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Real time monitoring of honey bee (Apis Mellifera L.) colony dynamics with Internet data delivery and behavior analysis using artificial neural networks

Robert Seccomb

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REAL TIME MONITORING OF HONEY BEE

(Apis Mellifera L.)

COLONY DYNAMICS WITH INTERNET DATA DELIVERY AND BEHAVIOR ANALYSIS USING ARTIFICIAL NEURAL NETWORKS.

By

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B.S. The Montana College of Mineral Sciences and Technology, 1987

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Real time monitoring of honey bee (*Apis Mellifera L*) colony dynamics with Internet data delivery and behavior analysis using Artificial Neural Networks.

Chairperson: David Opitz

Honey bees have been used for many years in evaluating environmental conditions. Recent technological developments have provided real time monitoring capability and continuous evaluation of bee behavior. Deviations in normal bee behavior often can be traced to the influence of factors such as swarming, predation, disease or pollution exposure. Using Artificial Neural Networks it is possible to evaluate bee flight activity and flag atypical behavior. To provide real time monitoring and evaluation, specially designed bee hives can be connected to the Internet for data delivery and ANN processing.
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ABBREVIATIONS

A/D. Analog to Digital

ANN. Artificial Neural Network

DAQ. Data Acquisition System

DOS. Disk Operating System, an operating system for personal computers

SNNS. the Stuttgart Neural Network Simulator
GLOSSARY

Bee Counter. A bidirectional counter system using a series of infrared emitters and detectors placed across the entrance of a bee hive.

Brood Chamber. The portion of a bee hive devoted to the development of the immature honey bee.

Condo. A specially designed honey bee hive containing a suite of electronic sensors connected to a bank of computers.

Forager. A caste of honey bees delegated to the collection of nectar and pollen.

Linux. A free Unix operating system clone for the personal computer.

Queen. A reproductively viable bee, responsible for egg laying and production of all the other bees in the colony.

Queen Right. Indicates a colony with a laying queen.

Robbing. When bees from other colonies invade a weak colony and carry off stored resources.

Swarm. A process where a large population of a bee colony leave to find a new hive.
CHAPTER 1
INTRODUCTION

In June of 1995, six specially designed honey bee hives were set up at an installation restoration site in Maryland. These represented the first version of a computer controlled, electronic biomonitoring system using honey bees (Apis mellifera L.). The two weeks trial run of this system formed a proof of concept: honey bees could be used as part of an automated pollution detection system. This thesis investigates the equipment and methods used to create such a system.

Years of previous work demonstrated the efficiency of honey bees in detecting a variety of environmental pollutants (Bromenshenk, J. J. et al., 1985; Bromenshenk, J. J., 1990; Bromenshenk, J.J., 1996). Traditional use of bees in a biomonitoring system required the scientist to: 1) collect samples of bees, wax, pollen, and honey for analysis; and 2) periodically inspect and measure several parameters inside the hive - a time consuming process. The next logical step was to remove or reduce the amount of work done by humans and place more of the measurement burden on an automated system. This progression lead to development of the first fully electronic honey bee condos. The condo was equipped with a suite of electronic sensors including infrared bee flight counters, temperature sensors, and weighing systems. It was then possible to accurately and continuously monitor honey bee colony behavior.

Certain aspects of bee behavior linked to weather have been observed for years such as bees don’t fly in the rain and bees don’t fly if it’s too cold. But, what behavioral
changes occur when bees are exposed to a pollutant? Smoke is commonly used by bee keepers to “calm” bees while the hive is being “worked.” Could a change in bee activity be observed electronically?

In July of 1996, 14 examples of the second generation of bee condos with enhanced electronics and software were deployed at the remediation site in Maryland, with an additional seven condos placed at a reference site, also in Maryland. One of the first experiments conducted was the use of smoke in changing bee activity. The results were an unqualified success: the electronic counters registered a drop in the number of bees leaving the hive, while the number of returning bees remained constant. Similar experiments and events demonstrated the effectiveness of the bee activity monitoring system.

Changes in bee flight activity can be observed either on the counter computer display, or by later analysis of data collected by the computer. This is a time and labor intensive task, and requires human discrimination of normal from abnormal activity, although certain statistical methods have demonstrated usefulness in reducing the amount of decision work needed. A requirement existed for a computer agent to analyze the incoming data stream and flag aberrant behavior for further investigation and chemical sampling. Investigating this requirement is the focus of this thesis.

In this thesis artificial neural networks are used to learn bee behavior and signal significant changes in recorded bee flight activity. Experiments show great promise for this technique. Certain gross changes in bee behavior such as swarming and robbing are accurately detected. Through the use of different network training schemes, various levels
of sensitivity have been observed, from detecting gross changes in colony behavior, such as swarming, to nearly anticipating the event.

The rest of this thesis details the following task steps:

Chapter 2. A description of the equipment, electronics, and computer software used in the bee monitoring system.

Chapter 3. Configuration and use of network systems to delivery data from remote sites.

Chapter 4. The experiments performed to use artificial neural networks to analyze the bee behavior data.

Chapter 5. Conclusion on the effectiveness of the automated bee biomonitoring system.
CHAPTER 2
DATA GATHERING SYSTEM

At the heart of the bee monitoring system is the bee, and no description of the bio-monitoring system would be complete without a basic explanation of bee biology.

2.1 Basic Bee Biology

Honey bees are social insects. The community unit is referred to as a colony. The colony lives in a hive, either a natural cavity in trees or rocks, or a man-made structure designed for bee keeping. Each colony consists of a large population of female worker bees, a small number of male drones, and a single queen. The queen is the driving force of the colony, since she is the only member that can lay fertilized eggs which develop into workers. Without a queen, the colony will eventually die off from lack of a work force.

The female worker bees perform different activities, depending primarily on the age of the worker. Foraging is performed by the oldest bees. The primary duty of forager bees is to harvest resources used by the colony. These resources include pollen, nectar, water, and tree sap or resin. Due to the variety of materials needed by a thriving colony, a forager bee becomes a multimedia sampling system, including bioavailable pollutants.

A normal, commercial bee hive contains from 50,000 to 100,000 bees. A smaller, nucleus, colony of 8,000 to 30,000 is used in the electronic system. The smaller colony exhibits the same behavioral patterns as a full size colony, but is lighter,
easier to deploy and sample, and with fewer bees to perform guard duty, less aggressive. With smaller colonies it is possible to sample more sites with greater replication at each site.

Due to the resource requirements of a colony, a variety of materials are brought into the hive. The bee bodies have a multitude of electrostatically charged hairs, which are useful in collecting pollen, but also pick up dust particles. Bees also collect liquids such as nectar and water. Due to the energy required to carry large loads, bee respiration rates are high during flight. Thus, the bee may inhale airborne contaminants. Bees also make a great effort to return to their own colony. Thus, nature has provided us with a system that will travel up to 14 kilometers (Gary, N.E., et al. 1978) and return to a single point, while sampling the environment they encounter. Perhaps most importantly, a realistic evaluation point is present; is a chemical substance biologically available and is it harmful to a biological entity? By collecting and chemically analyzing bees and the substances they gather, as well as documenting how well the colony flourishes, bees can be used to determine how hazardous or benign an area may be to the bees themselves, to insect pollination of plants, and possibly to other living organisms.

The bee monitoring system consists of four major components: the electronics platform or condo, the ALPHA Data Acquisition System (DAQ) system, the WeatherMAX weather station, and the bidirectional bee counter.

2.2 Bee Condo

The bee condo is a protective shell encasing a two-story mini hive (Figure 2.1).
The condo provides a stable and weather resistant platform for the suite of electronic sensors. The shell contains a number of doors and removable panels to allow access to the bee hive and working components. Electricity to power the various sensors and motors is provided to a power strip attached to the inside top of the condo.

The hive itself sits on a custom-made sandwich of polyethylene plates approximately 1 foot above the condo floor. Bees enter and leave the condo by passing through a slot formed by the poly plates (Figure 2.2). The poly sandwich is constructed with a large hole under the hive, with a glass funnel below which serves the dual purpose of a pollen hopper and a trap to collect dead bees. A pocket between two plates of polyethylene allows placing a screen between the hive and entrance slot.
Figure 2.2 Detail view of condo internal workings: A, poly plates; B, clock driven pollen collector.

This barrier can be a wire screen which prevents bees from escaping or a thin sheet of plastic with a number of 3/16\textsuperscript{th} inch holes. This plastic sheet is commonly called a pollen scraper; a bee may pass through it, but is forced to drop a portion of pollen which is dislodged from its hind legs by the screen. The poly sandwich also provides a base for the weighing system. Currently, the weighing system consists of a series strain gauges attached to aluminum beams upon which the hive rests on. As the weight of the hive changes, the aluminum beams deform. This deformation is translated into a resistance change in the strain gauges.

At the bottom of the condo is a clock driven pollen collector, which allows an
approximation of the time periods that bees collected the pollen. The collector is constructed of a heavy duty timer, with a pie plate, either plastic or aluminum, attached to the drive spindle. The timer makes one complete rotation every 24 hours. The location of the pollen in the pie plate indicates the time of day the pollen was collected. Sampling of pollen requires inserting the pollen scraper sheet.

