CITIES Webinar, August 12, 2020

REBUS Connect and Data-Driven Technologies from IEA EBC Annex 71 and on PhD project

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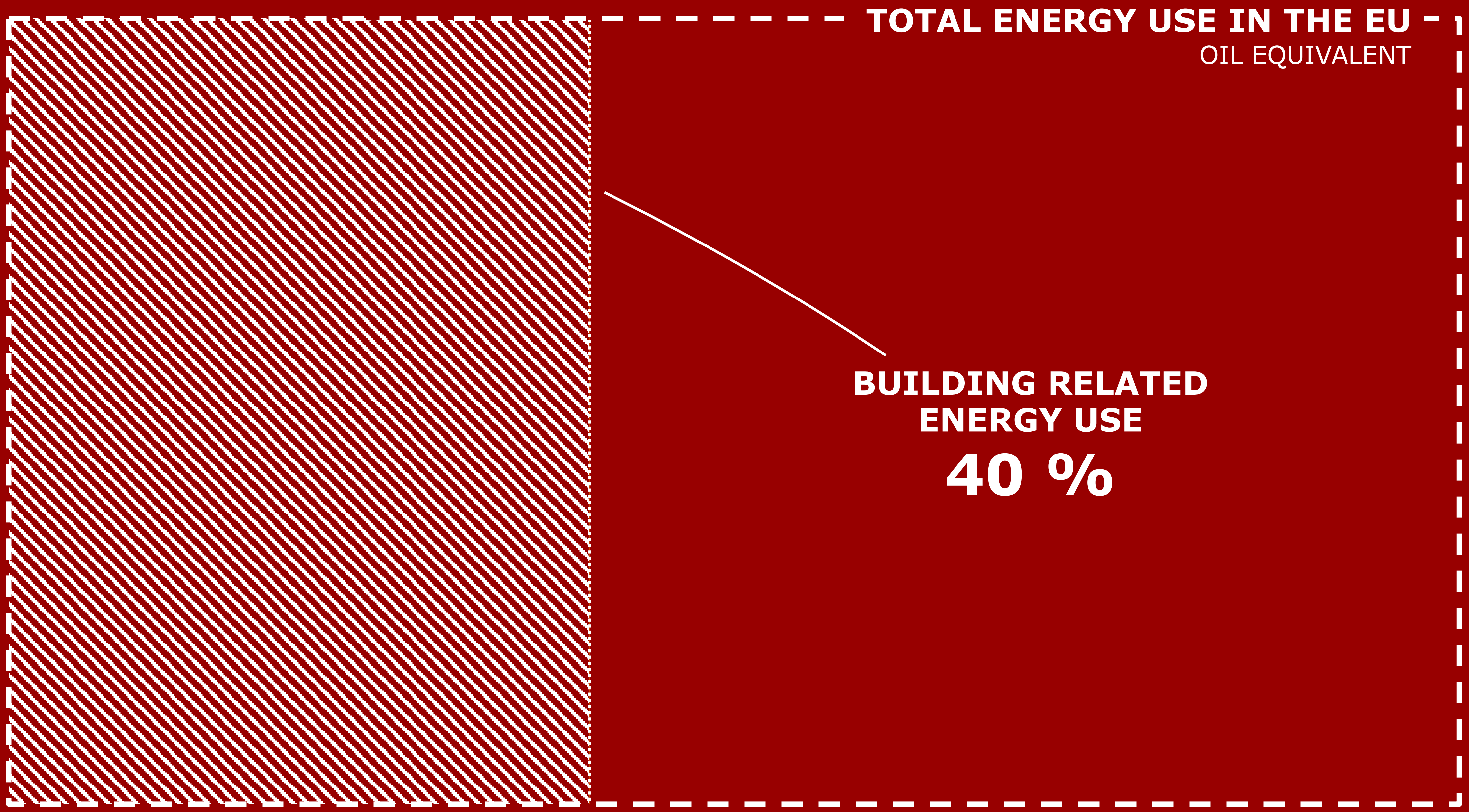
RENOVATING BUILDINGS SUSTAINABLY

