EBVC: Electronic Bee Veterinarian – Beyond Monitoring and Onto Control

Mst Shamima Hossain[1]✉, Meng-Chieh Lee[2⋆], Christos Faloutsos[2], Boris Baer[1], Hyoseung Kim[1], and Vassilis Tsotras[1]

[1] University of California, Riverside
{mhoss037, boris.baer, hyoseung, vtsotras}@ucr.edu
[2] Carnegie Mellon University
{mengchil, christos}@cs.cmu.edu

Abstract. Given a fleet of beehives, how can we help with thermoregulation, for healthier bees and increased honey production? The objective is to develop a complete thermal control system, comprising hardware and software, that monitors and analyzes internal hive temperature in real-time and autonomously activate the heater or cooler as needed.
We propose such a framework, 'EBVC' (Electronic Bee Veterinarian), which is: (a) *White-Box:* entirely based on first principles, physics equations, and control theory; (b) *End-to-End:* does sensing, analysis, optimization, and control; (c) *Practical:* beekeepers can 'set it and forget it', as the underlying methods are all scalable and linear on the input size, have no parameters or hyperparameters to tune, and require no customization for specific hive type, geographical location, etc. With reasonable assumptions that we list below, we estimate that EBVC will yield up to **$71** benefits per hive per year, thanks to increased honey production.

1 Introduction

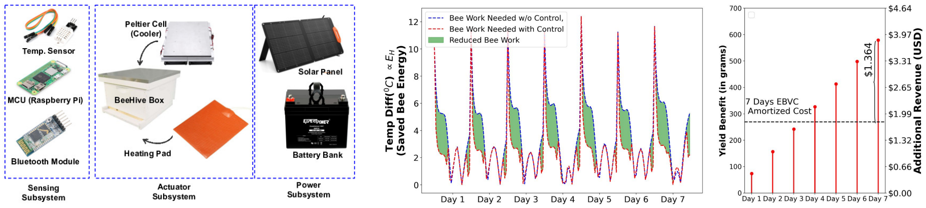
How can we design a closed-loop, cost-effective hive core temperature regulation system that improves honey yield by reducing bees' energy expenditure?

Motivation. Honeybees are vital pollinators [26], supporting one-third of global food production [27] and a $500 billion global pollination industry [28]. Maintaining brood (core hive) temperature at 33-36°C is critical [17], but each 1°C temperature deviation forces bees to use energy on thermoregulation rather than honey production, reducing beekeepers' yields.

Temperature control improves honey yield. Beekeepers often assist thermoregulation with sugar feeding and heating pads for cold [22]. Studies show external temperature assistance directly boosts honey production: a 1°C increase in June temperature correlates with 3.7 kg additional honey yield [18]; thermo-insulated hives produce about 35% more honey than conventional wooden ones [10].

Automatic control is technically feasible with current IoT technology. Off-the-shelf sensors and microcontroller units (MCUs) can continuously monitor

⋆ The work was done prior to joining Amazon.



(a) System Overview (Image Courtesy: Amazon.com) *(b) EBVC in action for one week*

Fig. 1: **EBVC boosts honey yield** *(a) hardware components; (b) left: estimated savings in honeybee cooling effort (green areas) (b) right: resulting honey (left-y axis) and dollar savings (right-y axis). The black dashed line is the estimated amortized cost of EBVC.*

hive temperatures, while inexpensive heating pads and Peltier coolers can be operated via simple on-off switching. These actuators can run for several hours per day using a solar-recharged battery pack (Sec. 4.1).

Limitations of Prior Work. Only EBVC matches all the specs (Table 1), namely both forecasting as well as control, tailored to beehives.

Our Approach. We propose EBVC, an end-to-end framework for automatic hive thermal regulation that integrates heating/cooling actuators with minimal in-hive sensing (Figure 1). Our system consists of:

(1) $\texttt{EBVC}_{\texttt{Model}}$: a physics-informed thermal model to predict core temperatures using in-hive sensor and easily-obtainable meteorological data; extended to model wall-temperature dynamics needed for our control optimization.

(2) $\texttt{EBVC}_{\texttt{Honey}}$: a honey production model based on bee thermoregulation energy costs; and

(3) $\texttt{EBVC}_{\texttt{Opt}}$: a control optimization algorithm that governs actuators to maximize honey yield.

