Selected Data Analytics Applications: Building Energy Saving

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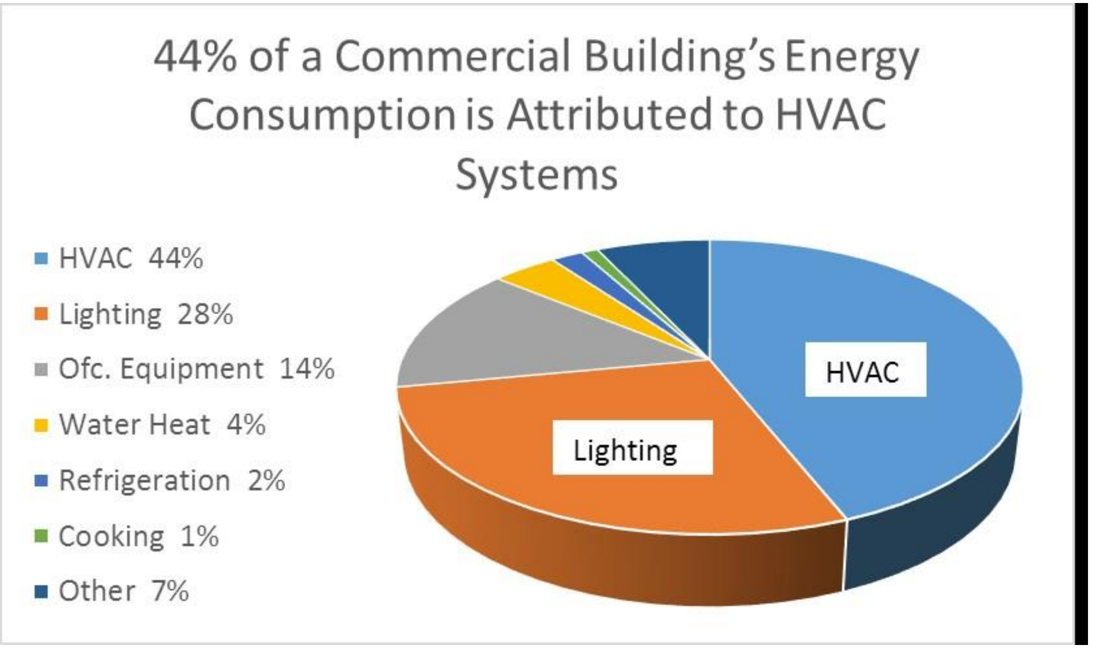
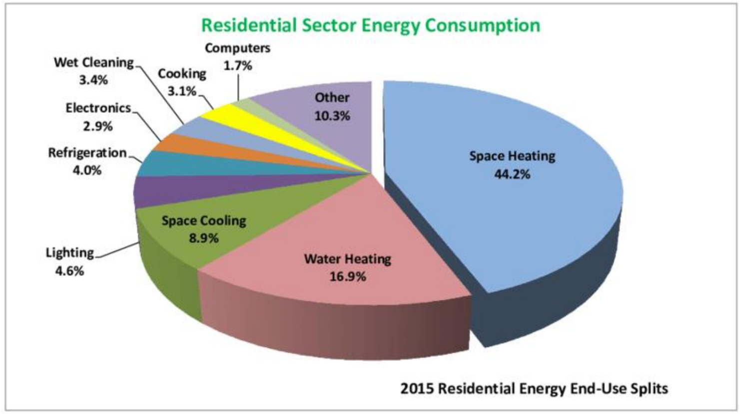
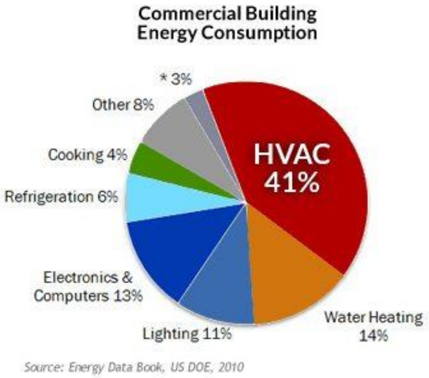
Building Energy Consumer

- Most commercial buildings or skyscrapers are equipped with a Heating, Ventilating, and Air Conditioning (HVAC) system.
- Lighting system
- Other Electric Appliances
- Electric Vehicles

Building Energy Consumer



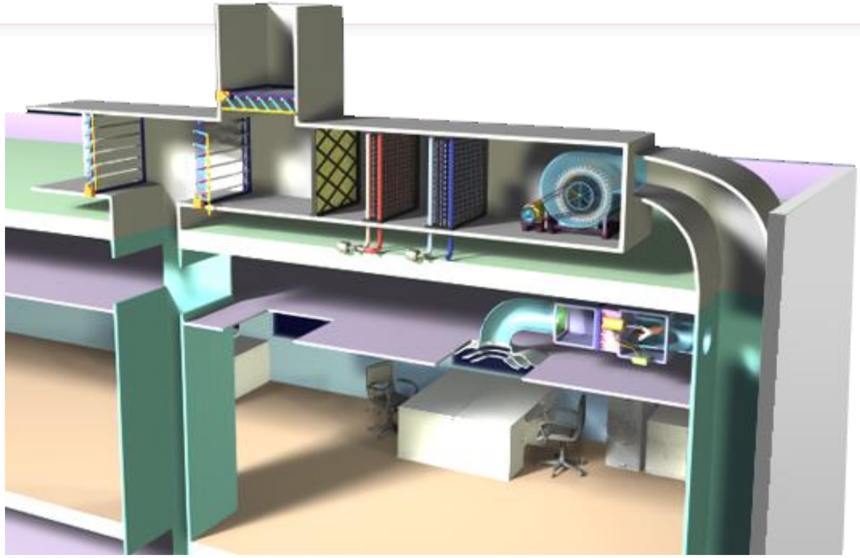




Heating, Ventilating and Air Conditioning

Temperature	*68°F (20°C) and 75°F (25°C)*
Humidity	*30% relative humidity (RH) and 60% RH*
Pressure	*A slightly positive pressure to reduce outside air infiltration.*
Ventilation	*Rooms typically have several complete air changes per hour*

Heating, Ventilating, and Air Conditioning

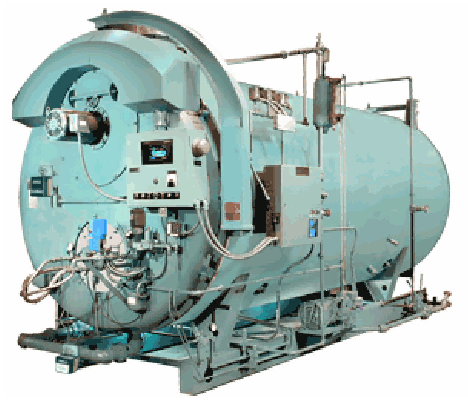


Mechanical Room: Boilers, chillers, pumps, heat exchangers…

Air Handling Units (AHUs): heat, cool, humidify, dehumidify, ventilate, filter and distribute the air.

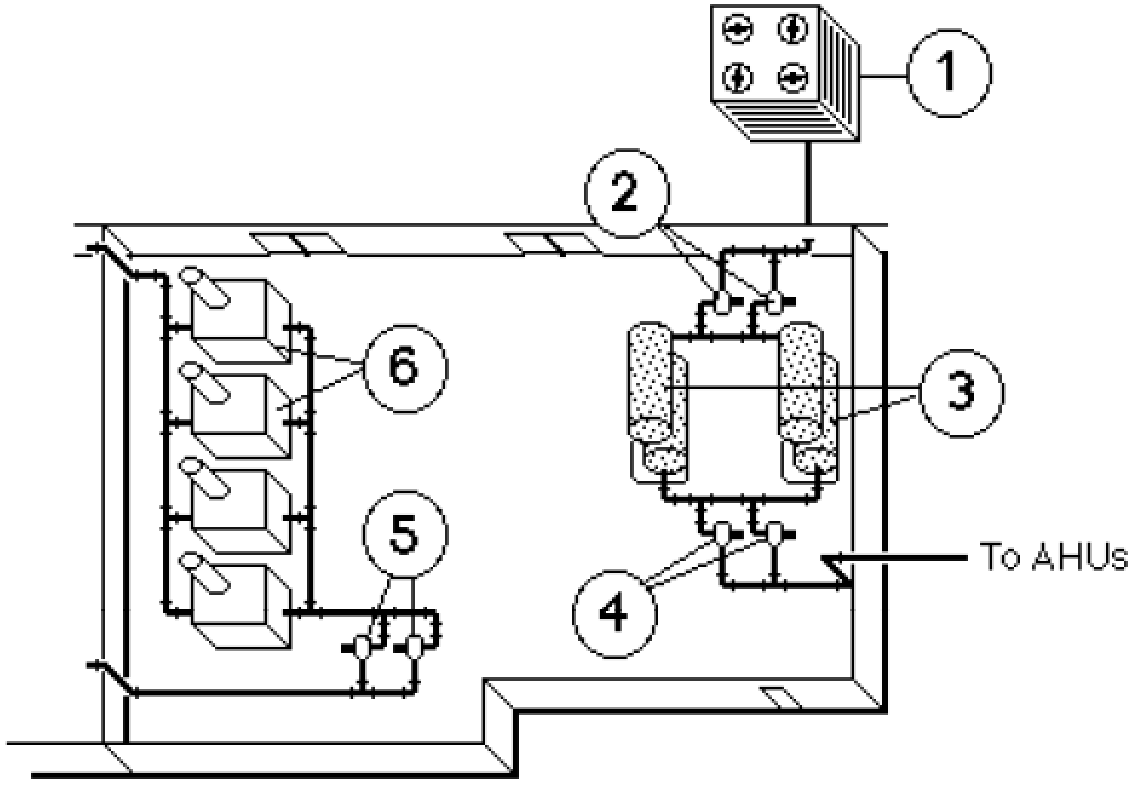
Room Controls: thermostats and Variable Air Volume (VAV) boxes

