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ABSTRACT

This paper focuses on experimental evaluation and verification of model free extremum seeking control, a real-time gradient descent optimization tool. There have been several publications illustrating the effectiveness of extremum seeking control applied to a variety of heating, ventilation, and air conditioning plants in simulation and on mini-split ductless air conditioning system test beds. However, possibly due to inaccessibility of commercially operational chiller plants for experimentation, an evaluation of extremum seeking has not been documented for a large scale in-service building chiller plant. In this paper, a single input extremum seeking control approach is applied to a 2200RT commercial building chiller plant at Chinatown Point mall in Singapore. The extremum seeking control algorithm selects a set point for the condenser water pump flow rate in order to find the value that minimizes the chiller plant's energy consumption. Evaluation experiments took place over a testing period lasting 5 week days and cycling through morning, daytime, evening, and night modes of operation. Results show that extremum seeking achieves as much as a 1.5% efficiency increase in comparison to a constant-input approach tuned by an expert chiller plant automation engineer; performance improvement is greatest in the off nominal mode where 3 chillers are running than in the nominal mode where 4 chillers are running.

1. INTRODUCTION

It is widely cited that chiller plants constitute a significant fraction of operational cost for large commercial buildings due to electrical energy expenditure and maintenance (Wang and Ma 2007). Minimizing these costs is accomplished through a combination of selection of efficient and properly sized equipment, monitoring and fault detection, and supervisory control; this paper focuses on supervisory control independent from the other aspects of chiller plant design and operation.

One of the challenges to improving the plant supervisory control is determining whether the scheme can account for changes to the optimal settings that happen over a chiller's normal life span and during off nominal operation. Because the life cycles of large commercial buildings and their HVAC systems are multiple decades long, and there are typically many different pieces of equipment that coordinate to produce the desired cooling, faults and maintenance may lead to suboptimal performance of set points chosen in the commissioning phase.

In their review of optimal supervisory control methods, the issue of a changing plant motivated (Wang and Ma 2007) to conclude that adaptive approaches were necessary to prevent performance degradation of the supervisory control strategy due to plant-model mismatch. Another conclusion from the review paper was that adaptive model-free approaches were not suitable for supervisory control due to issues with stability guarantees. However, recent research into the effectiveness of adaptive model free extremum seeking control applied to building chiller plants has suggested that in some cases model free control might not only be an effective means of supervisory control, but also possess some unique advantages in comparison to other approaches. The authors in (Mu et al. 2015; Mu, Li, House, et al. 2016a; Mu, Li, Salsbury, et al. 2016; Sane, Haugstetter, and Bortoff 2006; Tyagi, Sane, and Darbha 2006) have all shown that extremum seeking has the ability to perform real-time optimization as some combination of load, temperature, and fault conditions vary.

Extremum seeking control performs set point optimization via real-time gradient estimation and descent under the following assumptions (Tan et al. 2010):

1) The plant's frequency response dynamics are much faster than the dominant frequencies of controllable and uncontrollable input signals.
2) The plant's performance metric has a local minimum or maximum.

In many studies, a sinusoidal perturbation signal oscillating in the plant's quasi-steady state frequency range is applied about a nominal set point (Burns and Laughman 2012; Dochain, Perrier, and Guay 2011; Killingsworth and Krstić 2006; Moase, Manzie, and Brear 2010). By correlating the excitation signal with the excited plant output, a gradient of cost with respect to set point can be found and integrated to achieve the set point that minimizes the instantaneous cost of running the plant. Because extremum seeking requires no explicit plant model to perform optimization, its performance is robust to off-nominal conditions and slowly varying uncontrollable inputs that gradually change the plant's optimal settings. Once a change in the optimum is detected through sinusoidal perturbation, the controller's adaptation speed is limited by the plant dynamics (Krstić 2000). By following design procedures mentioned in (Burns and Laughman 2012; Li et al. 2005; Mu, Li, House, et al. 2016b), extremum seeking also does not seem to require significant calibration efforts for successful controller implementation. However, although extremum seeking has had success in experimental tests on HVAC equipment, a critical disadvantage of extremum seeking appears in (Burns, Laughman, and Guay 2016) and (Wang and Ma 2007), where authors express concern with the ability of model free control to deliver fast enough adaptation in realistic operational scenarios.