An access panel at the back of the condo is fitted with a nine-conductor, twist-lock, electrical connector. On the inside of the condo, leads from the connector are attached to the various sensing equipment, except the bee counter, which have their own connector. Sensors used in the past have been strain gauges, thermal transistors, relative humidity sensors, hot wire anemometers, and indicator switches.

2.3 ALPHA System

Due to the complex nature of information gathered for the bee monitoring system, no single interface can suitably manage the input. The ALPHA A-Bus™ system (ALPHA Products, Flanders, NJ) is used to monitor and log low priority sensors. These sensors typically do not change their output signals radically over a short time.

The ALPHA system used in the bee monitoring system consists of five main components: the MB-120 Motherboard, the SA-129 Serial Adapter, the AN-146 Bipolar 12-Bit A/D Converter, and two MX-155 32 Channel Multiplexers. Additionally, a custom-built difference amplifier is included to boost signals from certain sensors.

The setup of the ALPHA is straightforward, using documentation provided by
ALPHA Products. One multiplexer card is used for double ended sensors, such as strain gauges, in which a differential input between two lines is required. The other multiplexer card is used for single-ended sensors, such as temperature probes, where the input is relative to ground. In order to avoid using two A/D Converters, the output of the first multiplexer card passes through the home-built difference amplifier to one of the input channels on the second card (channel 32). With this setup it is possible to monitor 31 single-ended sensors and 16 double ended sensors with a single ALPHA system. The output of the second multiplexer card is connected to the A/D card. Finally, the serial card is connected to a computer using a nine or 25 pin serial connector.

A variety of sensors have been attached to the ALPHA system. Currently the sensor suite includes one or two thermal transistors (TS-111, ALPHA Products) placed over the brood chamber and the top of the nucleus hive. Bees will normally maintain a constant temperature of 33°C-36°C Celsius in the brood chamber (Seeley, T.D., 1995). When there is no brood, the thermal regulation breaks down until the core temperature nearly follows ambient. As evidenced by the ALPHA system, this happens normally in the fall, but also prior to swarming, or when the queen is no longer viable. The thermal transistors are calibrated in a straightforward manner; the sensors are enclosed in a plastic bag and immersed in a liquid (water) bath of a specific temperature. After the reading steadies, the raw millivolt output from the sensors and the actual water temperature, as determined by a NIST-traceable thermometer, is recorded. Five such readings at various temperatures (approx. 0°C, 10°C, 25°C, 40°C, and 50°C) are recorded.
A conversion function from millivolt to degrees Centigrade can then be calculated using simple linear regression.

Since bees do not fly at night, a photoresistor (CD-113, ALPHA Products) is connected to the ALPHA system. This sensor is calibrated for relative light intensity, with zero at total darkness, and 100 for bright daylight.

Occasionally, it is necessary for beekeepers to enter the condo, and examine the bee colony. Since normal flight activity during this time is disrupted, simple, normally closed micro switches are installed on the doors of the condo. These switches are connected to the ALPHA system, as a computer logged access indicator. This is useful for documenting when hives have been opened, so that flight activity during and immediately following this period can be disregarded.

Initially installed sensors included a relative humidity sensor (EMD-2000, Phys-Chem Scientific Corp.), and a weighting system using strain gauges (SG-13/350-LY13, Omega® Engineering, Inc, Stamford, CT). The RH system proved unreliable and inaccurate under field conditions, primarily due to excessive moisture in the hive shorting out the sensor. The strain gauge weighing system was chosen to better weigh the hives. However, the existing design is fragile and somewhat insensitive. A newer generation design currently is being developed to offset these limitations.

The initial proof of concept run in the summer of 1995 revealed a serious flaw in the DATACAM™ (ALPHA Products) software used to control and log the sensor data. Although it produced many fine graphs and displays, the data was stored in a proprietary format. When the data was later "unpacked," it contained no information.
This problem led to development of a program that provided a reliable data save in an easy to read format. Over the duration of this project, the program took on greater flexibility, including use of a variety of sensor input scaling schemes. Lastly, the program was ported to Linux and modified to export data to an Internet ready format.

2.4 WeatherMAX™ System

Weather has a profound effect on bee behavior. Daily occurrences such as rain and wind will keep bees from flying. Continued periods of cold weather shut down brood rearing. To track these external parameters, a WeatherMAX weather station (MAXIMUM®, New Bedford, MA) was installed and monitored at each test site. This device provided continuous monitoring of temperature, wind speed and direction, rain fall, relative humidity, and barometric pressure. The WeatherMAX™ connects to a personal computer using a special serial cable.

During the first year of operation, the Fourth Dimension History Logging Weather Software (MAXIMUM®) program was used to operate the WeatherMAX™. This is a well written and reliable DOS based program, but its major shortcoming was a lack of granularity in the data saved. The Fourth Dimension software saved sensor data averaged for a one hour period. Needless to say, this was far too coarse for determining bee activity changes based on weather events.

During the second year of operation, the Fourth Dimension software was replaced with the Weather View© (ControlWare, Amity, OR) program. This Windows based program allowed weather averages from one minute to one hour. This proved adequate for the next two years.
In January of 1998, the monitoring and control of the weather system were taken over by a new Linux based program developed at the University of Montana. In addition to running in a more stable multitasking environment, the new program performs more rigorous error checking and recovery, allows access to text logged data without stopping the monitoring process, and creates Internet available update files.

2.5 Bee Counter

![External view of a Bee Counter](image)

**Figure 2.3** External view of a Bee Counter

One of the most important, and successful, monitoring subsystems used is the bidirectional bee counters (Figure 2.3). The basic concept of using infrared emitters and detectors to count bees is not new (Lui, C. et al., 1990; Struye, M. H. et al., 1994), however previous versions were either limited to two or three bee passages, or prohibitively expensive. Bruce King, Ph.D. candidate, at the University of Montana, designed, tested, and deployed a relatively inexpensive system. Each bee counter is built with 14 channels, or passage ways, in which each bee entering or leaving must pass through. The channels are constructed in such a manner as to prevent more than one bee from traversing the passage at a time. Installed in the ceiling of each passage
is an infrared emitter. Beneath a Lexan® floor two infrared detectors are placed, head to head. In the process of passing through the channel, a bee is forced to block first one, then the other infrared detector. The output signal of each detector is connected to a Digibook™ (IoTech®, Inc. Cleveland, OH) system, with sustained signal acquisition of more than 200 times a second. The current configuration of the Digibook™ system will support up to 10 such bee counters. The Digibook system itself is connected by parallel port to a personal computer. Software written by Mr. King performs rigorous checking of the sequence in which the detectors are covered and uncovered, determines bee direction and number, and saves this information to various data files.

The counter itself is attached to the front of the condo, with the counter entryway in line with a hole cut in the door. This hole is aligned with the slot formed by the polyethylene plates on which the hive rests. Care must be taken to insure that the system is relatively bee tight; bees may only enter and leave the hive by passing through the bee counter.

2.6 Maryland Field Trials

The sponsor for the bee biomonitoring system is concerned about a series of hazardous waste sites on a federal installation outside of Baltimore, MD. It was therefore necessary for field researchers to transport equipment and bees from Montana to Maryland. In June of 1996, a double axle trailer loaded with 21 condos and 40 nucleus sampling hives with bees was hitched to my pickup truck and transported 2200 miles from Missoula, MT to Aberdeen, MD. During stops, a portable generator was started to run small fans in the condos to cool down the bees. Four inexpensive,
battery powered, electronic temperature sensors (Radio Shack) with extended probes were temporarily wired into the top of four hives. This allowed monitoring and recording of current, minimum, and maximum temperatures inside the colonies during transport. Additionally, a water misting system was installed in all the hives. During hot, dry periods, a RV pump was switched on to deliver a burst of water to the hives. Bees use water to evaporatively cool their hives. This transport system proved effective until encountering a huge thunderstorm in Ohio, at which time some of the bee colonies became waterlogged.

After arriving in Aberdeen, the 21 electronic condos were deployed in groups of seven at three sites: an estuary at a recently remediated area, a landfill site undergoing remediation, and a reference site in rural Maryland. At two of the sites, plastic sheds were installed to house computers, electronics and uninterrupted power supplies. At the third site, a modified aluminum truck tool box contained three laptop computers and the associated electronic systems.

During the next four months, each electronic hive site was checked three or four times a week. In addition to verifying continued correct operation, data collected by each system was retrieved manually. Copies of this data were made, and the originals sent back to Montana for storage and analysis. Approximately once every two weeks, samples for chemical analysis were collected from both the electronic hive sites and nucleus hives scattered throughout the entire facility area. These samples consisted of living forager bees from each site, dead bees captured in the dead bee traps, pollen, and carbo traps. Carbo traps are part of system used to collect information on organic,
volatile, and semi-volatile chemicals present in the hive atmosphere. All samples except the carbo traps were delivered to a chemical analysis site in Maryland. The carbo traps were sent to Montana for analysis by the University of Montana chemistry department.

In mid November, most data gathering were suspended. Except for seven electronic hives residing on the trailer, all computers were shut down, and the electronics removed and sent back to Montana for evaluation and re-calibration. All of the chemical sampling (non-electronic) nucleus colonies were stockpiled at one location on the federal site. Fourteen of the condos, less electronics, were stored at the reference site. The seven remaining condos, with electronics intact, were transported to the University of Delaware for experiments in overwintering nucleus colonies.

