Utilisation of Machine Learning in Control Systems Based on the Preference of Office Users

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List of symbols

↓	Decrease
↑	Increase
ANN	Artificial neural network
C-SVC	C-support vector classifier
DT	Decision Tree
KF	Kalman filter
GNB	Gaussian naive Bayes
KNN	k-Nearest neighbours
LR	Linear regression
LogR	Logistic regression
MLP	Multilayer perceptron
RF	Random forest

RHin	Inside relative humidity
RHout	Outside relative humidity
Tin	Inside temperature
Tout	Outside temperature
Ts	Skin temperature

Table S1. Synthesis of the main characteristics of occupant-centred systems based on users' preference.

Reference	Scope	Duration of the study	Identification of preferences	Algorithm(s)[1]	Variables	System assessment	Algorithm assessment (best case)	Comfort assessment	Energy savings
[1]	Control of lighting and shading systems through simulation	1 year	User-system interaction	KF	Attendance, illuminance, tin, time, feedback on light and shading	Number of interactions and energy savings	-	Interactions ↓ 80.0–85.0%	13.6–35.0%
[2]	Control of the lighting system	6 weeks	User-system interaction	Dynamic statistical analysis	Attendance, illuminance, switch position, time	Energy savings		-	23.2–73.2%
[3]	Control of the lighting system	12 weeks	User-system interaction	Dynamic statistical analysis	Attendance, illuminance, switch position, time	Number of interactions and users' satisfaction	-	18.1% of contested actions, in average + qualitative assessment	-

[1] For those papers that compared the algorithms' performance, the best result is in bold.

[4]	Control of the lighting system	10 days	Vote	Q-Learning	Illuminance, feedback on light	Users' satisfaction and energy savings	-	92.0% of acceptability	10%
[5]	Control of HVAC and lighting systems	1 year	Vote	Clustering	Tin, illuminance, attendance, feedback on light and temperature	Users' satisfaction and energy savings potential	-	78.0% of satisfaction	27–39.0%
[6]	Control of lighting and shading systems	1 year	User-system interaction	LogR	Switch position, shading position, attendance, illuminance, irradiance	Number of interactions	-	6.0% - 8.0% of contested actions	-
[7]	Control of the HVAC system	3 weeks	Vote	LogR, KNN, RF, SVM	Heart rate, Ts, tin, tout, RHin, RHout, CO2, openings status, illuminance, noise, feedback on set point temperature and preference	Accuracy	80.0%	-	-
[8]	Control of the HVAC system	1 year	User-system interaction	LogR	tin, tout, RHin, RHout, attendance, thermostat interaction	Number of interactions	-	Interactions ↓ ~87.0%	-

[9]	Control of the HVAC system	~ 3 months (summer)	Vote	ANN	Tin, CO2, RHin, light, air pressure and feedback on temperature	Energy savings and comfort	-	No change	20–40.0%
[10]	Control of the HVAC system through simulation	1 month (winter)	Vote	k-means	Attendance, feedback on temperature	Energy savings and comfort	-	70.8–73.6%	8.4–26.8%
[11]	Control of the HVAC system	5 months	User-system interaction	GNB, DT, C-SVC, MLP	Time, tin, tout, attendance, setpoint temperature	Accuracy and number of interactions	97.3%	Interactions ↓ aabout75%	4.0–25.0%
[12]	Control of the lighting system	2 months	User-system interaction	Q-Learning	Illuminance, switch position, attendance, time	LUR, UNC, LCR[2], user satisfaction	-	Qualitative assessment	-
[13]	Control of the HVAC system	6 days	Vote	LR	Tin, tout, RHin, RHout, Ts, heart rate, feedback on thermal satisfaction	Users' satisfaction and energy savings	-	Rate: 5.56/7.0	13.8%
[14]	Control of the HVAC system through simulation	3 weeks	Vote	ANN	Tin, RHin, pulse temperature, heart rate and feedback on thermal sensation	R^2, users' satisfaction and energy savings	0.89	↑ 85.0–100.0% of thermal sensation votes for comfort	↓ thermal load: 90.0% heating 30.0% cooling

[2] Light utilisation ratio, unmet comfort ratio, lights to comfort ratio

[15]	Control of the lighting system	1 day	Vote	ANN	Illuminance, attendance	Accuracy and users' satisfaction	88.5%	86.4% satisfaction	-
[16]	Control of the HVAC system through simulation	1 year	User-system interaction	Q-Learning	Attendance, tin, feedback on thermal sensation	Number of interactions	-	"too hot" feedback ↓ 40.0%	-
[17]	Control of HVAC, lighting and shading systems through simulation	3 years	User-system interaction	Dynamic statistical analysis, LogR	Attendance, illuminance, tin	Number of interactions and energy savings	-	Many scenarios	
[18]	Control of the HVAC system through simulation	10 days	User-system interaction	ANN	Tin, RHin, set point temperature	MAE[3], RMSE	0.5°C 0.6°C	-	-
[19]	Control of the HVAC system	9 days	Vote	LR	Tin, tout, RHin, RHout, CO2, Ts, heart rate, set point temperature, feedback on thermal sensation, satisfaction and RH	Users' satisfaction and energy saving	-	Rates: 5.2/7.0 and 5.3/7.0	10.0–20.0%

[3] *Mean absolute error*

[20]	Control of the HVAC system	4 months	User-system interaction	MLP	Tin, tout, RHin,, RHout, set point temperature	MSE[4]	0.28	-	
[21]	Control of the HVAC system	2 weeks	Vote	Branching dueling Q-network	Tin, tout, RHout, solar radiation, attendance, time, HVAC energy consumption, feedback on comfort	Users' satisfaction and energy savings	-	Acceptability ↑ 11.0%	13.9%
[22]	Control of the HVAC system	16 days	Vote	RF, SVM, DT, gradient boosting, ANN	Time, tin, RHin, heart rate, feedback on thermal sensation vote	Accuracy, users' satisfaction and energy savings	88.2%	Discomfort ↓ 33.0%	27.0%
[23]	Control of the HVAC system	21 days	Vote	Reinforcement learning-based	Tin, RHin, heart rate, Ts, feedback on thermal sensation	Users' satisfaction and energy savings	Optimisatio n	Discomfort ↓ 10.9%	No change
[24]	Control of the HVAC system	8 days	Vote	Multinomial LogR	Tin, tout, RHin,, irradiance, feedback on thermal preference	Users' satisfaction and energy savings	-	No change	28.0–- 35.0%

[4] *Mean square error*

[25]	Control of the HVAC system	90 minutes	Vote	RF	Tin, RHin, Ts, metabolism, feedback on thermal acceptability, comfort and sensation	Accuracy and users' satisfaction	84.0%	80% of acceptability	-
[26]	Simulation of the HVAC system	1 year	Vote	Extreme gradient boosting	Tin, tout, RHin,,	Users' satisfaction and energy savings	-	98.3–99.5% of acceptability	4.6–3.5%

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