This paper shows that despite limitations mentioned in previous works, extremum seeking control can outperform a manually calibrated baseline supervisory control approach on an in service large capacity chiller plant and show greater efficiency gains in off-nominal operation. The system under test is the 4 chiller, 2200 RT plant in operation at Singapore's Chinatown Point shopping center. The chillers' variable speed chilled water pumps, condenser water pumps, water chillers, and cooling tower fans allow for continuous nonlinear optimization of set points, while the number of chillers, pumps, and cooling towers in operation can be adjusted to find the minimum power point combination for a given cooling demand. To simplify the extremum seeking control problem, this paper focuses on applying extremum seeking control for the optimization of condenser water flow rate, while the number of pumps, fans, and chillers running is sequenced according to a fixed schedule; other continuous set points with greater savings potential could have been chosen for extremum seeking control, but the condenser water flow rate was determined to be less disruptive to operation than other candidate inputs. By verifying that extremum seeking performs well in a realistic operational scenario, this study supports prior conclusions that extremum seeking's adaptability and ease of implementation can outweigh the drawbacks of its slow performance when the building chiller plant loads are slowly time varying.

The rest of the paper is organized by the following sections: section 2 provides further details about the Chinatown Point chiller plant's components, operational rules, building automation system, and operational environment; section 3 gives an overview of the design of experiments, the manually tuned baseline controller implementation, and the extremum seeking controller design and implementation; section 4 presents the results of the extremum seeking experiment applied to the chiller plant and uses performance regressions to show that the extremum seeking controller slightly outperformed the baseline approach; finally, section 5 provides concluding remarks and opportunities for future work.

2. BUILDING AND PLANT DESCRIPTION

Singapore's Chinatown Point is a 99,203 square feet (land area), 25-storey commercial development comprising an office block and a 6-storey retail podium with two basement levels. The shopping mall operates between 9AM to 10PM daily, while the office hours are from 9AM to 6PM weekday and 9AM to 1PM on Saturdays. Figure 1 shows the components of Chinatown point's chiller plant, which consists of 4 equally sized 550RT chillers, 4 chilled water pumps, 4 condenser water pumps, and 2 cooling towers. Figure 2 shows the weekday chiller sequencing schedule according to the number of chillers in operation based on the time of day due to repetitive load conditions. In configurations with fewer than 4 chillers in operation, the combination of chillers running is varied to prevent a subset of chillers from accumulating too much run time.

Figure 2 shows that at around 8AM, all four chillers turn on in succession to handle an average load of almost 1300RT produced by the office and shopping mall and stay on until 7 in the evening, an hour after the office hours have ended. One chiller shuts down, leaving the remaining three to handle the shopping mall average load of about 850 RT until 9:30PM when 2 more chillers shut down in quick succession and a single chiller runs 2 hours before all of the chillers shut off. Table 1 gives the average run time percentage, load and ambient temperature conditions for each chiller calculated over the 5 day testing period considered in this paper.

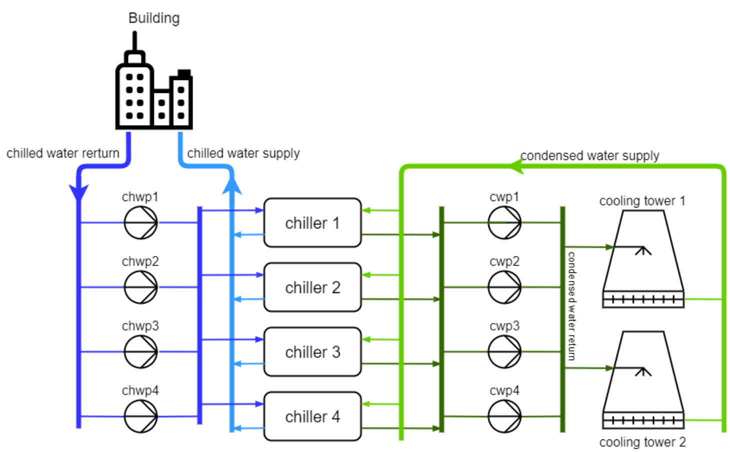


Figure 1. Illustration of Chinatown point chiller plant.

