IN^2 Final Report: Ibis Networks/WattIQ

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Technical Report
NREL/TP-6A65-75603
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Executive Summary

The Wells Fargo Innovation Incubator (IN^2) is a $30 million technology incubator and platform funded by the Wells Fargo Foundation. Co-administered by and housed at the National Renewable Energy Laboratory (NREL), IN^2's mission is to speed the path to market for early-stage, clean-technology entrepreneurs. Companies selected for participation in the program receive up to $250,000 in non-dilutive funding from Wells Fargo, technical support and validation from experts at NREL, and ongoing connections to organizations across value chains.

Ibis Networks (now WattIQ) is a full-stack cleantech company that provides plug-level energy monitoring and control to solve energy and asset management problems for the enterprise. The Ibis InteliSocket is a pass-through plug-load energy monitor and controller that is designed to reduce energy wasted by common 120 V plug-in devices in commercial office buildings, such as computer peripherals, conference room audiovisual (AV) equipment, and break-room appliances. The system can shut off supply power to these end uses via remote control, manual switches, pre-set schedules, or automated control algorithms. The scope of this IN^2 project was the development and refinement of "smart" learning behavior algorithms (LBAs), which could simplify installation processes and dramatically expand the sockets' capabilities and energy-saving potential by suggesting suitable control schedules that are based on monitored use patterns. While Ibis has the analytical and software expertise for algorithm development, the lack of test data, both in a controlled laboratory setting and in real-life deployment scenarios, represented a key barrier toward commercialization of the product. Assistance through the IN^2 program provided an opportunity to conduct the needed trial-and-error algorithm development.

The project included baseline field-data collection, laboratory testing, and field evaluation components, all of which were conducted on the NREL campus between April 2017 and July 2019.

The baseline data were obtained by monitoring and recording 120 V plug-load usage data in over 75 office cubicles, 16 conference and huddle rooms, five printer rooms, four kitchens, and the library. The laboratory testing consisted of setting up two mock workstations with representative office plug loads and running them through typical usage scenarios to develop and test the Ibis LBA. The plug loads were operated on a baseline schedule created by the NREL team to mimic typical office occupancy. The data collected from these mock offices were used by Ibis's LBA to develop predictions, and these predictions were then compared to actual schedules to evaluate accuracy. The final task was the field evaluation, designed to test the LBA against real office plug-load use, between the months May 2019 and July 2019. Ten cubicles of NREL employees were selected to represent a mix of fairly regular and more irregular occupancy patterns.

Overall, the results are encouraging and indicate there is promising potential for LBAs to create control schedules that reduce plug-load energy waste. A relatively simple algorithm that considered factors such as day of the week, season, and asset class was able to correctly forecast whether to turn outlets on or off 70% of the time based on limited training data. Furthermore, the errors in prediction were heavily asymmetric, with a false negative rate of only 3.2% (events that inconvenience users) versus a 36% false positive rate (missed opportunity for saving energy) in the field evaluation results. Future research should focus on reducing the false positive rate without markedly increasing the false negative rate, which would achieve more savings without adversely affecting user convenience. There is considerable potential for further improvement of the algorithm building on the learnings presented in this work.

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1 Technology Description

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Ibis Networks (now WattIQ) is a full-stack cleantech company that provides plug-level energy monitoring and control to solve energy and asset management problems for the enterprise. The Ibis InteliSocket is a pass-through plug-load energy monitor and controller that is designed to reduce energy wasted by common 120 V plug-in devices in commercial office buildings, such as computer peripherals, conference room audiovisual (AV) equipment, and break-room appliances. The system can shut off supply power to these end uses via remote control, manual switches, pre-set schedules, or automated control algorithms. The sockets use the Zigbee communication protocol to form a wireless mesh network that connects to the Ibis Inteligateway to upload data to the Ibis server. While the Ibis socket in its present generation is already at Technology Readiness Level (TRL) 8, which corresponds to IN^2 Tier 3, the company is currently developing and refining learning behavior algorithms (LBAs), which will improve installation processes and dramatically expand the sockets' capabilities and energy-saving potential by suggesting suitable control schedules that are based on monitored use patterns.