Explainability is a 'must': The reader may ask why not use deep-learning or foundation models (like Chronos [2, 25] or tabPFN forecasting [12]) with reinforcement learning [29]. The answer is explainability: bee-keepers emphatically and repeatedly mentioned [7] that they must know why a model takes an action.

Contributions. The main contributions of EBVC are:

1. **White-Box:** EBVC is completely transparent, by design: based on standard physics (thermal diffusion), P-control, and white-box optimization methods.
2. **End-to-End:** EBVC is a complete hardware-software system that automatically handles sensing, forecasting, and control with no human intervention.
3. **Practical:** Our EBVC system is designed after feedback from entomologists and bee-keepers; and we made it scalable, with no parameters to tune, and applicable to all hive types, geographical locations, and bee genotypes.

Reproducibility. Our code is open-sourced at https://github.com/rtenlab/EBVC.

2 Related Work

Table 1 summarizes the features of each family of methods. Notice that only our proposed EBVC fulfills all the specs.

Property \ Method	Prior systems[9]	Trad. control systems [6]	EBV+ [14]	EBVC (proposed)
Monitoring	✔		✔	✔
Forecasting			✔	✔
Controlling		✔		✔
White-Box		?	✔	✔
End-to-End				✔
Practical	?	?	✔	✔

Table 1: **EBVC wins**, *fulfilling all the specifications. '?' means 'maybe, depending on implementation'.*

Forecasting: Forecasting methods, such as traditional ones like ARIMA and derivatives [3, 4] up to very recent ones with foundation models (Chronos [2], tabPFN forecasting [12]) can not do actuator control (Table 1).

Control: There is also huge literature in control with Model Predictive Control (MPC) [32] and Reinforcement Learning (RL) being closely related (e.g., book by [29]). However, these methods cannot do precise forecasting, nor are they tailored towards the problem at hand.

Sensor-based beehive monitoring. Several sensor-based tools, such as temperature [9], humidity, CO2 [24] , acoustic signals [19], IR sensors or cameras at entrance [16], have been proposed for hive monitoring, but lack capabilities for analysis or temperature control. Existing control systems [6, 5, 15] are domain-specific and require significant modification for bee hive adaptation.

Thermal model-based beehive monitoring. Recent approaches like EBV and EBV+ [13, 14] model hive thermoregulation. But, they lack external control.

Other studies [21–23] modeled thermophysical process and microclimate dynamics in a Dadant hive, simulating optimal electric heating under varying winter conditions. However, the analysis is limited to specific season and hive design.

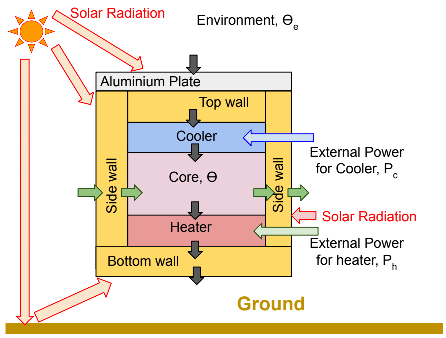
3 Dataset and Experimental Setup

Hive Data. We used the dataset from [14]: two months (August to September 2021: late summer) of hive temperature data per 20-minute interval from ten homogeneous Langstroth hives. In this dataset, five hives were treated by ice when the environmental temperature exceeded 35°C; the remaining control hives received no treatment . For EBVC, we focus on the following temperature data:

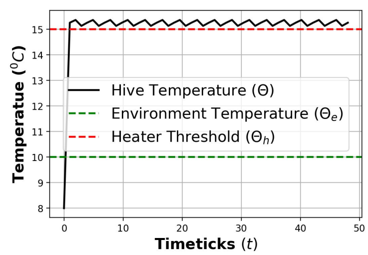
1. Peripheral temperature (top wall) data from the top outer frame near the food and honey preservation area.
2. Core temperature data from developing brood preservation area (susceptible to heat stress): Bees try to maintain the core area temperature of $33 - 36$°C.

Our aim is to regulate the top wall temperature to support optimal core temperature.