Electronic and chemical monitoring of the federal site resumed in June of 1997. Many of the bees used in the first year had failed to survive the winter, primarily due to small colony size and lack of stored resources. Replacement bees were shipped from Georgia, equipment restocked and deployed, and monitoring started by Dr. Bromenshenk, the overall project director. During this summer, a recently graduated biology student, Matthew Loeser, performed the field site data and chemical gathering. Again in November monitoring ceased and all equipment was put into storage.

The summer of 1997 also saw the installation of seven electronic hives in Montana at the University of Montana apiary. The primary use of these hives was enhancement of sampling techniques, advancing the electronic data gathering and delivery system, and conducting specific chemical dose-response on bee behavior and
Details and results of these field trials, as well as specific chemical detection, were presented to the contracting office by annual reports (Bromenshenk, J. et al., 1997).

2.7 Related Work

Use of an automated system to collect information about bee colonies is not new (Lui, C. et al., 1990), but all previous work has involved one of two colonies. With our system it is possible to monitor seven to ten colonies at each site. Additionally, we have data spanning more than two years. No other bee monitoring system has collected this quantity of data, nor performed extensive chemical sampling of the colonies.

2.8 Future Work

In April of 1998, Dr. Bromenshenk, Bruce King, and Jason Volkman flew to Maryland to start the latest round of monitoring and sampling. This is the earliest deployment of the electronic hives in Maryland. The unique behavior of bees during the spring nectar flow and the effect of deep rooted trees bringing water from a potentially polluted water table need to be investigated. It is hoped after this season a complete library of bee flight activity, from to spring to fall, will be collected, as well as continued monitoring of chemical exposure from the recently remediated site.
CHAPTER 3
INTERNET DATA DELIVERY

Data gathered by the electronic hives was collected, transferred and processed by hand. This created an unacceptable delay in determining important events that should have been investigated immediately. Since a number of the monitoring sites reside at remote locations, accessible during limited hours, systems were needed to transmit bee monitoring data to an accessible location.

3.1 Web Server

All field data gathering systems are now connected to Linux control computers that can be connected to the Internet (Figure 3.1). As described in Chapter 2, the ALPHA and Weather gathering systems run in the Linux operating environment. Each of these programs stores data in simple ASCII text files. For the counter system a special program was written to run on the Linux computer. This program communicates with the flight counter computer via a null modem serial cable. At 15 minute intervals, the counter computer transmits an ASCII text stream to the Linux computer containing flight activity logs for the previous 15 minutes. This data is written to an archive directory on the Linux system. Additionally, at the end of the sampling day, the counter computer transmits a binary file containing the complete transactions of the counter system, flight activity and operation parameters to the central system. Each Linux system is running the Apache web server software. The server software has been configured to allow access to the bee monitoring files with any web browser client.
Figure 3.1. Current data collection and delivery system. Most data acquisition systems are controlled by the Linux computer, except the flight counters, which communicate with the Linux system every 15 minutes.

We have successfully used Ethernet, phone, and radio modems to attach these remote systems to existing TCP/IP networks. The Bee Project observation hive is accessible via standard Ethernet connections at http://beekeeper.dbs.umt.edu. Our remote site at the Montana apiary is connected to the Internet using a pair of radio modems (DGR-115H, FreeWave Technologies, Inc.). These modems have a range of 20 miles with throughput of 115200 baud. Using the Serial Line Internet Protocol (SLIP) any remote site with a modem can be connected and accessed.

3.2 Java Data Display

Viewing static lists of sensor data is not generally helpful in determining when an important event has occurred, particularly for lay people. To aid in evaluating and displaying flight activity, ALPHA system, and weather data files, I wrote a graphing applet in Java™. This program reads the text data file and displays the information in series of
simple line graphs. The program preforms automatic scaling for all displayed data within the graph. The user may select which data series to graph from a selection of check boxes. Additionally, the user may want to display two or more series whose ranges do not coincide. For example, from the weather data, the barometric pressure ranges from 930 to 1070 millibars, whereas the temperature ranges from 12° to 50° C. If both series are plotted on the same graph, the temperature will be buried on the baseline, and the fine detail of barometric change will be lost. In this case, the user may select to plot one of the series on an alternate Y axis (Figure 3.2). The scale of this second axis is displayed on the right side of the graph.

As an enhancement of the real time data collection and display, the weather gathering program was modified to create weather data snapshots every 15 seconds. These snapshots come in two formats: a simple Hyper Text Markup Language (HTML) table containing the weather information, and a text file of the current weather values. A second Java applet was written to use the text file weather values. This applet displays the current weather conditions in a graphical “gauge and dial” manner (Figure 3.3). The current weather conditions are downloaded every 15 seconds and displayed at the client’s browser. To increase flexibility and usefulness, the user may toggle between the units used in displaying the data, such as temperature in Fahrenheit rather than degrees Centigrade.
Data Graph

The data download may take a while, please wait. File: weather/w010898.txt

Select attribute to draw/undraw

- Wind-Speed
- Wind-Direction
- Wind-Chill
- Inside-Temperature
- Outside-Temperature
- Outside-Temperature
- Barometric-Pressure
- Barometric-Change
- Inside-Humidity
- Outside-Humidity
- Dew-Point
- Current-Rain
- Daily-Rain
- Monthly-Rain

Figure 3.2. Historic weather Java graph. This applet will graph the archived data files for each data gathering system. An alternate Y axis allows display of series with different ranges.

3.3 Related Work

A number of Internet sites offer real, or near real time data delivery, such as the Biosphere II project (http://www.bio2.edu). However, most sites do not present the data in any graphical format. When a graphical display is available it is generally the output of a Common Gateway Interface (CGI) program running on the server. The Java applets developed at the University of Montana move the processing load from the server to each client machine. After initial applet and data download, the client’s browser operates independent of the server, reducing the overall network and system load.
Figure 3.3. Current weather conditions displayed using the Weather applet. This applet displays updated weather conditions every 15 seconds to any Java compatible web browser.

3.4 Future Work

The next major milestone will be using the Internet data delivery feature to automatically retrieve data from each remote monitoring site to a central storage and analysis computer. The project has recently purchased a high powered Pentium II based system for just this purpose. This system will contact each remote site every evening and pull down all data collected during the day. This computer will then preprocess the data for input into a number of analysis programs, including Artificial Neural Networks (ANN). The system will then perform ANN analysis, prepare reports and e-mail those reports to the project manager and system operator.
CHAPTER 4
ARTIFICIAL NEURAL NETWORKS

The previous two chapters described the method of collecting and delivering bee behavioral data from remote sites to a central processing and archival system. This chapter will present the use of Artificial Neural Networks (ANN) to process that data.

4.1 Background

At its most basic level, an ANN is a computer program designed to recognize patterns. Given a set of inputs, the ANN will produce an output associated with a similar input on which it has been trained. For example, a speech recognition ANN may be trained to learn the waveform of the word "Hello." Later, when the ANN is exposed to a waveform similar to "Hello," it may produce a partial match with the word Hello.

The basic building block of an ANN is the perceptron (Minsky, M.L.; Papert, S., 1969). This is a mathematical model based on the function of nerves in the retina of the human eye. A perceptron has a number of inputs, and a single output. Each input has a certain weight associated with it. The perceptron sums the weighted inputs, applies a threshold function to the sum, and outputs the result of the threshold function.

Mathematically this operation is represented as:

\[ O = g \left( \sum W_i a_i \right) \]

In this equation, \( a_i \) is the input value for link \( i \), \( W_i \) is the weight associated with link \( i \), and \( g(\cdot) \) is the threshold function, usually the sigmoid function. A perceptron is trained on a given set of inputs with an expected output. The process of training adjusts the weight \( W_i \)
for each link $i$ so that the output $O$ is equal to the expected output, within some tolerance.

Taken alone, perceptrons are limited in the functions they can simulate (Minsky, M.L.; Papert, S., 1969). By using multiple layers of perceptrons (Figure 4.1), with the output of one layer supplying the input to the next, complex non-linear patterns can be recognized.

![Multilayered neural network diagram](image.png)

Figure 4.1. A multilayered neural network. This network consists of 63 input nodes, 9 "hidden" nodes, and 2 output nodes.

A multilayered network can be trained in a similar manner as a perceptron, with the error in prediction being propagated back through the network, from output to input.
This system is known as a Feed Forward Back Propagation (FFBP) network (Rumelhart, D., et al., 1986). Such systems are the basis of many successes in the field of artificial neural networks.

4.2 Data Representation

Before using a neural network, we need to represent the data in format that is conducive to learning. To accomplish this goal two things need to be done: 1) determine the learning pattern, and 2) represent the data.

One simple learning problem would have used all data gathered as input to a neural network and select as output a general indicator of the usefulness of this particular pattern. However, this would require human analysis of more than one thousand data sets and assigning a subjective value to each one. A more objective target set is bee flight activity, since changes in flight activity have been observed during important events, such as rain, swarming, and chemical exposure (Lui, C., 1990; Bromenshenk, J.J., 1997). To implement this concept, the inputs to the neural network were all data excluding flight activity and the expected output would be the actual number of bees entering and leaving the colony.

Once a learning problem was selected, formatting the data for the Stuttgart Neural Network Simulator (SNNS) software was fairly easy; the training and testing pattern files are simple text files, containing an eleven-line header, values for the input nodes, and expected output values. All pattern files are included on the attached CDROM.

