IMPACT OF WINDOW OPENING [AND OTHER OCCUPANT BEHAVIOR] ON SIMULATED ENERGY PERFORMANCE IN RESIDENCE HALLS

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OVERVIEW

measured environmental conditions in 76 dormitory rooms in three pre-renovated buildings

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implemented each window-operation model in EnergyPlus building simulation

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developed logistic regression models for predicting window-usage

tested model performance in predicting window-operation in 15 dormitory rooms in post-renovated building

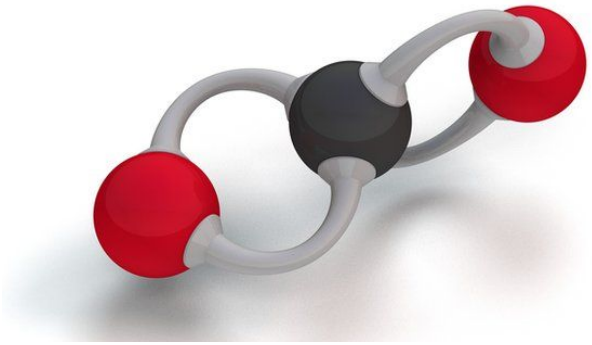
implemented this and other window-operation models from literature in EnergyPlus building simulation

compared the predictive capabilities of all models

OVERVIEW

also…

developed algorithm for estimating window state from CO_2 concentration & temperature decay



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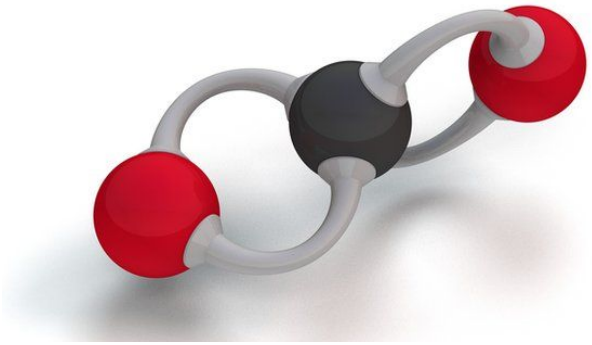

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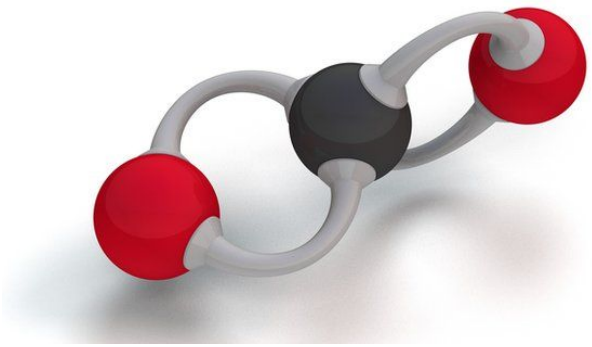
developed algorithm for estimating window state from CO_2 concentration & temperature decay

derived empirical occupancy and lighting schedules and

tested their impact in building performance simulation compared to default inputs



BACKGROUND

relative dearth of research in residential buildings (exceptions e.g. Andersen et al, 2013)

problem of thermal control in older residential buildings

relative ubiquity of CO_2 and temperature sensors

some limitations in past studies (Mahdavi & Tahmasebi, 2016)

OUR TEST BUILDINGS

	Res. Hall A	Res. Hall B	Res. Hall C
Year Built	1929	1925	1930
Renovations	**2013**	1983	
Floors	5	4	6
Number of Students	190	175	385

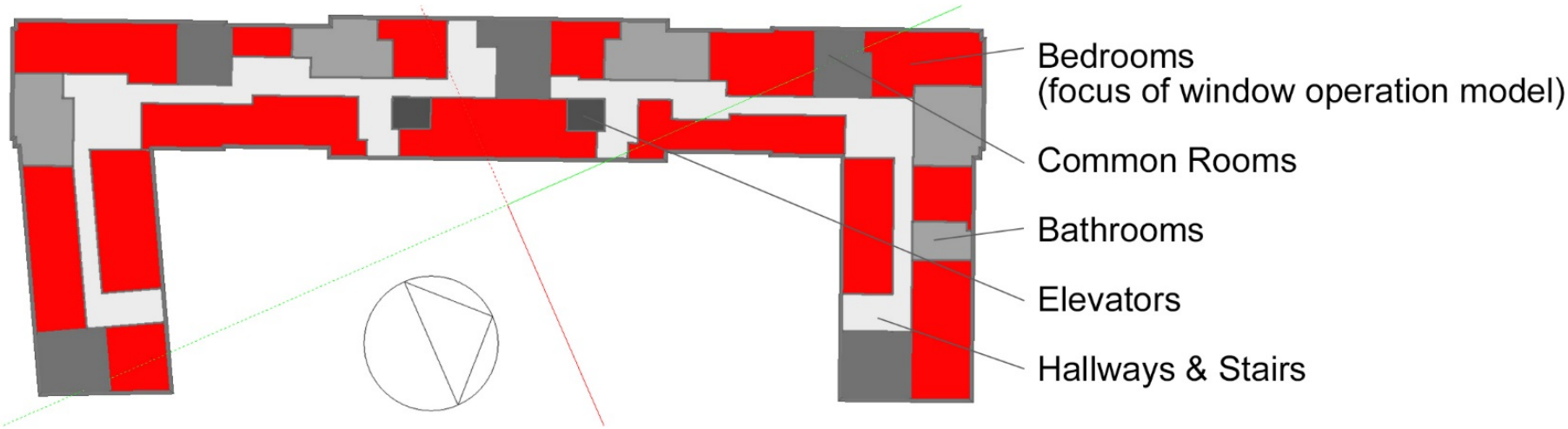
Window Type	Single-hung
HVAC System*	Steam heat, no air conditioning
Res. Hall A	Renovated to LEED Platinum, single-pane to double, insulation and ceiling fans added, lights replaced, rooms reconfigured, *radiators to fin-tube with adjustable flow-rate valves, *AC/mechanical ventilation added to common rooms

FIELD MEASUREMENTS

	Winter/Spring 2012 Apr 4- May 4	Winter/Spring 2013 Mar 2- Apr 23	Winter/Spring 2014 Apr 18- Apr 28
	Hall A Pre-renovation n=17		**Hall A** Post-renovation n=15
	Hall B n=19	**Hall B** n=21	
		Hall C n=19	
Avg. $T_{outdoor}$ (range)	11.9°C (7.9-23.8°C)	7.4°C (1.9-19.5°C)	9.1°C (3.4-14.5°C)