CIMIS Data. We used the hourly environmental temperature and solar radiation data (same date range as 2021 data) from the California Irrigation Management Information System (CIMIS) [1]. We selected CIMIS weather station 44, which matches our hive dataset location. We extracted "Air Temp (^{0}F)" and "Sol Rad (Ly/day)" from the database and converted them to °C and Wm^{-2}.



(a)



(b)

Fig. 2: (a)Simplified overview of our proposed system, EBVC. (b) Sanity check: Our fixed power on-off P-controller exhibits the expected 'saw-tooth' behavior (solid black line).

4 Proposed Framework: EBVC

Our EBVC consists of hardware and software. We describe each in the next subsection, and elaborate on the software parts in the rest of the subsections.

4.1 System Overview and Preliminaries

Hardware. Figure 2(a) gives a simplified overview the hardware of our system, with the following components:

1. *Actuation Subsystem.* A cooling plate mounted beneath the top wall and a heating plate placed above the bottom wall of the hive.
2. *Sensing Subsystem.* Temperature sensors at hive core area. This data feeds into our optimization algorithm, with publicly available meteorological data.
3. *Power Subsystem.* A solar panel with a rechargeable battery, whose limited daily energy budget requires careful scheduling of heater/cooler activation.
4. *Control Subsystem.* Figure 2(b) shows how the control subsystem works (heater example). It activates when hive temperature drops below (or exceeds, for cooling) a daily dynamic threshold, then toggles on and off to maintain it, resulting in a sawtooth temperature pattern.

Software. To control such hardware properly, we need:

1. *Thermal Model* for hive core temperature dynamics ($\texttt{EBVC}_{\texttt{Model}}$, Sec. 4.2)
2. *Honey Production Model* to estimate the amount of honey saved through thermal regulation ($\texttt{EBVC}_{\texttt{Honey}}$, Sec. 4.3) and
3. *Optimization Algorithm* to decide when to activate the heater/cooler, for the given energy budget ($\texttt{EBVC}_{\texttt{Opt}}$, Sec. 4.4)

Device Cost Breakdown. The estimated amortized cost is between \$62-\$90 per device per year (we omitted the details for lack of space). The price could go even lower, with mass production. Even as-is, the cost is below the break-even point (see Figures 1(b) and 5).

Symbols	Definitions	Units
$\Theta_e(t), \Theta(t)$	Environment, Hive core temperature	
$\Theta_{w_i}(t)$	Hive wall temperature: $i = \{b(\text{bottom}), t(\text{top}), s(\text{side})\}$	$^\circ$C
θ_{ideal}	Ideal core temperature	
$S(t)$	Solar radiation	Wm^{-2}
h	Hive health factor	
r_h, r_c	*Bees' thermoregulation capacity:* heating, cooling	N/A
P_h, P_c	*External source power:* heater, cooler	W
α_w	*Hive wall lumped heat absorption coefficient*	$^\circ\mathrm{CJ}^{-1}\mathrm{m}^{-2}$
k_w, k_a, k_h, k_c	*Lumped thermal conductivity:* wall, core, heater, cooler	s^{-1}
C_h, C_c	*Thermal Capacitance:* heater, cooler	$\mathrm{J}^\circ\mathrm{C}^{-1}$

Table 2: Symbols & Definitions

Symbols and definitions. Table 2 gives such a list. In the next subsections we describe our three software compoments mentioned above: thermal model, honey production model, optimization.

4.2 Thermal Model: $\texttt{EBVC}_{\texttt{Model}}$

Model 1 ($\texttt{EBVC}_{\texttt{Model}}$) *Given the environment temperature $\Theta_e(t)$, solar radiation $S(t)$, maximum thermoregulation capacity limit of bees (r_h, r_c), hive health factor h and controller power (P_h, P_c), hive core temperature $\Theta(t)$ obeys:*

$$\frac{\partial\theta(t)}{\partial t} = 6[(k_w + k' + k_a)(\theta_e(t) - \theta(t)) + \alpha_w S(t)] - h\sigma(r_c, r_h; \theta(t)) - P(t) \quad (1)$$

$$\textit{where} \quad \sigma(r_c, r_h; \theta(t)) = \frac{r_c r_h(1 - e^{\theta(t)})}{r_h + r_c e^{-\theta(t)}} \quad \textit{and}$$

$$(P, k') = \begin{cases} (-\frac{P_c}{C_c}, k_c) & \text{if } \theta(t) > +\delta_{\delta_{\theta_s}} \textit{ \& top wall} \\ (\frac{P_h}{C_h}, k_h) & \text{if } \theta(t) < -\delta_{\delta_{\theta_s}} \textit{ \& bottom wall} \\ (0, 0) & \textit{otherwise} \end{cases}$$

For simplicity, the (t) notation is omitted onwards. Next, we justify $\texttt{EBVC}_{\texttt{Model}}$, using concepts of heat transfer (physics) and P-controllers (control theory).

