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Research Note

Architecture of a decentralised decision support system for futuristic beehives

Vitalijs Komasilovs[a,1], Rob Mills[b,1,*], Armands Kviesis[a], Francesco Mondada[b], Aleksejs Zacepins[a]

[a] Institute of Computer Systems and Data Science, Faculty of Engineering and Information Technologies, Latvia University of Life Sciences and Technologies, Liela iela 2, Jelgava, LV-3001, Latvia

[b] Mobile Robotic Systems Group, École polytechnique fédérale de Lausanne (EPFL), Lausanne, CH-1015, Switzerland

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ABSTRACT

Honeybees are essential to human society, providing pollination services globally as well as producing honey and other valuable products. Effective management of apiaries should not only rely on beekeeper knowledge and skill, but also incorporate new information technologies. The options to identify, predict and prevent beekeeping problems are becoming more affordable and applicable. The interdisciplinary Horizon 2020 project HIVEOPOLIS focuses on developing a new approach in beekeeping, by creating novel mechatronic beehives and implementing new bio-hybrid ideas. These intelligent beehives aim to help honeybees to cope with adverse environmental factors and increase the survival rate of the bee colonies. This paper focuses on the software architecture design for these intelligent beehives, providing infrastructure for data management and decision support system operation. The presented infrastructure is suitable for highly dynamic and diverse environments where a multitude of components interact and exchange information across technology domains (embedded, cloud, UIs) in a reliable and secure way. Besides user support, the decision support system built upon this infrastructure enables closed-loop automated decision making and control.

1. Introduction

Honeybees are a key element in the nutritional supply of mankind on a global scale, as bees play a significant role as pollinators (van der Sluijs & Vaage, 2016). However, many harmful factors are together affecting health and abundance of bee colonies worldwide, including pesticides, habitat fragmentation, monoculture, pathogens, as well as technological and societal developments (Smith et al., 2013). Today beekeepers are facing various challenges, including the changes in the environment caused by climate change (Vercelli et al., 2021). There is no one solution to all mentioned challenges, but technological augmentation of the bee colony itself can help the bees to overcome some of the issues. For example, advances made in developing and deploying technologies internet-connected “smart-hives” are enhancing beekeeping and scientific research (Marchal et al., 2020). The multidisciplinary EU project HIVEOPOLIS (Ilgün et al., 2021) is developing a new generation of futuristic and intelligent beehives that include novel actuators to directly interact with the colony together with new hive architectures, besides sensing seen in smart hives. The goals are to partially mitigate challenging environmental conditions, and provide an additional value to the bee colony, to the beekeeper, and to the whole ecosystems. The hive concept is structured into “modules” that each focus on different aspects of honeybee life or management, such as the dancefloor, brood nest or storage. The core module provides central computation facilities to acquire and process the hive information and provide the decision support. In addition, the core module provides external connectivity, such that the hive and its management can use off-hive information sources, which the bees would not naturally have access to.

The aim of this communication is to describe the architecture of the data platform for the futuristic HIVEOPOLIS hive and to present the proposed data processing and analysis pipeline.

Long-term beehive monitoring systems, all aiming to provide insights about colonies in field scenarios, have measured various parameters including temperature (Zacepins et al., 2021), weight (Lecocq et al., 2015; Meikle et al., 2008), and combinations of measurements (Cecchi et al., 2020) and detailed environmental conditions

* Corresponding author.
E-mail address: rob.mills@epfl.ch (R. Mills).

[1] Equal contribution.

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(Edwards-Murphy et al., 2016). Offline logging requires periodic data retrieval (Meikle et al., 2008; Rafael Braga et al., 2020), while connected systems reduce labour, and crucially, yield the potential to respond to the data.

Technically, this has been achieved using SMS (Lecocq et al., 2015), via custom systems that first aggregate data at apiary-local nodes before being transmitted to central servers over the internet (Cecchi et al., 2020; Gil-Lebrero et al., 2017), or internet of things (IoT) technologies (Hong et al., 2020). Many of these systems aim to improve beekeeping management and its economic viability.