Data used in the training and testing of the neural networks was collected from five different sites over a two year period. These sites were Canal Creek (CC), Churchville
(CV), Old O-Field (OF), J-Field (JF), and the apiary at the University of Montana (MT).

Data is assumed to be from the 1997 field trials unless indicated by a 96 for the 1996 field trials.

4.3 Methodology

To maintain consistent, complete data representation for the initial and subsequent tests, a suite of pattern generation scripts was created. Any incomplete pattern “day” was not to be considered. Normally researchers are reluctant to ignore or discard data concerning a biological entity, but the bee monitoring program collected such a wealth of information that handling the data transfer, storage and processing posed significant challenges. Any few missing data days were inconsequential to the overall data set.

The first experiments with ANN did not involve any data scaling. In this case the network placed too much emphasis on input data with large values. Thus, all experiments in this thesis contain data scaled between 0.0 and 1.0. Table 1 lists the various sensor attributes, with expected values and scaling formulas.

For most experiments, the training method of choice was standard BackPropagation. Although this method is not the fastest, it does generally produce a good indication of how well a neural network can learn a given concept.
Table 4.1. Summary of sensors, values, and scaling. The scaled values were used in training the neural network.

All experiments were conducted using SNNS, except for one test using the University of Wisconsin BackPropagation program. The standard method of training a given network on a collection of patterns, then testing on one or more unseen patterns was used. Initial criteria for how well a network learned bee behavior were the Sum of Squared Error (SSE), and how closely the predicted flight activity "looked" like actual activity. Later experiments dropped the subjective "looks like" qualifier, for reasons explained in the next paragraph.

Matching predicted versus actual flight activity in a dynamic environment such as honey bee colonies in field settings is extremely difficult. There are still too many external influences and internal parameters that are not yet understood or measured. For instance, we currently have only rudimentary methods of determining local floral resources, such as pollen availability, and no method to determine the presence of a nectar flow. Also, we have no method to inform the ANN that dandelions will bloom
on the April 15 and produce pollen and nectar until May 5. Many deviations from actual versus predicted flight activity appear to the result of such nectar flows. Rather than attempt to predict exact flight activity, the later experiments used a more general metric of ANN accuracy. The Sum of Squared Errors is one such indicator. The SSE is calculated by the following equation.

\[ SSE = \sum (o_i - t_i)^2 \]

In the equation, \( o_i \) is the actual output from each output node \( i \), and \( t_i \) is the target, or expected, value of output node \( i \).

4.4 Neural Network Learning Experiments

The initial experiments included training and testing on a set of patterns, changing one thing (topology, training algorithm, etc.), retraining and retesting for the given pattern set, and comparing the results. The better method, usually determined by the SSE, was then used for subsequent experiments. Later experiments attempted to process the data in a pseudo real time mode. Lastly, experiments were conducted on the use of knowledge transfer. Some of the experiments performed are described in the following sections.

4.4.1 Learning Bee Behavior

The first test using neural networks was a simple "can the neural network use this data." In this experiment, all data for a given hive for an entire day was used for input. The expected output was the flight activity for that day. This produced a huge network (288 x 10 input nodes, 200 hidden nodes, and 178 x 2 output node). Taking four days at random (Canal Creek 10/01/96, 10/02/96, 10/19/96, 10/30/96) the neural network was trained to a very low error factor. The network had succeeded in memorizing those four
pattern days. It became apparent that there were simply too few patterns to learn as compared to the number of parameters in the network.

4.4.2 Sliding Windows

The second important test of a neural network was an enhancement of the previous approach. Rather than build a network that can process an entire day, a network to process two hours time slices of data was built. This was the first use of the "sliding window" in my network processing. In SNNS terminology this is referred to as subpatterns. If successful, this concept would be useful for a real time analysis system. Each five minute output of flight activity was generated from a network with inputs for an hour before and an hour after the expected event. For example a day's first pattern consists of weather and colony data from 5:00 a.m. to 7:05 a.m.. The target output is the flight activity from 6:00 a.m. to 6:05 a.m.. This window of data is then slid up (5:05 to 7:10 for input, 6:05 to 6:10 for output) to create the second pattern, and so forth. Weather one hour before an event may affect flight activity (was it warming up, was the sun shining?). Also, the weather after the event may affect flight activity. For instance, the monitoring system has clearly demonstrated that honey bees can anticipate a storm up to 30 to 50 minutes before the weather station records the event. Therefore bees seem to use information about upcoming weather events, which does affect bee behavior.

The results of training on the four patterns days are illustrated in Figures 4.2 and 4.3. Actual observed versus ANN learned flight activity comes close to a perfect match. However, four pattern days are still a small training population, as shown by the results of testing the network on the pattern for 10/08/96 (Figures 4.4 and 4.5).
Figure 4.2. Flight Activity Learned by the ANN for Four Pattern Days from the Canal Creek Site - Bees In. Each day demonstrates a different behavior dependant on weather.

Figure 4.3. Flight Activity Learned by the ANN for Four Pattern Days from the Canal Creek Site - Bees Out.
Figure 4.4. Actual and Predicted Flight Activity for Canal Creek 10/08/96 - Bees In. The ANN predicted flight activity in the afternoon which did not occur. This day was subject to cold and rain.

Figure 4.5. Actual and Predicted Flight Activity for Canal Creek 10/08/96 - Bees Out.
Using a similar network with the University of Wisconsin-Madison BackPropagation program to perform tenfold cross validation proved more rewarding. Cross validation is a method of training a network on a portion of a pattern set and testing on the remaining portion. In tenfold cross validation, 90% of the patterns are used to train a network, and 10% are used to test that network. This is repeated ten times using different permutations of the pattern sets. The results of this experiment are summarized in Table 4.2.

<table>
<thead>
<tr>
<th>Cross Fold Iteration</th>
<th>Number of Training patterns</th>
<th>Sum of Squared Error</th>
<th>SSE per Pattern</th>
<th>Number of Testing Patterns</th>
<th>Sum of Squared Error</th>
<th>SSE per Pattern</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>972</td>
<td>8.6092</td>
<td>0.0089</td>
<td>108</td>
<td>1.2792</td>
<td>0.0118</td>
</tr>
<tr>
<td>2</td>
<td>972</td>
<td>8.2902</td>
<td>0.0085</td>
<td>108</td>
<td>0.5145</td>
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<tr>
<td>3</td>
<td>972</td>
<td>6.0975</td>
<td>0.0063</td>
<td>108</td>
<td>0.8753</td>
<td>0.0081</td>
</tr>
<tr>
<td>4</td>
<td>972</td>
<td>6.5631</td>
<td>0.0068</td>
<td>108</td>
<td>1.1974</td>
<td>0.0111</td>
</tr>
<tr>
<td>5</td>
<td>972</td>
<td>7.3032</td>
<td>0.0075</td>
<td>108</td>
<td>0.7424</td>
<td>0.0069</td>
</tr>
<tr>
<td>6</td>
<td>972</td>
<td>7.5359</td>
<td>0.0078</td>
<td>108</td>
<td>0.5324</td>
<td>0.0049</td>
</tr>
<tr>
<td>7</td>
<td>972</td>
<td>7.3790</td>
<td>0.0076</td>
<td>108</td>
<td>0.6156</td>
<td>0.0057</td>
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<tr>
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<td>7.2782</td>
<td>0.0075</td>
<td>108</td>
<td>0.8607</td>
<td>0.0080</td>
</tr>
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<td>9</td>
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<td>0.0071</td>
<td>108</td>
<td>1.2764</td>
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</tr>
<tr>
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<td>0.7879</td>
<td>0.0073</td>
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<tr>
<td>Total</td>
<td>972</td>
<td>8.6816</td>
<td>0.0080</td>
<td>1080</td>
<td>8.6816</td>
<td>0.0080</td>
</tr>
</tbody>
</table>

Table 4.2. Results of 10-Fold Cross Validation

4.4.3 Reducing Training/Testing Time

Although these results were promising, given the vast quantity of data available for analysis, it became necessary to implement methods to decrease training time. Tests were run to determine if a different data averaging scheme would be useful. In previous tests, data was averaged or summed over a five minute interval, with a two hour sliding window. The next experiments used a combination of five minute or 15
minute averages, with one or two hour "sliding windows." Data from five different
condos from four different sites was picked at random. The results are displayed in
Figures 4.6 and 4.7. The 15 minute average version performs as well as the five
minute version. Window size seemed to have little real impact on learning. This
justified using 15 minute averages in all subsequent experiments. I chose to continue
using the larger window, although the smaller one hour window may be useful in the
future. This smaller window should allow a faster response to abnormal bee behavior
when used in the time data processing mode.

4.4.4 Processing Seasonal Data

The bee biomonitoring project collected data for two summer seasons. It was
worthwhile to see how colony behavior changed during the monitoring period. To do
this, methods for using the ANN system to learn the behavior trends were explored.

Three different training schemes were investigated, using a method similar to the
sliding window. Each uses pattern files containing data for a number of days. The
network is first trained on some set patterns representing consecutive, but not
necessarily contiguous, days. Then the accuracy of the network is tested using the next
consecutive pattern day. The three methods tested were:

1. *Single day training*. Each training pattern consists of only a single day's
representation of data, using the trained network without reinitialization.
This produces an adaptive network that prefers more recently observed
behavior. Training time is fixed.