Buildings are becoming increasingly energy efficient, thanks to modern construction practices and advances in major end-use equipment such as heating, ventilation, and air-conditioning (HVAC) systems and lighting. Meanwhile, plug loads are growing both in diversity and sheer number and are accounting for an increasing fraction of the total building load. The use of metering and control tools in coordinated energy-saving efforts have shown up to 40% savings on managed plug-load devices, which can equate to 5-10% savings of overall commercial building energy. (Mercier and Moorefield, 2001) While the savings projections are compelling, a primary challenge in mitigating plug-load energy use is the hassle involved in implementing controls for each separate plug-in device throughout an office space or an entire building. The task is further complicated when operational schedules change throughout the year due to weather events, seasonal operation, or other business reasons.

Today, Ibis customers use the online Ibis platform to manually implement schedule-based controls for depowering individual or groups of equipment. While this manual method can be effective at saving energy, it can also be time-consuming to set up. Instead, the large body of energy data that Ibis sockets collect can be leveraged with machine learning algorithms to automate the implementation of controls. The R&D required to enhance the socket with this "smart" capability is the scope of this IN^2 project. The company's goal is to develop effective LBAs so that the Ibis system can take a global view of work patterns within a building or organization, learn optimal schedules, and automatically implement suitable controls that continually self-adjust over time.

The LBA-based approach to plug-load management offers several attractive advantages:

- It frees building managers from the task of setting up individual controls for categories of plug-in equipment, as well as constant monitoring and adjustments.

- It enhances energy-saving potential because it removes manual "trial and error" testing and can ensure maximum savings even as operational conditions change over time.

Similar approaches exist for advanced HVAC and lighting systems, but such algorithms have not been fully developed for plug loads. Ibis addresses this gap and provides a pathway to move the industry forward by demonstrating a proof-of-concept through laboratory- and field-based testing. The work presented here is a steppingstone to further development and integration of this strategy into marketable products.

2 Project Description

While Ibis had the analytical and software expertise for algorithm development, the lack of test data, both in a controlled laboratory setting and in real-life deployment scenarios, represented a key barrier toward commercialization of the product. Assistance through the IN^2 program provided an opportunity to conduct the needed "trial and error" algorithm development.

NREL provided technical support in the areas of:
- Baseline field data collection,
- Laboratory testing,
- Field evaluation, and
- Associated data analysis throughout the above phases.

NREL provided the sites for data collection. Field-based data were collected primarily in NREL's Research Support Facility (RSF), a 362,000-square-foot, LEED-platinum, net-zero energy office building located on the NREL campus. Laboratory testing was conducted in the Systems Performance Laboratory (SPL) within the Energy Systems Integration Facility (ESIF), a state-of-the-art DOE user facility designed to evaluate the integration of emerging energy technologies.

2.1 The Predictive Model

The Ibis LBA used a single predictive model that was trained using plug load energy data, metadata for each device including the type of equipment that was plugged in, and information about the day of week and season. The algorithm then made predictions for individual devices based on the device's own history of behavior, as well as the influence of what we knew about that class of equipment, and the overall history of usage by day of week, season, and other time-related factors. This approach "pools" information from many devices to help make predictions about individual devices, and this pooling can lead to error tradeoffs, where decreasing one kind of error may result in inadvertently increasing error elsewhere. This is fundamental to predictive algorithms and is not unique to this type of application or energy analysis in general.

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2.2 Baseline Data Collection, Laboratory Testing, and Field Evaluation

The first and longest running task in this project was the baseline field data collection, which was set up to monitor and record 120 V plug-load usage data in over 75 office cubicles, 16 conference and huddle rooms, five printer rooms, four kitchens, and the library (see Figure 1.) Most of the monitoring was conducted in the RSF, with a small subset of sockets deployed in Denver West Building 52, a nearby off-campus office space leased by NREL. These data provided key insights into the usage patterns of office equipment in a commercial office environment. No controls were implemented as part of the baseline data collection, so the Ibis sockets functioned solely as data loggers. Gateways were placed in close proximity to the sockets throughout the deployment areas to upload data from the all of the sockets to the Ibis server.

Figure 1. Deployment in NREL cubicles

Left: Ibis sockets were deployed in NREL cubicles to monitor and record office plug-load usage data. Right: Each socket has one “controlled” outlet (labeled in green) and one “always on” outlet. During the baseline data collection both outlets operated in “always on” mode.

The laboratory testing consisted of setting up two mock workstations with representative office plug loads and running them through typical usage scenarios to develop and test the Ibis LBA. A photo of the set-up and a list of plug loads used are shown in Figure 2. The plug loads were operated on a baseline schedule created by the NREL team to mimic typical office occupancy. Where possible, equipment operation was automated using the Windows Task Scheduler and Wi-Fi-connected smart plug load controllers. The data collected from these mock offices were used by Ibis’s LBA to develop predictions, and these predictions were then compared to actual schedules to evaluate accuracy. This method enabled virtual testing of the Ibis algorithms without implementing controls, by allowing the team to compare when the socket *would have* shut off supply power to when the plug load was actually in use.