typical bedroom

HALL A: TYPICAL FLOOR PLAN

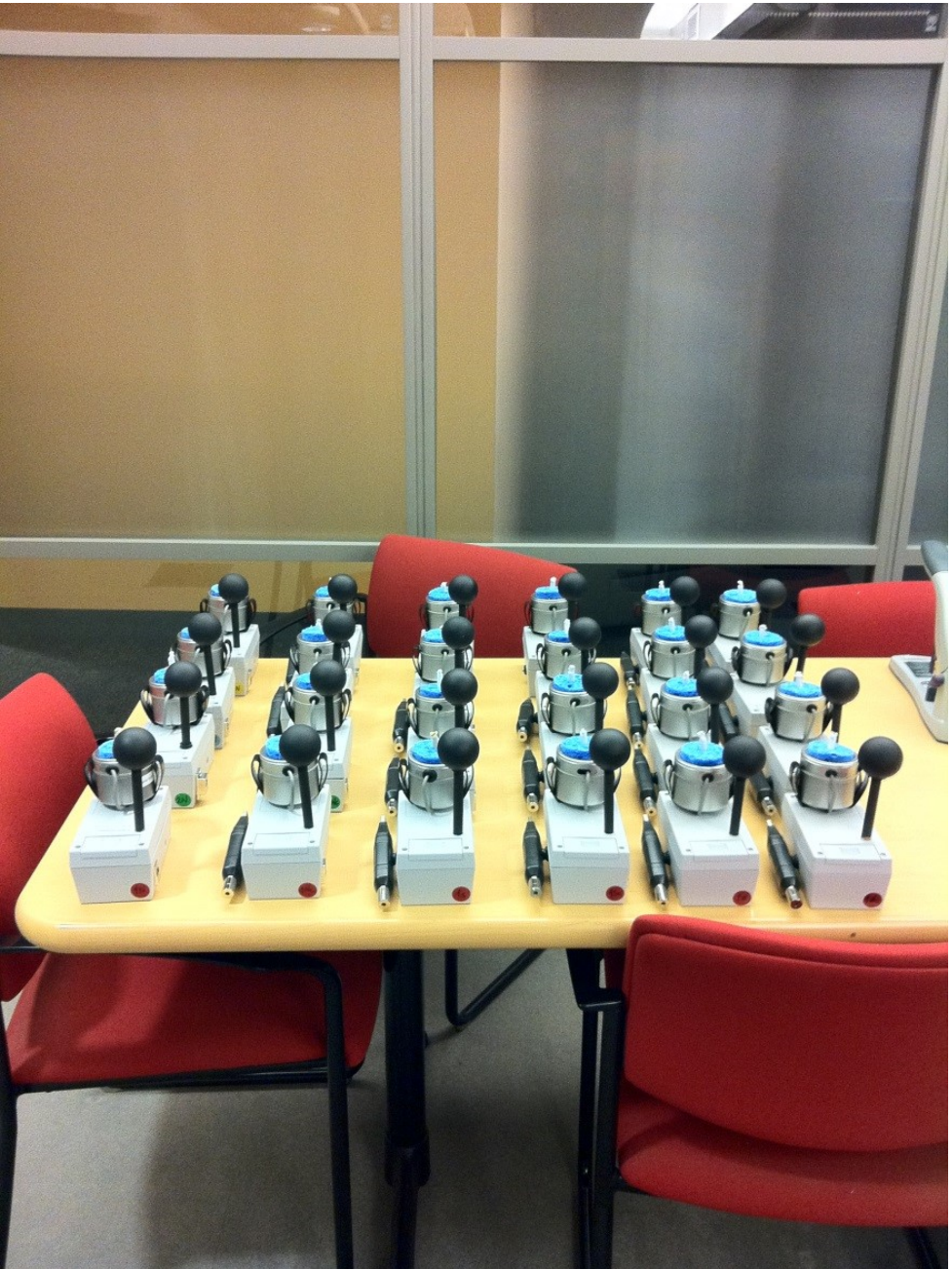


= naturally ventilated

= mechanically ventilated

= mechanically cooled

SENSORS



CO_2 concentration*

black-bulb temperature

dry-bulb temperature

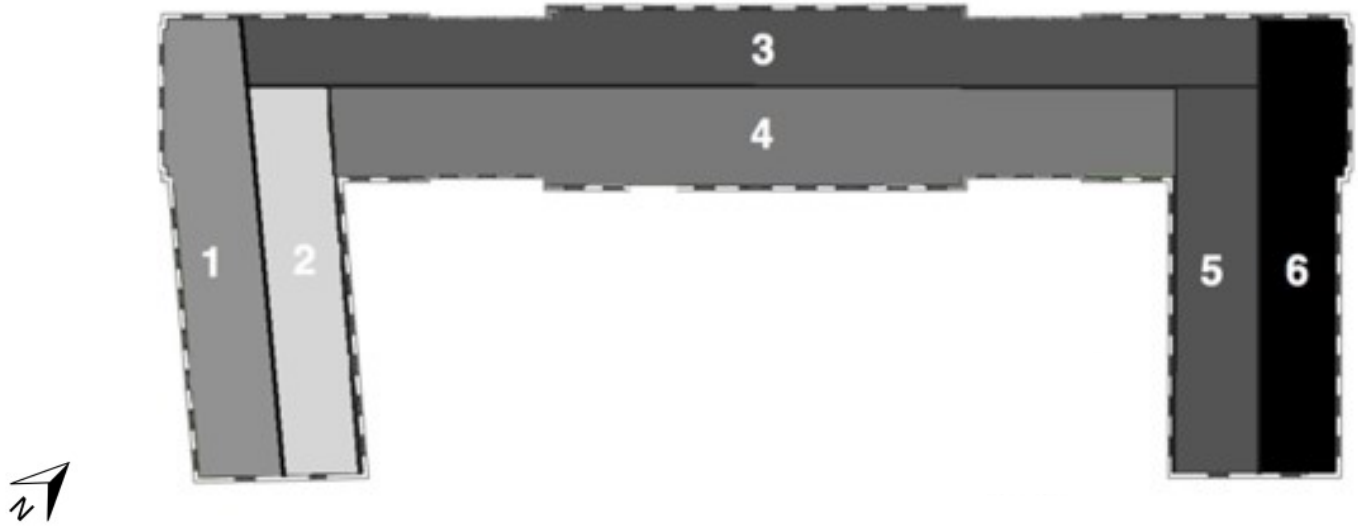
relative humidity

noise

logging interval: 5 minutes

*rated accuracy of ± 30ppm ± 3% of measured value.
adjusted to 400 ppm calibration gas before deployment.
spot checked with 400ppm and 3000ppm calibration gas after deployment.