Heating, Ventilating, and Air Conditioning



Boiler

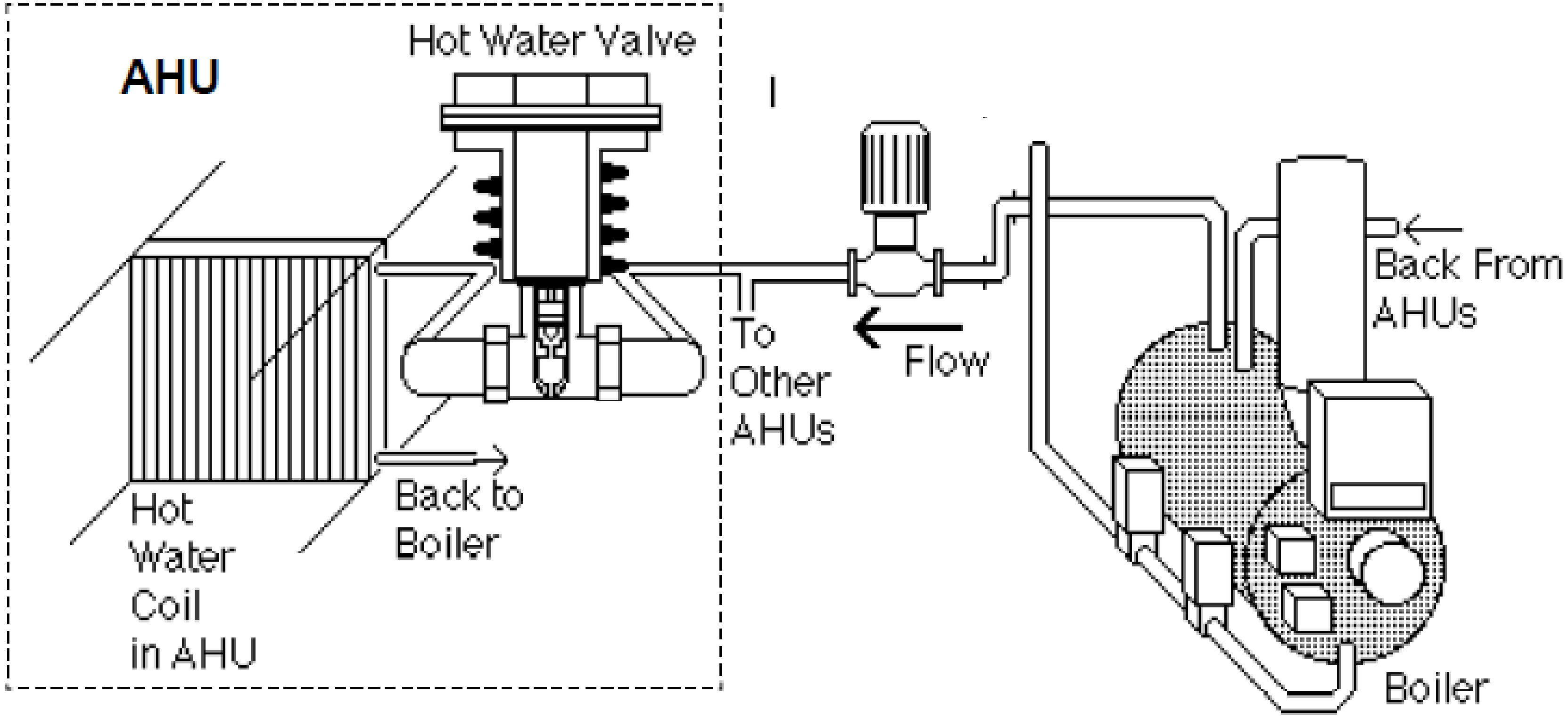
Chiller



Mechanical Room

Heating, Ventilating, and Air Conditioning

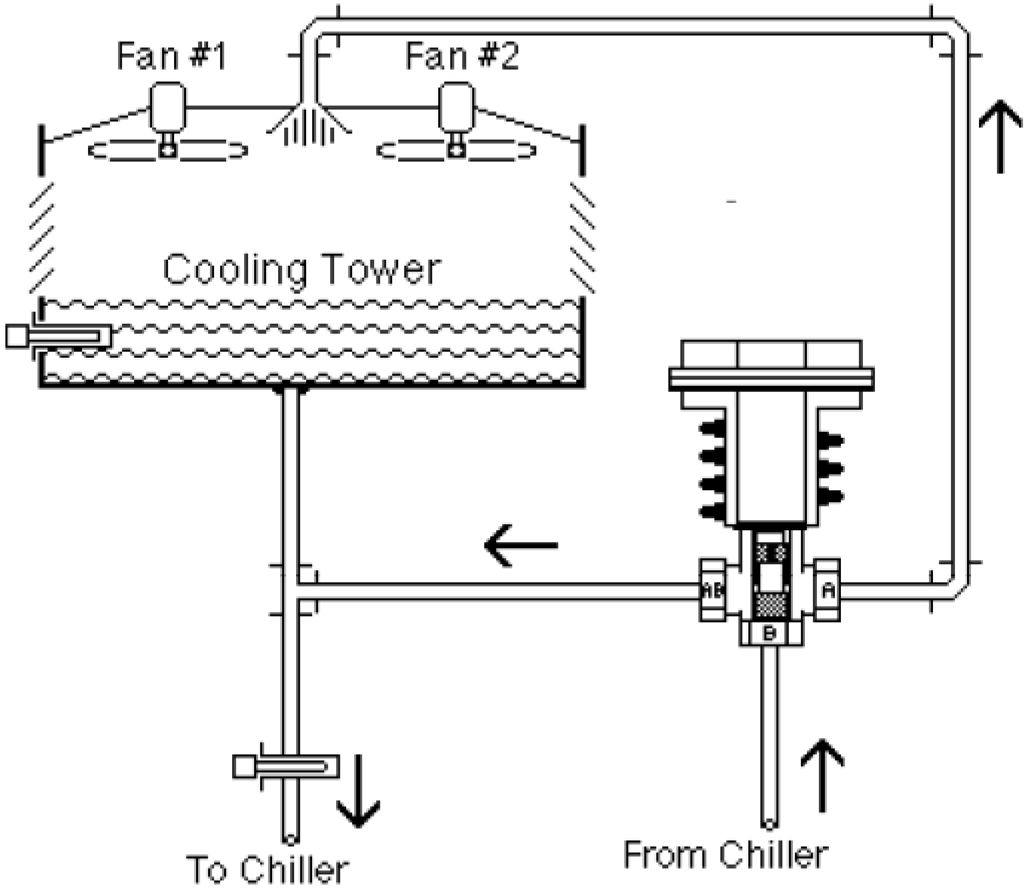
Heating system



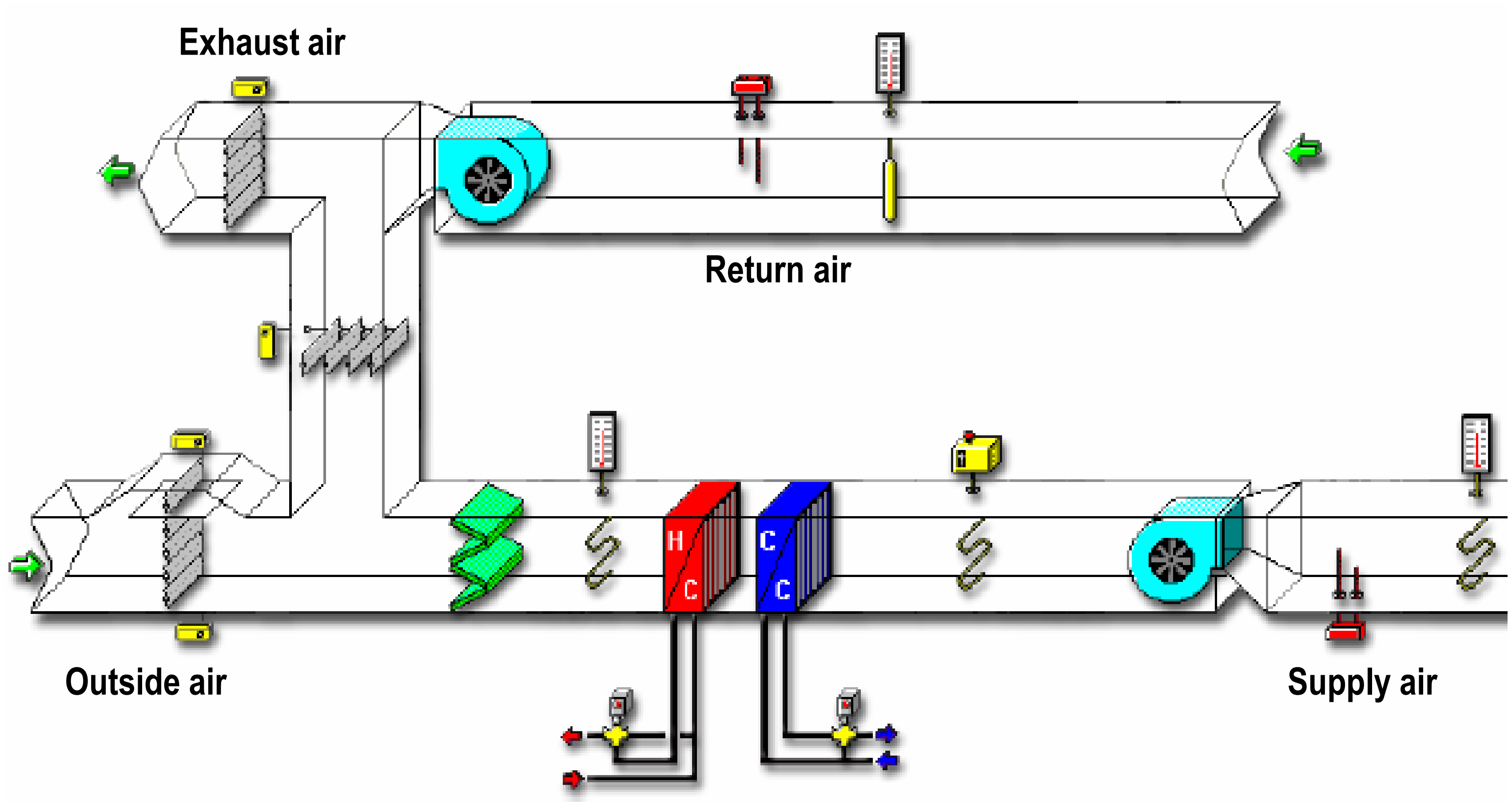
Also to radiators, terminal reheat, domestic hot water.

Heating, Ventilating, and Air Conditioning

Cooling system



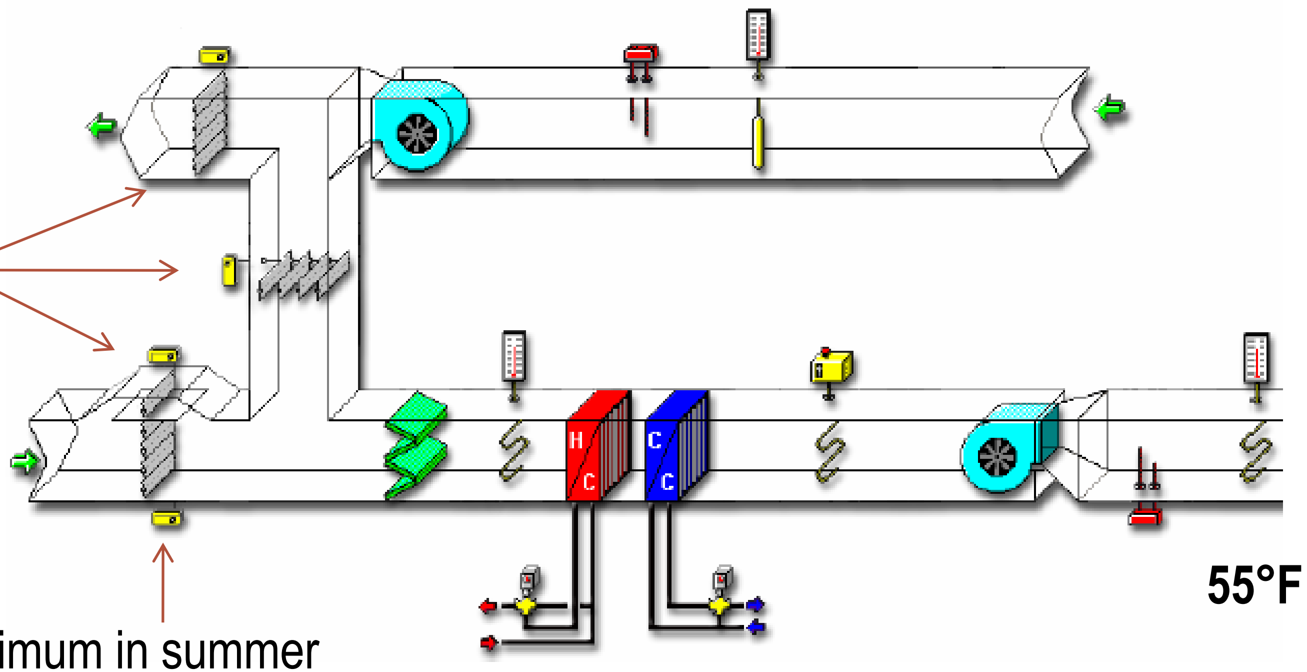
Heating, Ventilating, and Air Conditioning



Heating, Ventilating, and Air Conditioning

Economizer

Linked

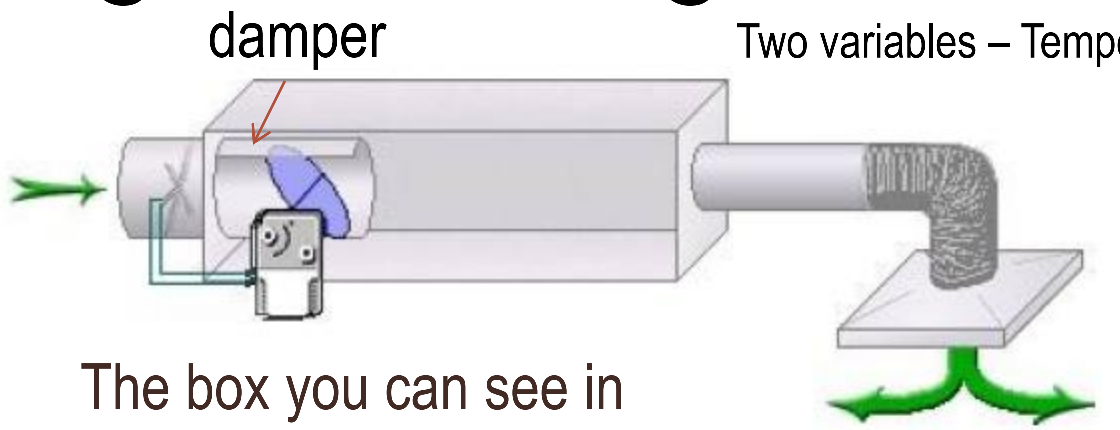


Minimum in summer
More outside air in winter

Heating, Ventilating, and Air Conditioning

Two variables – Temperature & Air Volume

VAV Box



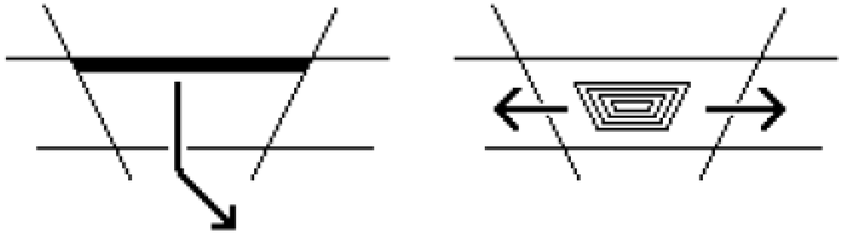
The box you can see in the hallway.

IF temperature too high

First reduce reheat till fully closed
Then increase air volume

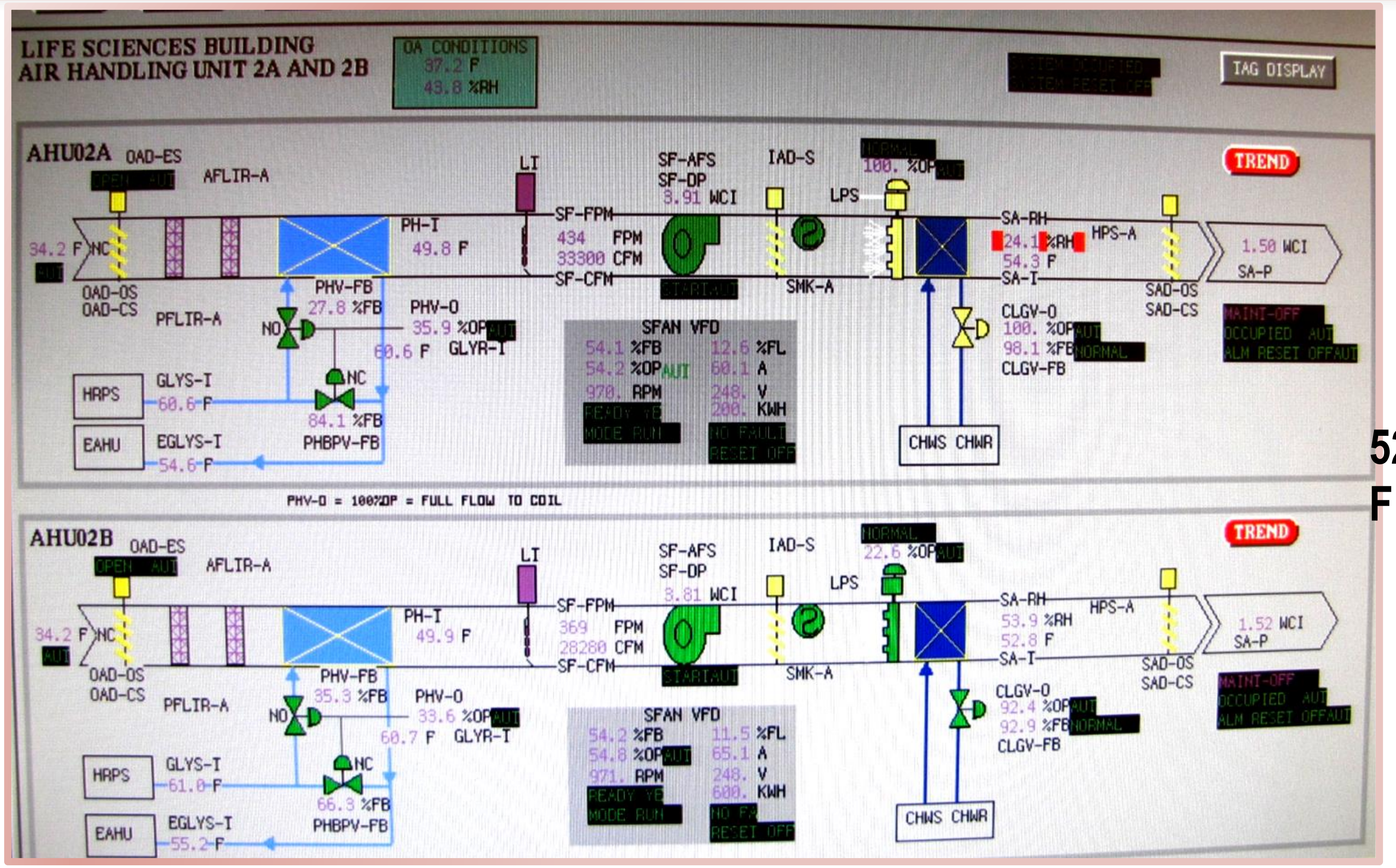
IF temperature too low

First reduce air volume till minimum
Then start reheat



Air Diffusers

HVAC System Condition Monitoring



52°
F

The HVAC Research

What data scientist do in conducting the HVAC research?

We start from learning the domain knowledge, analyzing system from the physics side, conducting experiments for collecting data, and next going into data analytics.

Ref: A. Kusiak, M. Li, and F. Tang, "Modeling and optimization of HVAC energy consumption," Applied Energy, Vol. 87, 3092-3102, 2010.

Ref: A. Kusiak and M. Li, "Cooling output optimization of an air handling unit," Applied Energy, Vol. 87, pp. 901-909, 2010.

