Application of Neural Networks for Honey Bee Colony State Identification

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***Abstract*—During the honey bee colony's life cycle different colony states can be observed. At certain situations some of the states can negatively impact colony's development (broodless state, swarming) resulting in possible colony's death and increase of beekeepers costs. On the other hand, when honey bee colony is in active brood rearing stage (at the preferable period) it is a sign that the colony is capable of reproduction. By knowing in which state the bee colony are at a specific moment, without opening the hive, beekeeper can improve his apiary management, e.g., timely prepare for further actions. Within the „Application of Information Technologies in Precision Apiculture" (ITAPIC) project, colony monitoring was performed using one temperature sensor per honey bee hive. This gives enough data to examine temperature dynamics and allows to determine the patterns of the given honey bee colony states. Based on these data, it is possible to develop a honey bee colony state identification process. This can be achieved by inspecting the temperature data and developing algorithms for each honey bee colony state or by applying neural networks. Neural networks are widely used for various tasks, including tasks related to classification and data processing. In this paper authors propose a method for honey bee colony state (commencement of brood rearing period and swarming) detection using neural networks with supervised learning.**

Keywords*—honey bee; temperature monitoring; Precision Beekeeping; Precision Apiculture; neural networks

I. Introduction

In general, honey bee colonies annual cycle can be divided in two periods – a „quiet" winter period and an active summer season [1]. However, some beekeepers have divided the seasonal cycle into several smaller periods – replacement of overwintered bees, bee development in spring, active summer period, preparation for winter period, „quiet" winter period [1]. During these periods, several honey bee colony states can be observed, such as swarming, broodless state, death of colony and other [2]. Honey bee colony state early detection or detection at all gives valuable information to the beekeeper and determines his further actions, if needed.

This paper focuses on two honey bee colony state detection – brood rearing commencement period (opposite broodless sate) and swarming. Bee reproduction can be divided in two ways – individual bee breeding specimen and swarming, when a queen with a large number of worker bees leave the hive to establish a new nest [1], [3]. Several studies have been devoted to honey bee swarming detection [4], [5], [6], [7], [8], but there is still options for further investigations and improvements.

Information technologies (IT) nowadays are major component in almost all fields. Beekeeping is no exception, as a new sub branch of Precision Agriculture (PA), called Precision Beekeeping (PB), was recently defined [9]. Information technologies can improve the overall management of beekeeper's apiary, e.g., it can help in honey bee colony monitoring, e.g., real time temperature monitoring [2],[10], providing the beekeeper with information about the hive, without opening it. Systems, that could automatically warn beekeeper about disturbances in honey bee colony development (critical colony states [2]), development and implementation need more attention.

Neural network is a part of IT and important tool in artificial intelligence (AI) and have a long history (dates back in 1943 [11]). Since then, several types of neural network have been defined; they have been adjusted to help to solve different type of problems. They are used in applications related to, e.g., pattern recognition, robotics, prediction and forecasting and other.

There are several studies related to neural network usage in PA (reviewed in [12]). However the usage of neural networks in the field of beekeeping in order to detect honey bee states is not very common, but there are studies related to honey bee colony management, e.g., [13] was aimed to image segmentation to determine bee forage areas.

The aim of this paper is to describe a method for detection of commencement of brood rearing period and swarming using a neural network based approach.

II. The Experimental Site

Ten beehives were monitored from 9th December 2014 till 31st August 2015 in Strazdu iela 1, Jelgava, Latvia (N 56°, 39', 45'' and E 23°, 45', 15'').

Wooden hives with outside dimensions 47×47×27 cm and inner dimensions 38×38×27 cm were used. During the period from 9th December to 9th March thermal insulation material was placed above the hives body.

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Each beehive was equipped with one digital thermometer DS18S20 (accuracy: ±0.5°C, more information in: https://datasheets.maximintegrated.com/en/ds/DS18S20.pdf) that was placed above the frames. All sensors were connected together to form a 1-Wire network. Data were gathered using Raspberry Pi device and stored in a remote MySQL database every 60 seconds [10].

Beekeeper, who works at the site, was instructed to record observed swarming events during the period from May to August.

III. Temperature Patterns for Honey Bee Colony State Identification

A. Brood rearing temperature pattern

During the active brood rearing period, honey bees keep their brood temperature at 34-36°C [14], [15]. In spring the temperature increase in beehive is more significant because of the preparation for summer [16]. So the main characteristic of this pattern is the temperature rise above 30°C (in the range of 34-36ºC), where the temperature is kept at that level.