SENSOR LOCATION



one set of sensors per orientation, as shown

on multiple floors

OTHER DATA COLLECTION

weather 1.5 km away

hourly whole-building steam usage from district plant

hourly electricity*

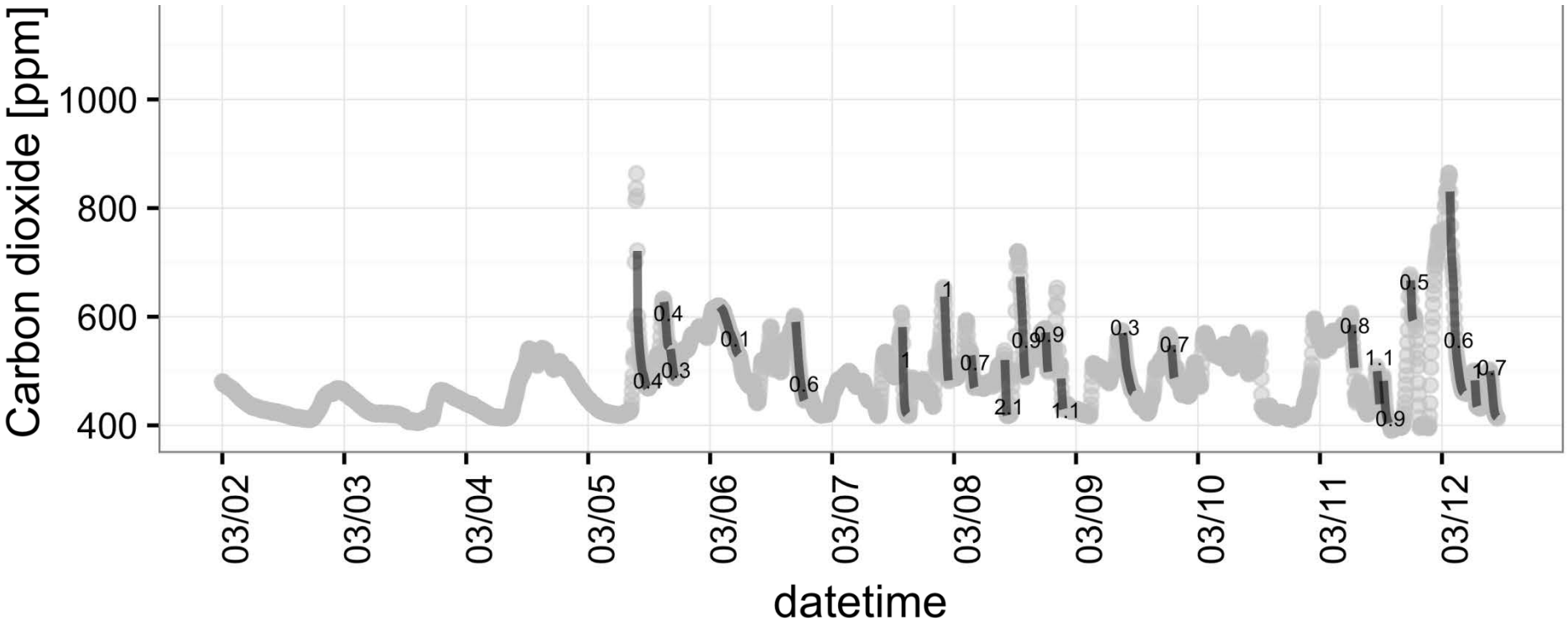
occupant questionnaires

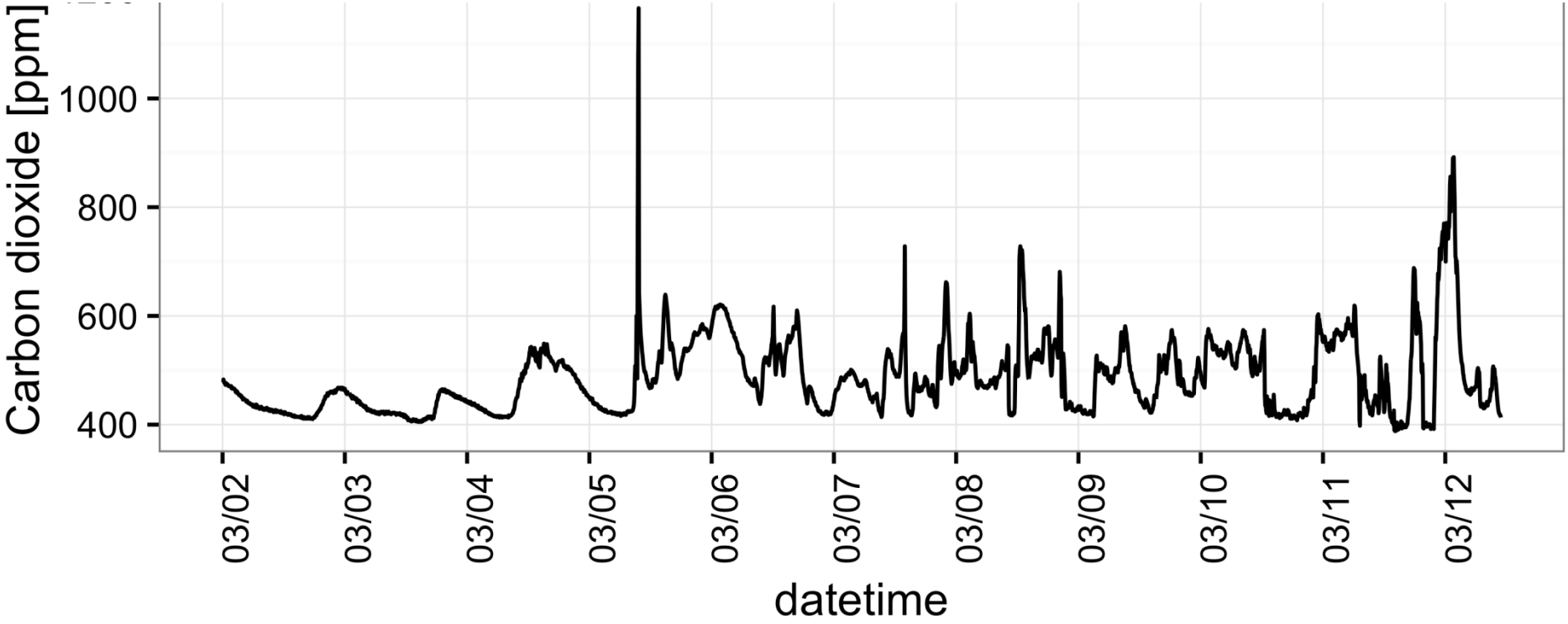
activity-tracker (wrist monitor)

*sub-metered post-renovation

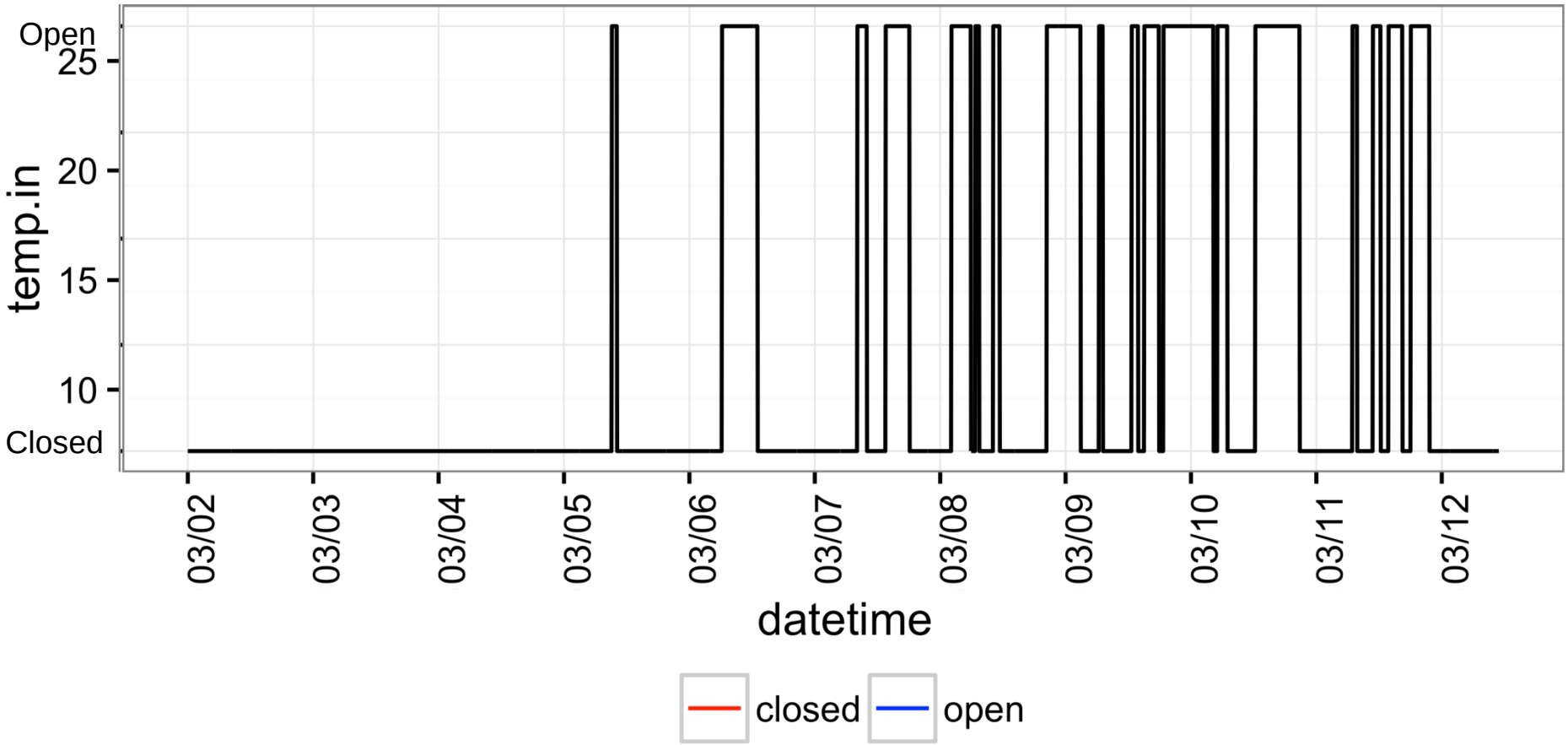
WINDOW STATE CLASSIFICATION

AIR EXCHANGE RATE ESTIMATION




Carbon dioxide [ppm]
1000
800
600
400
03/02
03/03
03/04
03/05
03/06
03/07
03/08
03/09
03/10
03/11
03/12
datetime