Ref: X. Wei, G. Xu and A. Kusiak, "Modeling and optimization of a chiller plant," Energy, Vol. 73, pp. 898-907, 2014

Ref: A. Kusiak, M. Li, and Z. Zhang, "A data-driven approach for steam load prediction in buildings," Applied Energy, Vol. 87, pp. 925-933, 2010

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Physical System

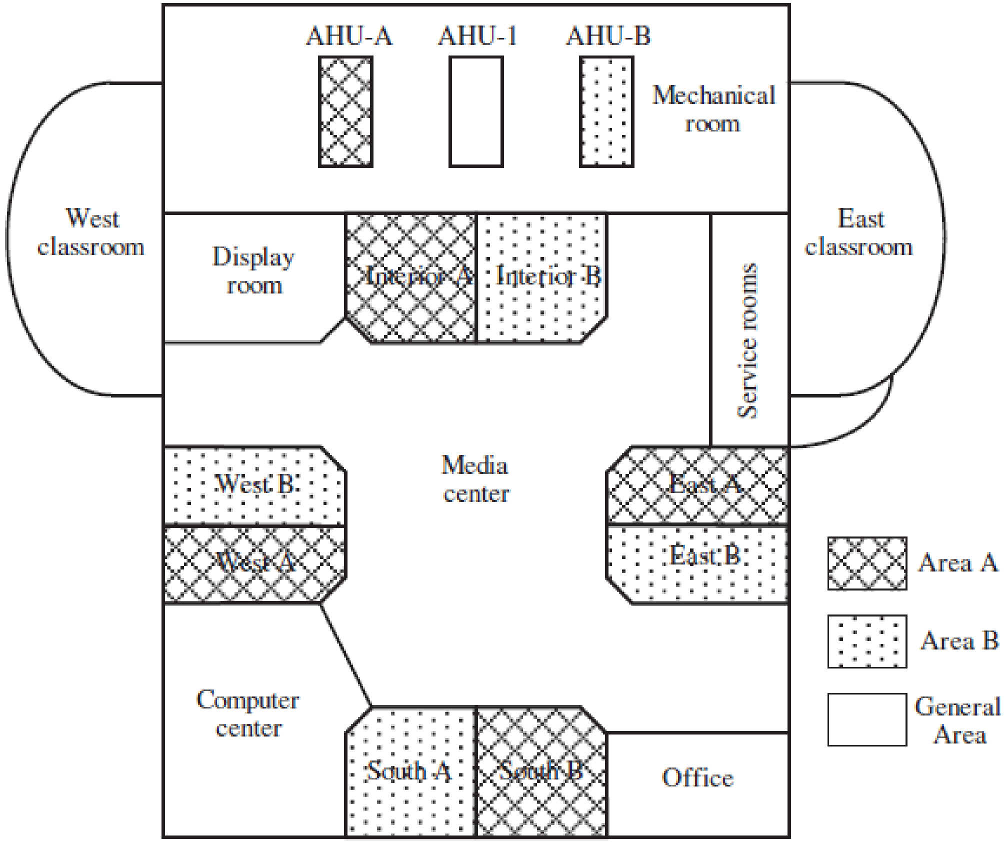

Fig. 1. Basic description of ERS facility.

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Design of Experiments from Statistics

Table 1
Factorial design experiment.

Internal load	Coded value	SA setpoint	Coded value	SP setpoint	Coded value
Stage 2	–1	56	–1	1.2	–1
Stage 3	1	57	1	1.4	1

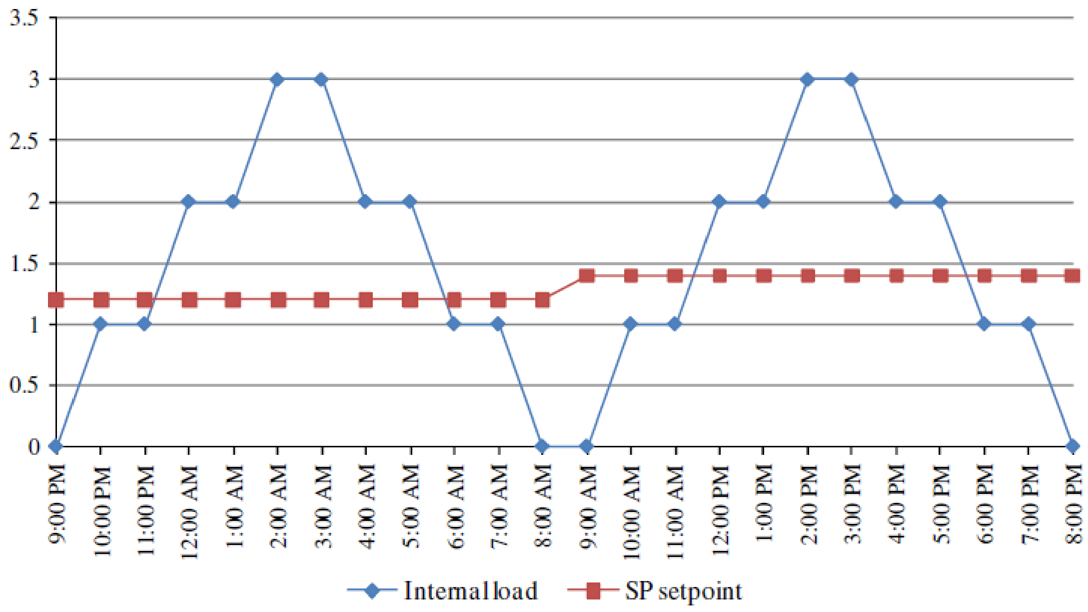

Fig. 2. Illustration of changes of the simulated load and the static pressure setpoint.

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After data collection

Table 4
Data description.

Data set	Description	No. of instances
1	Parameter selection; algorithm selection; random sampling from preprocessed data	129 observations
2	Model training; a random sample of 85% of the preprocessed data	658 observations
3	Model test; the remaining 15% of the data (excluding the training data)	116 observations

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Feature selection

By boosting tree

Table 5
Predictor importance produced by the boosting tree algorithm.

Parameter	Importance
Chilled water entering temperature (stdev)	100
Chilled water entering temperature (mean)	77
Solar normal flux (mean)	68
Solar normal flux (stdev)	57
Outside air temperature (mean)	56
Cooling coil entering air temperature (mean)	51
Infrared radiation (stdev)	43
Cooling coil entering air temperature (stdev)	42
Outside air temperature (stdev)	40
Infrared radiation (mean)	37

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Data-driven model formulation

Table 7
Parameter description.

Parameter	Description	Unit
x_1	Internal load	Discrete
x_2	Internal load at previous time interval	Discrete
x_3	Supply air temperature setpoint	F
x_4	Supply air static pressure setpoint	WG
v_1	Chilled water entering temperature (mean)	F
v_2	Chilled water entering temperature (stdev)	F
v_3	Outside air temperature (mean)	F
v_4	Solar normal flux (mean)	B/HFt2
v_5	Solar normal flux (stdev)	B/HFt3

$$y = f(x_1, x_2, x_3, x_4, v_1, v_2, v_3, v_4, v_5) \tag{1}$$

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Model selection

Table 8
Algorithms selection for building the total energy model.

Algorithm	MAE	Std of MAE	MAPE (%)	Std of MAPE (%)
C&RT	1019.9168	941.5114	5.26	4.43
CHAID	2292.1561	2438.1754	11.23	11.30
Boosting tree	1943.2698	1658.7942	9.75	7.60
Random forest	1864.6265	1983.4052	9.46	8.36
MARSplines	1702.8106	1464.0291	8.67	6.54
MLP	915.0163	977.6062	4.66	4.20
MLP ensemble	719.1084	689.6606	3.77	3.50
SVM	1531.7237	1297.2686	7.62	5.61

$$\mathrm{AE} = |\hat{y} - y| \tag{2}$$

$$\mathrm{MAE} = \frac{\sum_{i=1}^{N} \mathrm{AE}(i)}{N} \tag{3}$$

$$\mathrm{APE} = \left|\frac{\hat{y} - y}{y}\right| \tag{4}$$

$$\mathrm{MAPE} = \frac{\sum_{i=1}^{N} \mathrm{APE}(i)}{N} \tag{5}$$

$$\mathrm{Std\_AE} = \sqrt{\frac{\sum_{i=1}^{N} (\mathrm{AE}(i) - \mathrm{MAE})^2}{N-1}} \tag{6}$$

$$\mathrm{Std\_APE} = \sqrt{\frac{\sum_{i=1}^{N} (\mathrm{APE}(i) - \mathrm{MAPE})^2}{N-1}} \tag{7}$$

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The model implementation

Table 9
Training and test results of the four models.

	MAE	Std of AE	MAPE (%)	Std of APE (%)
Chiller energy model				
Training	541.0405	513.6529	5.03	5.23
Testing	645.0991	539.3706	5.99	5.79
Fan energy model				
Training	286.9700	305.8468	5.49	6.90
Testing	383.2912	488.5904	7.21	12.62
Pump energy model				
Training	6.9087	20.6677	0.23	0.80
Testing	6.2690	5.1443	0.21	0.17
Reheat energy model				
Training	53.3107	113.6242		
Testing	49.1659	112.1540		

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NN Ensemble

Table 10
Summary of four MLP ensemble models.

Chiller energy model			Fan energy model		
Network structure	Hidden activation function	Output activation function	Network structure	Hidden activation function	Output activation function
MLP 9-31-1	Hyperbolic function	Identity function	MLP 9-40-1	Exponential function	Logistic function
MLP 9-35-1	Hyperbolic function	Logistic function	MLP 9-40-1	Hyperbolic function	Logistic function
MLP 9-10-1	Logistic function	Identity function	MLP 9-17-1	Logistic function	Identity function
MLP 9-14-1	Logistic function	Exponential function	MLP 9-35-1	Logistic function	Logistic function
MLP 9-10-1	Logistic function	Exponential function	MLP 9-20-1	Hyperbolic function	Exponential function
Pump energy model			Reheat energy model		
MLP 9-29-1	Logistic function	Logistic function	MLP 9-30-1	Hyperbolic function	Exponential function
MLP 9-5-1	Logistic function	Logistic function	MLP 9-25-1	Exponential function	Logistic function
MLP 9-21-1	Logistic function	Exponential function	MLP 9-23-1	Exponential function	Logistic function
MLP 9-5-1	Logistic function	Identity function	MLP 9-38-1	Exponential function	Exponential function
MLP 9-5-1	Logistic function	Identity function	MLP 9-8-1	Hyperbolic function	Logistic function

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Visualization of Results

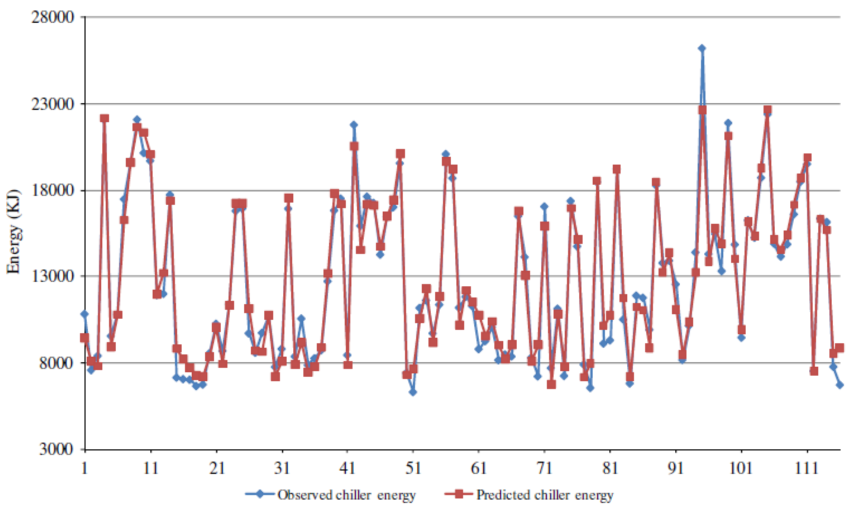

Fig. 3. Test results for the chiller energy model.

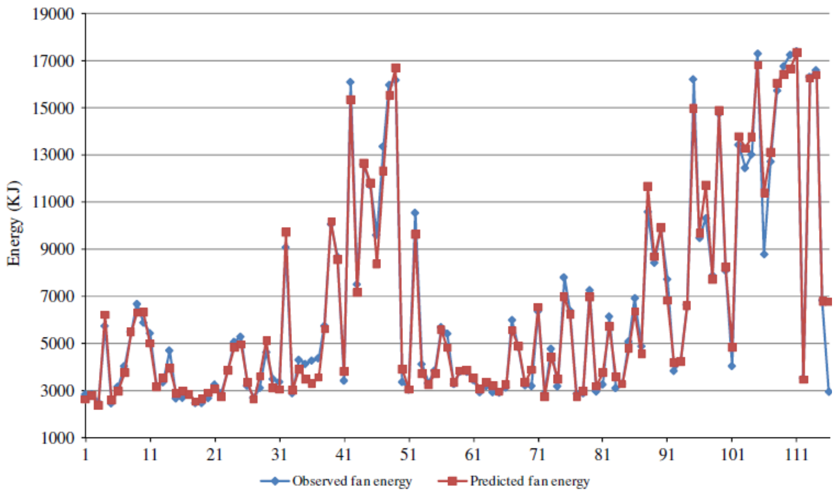

Fig. 4. Test results for the fan energy model.

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Visualization of Results

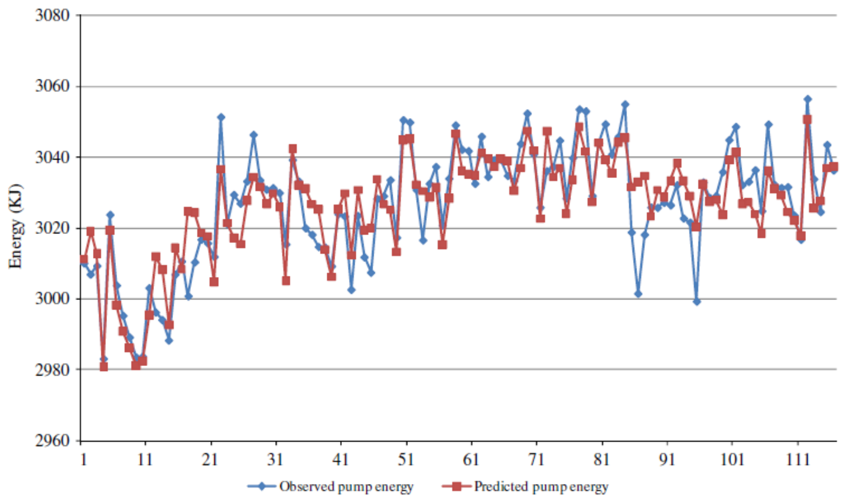

Fig. 5. Test results for the pump energy model.