Justification. In $\texttt{EBVC}_{\texttt{Model}}$, we use relative temperatures (noted as $\theta_X = \Theta_X - \theta_{ideal}$ i.e., $X = e$ if environment temperature and so on) to ideal core temperature, θ_{ideal} as bees try to maintain θ_{ideal} within $33 - 36°C$.

Step 1: Physics - Thermal Diffusion & Newton's Law of Cooling. The first term in Eqn. (1) model heat flow into an empty hive core without solar and bee activity based on heat transfer principles [8].

Step 2: Physics - Solar Radiation Effect. The fourth term in Eqn. (1) represents heat gain from solar radiation.

Step 3: Control Theory - Sigmoid P Controller. The second-last term in Eqn. (1) models bees' thermoregulation via a feedback loop [14] (if bees are left alone). Bee count limits cooling/heating capacity (r_c, r_h): fixed for similar structured hives and geography. The health factor ($0 < h \leq 1$) scales this response, $\sigma(r_c, r_h; \theta)$: higher h indicates a stronger hive with less Θ fluctuation and vice-versa.

Step 4: Control Theory - On-Off Controller. The last term models a fixed-power on-off P-controller [20] for the installed heater and cooler. Since bees regulate Θ

toward θ_{ideal}, our controller mimics this behavior [13]: activating cooling when $\theta > \delta_{\theta_s}$ and heating when $\theta < \delta_{\theta_s}$, i.e., when no bees are present.

Extension of $\texttt{EBVC}_{\texttt{Model}}$. We also extend $\texttt{EBVC}_{\texttt{Model}}$ to model hive wall temperature dynamics, θ_{w_i}, assuming no active thermoregulation effect from bees on θ_{w_i},

$$\frac{\partial \theta_{w_i}}{\partial t} = (k_w + k')(\theta_e - \theta_{w_i}) + k_a(\theta - \theta_{w_i}) + \alpha_w S - P \tag{2}$$

Here, θ_{w_i} denotes relative wall temperature for $i \in \{\text{top: t, side: s, bottom: b}\}$. With uniform wall properties, all walls have the same temperature unless a heater/cooler is installed. k_w is structure-dependent, while k_a and $\alpha_w = x_w k_w$ vary with internal hive conditions and sun exposure.

4.3 Honey-Production Model: $\texttt{EBVC}_{\texttt{Honey}}$

Here, we introduce $\texttt{EBVC}_{\texttt{Honey}}$, a model to estimate honey yield gains from external thermal regulation. Since real-world data do not provide simultaneous controlled and uncontrolled temperature measurements for the same hive, we rely on reconstructed temperature for both scenarios. Assuming accurate reconstruction, this allows for a fair comparison to estimate yield under external control.

Model 2 **($\texttt{EBVC}_{\texttt{Honey}}$)** *Given we activate the heater or cooler to reduce bees' heating effort (when $\hat{\theta} > \hat{\theta}_w$ or $\hat{\theta} < \hat{\theta}_w$), the saved honey consumption is,*

$$H_H(t) = 3|(\hat{\theta}_w - \hat{\theta}) - (\frac{1}{6}(\sum_{n=1}^{5} \hat{\theta}_w + \hat{\theta}_{w_{b,adj}}) - \hat{\theta}_{adj})| \tag{3}$$

$$H_C(t) = 12|(\hat{\theta}_w - \hat{\theta}) - (\frac{1}{6}(\sum_{n=1}^{5} \hat{\theta}_w + \hat{\theta}_{w_{t,adj}}) - \hat{\theta}_{adj})| \tag{4}$$