WINDOW STATUS- DETECTION



[CURRENT WORK]

validating CO_2 and temp. decay algorithms

deployed all previous sensors, plus:

- window state sensors
- occupancy sensors
- illuminance meters

[outside the scope of today's presentation]

WINDOW STATE MODELS

EXAMPLE LOGISTIC REGRESSION MODEL

$$logit(p_i) = \beta_0 + \beta_1 temp_{outdoor,i} + \beta_2 temp_{indoor,i} + \beta_3 time_of_day_i$$

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OUR MODELS

Custom 1: $T_{outdoor,}$ Time of Day

Custom 2: $T_{outdoor,}$ $T_{indoor,}$ Time of Day

Custom 3: $T_{outdoor,}$ $T_{indoor,}$ $CO_{2,\ indoor,}$ Time of Day

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COMPARISON MODELS FROM LITERATURE

$T_{indoor} > 26$

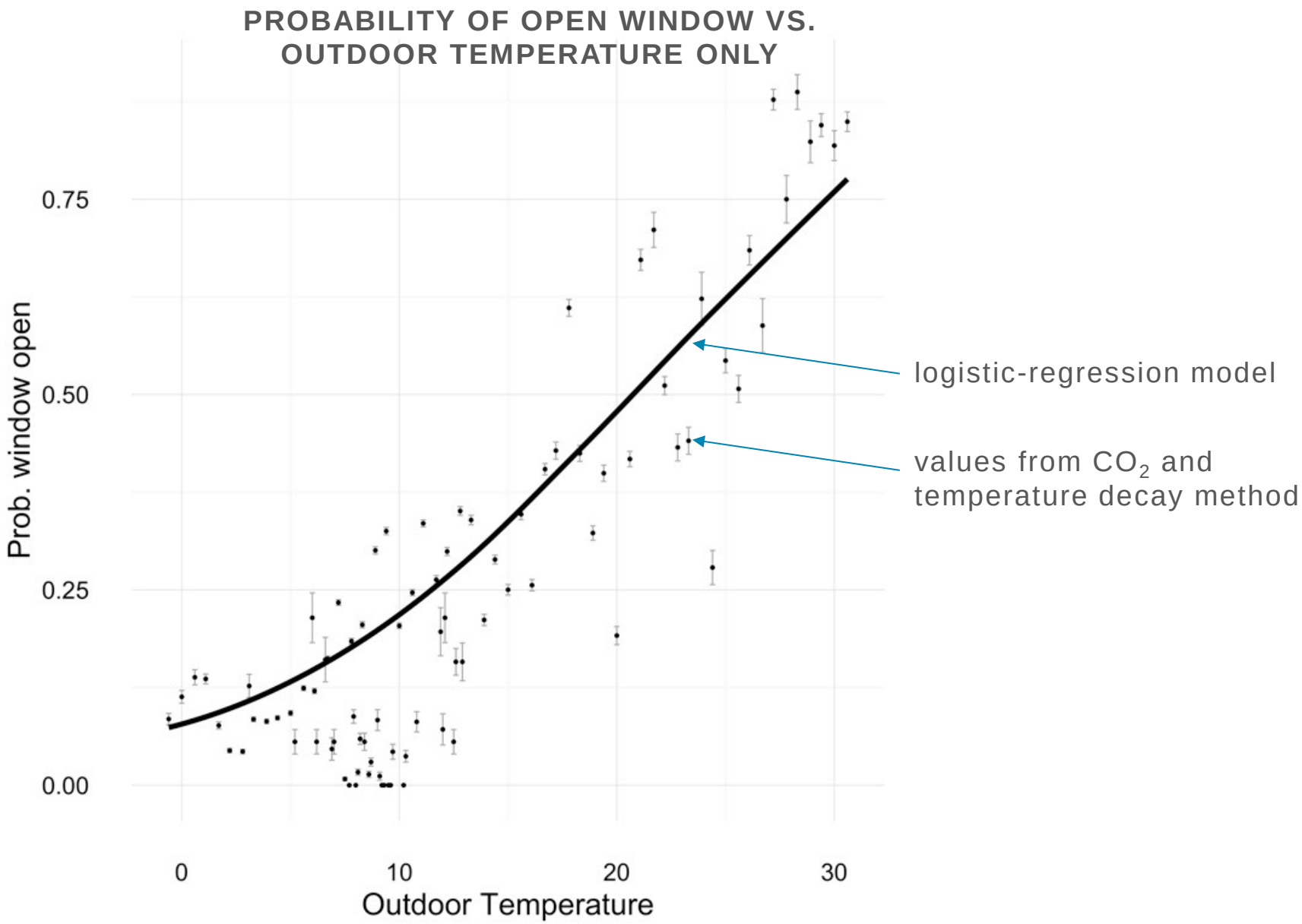
AdaptiveThermal Comfort [“Humphreys Algorithm” (Rijal et al, 20007)]

