







REDUCEDHEATCARB

Research on Energy Data Utilization for Carbon Emission Decline

by **H**eat pumps and **E**fficiency, while **A**ssuring **T**hermal **C**omfort **A**chievement in **R**esidential **B**uildings

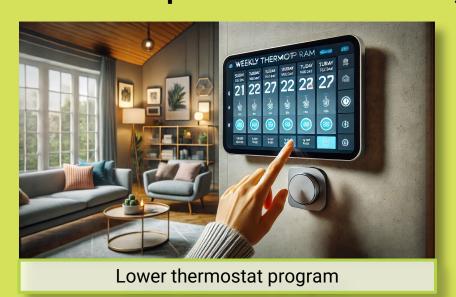
Who?

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What?

Can we predict the expected effect of the interventions below for a specific home using a few weeks of monitoring data, more accurately than label inspections or address-specific data from online registries? Is online thermostat data sufficient, or do we also need smart meter or additional measurement device data?

Heating Interventions





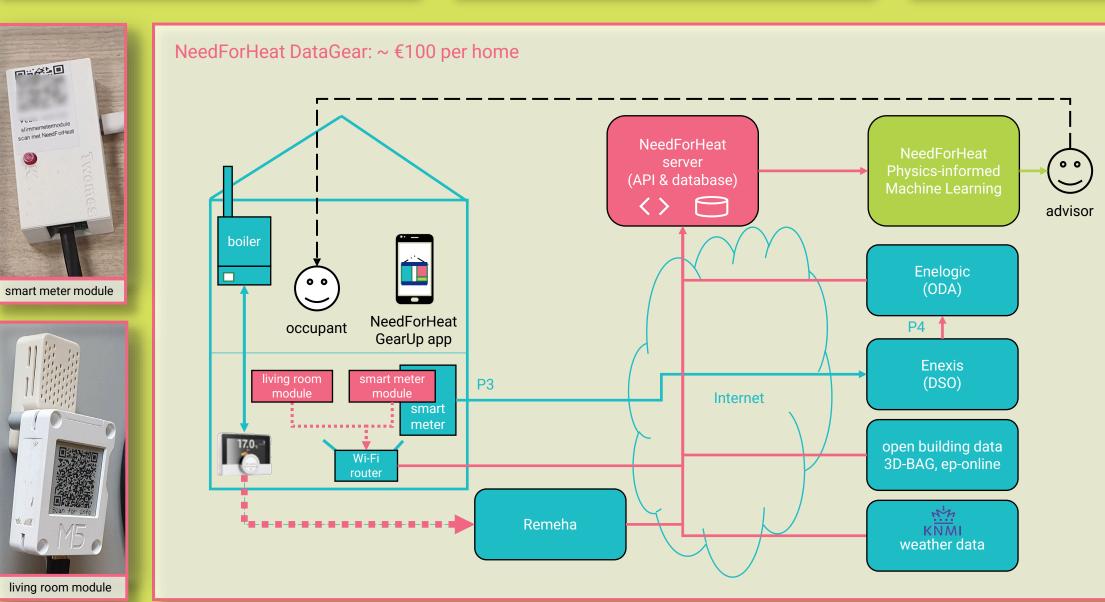




Data Collection



Open-source software & hardware



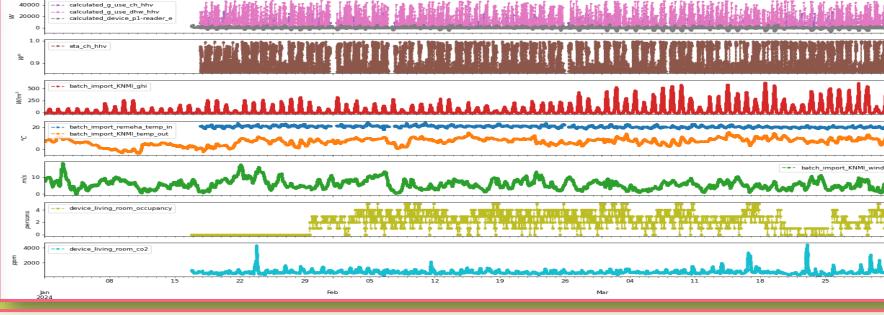
	1	Time Series Data Collected						
	ı	Category	Measured Data	Remeha	KNMI	Enelogic	Living R.	Smart M.
	ı	Comfort	setpoint temperature & program	✓				
	ı		indoor temperature	✓			✓	
	ı	Weather	outdoor temperature	√	✓			
ı	ı		wind		✓			
	ı		sunshine: global horizontal irradiation		✓			
	ı	Installation	supply & return temperature	✓				
	ı		load, CH/DHW, max supply temperature	✓				
	ı	Energy	electricity used & returned			✓		✓
	ı		gas used			✓		✓
		Occupancy, Ventilation	CO ₂ concentration				✓	
			occupancy (Bluetooth presence)				✓	