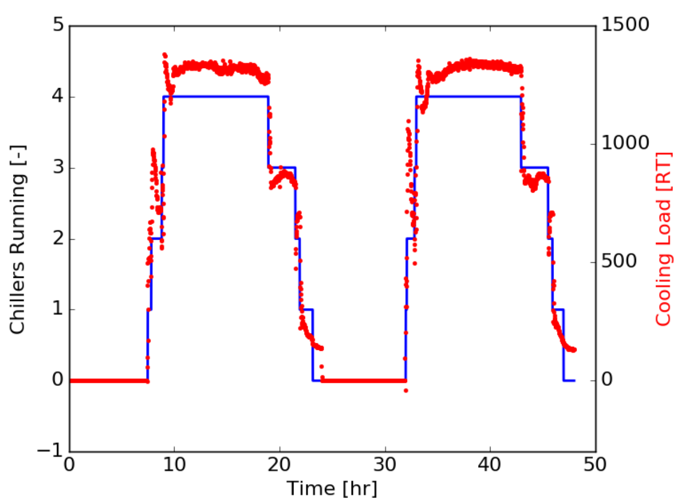


Figure 2. Weekday sequencing schedule and load profile.

Table 1. Operating condition statistics over the testing week for the Chinatown point chiller plant.

Chillers Running	Run Time $[\%]$	Average Load $[RT]$	Average Wetbulb $[^{\circ}C]$	Standard Dev. Load $[RT]$	Standard Dev. Wetbulb $[^{\circ}C]$
0	32.5	2.4	24.7	26.1	0.5
1	9.1	196.7	25.1	102.3	0.4
2	5.1	742.8	25.1	140.7	0.6
3	11.5	857.7	25.3	70.3	0.6
4	41.8	1280.9	25.7	53.6	0.7

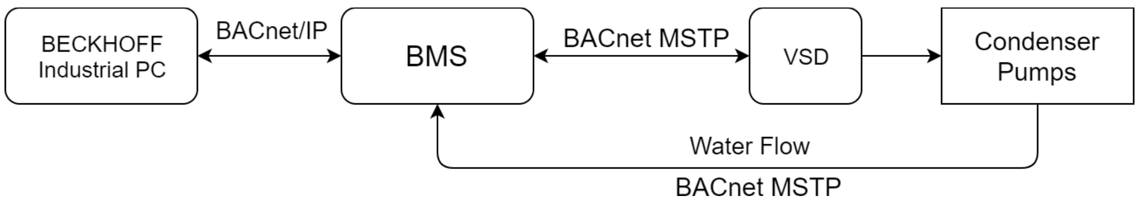


Figure 3. Control setup of the ESC in the chiller plant.

Comparing the mean load and wet bulb temperature with their respective standard deviations shows that there is low variation in operating conditions. As stated in the introduction, several studies in extremum seeking have shown that it can perform well when subjected to nearly constant plant disturbances, which makes Chinatown Point a potentially favorable plant for application.

Both the extremum seeking and baseline control algorithms were programmed using Python 3.6.2 programming language running on an industrial PC. This industrial PC consists of an Intel Core i5-4400E together with 4GB of RAM with Microsoft Windows 7 operating system. Figure 3 shows the control setup schematic. The PC communicates with the building management system (BMS) through BACnet/IP protocol; it sends commands to the BMS to control the pumps' VSDs and queries flow rate data also through this BMS. To provide enough time for the Python programming language and BACnet/IP protocol to send commands and query data, a sampling time of 7 seconds is chosen to ensure a consistent/reliable sampling rate.

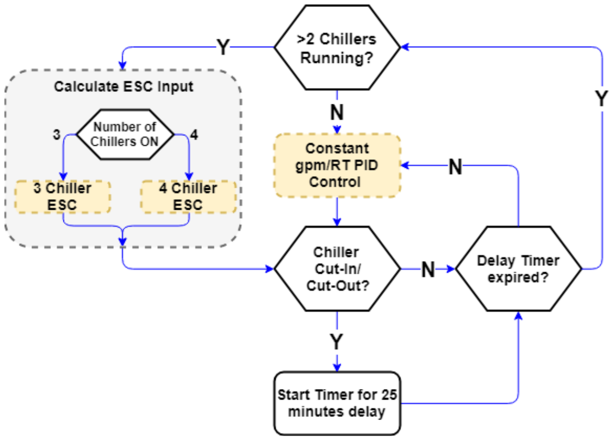
3. CONTROL LOGIC AND DESIGN OF EXPERIMENTS

Due to the chiller plant under study being in service, experimentation on the plant was limited to comparing extremum seeking control (ESC) and a constant input baseline control (BLC) tuned by an expert chiller plant automation engineer. To analyze the performance of each approach, data was collected with each control law in the loop and then regressions were used to relate external conditions to the total power consumed by the system.