Haldi (LESO Office): $T_{outdoor,}$ $T_{indoor,}$

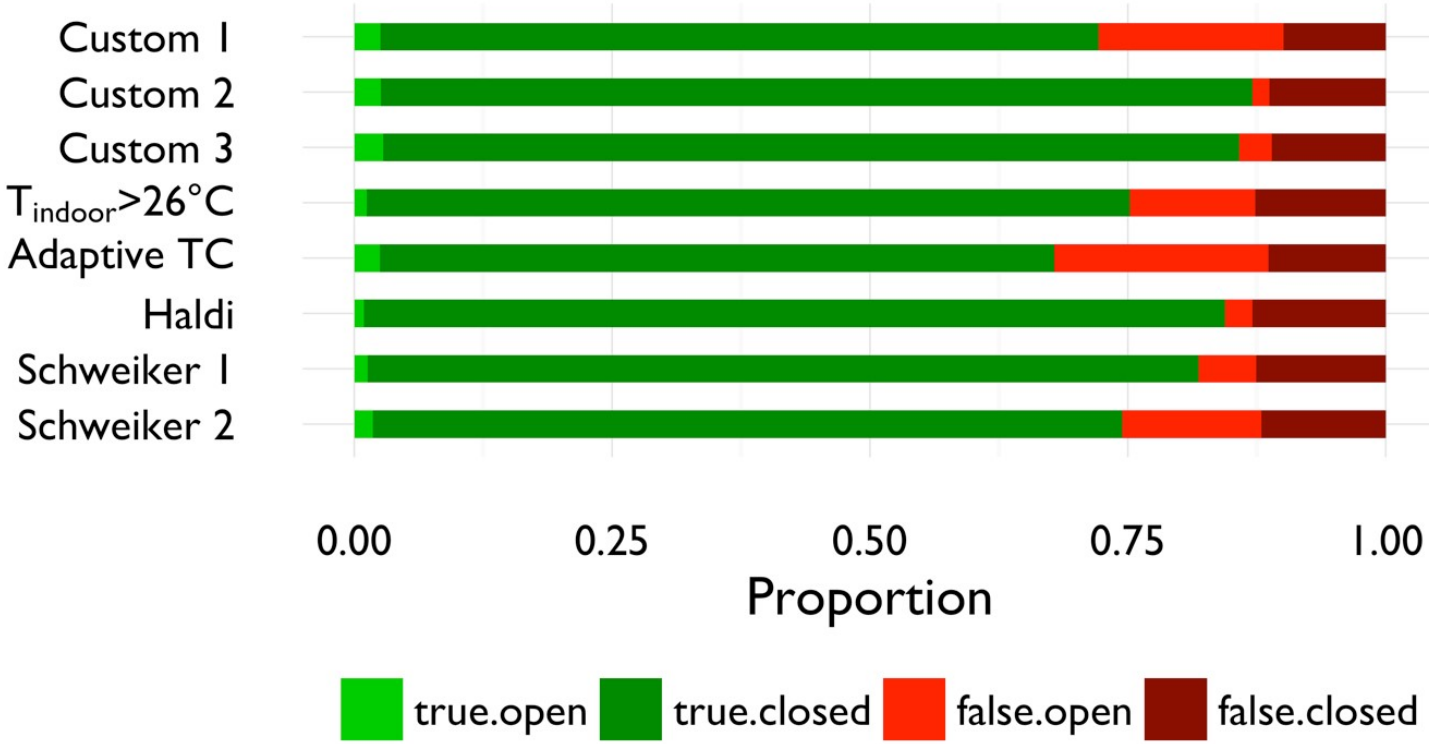
Schweiker1 (Neuchatel Apts): $T_{outdoor,}$ $T_{indoor,}$

Schweiker2 (Tokyo Res. Hall): $T_{outdoor,}$ $T_{indoor,}$

EXAMPLE MODEL RESULTS



PERFORMANCE IN PREDICTING WINDOW STATE



ACCURACY

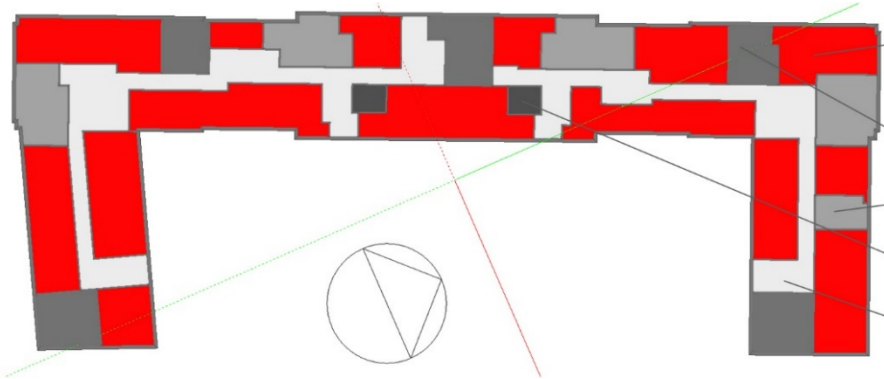
Custom 2 ($T_{outdoor}$, T_{indoor}, Time of Day):	87%
Adaptive Thermal Comfort:	68%
Haldi:	84%

IMPLEMENTING WINDOW MODELS IN BUILDING PERFORMANCE SIMULATION

in only 60 out of 120 zones

EnergyPlus, EMS, E+ Runtime Language

compared hourly steam usage to measured



PERFORMANCE OF EACH MODEL PREDICTING HOURLY STEAM USE

Model	Annual Total MWh (MMBtu)	% Error	Hourly NMBE	Hourly cvRMSE
Metered	1079 (3680)	N/A	N/A	N/A
Custom 1	1138 (3882)	5.5%	5.5%	19.1%
Custom 2	**1081 (3690)**	**0.2%**	**0.3%**	**17.2%**
Always open	1857 (6337)	72%	72.2%	96.9%
Always closed	969 (3305)	-10%	-10.2%	19.9%
T>26	965 (3294)	-10%	-10.5%	20.0%
Adaptive TC	1006 (3433)	-6.8%	-6.7%	25.1%
Haldi (Swiss Office)	1109 (3783)	2.8%	2.8%	17.4%
Schweiker 1 (Tokyo Res.)	1028 (3506)	-4.8%	-4.7%	18.2%
			(* ASHRAE 14 recommends: <10%)	(* ASHRAE 14 recommends: <30%)

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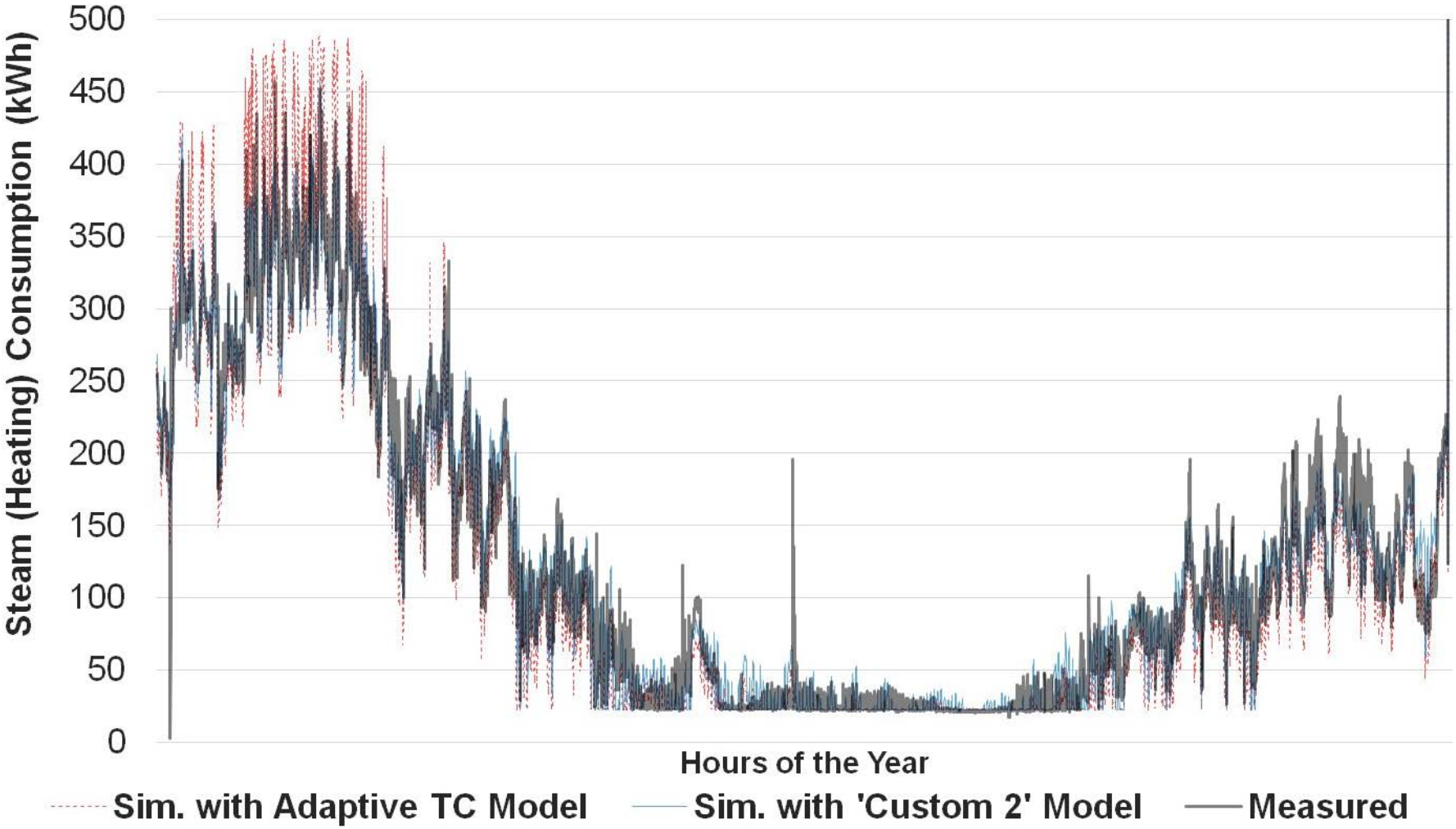
COMPARING PREDICTED AND MEASURED STEAM CONSUMPTION