In addition to monitoring honeybees, certain systems have been applied to help bees regulate their microclimate, including passive (Abbott, 2016) and active (He et al., 2020) approaches. Heating hives (Owens, 1971) was shown to reduce overwintering food consumption. Konya (2007) described a device that rotates the brood frame daily to prevent swarming. Robotics to influence behaviours of various animals, such as groups of cockroaches (Halloy et al., 2007), fish (Faria et al., 2010), and honeybees (Bonnet et al., 2019), have been demonstrated in laboratory conditions. Work with honeybees have shown interactions with individual foragers using motion (Michelsen et al., 1992) and small groups using temperature (Bonnet et al., 2019) and vibrations (Schmickl et al., 2021). The field of animal-robotic interactions aims to better understand social behaviours in animals (Krause et al., 2011), using robots that generate cues to which the animals respond, that is, the stimuli are designed to be perceived as from other animals. These interaction modalities are thus promising for new applications involving complete honeybee colonies in the field.

In the field of precision beekeeping, some decision support systems (DSSs) and expert systems have been proposed, mostly dealing with honeybee health (Mahaman et al., 2002), beehive placement scheduling (Vlad, Ion, Cojocaru, & Ion, 2012), and colony state identification (Edwards-Murphy et al., 2016; Kridi et al., 2016). Predictive modelling frequently serves as the foundation of such systems for tasks such as: improvement and filtering of measured parameters (Jia et al., 2023), predicting foraging patterns (Majewski et al., 2023) and predicting honeybee activity (Andrijević et al., 2022). Although DSS definitions usually include user interactivity, in precision beekeeping, a DSS could make some urgent and important decisions automatically (Zacepins et al., 2015). Here, by performing actions without human expert involvement, a DSS may resemble an expert system.

In the HIVEOPOLIS system, we aim to augment the survival of a bee colony by going beyond remote monitoring as used in smart hives and localised regulation, by also embedding robotic actuation systems to influence animal behaviours in ways that are beneficial to them. This therefore requires advances in colony state perception and predictive models to explore different outcomes for the colony, so to provide decision support - and in certain cases achieve an expert system: a beehive that operates without human intervention. Fulfilling these goals requires a systematic approach to the orchestration of computational processes and local data management, which is described in this communication.

Section 2 presents the architecture of our data platform, and section 3 describes and illustrates the decision support system implemented on the data platform.

2. A decentralised data platform

The physical structure of the HIVEOPOLIS beehive is actively evolving towards sustainable and bee friendly design (see Fig. 1; Ilgün et al., 2021). The central core module is considered as a backbone of the hives and provides power, local connectivity, and communication infrastructure. It acts as a single access point to the hive, offering a unified approach for off-hive data exchange with cloud services.

One of the key roles of the core module is to collect sensory information from the various modules, store it and make it available for downstream data consumers. These include a) the models and algorithms deployed “on-hive” as a part of an embedded decision support system, and b) the external services for “off-hive” data analysis. Bidirectional hive–cloud communication allows the use of different external data sources (e.g., other HIVEOPOLIS hives, public and private databases, environmental maps, web services) to build a decision support system. This section describes the on-hive and cloud-based elements of the integrated data processing platform, as shown in Fig. 2.

2.1. Structure and function of internal elements

The central core software (Fig. 2, left) is developed to manage “on-hive” data and facilitate its exchange between various logical components. Drivers are the main linking points between data platform software and hive hardware. Optionally, hardware specific protocols are handled by parsers (e.g. weather station). Collected sensory data is stored locally for “on-hive” data analysis and distribution to downstream consumers. “Off-hive” components (Fig. 2, right) represent various cloud services and information sources beyond the scope of a single hive (e.g. apiary or region level). The decision support system (DSS) is implemented as models connected to common data exchange infrastructure, and activated either by upstream components or on timers (described in section 3).

Fig. 1. Prototypes of the HIVEOPOLIS beehives, combining bee living volume and space for bee-supporting technology in a tree trunk exterior form. (a) “Mitochondria”-inspired architecture with a continuous surface for honeycomb. (b) Star topology, with traditional frames and space for the electronics. Images are provided by Pollenity.