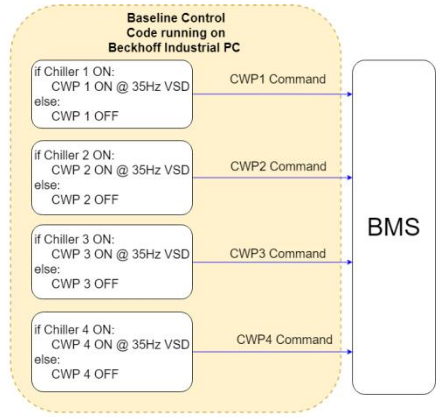
3.1 Control Strategies

This section compares the proposed extremum seeking control approach with its constant input baseline counterpart. Figure 4 (a) shows that the extremum seeking control approach chooses the condenser water flow rate set point during long steady periods of operation with 3 or 4 chillers; with fewer than 3 chillers or up to 25 minutes after a change in chiller status, the condenser water flow rate is modulated to maintain a constant ratio with the cooling load. It is necessary to wait before engaging extremum seeking control after the number of chillers changes to prevent transient power consumption data from corrupting the gradient estimate.

Meanwhile, the baseline control shown in Figure 4 (b) modulates the condenser water flow rate indirectly by keeping the number of pumps on equal to the number of chillers on and keeps the variable speed drive set point constant at 35 Hz. Figure 5 shows the block diagram of the classical extremum seeking algorithm used in this paper. ESC parameters shown in the diagram and in Table 2 were found from a 2 hour and 40 minute identification experiment. The report from this experiment as well as the ESC code can be found on this paper's GitHub repository (Vu 2018).



(a)



(b)

Figure 4. (a) Chinatown Point ESC supervisory control state diagram. **(b)** Baseline control logic.

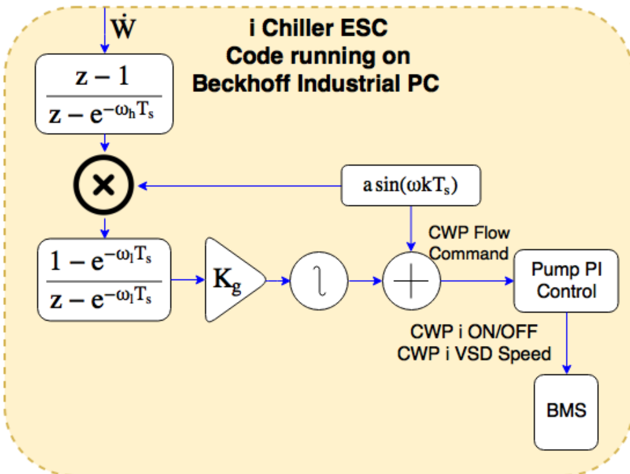


Figure 5. Discrete time implementation of the classical extremum seeking control algorithm.

Table 2. Extremum seeking controller parameters.

Parameter Description	Symbol	Value
Sinusoid perturbation frequency	ω	$0.015\ rad/s$
Sinusoid perturbation amplitude	a	$115\ gpm$
Sample time	T_s	$7\ s$
High and low pass filter cutoff frequencies	$\omega_l = \omega_h$	$0.0075\ rad/s$
Gradient descent gain	K_g	$27.8\ gpm^2/kW$

While the ESC and baseline controllers modulate the condenser water flow rate, the cooling tower fan speed is fixed at its maximum value, the chilled water supply temperature set point is fixed at 7.5^oC, and the chilled water pump speed is adjusted to maintain a constant ratio between the cooling load and the chilled water flow rate.