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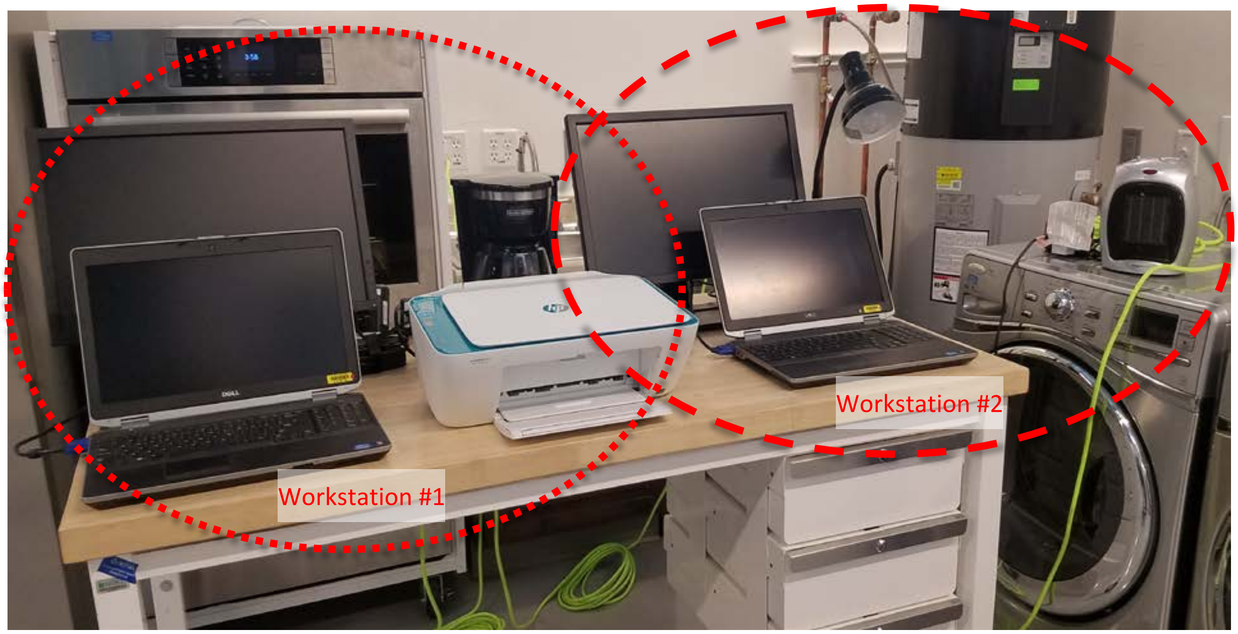

Figure 2. Testing in the Systems Performance Lab

Two workstations were set up in the SPL for laboratory testing. Workstation #1 (left, dotted line) consisted of a Dell laptop, external monitor, coffee maker, and printer. Workstation #2 (right, dashed line) consisted of a Dell laptop, external monitor, desk lamp, and space heater.

The final task was the field evaluation, designed to test the LBA against real office plug-load use. Ten cubicles of NREL employees were selected to represent a mix of fairly regular and more irregular occupancy patterns. Two rounds of virtual testing of the LBA-generated predictions were conducted, using a similar process to the laboratory tests. Each virtual round lasted for two work weeks. In a third and final round of testing, controls were implemented for two and a half work weeks based on predicted arrival and departure times. Each schedule for this field test was forecasted to 15-minute granularity, yielding 96 forecasted data points per device in each of the ten cubicles per day. The forecasted values were provided by Ibis, and actual usage and occupancy of the cubicles was determined by NREL, looking at raw consumption data. Comparison of the forecasts with actual data provided scoring for each 15-minute interval for the field test. After the controls portion of the field evaluation concluded, the participants were asked to respond to a survey about their experiences.

2.3 Scoring Methodology

The laboratory testing and field evaluation results were analyzed using an error or “confusion” matrix (Kohavi and Prevost 1998; Townsend 1971), which contrasts predicted and observed class counts in a discrete classification problem. Table 1 provides operational definitions used in scoring the tests.