B. Swarming temperature pattern

By examining data at the time the swarming events were observed by the beekeeper, it was found that all these events have similar pattern – there is a temperature increase (from 34–35°C) (by 1.5 – 3.4°C) at the approximate time the swarming event was observed. This increase lasts about 8 to 20 minutes till the temperature starts to decrease and stabilizes back to 34–35°C (Fig. 1). [17]

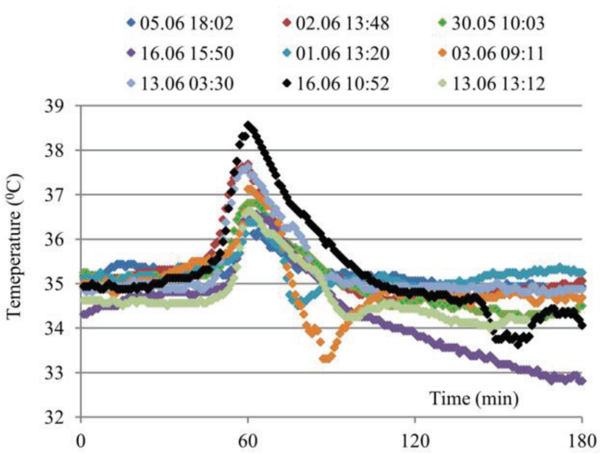

Fig. 1. All detected swarming events [17] at 3h interval

Taking into account the characteristics of described patterns, neural network was designed and training and test data sets were prepared. Due to different temperature dynamics of investigated honeybee states, a separate neural network was applied for each state.

C. Developed neural network

1) Neural network design

Design of neural network is related to definition of the problem – what is the purpose of the network. In our case, artificial neural network with back-propagation learning algorithm for temperature pattern recognition was chosen. Back-propagation is a simple, computationally efficient algorithm that usually works. But the challenging task is to design and train the network to work well, as there are several factors involved – layer count, neuron count in layers, learning rate value, training and test sets etc. [18].

Developed network consists of three layers – input, hidden and output. Additional neuron called "bias" with value +1 was added to input and hidden layer, giving extra weights for the whole network. Hidden layer count was determined empirically, in our case it was 1.

Neuron count for hidden layer was selected by rule (1):

$$n_{hidden} = 2 * (n_{input} + n_{output}) / 3 \quad (1)$$

The variables n_{hidden}, n_{input}, n_{output} represents neuron count in hidden, input and output layers respectively.

Neuron count of 60 was selected for input layer and one neuron was selected for output layer, as it needs to only output values like 1 (true) or 0 (false).

Data for the input layer were normalized using (2):

$$value = \frac{(x - \min Input) * (\max New - \min New)}{\max Input - \min Input} - \min New \quad (2)$$

Where *value* is the new mapped value; *x* is the input value, *minInput* and *maxInput* represents the minimum and maximum of the input value, respectively; *maxNew* and *minNew* are the new maximum and minimum values, respectively.

Using (2) input values were scaled to range that the input values are close to 0, to get faster convergence of back-propagation learning algorithm [18]. Range of [-1;1] was selected.

2) Neural network training

Stochastic or online learning was used in network training. Sigmoid function (3) was selected as an activation function with the constant (c) value of 1. The higher the constant value, the more closer the sigmoid's shape is to step function [19].

$$S_c(x) = 1 / (1 + e^{-cx}) \quad (3)$$

At the beginning the neural network was initialized with weights of a random value from range [-1;1]. Difference between network output and target value (the expected value) was calculated using Mean Squared Error (MSE) (4) as described by [19]:

$$E = \frac{1}{2}\sum_{i=1}^{p}\|o_i - t_i\|^2 \quad (4)$$

Where p is the p-th pattern; E is the MSE; o_i – output form network and t_i is the target (ideal) output.

Gradient descent was applied to the learning process to reduce the error. The neuron weights were updated by increasing their weights with (5):

$$\Delta w_i = -\eta \frac{\partial E_t}{\partial w_t} + \alpha \Delta w_{t-1} \quad (5)$$

Where η is the learning rate, E_t represents the error of t-th pattern, w_t is the t-th pattern's weight, α is the momentum and Δw_{t-1} – previous value of Δw.

There are two values that have a significant impact on neural network's training – learning rate (η) and momentum (α). Learning rate determines the „speed" of error reduction or in other words – the learning process. Neural network will learn slower, if the value will be low. Setting this value too large can give negative effect – divergence can occur [20]. The values of learning rate and momentum, that are usually in the range of (0;1), were determined empirically (different values were tested to determine the impact on network's performance (the network learning process should result in reaching the desired precision rather than exceeding the epoch count)) and were set to 0.2 and 0.8 respectively. Both of them were set globally for all weights, although there are articles that suggest different methods [18], [21]. The maximum epoch count was set to 10^4, precision – 10^{-4}.