We use $H_H(t)$ for saved honey consumption during heating and $H_C(t)$ for cooling. $\hat{\theta}_w$ and $\hat{\theta}$ are the reconstructed wall and core temperatures without external thermal regulation, while $\hat{\theta}_{w_{b,adj}}$, $\hat{\theta}_{w_{t,adj}}$ and $\hat{\theta}_{adj}$ represent the regulated case. Bees' heating effort is measured by the wall and core temperature gap; reducing this gap reflects energy (and honey) savings. During heating, we use the average wall temperature, since the heater needs to offset environmental effects on all walls. Based on expert opinion and experiments, bees consume 3g of honey to reduce the wall–core temperature gap by 1°C. Thus, reducing this difference by 1°C yields an equivalent honey saving. Similarly, the bees' cooling effort is proportional to the core and wall temperature difference, and each 1°C reduction translates to an equivalent amount of honey preserved. Here, we assume reducing the wall-core temperature gap by 1°C during cooling yields 12g of honey saving. Detailed explanations are omitted due to space constraints.

In the next section, we present our optimization objective function, $\texttt{EBVC}_{\texttt{Opt}}$ (alternatively, profit function) to maximize the profit in terms of the bees' saved energy and find out the corresponding controller parameters.

4.4 Control Optimization Objective: $\texttt{EBVC}_{\texttt{Opt}}$

We formulate our control optimization problem using a Model Predictive Control (MPC) approach. Given a daily electrical energy budget B and our predictive thermal model $\texttt{EBVC}_{\texttt{Model}}$, we solve an optimization problem to schedule heater and cooler operations to maximize yield benefit, quantified as honey savings through reduced bee energy expenditure:

$$\max_{T_H, T_C} \sum_{i,j=1; i \neq j}^{I} \left(T_{H_i} E_{H_i} + T_{C_j} E_{C_j} \right), \quad \text{such that} \quad (T_{H_i} P_h + T_{C_j} P_c) \leq B \tag{5}$$

$$\text{where,} \quad E_H \propto |(\hat{\theta}_w - \hat{\theta}) - (\frac{1}{6}(\sum_{n=1}^{5} \hat{\theta}_w + \hat{\theta}_{w_{b,adj}}) - \hat{\theta}_{adj})| \tag{6}$$

$$E_C \propto e_C |(\hat{\theta}_w - \hat{\theta}) - (\frac{1}{6}(\sum_{n=1}^{5} \hat{\theta}_w + \hat{\theta}_{w_{t,adj}}) - \hat{\theta}_{adj})| \tag{7}$$

$$T_H \in \{\mathbf{0}_{\{\hat{\theta}_{adj}(i) < -\delta_{\theta_s}\}}, \mathbf{1}_{\{\hat{\theta}_{adj}(i) < -\delta_{\theta_s}\}}\} \tag{8}$$

$$T_C \in \{\mathbf{0}_{\{\hat{\theta}_{adj}(j) > +\delta_{\theta_s}\}}, \mathbf{1}_{\{\hat{\theta}_{adj}(j) > +\delta_{\theta_s}\}}\} \tag{9}$$

$$\hat{\theta}_{w_{b,adj}} \leq H_L - \theta_{ideal}; \hat{\theta}_{w_{t,adj}} \geq C_L - \theta_{ideal}$$

Here, $\hat{\theta}_w$ and $\hat{\theta}$ are the one-day ahead forecasted wall and core temperatures without external thermal regulation, while $\hat{\theta}_{w_{b,adj}}$ and $\hat{\theta}_{adj}$ represent the same for regulated case. I denotes the optimization period (i.e., number of samples per day), and $e_C = \frac{r_h}{r_c} \approx 4$ captures the relative energy cost: bees expend approximately 4 times more energy for cooling than for heating (see Sec. 5), consistent with our earlier calculation that cooling requires roughly 4× more honey than heating. E_H and E_C represent the energy saved by bees when the heater and cooler are activated, respectively, and are directly proportional to the amount of honey saved through external control. T_H and T_C are binary activation schedules for the heater and cooler (1 = on, 0 = off). The controller operates under the following conditions: (i) the current time point yields the highest bee energy saving relative to others; and (ii) sufficient budget remains, e.g., if turning the heater on at time i yields more bee energy savings than at $i+1$, and only one activation is affordable, time i is chosen. To prevent thermal damage, H_L and C_L set safety limits on the minimum and maximum wall temperatures during heating and cooling.