2. *Accumulated days training*. After the network has been trained on a
ANN Training of Bee Flight Activity
5 minute data interval

Figure 4.6. Flight Activity with Two Window Size - 5 Minute Averages. This graph depicts actual and learned flight activity from five different condos.

ANN Training of Bee Flight Activity
15 minute data interval

Figure 4.7. Flight Activity with Two Window Sizes - 15 Minute Averages. In this example a 15 minute average/sum was used, with two different size “sliding windows.”
pattern day that pattern is added to the training set. The network is not reinitialized. This method retains knowledge learned from previous training, with a bias toward older concepts learned. Training time increases linearly.

3. _Accumulated days training with reinitialization_. Similar to method two, but the network weights are randomly reset before training. This effectively "wipes out" any concepts previously learned. This method gives equal bias to all pattern files, which may prove more effective in detecting chronic behavioral changes. Training time is similar to method 2.

Using the Sum of Squared Error has been useful in determining which pattern days are of interest. For example, Figure 4.8 plots the SSE for pattern days for the Churchville hive #1 for summer of 1997. Each of the three training schemes are represented on the graph. This data is interesting in that the colony swarmed on September 1. The SSE for that pattern day (day 21) shows a moderate to large spike, depending on the training scheme used. Swarming is a natural behavior of bees and the SSE flagged the incident.

Of perhaps more interest is the SSE spike at pattern day 31. Clearly there is a great deal of flight activity for a weak hive. However, upon examining the field logs for this site and day, it had been reported that bees from the surrounding colonies were raiding the weak colony of its stored resources. This observation can be substantiated on closer inspection of the flight activity (Figure 4.9). Bees are entering the hive first,
ANN Testing - Various Training Schemes
CV Hive 1 - Single, Accum, and Reinit

Figure 4.8. Comparison of Single Day, Accumulated, and Reinitialized Testing of the ANN. After the first two weeks of training, each of the three methods exhibits convergence and intervention of events.

Actual vs. Predicted Flight
CV Hive 1 9/25/97

Figure 4.9. Actual and Predicted Flight Activity for the Robbing Event - Churchville Hive #1. Closer examination indicates bees entered the hive first from the outside.
then leaving. Obviously the flight counters are being triggered by bee from neighboring colonies.

Spikes appearing later in the season are explained by hive manipulation by keepers. At one point the colony was replaced with a strong colony. Later in the summer simple dose-response experiments were conducted using hives at this site, which explains the spikes at the end of the graph. This particular hive was not subjected to these experiments, but the surrounding hives were, and had an impact on the subject hive.

Similar graphs for all site/hives are contained in Appendix E. Each of these demonstrates spikes for known abnormal events. Significant events are noted, with explanations, as well as postulation on unknown events.

4.4.5 Knowledge Transfer

The previous experiments produced an interesting concern. Most network training required one to two weeks of data before a reasonably good predictive model was built. It became apparent that knowledge transfer may speed up the learning so that the predictive ability of the network could be used almost immediately. To accomplish this, a network was trained on a colony or group of colonies. This pre-trained network was then applied to a completely different colony. Three different knowledge transfer ideas were tested:

1. *Hive to Hive.* A network trained on one colony was used as the starting network for a second colony. This would apply to a “train and deploy” method. The colony’s behavior would be learned at one location, and
then deployed at a different location.

2. **Site to Hive.** A network would be trained on the flight data of all colonies at a given site. This network could then be used on a colony at a different site. In the experiment done, data from the Maryland reference site was used to train a network, and then the network was applied to one of the test sites.

3. **Year to Year.** Data from a site in 1996 is used to train a network. That network is then used on data from the same site in 1997.

An example of each of these experiments is displayed in Figure 4.10, 4.11, and 4.12. For the Site to Hive Knowledge Transfer (Figure 4.11) a network trained on all valid patterns from the reference site at Churchville was applied to Hive #1 at the Old O-Field site. The three lines plotted are:

1. **Single Day Testing.** As a comparison, the Single Day training scheme used on an un-initialized network for the O-Field hive.

2. **PreTrained Network Testing.** Using the network trained on Churchville data, each day of O-Field data is tested. No additional training occurs.

3. **PreTrained with ReTraining.** Using the Churchville network, each O-Field day is tested. After the pattern is tested, the network is retrained (using Single Day Method) on that pattern. This adapts the pre-trained network to the personality of the new hive.
Knowledge Transfer - Hive to Hive
CC Hive 3 Network to JF Hive 3

Figure 4.10. Knowledge Transfer - Hive to Hive. The network was trained on a colony at one location. This colony was then moved to a second location.

Knowledge Transfer - Site to Hive
CV Site Network to OF Hive 1

Figure 4.11. Knowledge Transfer -Site to Hive. Using a network trained on the reference site condos, effective prediction becomes almost immediate.
Figure 4.12. Knowledge Transfer - Year to Year. This network was trained on data from the Old O-Field 1996 field trials. The network was then applied to colonies at the same site during the 1997 trials.
On pattern day five (08/01/97) a significant, undocumented event occurred. Both pre-trained testing methods indicate a noticeable spike. There's no observable reason for this event; weather files indicate a nice day, yet the bees refused to fly until late in the day. If the system had been operational in a real time mode a field technician would investigate the situation.

4.5 Discussion and Conclusions

The early experiments demonstrated that bee flight behavior, with respect to weather, could be learned by an artificial neural network. A scaling system was worked out as well as a usable averaging scheme. A 15 minute data average was chosen for all experiments, using a two hour sliding window. Although none of the training schemes tested provides an exact match of predicted to actual flight activity, without which an irrefutable indicator of a toxic event is possible, they do give indications of significant events, natural or otherwise. Removing much of the influence of weather has produced a "pretty good" model of when and with what frequency bees should be flying. Some of the shortcomings have already been mentioned; nectar flows and unmeasurable external forces. However, it is interesting to note the effectiveness of the ANN system in detecting important events such as swarming and robbing. Although the system is not complete, and may indicate some false positives, it is sufficiently mature to be used in field work. Just by reducing the number of times actual chemical sampling and human inspection is required, as well as those time periods when other measurements should be taken, will be a significant improvement on routine colony maintenance.
Knowledge transfer has produced some interesting results. Given a climate and habitat similar to a testing site, the ANN can fairly quickly adapt to an individual colony's behaviors, and produce reasonable predictions. Even using a non-adaptive network yields useful information. Conversely, using data from a different region and climate, the results are less than spectacular (see the comparison of the MT site to the O-Field site, Appendix F). The exact reason for this behavior requires additional experimentation; however this could be due to the differing day length, forage available, and climate influences. The application of knowledge transfer also may provide a comparison of the validity of a reference site. If the reference site truly approximates conditions at the other sites, it should be able to be used in this manner. Obviously, the Churchville reference site can be used as a starting point for ANN for the Maryland sites, but such a network would require additional acclimation before being useful in a different locale.

4.6 Related Work

The army is proposing to use ANNs to analyze human EEG reading in real time (http://wrair-www.army.mil/depts/behavbio/rtma.htm.) However, the EEG of rested and sleep deprived humans appears to be a simple problem. No one is attempting to predict the flight activity of honey bees on a day to day basis.
4.7 Future Work

Now that an adequate system of event indication has been created, some concepts that previously proved computationally expensive will be re-evaluated. At one stage the five minute averages were abandoned in favor of 15 minute averages. It would be informative to perform similar experiments using this averaging scheme. As well, using a smaller sliding window, and asymmetric windows with the smaller average may prove rewarding. Although it is doubtful (in the author's opinion) if any of these methods will produce a more accurate prediction of flight activity, the reduced time from collection to response would be of profound benefit.

Each of the three training schemes used has its own advantage. It may prove interesting to use these three methods in an ensemble of networks. Numerous separate decisions concerning a pattern day would be made and then combined in some manner to give a single indicator. Conversely, the Single Day and Accumulated methods may be combined into a single ANN, perhaps with an accumulation scheme that uses only a two week window of data. Thus previous behavior would be retained, but the network would train faster and adapt to changing behavior.

An ultimate goal is implementation of a real, or near real, time analysis system, using the methods described. Data from the Montana site is now available for analysis within 15 minutes of being collected. Access to data from other sites varies from a day to a week, but it is envisioned that all remote sites will soon provide data within one day. To analyze the weather and flight data within one day, with a simple indication of the colony performance, is an important step in the real-time biomonitoring/chemical
sampling of a site. Even so, human intervention is required to examine the colony and start chemical pumping systems. It is envisioned that each site will host a sufficiently powerful computer system that will perform the ANN analysis and trigger chemical pumping systems, as well as notify concerned investigators, automatically. A test of this type of system will be conducted soon, using the Montana test site.
CHAPTER 5
CONCLUSIONS

A revolution in the field of biomonitoring has taken place. Based on solid research and previous application, a real-time monitoring and response system using a terrestrial species is now a reality. Honey bees have long been used for environmental evaluation; using modern computer technology the environmental situation in remote sites can now be interrogated, evaluated, and quantified. A near real-time indication of behavioral performance is available.

In the past many of the honey bee based bioassessment methods used have been destructive in nature, such as vacuuming bees from the front entrance. In the past three years nondestructive methods have been used effectively. Using emergent technology based on proven data acquisition and chemical sampling, the chemical and biological status of honey bee colonies can now be rapidly determined. Behavioral data is available almost immediately using computer systems connected to Internet/Intranet structures. This could be described as bee husbandry by remote control.

