can go to the hive to inspect the condition of the colony. If no source of the alert can be identified, the SD card can be extracted from the hive. The file, containing the sounds which triggered the alarm, can be analysed for an explanation of the alarm.

For testing the developed prototype, the sounds of different hives in various stages of the swarming process were required. A mature beehive typically only produces between one and three swarms per year, so, to get a clear indication of the prototype performance, a series of high quality recordings of swarming hives and piping hives were used in a controlled laboratory environment to simulate the sounds and volume levels of a live beehive.

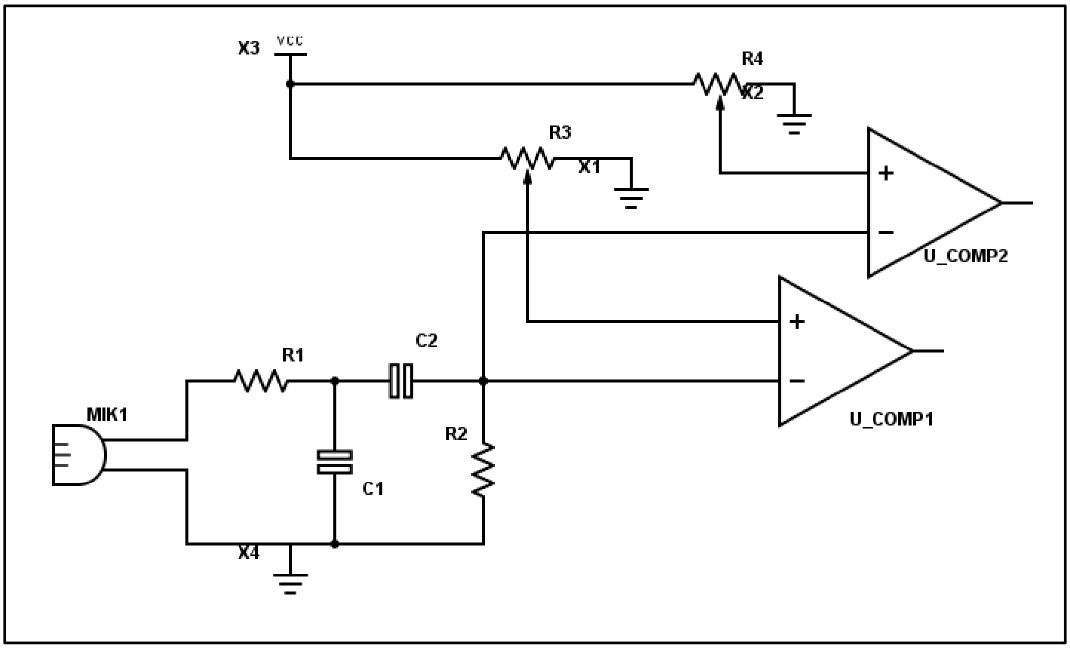

Figure 6.3 – Schematic overview of acoustic wake-up circuit

6.2.3.2 Sensors

Two microphones were selected for use in the node, for separate audio applications. The first was a low power (17 µA at 0.9 V) analogue MEMS microphone INMP801 for use in the interrupt circuit. It allowed for continuous (24/7) monitoring of the sound levels in the hive with a low energy consumption rate. This microphone was combined with an interrupt circuit designed to detect sound levels and frequencies of interest in the hive. In laboratory tests an alternative MEMS microphone was used (ADMP401) but which is now obsolete. The second microphone selected for use in the prototype was a high quality omni-directional foil electret microphone (CEM - C9745JAD462P2.54R), it had a higher power consumption (max 0.5 mA at 1.5 V). The output was amplified to give a high-quality output for sampling. This microphone was used in the high frequency, high energy consumption sound recording circuit, which was duty cycled to maximise energy performance. Energy harvesting from a solar panel was also included to extend the lifetime of the node.

The prototype was developed using off-the-shelf solutions for processing, energy harvesting, and networking. Separate processing units were used - one to achieve the frequency requirements of the more intense activities (sampling and storage of audio data), and one low power unit to preserve battery life during less demanding activities (energy harvesting, networking, and controlling sleep cycles as described in Chapter 3).

6.2.3.3 Acoustic interrupt circuit implementation

To design the acoustic interrupt circuit for detecting in-hive events a power spectral density analysis of several high-quality recordings was performed. These recordings were sampled at 6.3 kHz, which was also the frequency of the WSN node. The results of this analysis are shown in Figure 6.4. A calm, healthy beehive (A) where swarming is not happening has one very distinct peak in the 200-300 Hz range, this was expected, as the vast majority of bees, excepting the queen bees, produce sounds in this frequency range when they move their wings during their typical hive activities.

In Figure 6.4 (B) the frequency spectrum of a hive with a cell containing a new “virgin” queen is presented. The feature of most interest was the peak at approximately 500 Hz. This is the frequency range of the “piping” action, which occurred when the new queen is preparing to hatch. In Figure 6.4 (C) a single “toot” produced by the queen was analysed and the peak around 480 Hz was clear. There are also various sounds detected in the analysis at higher (>1 kHz) frequencies, these were produced by the bees present in the hive as it prepared for the swarming event to begin.

The piping sound usually started 6-8 hours before the swarming action begins and is an important indicator for the beekeeper. This sound was selected as important to identify immediately. A band pass filter on the output of the MEMS microphone in the range 300-700 Hz selected the relevant frequencies for piping sounds, and a comparator provided a wake-up signal for the microcontroller when the sound volume reached the desired threshold.

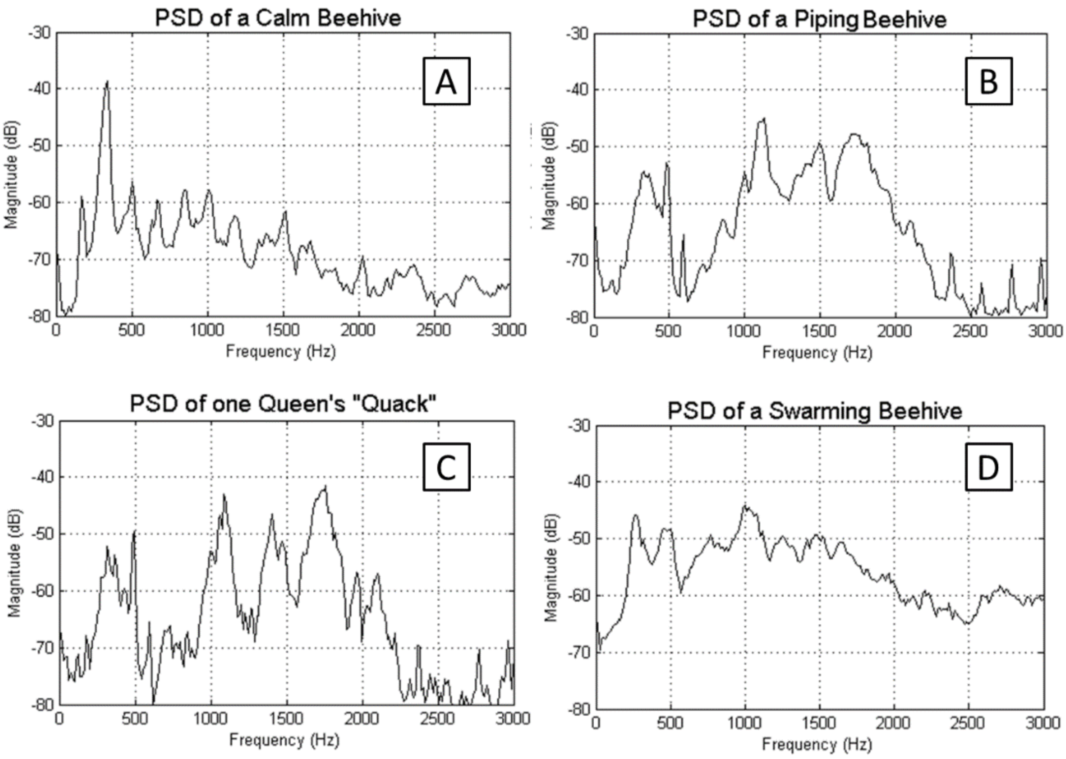

Figure 6.4 – Power-spectral density of beehive sounds

The frequency spectrum of an actively swarming hive is shown in Figure 6.4 (D), the frequency components were in the same range as in the earlier piping hive, but the power levels had increased for most frequencies. This showed that the volume of the sound during a swarm was much higher than for a calm beehive. There were other important events which cause the bees to increase the power level of their sound, including interference from intruders (humans or animals).

A series of distinct peaks in the 1 kHz and higher range can be seen in each PSD example. This is a result of the short recordings used, individual bees interfering with the recording, and background noise/interference, all frequencies commonly associated with honey bees lie in the less than 1 kHz range (see higher quality, longer recordings in Section 6.2.4).

These events are important for the beekeeper to address as quickly as possible. For these reasons, a second wake up signal to the microcontroller was required, based solely on the amplitude of the sound detected by the MEMS microphone. This was developed using another comparator with a set threshold. A block diagram of the interrupt circuit is shown in Figure 6.2, along with the wake-up signal's response to a recording of a swarming hive in Figure 6.7.

6.2.3.4 Node architecture

Figure 6.2 shows the architecture of the sound based wake-up node. The interrupt circuit generated a wake-up signal as described in the section above. This signal was passed to the off-the-shelf ATmega based platform as an interrupt. This platform could not operate at a high enough frequency to sample the microphone output at the desired rate of at least 6 kHz while storing the data on an SD. This platform acts as the "master" processor in the system.

The processing unit used for recording and storing the in-hive sounds was another off-the-shelf platform. This system was based on a Freescale Semiconductor MK20DX256VLH7 which had an ARM Cortex-M4 architecture, and featured a 72 MHz clock speed, 64 KB of RAM, and a 16-bit analogue to digital converter. These features made it ideal for sampling high quality audio, and storing these data in an SD card adaptor (microSD Card PROTO Board). This system was far more power hungry than the master processor (up to 185 mA vs. 15 mA) and did not have a built in RTC.

6.2.3.5 Energy harvesting and power performance

The interrupt circuit was the only part of the system designed for continuous use and was therefore designed to operate at a minimum power level. The "master" processor utilised its ultra-low power sleep mode to minimise consumption until an interrupt. The radio, sensors, and sound recording circuit were all duty cycled as they were power hungry. A solar panel (111 X 91 mm, Max output 6.5V at 205 mA) was utilised to harvest energy. The goal was to achieve energy neutral operation. The results of a power analysis can be found in Section 6.2.3.8.