EBC
Energy in Buildings and Communities Programme

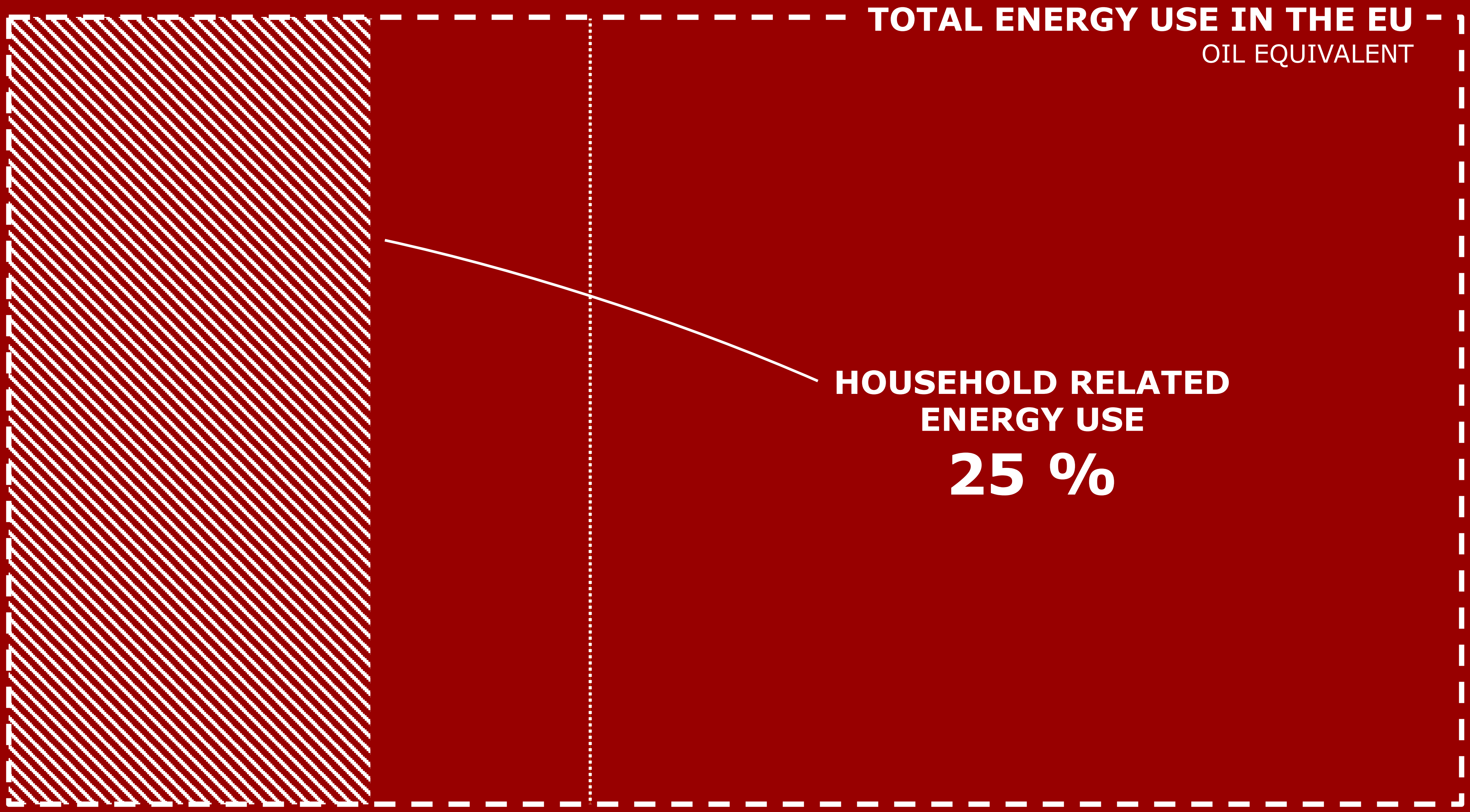
SMARTTUNE

CITIES
Centre for IT Intelligent Energy Systems

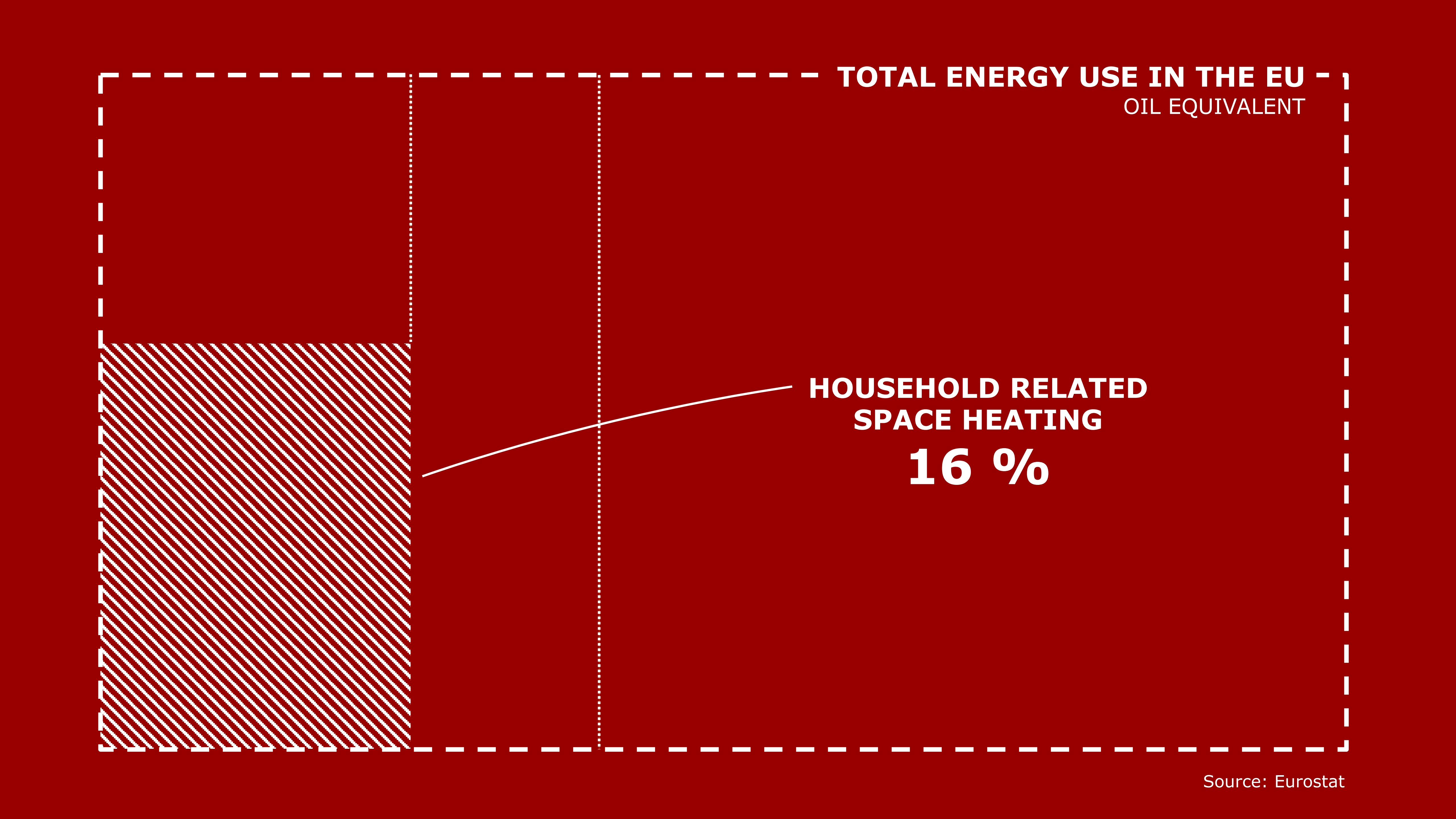
