



Applying the Long-Term Memory Algorithm to Forecast Loss of Thermoregulation Capacity in Honeybee Colonies

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1 - Introduction

Motivation

- Bees are the most important group of **pollinators** [Klein et al. 2007, Brown et al. 2016];
- Honeybee colonies have dwindled in rates of 30% colony deaths overwinter due to climate change and the use of agrochemicals;
- Whatever the causes, they all converge to the same point; harming the thermoregulation capacity of the colonies.





Figura 1. Abelhas em atividade de polinização. Fonte: http://www.jornalentreposto.com.br/99-arquivos/1481-insetos-polinizadores-melhoramprodutividade-agricola

1 - Introduction

- Apicultura de precisão
 - RSSF e IoT;
 - Monitoramento remoto de apiários;
 - o Mineração e análise de dados.

Proposta

- In this paper, we used machine learning techniques to predict homeostasis loss.
- We apply the Long Short-Term Memory (LSTM) algorithm to forecast the thermoregulation capacity (i.e. homeostasis) loss in honeybee colonies.

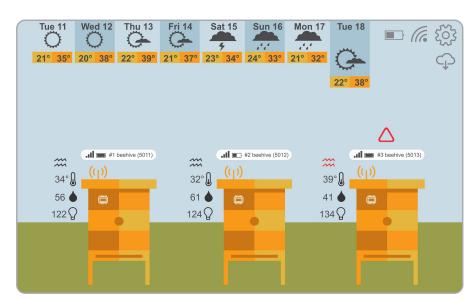


Figure 2. Dashboard overview of a general remote beehive monitoring system.

2 - Related works

- In tropical climate, [Kridi et al. 2016] recognized thermal patterns to detect bees' pre-abandonment scenarios;
- In temperate climate, the hotter the bees perform the foraging, which impacts the development of the pupae and the division of labor of the bees [Winston 1991];
- The seasons of the year are also very important to the colony behavior [Maciel et al. 2018].
- Thus, the loss of internal temperature control is an important indicator related to the colony health, and may indicate if it is facing a problem.

Dataset

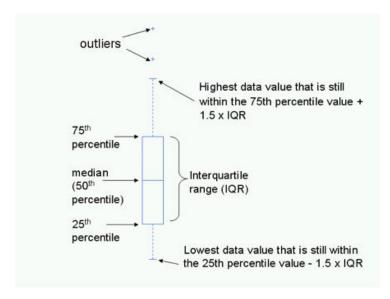
- Six different beehives;
- An apiary located in the city of Newcastle upon Tyne, England;
- Collected from September to November in 2017;

Table 1. Summary of beehive analyzed with good thermoregulation

beehives	latitude	longitude	#samples	period	sampling	therm.
9803	-1.628	54.971	603	Sep 3th-Nov 6th	2hs	w.r.
9837	-1.516	54.994	1456	Sep 3th-Nov 6th	1h	n.r.
9841	-1.617	54.979	638	Sep 5th-Nov 6th	2hs	n.r.
9848	-1.599	55.016	502	Sep 5th-Nov 2th	2hs	n.r.
54440	-1.628	54.971	606	Sep 3th-Nov 6th	2hs	n.r.
54460	-1.616	54.970	1024	Aug 5th-Nov 6th	2hs	w.r.

- Preprocessing
 - Exploratory Data Analysis (EDA)
 - Basic statistics (mean, the standard deviation, and quartiles), and the skewness.
- Detection and removal of anomalies
 - Interquartile Range;
- Data Resizing (Min-Max scaling)

$$x_{new} = \frac{x - x_{min}}{x_{max} - x_{min}}.$$



Describing Interquartile Range and Outliers Fonte:

https://images.app.goo.gl/KXWyySHj21uSkP9z5

- Long Short-Term Memory (LSTM)
 - Long Short-Term Memory (LSTM) is a specific RNN architecture that was designed to model temporal sequences and their long-range dependencies more accurately than conventional RNNs [Sak et al. 2014].

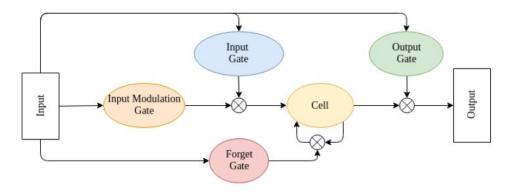


Figure 2. A LSTM memory cell

Experiment Setup

- The data was separated in train (67%) and test (33%) sets;
- LSTM architecture with 4 hidden layers;
- A number of epochs equal to 100;
- The back propagation parameter (look back) was setted in 4 timestamps.