3) Training data sets

It was found, that in the start of active brood rearing period, the temperature increase is much slower than when bees are preparing to swarm. As the main characteristic of this pattern is that when the temperature reaches about 34-36ºC it is kept at that level, there is no need to follow each minute of this temperature growth, but rather to detect it's occurrence. As a result 60 data points were selected, where each data point represents temperature value after 20 minutes. So a 20 hour period (Fig. 2) was selected.

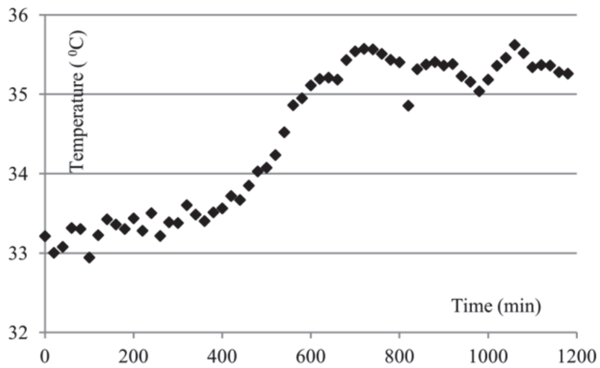

Fig. 2. Example of trained brood rearing pattern

Swarming pattern inspection revealed that 1 hour period is sufficient to detect swarming, as the temperature rise lasts for 8-20 minutes. Therefore, 60 neurons were selected for input, where each neuron corresponds to temperature data at each minute in 1 hour interval. The swarming pattern (Fig. 3) was trained so it would be possible to detect the bee take-off as early as possible. We assume that the take-off starts at the point where the maximum temperature is reached and the temperature starts to drop.

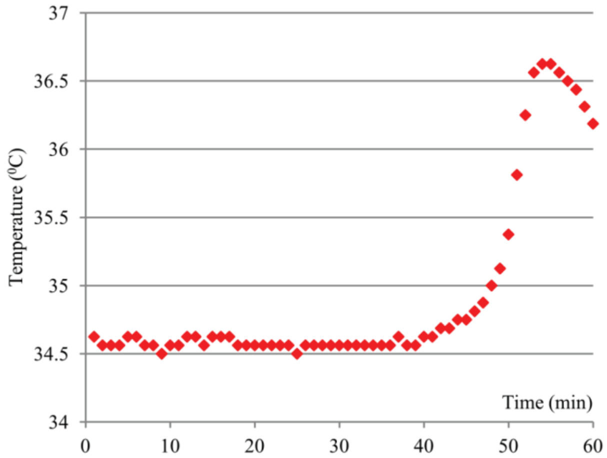

Fig. 3. Example of trained swarming pattern

Data sets were prepared in „.csv" files (one file per honey bee state), where data points were delimited with comma and the target value (the expected output) was added at the end. 929 samples in total were used for swarming pattern training, and 202 samples were used for brood rearing period commencement pattern training. To increase the networks reliability, only about half (5) of swarming samples were used in training set for swarming pattern training, and 2 samples for brood rearing commencement pattern.

The neural network was developed in C# programming language and was applied for swarming and brood rearing state detection. To recognize each of these states a separate network of the same design was applied for each state.

IV. Results and Discussion

Developed neural network was applied to test historical honeybee colony temperature data in order to detect the start of brood rearing period and swarming events. Additional data preprocessing was done to train and test neural network for brood rearing state, because only data at every 20 minutes were selected (explained in section III), but data at every minute were selected for swarming state training and testing.

Both patterns where trained on a computer with the following specification:

- processing unit: Intel i7 at 3.6GHz
- memory: 8GB
- operating system: 64-bit Windows 7 SP1

Network training was run 10 times to calculate average time and average epochs. Neural network's, with learning rate of 0.2 and momentum of 0.8, results for pattern training are summarized in Table 1.

TABLE I. NEURAL NETWORK TRAINING RESULTS

Parameter	Pattern			
	Commencement of brood rearing		***Swarming***	
	Time (s)	***Epochs***	***Time (s)***	***Epochs***
Average	105.1	1389	192.8	761
Standard deviation	62.79	952.29	62.34	239.13

A. Brood rearing period commencement detection

During historical temperature data examination, pattern of brood rearing period commencement was found in 7 bee colony temperature data (in May), the actual temperature increase was not found in 2 bee colony stored data due to technical difficulties with the monitoring system, but the fact, that temperature has risen was detected. One bee colony did not survive the winter period.