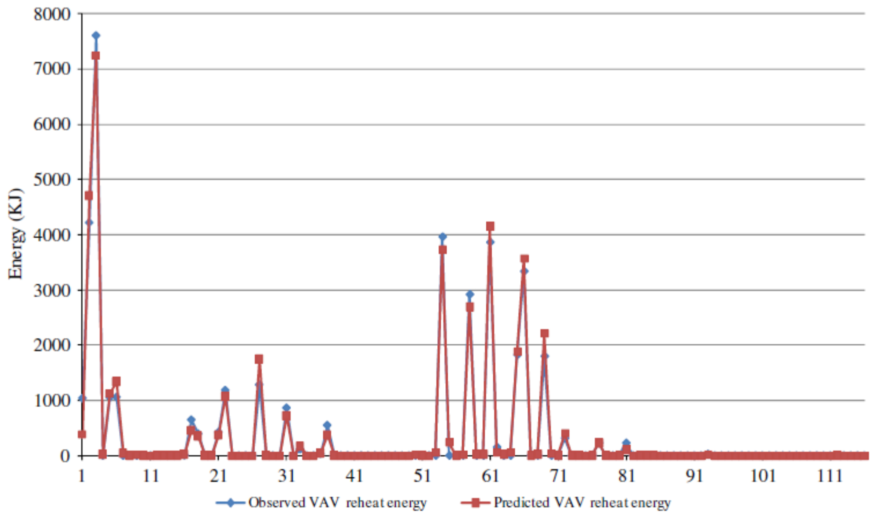

Fig. 6. Test results for the reheat energy model.

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Optimization model formulation and solving

$$
\begin{aligned}
\min_{x_1,x_2} \quad & \text{Obj} \\
\text{s.t.} \quad & \text{Obj} = \sum_{i=1}^{4} f_i(x_1, x_2, x_3, x_4, v_1, v_2, v_3, v_4, v_5) \\
& 50 \leqslant x_1 \leqslant 65 \\
& 1.2 \leqslant x_2 \leqslant 1.8
\end{aligned}
\tag{8}
$$

PSO Updates

$$
\begin{aligned}
q_i &\leftarrow \omega q_i + c_1 rand()(\hat{p}_i - p_i) + c_2 rand()(\hat{g} - p_i) \\
p_i &\leftarrow p_i + q_i
\end{aligned}
$$

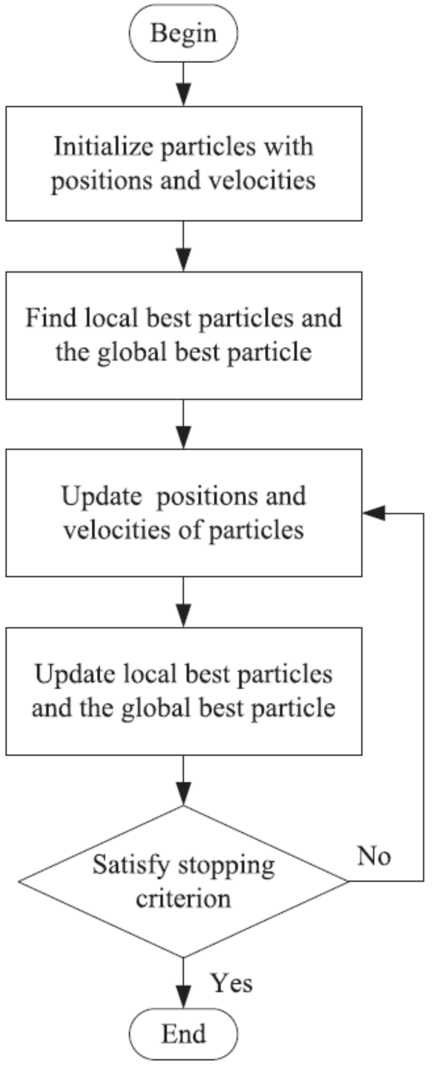

Fig. 7. Flowchart of the PSO algorithm.

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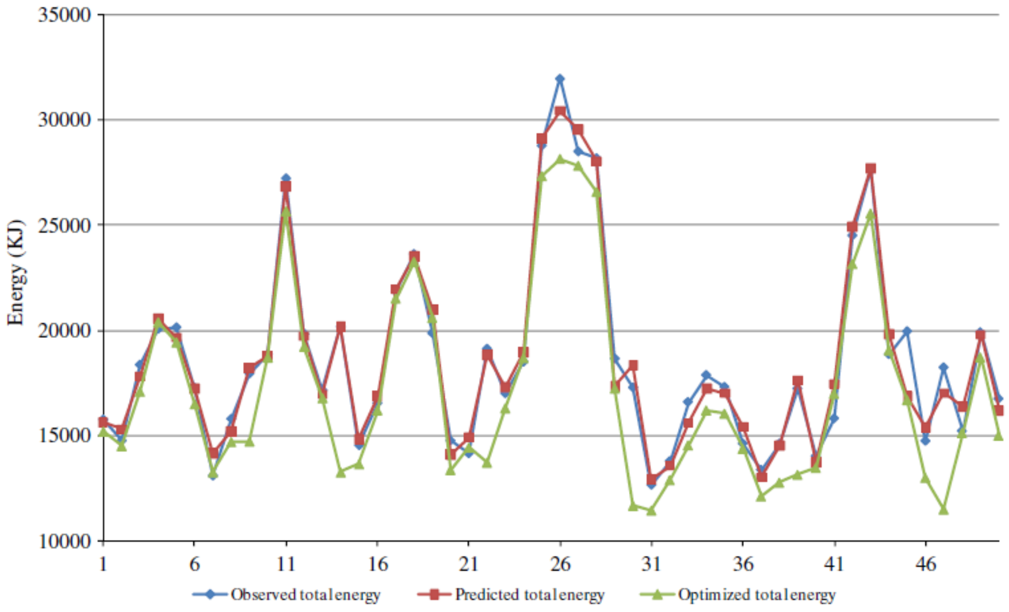

Fig. 8. The total energy before and after optimization.

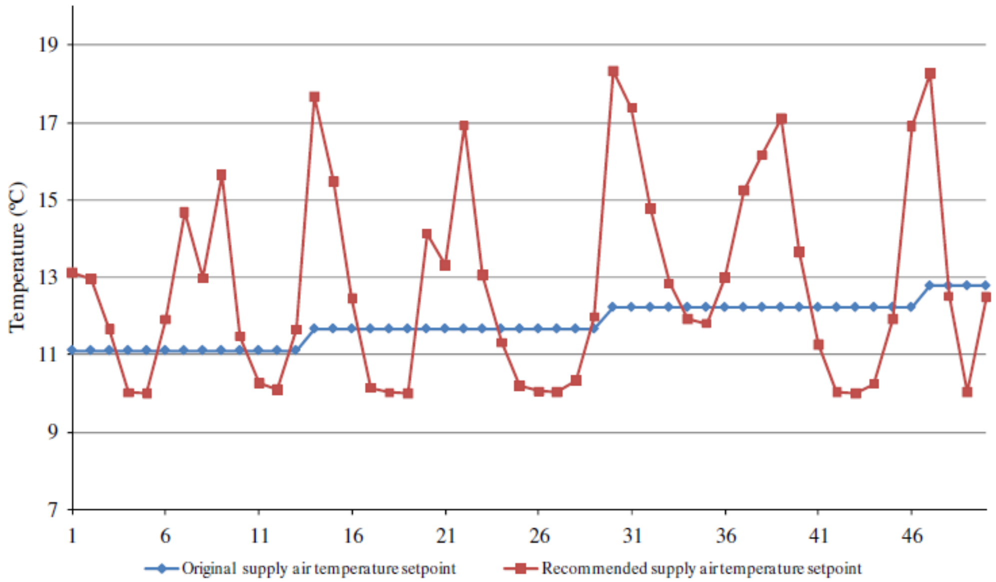

Fig. 9. The air temperature setpoint before and after optimization.

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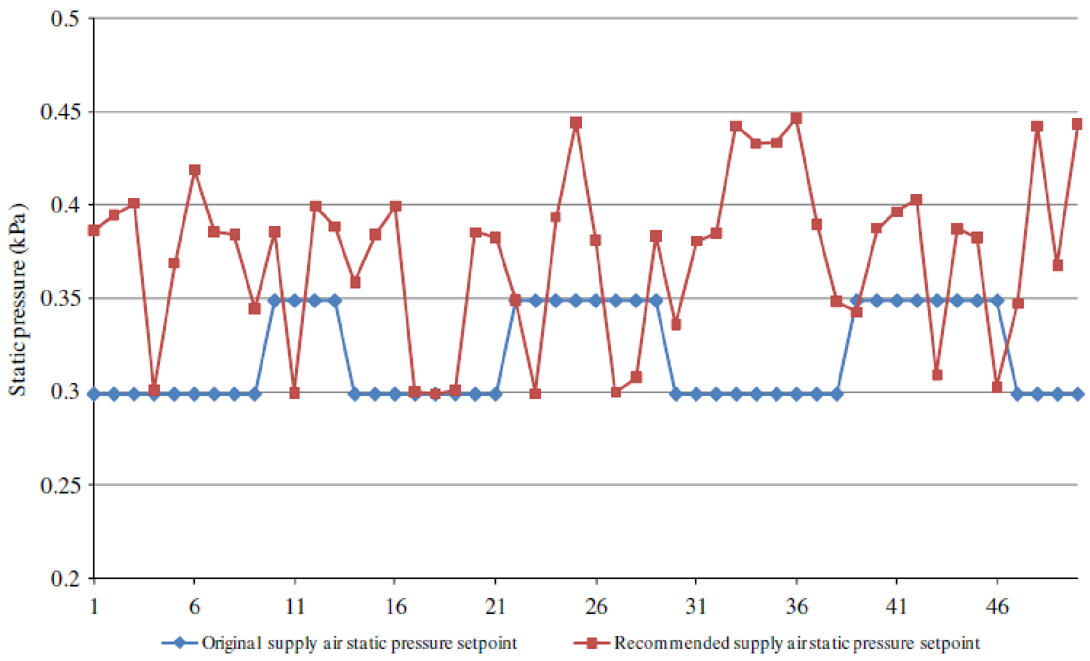

Fig. 10. The supply air static pressure setpoint before and after optimization.

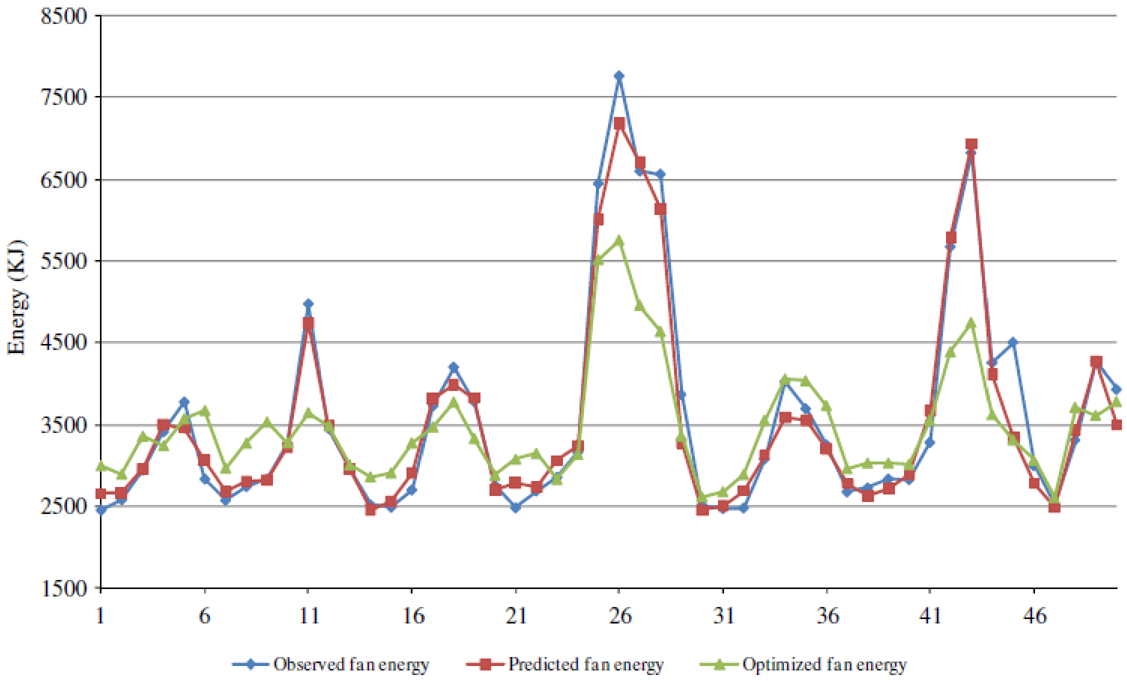

Fig. 11. The fan energy before and after optimization.

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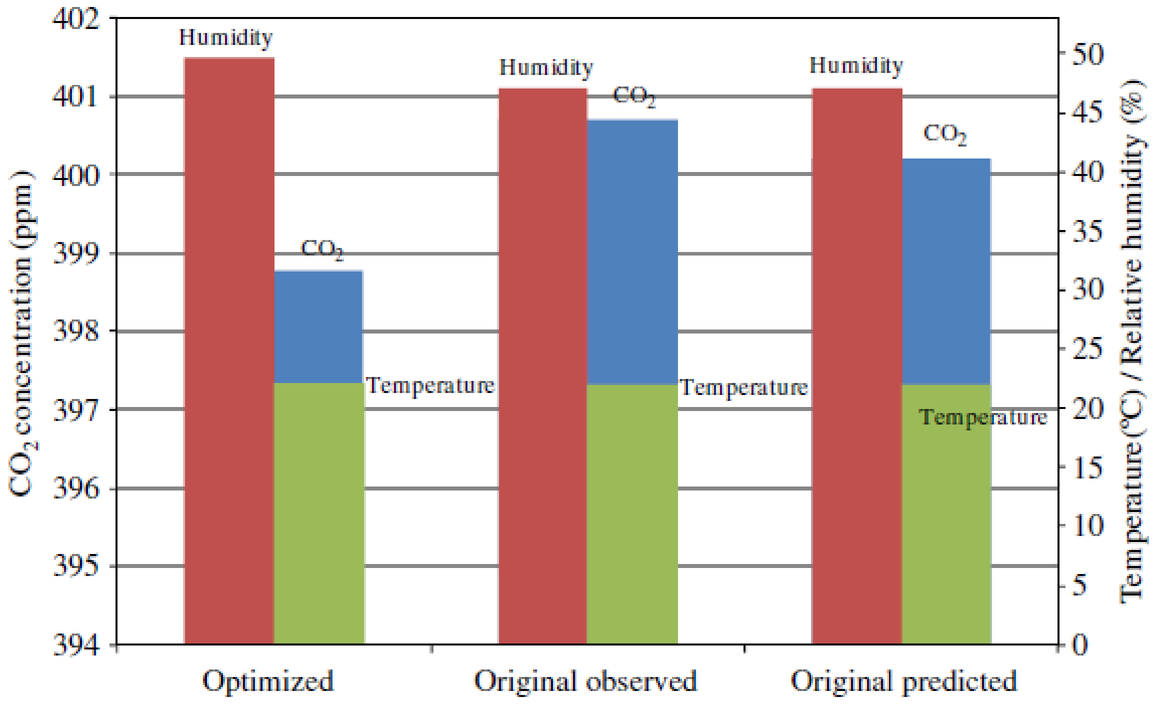

Fig. 16. Comparison of the IAQ metrics before and after optimization.