Evaluation Metrics

- (i) MAE is the mean for all recorded absolute errors;
- (ii) MAPE is the mean absolute percentage error;
- (iii) RMSE measures the average of the squares of the errors, that is, the average squared difference between the estimated values and what is estimated;
- (iv) R 2 provides a measure of how well observed outcomes are replicated by the model,
 based on the proportion of total variation of outcomes explained by the model.

Results

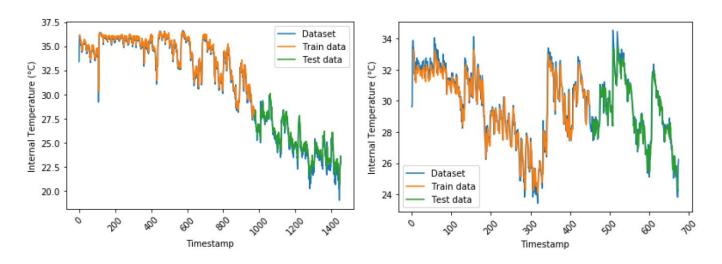


Figure 3. LSTM fitting (hive #9837)

Figure 4. LSTM fitting (hive #9841)

Results

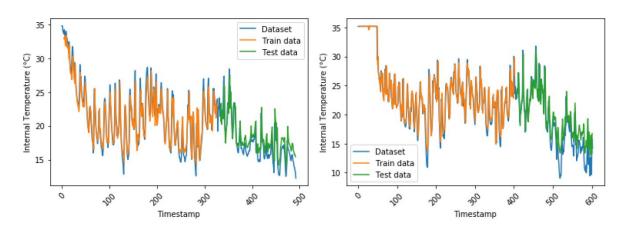


Figure 5. LSTM fitting (hive #9848)

Figure 6. LSTM fitting (hive #54440)

Table 2. Evaluation Metrics for LSTM Algorithm for not thermoregulated beehives

Beehive	RMSE Train	RMSE Test	MAE	MAPE	\mathbb{R}^2
9837	0.49	0.73	0.5651	2.3424	0.8876
9841	0.77	0.83	0.5658	1.9388	0.8543
9848	1.79	1.72	1.4282	8.3675	0.6978
54440	1.74	2.46	2.0794	13.614	0.7427

Results

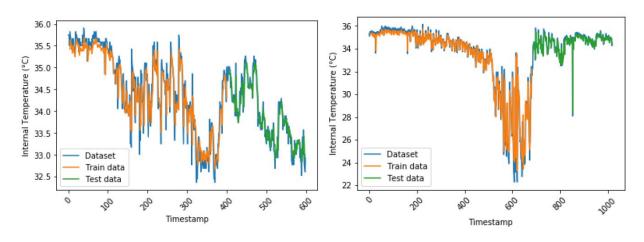


Figure 7. LSTM fitting (hive #9803)

Figure 8. LSTM fitting (hive #54460)

Table 3. Evaluation Metrics for LSTM Algorithm for thermoregulated beehives

Beehive	RMSE Train	RMSE Test	MAE	MAPE	\mathbb{R}^2
9803	0.38	0.25	0.1854	0.5478	0.8677
54460	0.93	0.64	0.3102	0.9098	0.1276

Discussion

- The **high amplitude** of temperature and a declining pattern indicate a sign of thermoregulation losses;
- According to [Heldmaier 1987] the colony capacity to survive cold depends on maintenance of a steady state temperature, about 35°C;
- Some beehives the temperature fell more than 10°C, this could already be a sign of trouble;
- In extreme conditions of cold weather the bees take a protective behavior and start a phonomena called the diapause.
- Loss in the thermoregulation capability <-> high temperatures;
 - o brood death, wax melting, honey dehydrated;

Conclusion

- General proposal objective
 - Predict thermoregulation loss;
- Main contribution
 - A trained Long Short-Term Memory (LSTM) algorithm to forecast the thermoregulation capacity loss;
- Results
 - Our results showed an error of only 0.5% in prediction for well-thermoregulated beehives;
 - The proposed solution was capable of predicting the thermoregulatory capacity loss of a colony up to **8 hours** before the homeostasis is lost in the nest.
- In perspective
 - We intend to inform others features to LSTM, like internal humidity, hive activity, mean fanning, mean flight noise, weight, external temperature, and external humidity.

Perguntas?

Obrigado!

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