OCCUPANCY AND SLEEP SCHEDULES

OCCUPANCY AND SLEEP SCHEDULES

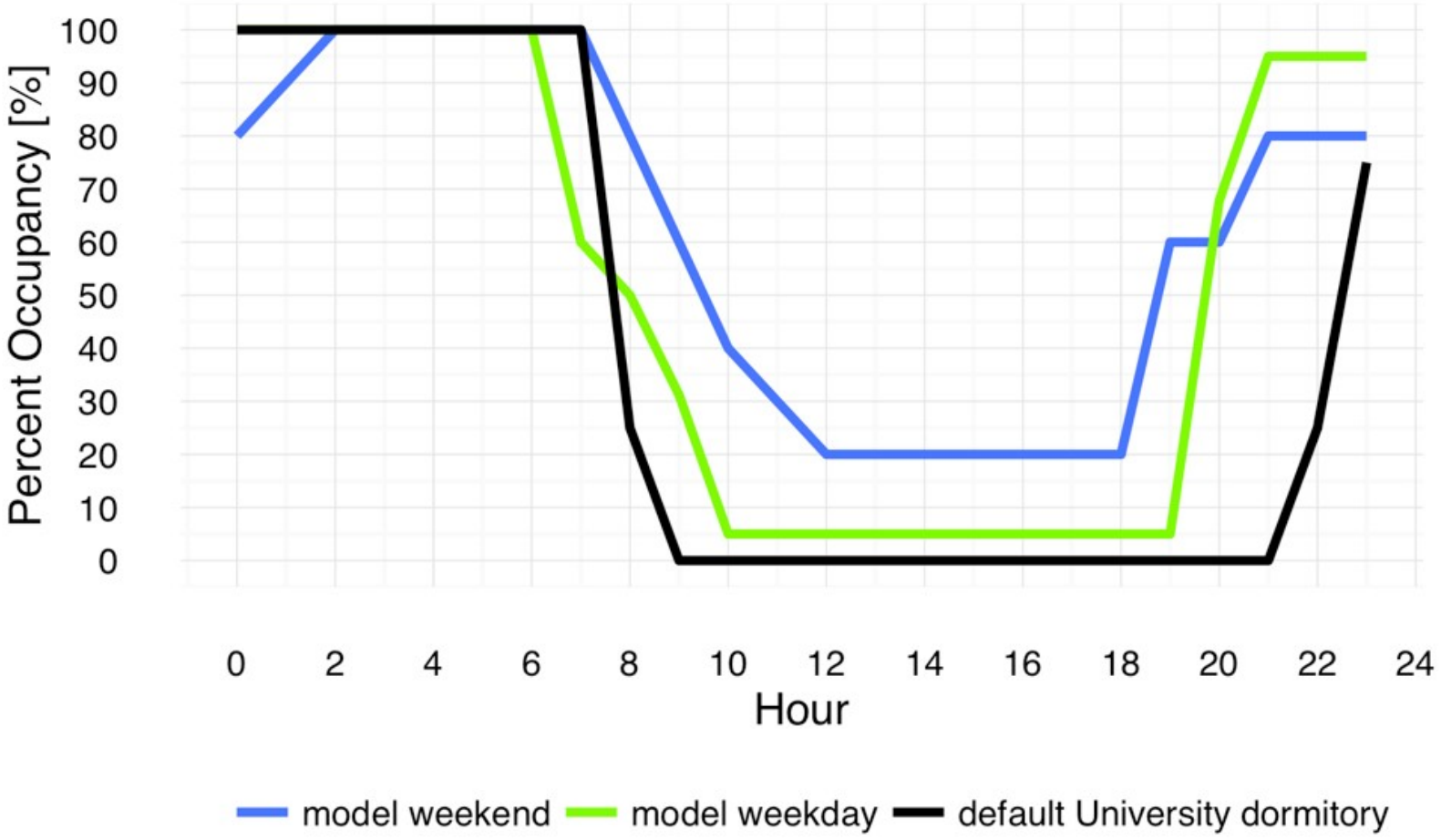
based on CO_2 concentrations and decays

and occupant questionnaires

based on activity-tracker data

(used to influence lighting schedules in model)

CUSTOM OCCUPANCY VS DESIGNBUILDER DEFAULT* SCHEDULES



*DesignBuilder ”University Dorm Bedroom” schedule,
based on U.K.’s National Calculation Methodology 2013

OBSERVED SLEEP SCHEDULES

	Mean	Median	Standard Deviation
Sleep Onset Time	01:54 am	01:36 am	2.88hr
Sleep Wake Time	08:34 am	08:37 am	2.31hr
Sleep Duration Per Night (not used in BPS)	6.3 hr	6.8 hr	2.25 hr

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CUSTOM LIGHTING SCHEDULES

Custom Lighting Schedule: mean wake time to sunrise, sunset to mean sleep onset time, when occupied

Default DesignBuilder Lighting Schedule: **9:00am** to 10:00am and **10:00pm to 1:00am**, regardless of occupancy

Custom schedule resulted in a **41%** increase in lighting energy use

KEY FINDINGS

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The annual error (between simulated and measured steam use) of different models varied from 0.2-10%, a substantial difference when evaluating Energy Conservation Measures.

The results demonstrated that **occupant behavior assumptions can have a substantial impact on payback calculations for upgrades**, such as lighting or heating system improvements.

FUNDING

Harvard University Climate Change Solutions Fund

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THANK YOU

Bing Dong and Farhang Tahmasebi for simulation and EMS coding advice

THANK YOU

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WINDOW STATE MODELS

OUR LOGISTIC REGRESSION MODELS

Model 1 $logit(p_i) = \beta_0 + \beta_1 temp_{outdoor,i} + \beta_2 time_of_day_i$

Model 2 $logit(p_i) = \beta_0 + \beta_1 temp_{outdoor,i} + \beta_2 temp_{indoor,i} + \beta_3 time_of_day_i$

Model 3 $logit(p_i) = \beta_0 + \beta_1 temp_{outdoor,i} + \beta_2 temp_{indoor,i} + \beta_3 CO_{2\ indoor,i} + \beta_4 time_of_day_i$

MODELS FROM LITERATURE

T>26 $Window_{close-open} = temp_{indoor} > temp_{outdoor}|_{temp_{outdoor}>26℃}$

Adaptive$_{TC}$ $Window_{close-open} = temp_{indoor} > 18.8 + 0.33\ temp_{outdoor,rm}|_{temp_{outdoor}>10℃}$;