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Chilling Process Physics

Chiller part load ratio: $PLR = Q_{chl}/Q_{chr}$ (1)

Power and chiller part load: $kW = a + bPLR + cPLR^2 + dPLR^3$ (2)

Cooling load: $Q_{chl} = C_{pw} m_w (T_{chwr} - T_{chws})$ (3)

Data-driven approximation: $y_1(t) = f_1\left([y_1(t-d)]_{d \in D_y}, [x(t-d)]_{d \in D_x}, [v(t-d)]_{d \in D_v}\right)$ (5)

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Optimization Model

$$
\begin{aligned}
&\min\ y_1 \\
&y_1(t) = f_1([y_1(t-d)]_{d \in D_y}, [x(t-d)]_{d \in D_x}, [v(t-d)]_{d \in D_v}) \\
&y_2(t) = f_2([y_2(t-d)]_{d \in D_y}, [x(t-d)]_{d \in D_x}, [v(t-d)]_{d \in D_v}) \\
&y_3(t) = f_3([y_3(t-d)]_{d \in D_y}, [x(t-d)]_{d \in D_x}, [v(t-d)]_{d \in D_v}) \\
&\text{subject to :} \\
&x_i \in S_{x_i} \quad i \text{ is the number of controllable vectors} \\
&y_j \in S_{y_j} \quad j = 2, 3
\end{aligned}
\tag{6}
$$

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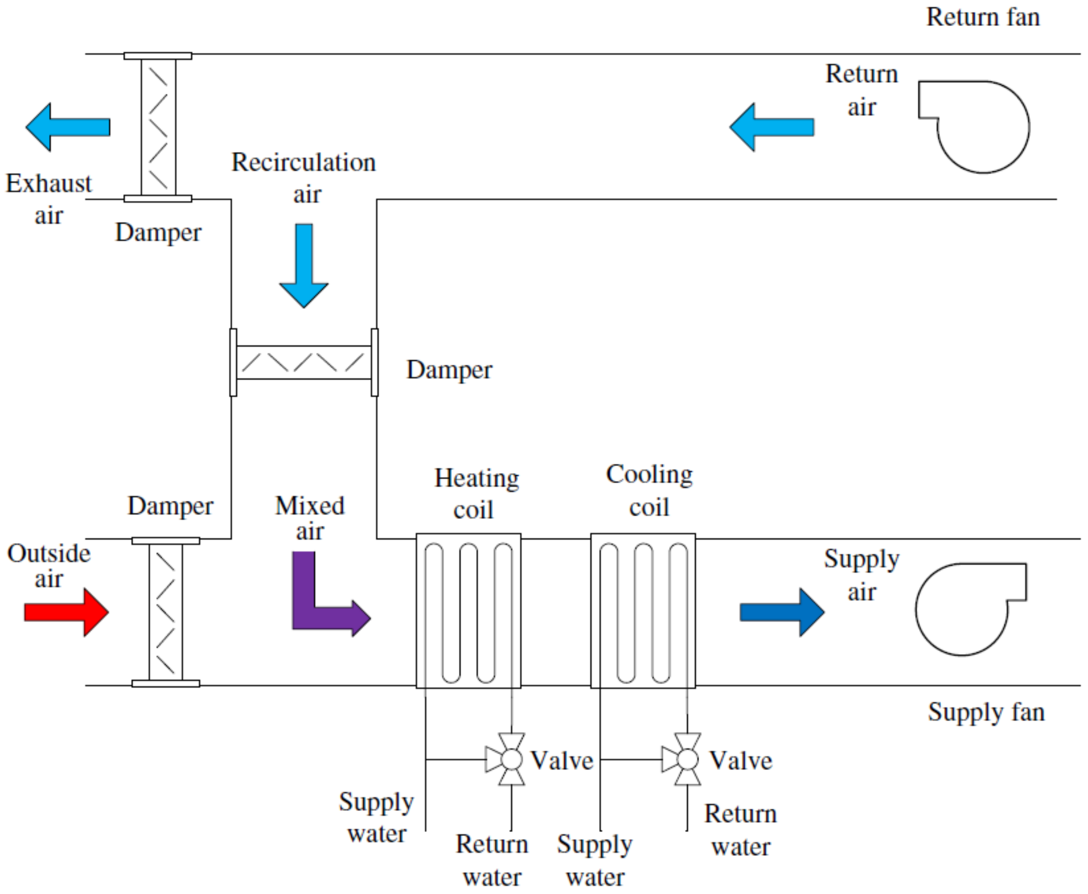

Fig. 1. Schematic diagram of the AHU.

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Feature selection

Table 1
Variables selected for building model (6) at t time stamp.

Variable	Point name	Description	Unit
$x_1(t)$	CHWC-VLV	Chilled water coil valve position at time t	% Open
$x_1(t-4)$	CHWC-VLV	Chilled water coil valve position at time $t-4$	% Open
$x_2(t)$	SF-SPD	Supply fan VFD speed at time t	% Spd
$v_1(t-4)$	CHWC-EWT	Chilled water coil entering water temperature at time $t-4$	°C
$v_2(t-3)$	OAD-TEMP	OA duct temperature at time $t-3$	°C

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Data-driven Models

Cooling output

$$y_1(t) = f(y_1(t-1), y_1(t-2), y_1(t-3), y_1(t-4), x_1(t), x_2(t), x_1(t-4), v_1(t-4), v_2(t-3)) \quad (7)$$

Supply air temperature

$$y_2(t) = f(y_2(t-1), y_2(t-2), y_2(t-3), y_2(t-4), x_1(t), x_2(t), x_1(t-4), v_1(t-4), v_2(t-3)) \quad (11)$$

Supply air humidity

$$y_3(t) = f(y_3(t-1), y_3(t-2), y_3(t-3), y_3(t-4), x_1(t), x_2(t), x_1(t-4), v_1(t-4), v_2(t-3)) \quad (12)$$

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Model selection

Table 2
Prediction accuracy of cooling output models built by four different data mining algorithms.

Cooling output					
	MAE	Std	MRE (%)	Max	Min
MLP NN	0.1841	0.1666	0.20	1.5686	0.0008
Random forest	0.2018	0.1770	0.22	1.3473	0.0001
Boosting tree	0.2475	0.2280	0.27	1.5004	0.0004
SVM	0.1938	0.1532	0.22	0.7682	0.0002

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Model accuracy visualization

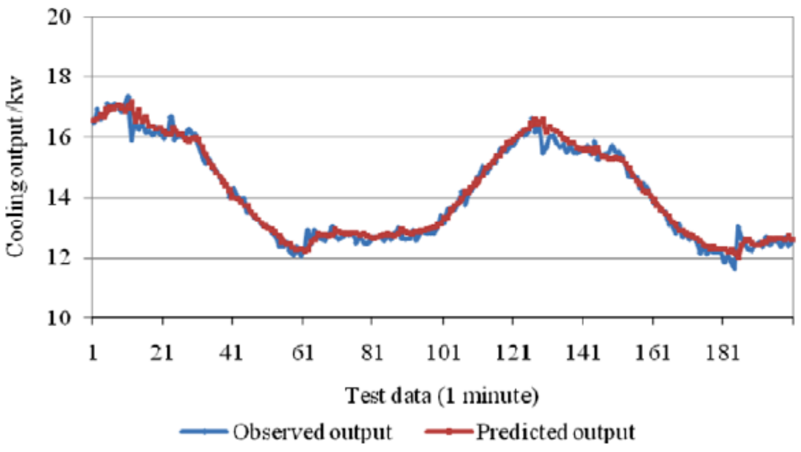

Fig. 2. Validation of the cooling output model with 200 test points.

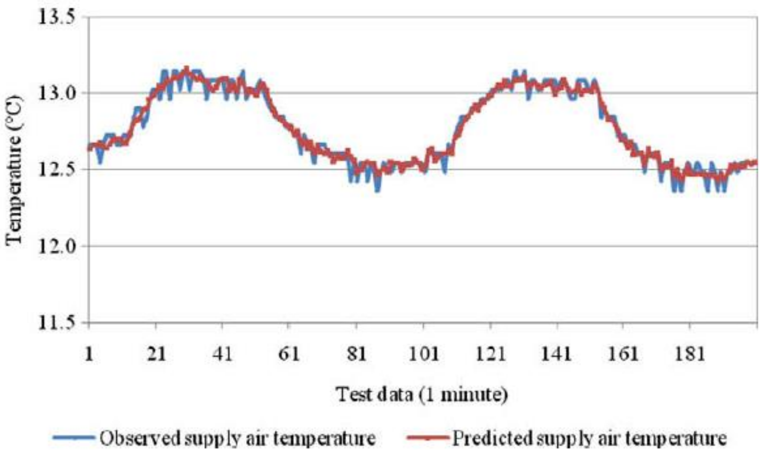

Fig. 3. Validation of the supply air temperature model with 200 test points.

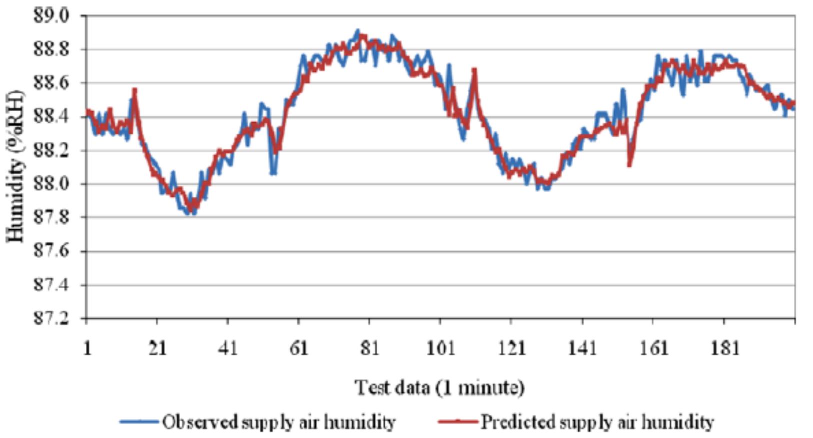

Fig. 4. Validation of the supply air humidity model with 200 test points.

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Data-driven Optimization Model

$$\begin{aligned}
&\min_{x_1(t),x_2(t)}(y_1(t))\\
&\text{subject to:}\\
&y_1(t) = f(y_1(t-1), y_1(t-2), y_1(t-3), y_1(t-4),\\
&\qquad x_1(t), x_2(t), x_1(t-4), v_1(t-4), v_2(t-3))\\
&y_2(t) = f(y_2(t-1), y_2(t-2), y_2(t-3), y_2(t-4),\\
&\qquad x_1(t), x_2(t), x_1(t-4), v_1(t-4), v_2(t-3))\\
&y_3(t) = f(y_3(t-1), y_3(t-2), y_3(t-3), y_3(t-4),\\
&\qquad x_1(t), x_2(t), x_1(t-4), v_1(t-4), v_2(t-3))\\
&12.2 \le y_2(t) \le 13.3\\
&87 \le y_3(t) \le 90\\
&50 \le x_1(t) \le 90\\
&70 \le x_2(t) \le 75
\end{aligned} \tag{13}$$

$$\begin{aligned}
&\max\{0, 12.2 - y_2(t)\} + \max\{0, y_2(t) - 13.3\}\\
&\quad + \max\{0, 70 - y_3(t)\} + \max\{0, y_3(t) - 90\}
\end{aligned} \tag{14}$$

$$\begin{aligned}
&\min_{x_1(t),x_2(t)}(obj_1, obj_2)\\
&\text{subject to:}\\
&y_1(t) = f(y_1(t-1), y_1(t-2), y_1(t-3), y_1(t-4),\\
&\qquad x_1(t), x_2(t), x_1(t-4), v_1(t-4), v_2(t-3))\\
&y_2(t) = f(y_2(t-1), y_2(t-2), y_2(t-3), y_2(t-4),\\
&\qquad x_1(t), x_2(t), x_1(t-4), v_1(t-4), v_2(t-3))\\
&y_3(t) = f(y_3(t-1), y_3(t-2), y_3(t-3), y_3(t-4),\\
&\qquad x_1(t), x_2(t), x_1(t-4), v_1(t-4), v_2(t-3))\\
&50 \le x_1(t) \le 90\\
&70 \le x_2(t) \le 75
\end{aligned} \tag{15}$$

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Optimization Results

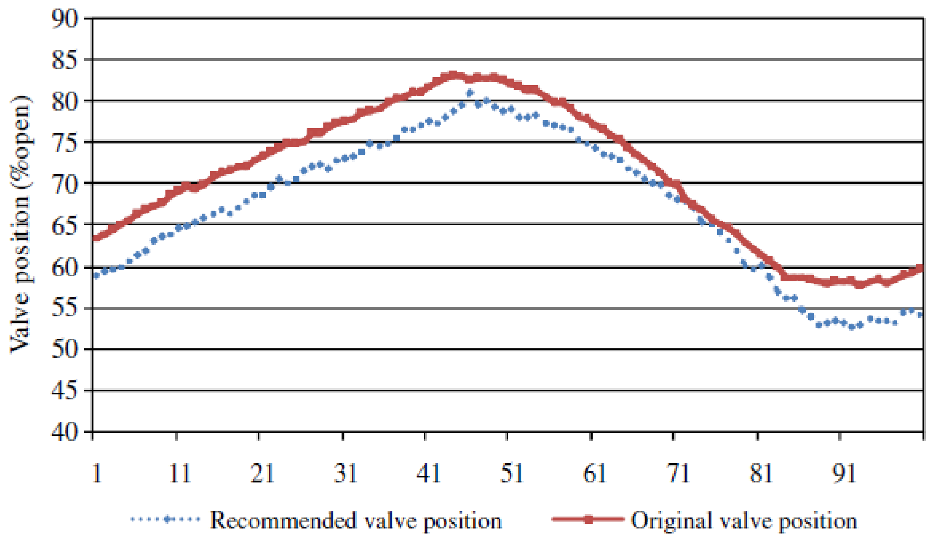


Fig. 13. The first 100 points of the recommended valve position.