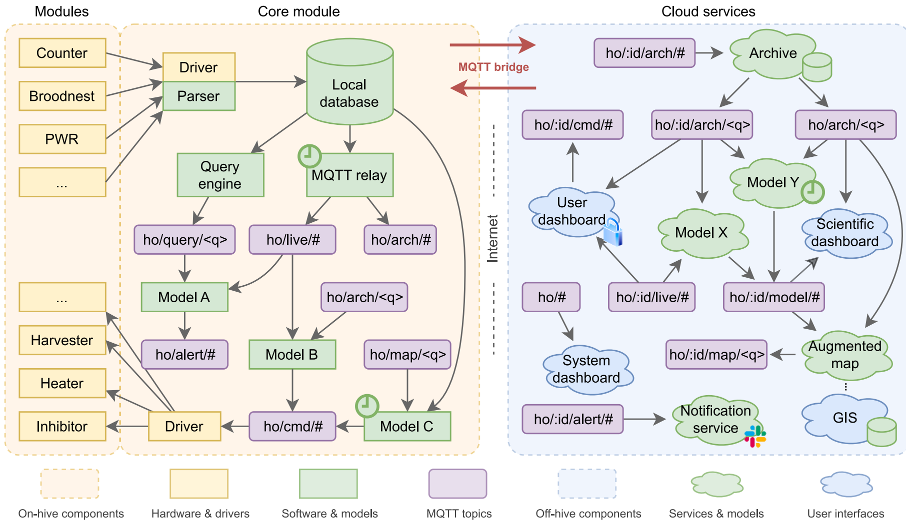

Fig. 2. Components of the "on-hive" data platform (left) and "off-hive" cloud services (right), organised into data flows and processing units.

2.2. On-hive database

An open-source time-series database, InfluxDB, was selected for persistent data storage. Data points in the time-series database are measurements or events, which the database controls, down-samples, and indexes over a period of time. In our context, this includes data from sensors, identified events, and technical information about "on-hive" systems. Since HIVEOPOLIS modules continuously provide a lot of sensory and event-based data, InfluxDB applies data retention policy to store only operational data locally and transfers historical data to cloud storage if needed. For lower-end embedded platforms, SQLite was also tested as persistent data storage with minor API changes. The operational requirements of an individual hive include only short-term data storage and do not grow over time. Accordingly, the current provision of storage and RAM is anticipated to cover foreseeable future needs. Thus the architecture is sustainable and well matched to the requirements for our use-case. These are similar needs for IoT applications (Nasar & Kausar, 2019).

2.3. Data exchange infrastructure

Data exchange both within the core module as well as between cloud services relies on MQTT, a lightweight machine-to-machine transport protocol based on a publish/subscribe messaging model that is well suited to IoT applications (Mishra & Kertesz, 2020). Any type of data exchange between components is organised via messaging and includes raw and processed sensory information, modelling and external service results, commands. Messages are distributed in multi-cast manner from publishers to subscribers according to strict topic hierarchy. Protobuf data structures were used to unify embedded and cloud components. Depending on consumer capabilities, messages are encoded either as JSON or binary payloads. The data exchange point – the MQTT broker – is responsible for decoupling both types of clients (publishers and subscribers), ensuring that dynamic changes in the connections do not affect the rest of the system. The broker is also responsible for client authentication and authorization via fine grained access control lists (ACLs) which ensure that messages are not accessible for non-authorized clients. Local MQTT topics with pattern `ho/#` are automatically mapped to global topics prefixed with hive identifier like `ho/hiveA/#`. This mechanism allows transparent, secure, fail-safe and extensible integration with external services, such as cloud data sources and various programming and user interfaces (see section 2.5).

2.4. On-hive components of the data platform

Sensory and event data originate in the hardware modules and arrive via their drivers. Upon receiving data, packets are parsed and converted to the native format for write operations and passed to the database instance. Stored data is consumed by various software components. The MQTT relay queries the latest data points from the database on a regular basis and propagates results via specific MQTT topics: a live and an archive stream of data points are published for other components to use. Importantly, these streams also appear externally allowing cloud components of the HIVEOPOLIS ecosystem to react seamlessly. We elaborate on the external connectivity below (section 2.5).

The query engine implements a request/response protocol for other components to obtain detailed information on-demand from the database. It consists of two related MQTT topics: one for sending the request, and the other for receiving the response. In order to distinguish between multiple and, potentially, parallel requests, the requesting client is responsible for using a unique suffix for the topics, such as a UUID.

Models represent various types of software components, each capable of performing transformations and reasoning upon received information and producing results that are used by other components (see sections 3.2 & 3.3).

Finally the feedback loop from bee sensing and perception to actuating and modulating the bees is closed at the "command" driver which translates published commands to actual instructions for hardware actuators. Command authorization is handled by the MQTT broker as described above.