Innovation Fund Denmark

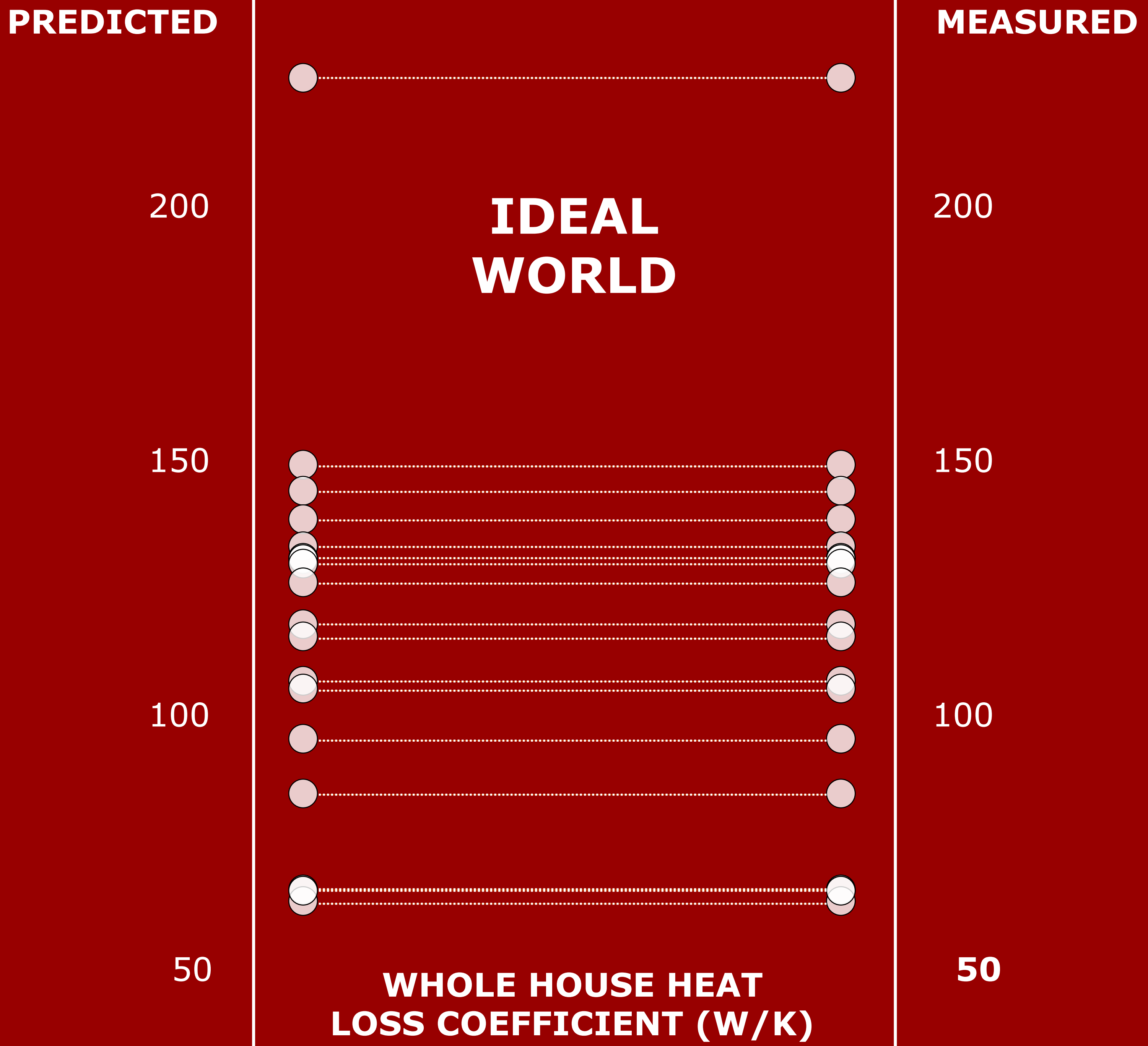


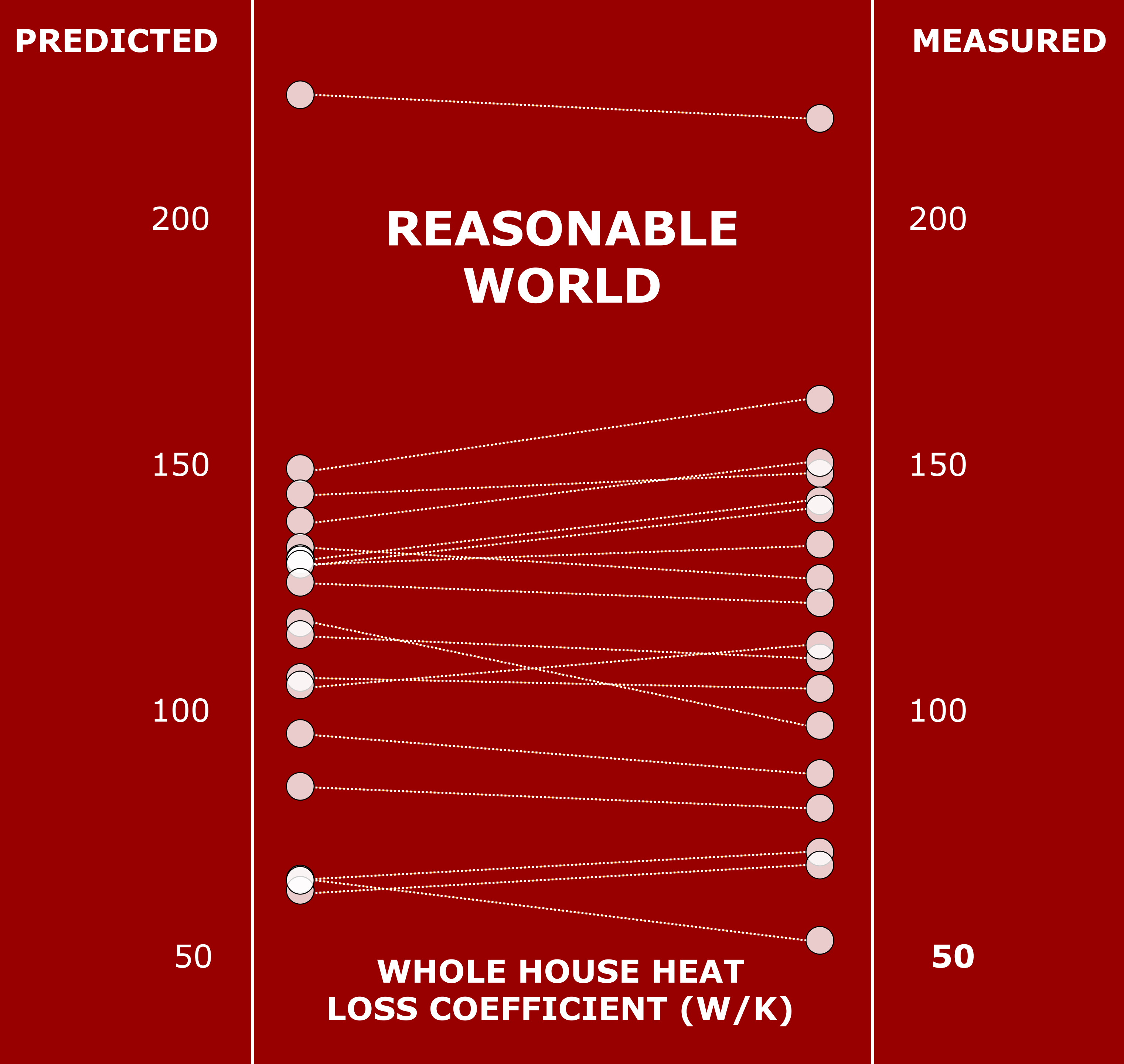
Source: Eurostat

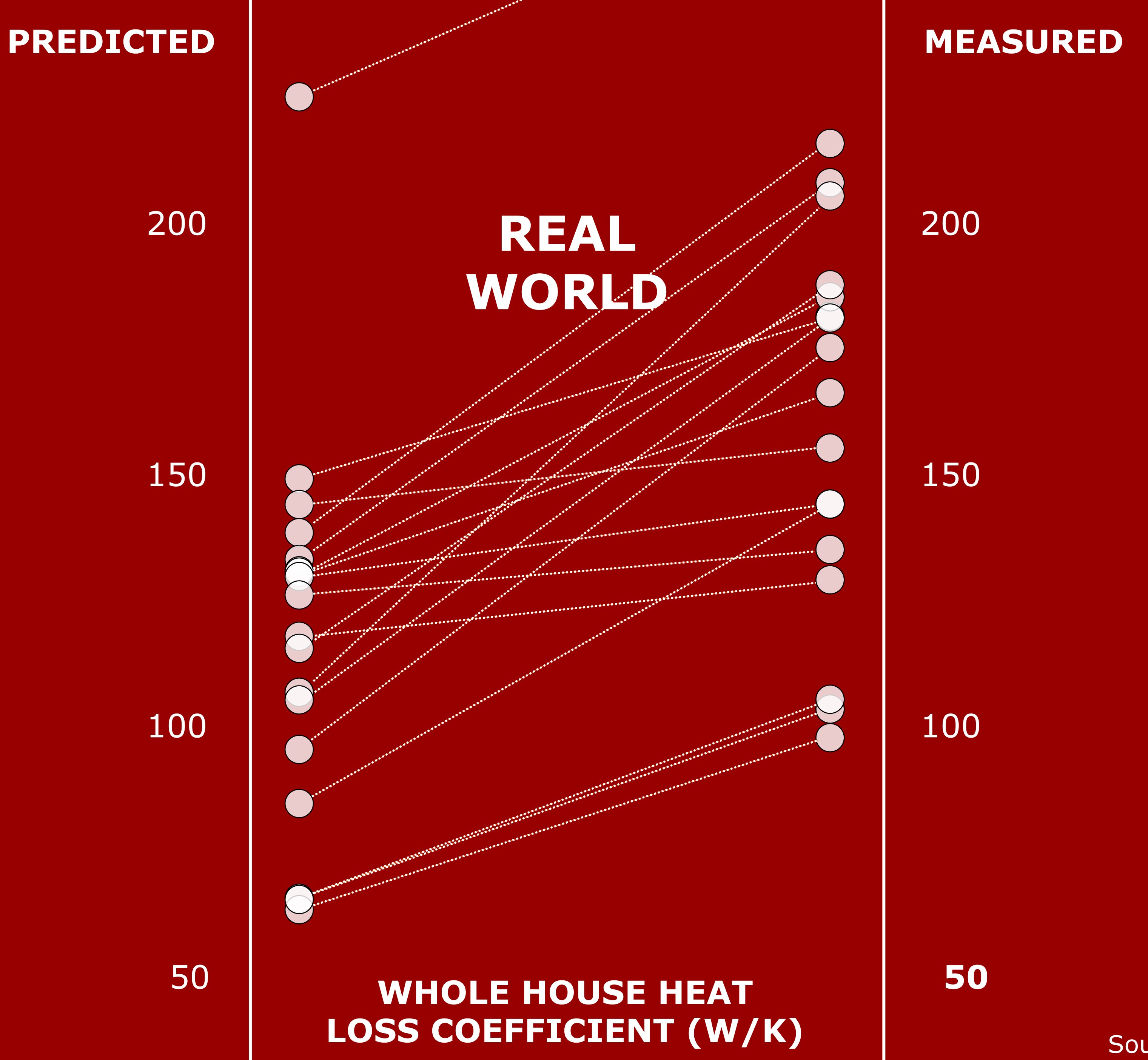


Source: Eurostat


TOTAL ENERGY USE IN THE EU
OIL EQUIVALENT
HOUSEHOLD RELATED
SPACE HEATING
16 %
Source: Eurostat


PREDICTED
MEASURED
200
150
100
50
200
150
100
50
IDEAL
WORLD
WHOLE HOUSE HEAT
LOSS COEFFICIENT (W/K)