Our goal is to find T_H, T_C such that total electrical energy spent fits B, and maximizes bees' saved energy.

Dynamic Optimization. How can we dynamically schedule controller operation for maximum yield benefit? Algorithm 1 outlines $\texttt{EBVC}_{\texttt{Opt}}$ that takes past p days of temperature sequence $(\Theta_{\mathcal{E}}, \Theta)_p$ and solar radiation data $(\mathcal{S}_{R,p})$ as input and returns optimized controller operation schedule (T_C, T_H) as outputs.

One-day ahead forecast. Given, the past p days of temperature sequences and the maximum thermoregulation ability (r_c, r_h) (Details in Sec. 5), we first reconstruct Θ by minimizing reconstruction error and change in consecutive

Algorithm 1: $\texttt{EBVC}_{\texttt{Opt}}$

Input: (i) Past data, $\mathcal{D}_p = \{\Theta_{\mathcal{E}}, \Theta, \mathcal{S}_R\}_p$ (ii) $\{r_c, r_h\}$
Output: $\mathcal{T} = \{T_C, T_H\}$

1 Reconstruct Θ_p to find h and θ_{ideal} for the last day
2 Forecast $\hat{\Theta}_{p+1}$ based on h and θ_{ideal}
3 Find $\mathcal{T}$ to optimize Eqn. (5) for $\leq B$ // *e.g. greedy algo*

health factor h values [14]. This gives us an estimate of daily h and ideal core temperature θ_{ideal}. Then we use the last day's $\{h, \theta_{ideal}\}$ to forecast the next day's Θ assuming the same thermoregulation parameters as the previous day.

Find optimal operation schedule for B. Finally, we use the greedy algorithm to plan for an optimal controller operation schedule. We choose such a combination of operation times T_H (Eqn. (8)) and T_C (Eqn. (9)) within the given energy budget B that maximizes Eqn. (5).

5 Experiments

We conduct experiments to answer the following questions:

Q1. How accurate is $\texttt{EBVC}_{\texttt{Model}}$ in forecasting Θ and Θ_{w_t}?
Q2. How accurately $\texttt{EBVC}_{\texttt{Honey}}$ captures yield benefit of the ice-pack experiment?
Q3. How well does $\texttt{EBVC}_{\texttt{Opt}}$ perform in maximizing yield for control hives?

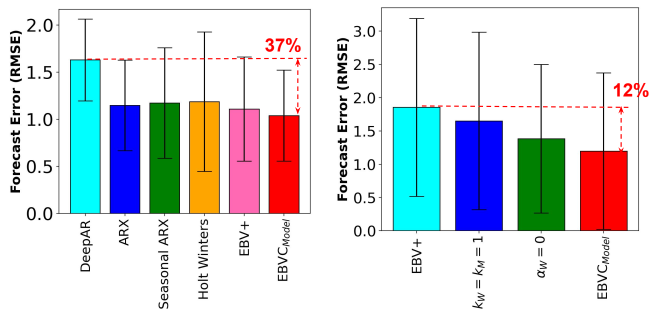
Experimental Setup. All experiments are done on a Samsung Galaxy Book4 Pro 360 laptop (Intel i7, 16GB RAM). We used hourly-averaged temperature data. To ensure field deployability, `EBVC` avoids interpolation and handles missing data directly. To estimate $\{r_c, r_h\} = \{124, 428\}$ for reconstruction and forecasting, we used Eqn. (1) and bi-level optimization objective described in [14].

Hive-Specific Parameter Estimation. We use ten (non-treated) days of peripheral Θ_{w_t}, core Θ, and corresponding (Θ_e, S) to estimate k_w, k_a, x_w using Eqn. (2). We use the estimated k_w from one hive (chosen randomly) to estimate k_a and x_w for other hives, e.g., control hive-1: $k_w = 0.29, x_w = 0.012, k_a = 0.46$ and treated hive-1: $k_w = 0.29, x_w = 0.0017, k_a = 0.41$. Parameter values for other hives are omitted due to space constraints.