Neural network found possible commencement of brood rearing period for every colony (Fig. 4), except the one that died. All these cases were verified by investigating the historical data. None of these cases were verified on site by opening beehives. The start of brood rearing period in April was found in 5 bee colony data. 4 bee colonies appeared to start brood rearing in May.

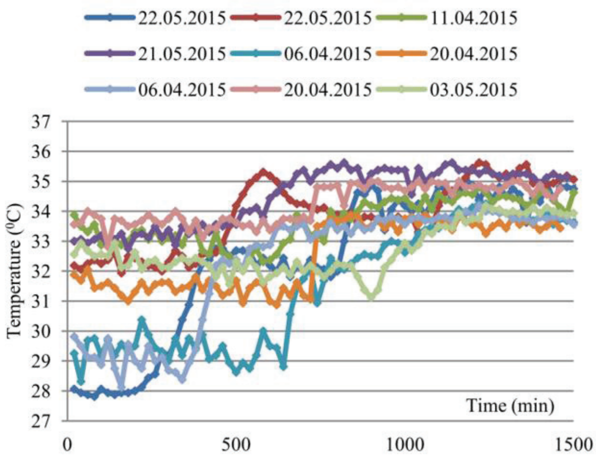

Fig. 4. Detected start of brood rearing

B. Swarming event detection

Beekeeper observed 8 swarming events during the period of May – June. 9 events that correspond to the described swarming pattern were found during temperature data inspection. We assume, that the 9th event was swarming, as it corresponds to the swarming pattern. It occurred at night (13.06.2015 3:30AM) and thus was not observed by the beekeeper [17].

Neural network detected 11 possible swarming events. 9 of them were those observed by the beekeeper and that were found in data inspection, but 2 were not observed. Investigation of those 2 cases revealed that their pattern was very similar to the swarming (Fig. 5). Interesting is that both cases appeared approximately at 5:00PM in different days (13.06.2015 and 19.06.2015), and therefore one of the reasons why these events were not observed on site, could be that beekeeper's working day was over. Another reason could be some environmental noise that might have stressed the bees to cause the temperature rise. Although the last assumption is less convincing, as the temperature growth occurred only for those two colonies at the corresponding times.

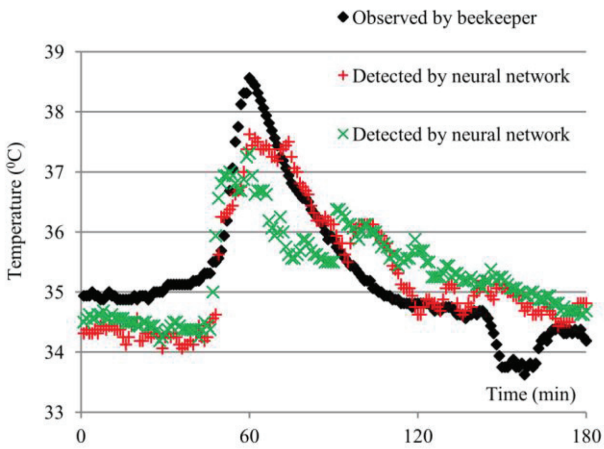

Fig. 5. Patterns found by neural network compared to observed one in 3 hour interval

V. CONCLUSIONS

Swarming pattern shows a temperature increase by 1.5 – 3.4°C (reaching temperature near 39°C in some cases), that persists approximately from 8 to 20 minutes. Brood rearing usually starts at early spring and has a characteristic of slow temperature increase up to 36°C where the temperature is kept at that level throughout all active brood rearing period.

Developed neural network was applied to detect two honey bee colony states – brood rearing and swarming. For each state a separate network was applied. Neural network's training took approximately up to 2 min for brood rearing pattern training and approximately up to 4 min for swarming pattern training.

During neural network testing phase, the start of brood rearing period was detected for all 9 honey bee colonies that survived the wintering (1 colony did not survive). Brood rearing appeared in April for 5 colonies and in May for 4 colonies.

Neural network detected 11 possible swarming cases, from which 9 were known (8 were observed by beekeeper and 1 was found during data review and matched the swarming pattern). The 2 extra cases were assumed to be swarming as well as they were very similar to such pattern.

It was concluded that data from one temperature sensor per hive gives enough data to detect states like brood rearing and swarming. This study showed that artificial neural networks can be successfully applied to honey bee colony state detection.

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SEVENTH FRAMEWORK PROGRAMME

ITAPIC Application of Information Technologies in Precision Apiculture