PREDICTED
MEASURED
REASONABLE WORLD
200
150
100
50
200
150
100
50
WHOLE HOUSE HEAT LOSS COEFFICIENT (W/K)



Source: J. Wingfield et al., 2011

RE+BUS

RENOVATING BUILDINGS SUSTAINABLY

EBC

Energy in Buildings and Communities Programme

Annex 71:

Building energy performance assessment based on in-situ measurements

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Semi-parametric modelling of sun position dependent solar gain using B-splines in grey-box models

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A R T I C L E I N F O

Keywords:
Solar gain modelling
Grey-box modelling
Splines
Thermal dynamics
Building energy
Solar heat collectors

A B S T R A C T

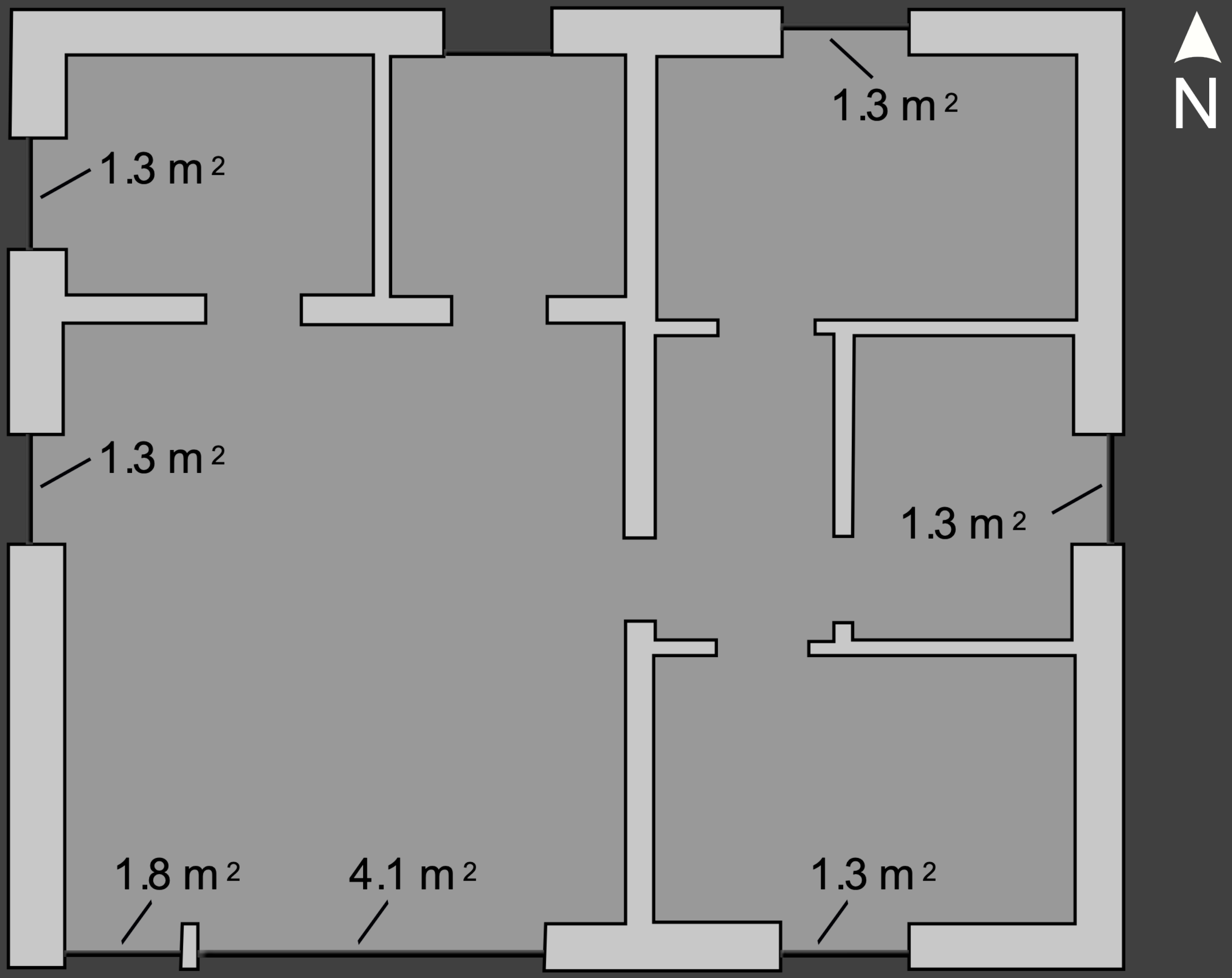
Modelling the effects of solar irradiation plays an important role in various applications. This paper describes a semi-parametric (combined grey-box and spline-based), data-driven technique that can be used to model systems in which the solar gain depends on the sun position. The *solar gain factor* is introduced, i.e. the absorbed fraction of measured solar irradiation, and estimated as a continuous non-parametric function of the sun position. The implementation of the spline-based solar gain factor in a grey-box model framework is described. The method is tested in two case studies—in a model of the internal temperature of a dwelling in Aalborg, Denmark, and a model of the return temperature of a solar collector field in Solrød, Denmark. It is shown that the solar gain factor as a function of sun position is able to account for structural variations in solar gain that may occur due to factors such as shading obstacles and window or absorber orientation. In both test cases, the spline-based solar gain function improved the model accuracy significantly, and largely reduced structural errors in prediction residuals. In addition, the shape of the estimated function provided insight into the dynamics of the system and the local solar input characteristics. Accurate representation of such site characteristics was not possible with