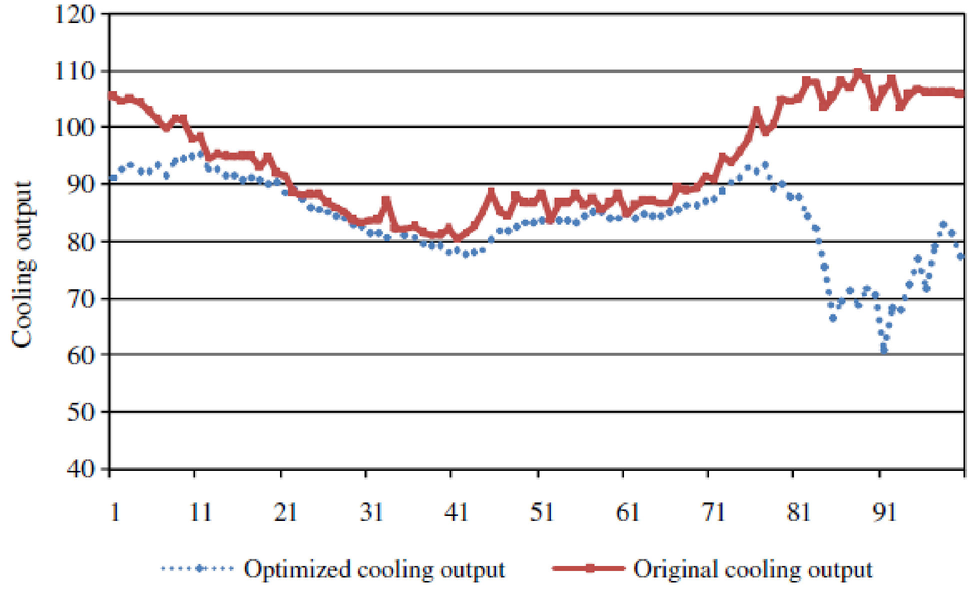


Fig. 12. The first 100 points of the optimized cooling output.

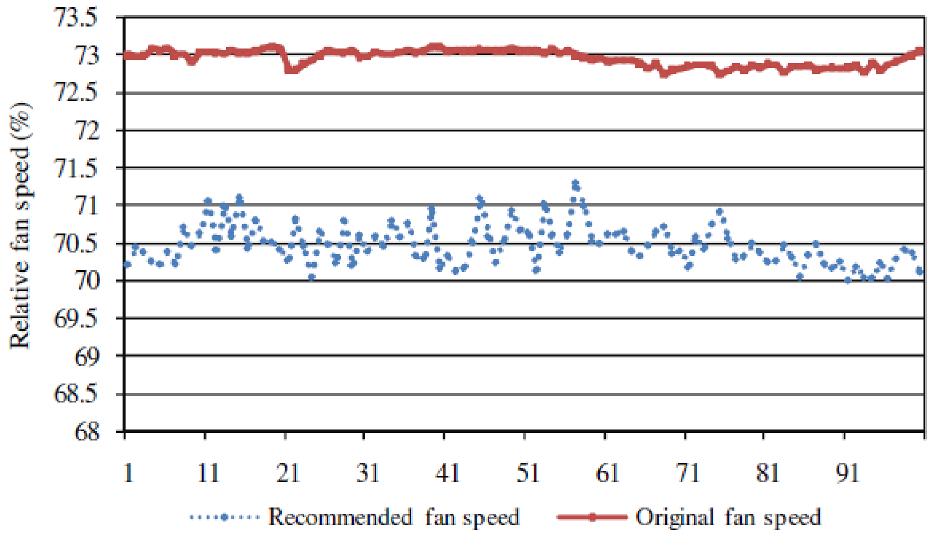


Fig. 14. The first 100 points of the recommended supply air relative fan speed.

The HVAC Research 2

Optimization Results

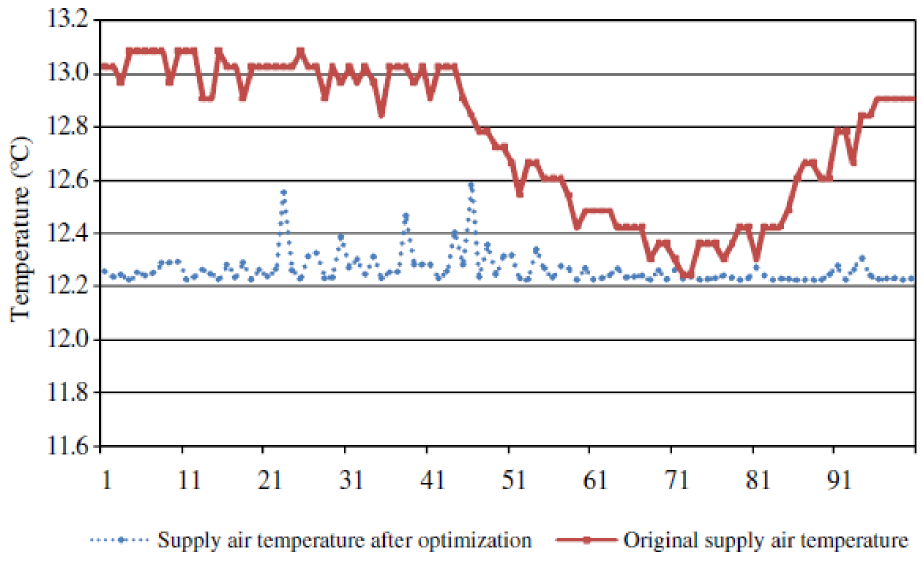


Fig. 15. The first 100 points of the measured and optimized supply air temperature.

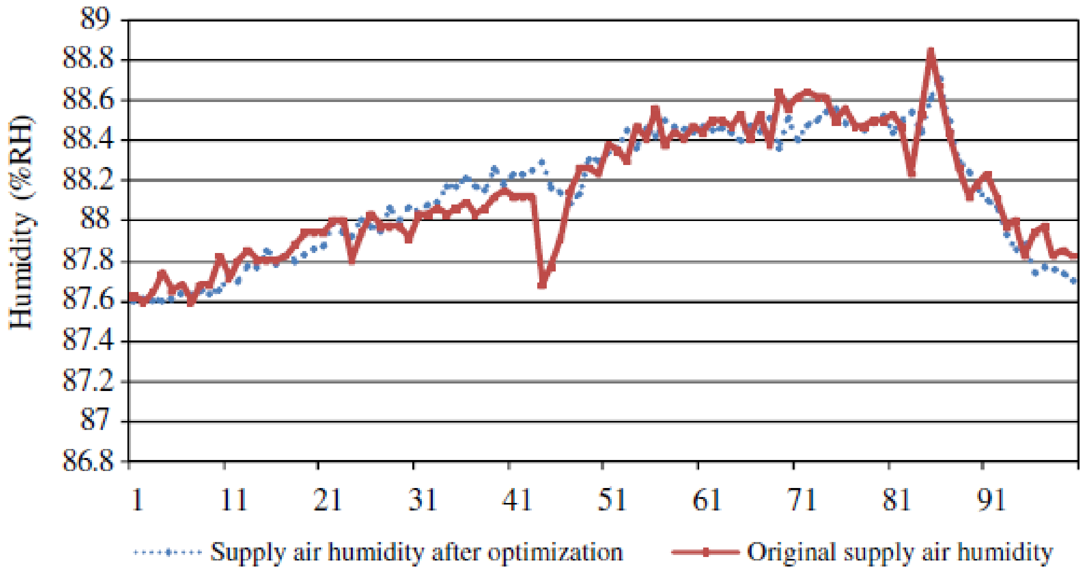


Fig. 16. The first 100 points of the measured and optimized supply air humidity.

The HVAC Research 3

Steam Load Modeling

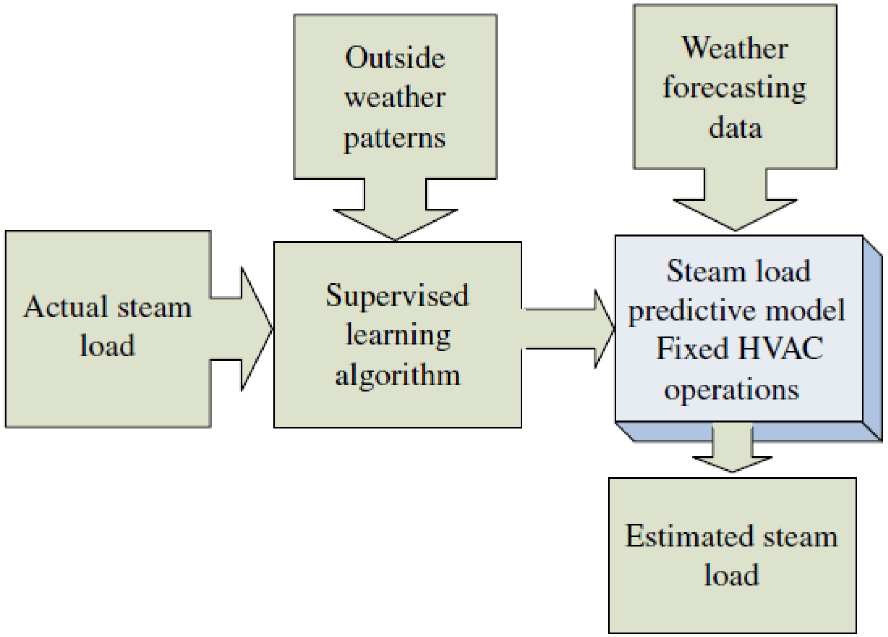


Fig. 1. Modeling process.

The HVAC Research 3

Data description

Table 1
Data set description.

Data set	Time period	Description
Training data set	1/1/2004–12/31/2005	722 Observations; used for parameter selection, algorithm selection, and data split
Validation data set	1/1/2006–12/31/2006	357 Observations; used for parameter selection, validation of the algorithm, and data split
Test data set	1/1/2007–12/31/2007	364 Observations; used to test models

The HVAC Research 3

Feature extraction

Table 2
Descriptions of transformed parameters.

Transformed Parameter	Description	Unit
Total_day	Total steam load per day	klbs
Temp_mean	Mean value of the outside air temperature per day	°F
Temp_std	Standard deviation of the outside air temperature per day	°F
Temp_max	Maximum value of the outside air temperature per day	°F
Temp_min	Minimum value of the outside air temperature per day	°F
Humidity_mean	Mean value of the outside air humidity per day	RH
Humidity_std	Standard deviation of the outside air humidity per day	RH
Humidity_max	Maximum value of the outside air humidity per day	RH
Humidity_min	Minimum value of the outside air humidity per day	RH

The HVAC Research 3

Feature selection

Table 4
Predictor rank and importance produced by the boosting tree algorithm.

	Variable rank	Importance
Temp_mean	100	1.000000
Temp_max	85	0.852059
Temp_min	68	0.678650
Humidity_mean	56	0.560133
Humidity_min	48	0.481238
Humidity_max	39	0.386233
Temp_std	37	0.372589
Humidity_std	35	0.347607

Table 3
Correlation coefficient values between different parameters.

Parameters	Temp_mean Total_day	Temp_std Total_day	Temp_max Total_day	Temp_min Total_day	Humidity_mean Total_day	Humidity_std Total_day
Correlation coefficient	−0.3906	−0.1789	−0.3928	−0.1458	0.162	−0.2228
Parameters	Humidity_max Total_day	Humidity_min Total_day	Temp_std Temp_mean	Temp_max Temp_mean	Temp_min Temp_mean	Humidity_mean Temp_mean
Correlation coefficient	−0.0034	0.2067	0.2772	0.9188	0.4702	−0.1008
Parameters	Humidity_std Temp_mean	Humidity_max Temp_mean	Humidity_min Temp_mean	Temp_max Temp_std	Temp_min Temp_std	Humidity_mean Temp_std
Correlation coefficient	0.2821	0.0931	−0.2097	0.5584	−0.5739	−0.439
Parameters	Humidity_std Temp_std	Humidity_max Temp_std	Humidity_min Temp_std	Temp_min Temp_max	Humidity_mean Temp_Temp_max	Humidity_std Temp_max
Correlation coefficient	0.4232	−0.222	−0.4808	0.2409	−0.1988	0.3696
Parameters	Humidity_max Temp_max	Humidity_min Temp_max	Humidity_mean Temp_min	Humidity_std Temp_min	Humidity_max Temp_min	Humidity_min Temp_min
Correlation coefficient	0.0401	−0.3149	0.315	−0.1433	0.2977	0.2627
Parameters	Humidity_std Humidity_mean	Humidity_max Humidity_mean	Humidity_min Humidity_mean	Humidity_max Humidity_std	Humidity_min Humidity_std	Humidity_min Humidity_max
Correlation coefficient	−0.5734	0.7742	0.9187	−0.0072	−0.8027	0.554

The HVAC Research 3

Feature selection

Table 6
Four scenarios of parameter selection.

Scenario	Selected parameters	Description
1	Temp_mean, Humidity_min	Based on selection procedure in Section 3.1
2	Temp_mean, Temp_std, Temp_max, Temp_min, Humidity_mean, Humidity_std, Humidity_max, Humidity_Humidity_min	All eight temperature and humidity inputs
3	Temp_Temp_max, Temp_mean, Humidity_std, Humidity_min	Based on correlation coefficient of Table 3
4	Temp_mean, Temp_max, Temp_min, Humidity_mean, Humidity_min	Based on the boosting tree algorithm

The HVAC Research 3

Model selection

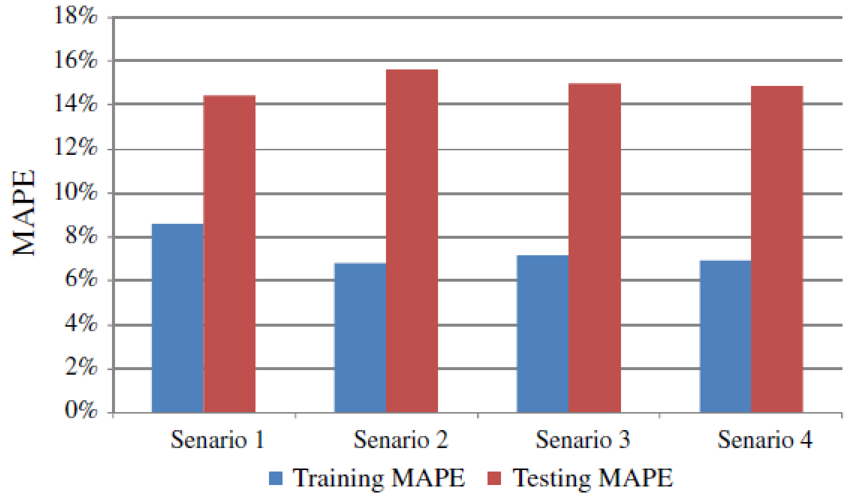


Fig. 2. MAPEs for the four parameter selection scenarios of Table 6.

Table 5
Training and testing accuracy results for models extracted with different data-mining algorithms.

Data Set	Algorithm	MAE	Std_AE	MAPE (%)	Std_APE (%)
Training 2004–2005	CART	133.2204	165.6246	3.30	4.49
Testing 2006	CART	649.1558	530.2855	18.15	16.71
Training 2004–2005	CHAID	405.3211	352.1727	9.90	10.24
Testing 2006	CHAID	577.5735	440.2995	16.20	13.70
Training 2004–2005	Exhaustive CHAID	398.4697	347.7473	9.71	10.12
Testing 2006	Exhaustive CHAID	569.5217	434.9203	15.87	13.28
Training 2004–2005	Boosting tree regression	365.7726	334.6696	9.18	10.34
Testing 2006	Boosting tree regression	540.3095	408.6700	15.18	12.88
Training 2004–2005	Random forest	360.6245	319.8897	9.05	10.14
Testing 2006	Random forest	561.6843	407.1481	15.99	13.38
Training 2004–2005	MARSplines	344.1872	345.7752	8.75	10.77
Testing 2006	MARSplines	512.4989	413.0148	14.47	12.98
Training 2004–2005	SVM	439.9067	353.3947	11.35	12.18
Testing 2006	SVM	648.5277	431.8684	18.56	14.67
Training 2004–2005	MLP	340.5511	341.5077	8.65	10.57
Testing 2006	MLP	512.6047	414.7041	14.53	13.14
Training 2004–2005	MLP ensemble	338.7780	340.8402	8.60	10.52
Testing 2006	MLP ensemble	510.1599	412.7694	14.44	13.06
Training 2004–2005	*k*-NN	299.6001	311.2201	7.57	9.36
Testing 2006	*k*-NN	548.8362	423.5867	15.29	13.18

The HVAC Research 3

Model pool

Table 11
Test results for each month of 2007.