2.5. Cloud services interacting with the data platform

Several cloud services are available for individual HIVEOPOLIS hives as depicted in Fig. 2 (right). For a large network of hives, the total transmitted data to/from the cloud are expected to become substantial. Horizontal scaling, load balancing and other routine big data handling techniques should be applicable. Thus the key technologies are selected considering these aspects: both InfluxDB and MQTT are designed for high load systems, while custom components are built and deployed using Docker platform.

The archive is used for the long-term storage for historical data points. It implements various query schemes, such as detailed per-hive data requests for hive owners. Models represent various cloud services responsible for transforming and interpreting the incoming information and producing additional insights for decision making. In contrast to "on-hive" models, the cloud ("off-hive") models can be computationally expensive and/or consider multi-hive data for apiary management and strategic planning, like evaluating bee apiary locations (Komasilova et al., 2020).

The augmented map enhances various data sources with geospatial information, such as weather forecasts or resource estimations at a given location (Komasilova et al., 2021). The notification service implements alerts and notifications over various channels, such as Slack. User interfaces provide useful insights about current or historical information for authorised users, and enable them to send commands and configuration to the hives.

Since each hive includes consumers of "off-hive" data, the requirements are distinct from a network of purely sensory systems more typical for smart hives. In the latter case, the architectures are designed for upstream data, while the HIVEOPOLIS design considers bidirectional data flows.

3. Decision support systems in beekeeping

A decision support system (DSS) provides infrastructure for data analysis. The understanding of the term DSS is domain-specific. As identified by Zacepins et al. (2015), a DSS can be applied in beekeeping to automatically analyse and interpret data acquired from a single bee colony, and can facilitate and improve a beekeeper's work in apiary management. The main outcomes of a DSS are detected states of individual bee colonies, and tasks and actions the beekeeper should consider when specific states are detected. The DSS architecture considered here follows general theoretical concepts (Marakas, 2002).

3.1. DSS implementation in HIVEOPOLIS

By measuring different parameters, several colony states can be distinguished – such as active brood rearing, broodless, swarming, colony death. Bees perform collective thermoregulation of their hive as temperature is extremely important to their development and health (Stabentheiner et al., 2021). Accordingly, temperature patterns can be used in state identification. The colony weight represents another valuable indicator for various activities of a bee colony, including resource consumption, the start of the nectar flow, swarming and/or absconding (Meikle et al., 2008; Zacepins et al., 2021).

Fig. 3 shows potential bee colony states that can be identified within the HIVEOPOLIS system, and the corresponding input parameters needed. These inputs can be scalar values read from sensors, like temperature, weight, number of bees at the entrance, but also more complex data structures, like comb image scans, detected dance patterns obtained from the HIVEOPOLIS innovative solutions. States are identified via models and reported to end users for decision support together with suggested manual beekeeping operations, such as hive cleaning. In contrast to conventional smart-hives where a beekeeper is always the actor for suggested operations, the HIVEOPOLIS system facilitates some automatic actions directly, like emergency closure of the gates. Automatic operations help to save time for the beekeeper, especially if the apiary is located far from the beekeeper. Specific models identifying bee colony states underpin the comprehensive DSS. Besides colony state identification (section 3.2), technical components are monitored to avoid harm to the colony by electronics or mechatronics (section 3.3).

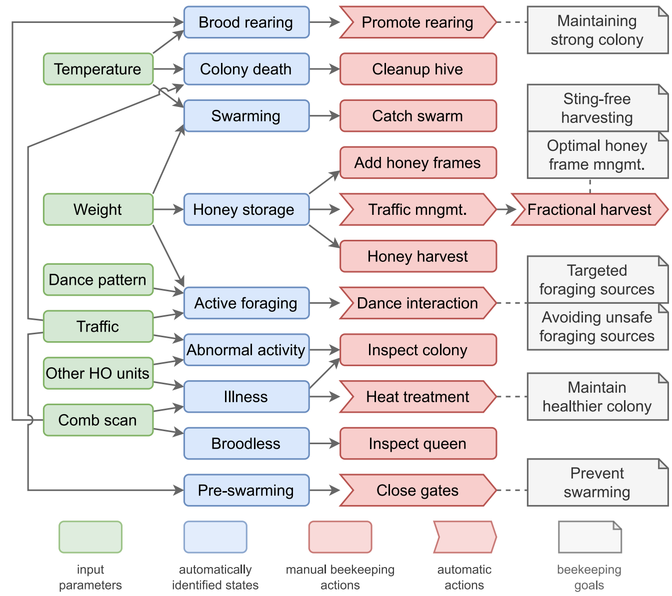

Fig. 3. Target bee colony states, the required input data to identify them, and appropriate actions to maintain a successful apiary.