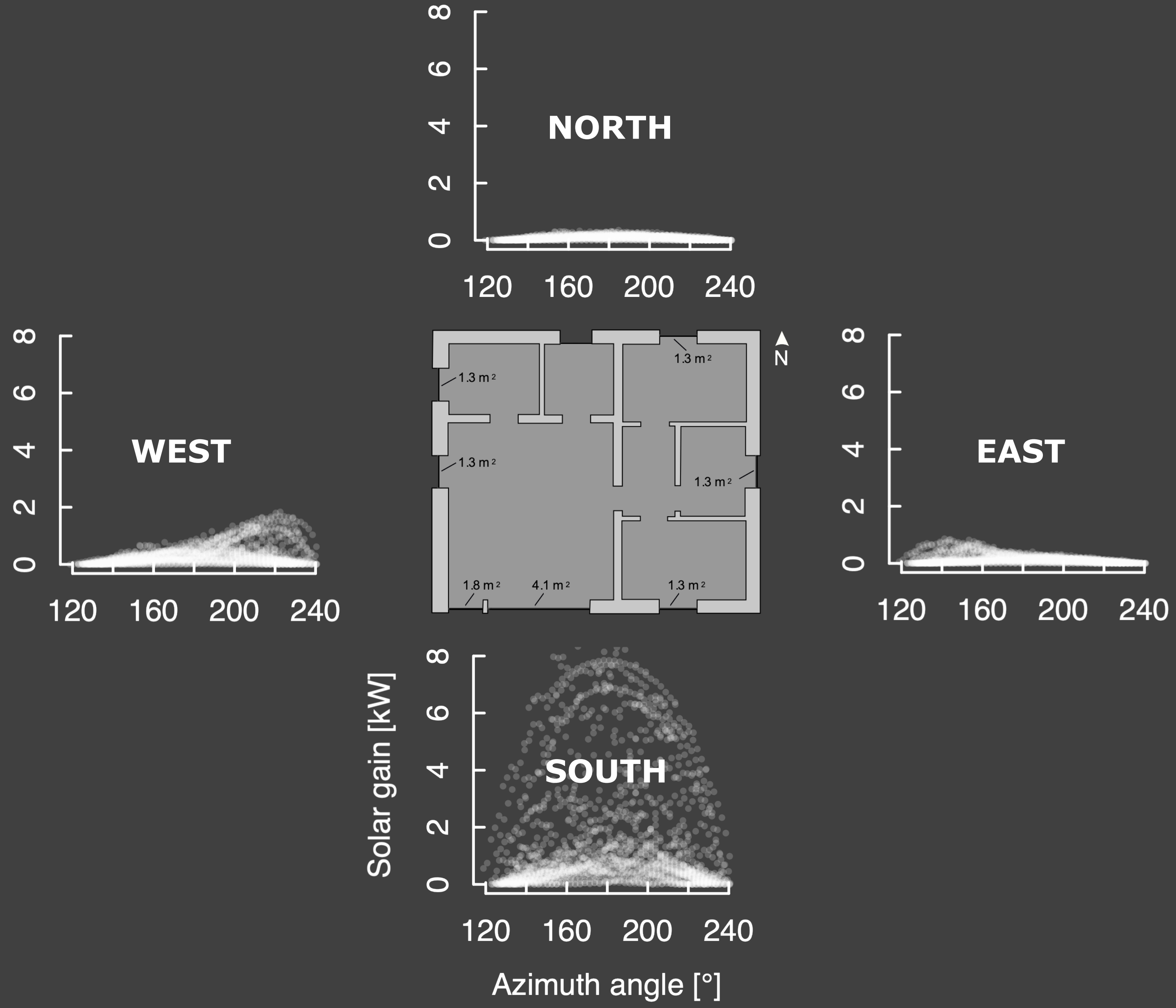
A TYPICAL GREY-BOX MODEL

$$
\mathrm{T_i T_w}\begin{cases}
\mathrm{d}T_\mathrm{i} = \frac{1}{C_\mathrm{i}}\left(\frac{T_\mathrm{w} - T_\mathrm{i}}{R_\mathrm{wi}} + \Phi_\mathrm{heat} + \mathrm{gA}\, I_\mathrm{g}\right)\mathrm{d}t + \sigma_\mathrm{i}\,\mathrm{d}\omega_\mathrm{i} \\
\mathrm{d}T_\mathrm{w} = \frac{1}{C_\mathrm{w}}\left(\frac{T_\mathrm{i} - T_\mathrm{w}}{R_\mathrm{wi}} + \frac{T_\mathrm{a} - T_\mathrm{w}}{R_\mathrm{wa}}\right)\mathrm{d}t + \sigma_\mathrm{w}\,\mathrm{d}\omega_\mathrm{w} \\
T_\mathrm{i}^{*} = T_\mathrm{i} + \epsilon
\end{cases}
$$

SOLAR GAIN

THE FRAUNHOFER TWIN HOUSE




NORTH
WEST
EAST
SOUTH
1.3 m2
1.8 m2
4.1 m2
N
Solar gain [kW]
Azimuth angle [°]
0
2
4
6
8
120
160
200
240