Month	MAE	Std of MAE	MAPE (%)	Std of MAPE (%)
January	229.6125	127.6796	4.07	2.08
February	470.6864	218.3952	7.39	2.61
March	376.4847	202.0408	10.71	8.11
April	729.2874	547.4329	17.10	10.23
May	591.0668	497.8888	17.64	16.10
June	640.7030	417.8491	16.19	10.48
July	692.3318	104.5319	17.82	3.21
August	717.4539	144.6213	18.61	4.55
September	1030.7757	439.0330	31.74	17.99
October	297.9699	253.0848	10.31	11.81
November	1319.8354	562.1025	52.62	26.18
December	356.0059	111.7109	6.15	1.79

Table 10
Descriptions of the four MLP ensemble models.

Model	NN structure	Activation function at hidden layer	Activation function at output layer
1	MLP 2-8-1	Logistic function	Sine function
	MLP 2-7-1 (3)	Hyperbolic tangent function	Sine function
	MLP 2-9-1	Logistic function	Sine function
2	MLP 2-7-1 (3)	Hyperbolic tangent function	Sine function
	MLP 2-8-1 (2)	Logistic function	Identity function
3	MLP 2-4-1	Exponential function	Logistic function
	MLP 2-4-1	Exponential function	Identity function
	MLP 2-6-1	Exponential function	Sine function
	MLP 2-6-1	Exponential function	Identity function
	MLP 2-8-1	Exponential function	Logistic function
4	MLP 2-7-1 (3)	Hyperbolic tangent function	Sine function
	MLP 2-4-1	Logistic function	Hyperbolic tangent function
	MLP 2-8-1	Hyperbolic tangent function	Sine function

The HVAC Research 3

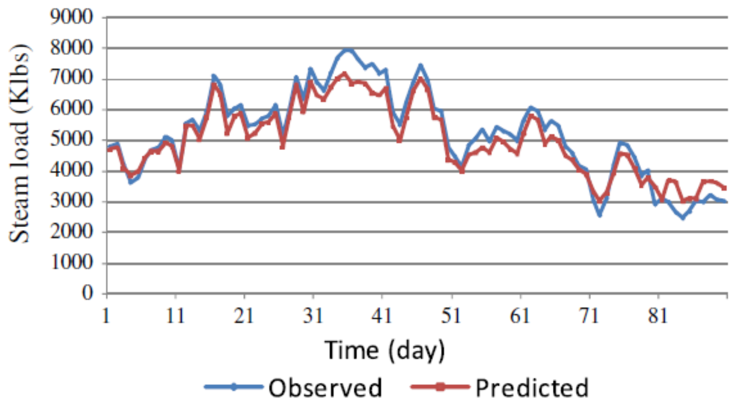


Fig. 8. Test results of January, February, and March of 2007.

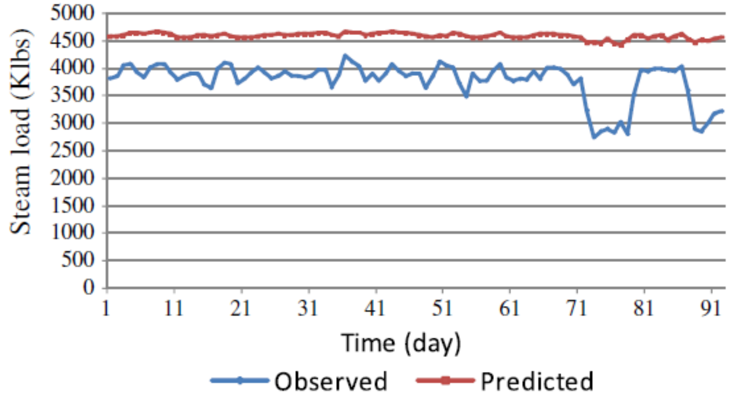


Fig. 10. Test results of July, August, and September of 2007.

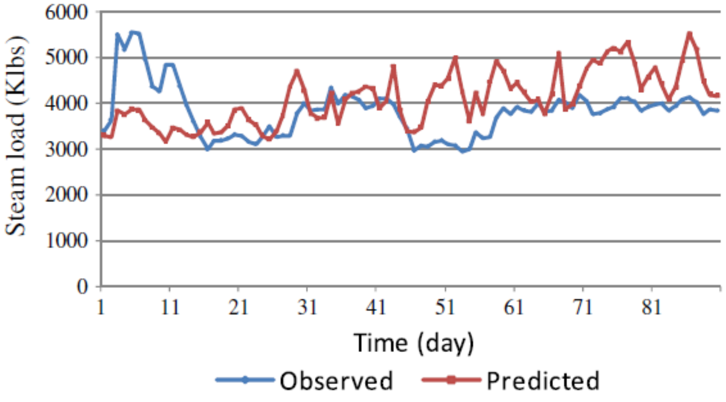


Fig. 9. Test results of April, May, and June of 2007.

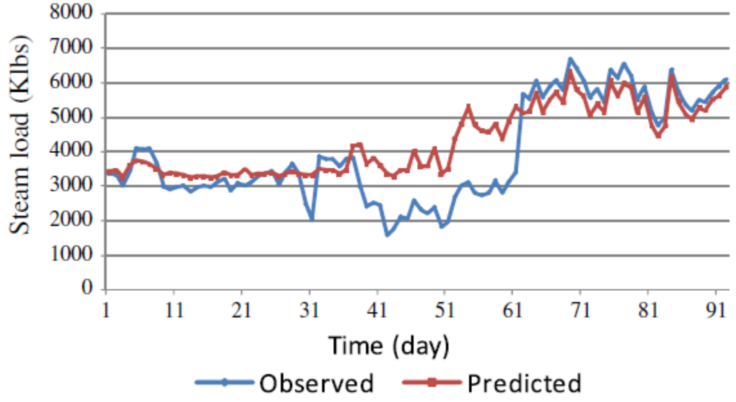


Fig. 11. Test results of October, November, and December of 2007.

The HVAC Research 4

Modeling and Optimization Chiller Plant

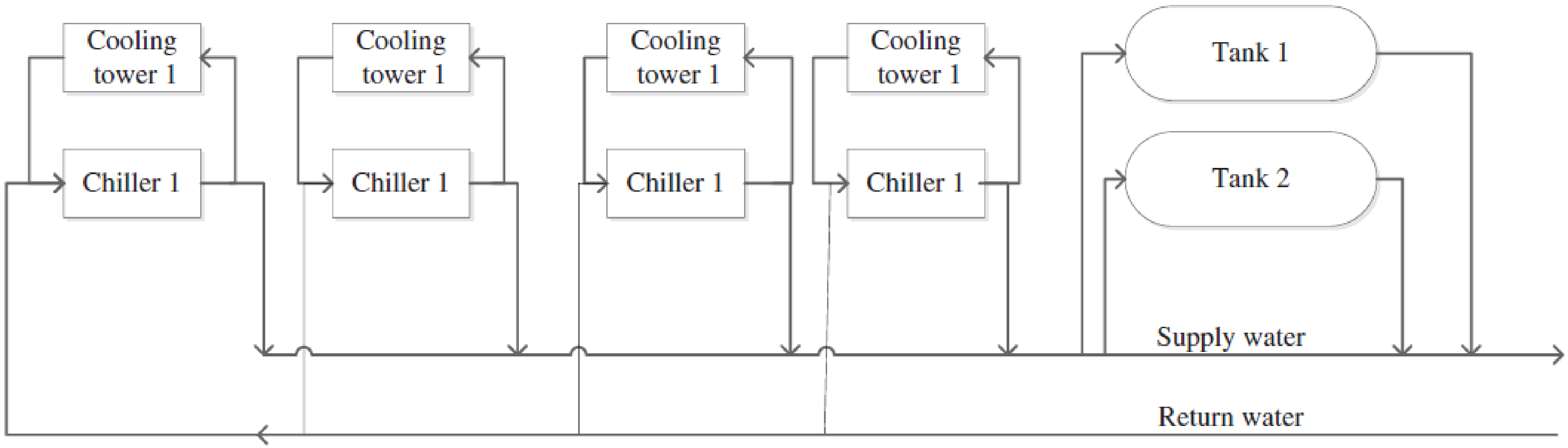


Fig. 1. Schematic diagram of a typical chiller plant.

The HVAC Research 4

External and internal impact

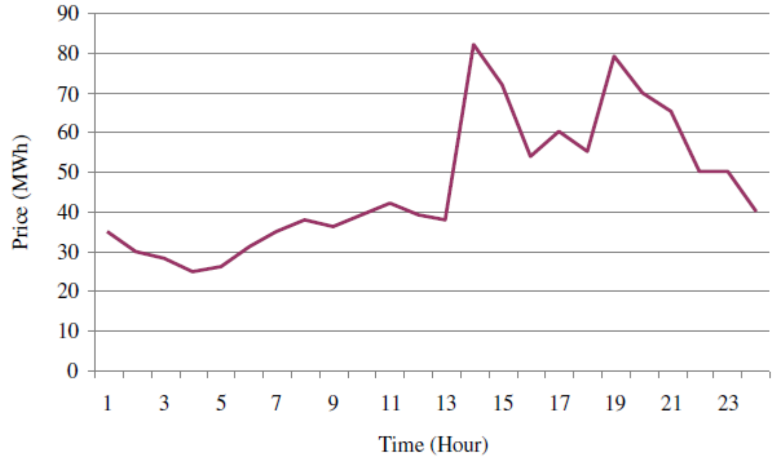


Fig. 2. The fluctuated hourly electricity price in a typical day.

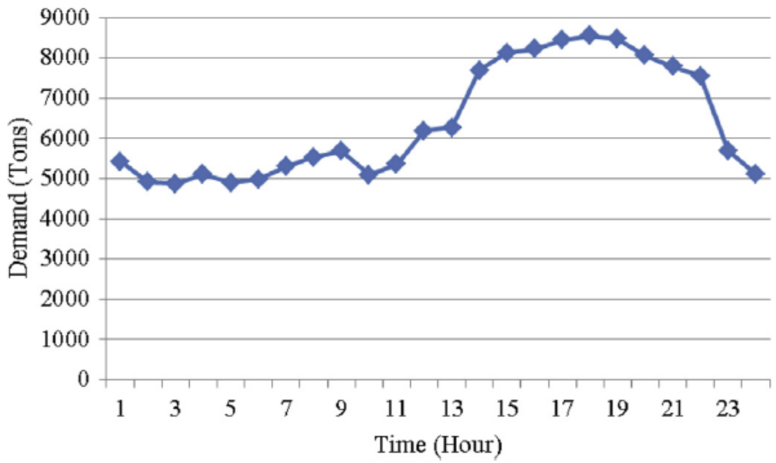


Fig. 3. The demand of cooling load in a typical day.

The HVAC Research 4

Plant operational cost

$$P_{\text{total}} = \sum_{t=0}^{T}\left(p_t \sum_{i=1}^{N} u_{it} \cdot x_{it}\right) \qquad u_{it} = f_i(q_{it}, \Delta t_{it}, h) \quad (i = 1, 2, 3, 4;\ \ t = 0, 1, \ldots, T) \qquad (3)$$

$$\Downarrow$$

$$P_{\text{total}} = \sum_{t=0}^{T}\left(p_t \sum_{i=1}^{N} f_i(q_{it}, \Delta t_{it}, h) \cdot x_{it}\right) \qquad (4)$$

The HVAC Research 4

Information description

Table 1
Nominal capacity of the four chillers.

Chiller No.	Nominal capacity
1	3000 tons
2	3000 tons
3	2577 tons
4	2577 tons

Table 2
Data parameters from the chiller plant.

No.	Parameter name	Description
1	chw_tons_1	Cooling produced by chiller 1
2	chw_tons_2	Cooling produced by chiller 2
3	chw_tons_3	Cooling produced by chiller 3
4	chw_tons_4	Cooling produced by chiller 4
5	chr_kw_1	Power of chiller 1
6	chr_kw_2	Power of chiller 2
7	chr_kw_3	Power of chiller 3
8	chr_kw_4	Power of chiller 4
9	temp_diff_1	Temperature difference of condensing water of chiller 1
10	temp_diff_2	Temperature difference of condensing water of chiller 2
11	temp_diff_3	Temperature difference of condensing water of chiller 3
12	temp_diff_4	Temperature difference of condensing water of chiller 4
13	enthalpy	Enthalpy of ambient air of this research

The HVAC Research 4

Feature selection

Table 4
Parameters selected for building energy consumption model of units 1–4.

Input	Parameter name
q_1	chw_tons_1
Δt_1	temp_diff_1
q_1	chw_tons_2
Δt_1	temp_diff_2
q_1	chw_tons_3
Δt_1	temp_diff_3
q_1	chw_tons_4
Δt_1	temp_diff_4
h	enthalpy

The HVAC Research 4

Data-driven model performance

Table 5
Performance of the models predicting the energy consumption of the four units.