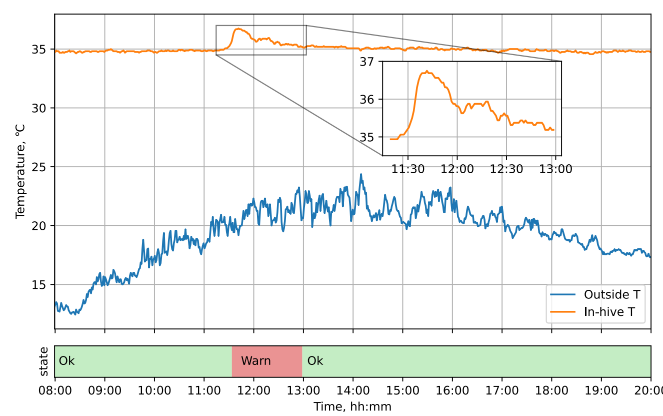

Fig. 4. Example of temperature data for a swarming event measured by temperature sensor above brood frames inside the hive.

3.2. Colony state modelling illustration

To demonstrate the operation of the data platform and the DSS, we provide an example of historically recorded temperature data of a brood-rearing colony with stable in-hive temperature and colony swarming event (Fig. 4). These parameters are used in a colony state detection model (Kviesis et al., 2020): a fuzzy-logic based component detects anomalies in temperature data, while a pre-trained neural network classifies swarming events among the anomalies. The active thermoregulation mentioned above means that there is no correlation between in-hive and external temperatures (Pearson correlation, $R^2 = 0.085$, $p < 0.001$) when the colony is in a brood-rearing state.

At first the data required for the state detection model is retrieved via the query engine, pre-processed and then run through the model. This occurs in real-time, as soon as a new data point is recorded. The model uses a set of rules describing the occurrence of specific states. If abnormality is detected, like in this example, the in-hive temperature is outside the usual temperature range (above the brood frames it is usually 34 $^{\circ}C$–36 $^{\circ}C$), a separate model is triggered for swarming pattern recognition.

Detection of abnormal states is crucial for the beekeeper as it affects the overall performance of the apiary, so the beekeeper should be notified and advised to take urgent action, here, by sending an alert to a notification service, which delivers a message to the beekeeper via Slack. The DSS suggests for the user to visit the apiary and inspect this specific colony. By having this information, the beekeeper, as the decision maker, chooses appropriate action, considering the distance and time to the apiary (Zacepins et al., 2021).

3.3. Infrastructure state modelling illustration

In addition to detecting key biological events, our framework is used to detect system events. A general goal is to detect failures or errors in hardware, with the underlying aim of protecting bees from harm due to malfunction hardware.

The HIVEOPOLIS power supply unit measures current per channel (i.e., per module) and also has a per-channel switch. Certain modules featuring actuators can reach several amps peak current usage. These and other modules can have low sense-only current usage, e.g., $I < 100$ mA. Modules with static power consumption can be guarded using simple protection such as fuses. But in a module with actuators, a risk exists where the baseline current is exceeded but within the bounds of actuator full activation, (e.g., 100 mA $< I_{failure} <$ 3000 mA). Since a module's activation level is in general variable (e.g. due to colony behaviour), there is no straightforward reference level for power consumed. However, in some cases the robotic systems may provide internal state sufficient to predict the expected current consumption. The resistive heating scenario employed in the brood nest module (Barmak et al., 2023) provides one such example.

The marginal current consumed is approximately linearly related to the PWM duty cycle D_a, meaning that knowing the activation levels per actuator a, we can estimate the current. The theoretical estimate is simply $I_a = D_a \cdot R \cdot V_{dd}$, where R is the actuator resistance and V_{dd} is the supply voltage, and can be summed across all actuators, $I_{predicted} = \sum_a I_a = \sum_a D_a \cdot R \cdot V_{dd}$. If the measured current exceeds the prediction, we can enter a warning state and potentially disable the power supply to the module, limiting damage to colony and equipment.