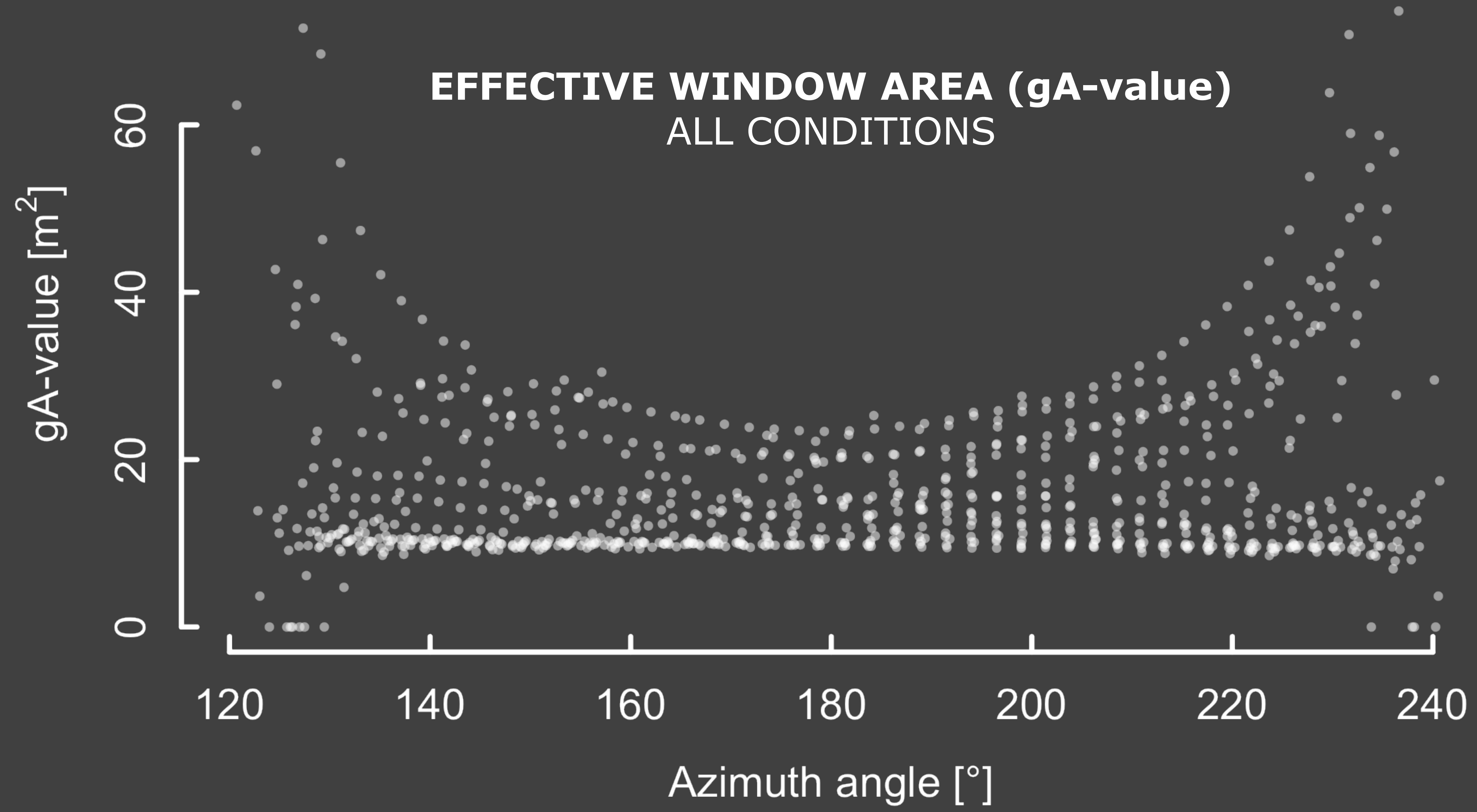
Sum of solar gains from
the North, South, East, and West

Effective window area

$$\mathrm{gA} = \frac{\sum \Phi_{\mathrm{s}}}{I_{\mathrm{g}}}$$

Global solar irradiation

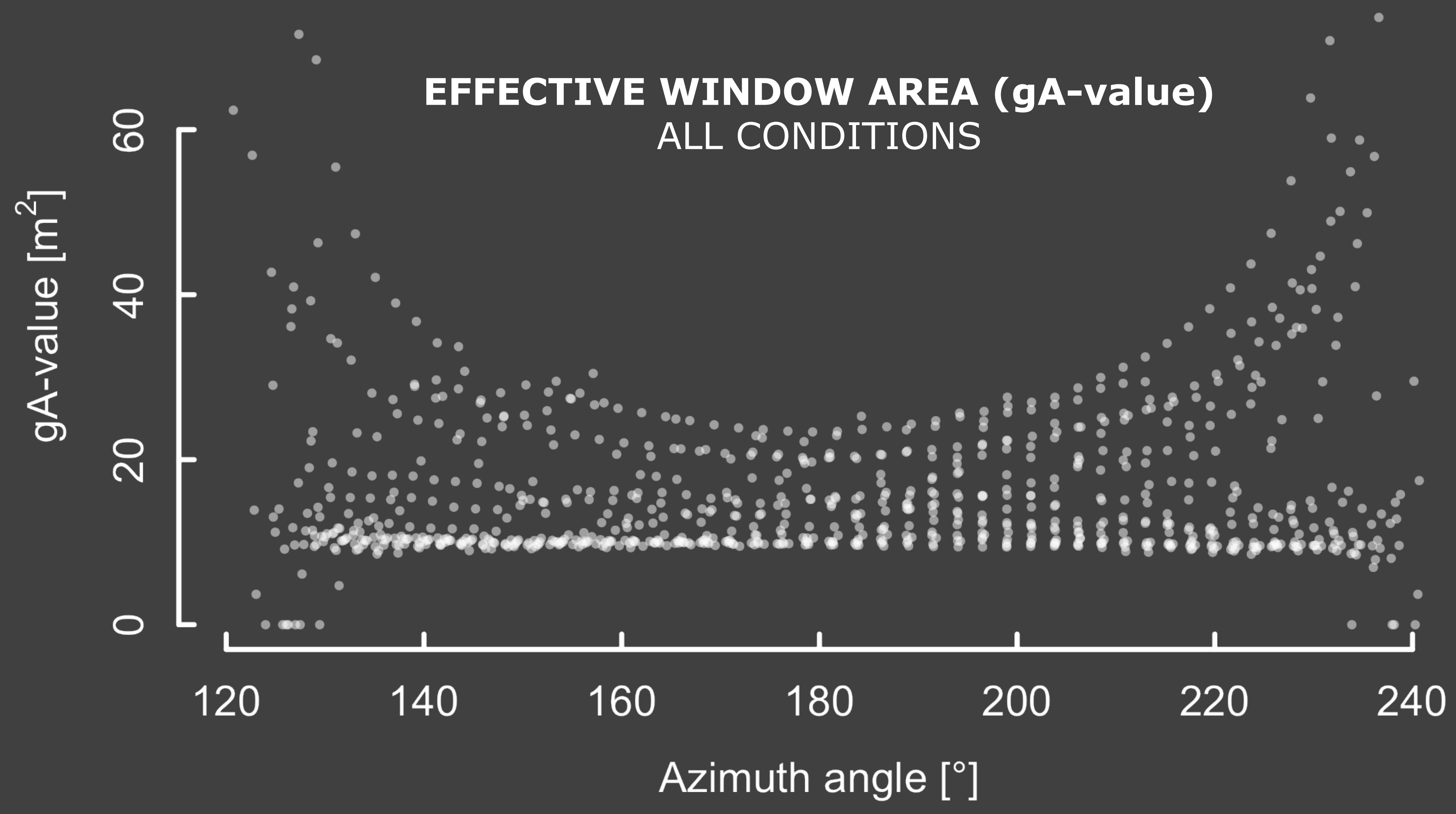
EFFECTIVE WINDOW AREA (gA-value)
ALL CONDITIONS