Even with these developments, a skilled bee expert is required to make the discrimination between a normal, viable colony and one undergoing stress. Using artificial neural networks, much of the mundane tedium of interpreting flight activity in relation to weather has been removed. ANNs can effectively learn honey bee flight activity, adapt a general bee behavior model to an individual colony, and indicate conditions that need closer inspection. This eliminates the need for a human expert to
evaluate all data concerning a colony and make an informed decision. Particular days or colonies of concern will still require human intervention, but much of the day to day running of the monitoring system will be automated. Using a local computer decision making system, a method of automated sampling and remote notification is possible. Although the ANN system is not perfect, and may indicate some false positives, the reduction in sheer routine sampling will be of great benefit to the field technicians and chemical analysis team.

Knowledge transfer has demonstrated some interesting ideas. Using data collected from colonies at a similar locale, the basic behavior can be pre wired into the prediction system. Each colony has its own behavioral traits and some adaptation is required, but the system provides useable predictions with fewer training patterns in a real time mode.

To prove the correctness of the ANN prediction system, it will be necessary to conduct scientific dose/response experiments using a suite of known chemical agents. Some preliminary experiments of this nature were conducted at the Montana site. The ANN indicates many spikes in behavior for much of the summer (Appendix B). Unfortunately, many of theses experiments were performed in an ad hoc manner. Additionally, this site was visited almost daily by the bee crew. A more rigorous set of experiments along this line is planned for the summer of 1998.

Although the work on using ANNs to predict bee behavior is far from complete, the general concept is sound. Future work involves the incorporation of additional sensing system, including harmonic radar tracking systems and individual bee tagging.
A system to measure incoming resources is being contemplated, which will have a
great impact on the ability of the ANN to predict flight activity. In the near future it is
envisioned that the complete system will be a useful tool in the field of biomonitoring
APPENDIX A

ALPHA Program Operation Manual
Introduction

The ALPHA data gathering system is fairly simple and flexible DOS based program from interfacing with the ALPHA DAQ product. The program will run on almost any PC system from an 8088 to a Pentium with a serial port, hard drive, and floppy drive. The program incorporates automatic system recovery and rarely requires any outside monitoring.

Running the Program

The program is run by simply changing to the directory in which the program and data files reside (usually the alpha directory) and starting the program. A typical session would be started thus:

DOS> cd \alpha
DOS> alpha
...

The program runs in an enhanced text mode, with simple data display windows. At the bottom of the screen is the status bar, containing startup information, a running clock, the last significant event (data save, etc) and instructions to stop the program. The rest of the screen contains information gathered from the ALPHA system, displayed in a simple text format. The data for up to 36 different sensors can be displayed on the screen.

The program has two command line options to select the communication port and data save interval. The default comm port is 1 and the default save interval is 5 minutes. To change either one requires starting the program with the appropriate options. For example:

DOS> alpha c2 t10

will instruct the alpha program to use comm port 2 and save data to the hard drive at 10 minute intervals. These options can be entered in any order, and either option need not be changed. For instance:

DOS> alpha c2

changes the comm port to 2 and uses the default save interval of 5 minutes.
To stop data gathering at any time, press the escape key <Esc>.

The DAQ and CONTROL files

Within the alpha directory is one or more control files used by the alpha program. DAQ.DAT is used to determine where and what sensors are installed, as well as the necessary conversion from raw millivolt readings to the appropriate sensor units. This file is required, and the alpha program will display a fatal error if this file is not found. The second file, CONTROL.DAT, is used to operate the output relay system on the ALPHA product. This file is optional, and a warning message will be displayed if the file is not present. Both of these files can be modified using any text file editor. An example of each file is as follows:

DAQ.DAT

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<th>CONNECT-TYPE</th>
<th>CHANNEL</th>
<th>VARIABLE</th>
<th>SCALE</th>
<th>METHOD</th>
<th>X-COEFF</th>
<th>CONST</th>
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<tbody>
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<td>33</td>
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<td>test-weight</td>
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</tr>
<tr>
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<td>1</td>
<td>test-air</td>
<td>n</td>
<td>linear</td>
<td>0.0</td>
<td>0.0</td>
</tr>
</tbody>
</table>

MUX-PORT - the multiplexer port the sensor is connected to. In the Bee Alert system, all single input sensors (temp, rh, etc) are on MUX-PORT 32, all dual input sensors (weight, air) are on MUX-PORT 33.
CONNECT-TYPE - single (s) or dual (d)
CHANNEL - the mux channel the sensor is on. This can be from 0 to 31 for single input sensors, and from 0 to 15 for dual. See the multiplexer deccription documentation.
VARIABLE - a user supplied variable name, this will be used in both the display and data save file. $dummy is a reserved name. This allows changing a port or channel without actually sampling data from the ALPHA system.
SCALE - whether or not to convert the raw millivolt input to the correct sensor value.
METHOD - Scaling conversion method, one of linear, pow, exp, or log.
X-COEFF - used in conversion. In a simple linear conversion \(y=mx+b\) this corresponds to the slope value (m).
CONST - used in conversion. This corresponds to the y intercept (b) in the linear conversion.

CONTROL.DAT

<table>
<thead>
<tr>
<th>PORT</th>
<th>BIT</th>
<th>VARIABLE</th>
<th>PULSE_TIME</th>
<th>START_VALUE</th>
<th>END_VALUE</th>
</tr>
</thead>
<tbody>
<tr>
<td>48</td>
<td>0</td>
<td>$time</td>
<td>0</td>
<td>05:56.00</td>
<td>06:10.00</td>
</tr>
<tr>
<td>48</td>
<td>1</td>
<td>$time</td>
<td>0</td>
<td>06:00.00</td>
<td>19:00.00</td>
</tr>
<tr>
<td>48</td>
<td>5</td>
<td>$time</td>
<td>0</td>
<td>08:00.00</td>
<td>21:00.00</td>
</tr>
<tr>
<td>PORT</td>
<td>BIT</td>
<td>VARIABLE</td>
<td>START_VALUE</td>
<td>END_VALUE</td>
<td></td>
</tr>
<tr>
<td>------</td>
<td>-------</td>
<td>----------</td>
<td>-------------</td>
<td>-----------</td>
<td></td>
</tr>
<tr>
<td>48</td>
<td>4</td>
<td>chamber-temp</td>
<td>0</td>
<td>25.0</td>
<td>100.0</td>
</tr>
<tr>
<td>55</td>
<td>5</td>
<td>chamber-rh</td>
<td>0</td>
<td>0.0</td>
<td>50.0</td>
</tr>
<tr>
<td>55</td>
<td>6</td>
<td>$time</td>
<td>10</td>
<td>10:00:00</td>
<td>21:00:00</td>
</tr>
</tbody>
</table>

- where -

PORT - the relay port to use. In the chamber we have two relay cards, one at port 48 and the other at port 55.
BIT - which "bit" to turn on. Each relay is turned on or off by one bit.
VARIABLE - which variable controls the "bit" or relay. $time is a reserved variable indicating the use of the system clock to control this relay. If the variable name matches a variable name in the DAQ.DAT file, the value of this variable is used.
PULSE_TIME - "pulse" this bit on and off at this interval. Here we will turn on bit 6 for 10 minutes, and then turn it off for 10 minutes, and so on.
START_VALUE - when to turn this bit on. If the variable is $time this is a time value. If a variable is used, this is the minimum value at which the relay should be switched on.
END_VALUE - the corresponding off time or value.

The Data Save File

Each day the alpha system is running a data file is created in the alpha directory. The file name format is simple MMDDYYYY.TXT, where MM is the month, DD is the day, and YYYY is the year. Hence the file 11081996.TXT is the datafile containing the sensor log for November 8th, 1996. The data file lists each variable in column format, with the variable name at the top of each column. In addition, the time of each data save is listed in the first column.

If the default 5 minute save interval is used, each entry will be approximately 5 minutes later than the previous. The alpha program is capable of more than one sensor sweep during a 5 minute period, so all reading of a sensor are averaged during this period to get the final saved value. As a warning, it is possible to have so many sensors that a sweep may not be completed before a datafile save, so avoid using very small save interval with many sensors.

After midnight, if a floppy disk is detected in the floppy drive, the data for the previous day will copied to the floppy. This allows data to be evaluated without taking the system off-line. It is not necessary to have a floppy ready; data will not be lost. It still remains on the hard drive. If a floppy is not used, or a copy failure occurs, the alpha program can be halted <Esc>, the appropriate data files copied, and the program restarted.