6.2.3.6 System software

The node sampled the sound within the beehive four times per day, as well as any time an interrupt was generated by the circuit. The "Master" processor handled the interrupts, communication, RTC and duty cycling. Firmware for the operation of the master processor had a schedule as follows:

- Wait for sound interrupt or RTC interrupt
- Turn on the sound recording circuit and processor
- Turn on XBee module and connect to network
- Send RTC time and date to recording processor via UART.
- Sample temperature sensor (average over 10 samples)
- Sample humidity sensor (average over 10 samples)
- Send temperature, humidity, and RTC data to base station
- Delay 40 seconds, turn off all peripherals and sleep

Separate software was required for the audio recording processor, which was completely shut down in between sampling events to preserve energy. The time and date were passed to the recording processor over the UART connection to effectively name SD files. Firmware was written for the audio recording processor as follows:

- When turned on, set ADC resolution to 12 bits, and averaging to 4 samples
- Initialise SD card
- Receive time and date over UART and create new file on SD card with these data.
- Sampling loop for 30 seconds:
  - Read ADC and write value to SD file
  - Delay 70 µs
- Check average sample time = 158 µs
- Close SD file and wait to be shut down

6.2.3.7 Results - recorded audio

An example of a normalised recording of a calm beehive during the summer season is shown in Figure 6.5. Some examples of the audio files recorded by the demonstration system in experiments are plotted in Figure 6.6 (piping taking place) and Figure 6.7 (swarming hive). It can be seen that the audio recording block of the demonstration was operating at a high enough frequency to observe the sounds effectively and that the microphone input was correctly set up to capture all of the events successfully. The difference in volume levels between the calm and swarming colonies can be observed easily, and the distinct frequency change associated with piping can also be seen. These collected recordings demonstrate the effectiveness of the acoustic wake-up node.

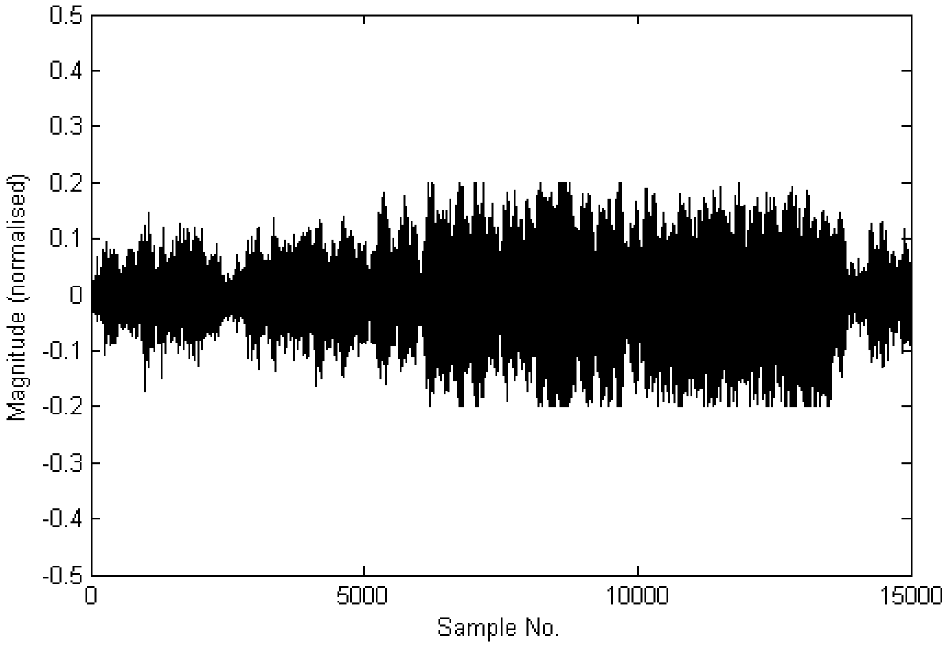

Figure 6.5 – Normalised recording of a calm beehive

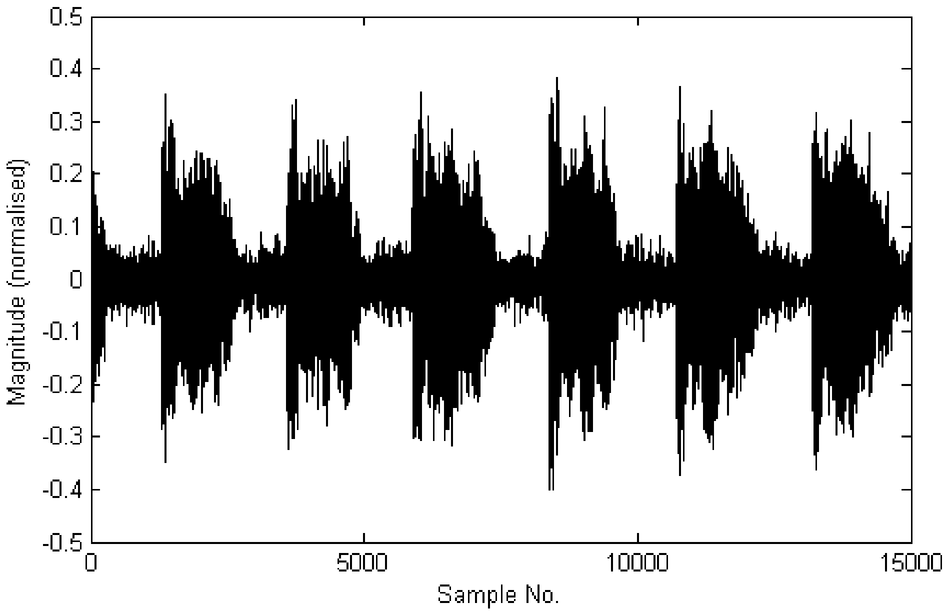

Figure 6.6 – Normalised recording of a piping queen

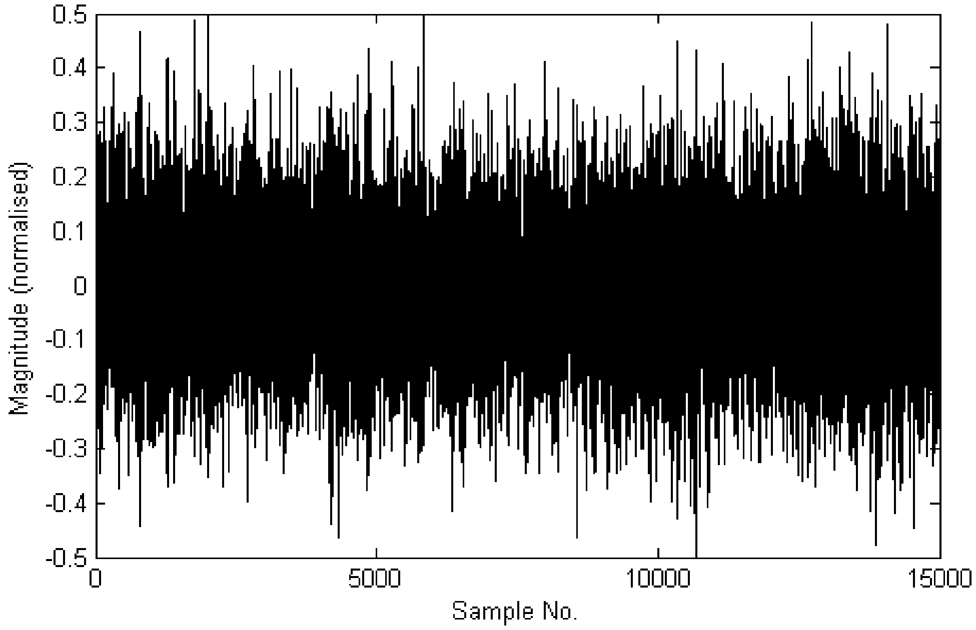

Figure 6.7 – Normalised recording of a swarming hive

6.2.3.8 Results - power and energy analysis

To confirm that the system was low power and self-sustaining, a power analysis and energy budget calculation were performed. For the power analysis (Table 6.1) a worst-case scenario (highest current draw) for each of the systems operations was taken. It is clear that design of the interrupt circuit was quite low power, as desired. It was also confirmed that the recording block consumed a large amount of power, as predicted.

Table 6.1 – Power analysis – acoustic wake-up node

<table>
<tr><th rowspan="2">Unit</th><th colspan="4">Power Results</th></tr>
<tr><th>Task</th><th>Current (mA)</th><th>Voltage (V)</th><th>Power (mW)</th></tr>
<tr><td>Interrupt</td><td>On</td><td>0.85</td><td>3.00</td><td>2.55</td></tr>
<tr><td rowspan="2">Master µC</td><td>Awake</td><td>15.00</td><td>3.70</td><td>55.50</td></tr>
<tr><td>Asleep</td><td>0.55</td><td>3.70</td><td>2.05</td></tr>
<tr><td rowspan="2">Recording µC</td><td>Processor & Microphone</td><td>115.00</td><td>5.00</td><td rowspan="2">773.00</td></tr>
<tr><td>SD</td><td>60.00</td><td>3.30</td></tr>
<tr><td>Radio</td><td>On</td><td>220.00</td><td>3.30</td><td>726.00</td></tr>
</table>

The aim of the energy budget (Table 6.2) was to confirm that the system was energy neutral when used in conjunction with the solar panel described above (maximum output 6.5 V at 205 mA). To achieve this, the energy consumed by the system in a typical day (5 scheduled recordings) was calculated based on the power analysis results. The energy of each additional recording (e.g. triggered by the interrupt circuit) was calculated. The energy provided by the solar panel with an average Irish day's amount of direct sunshine (2 hours) at an efficiency of η=0.44 (3.5.2) was also calculated. It was found that the solar energy provided in one day exceeded the energy consumed, and the system is therefore energy neutral.

Table 6.2 – Energy budget – acoustic wake-up node

Unit	**Energy Budget for one 24-hour cycle**			
	Task	***Power (mW)***	***On Time (mins)***	***Energy (J)***
Interrupt	On	2.55	1440.00	220.32
Master µC	Awake	55.50	15.00	49.95
	Asleep	2.05	1435.00	177.12
Recording µC	Processor & Microphone	773.00	5.00	231.90
Radio	On	726.00	15.00	653.40
Total Expenditure:				1272.00
Each additional Recording:		773.00	1.00	186.96
		781.50	3.00	
Income from Solar Panel @ η=0.44		586300.00	120.00	4220.00

6.2.4 Long term monitoring of colony sounds

One of the objectives suggested in Section 6.2.1 was to inform the design of a node which could use sound to detect and classify the status of the hive. The most effective method for achieveing this in a low power WSN based system with restricted processing power is to use a custom designed audio processing circuit expanded significantly from the one described in Section 6.2.3. This would avoid the significant processing load of implementing a machine learning technique with audio classification capabilites (such as neural networks). It would also allow for interrupts similar to those demonstrated in 6.2.3 when rare, asynchronous, hive events such as piping occur, which software techniques would need to run continuously to detect.