Because the BLC uses a constant input control strategy, there is no mechanism for retuning the variable speed drive set point as the plant changes. By contrast, ESC allows recursive calculation of control inputs according to information about the cost function that is found from excitation signals. The power measurement, $\dot{W}$, is fed to a discrete time high pass filter to remove the constant offset and produce a signal oscillating at ω that is proportional to the gradient. The high pass filtered signal is correlated with the input sine wave to produce a constant signal proportional to the gradient, which goes through the low pass filter with negligible attenuation. This gradient estimate is then scaled and integrated to perform gradient descent. The updated flow command is the sum of the current value stored by the integrator and the current output of the dithering sinusoidal signal.

3.2 Experiment

The baseline approach was run from Monday-Wednesday, March 5-7, 2018, while ESC was run from Thursday-Friday, March 8-9, 2018. Data from each experiment was labeled with the following attributes: 1) number of chillers in operation 2) whether the plant's steady state delay timer had expired since the last change in the status of one or more chillers 3) whether ESC or BLC was running at the time. The following data was discarded: "transient" data, which was either collected within 25 minutes of a chiller status change or during after-hours operation with fewer than 3 chillers in operation. Regressions between total power, the cooling load $\dot{Q}$, wet bulb temperature T_{wb} , relative humidity RH , and total system power $\dot{W}$ were performed to estimate the power consumption of each approach over a range of operating conditions. The condenser water flow rate was excluded from the regression due to dependence on the three independent environmental conditions; in the baseline control approach, the condenser water flow rate is adjusted according to the number of chillers running, which is a function of time, while in ESC the condenser water flow rate is changed to track the optimal input. In each regression, the data was randomly shuffled with identical seeding and 80% of the data was used for training while the remaining 20% was used for testing. Mean absolute percentage error (MAPE) was used to evaluate regression fits, where a perfect fit score is 0.

Equation (1.1) gives the linear model used to estimate total power, where $\hat{\dot{W}}_{law}$ represents the power predicted by the supervisory control law in operation, the subscript i in $a_{i,law}$ represents the index number, and the subscript law represents the control law used, which can be BLC , ESC , or $diff$, the difference in power consumption between the control strategies.

$$\hat{\dot{W}}_{law}(\dot{Q},T_{wb},RH) = a_{1,law} + a_{2,law}\dot{Q} + a_{3,law}T_{wb} + a_{4,law}RH \tag{1.1}$$

Using (1.1), the power savings or losses over different operating conditions is $\hat{\dot{W}}_{diff} = \hat{\dot{W}}_{BLC} - \hat{\dot{W}}_{ESC}$, where $a_{i,diff} = a_{i,BLC} - a_{i,ESC}$. Because the baseline control has been carefully tuned and there is uncertainty in the measurements of the operating environment, it is important to use several metrics to increase robustness of evidence for or against the effectiveness of extremum seeking and ensure that there is statistical significance to the findings. Four metrics are used to classify the performance of the ESC versus the baseline, where each metric is applied to the cases of 4 chillers running and 3 chillers running:

1. The average savings over minimum and maximum recorded operating conditions, given by equation (1.2), where $\Delta x \equiv x_{\max} - x_{\min}$. This metric indicates potential savings over all expected operating conditions.

$$\%\mathrm{SV}_{avg} = \frac{100}{(\Delta\dot{Q})(\Delta T_{wb})(\Delta RH)} \int_{\dot{Q}_{\min}}^{\dot{Q}_{\max}} \int_{T_{wb,\min}}^{T_{wb,\max}} \int_{RH_{\min}}^{RH_{\max}} \frac{\hat{\dot{W}}_{diff}(\dot{Q},T_{wb},RH)}{\hat{\dot{W}}_{BLC}(\dot{Q},T_{wb},RH)} d\dot{Q}dT_{wb}dRH \tag{1.2}$$

2. Average savings calculated over a range of real environment data inputs, given by equation (1.3). This metric indicates potential savings over observed weather patterns.

$$\%SV_{data} = 100\frac{1}{N}\sum_{i=1}^{N}\frac{\hat{\dot{W}}_{diff}}{\hat{\dot{W}}_{BLC}} \tag{1.3}$$

3. The predicted power loss from using the baseline control, as determined by the difference between the power predicted by the ESC regression $\hat{\dot{W}}_{ESC}$ and the power $\dot{W}_{BLC}$ measured on days when the baseline control was running. The number of data points collected on baseline days is represented by N_{BLC}.