Adding or Replacing Sensors

If the sensor being replaced is the same type (temperature for temperature), simply replace
the sensor at the connector, and edit the DAQ.DAT file to reflect the new calibration values for this sensor. New sensors should have calibration values corresponding to the X-Coefficient and Constant entries in the DAQ.DAT file. If adding sensors, a new line for each new sensor should be added to the DAQ.DAT file. Call if you can’t figure it out. Sorry about being short about this, the “official” users manual will include more ;)}
APPENDIX B

Temperature Probe Calibration Example
### Temperature Probe Calibration - Batch A

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>10.4</td>
<td>528</td>
<td>521</td>
<td>548</td>
<td>575</td>
<td>570</td>
<td>568</td>
<td>563</td>
</tr>
<tr>
<td>14.1</td>
<td>604</td>
<td>593</td>
<td>619</td>
<td>624</td>
<td>634</td>
<td>627</td>
<td>620</td>
</tr>
<tr>
<td>19.3</td>
<td>707</td>
<td>689</td>
<td>712</td>
<td>710</td>
<td>724</td>
<td>723</td>
<td>718</td>
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<tr>
<td>22.7</td>
<td>776</td>
<td>755</td>
<td>783</td>
<td>783</td>
<td>792</td>
<td>789</td>
<td>782</td>
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<td>23.6</td>
<td>810</td>
<td>794</td>
<td>807</td>
<td>804</td>
<td>805</td>
<td>808</td>
<td>798</td>
</tr>
<tr>
<td>24.6</td>
<td>834</td>
<td>826</td>
<td>846</td>
<td>849</td>
<td>840</td>
<td>841</td>
<td></td>
</tr>
<tr>
<td>26.5</td>
<td>868</td>
<td>854</td>
<td>876</td>
<td>870</td>
<td>869</td>
<td>864</td>
<td></td>
</tr>
<tr>
<td>34.9</td>
<td>1030</td>
<td>1012</td>
<td>1018</td>
<td>1015</td>
<td>1020</td>
<td>1019</td>
<td>1005</td>
</tr>
<tr>
<td>36.2</td>
<td>1053</td>
<td>1034</td>
<td>1040</td>
<td>1034</td>
<td>1024</td>
<td>1041</td>
<td>1027</td>
</tr>
<tr>
<td>40.0</td>
<td>1128</td>
<td>1104</td>
<td>1116</td>
<td>1102</td>
<td>1116</td>
<td>1080</td>
<td>1093</td>
</tr>
<tr>
<td>43.3</td>
<td>1195</td>
<td>1180</td>
<td>1185</td>
<td>1187</td>
<td>1189</td>
<td>1173</td>
<td>1170</td>
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<td>44.6</td>
<td>1230</td>
<td>1196</td>
<td>1212</td>
<td>1186</td>
<td>1209</td>
<td>1175</td>
<td>1176</td>
</tr>
<tr>
<td>47.7</td>
<td>1284</td>
<td>1271</td>
<td>1272</td>
<td>1285</td>
<td>1285</td>
<td>1263</td>
<td>1260</td>
</tr>
<tr>
<td>50.8</td>
<td>1354</td>
<td>1347</td>
<td>1341</td>
<td>1375</td>
<td>1357</td>
<td>1336</td>
<td>1330</td>
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</tbody>
</table>

Regression Output: RAW-A1

<table>
<thead>
<tr>
<th>Constant</th>
<th>Std Err of Y Est</th>
<th>R Squared</th>
<th>No. of Observations</th>
<th>Degrees of Freedom</th>
</tr>
</thead>
<tbody>
<tr>
<td>-15.86338</td>
<td>0.337204</td>
<td>0.9993685</td>
<td>14</td>
<td>12</td>
</tr>
</tbody>
</table>

Regression Output: RAW-A2

<table>
<thead>
<tr>
<th>Constant</th>
<th>Std Err of Y Est</th>
<th>R Squared</th>
<th>No. of Observations</th>
<th>Degrees of Freedom</th>
</tr>
</thead>
<tbody>
<tr>
<td>-15.41743</td>
<td>0.5281546</td>
<td>0.9984507</td>
<td>14</td>
<td>12</td>
</tr>
</tbody>
</table>

Regression Output: RAW-A3

<table>
<thead>
<tr>
<th>Constant</th>
<th>Std Err of Y Est</th>
<th>R Squared</th>
<th>No. of Observations</th>
<th>Degrees of Freedom</th>
</tr>
</thead>
<tbody>
<tr>
<td>-17.88967</td>
<td>0.4835899</td>
<td>0.9987011</td>
<td>14</td>
<td>12</td>
</tr>
</tbody>
</table>

Regression Output: RAW-A4

<table>
<thead>
<tr>
<th>Constant</th>
<th>Std Err of Y Est</th>
<th>R Squared</th>
<th>No. of Observations</th>
<th>Degrees of Freedom</th>
</tr>
</thead>
<tbody>
<tr>
<td>-17.98442</td>
<td>0.9939904</td>
<td>1.0401974</td>
<td>14</td>
<td>12</td>
</tr>
</tbody>
</table>

Regression Output: RAW-A5

<table>
<thead>
<tr>
<th>Constant</th>
<th>Std Err of Y Est</th>
<th>R Squared</th>
<th>No. of Observations</th>
<th>Degrees of Freedom</th>
</tr>
</thead>
<tbody>
<tr>
<td>-18.50761</td>
<td>0.6814799</td>
<td>0.9974206</td>
<td>14</td>
<td>12</td>
</tr>
</tbody>
</table>

Regression Output: RAW-A6

<table>
<thead>
<tr>
<th>Constant</th>
<th>Std Err of Y Est</th>
<th>R Squared</th>
<th>No. of Observations</th>
<th>Degrees of Freedom</th>
</tr>
</thead>
<tbody>
<tr>
<td>-19.31305</td>
<td>0.6539259</td>
<td>0.997625</td>
<td>14</td>
<td>12</td>
</tr>
</tbody>
</table>

Regression Output: RAW-A7

<table>
<thead>
<tr>
<th>Constant</th>
<th>Std Err of Y Est</th>
<th>R Squared</th>
<th>No. of Observations</th>
<th>Degrees of Freedom</th>
</tr>
</thead>
<tbody>
<tr>
<td>-19.31305</td>
<td>0.5281546</td>
<td>0.9984507</td>
<td>14</td>
<td>12</td>
</tr>
</tbody>
</table>
Please note that the raw values for probe A6 are not present. The raw values were not close enough to being linear. A6 is being checked for bad connections.
APPENDIX C

WeatherMAX™ Specifications
WeatherMAX Specifications
This chart shows the Range, Resolution and Accuracy of the WeatherMAX’s functions

<table>
<thead>
<tr>
<th>Function</th>
<th>Measurement Range</th>
<th>Resolution</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wind Speed</td>
<td>0-255 MPH</td>
<td>1 MPH</td>
</tr>
<tr>
<td>Wind Direction</td>
<td>16 Compass Points</td>
<td>22.50°</td>
</tr>
<tr>
<td>Temperature - Outdoor</td>
<td>-40 - 122°F</td>
<td>.1 or 1°F</td>
</tr>
<tr>
<td>Temperature - Indoor</td>
<td>50 - 122°F</td>
<td>.1 or 1°F</td>
</tr>
<tr>
<td>Barometric Pressure</td>
<td>27.5 - 31.5 in Hg</td>
<td>.01 in Hg</td>
</tr>
<tr>
<td>Relative Humidity - Inside</td>
<td>10 - 90% RH</td>
<td>1% RH</td>
</tr>
<tr>
<td>Relative Humidity - Outside</td>
<td>20 - 90% RH</td>
<td>1% RH</td>
</tr>
<tr>
<td>Rainfall</td>
<td>0 - 99.99&quot; of Rain</td>
<td>.01&quot;</td>
</tr>
<tr>
<td>Windchill</td>
<td>-119 to 122°F</td>
<td>1°F</td>
</tr>
<tr>
<td>Dew Point - Outside</td>
<td>-7 to 115°F</td>
<td>1°F</td>
</tr>
<tr>
<td>Pressure Rate of Change</td>
<td>-4 to +4 in Hg/HR</td>
<td>.01 in Hg</td>
</tr>
<tr>
<td>Time</td>
<td>AM/PM 12:00 - 11:59</td>
<td>1 minute</td>
</tr>
<tr>
<td></td>
<td>24 hr/00:00 - 23:59</td>
<td></td>
</tr>
</tbody>
</table>

Accuracy

<table>
<thead>
<tr>
<th>Function</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wind Speed - Total System</td>
<td>±2.1 mph</td>
</tr>
<tr>
<td>Wind Direction - Indicator</td>
<td>0 error Display System</td>
</tr>
<tr>
<td>Temperature - Indoor - Indicator</td>
<td>±1.5°F</td>
</tr>
<tr>
<td>Temperature - Outdoor - Indicator</td>
<td>±1.5°F</td>
</tr>
<tr>
<td>Barometric Pressure</td>
<td>±.08&quot; Hg</td>
</tr>
<tr>
<td>Relative Humidity - Inside</td>
<td>±8% RH</td>
</tr>
<tr>
<td>Relative Humidity - Outside - Total System</td>
<td>±8% 20-80% RH 0-50°C</td>
</tr>
<tr>
<td>Rainfall Indicator</td>
<td>0 error Display System</td>
</tr>
<tr>
<td>Time</td>
<td>±1 minute/month</td>
</tr>
<tr>
<td>Temperature Sensor</td>
<td>±1°F</td>
</tr>
<tr>
<td>Wind Direction Sensor</td>
<td>±11.25°</td>
</tr>
<tr>
<td>Rain Collector</td>
<td>±0.1&quot;/inch</td>
</tr>
</tbody>
</table>
APPENDIX D

Pertinent Extracts from Field Logs
11/6/96  1700
Robbing experiment.
Placed 3 quarts 2:1 syrup in 1-5 gallon barrel.
With 3-inch wooden disk; floats appear 6 p.m.
Firm front at condens.
Syrup has definite citrus odor.
Computed enriched on-line.