To enable this design, a long term sound data collection experiment was performed on several hives over 12 months. The objective was to collect an extensive set of high quality recordings for several important hive states which are associated with different colony sounds.

6.2.4.1 Design

To gather the large amount af data required for this analysis, 30 Yulass USB sound recording devices were used. These off-the-shelf devices used a MEMS microphone (frequency response: 20 Hz – 20 kHz) to record sound and store it on their on-board 8 GB Flash memory. Each of these devices were powered using an external 2,200 mAh rechargable battery to allow for continuous sound collection for the lifetime of the battery. Each recording device was installed in a hive of interest and had enough memory to collect data for 48 hours, after which time it was removed, replaced with another device, and taken back to laboratory for data extraction, analysis, and recharging.

Each device was installed in the same position in each of the hives – inside the roof cavity. This guranteed that changes in recorded volume or frequency were due to colony behaviour. It also allowed and developed nodes based on these recordings to have an estimate of performance when placed in the roof cavity. The sound files generated were .WAV files sampled at 16 kHz, which provides high quality data for the <3 kHz range of interest when analysing honey bee colonies.

The collected data files were stored on two 2 TB hard drives for backup. The files were stored by date together with notes documents outlining time periods of interest and the general conditions of each subject hive.

6.2.4.2 Results and Analysis

The first set of recordings collected were from healthy hives, during the main honey flow in May 2016. The power spectral density (PSD) of six randomly selected 5-minute samples throughout this deployment are shown in Figure 6.8 A, and the average PSD for the entire deployment is shown in Figure 6.8 B.

The key peak which was identified in the average PSD file was found to be in the 50 – 100 Hz range, with a magnitude of -54 dB. The overall magnitude of the PSD dropped off to below -80 dB in the higher frequency range.

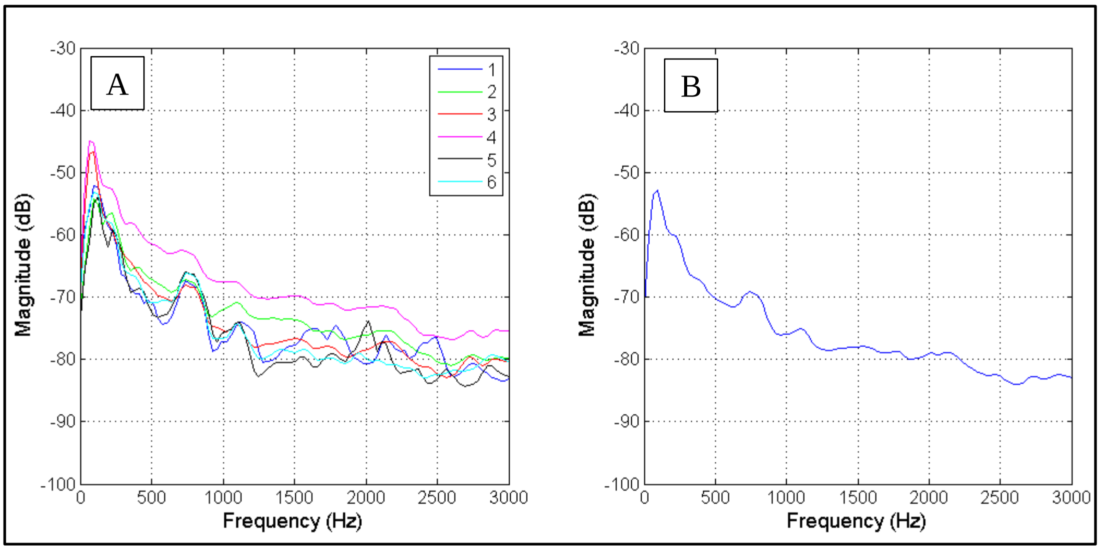

Figure 6.8 – PSD of typical summer colony recordings

Another key set of recordings were those collected from hibernating colonies, where the colony has stopped brood rearing, and has formed a Winter cluster with the queen bee at its centre. These were collected from hives in January of 2017. Figure 6.9 A shows the PSD of six 5-minute examples, and Figure 6.9 B shows the average PSD of the deployment.

The overall magnitude of the PSD for the hibernating colonies was found to be far lower than that of the active hive described above. The average PSD remained below -85 dB in most of the frequency range. Two peaks were identified at -74 dB in the 0-100 Hz range, and -77 dB in the 250-300 Hz range.

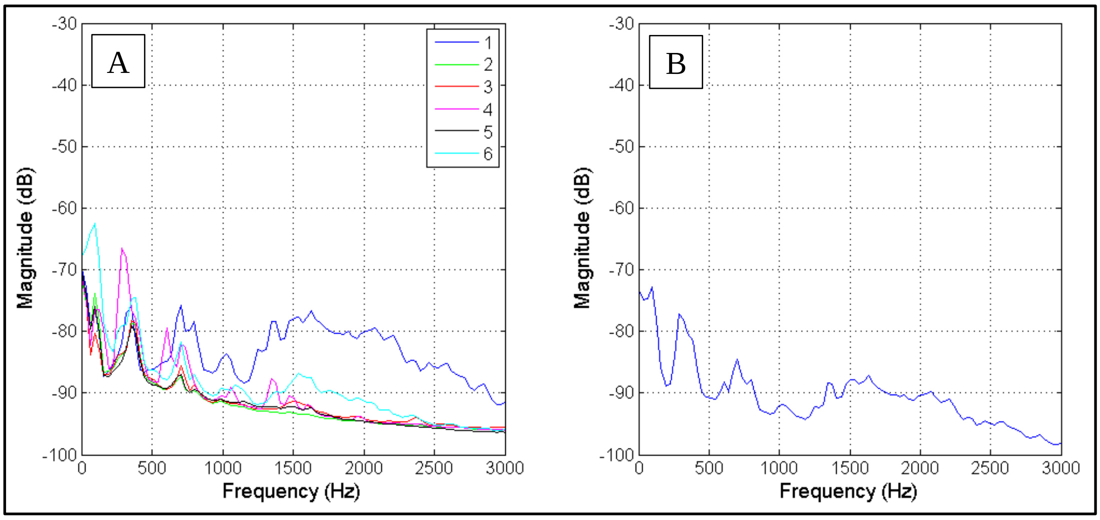

Figure 6.9 – PSD of hibernating colony recordings

Another key colony condition of interest is swarming, which was captured in June 2016. A large amount of data were collected from a hive immediately after the queen had left with the primary swarm. In this hive, there were two new queens preparing to hatch and fight, possibly leading to another swarm. Figure 6.10 A shows six 5-minute examples of a post-swarm hive, and Figure 6.10 B shows the average PSD over the 48 hours following the departure of the prime swarm.

The post-swarm hive had a significantly higher magnitude than the normal summer hive described above in the 200 – 600 Hz range. The peak of the PSD was found to be at -47 dB in the 50-150 Hz range.

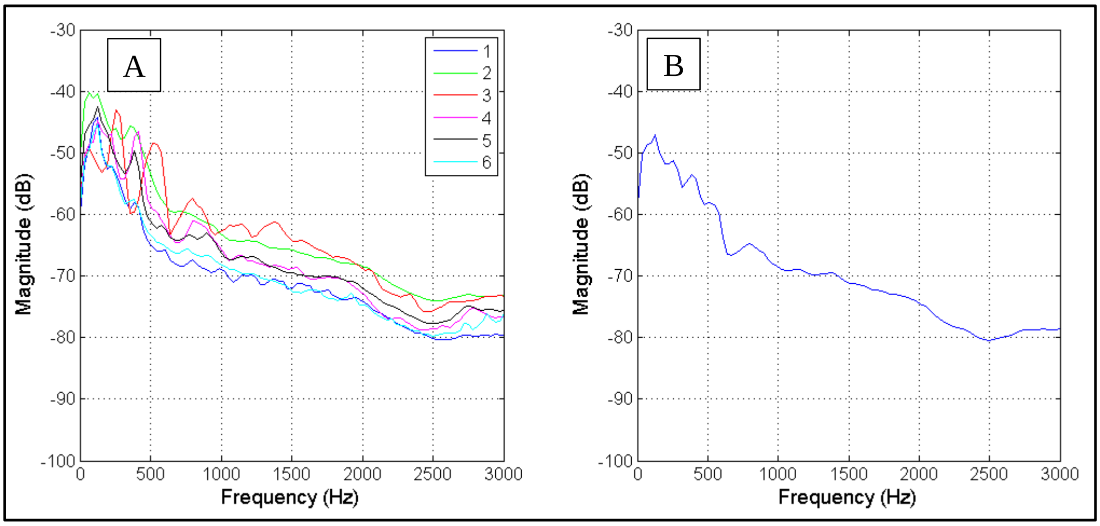

Figure 6.10 – PSD of recordings of a post-swarm colony

Supersedure is another colony event relating to queens. Towards the end of the active season, a colony with an old queen will remove her and replace her with a daughter without swarming. This was observed in a hive in September 2016, Figure 6.11 A shows the PSD of six 5-minute samples from the 76 hours following the removal of the queen, and Figure 6.11 B shows the average PSD for this 76 hours.

The PSD of a superseded hive has an almost identical profile to that of a post-swarm hive, with the exception of the 600-800 Hz range, which was found to be approximately 5 dB higher in the superseded hive. This is unsurprising as in both hives new queens are being reared and will fight for control of the hive upon hatching.