$$\%LS_{BLC} = 100\sum_{i=1}^{N_{BLC}} \frac{(\hat{\dot{W}}_{ESC,i} - \dot{W}_{BLC,i})}{\dot{W}_{BLC,i}} \tag{1.4}$$

4. The predicted power saving from using extremum seeking control instead of the baseline control, as determined by the sum of N_{ESC} percent differences between actual power measured during the ESC test, $\dot{W}_{ESC}$, and the power predicted by $\hat{\dot{W}}_{BLC}$.

$$\%SV_{ESC} = 100\sum_{i=1}^{N_{ESC}} \frac{(\hat{\dot{W}}_{BLC,i} - \dot{W}_{ESC,i})}{\dot{W}_{BLC,i}} \tag{1.5}$$

4. RESULTS AND DISCUSSION

Table 3 gives model fit statistics for the ESC and BLC regressions, which were performed using the Scikit Learn Python Machine Learning Toolbox (Pedregosa et al. 2012). The ESC and BLC predictions had strong prediction accuracy, with mean absolute percentage error scores of no more than 0.92%. Table 4 reports the 4 performance evaluation metrics from the previous section for the cases of 3 and 4 chillers running. Each metric was augmented by a margin calculation over the worst case MAPE, which assumes that the prediction error is in the direction of least savings.

Comparing the MAPE from Table 3 to the savings in each metric indicates that the ESC slightly outperformed the baseline strategy by statistically discernable margins that are consistent across all four performance metrics. Savings with 3 chillers in operation are higher than savings with 4 chillers in operation, which was expected because the baseline control pump VSD frequency was hand-tuned for operation with 4 chillers, but not 3; during 3 chiller operation, ESC automatically improves the guess of the optimal condenser water flow rate in a region where there is less knowledge about optimal plant settings.

Figures 6 and 7 compare the ESC condenser water flow input to the scheduled baseline control input, which follows the same pattern each day. During 4 chiller operation, the ESC oscillates about a condenser water flow rate approximately 300 gpm lower than the baseline flow; during 3 chiller operation, the ESC chooses a condenser water flow rate that is approximately 700 gpm lower than the baseline control, which could account for the increase in savings observed in Tables 3 and 4. These results suggest that the ESC can automatically retune the optimal set point following a change in plant configuration such as a pump or chiller going in or out of service.

Figure 7's close up views of steady state operation periods show that the trend of measured power during ESC operation is noticeably lower than the power consumption predicted by the baseline regression during periods [2], [3], and [4]. Consistent with the trend of greater savings during 3 chiller operation, periods [2] and [4] show that the power consumption of the extremum seeking controller rarely exceeds the power consumption predicted by the baseline regression.

Table 3. Model fit scores for the baseline and ESC regressions.

Regression	Training Data MAPE [%]	Testing Data MAPE [%]
$\hat{\dot{W}}_{BLC}$	0.88	0.91
$\hat{\dot{W}}_{ESC}$	0.92	0.92

Table 4. Performance of ESC against baseline according to 4 metrics from Section 3.2.

Metric	3 Chillers ON	3 Chillers ON [% Margin over Worst MAPE]	4 Chillers ON	4 Chillers ON [% Margin over Worst MAPE]
$\%SV_{avg}$	2.41	1.49	1.16	0.24
$\%SV_{data}$	2.10	1.18	1.16	0.24
$\%LS_{BLC}$	2.27	1.35	1.15	0.22
$\%SV_{ESC}$	1.96	1.04	1.15	0.22