Objective	Data Set	MAE	MAPE	Std_AE	Std_MAPE
Unit 1	Training	30.18	1.77%	25.17	1.49%
	Validation	29.84	1.74%	24.73	1.46%
	Test	31.41	1.84%	25.79	1.53%
Unit 2	Training	25.01	1.49%	22.42	1.38%
	Validation	24.82	1.48%	24.17	1.50%
	Test	23.51	1.39%	21.54	1.29%
Unit 3	Training	52.15	2.92%	60.78	3.74%
	Validation	76.01	4.30%	79.59	4.82%
	Test	62.12	3.45%	74.25	4.43%
Unit 4	Training	23.29	2.33%	22.30	2.39%
	Validation	22.07	2.31%	29.73	3.27%
	Test	20.90	2.15%	18.99	2.29%

The HVAC Research 4

Optimization model formulation

$$\min \; P_{total}$$
$$\text{subject to :}$$
$$\mathrm{P_{total}} = \sum_{t=0}^{T} p_t \sum_{i=1}^{N} u_{it} \cdot x_{it}$$
$$\mathrm{u_{it}} = f_i(q_{it}, \Delta t_{it}, h)$$
$$\gamma \mathrm{Q_i} \le q_{it} \le Q_i$$
$$\Delta t_{\min} \le \Delta t_{it} \le \Delta t_{\max}$$
$$\mathrm{S_{t-1}} + \sum_{\mathrm{i=1}}^{\mathrm{N}} x_{it} u_{it} \ge D_t$$
$$S_{t-1} + \sum_{\mathrm{i=1}}^{\mathrm{N}} x_{it} u_{it} - D_t \le C$$
$$S_0 = S_T = 0$$
$$\mathrm{x_{it}} \in \{0, 1\}$$

The HVAC Research 4

Optimization procedure

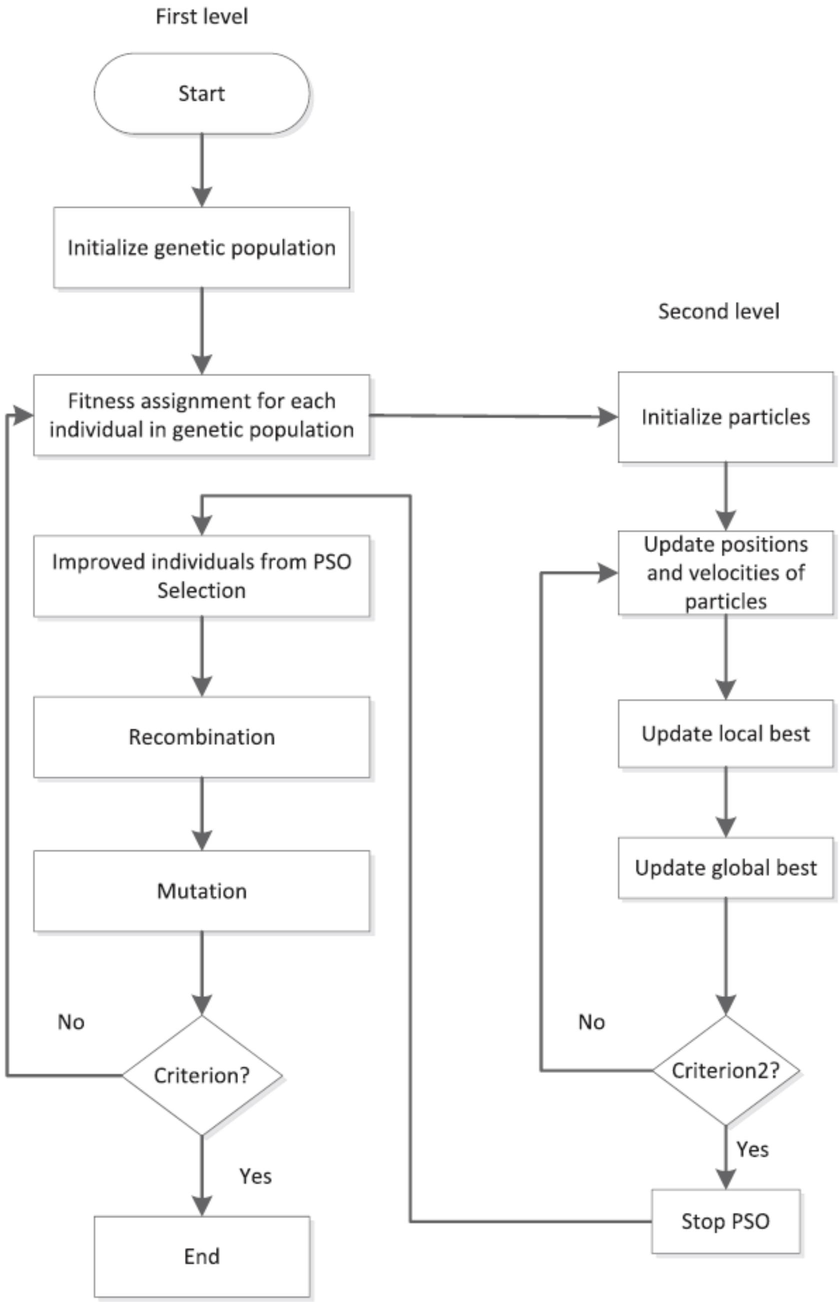


Fig. 4. . the flow chart of the two-level intelligent algorithm.

The HVAC Research 4

Visualization

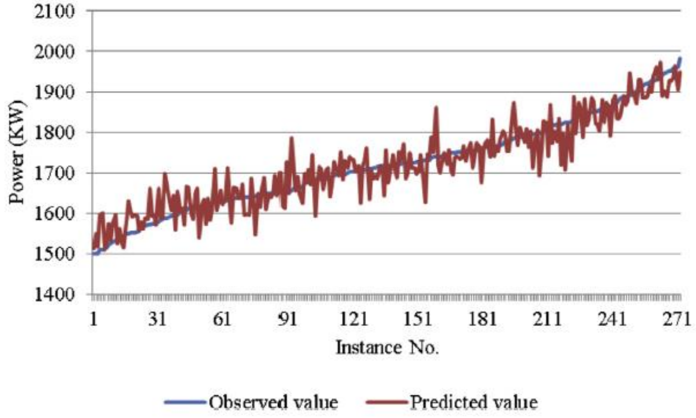


Fig. 5. Observed and predicted values of the energy consumption of unit 1.

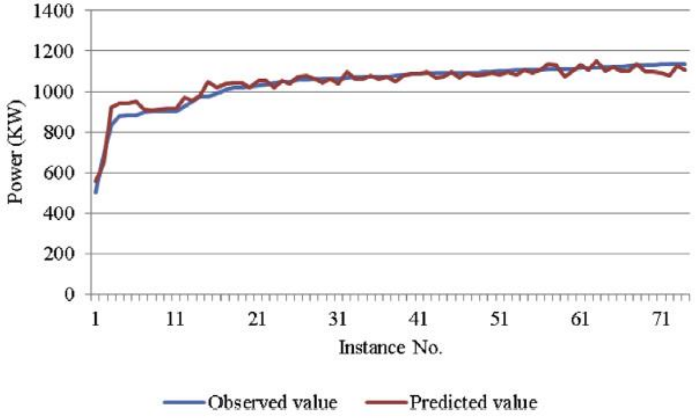


Fig. 8. Observed and predicted values of the energy consumption of unit 4.

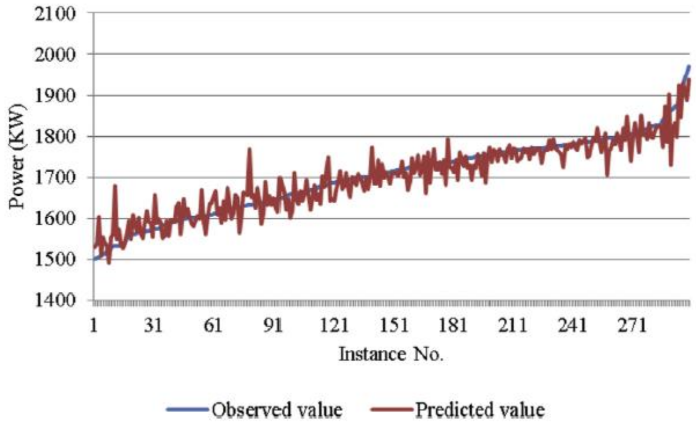


Fig. 6. Observed and predicted values of the energy consumption of unit 2.

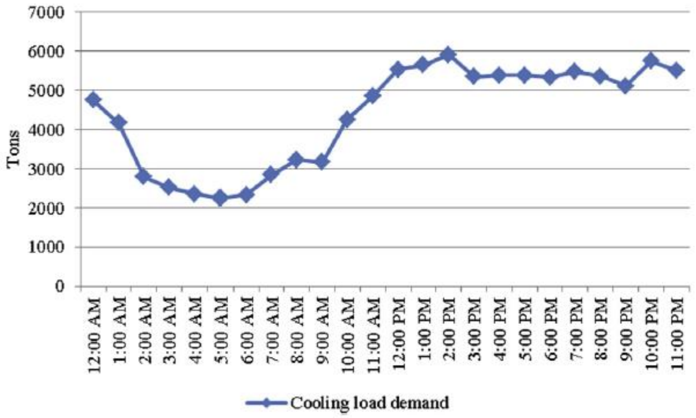
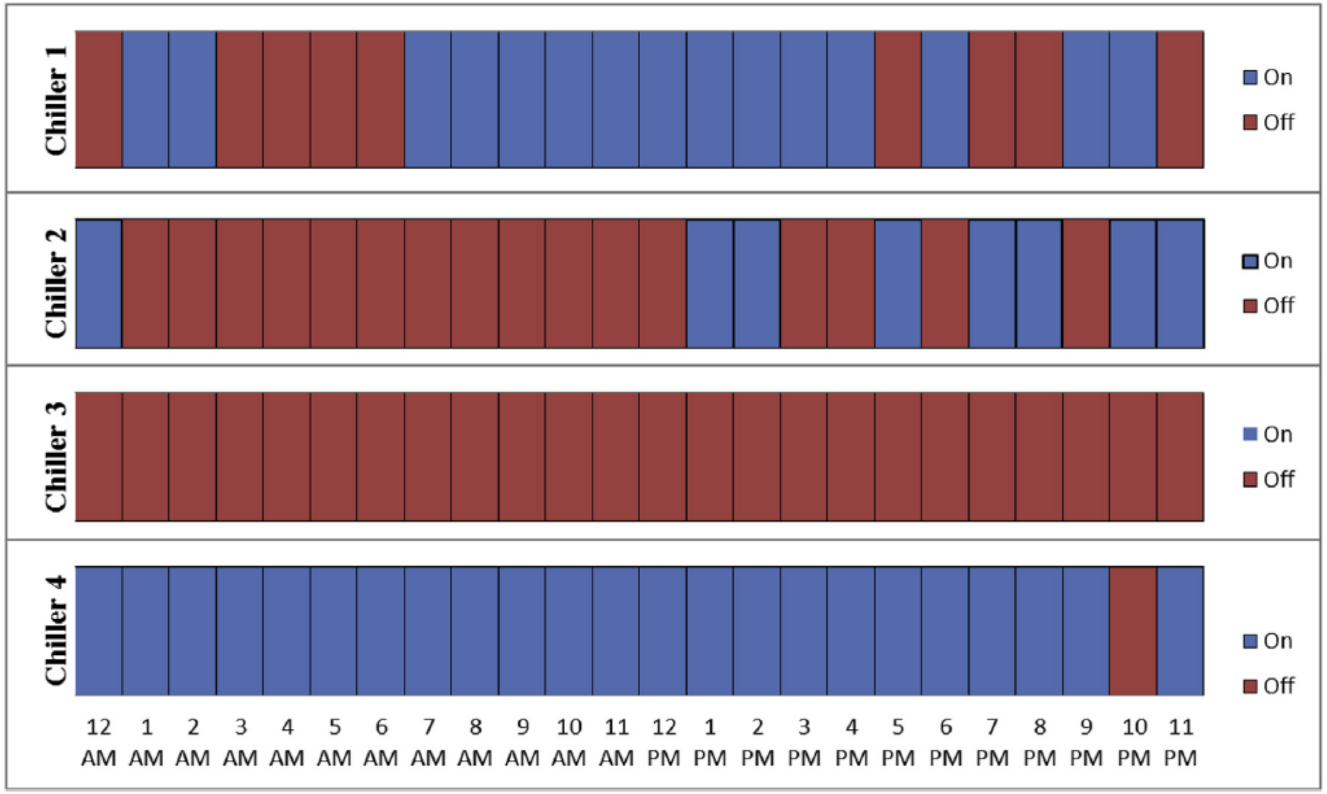


Fig. 9. The cooling load demand on June 1, 2011.

The HVAC Research 4

Optimized schedule



The HVAC Research 4

Table 7
The recommended cooling load (optimal chilled water flow) for four chillers on July 16, 2011.

Time	Recommended cooling for chiller 1 (Tons)	Recommended cooling for chiller 2 (Tons)	Recommended cooling for chiller 3 (Tons)	Recommended cooling for chiller 4 (Tons)
12:00 AM	0	2995	0	1921
1:00 AM	2762	0	0	2579
2:00 AM	0	2645	0	2579
3:00 AM	0	2624	0	2501
4:00 AM	2597	0	0	2457
5:00 AM	2603	0	0	2432
6:00 AM	2627	0	0	2522
7:00 AM	2997	0	0	2578
8:00 AM	2990	2997	0	0
9:00 AM	1589	2996	0	1593
10:00 AM	1540	2986	0	1674
11:00 AM	2642	2720	0	2352
12:00 PM	1505	2940	1487	2578
1:00 PM	2999	2999	0	2578
2:00 PM	1568	2937	1797	2564
3:00 PM	1501	2879	2555	2578
4:00 PM	2905	2972	1814	2570
5:00 PM	2995	2999	1719	2577
6:00 PM	2979	2985	1703	2550
7:00 PM	2954	2947	1674	2580
8:00 PM	2921	2985	1363	2558
9:00 PM	1529	2943	2535	2575
10:00 PM	1990	2968	0	2556
11:00 PM	2984	2997	0	1460

(Note: the value zero indicates the corresponding chiller is turned off).

The HVAC Research 4

Power saving

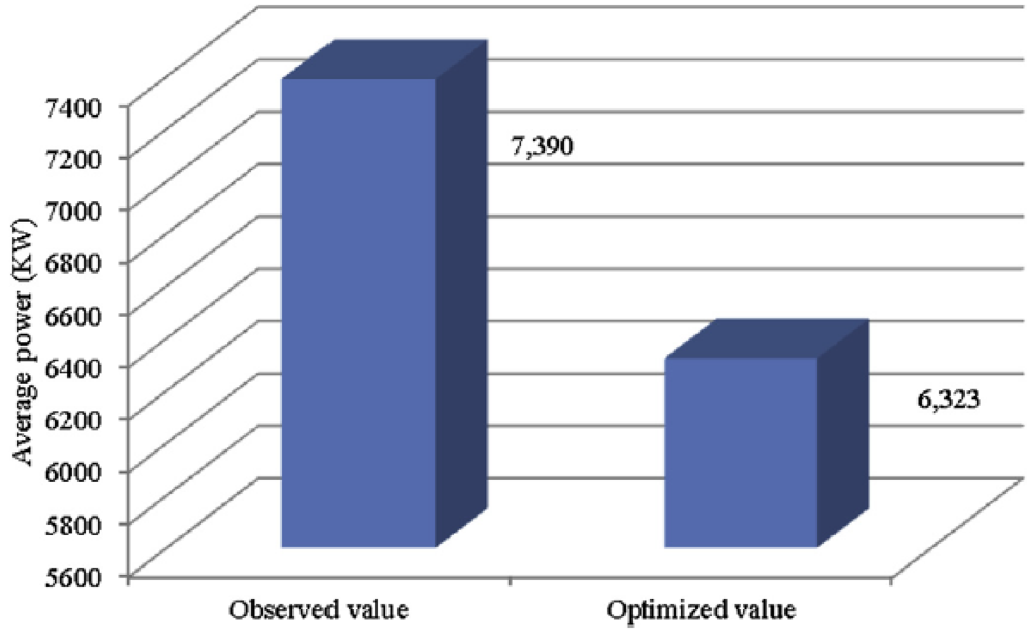


Fig. 19. The observed and optimized average power of the chiller plant of the two days.

The HVAC Research Real Implementation

What else for the real implementation of big data and AI techniques for HVAC

- Energy Internet and Energy System Integration
- Smart Meters
- Cloud computational services
- Real time responses of the HVAC system operation for energy saving
- Interactions with the power grid