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Table 1. Confusion Matrix Key for Accuracy Scoring

	Positive Real Occupancy	**Negative Real Occupancy**
Positive Predicted Occupancy	True Positive: Device is controlled to be “on” when it should be on.	False Positive: Device is controlled to be “on” when it should be off, resulting in lower energy savings.
Negative Predicted Occupancy	False Negative: Device is controlled to be “off” when it should be on, a noticeable inconvenience for people.	True Negative: Device is controlled to be “off” when it should be off.

There are four components in a binary confusion matrix: true positive (TP), true negative (TN), false positive (FP), and false negative (FN). A true positive or negative means that the forecasted control schedule was correct in predicting whether a device would be on (true positive) or off (true negative). The main diagonal cells in the matrix represent accurate predictions; antidiagonal cells represent prediction errors. Not all prediction errors have the same effect, and the confusion matrix helps explain how prediction error is a compromise between inconveniencing users and not capturing potential energy savings.

From the data in the confusion matrix, various quantitative measures of classification (and thus prediction) performance are available. Total accuracy is defined as (TP + TN) / (TP + TN + FN + FP), or the fraction of true predictions compared to all predictions. The false positive rate is defined as FP / (FP + TN), and the false negative rate is defined as FN / (FN + TP). Other measures relevant to this project include “sensitivity,” which in this case gives the proportion of time slots that had actual occupancy and consumption that were forecasted correctly, defined as TP / (TP + FN); and “false discovery rate (FDR),” which is the rate of false positive predictions compared to all positive predictions: FP / (FP + TP). In the context of this study, sensitivity and FDR help measure the degree to which the LBA is “biased” towards preventing one type of prediction error over the other. An algorithm that made prediction errors randomly would, for example, have sensitivity and FDR rates that were roughly equal.

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3 Results and Discussion

3.1 Laboratory Test Structure and Results

Laboratory testing was aimed at confirming when the LBA had progressed sufficiently to make useful predictions about when equipment would be in use, given a two-week observation period to obtain training data. The LBA was trained on its ability to "fit" existing patterns. Ibis reported to the NREL team the times at which the LBA indicated that each lab device switched on and off. The test was conducted in a single-blind manner as described above, training for several weeks and then predicting usage for the same devices. NREL then scored the Ibis LBA determinations against the actual schedule of lab device state changes, producing a confusion matrix allowing us to look at accuracy alongside false positive and false negative predictions.

Raw results are given in Table 2, and accuracy metrics are summarized in Table 3. Ibis performed extremely well in the laboratory tests, earning an accuracy rate of 95%. The plug load usage schedules in the laboratory were more tightly controlled than would normally be seen in a real office environment, but there was some variability in the schedules introduced because a few appliances required manual control.

Table 2. Confusion Matrix from Laboratory Test Results

426 True Positives	17 False Positives
70 False Negatives	1119 True Negatives

Table 3. Laboratory Accuracy Metrics

Total Accuracy	(TP + TN) / (TP + TN + FN + FP)	95%
False Positive Rate	FP / (FP + TN)	1.5%
False Negative Rate	FN / (FN + TP)	14%
Sensitivity	TP / (TP + FN)	86%
False Discovery Rate (FDR)	FP / (FP + TP)	3.8%

3.2 Field Evaluation Structure and Results

For the field evaluation, occupancy and equipment usage were forecasted for each upcoming day based upon previously observed time series data. A higher prediction error was expected in the field than during laboratory testing because real work patterns are likely more variable than what we might mimic in the laboratory, and more importantly, certain patterns were expected in the errors. For example, it should be easier to predict when spaces and equipment are turned on in the morning, than detecting periods where equipment could be turned off in the middle of the work day, given that meeting schedules and typical day-time movement within the office may not have strong repetitive patterns.

Ten office cubicles were instrumented with Ibis sockets and the LBA gathered two weeks of baseline training data. The LBA was used to make day-ahead predictions for each device, predicting when the cubicle and its devices were expected to be occupied and powered on. Each day, the previous day's data was added to the training set and a new day-ahead prediction was

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made. There were three separate rounds of evaluation, with each round of controls based on the previous two weeks of collected data. In the first two rounds, the sockets were used as data loggers with no controls in place. In the third round, controls were implemented based on the LBA predictions.