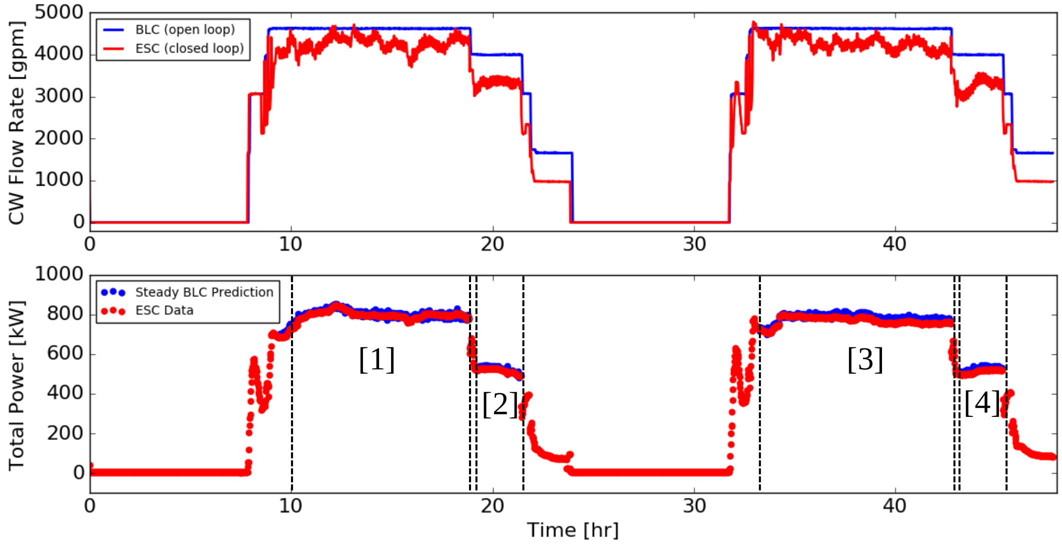


Figure 6. (Top): Comparison of ESC condenser water flow rate to BLC condenser water flow rate. (Bottom): Comparison of ESC power data to power predicted by BLC regression.

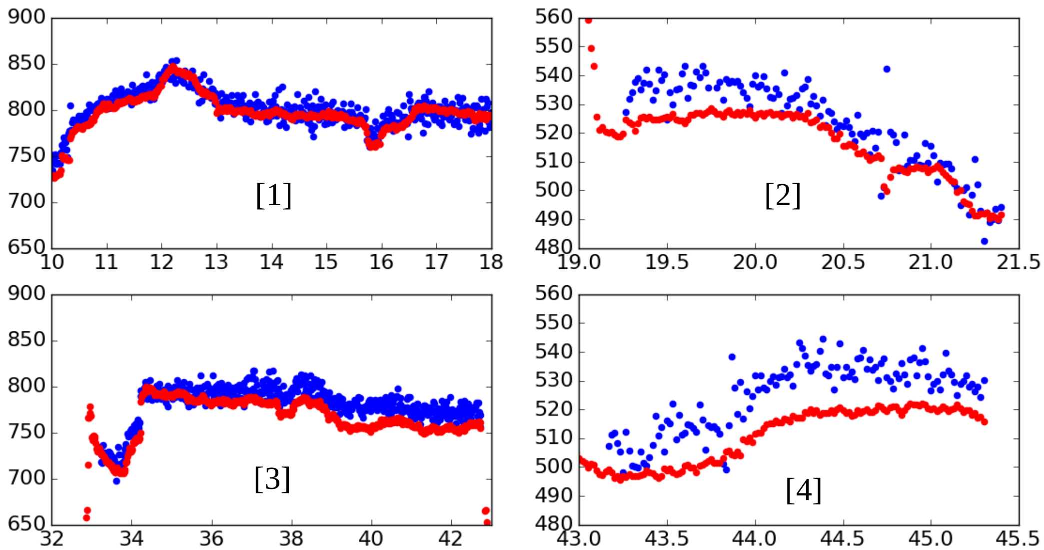


Figure 7. Close up views of the comparison between BLC power total power prediction (scatter) and measured total power under ESC. BLC predictions are rarely lower than measured ESC power in segments [2], [3], and [4].

6. CONCLUSIONS

This paper examined the effectiveness of using an extremum seeking supervisory controller to choose a condenser water flow set point for a 4 chiller, 2200RT chiller plant in operation at Chinatown Point mall in Singapore. The plant sees long periods of slow variations in load, wet bulb temperature, and humidity throughout its day to day operation. A five day test showed that extremum seeking slightly outperforms a hand-tuned, open-loop constant input baseline supervisory control strategy and demonstrates that savings during extremum seeking operation were greatest for off-nominal 3 chiller operation. While a baseline control strategy is effective for a plant like Chinatown point that operates under constant conditions, the results indicate that extremum seeking is effective for re-optimizing inputs after unexpected plant reconfiguration or maintenance that may render the baseline control inputs suboptimal. Future work includes adding inputs such as the cooling tower fan speed to the extremum seeking supervisory control and using second order derivative estimates to improve reliability of ESC input convergence.

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