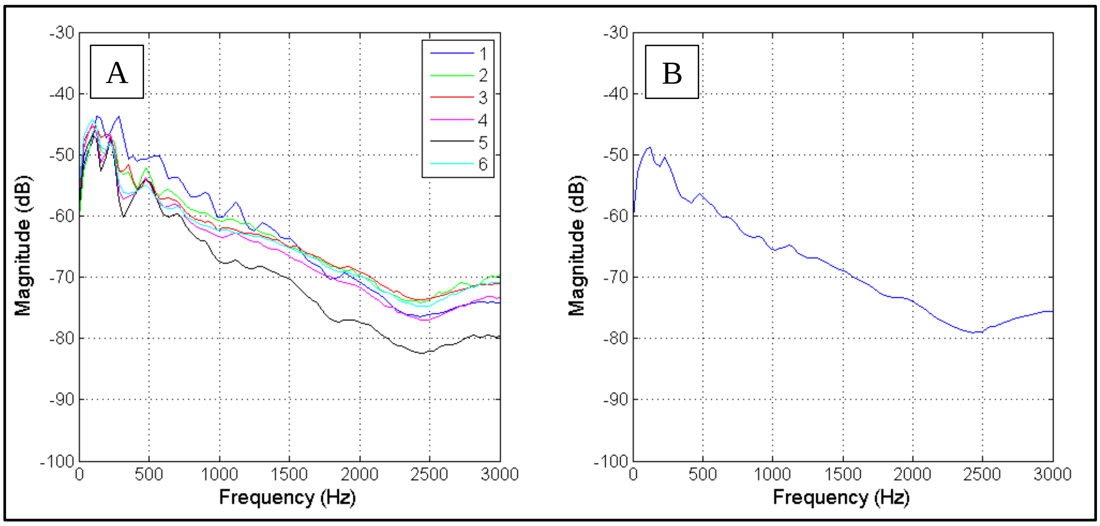

Figure 6.11 – PSD of recordings of a superseded colony

In July of 2016, one of the observed hives was found to be filled primarily with drones. It was observed that the colony population was made up of more than 50% drones. This is an important problem to be able to identify, as it is associated with both queen and worker problems. Figure 6.12 A shows the PSD of six 5-minute sound examples, and Figure 6.12 B shows the average PSD for the entire duration of the recording. In the drone filled hive, two distinct peaks were detected at -41 dB in the 100-200 Hz range, and -44 dB in the 250-350 Hz range. The drone filled hive has the highest recorded magnitude of any of the recordings made during the experiment in the <800 Hz range, but had typical characteristics above that range.

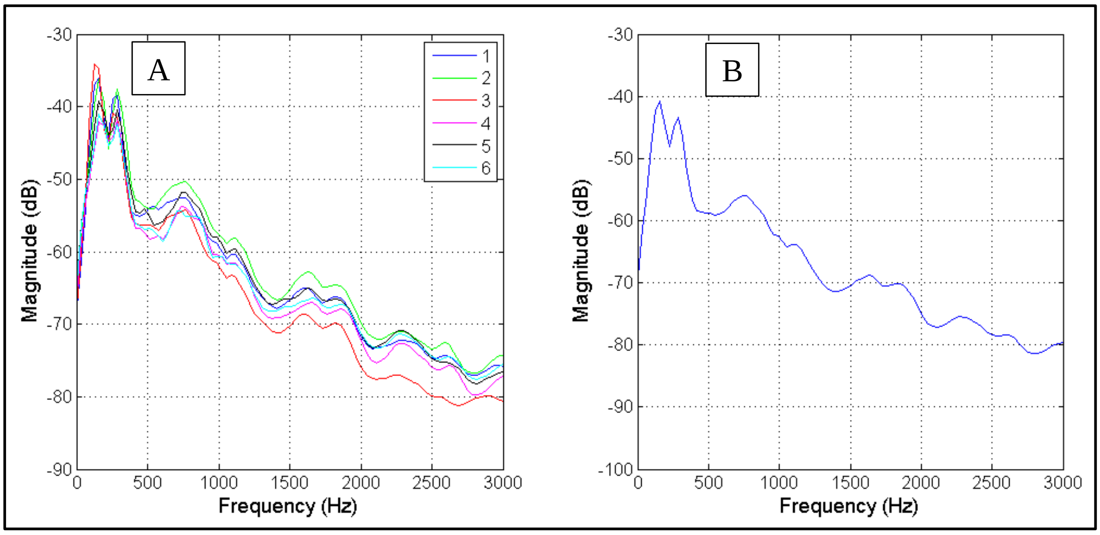

Figure 6.12 – PSD of recordings from a primarily drone filled colony

Throughout the recording of the swarming in June 2016 hive described above and illustrated in Figure 6.10, several instances of piping were noted. These instances were extracted from the sound files and analysed separately to help compare piping and non-piping colonies. Figure 6.11 A shows the PSD of six examples of piping, and Figure 6.11 B shows the average PSD of all of the collected examples. The PSD shows a clear peak at -50 dB in the 75-175 Hz range, which would be typical from previous observations in a swarming hive. There is also a distinct peak in the 350-450 Hz range of -58 dB, this is expected to be the impact of the piping noise itself, similar to the distinct peak observed in Figure 6.4. It is expected that the location of this peak could be used together with the information from Chapter 2 and Table 2.2 to estimate the age and number of queens in the hive.

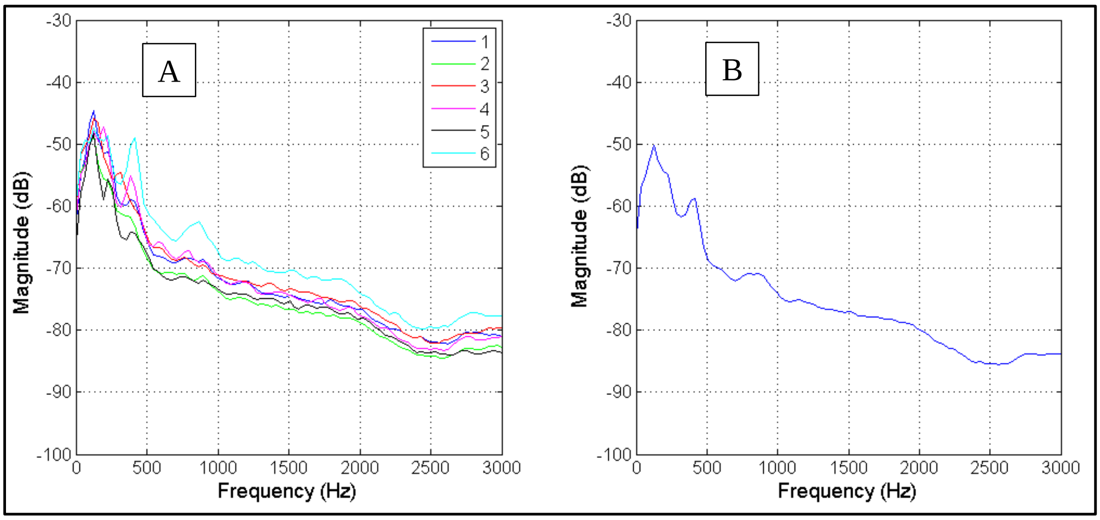

Figure 6.13 – PSD of a piping colony

6.2.5 Summary

The results of the development of a solution for detecting sudden increases in the sound volume from a colony in the case of colony alarm or swarming, as well as the specific sounds associated with piping are presented. When an imminent swarming event is suspected the node made a short, high quality recording of the hive sound as well as sending an alert to the beekeeper through the network. This system was successfully integrated into the WSN described in Chapter 3, while increasing the energy requirements of the node by only 186.96 J per recording.

Many recordings from hives in the field were collected to facilitate future development of the wake-up circuit into a classification circuit. An analysis of these data is presented together with an analysis into the peaks and characteristics which define each colony status. The average PSD analyses for each of the six hive states observed are shown together for comparison in Figure 6.14: : A – Summer colony; B – hibernating colony; C – post-swarm colony; D – superseded colony; E – drone filled colony; F – piping colony.

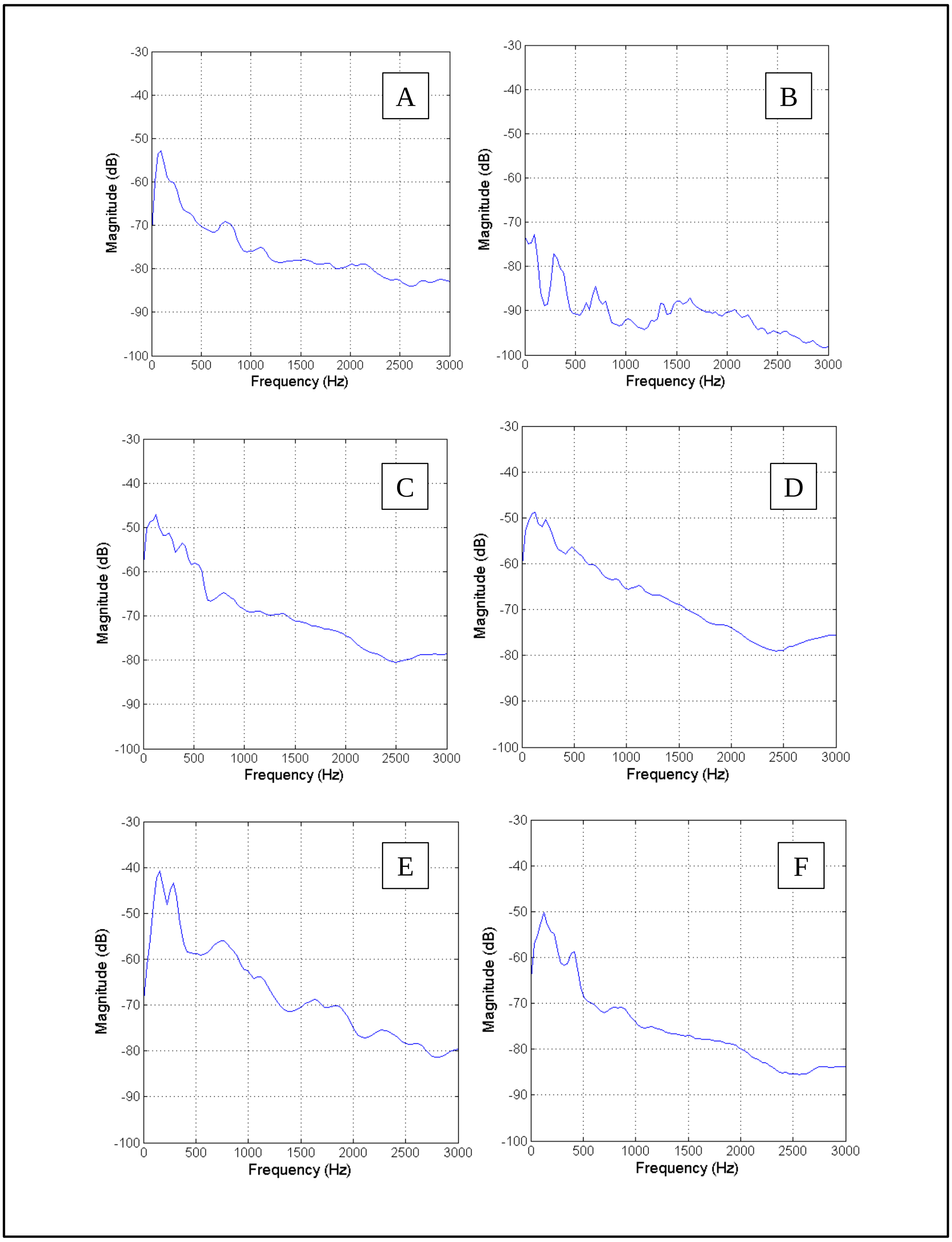

Figure 6.14 – Comparison chart of all six average PSD analyses

6.3 Weight Monitoring of Beehives

6.3.1 Introduction

Beehive weight is a key indicator of the productivity and condition of the honey bee colony; studies on how to effectively determine beehive weight have been carried out since the birth of apiculture. The USA Department of Agriculture released a document in 1925 outlining the effects of the weather on apiaries. It concluded that factors like ambient temperature, hours of sunshine, variation in temperature, and humidity can affect the weight of the beehive. The most commonly utilized method of weighing is to place a mechanical balance under the beehive, then adjust the scale as the weight changes.