$temp_{indoor} > 22.6\ + 0.09\ temp_{outdoor,rm}|_{temp_{outdoor}<10℃}$

Haldi $logit(p_i) = \beta_0 + \beta_1 temp_{outdoor,i} + \beta_2 temp_{indoor,i}$

Schweiker1 $logit(p_i) = \beta_0 + \beta_1 temp_{outdoor,i} + \beta_2 temp_{indoor,i}$

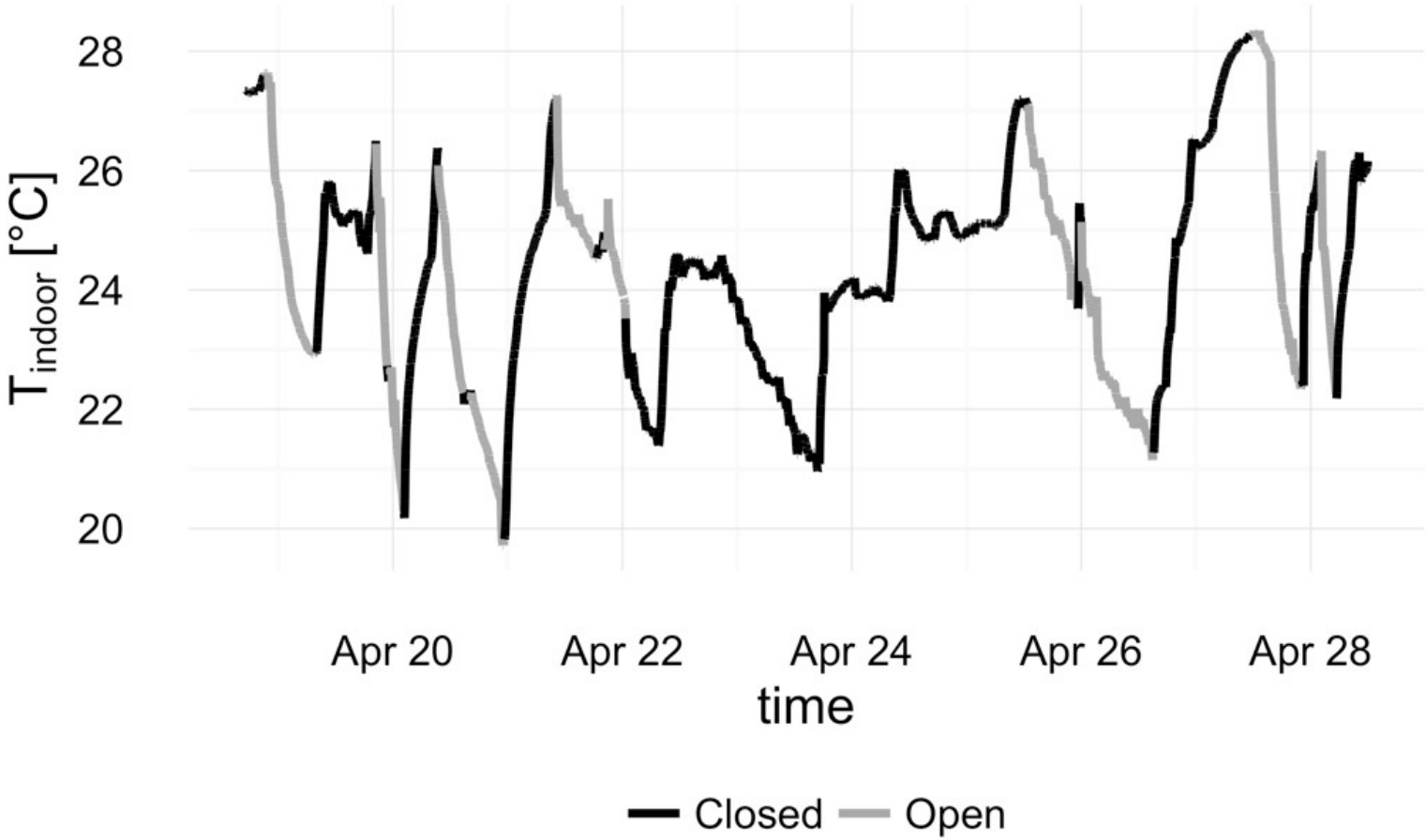
Schweiker2 $logit(p_i) = \beta_0 + \beta_1 temp_{outdoor,i} + \beta_2 temp_{indoor,i}$

WINDOW STATE MODELS: MODEL PARAMETERS

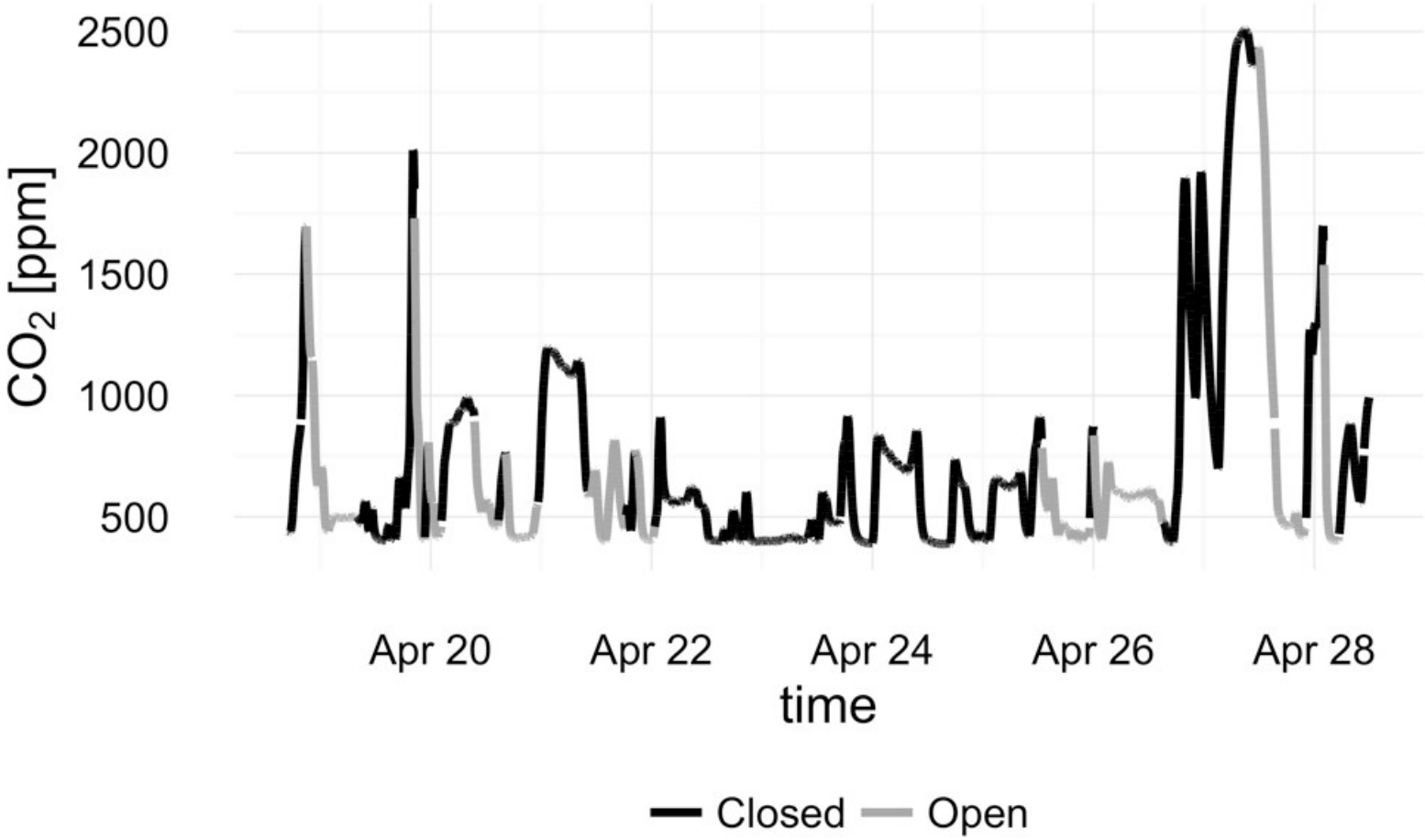
	Custom 1	Custom 2	Custom 3	Haldi (LESO)†	Schweiker 1 (Neuchatel)‡	Schweiker 2 (Tokyo)‡
Intercept	-2.428*	2.486*	8.05*	0.794	0.711	-3.737
$T_{outdoor}$	0.135*	0.154*	0.159*	0.1476	0.3813	0.0497
T_{indoor}		-0.229*	-0.218*	-0.1541	-0.3077	0.0886
$daytime_{morning}$	-0.277*	-0.326*	-0.424*	NA	NA	NA
$daytime_{evening}$	0.067*	0.064*	-0.059*	NA	NA	NA
CO_2			-0.001*	NA	NA	NA