5.1 Q1: Forecasting Capability

Experimental Setup. Given (i) seven days of data (Θ, Θ_e, S, P), we forecast hourly Θ for the next 14 days and (ii) per day (Θ_e, S, Θ) and fixed (k_w, k_a, α_w), we forecast (reconstruct) daily Θ_{w_t} to be used for $\texttt{EBVC}_{\texttt{Honey}}$ and $\texttt{EBVC}_{\texttt{Opt}}$ later.

Baselines. For Θ forecast, we compared $\texttt{EBVC}_{\texttt{Model}}$ with state-of-the-art time series models: (i) ARX and seasonal ARX [3], (ii) Holt-Winters [11], (iii) DeepAR [30], and (iv) thermal-model based `EBV+`. For `EBV+` and $\texttt{EBVC}_{\texttt{Model}}$, we estimate parameters (h, θ_{ideal}) from the inputs, then use the final day's parameters along with Θ_e, S, and $P = 0$ (for $\texttt{EBVC}_{\texttt{Model}}$) for forecasting Θ.



(a) Core Temperature, Θ *(b) Top Wall Temperature, Θ_{w_t}*

Fig. 3: <u>EBVC$_{\texttt{Model}}$ **wins**</u> *against baseline in terms of core and wall temperature forecasting accuracy (up to 37% & 12% improvement). Error bars show 1 standard deviation.*

We show the impact of introducing thermal conductance and solar radiation for Θ_{w_t} forecast. Baselines are: (i) EBV+ ($k_w = k_a = 1$ with no solar radiation $\alpha_w = 0$), (ii) $k_w = k_a = 1$ and location-specific α_W, (iii) hive-specific k_w, k_a with $\alpha_W = 0$, and (iv) EBVC$_{\texttt{Opt}}$ (hive-specific k_w, k_a and location specific α_W).

Accuracy. Figure 3(a) shows the average core temperature forecasting RMSE for all methods. EBVC$_{\texttt{Model}}$ shows an average improvement of up to 37% over baselines in terms of accuracy and performs comparably to EBV+. However, EBVC$_{\texttt{Model}}$ offers greater robustness due to its inclusion of additional parameters such as thermal conductance, solar radiation effects, and external control. As shown in Figure 3(b), EBVC$_{\texttt{Model}}$ improves top wall temperature reconstruction accuracy by 33% over EBV+; critical for the effectiveness of EBVC$_{\texttt{Honey}}$ and EBVC$_{\texttt{Opt}}$.

5.2 Q2: Capturing the Effect of Ice-packs

Baseline. We validate EBVC$_{\texttt{Honey}}$ by comparing its estimated honey savings with the actual increase in stored honey measured between the start and end of the experiment. Honey storage was recorded in terms of the number of nectar frames, with inspections conducted biweekly on Aug 4, Aug 18, Sep 1, Sep 15, and Sep 29. For estimation, we assumed that one deep Langstroth nectar frame yields approximately 4.5lb ($\approx$ 2039g) of honey after dehydration and capping.

For EBVC$_{\texttt{Honey}}$, we used Eqn. (4) to estimate the net daily honey savings (ice-treatment effect minus residual effect). According to beekeeper notes, ice packs were applied around 9 AM that melted throughout the day. Daily estimates are not available for all days. We therefore compute the average savings between each pair of inspections and multiply by the corresponding gap to approximate total honey savings. Note that ice treatment was done 15 days in 2-month period.

Results. Figure 4(a) illustrates the impact of a 3-day ice treatment. The blue and red dotted lines show estimated bee workload (temperature difference via Eqn. (7)). The cyan shaded area highlights saved energy during the day due to ice cooling, while the orange shaded area shows the added burden at night due to residual cooling effects.

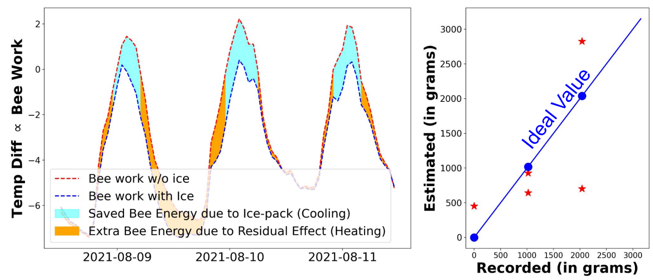
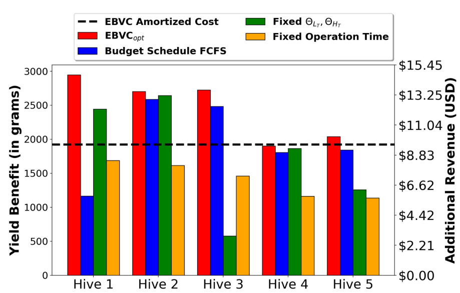