Subjects & Data



Dataset & metadata





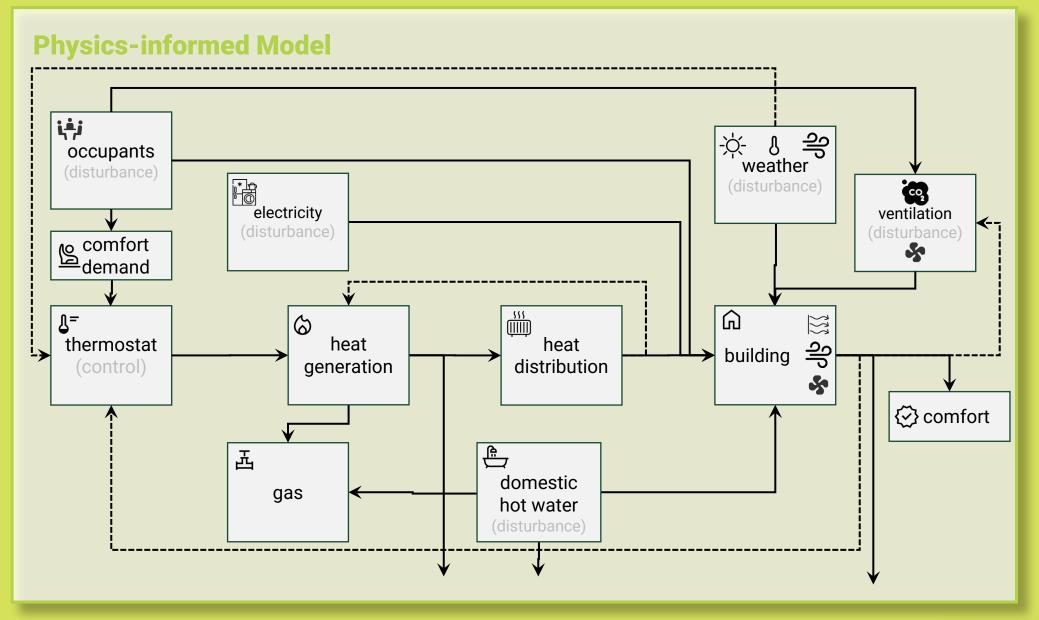
3350 homes invited; 171 survey responses (5%); 45 included (26%); 42 invited (93%); 20 monitored fully (48%); 52.7 M data points measured; 49.9 M sane; 350 M after temporal interpolation (1 min interval)

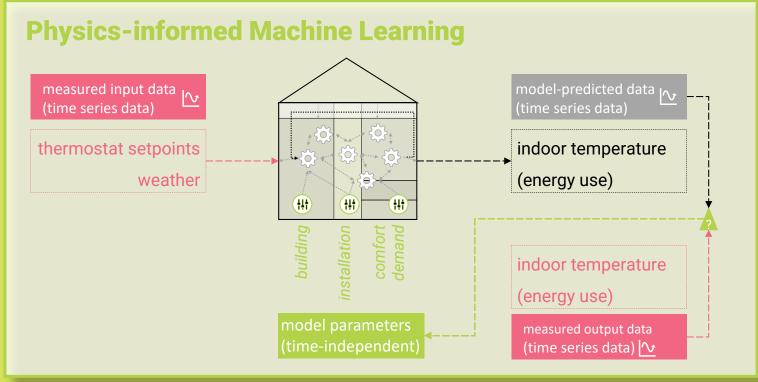
Analysis Method



GEKKO Python

model implementation





GEKKO Python Model Implementation (Core)

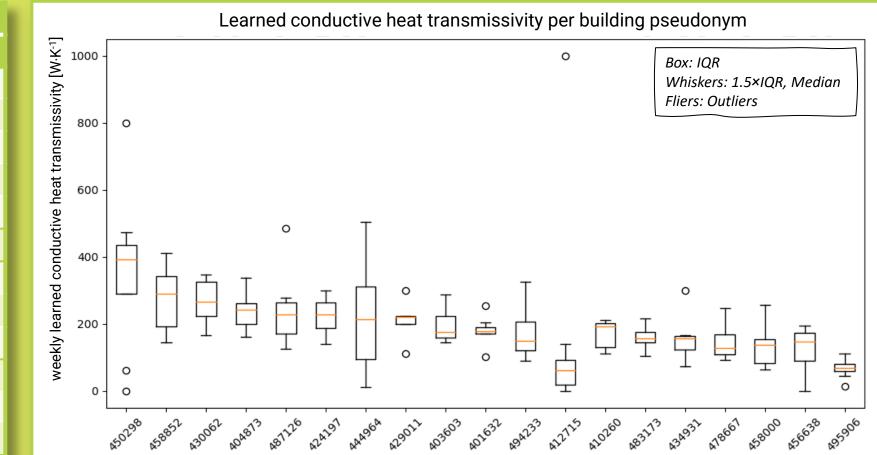
n.Equation(temp_indoor__degC.dt() == ((heat_gain_bldng__W - heat_loss_bldng__W) / (th_mass_bldng__Wh_K_1 * s_h_1))) m.options.IMODE = 5 m.options.EV_TYPE = 2

Preliminary Results



Scan for more results

Unit Description Building $W \cdot K^{-1}$ Conductive heat transmissivity of the building Thermal mass of the building Thermal inertia of the building τ_{bldng} Effective total horizontal solar aperture m m^2 Effective total infiltration aperture of the building W_0 Average efficiency of the heat generation system **Heat Generation** Heat transmissivity of the heat distribution system W·K **Heat Distribution** C_{dist} Thermal mass of the heat distribution system Thermal inertia of the heat distribution system τ_{dist} °C⋅wk Comfort Demand: time-weighted average temperature setpoint Comfort K⋅wk⁰ Heat Demand: time-weighted average indoor-outdoor difference $\Delta T_{\text{in;out;avg}}$



Preliminary Conclusions

Building parameters: Can be learned from a few weeks of data.

 wk^0

Heat generation efficiency: Calculable from monitored data.

Heat Performance Signature: Parameters to Learn

• Ventilation: Learnable from CO₂ and occupancy but may not significantly enhance heat loss predictions.

Comfort: proportion of time indoor temperature in comfort zone

- Heat distribution parameters: Learning in progress.
- Compare intervention prediction with label inspections and address-specific data: Future task.
- Online thermostat data sufficiency: Future task.

.solve(disp=False)