A simple rule of thumb developed by beekeepers, is to use a basic tension scale e.g. a luggage weight scale, tilt the beehive on one side and double the value determined. The objective of weighing the colony during the honey production season is to determine when the hive's honey stores have reached maximum capacity, and then harvest them. This is difficult to achieve with the traditional, inaccurate weighing methods. The main difficulty surrounding hive weight measurement is that to gain an accurate picture of the hive status it is necessary to weigh several tens of kilograms but to an accuracy of tens of grams. The high resolution is necessary to measure honey production, colony size, and colony health, which can cause weight changes of 10's of grams.

6.3.2 Weight measurement

One of the most utilized sensors used in weighing applications are load cells. The combination of both mechanics of materials and resistive theory has produced a sensor design that can be used to measure changes in weight reliably. The load cell utilised in this work operated by measuring the deflection of a beam upon which the load to be measured had been placed. The beam adhered to Poisson's ratio, where a beam, when in tensile straining, extends in length in the direction of the force, but its cross-sectional area (CSA) contracts. When a beam experiences bending, its top surface experiences a tensile strain and its bottom surface experiences a compressive strain (depending on the direction of bending). If the beam is behaving elastically, then the strain is directly proportional to stress, and hence to the applied force. These changes in the beam can be used to measure the force applied precisely, using strain gauges.

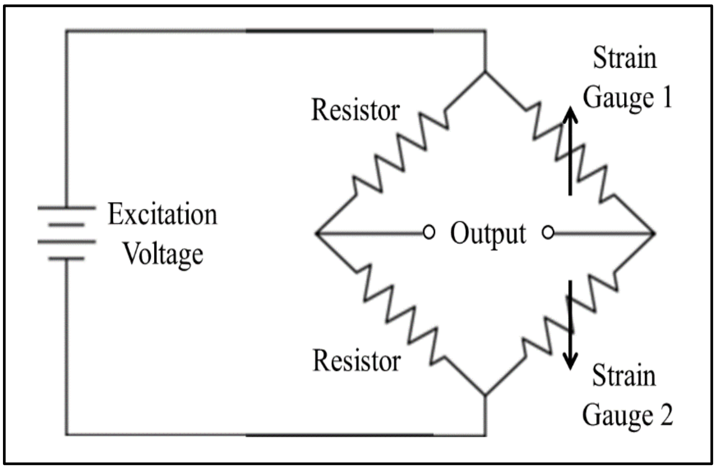

Figure 6.15 – Strain gauge Wheatstone bridge circuit

The circuit that is traditionally used with load cells is the Wheatstone-Bridge. The circuit design of the bridge can vary, depending on the number of strain gauges used. A greater quantity of cells provides greater precision. Figure 6.15 describes a Half Wheatstone Bridge circuit, utilizing two strain gauges on a beam, where one is fixed to the top surface, while the other is bonded to the lower surface. The two measured strains are usually equal and opposite, doubling the output of the bridge circuit. This arrangement can be considered a single load cell. The difference in current drawn between the positive strain gauge and the negative strain gauge can describe an applied force with great accuracy, in terms of a voltage output difference. This value can then be used to describe the varying weight.

6.3.3 Hardware and system design

6.3.3.1 Load sensor

For the prototype described in this paper, an AMS-750 Load Cell was used (Figure 6.16). Developed by Hanyu, the AMS was a Single Point Impact Cell (SPIC). The design of a SPIC differed greatly from other configurations, to allow greater deflection of the beam. This not only increased the range of loads it can withstand but can also be used to introduce a safety stop to protect the strain gauges from overloading. The AMS was a four-wire load sensor, with two excitation wires (power and ground) and two signal wires (positive and negative signal). The Wheatstone-Bridge circuit was integrated into the sensor. It had a rated loading of

750 kg and an accuracy grade of 0.02% full scale. For outdoor applications, such as the one described in this paper, the load cell was also rated IP65, which guaranteed protection from dust and water jets.

Figure 6.16 – AMS load sensor [175]

6.3.3.2 Analogue to digital converter

To create a weight sensing node which was extremely accurate over a large input range (up to 200 kg) an ultra-accurate analogue to digital converter (ADC) was vital. For this system, the Analog Devices AD7190 was selected, which is an ultra-low noise, 24-bit ADC with 2 differential inputs, designed for accurate weighing scales applications. It also had an SPI interface which made it ideal for use in an embedded system such as the one described in this paper. At the desired gain (G = 128) the AD7190 had 16 bits of noise free output. The maximum output of the AMS-750 load cell was 750 kg; therefore the minimum theoretical detectable weight change was calculated to be 11.4 g.

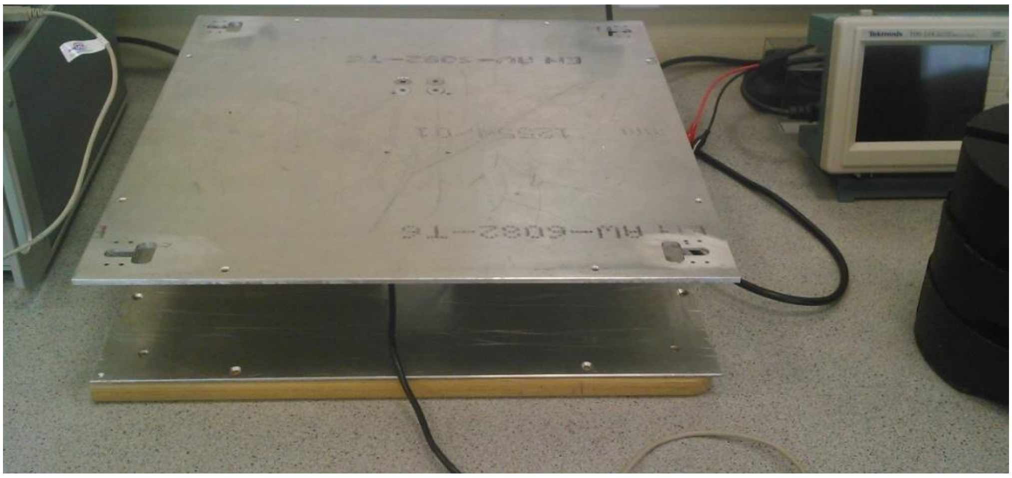

Figure 6.17 – Platform weighing scale

6.3.3.3 Wireless platform and node architecture

A dedicated weight measurement node was developed using the same platform as described in Chapter 3. The platform was interfaced with the ADC and load sensor via SPI (Serial Peripheral Interface), and firmware was written to wake up, sample the weighing scales, transmit the reading to the base station, and return to sleep mode four times in a 24 hour cycle. These readings correspond to the four weight levels of interest every day: night-time when all bees are in the beehive, the morning before foraging for pollen and nectar has begun, midday when the maximum number of bees are out foraging, and the evening when all of the pollen and nectar for the day have been collected and the bees are returning to the beehive.

6.3.3.4 Mechanical design

The load cell was designed to operate as a platform weighing scale (mechanical design implemented by Darren Fitzgerald, a MEngSc student in the Department of Electrical and Electronic Engineering at University College Cork [176]) that would be fitted to the base of the brood chamber, as shown in Figure 6.17. This was achieved by fixing the load cell to two spacer blocks and two aluminium plates (base and platform). The recommended power supply to the load cell was 10 V.

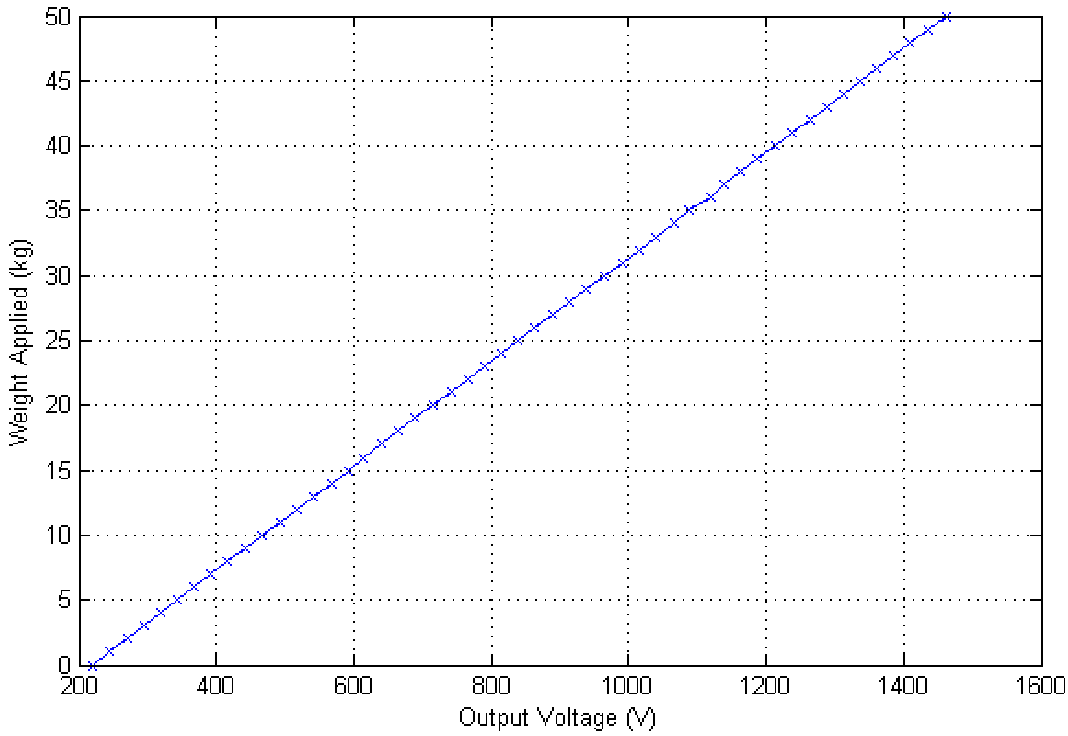

Figure 6.18 – Output voltage of scales

6.3.4 Results

The output voltage of the load cell system varied as expected in response to loads of 0 to 50 kg. Using standard, calibrated 1 kg weights, incrementally applied to the platform, the output voltage for the bridge was recorded. The data points plotted confirmed the load cell was linear. The noise at kg level increments was low, with little or no effect on the output value, making it very suitable for applications in estimating honey productivity. From the initial experiment, Figure 6.18, was generated.