Fig. 4: $\underline{\texttt{EBVC}_{\texttt{Model}}\ \textbf{is accurate}}$*: it estimates the yield benefit of ice-pack on $\Theta(t)$: saved honey estimate over 2 months (red stars) match closely with recorded ones (blue line).*

Figure 4(b) compares the observed increase in stored honey during the experiment (blue dots) with $\texttt{EBVC}_{\texttt{Honey}}$'s estimated increase (red stars). Each point represents one treated hive with ice-packs. The red points lie close to the reference line with slope 1, indicating strong agreement. As the values were recorded based on changes in the number of nectar frames (rather than direct weight), and $\texttt{EBVC}_{\texttt{Honey}}$ estimates honey in grams, minor discrepancies are expected.

5.3 Q3: Profit Optimization

Baselines. We compare $\texttt{EBVC}_{\texttt{Opt}}$ against the following baselines: (i) dynamic thresholds (Θ_{H_T}, Θ_{L_T}) without energy budget scheduling (FCFS: first-come, first-served); (ii) fixed thresholds ($\Theta_{H_T} = 36°\text{C}$, $\Theta_{L_T} = 33°\text{C}$) with adaptive budget scheduling; and (iii) fixed controller operation windows (9AM − 1PM and 12AM − 4AM) with dynamic thresholds. The fixed threshold and controller operation window are based on existing literature and expert recommendations.



(a)

Parameters	Values
B	200W
P_H, P_C	20W, 50W
$\frac{P_H}{C_H}, -\frac{P_C}{C_C}$	30 °C, −30°C
k_c, k_h	$0.1 * k_w, k_w$
H_L, C_L	45°C, 25°C
beekeeper's revenue	2/lb(= 453g) of honey [31]

(b) Experimental Setup

Fig. 5: $\underline{\texttt{EBVC}_{\texttt{Opt}}\ \textbf{gives the highest}}$ *yield benefit (in grams) and beekeeper's revenue (in USD) among all baselines; moreover, it is consistently profitable (at or above the black dashed 'break-even' line). Twin y-axes (left: grams; right \$ revenue).*

Results. Figure 5 presents the yield benefit (in grams of honey) and the beekeeper revenue (in USD) for each control hive over the two-month experiment period. $\texttt{EBVC}_{\texttt{Opt}}$ consistently achieves the highest yield benefit across all hives, thanks to adaptive energy budget scheduling based on available resources. In California (where the dataset was collected), bees typically produce honey for about six months each year, e.g., for control hive 1, beekeepers are projected to gain an annual economic benefit of $\sim$ \$71 compared to no external control.

The black line in Figure 5 represents the estimated amortized cost of operating our system, EBVC, over a two-month period. The amortized cost for the system is calculated considering $62 per device per year because the difference in the cost comes from battery size. For our experiments, we used the lowest assumed power requirement of 200W. As shown, the additional revenue generated by EBVC consistently exceeds or matches this cost —resulting in a net annual revenue gain of up to $8.62 per hive. Bees produce honey only during part of the year, but they consume it year-round for thermoregulation. Since our system helps reduce this consumption, we amortize its cost over the full year, while calculating additional honey yield over the six-month production period.

6 Conclusion

The proposed EBVC method proposes a system to help hives maintain a healthy temperature, to improve honey production, honey-bee health, with all the additional benefits (pollination, agriculture). Our method has the following desirable characteristics that no other method enjoys:

- **White-Box:** it is based on well-understood components (thermal diffusion, 'P'-controllers)
- **End-to-End:** it is a complete, autonomous system, with software and hardware, without human intervention and parameter tuning.
- **Practical:** it is carefully designed to match the specs of end users (beekeepers): it is scalable, explainable, and general (applicable to any geographical location, any honey-bee subspecies). Moreover, we estimate that EBVC will provide significant savings (up to ≈$71 per year)

Reproducibility. Our code is open-sourced at https://github.com/rtenlab/EBVC.

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