11/7/96  8:45
Condenser 2 & 3 already active.
No bees at feeder.
Condenser 1 very active.
9:20 got still no bees in feeder barrel.
but I've got 5 buzzing in the bed at the inch packed over by the 1BRRD trailer.

10:30 bees in feeder barrel ~10 to 20 bees in.
or around feeder.
Condenser 2, 3, 6 & 7 very active.

11:55 lots of bees in feeder.
All condens active.

14:00 barrel full of bees.
All three floats covered with bees ~1 inch thick.
<table>
<thead>
<tr>
<th>Date</th>
<th>Time</th>
<th>Condition</th>
<th>Color</th>
<th>Temperature</th>
</tr>
</thead>
<tbody>
<tr>
<td>29 Sep 97</td>
<td>MRL 1330</td>
<td>1</td>
<td>2000</td>
<td>11.5</td>
</tr>
</tbody>
</table>

Ferrous activity on the perch, very unusual. Some aggressive behavior, observed, but no single cone appears to be being robbed. Free staging colony 302 at SFD. I closed off its entrance to the width of a pencil (11345). I believe I am already seeing a decrease in the number of bees on the perch at 1400.

Rain gauge was slightly filled, so when I finally got water went through the guage. Replaced fan in cone B.

Replaced probes in cone C. Replaced probes C2 with V1 and V2. V2 is inserted in the middle while V1 is inserted on top. V2 is reading 4°C, while V1 is reading as 4°C. Day data values were changed.
18th Sept 1977 Mul 2830

S8 Pollen collected from

29 Pollen collected. Ants clogged up each cell so it had stopped running.

43 28 collected sugar, cap and tray debris found pollen suspect.

20 Sept 1977 1300 Mul

28 Pollen collected. Tray disconnected from clicker so all pollen lumped together.

43 No pollen to be collected.


20 Sept 1977 1400 Mul

Nectar strip inserted in all rows and free standing trees.

23 Sept 1977 1700 Mul

For in 28(6) had gone out. Needs to be replaced.

25 Sept 1977 1500 Mul

Pond 43(1) appears to be being robbed. It was a great deal of activity, but there's not many bees in the colony to produce nectar.
APPENDIX E

SSE Evaluation Graphs for All 1996-1997 Field Data
Useful 1996 data was not available until late August. Being the end of the season, bee flight activity was erratic at best.

Most of the colonies were already being medicated and force fed.

On November 6, an induced robbing event was created at the CC site, using a sugar syrup solution placed in an open container in the bee yard.

This event appears as a spike in the end of most SSE charts for the CC site.

Hives 2 and 5 contained weak populations near the end of the season.
The robbing event is very clear on the SSE graph for hive 4. The event lasted two days, with moderate activity on the first day and increased on the second day, as noted by the spike on pattern day 34.
Hive 7 contained the strongest colony at the CC site. For most of the monitoring period the activity was normal. The robbing event is seen clearly on pattern day 34. The Single day method of training seems most sensitive to dramatic day to day changes in flight activity.
The O-Field site was a landfill site, containing a variety of explosives and chemicals.

Colonies in hives 2, 5, and 6 were queenless by mid September. Attempts to requeen these colonies were unsuccessful.
The colony in hive 4 maintained foraging and health. The spikes in the SSE graph are reasonable small. The spike on pattern day 10 (10/08/96) appears to indicate that bees should have been flight but were not. More importantly, the spike at pattern day 17 (10/28/96) is noted by all three training schemes. Flight activity indicates a dip in mid day. Storm?

Again, colonies in 5 and 6 were weak.
Hive 7 contained a booming population. Toward the end of the season, this colony was prospering as nearby colonies died out. On more than one occasion bees from neighboring hives "moved in." It is also possible that this colony raided their weaker neighbors.
The 1997 field trials began earlier than the previous year; generally usable data was available starting in late July.

The CC hives continued to monitor a remediated site until September 4, when they were moved to the J-Field site.

In practice, I ignore the results for the first 14 days of training. Until that time the ANN hasn't built up much of a knowledge base.

All colonies at the CC site have marked activity after day 14. But most spikes do not exceed ten. This appears to be the cutoff at which some detectible event can be determined.

On or about pattern day 17 (8/18/97) all SSE graphs have indications of an event. At this time the field technician was performing chemical pumping, collecting pollen, and using a smoker.
Normally, when the field technician is working the hives, the door ajar switches would indicate the event. However, it appears that some of these switches were not functioning on days when pollen collection was performed. Much of the "noise" in the SSE graphs is the result of using data collected during these periods.
On pattern day 19 (08/18/97) the colony in hive 7 stayed in for the early of the day, and foraged later in the afternoon. It appears to have rained briefly and heavily early in the day. This event perturbed training, so that the next day's normal flight activity caused a larger spike.
The behavior at the Churchville colonies has already been described in the text. The swarming of colony #1, the subsequent robbing and mini chemical test of the other colonies show as similar spikes across all the colonies.
ANN Testing - Various Training Schemes
CV Hive 7 - Single, Accum, and Reinit

Pattern Day

SSE

Single Day Testing  Accumulated Testing  Reinitialized Testing
The colonies at J-Field were originally at the Canal Creek site. On September 4, 1997, the colonies were relocated at a different site on the Maryland federal installation. Since this was rather late in the season, the flight activity is expected to be less than normal.
The increasing SSE spike near the end of the hive 4 plot is probably due to another robbing event. Actual flight activity is high, and robbing of a nearby nucleus colony was observed by the field technician.
On pattern day 17 (10/04/97) the actual flight activity was higher than expected. There was no observed reason for this behavior. Perhaps some additional robbing was going on.
It hard to describe all the events, planned or otherwise, that occurred at the MT site. As this is the Bee Projects main test site for all chemical exposure experiments, electronics testing, and real time data delivery, many events defy explanation.

The colony in hive 3 was queenless.
Later spikes are the result of chemical dose/response test. Primarily these experiments concerned using methanol, an important ingredient in Bee Go, in the hives.
On pattern day 18 (10/14/98) the flight counter program terminated before bee flight activity stopped, due to the long day length. This appears to have caused a rebound effect on the next day.
Monitoring continued on the landfill site for the second year. No noteworthy events were witnessed by the field technician during this run. However, access to this site is restricted, so daily observations were not possible.

The spikes in the Single Day Testing on all these graphs are probably the result of lost data. The collection systems were offline from 09/18/97 to 09/27/97. Since the Single Day Testing system is the most adaptive, it recognizes a dramatic change in flight activity from one day to the next. Without the intervening days, this method does not know that behavior has changed.
This colony was observed to be healthy and productive. Perhaps over productive?
Another example of missing data. From 08/07/97 to 08/23/97 data was missing or invalid. This is particularly bad in that the break occurred early in the training process. After learning pattern day 10 (08/07/97), the ANN was subjected to data from 08/23/97. If the ANN had learned enough basic bee behavior the spike at pattern day 11 probably would not have been so sharp.
APPENDIX F

SSE Evaluation Graphs
for
Knowledge Transfer Experiments
Using the CC site networks for the JF site colonies was an obvious choice for the Hive to Hive Knowledge Transfer experiments. These experiments took the networks trained from the SSE evaluations experiments and used them as the starting network for the JF site.

Initial peaks in these graphs may be explained by the relocation. Bees generally need to take an orientation flight to familiarize themselves with local landmarks. If these landmarks change, the bees may be confused, and require reorientation flights.
The probable robbing event is predicted using the knowledge transfer networks. Interestingly, the PreTrained Network Testing shows continued deviation from normal activity as the days pass. Since this method does not include information about resource depletion, it assumes flight activity to remain high.
The SSE spike at pattern day 13 (09/28/97) is a good indication of why knowledge transfer is useful. A brief rain show occurred that day. The Single Day Testing method is missing the important fact that bees don’t fly in the rain, something both knowledge transfer tests retained.
For this site to hive knowledge transfer, a network was trained on all pattern files for all colonies at the Churchville reference site.

All colonies exhibit an SSE spike at pattern day 5. There was a light wind in the afternoon, no more than 7 mph; not enough to keep bees from flying.
A healthy, productive colony
Knowledge Transfer - Site to Hive
CV Site Network to OF Hive 7

Single Day Testing
PreTrained Network Testing
PreTrained with ReTraining
Similar to the previous site to hive experiments, these used a network trained on the MT reference site. Not the SSE spike at pattern day 5 is missing. The behavior need here was obviously learned from the Montana bees.

However, overall behavior is dissimilar, as seen by the inability of the PreTrained Network Testing to match flight activity. This may be due to the differing day lengths and foliage between Montana and Maryland.
Again, we see the spike for pattern day 35, where ten days worth of data is missing.
Here, both the Single Day Testing and the PreTrained with ReTraining methods indicate a spike at pattern day 11. Again, a case of 16 lost days of data.
For the year to year knowledge transfer, data from the 1996 field trials at O-Field are used to prime the network for the 1997 data. The unexplained SSE spike at pattern day 5 has returned, but the later spikes due to missing data are less pronounced.
This colony has some strong activity. Perhaps doing a little robbing?
It is unknown why the SSE spike at pattern day 2 occurred. The network predicted low flight activity, when the actual flight activity was quite high.
REFERENCES