For the second experiment, known weights were applied to the load cell when connected to the WSN node, and the output of the system was recorded. Table 6.3 was produced and the error of the ADC readout was calculated. This method of weighing proved to have low variation between the actual weight and the ADC's weight, with slight variation with the 5 kg weights.

Table 6.3 – Experimental results

Weight (Kg)	Average ADC Reading (kg)	Error (%)
0	0.0024	-
1	0.9967	0.33%
2	1.9975	0.12%
3	3.0153	0.51%
4	4.0155	0.39%
5	4.9418	1.16%
10	10.0184	0.18%
15	14.9397	0.40%
20	20.0186	0.09%
25	24.936	0.26%
30	29.98	0.07%
35	34.93	0.20%
40	39.98	0.05%
45	44.91	0.20%
50	49.97	0.06%

The minimum detectable weight calculated was estimated to be 11.4 g. To confirm that the system could detect weight changes in this range the lowest available standard weights, in steps of 10 g were applied to the scale while observing the ADC and node output. Figure 6.19 shows the output response to a series of 10 g weights being applied. The changes of 10 g were identified by the system, with a small amount of noise. It is possible, together with some with some signal processing (low pass filters) to reduce the impact of this noise and by also averaging the ADC output, that changes of the beehive weight in the range of tens of grams could be detected.

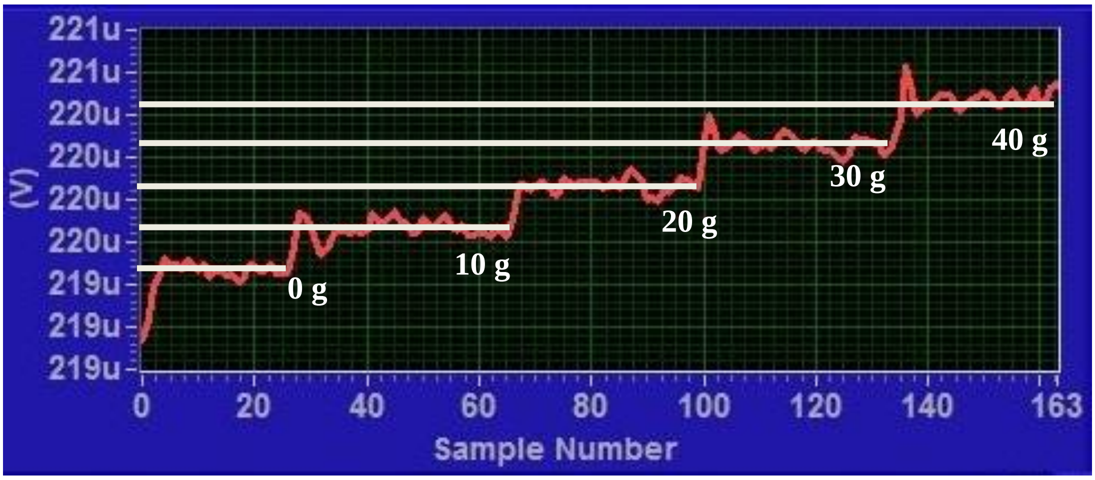

Figure 6.19 – Output voltage of 0 to 40g, in steps of 10g

A power analysis of the dedicated weight measurement WSN node was performed to confirm that the final prototype had suitable low power performance; the results of this analysis are shown in Table 6.4. The load cell was found to be the most power hungry component, as expected. To prevent this sensor from dramatically affecting the energy performance of the system the design of the prototype was revised to instruct the microcontroller to disconnect the load cell from the power supply when it was not actively being read.

All other components in the system are low power, or heavily duty cycled to maximise energy performance. A solar panel (234 x 160 mm, maximum output 7 V at 500 mA) was included in the final design of the system to allow a long term, self-sustaining deployment of the system in remote locations with little or no access to power lines.

Table 6.4 – Power analysis – weight node

System Block	Power Results			
	Task	***Current (mA)***	***Voltage (V)***	***Power (mW)***
Load Cell	On	20.00	10.00	200.00
ADC	On	10.00	5.00	50.00
Xbee Radio	Send	220.00	3.30	726.00
Master µC	Awake	15.00	3.70	55.50
	Asleep	0.55	3.70	2.05

Table 6.5 – Energy budget - weight noide

Unit	Energy Budget for one 24-hour cycle			
	Task	***Power (mW)***	***On Time (mins)***	***Energy (J)***
Load Cell	On	200.00	15.00	180.00
Master µC	Awake	55.50	15.00	49.95
	Asleep	2.05	1425.00	177.27
ADC	On	50.00	15.00	45.00
Radio	On	726.00	15.00	653.40
Total Expenditure:				1105.62
Income from Solar Panel @ η=0.44		586300.00	120.00	4,220.00

6.3.5 Summary

This section outlines the design and development of a platform weighing scale, for deployment as part of the sensor network described in Chapter 3. The results of the tests led to the conclusion that this design of platform scale, along with the infrastructure of data collection and distribution was a viable solution to accurately measure weight levels of the beehive. A significant aspect of the experiment was the ability to characterise and read small weight change, in the order of 10 g. The system was integrated into to a WSN node to provide a flow of information between the smart weighing scale and the base station. To provide an self-sustaining solution, a solar cell, along with a lithium ion polymer battery was used to deliver power to the system.

6.4 Image Processing of Beehives

6.4.1 Introduction

Visual inspection of the hive is one of the most important activities in which a beekeeper engages, it is used to examine the condition of the honey bees, including the number of workers and drone bees, the development of the bees, and examine for queens. Visual inspection also allows the keeper to detect a range of diseases by removing frames and examining them. However, a thorough inspection is a time consuming and invasive process, which aggravates the honey bees, exposes the inside of the colony to the external weather conditions, and can lead to bees being crushed when the keeper moves frames. Infrared cameras providing high quality images of the hive interior to the beekeeper remotely, such as the ones described in this work, have the potential to provide information on colony condition and disease, thereby reducing the frequency of physical inspections. Many beehives are kept in remote or rural locations. Inspections of hives in such locations require long journeys. They are also often placed in farmland or forests where they may be near livestock or other animals which can knock over a hive. Hives can also be knocked over in high winds. In all such cases, it is vital to reassemble the hive as soon as possible after falling to minimise losses. The system in this paper eliminates the need to inspect every hive for such damage regularly.

6.4.2 System functionality

6.4.2.1 Sensor node architecture

Two different development platforms were used in the prototype, the off-the-shelf platform used to develop the WSN nodes described in Chapter 3. To use camera sensors effectively, a second, more powerful processor was required. The controller chosen was the Raspberry Pi Model B. It had 512 MB of RAM, HDMI connection, 2 USB ports and 26 GPIO pins. It also had an SD card slot, which was used to store the image data. Similarly to the dedicated audio processing unit in Section 6.2.3 the existing platform is used as a low power “Master” which can turn off the Raspberry Pi to save energy.

The imaging node had a dedicated SIM900 (SIMCom) GSM/GPRS module to facilitate the higher networking load of imaging. This module has ultra-low power operation (30uA) and provided phone call, SMS and FTP upload/download operations. GSM/GPRS networking was selected to suit the remote deployments of many beehives.

6.4.2.2 IR Camera

In this research, an infrared sensor allows the tracking of the activity in the hive throughout the winter months so as to gain a better picture of the overall activity in the hive. During the summer months, the beekeeper often opens the beehive roof to visually inspect the colony. During the winter, bad weather, or at night opening the hive can damage the colony by allowing it to get cold or damp. A thermal imaging node with a Raspberry Pi was developed to provide the keeper with an image that describes the activity within the hive. The sensor used was the FLiR Lepton Thermal Camera, which is a longwave infrared imager (Figure 6.20). It has an 80 X 60 pixel resolution, is sensitive to wavelengths in the 8 – 14 µm range, has SPI and I2C (Inter-Intergarted Circuit) connectivity and a low operating power of 150 mW.

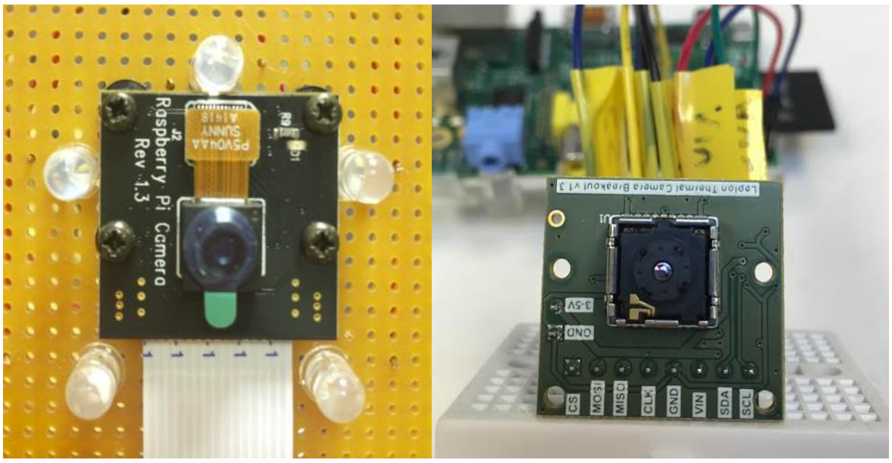

Figure 6.20 – Infrared camera module and thermal imaging module

Bees are not able to see light in the infrared spectrum (1 mm – 750 nm). Using infrared light to flood the inside of the hive, then taking an IR picture of the colony's activities, allows monitoring of the bee hive, even during the night, while remaining completely undisruptive to the bees in a live deployment. The camera chosen for the prototype was the Pi NoIR camera (Figure 6.20). The sensor had a 5 megapixel resolution and supports video up to 1080p. The NoIR was designed to interface with the Raspberry Pi board, and there were many existing libraries available to use the camera and Pi together for video and image capture.