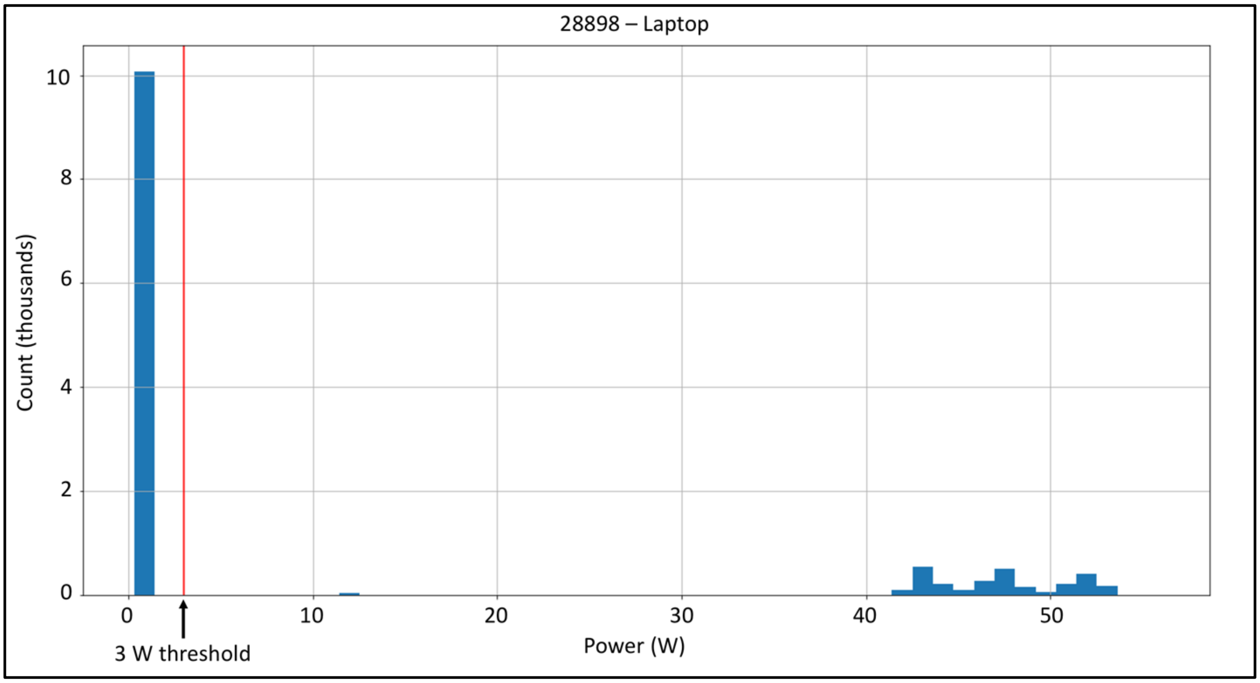

Figure 3. Example Histogram of Device Power Level

A histogram of power levels was created for each end-use device in order to define a threshold for when the device is "on" versus "off." This process relied partly on engineering judgement. In the above example, the laptop was considered "on" when its power draw exceeded 3 W.

For the first two rounds, Ibis reported the predicted schedules to the NREL team and NREL scored the accuracy of the predictions in comparison to the measured data using confusion matrices. Predictions (or hypothetical controls) were created for both outlets on the Ibis sockets, even though only the bottom outlet could be controlled. This gave Ibis the opportunity to predict twice as many loads. To determine when the devices were on versus off, NREL created histograms of the different power levels for each device (see example in Figure 3.) The team visually analyzed the histograms to determine a unique threshold power level for each device, often a few watts. When power was measured above this threshold, the device was considered to be on, and when the power was below the threshold, the device was considered to be off. For most data points it was clear whether the device was on or off because its power was well above or below the threshold; however, there were some instances where the device's state seemed ambiguous, especially during the transition intervals during which a device was being turned on or off by the user. Each one-minute interval during the study period was scored as either a true positive, true negative, false positive, or false negative, and the results were aggregated to assess the LBA's overall accuracy.

Given that forecasting accuracy (and thus the effectiveness of algorithmic control schedules) involves a tradeoff between potentially inconveniencing users and achieving optimal savings,

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Ibis adjusted LBA parameters between each round of field testing in order to explore how the details of the algorithm affect the balance between savings and convenience.

A similar scoring method was used in the third round, where controls were actually implemented for the "controlled" (bottom) outlet of each socket. Predictions were still made for the uncontrolled outlet, again for the purpose of acquiring more data. True positives, true negatives, and false positives arose in the same manner as before; however, for the controlled loads false negatives were only detected if the occupant overrode the socket controls. According to post-field evaluation survey results, at least five participants used the override button at least once in order to correct a false negative. Two of these five respondents reported using the override button multiple times during the course of the study. A single participant was responsible for the majority of total override events. That participant reported staying later than the forecasted controls on some days and also arriving earlier on other days.