* Statistically significant ($p<0.001$); †Haldi and Robinson, 2010; ‡Schweiker et al., 2012

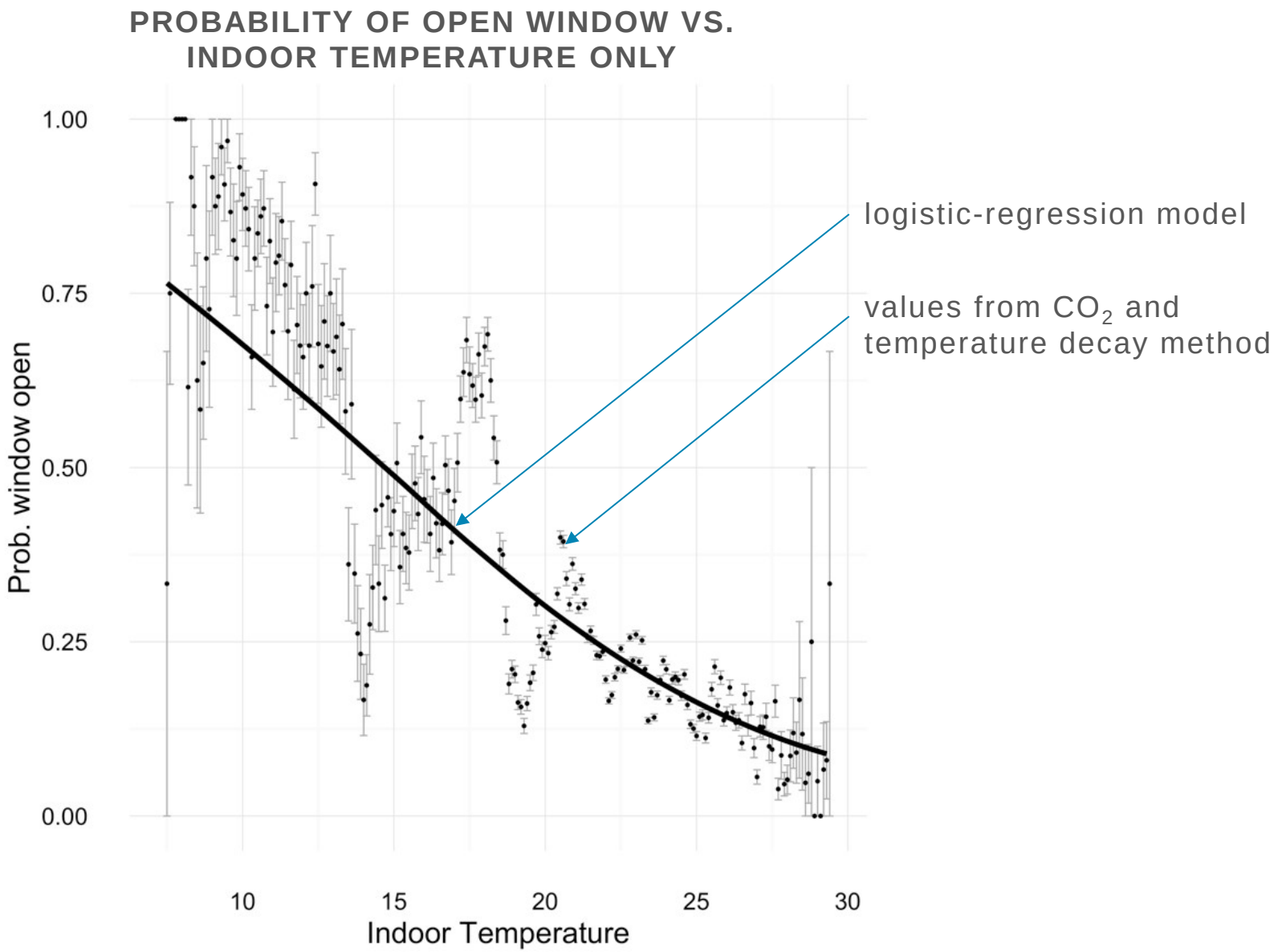
WINDOW STATE CLASSIFICATION IN RELATION TO T_{INDOOR}



WINDOW STATE CLASSIFICATION IN RELATION TO CO_2



EXAMPLE MODEL RESULTS



PERFORMANCE OF CROSS-VALIDATION MODELS

Model Name	TPR [%]	FPR [%]	Accuracy [%]	Proportion openings [%]	Wopen duration [min]	Wclosed duration [min]	Actions
Monitored	100.0	0.0	100.0	13.8	125.0	1580.0	1.4
Custom 1	18.2	129.3	72.2	2.0	112.0	930.0	1.5
Custom 2	18.6	11.9	87.1	4.5	183.0	979.0	3.13
Custom 3	20.2	22.9	85.8	6.3	210.0	922.0	2.19
T>26	8.8	87.9	75.2	12.8	177.0	621.0	4
Adaptive TC	18.0	149.9	67.9	22.7	220.0	506.0	3.6
Haldi	6.8	19.3	84.4	3.8	76.0	771.0	3.1
Schweiker 1	9.4	40.5	81.9	7.0	204.3	810.0	1.7
Schweiker 2	12.9	97.3	74.5	14.6	279.6	645.9	1.6

OTHER MODEL ASSUMPTIONS

Occupant Density			0.12 people/m^2 (0.01 people/ft^2)
Maximum Plug-Load Power Density			7.5 W/m^2 (0.7 W/ft^2)
Maximum Lighting Power Density			6W/m^2 (0.6W/ft^2)
Heating Set-Point			24 ˚C (75 ºF)
Envelope Characteristics			
	Glazing:	External Wall:	Roof:
U-value	2.7 W/m^2-K ºC (0.5 Btu/hr-sq ftºF)	0.3 W/m^2-K ºC (0.05 Btu/hr-sq ftºF)	0.2 W/m^2-K ºC (0.04 Btu/hr-sq ftºF)
Detail	Visible Transmittance: 0.72	Construction: 1. Face Brick, Thickness 30.5 cm 2. Air Space, Thickness 0.67 cm 3. MinWool Batt , Thickness 8.9 cm 4. Polystyrene, Thickness 1.9 cm 5. Gypsum board, Thickness 2.5 cm	Construction: 1. Surf Air Film Slope 2. Slate, Thickness 1.3 cm 3. Gypsum Board, Thickness 7.6 cm 4. MinWool Batt, Thickness 16.5 cm 5. Gypsum Board, Thickness 1.6 cm