Fig. 5 shows the theoretical relationship as well as ordinary linear regression fitting measured data. The predictions enabled by this simple fitting illustrate a severe failure at the end of the time series. The safety model illustrated here would have been able to identify the anomalous state and alert a human or directly cut the power supply to the module. However, it was not yet developed and the electrical failure damaged the wax honeycomb inside the hive.

4. Discussion

This communication presented the architecture of a data processing platform for futuristic beehives comprising multiple modalities of robotic interaction with the honeybees. We described the data processing architecture, and illustrated the functionality of key elements including the DSS with example models. The data architecture aims to keep the beekeeper informed about the colony's current state, and in certain cases use the robotic subsystems to automatically enact the DSS recommendations.

Our implementation includes several trade-offs, including the provision of "in-hive" data processing, an embedded Linux system that supports flexible programming options, and continuous availability of external services. These choices support an active research project but as components mature, each could be modified within the same overall architectural design.

The presented framework is designed with the aim of automated actions as an endpoint. However, this goal has potential barriers in mechatronic systems and data interpretation. On one hand, recommending or automating a specific action can follow the detection of swarming, or detecting certain pathogens Bikaun et al. (2022). On the other hand, data analysis can identify various abnormal states (e.g., without a queen, Soares et al., 2022), but require human inspection and expertise to clarify their root causes. Human expertise and manual beekeeping actions are still expected to play a major role (Fig. 3). DSSs can enable an event-based, rather than time-based inspection regime. A beekeeper can focus on hives that need attention, acting earlier where problems are suspected, but also reducing the number of hive openings for healthy colonies.

Bio-hybrid hives could take direct actions before it is practical for a beekeeper to arrive. This may simply streamline operations, e.g., by moving bees away from honeycombs that are ready to be harvested. But timely intervention may even make qualitative differences, e.g., temporarily delaying swarming for suitable rehousing. Steering foragers away from hazardous areas is an ambitious goal, outlined in Ilgün et al. (2021), that requires a multitude of technical systems: a) in the hive – perceiving specific communication signals to quantify foraging location, and b) external – information of the hazards, to decide whether to

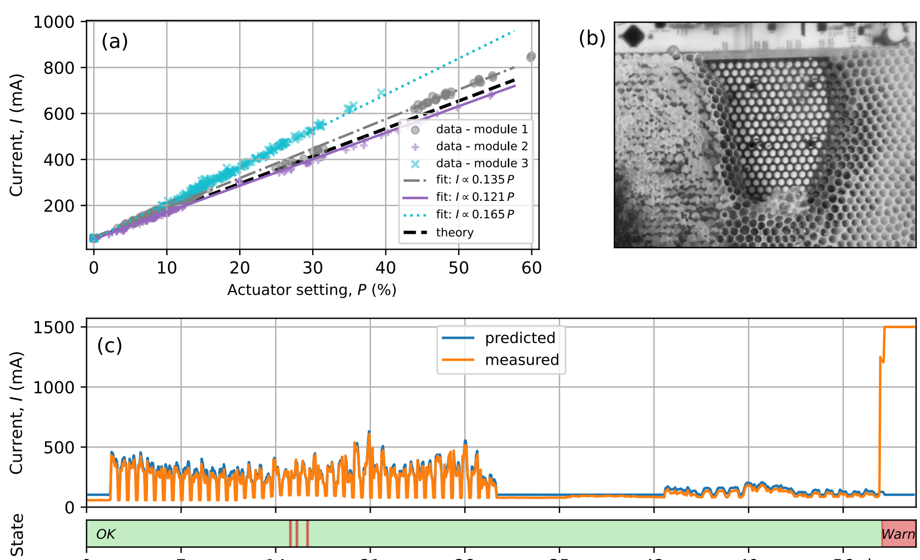

Fig. 5. Detecting failures in the brood nest thermal robotic system. (a) Relationship between internal metric (actuator level) and current consumption, with similar fits across three instances. (b) Honeycomb damage resulting from electrical failure (c) A simple warning system comparing the predicted and measured current consumption. This model identified a system failure on day 58 (post-hoc, see panel b).

employ actuating systems.

Integrating technology into living societies such as beehives presents challenges including the dark compact environment, avoiding disturbing natural behaviour, and data interpretation and predicting anomalous states. Information orchestration and hive state identification, the focus of the present paper, are critical aspects in such bio-hybrid beehives. Together with advances in bee-interactive robotics, this has the potential to support and increase the resilience of these pollinator superorganisms that are essential to our nutritional supply.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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