Overall, the field evaluation results are encouraging (total accuracy across all three rounds is 70%) and indicate there is promising potential for LBAs to create control schedules that reduce plug-load energy waste. Table 4 gives the raw results for predictions versus observed usage across the field test rounds; Table 5 gives the accuracy metrics.

Table 4. Confusion Matrix from Field Evaluation Results

Round 1	76,427 True Positives	99,396 False Positives
	943 False Negatives	237,293 True Negatives
Round 2	77,939 True Positives	133,962 False Positives
	4,104 False Negatives	237,469 True Negatives
Round 3 (controls implemented)	39,779 True Positives	122,759 False Positives
	1,473 False Negatives	171,237 True Negatives

Table 5. Field Evaluation Accuracy Metrics

		Round 1	**Round 2**	**Round 3**	**Mean**
Total Accuracy	(TP + TN) / (TP + TN + FN + FP)	76%	70%	63%	70%
False Positive Rate	FP / (FP + TN)	30%	36%	42%	36%
False Negative Rate	FN / (FN + TP)	1.2%	5.0%	3.6%	3.2%
Sensitivity	TP / (TP + FN)	99%	95%	96%	97%
False Discovery Rate (FDR)	FP / (FP + TP)	57%	63%	76%	65%

The pattern of errors provides useful information for future efforts. Round 1 is clearly the optimal configuration found in these field tests. The adjustments made in Rounds 2 and 3 that assumed occupancy between 9:00 a.m. and 5:45 p.m. tended not to improve the balance between savings and convenience, and the initial parameters and configuration used in the LBA for Round 1 should serve as the basis for ongoing research. Round 2 had a higher false negative rate

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due to a lamp being left on overnight and a laptop left in the docking station overnight, causing a higher-than-usual power draw. Both sources of false negatives in Round 2 would have had no effect on user convenience, but given the rules for scoring, predictions were necessarily included.

The distribution of the timing for FN events is concentrated around two time periods: around 8:00 a.m. and around 5:45 p.m., reflecting the inherent variability in when people arrive at the office and when they leave. Detailed inspection of the FN events reveals that 64% of the FNs are attributable to two participants whose schedules were markedly more variable than the other cubicles' occupants observed during this study.

The feedback from the user survey was overwhelmingly positive, with only one respondent saying that they would not volunteer for a similar control program in the future. (This person also acknowledged that their difficulties during the control period may have been unrelated to the Ibis sockets.) The majority of respondents said that they had to override the controls at least once during the control period, but that the override process was simple and not an inconvenience. Several people noted that the override process was simple because the project team had provided instructions ahead of time on what to do if an override was required, which underscores the importance of user education at commissioning.

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4 Future Work

This work demonstrates the potential for LBAs to synthesize control schedules to save energy from plug loads. A relatively simple algorithm that considered factors such as day of the week, season, and asset class was able to correctly forecast whether to turn outlets on or off 70% of the time based on limited training data. Furthermore, the errors in prediction were heavily asymmetric, with a false negative rate of only 3.2% (events that inconvenience users) versus a 36% false positive rate (missed opportunity for saving energy) in the field evaluation results.

Future research should focus on reducing the false positive rate without markedly increasing the false negative rate, which would achieve more savings without adversely affecting user convenience. In this study, we explored some algorithm variants, and were able to understand how the balance shifted with some of the changes attempted. There is considerable potential for further improvement of the algorithm building on the learnings presented in this work.

Developing stronger predictive models for individual workers would enable wider varieties in schedules to be captured more accurately. Weighting individual-level variability more strongly in an LBA for automating plug load controls may help reduce the impact of the error tradeoffs and yield automated plug-load controls that achieve near-optimal savings with minimal disruption to user behavior.

Additional use cases for various control strategies for categories of plug-load equipment and how those controls would best integrate with other building systems are worth exploring. Building systems could provide inputs to enhance occupancy signals for the LBA, or conversely, building systems could make use of the plug-load data to influence their own controls, providing a more integrated and holistic approach to energy management. For example, the Ibis system could be connected to occupancy sensors for building lighting systems. The additional occupancy data would provide opportunity for a more sophisticated automated control algorithm, but many decisions would need to be made to maximize the benefit potential, such as how to prioritize disparate streams of information for optimal plug-load strategy, as well as which direction(s) information would flow.

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