6.4.3 Implementation

To implement both cameras into the design, the software deployed on the Raspberry Pi modules were turned on and took a picture five times per day and stored them on an SD card with a time stamp. The image files were saved to the SD card so the beekeeper could collect them for inspection. The images could also be retrieved from the SD through the network by the GSM/GPRS module and uploaded to a server via FTP. It was calculated that with an average jpeg image size of 3 MB, and an SD card of 8 GB then the beekeeper would only have to replace the SD every 111 days. A lossless image format such as PNG should be used to allow more effective processing of the collected images. This would lead to a significant increase in file size, which could be handled by deleting images with similar outputs, or replacing the SD more often.

6.4.3.1 Fall and movement detection

As part of the GPRS enabled WSN node which was described above, it was proposed to alert the beekeeper via SMS, and trigger an image capture of the camera system above when crucial physical beehive events are detected. This was achieved with an accelerometer interrupt when the hive is found to be moving (for beehive security). The accelerometers measure the tilt and orientation of the hive lid, and, using these data the sensor node can alert the bee keeper if this tilt reached a critical point. The accelerometer used was the LIS331DLH. This is a “nano” 16 bit digital output, low-power, linear accelerometer which detects up to ±8g. It measured acceleration values in the range of ±2g at a 16 bit resolution. The equation used to calculate the angle of tilt of the hive on each axis was as follows:

$$Angle_{x,y,z} = \frac{180}{\pi} \times \left(\sin^{-1}\frac{A_{Vx,Vy,Vz}}{1000}\right) \tag{11}$$

Where $A_{Vx,Vy,Vz}$ is the output of the accelerometer for the X, Y, or Z axis respectively. This angle was monitored and, if it was found to be changing, an interrupt was generated and an alert was sent to the bee keeper. This is accomplished within the design by either sending a message through the Zigbee network or a SMS.

6.4.4 Results

6.4.4.1 Infrared camera

A test was run of the camera within an empty hive in a laboratory for 4 days. It was found that little to no change in quality of the pictures throughout the course of the day, even as the amount of light in the surrounding room changed. These images were clear and of high enough quality for the beekeeper to identify bees and assess their condition. Careful placement of the cameras within the hive space to capture the frames at an angle which would be of most use to the keeper will be required in future deployments.

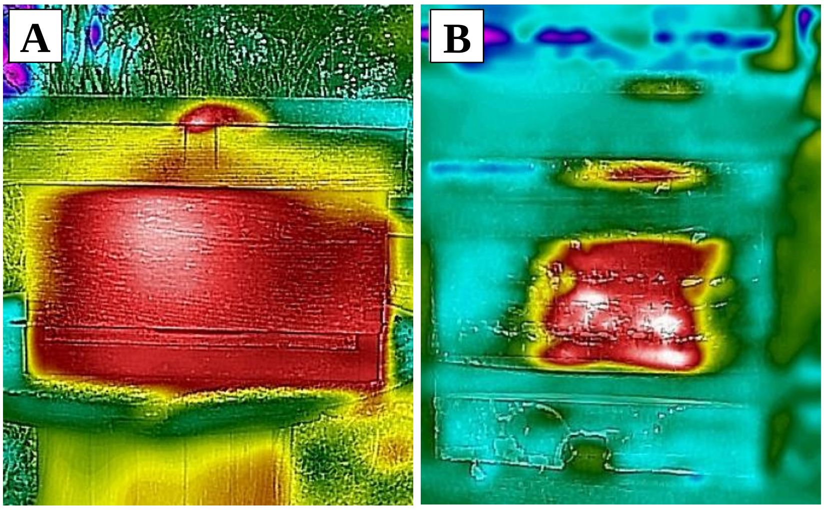

Figure 6.21 – Images captured by thermal imaging FLIR camera

6.4.4.2 Thermal imaging node

The thermal imaging node was tested by bringing it to the site of the live apiary used in previous experiments and capturing an image of a specific hive on several different days from a selected location 5 metres from the hive. to capture the changing hive conditions during different weather patterns. Two such images can be seen in Figure 6.21. In Figure 6.21 (A) the temperature of the hive is much higher and the hot air escaping through vents at the top of the hive allowing the bees to control their conditions can be seen. In Figure 6.21 (B) the ambient temperature is far cooler and the bees gathering together in the centre of the hive can be clearly seen. In both images, the lower temperature of the surrounding environment is easily distinguishable from the hot areas created by the honey bee clusters in the hive. Image processing to estimate the size of these “hot spots” could be used in conjunction with the data from the other sensors (temperature, humidity, sound, CO2) to estimate a variety of factors, such as: number of bees foraging, health of the hive, hibernation, or swarming.

6.4.4.3 Fall/movement detection

To test the fall/movement detection node several laboratory tests were run of the hive being knocked over and opened. In the experiment, the hive was set up in the laboratory as it would be in the field. The hive was then moved and knocked over repeatedly. Finally, it was brought to rest again. The resulting movement detected by the node is shown in Figure 6.22.

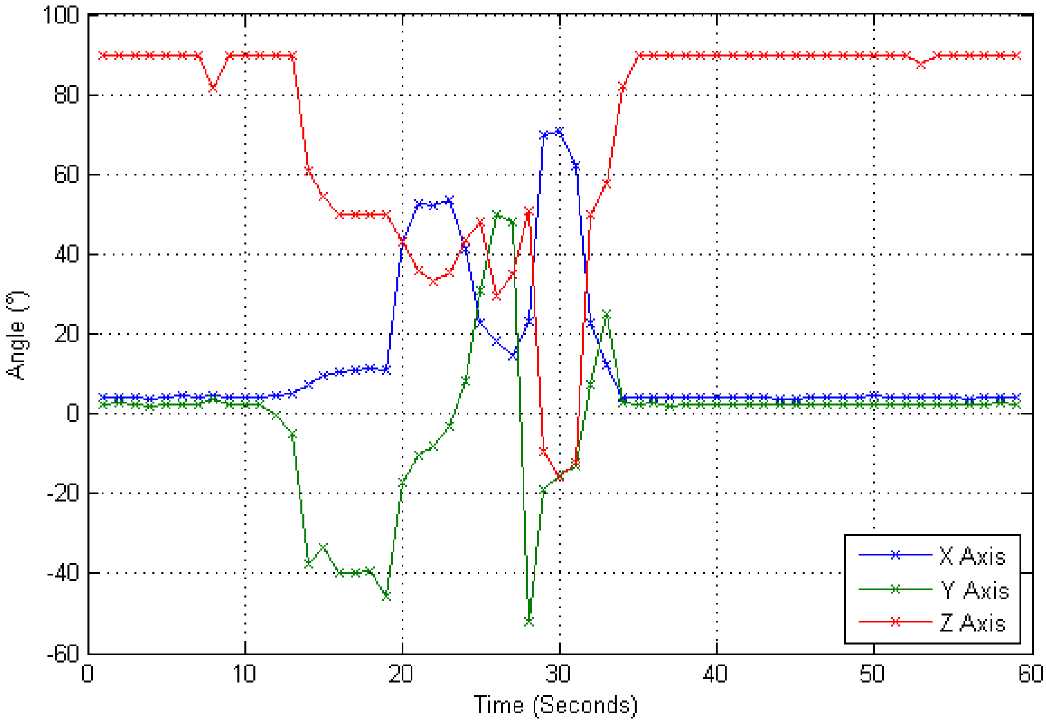

Figure 6.22 – Results of movement detection test

6.4.4.4 Power and energy analysis

For the system to be truly autonomous it was necessary for it to be energy neutral. This was achieved through the implementation of energy harvesting through solar panels and energy storage in a 1000 mAh battery (storage in the case of several days with no sunshine). To test that the system would be energy neutral for long deployments with little sunshine such as Ireland a power analysis and energy budget were undertaken. This power analysis assumed the worst-case scenario of maximum current draw for each of the nodes' operations over 5 samples per day.

For the energy budget, the total energy used by the nodes in the worst case was calculated. Sufficient energy was harvested by the solar panel (525 x 345 mm max operating output of 20W) in 2 hours of typical direct sunshine in Ireland, where an efficiency of η=0.44 can be expected (determined in chapter 3). The result was that the energy provided by the solar panel exceeded the requirements, and the system was energy neutral. The results of the power and energy analysis are shown in Table 6.6 and Table 6.7.

Table 6.6 – Power analysis – imaging node

Unit	**Power Results**			
	Task	***Current (mA)***	***Voltage (V)***	***Power (mW)***
Movement	µC on + Sense	30.00	3.70	111.00
	µC Sleep	0.55	3.70	2.03
	Send	220.00	3.30	726.00
Thermal Imaging	µC on + Sense	780.00	5.00	3900.00
	µC Sleep	0.55	5.00	2.75
	Send	220.00	3.30	726.00
Infrared Imaging	µC on + Sense	765.00	5.00	3820.00
	µC Sleep	0.55	5.00	2.75
	Send	220.00	3.30	726.00

Table 6.7 – Energy budget– imaging node

Unit	**Energy Budget for one 24-hour cycle**			
	Task	***Power (mW)***	***Function Time (min)***	***Energy (J)***
Movement	Sense	111.00	15.00	99.90
	Send	726.00	5.00	217.80
	Sleep	2.03	1420.00	175.30
Thermal Imaging	Sense	3900.00	5.00	1170.00
	Send	726.00	5.00	217.80
	Sleep	2.75	1430.00	237.60
Infrared Imaging	Sense	3820.00	5.00	1146.00
	Send	726.00	5.00	217.80
	Sleep	2.75	1430.00	237.60
Total Expenditure:				3719.00

6.5 Discussion

In Chapter 2 the value of sound measurements, visual inspection, and weight measurement were highlighted. The solution presented in Chapter 3, while providing a valuable dataset about the conditions inside the hive, did not provide access to any of these three values. The main challenge for implementing these solutions was the computational complexity and energy demand of measuring sound and imagery, and the lack of available solutions for wide range weight measurement with high resolution.

In this chapter, a solution for detecting sudden increases in hive volume due to swarming or alarm, as well as piping sounds associated with swarming is presented. This is implemented using a combination of a dedicated acoustic wake up circuit, and a dedicated audio processor which could be disabled unless required to save energy. Using this combination of techniques, important hive sounds could be detected and recorded without dramatically reducing the energy or networking performance of the WSN solution. Analysis and data collection which form the preliminary work for a larger circuit with a classification wake up is also presented.

To enable weight measurement as part of the hive WSN, a wide range Single Point Impact load cell was utilised together with an ultra-low noise, 24-bit ADC. The combination of a wide range load cell and a high accuracy ADC allowed for detection of weight changes as low as 11.4 g. The load cell had a dedicated power supply which was heavily duty cycled when weight measurement was not taking place to reduce the energy draw to suit the low-energy WSN concept.

Preliminary work demonstrating the usefulness of thermal and infrared imaging in the hive was also presented. A thermal camera and an IR camera were each implemented on an individual WSN node. Each node used a Raspberry Pi for image collecting, processing, and storage, which was disabled by the core WSN node architecture described in Chapter 3 to reduce energy demand.

With some further work, each of these solutions could be seamlessly integrated into the WSN described in Chapter 3 and 4. The data and alerts collected from the weight, sound, and imaging sensors could be utilised together with the software classification techniques described in Chapter 5 to create a comprehensive solution for both research into honey bee biology and behaviour, as a tool for evaluating and improving beekeeping practices, and as an automated beekeeping tool using actuation and a comprehensive awareness of hive conditions to maintain an ideal hive temperature. Parts of this work were published in several peer reviewed conference proceedings [177-179].

7 Conclusions

7.1 Overview

This thesis presents the use of embedded systems technology to improve honey bee health and therefore, productivity; by developing in-hive monitoring systems and algorithms to classify the colony status as well as mechanisms to influence and improve hive conditions. In-hive monitoring, together with actuation, also enables the beekeeper to change hive parameters such as airflow, which, in turn, permits bees to engage in activities linked to production instead of modifying conditions within the hive.

Specific tasks were achieved to realise this goal: Wireless Sensor Network (WSN) technology was used successfully to monitor a honey bee colony in the hive and collect a database of key information about its activity and environment; these data and resulting insights were used together to propose and demonstrate mechanisms to influence the hive conditions for effective control of beehive temperature; these collected data were also used to successfully inform the design of signal processing and machine learning techniques to characterise and classify the colony status using collected data and audio signals; and the use of high data volume sensors was investigated to aid in understanding specific conditions of the hive, which was presented together with integration of these high volume data sensors into the low-power and low-data rate WSN framework without reducing reliability or energy performance was also investigated.

7.2 Contributions

7.2.1 Wireless sensor networks for instrumentation of beehives

The use of an in-hive wireless sensor network for monitoring of hive conditions was proposed and explored. An in-hive end device node with five sensors (temperature, humidity, carbon dioxide, oxygen, and 3-axis acceleration), solar energy harvesting, and low-power ZigBee connectivity was designed and developed. A sink node with solar energy harvesting and multi radio connectivity (ZigBee and 3G/GPRS) was also developed, to aggregate data from multiple hives and store them in a secure database. Key mechanical design considerations for the in-hive nodes included: protecting the platform from the harsh in-hive temperatures and humidity while allowing the sensors to sample effectively using and IP65 rated enclosure; integrating the end node into the roof of the hive to allow the beekeeper to continue normal hive maintenance throughout long-term deployments; and preventing the bees from accessing the sensors.

The design and performance of this sensor network was evaluated following in-field testing on beehives, leading to self-sustaining energy performance and a sampling frequency which collected data at the important times in the colony's diurnal cycle. An Energy-Aware Adaptive Sampling Algorithm (EASA) was proposed and explored as an option for increased node lifetime in future studies.

The comprehensive dataset collected from five separate deployments of these sensors, throughout the different key beekeeping seasons were presented, together with the local weather conditions for each deployment.

7.2.2 Actuation for airflow and temperature control in beehives

The importance of airflow and thermoregulation in the beehive is well documented in the literature as being important to both the health and productivity of the colony. To propose improved methods of ventilation and temperature control, a computer simulation of the thermodynamics in the standard National beehive was undertaken. The results of this simulation were validated through comparison of the results with the results of an experimental hive, and were found to comply to within a margin of 10%.

An alternative geometry for the crown board component of the hive, using five ventilation holes instead of the standard one-hole layout, was proposed to improve the ventilation and temperature in the National beehive. The two geometries were compared in simulations and experimentally. The five-hole design was found to provide significantly improved ventilation in simulations and laboratory experiments, but will require further validation on hives with bees inside to examine the response of the colony. A lead-screw based mechanism was proposed, in conjunction with this alternative geometry, to create a method of adjusting the airflow within the hive to suit the requirements of the colony, and to allow accurate control methods to be implemented. The mechanism was fabricated and evaluated experimentally in the laboratory, and found to have a limited error of 0.3 mm after 50 complete cycles. This error is well within the tolerance level of the design, which included inlet covers 10% larger than required.

A control system was proposed to utilise the above mechanism together with the already implemented hive monitoring WSN to maintain a suitable temperature within the hive by adjusting the airflow. These elements used together formed a temperature control WSAN for the hive. A PID controller design was selected for the controller system. This controller was implemented on one of the network nodes which provided the input to the mechanism. The controller was experimentally tested in a controlled environment on a demonstration beehive and found to be highly effective. An appropriate temperature for brood development was achieved within 7 minutes of initialisation, and with steady state being reached by minute 18. There was negligible steady state error (0.0047%) and overshoot of <0.25 °C. The design of the WSAN was identified as suitable for real world control of beehive conditions.

7.2.3 Machine learning for honey bee health

A decision tree was developed which classified the hive as being in one of ten possible states. The algorithm was found to classify accurately the hive in 95.38% of cases. From the meteorological analysis a short term, local, weather prediction decision tree was proposed using in-hive CO_2 levels (95.4% accuracy, to be validated in future studies). This algorithm predicted rain patterns local to the specific hive monitored. These algorithms were deployed on the 3G/GSM enabled node and increased energy requirements by just 5.35%. Machine learning is used to apply established beekeeping knowledge automatically to the collected data, allowing early identification of poor health so as to take remedial action, as well as analysis of behaviour.

A second hive classification algorithm was developed using Random Forest techniques. This algorithm did not need access to data from outside the networks, memory of previous measured data, and used only four inputs, while achieving an accuracy of 93.5%. While it was not possible to implement this algorithm on the existing node described in Chapter 3 due to code size restrictions on the 8-bit ATmega1281 microcontroller, this algorithm could be implemented on a larger microcontroller in a future system.

7.2.4 Advanced monitoring in the hive

The design, development, and test of a wireless senor network node for continuously monitoring the audio events within a live beehive were described. To achieve this, the range of frequencies related to important in-hive events (specifically swarming) was identified through analysis of high quality recordings of beehives in various stages of the swarming process.

An interrupt circuit was designed to provide an acoustic wake-up signal to the node when an event within the defined frequency range occurred, or when the overall volume of the colony's activity rose above a specified threshold. This wake-up circuit allowed the solution to be ultra-low power, by turning on the power-hungry recording circuits only when they were explicitly required. The developed solution was powered by a 6600 mAH rechargeable battery with a solar panel for energy harvesting. A power analysis and energy budget confirmed that the final solution was energy neutral, providing additional energy to the battery for recharging, even in the case of several recording alerts in a single day.

To enable weight measurement as part of the hive WSN, a wide range Single Point Impact load cell was utilised together with an ultra-low noise, 24-bit ADC. The combination of a wide range load cell and a high accuracy ADC allowed for detection of weight changes as low as 11.4 g. The load cell had a dedicated power supply which was heavily duty cycled when weight measurement was not taking place to reduce the energy draw to suit the low-energy WSN concept.

Preliminary work demonstrating the usefulness of thermal and infrared imaging in the hive was also presented. A thermal camera and an IR camera were each implemented on an individual WSN node. Each node used a Raspberry Pi for image collecting, processing, and storage, which was disabled by the core WSN node architecture described in Chapter 3 to reduce the node's energy demand.

7.3 Future Work

It would be very valuable as a first future step to engage in further deployments of the in-hive WSN described in Chapter 3. This would not just provide an expanded dataset to further train and validate the decision trees described in Chapter 5, but also provide datasets demonstrating the hive conditions during events that were not monitored during this research. For example, it would be valuable to monitor hives during each of the conditions identified as important in Table 2.3. This was not possible to achieve during this research due to these problems not affecting the hives used in the current research. It is essential to be able to detect or anticipate such conditions using the in-hive sensors utilised Chapter 3.

The microcontroller used as the core processing platform for the system (8-bit ATmega1281) reached its limit for memory and processing several times during this research. A key step in future work will be to redesign the system with a more powerful 16 or 32-bit processor with more memory and program space. Further energy harvesting may be required to support this increase while maintaining self-sustaining operation.

For the WSAN system described in Chapter 4, it would be useful to build a water proof version of the prototype. This would enable an in-field deployment on a beehive to observe the temperature and airflow effects, and how the mechanism itself affects the behaviour of the colony. It would also be valuable to implement the identified energy saving techniques form Chapter 4 to allow the deployment to have an extended lifetime. Finally, to further improve the airflow, ultra-silent fans could be embedded in the roof of the hive.

In the future, it will be important to collect an extensive dataset using multiple deployments (>100 datasets) on a variety of different beehives. This will provide an extensive pool of training data, on which it will be suitable to apply other classification techniques such as Bayesian classification [180] or Neural Networks [181]. To implement these algorithms, and the Random Forest described in this work, it will be necessary to design a new in-hive WSN platform with better processing abilities, such as an ARM based system. The output from the sensor nodes described in Chapter 6 will need to be incorporated into the classification decision tree, for more in-depth analysis.

Future work for the acoustic wake-up node described in Chapter 5 needs to include miniaturisation of the node, and introducing other energy harvesting sources. A demonstration deployment of the node at the same site of the existing bee sensor network will also need be put in place to show the system's response to a live beehive. The analysis described in Section 6.2.4 should be used to design a new interrupt circuit which both detect changes in the hive sounds, and attempt to classify the sound it is detecting, using hardware for energy performance.

Before the weight sensor node described in Chapter 6 can be integrated into a hive, the scale must be completely weather protected. Future work needs to address stabilisation of the platform against wind, and improvement of the noise performance of the system. Techniques for monitoring hive weight without needing to manually lift and move the hive itself will also need to be explored, as hive weight is the fundamental measure of honey production.

For the infrared and thermal imaging nodes described in Chapter 6, consideration needs to be given to: improving the prototype's physical design to allow long term deployments and data collection for analysis; investigating utilising a dedicated microcontroller for improved energy performance; and applying some machine learning image classification to detect changes in the hive, such as the waggle dance inside the hive using the infrared camera, and the onset of winter clustering or fanning, using the thermal camera.

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