IF WE CAN ESTIMATE THE EFFECTIVE WINDOW AREA (gA-value)…

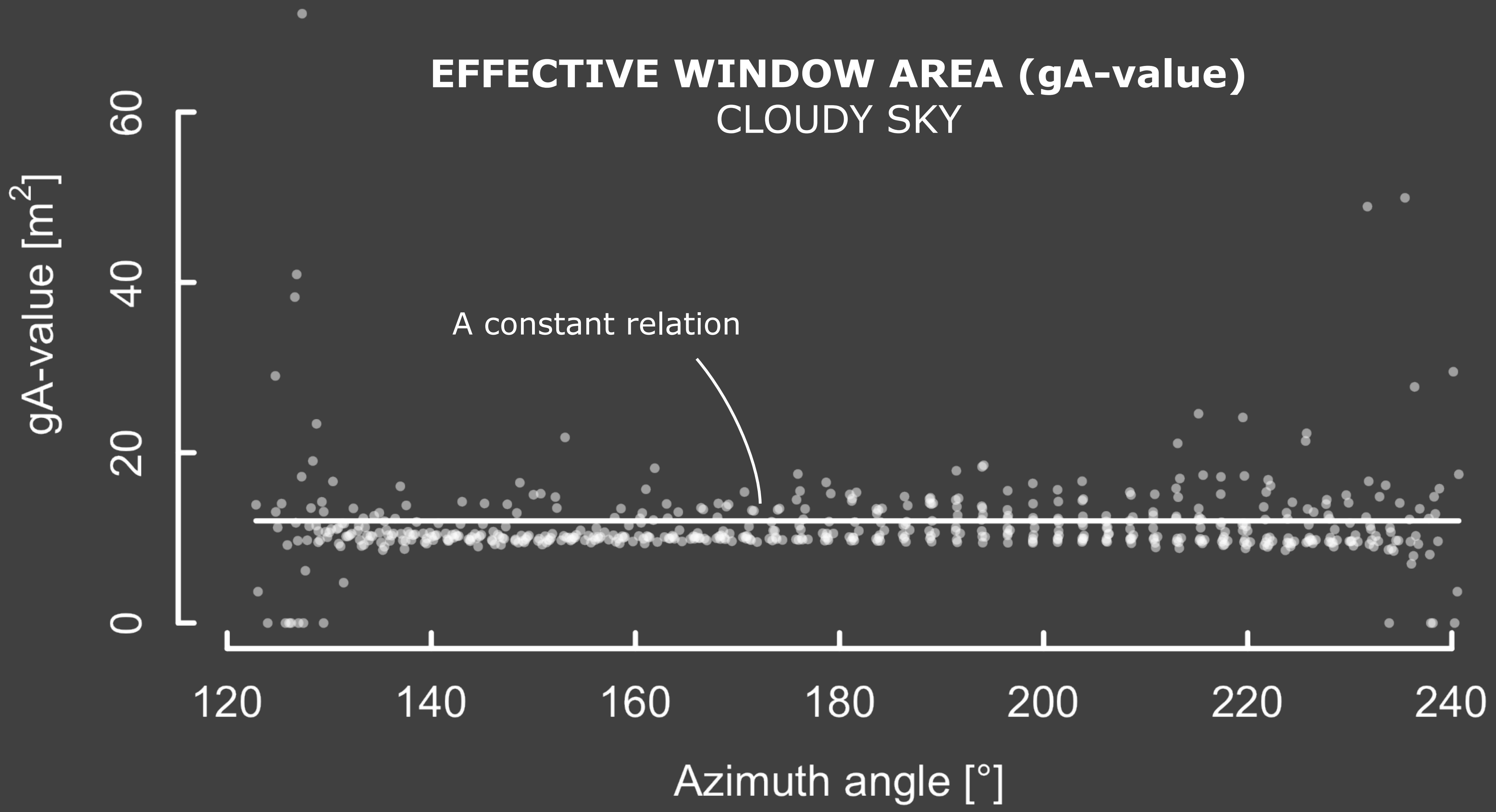
$$\mathrm{gA} = \frac{\sum \Phi_\mathrm{s}}{I_\mathrm{g}}$$

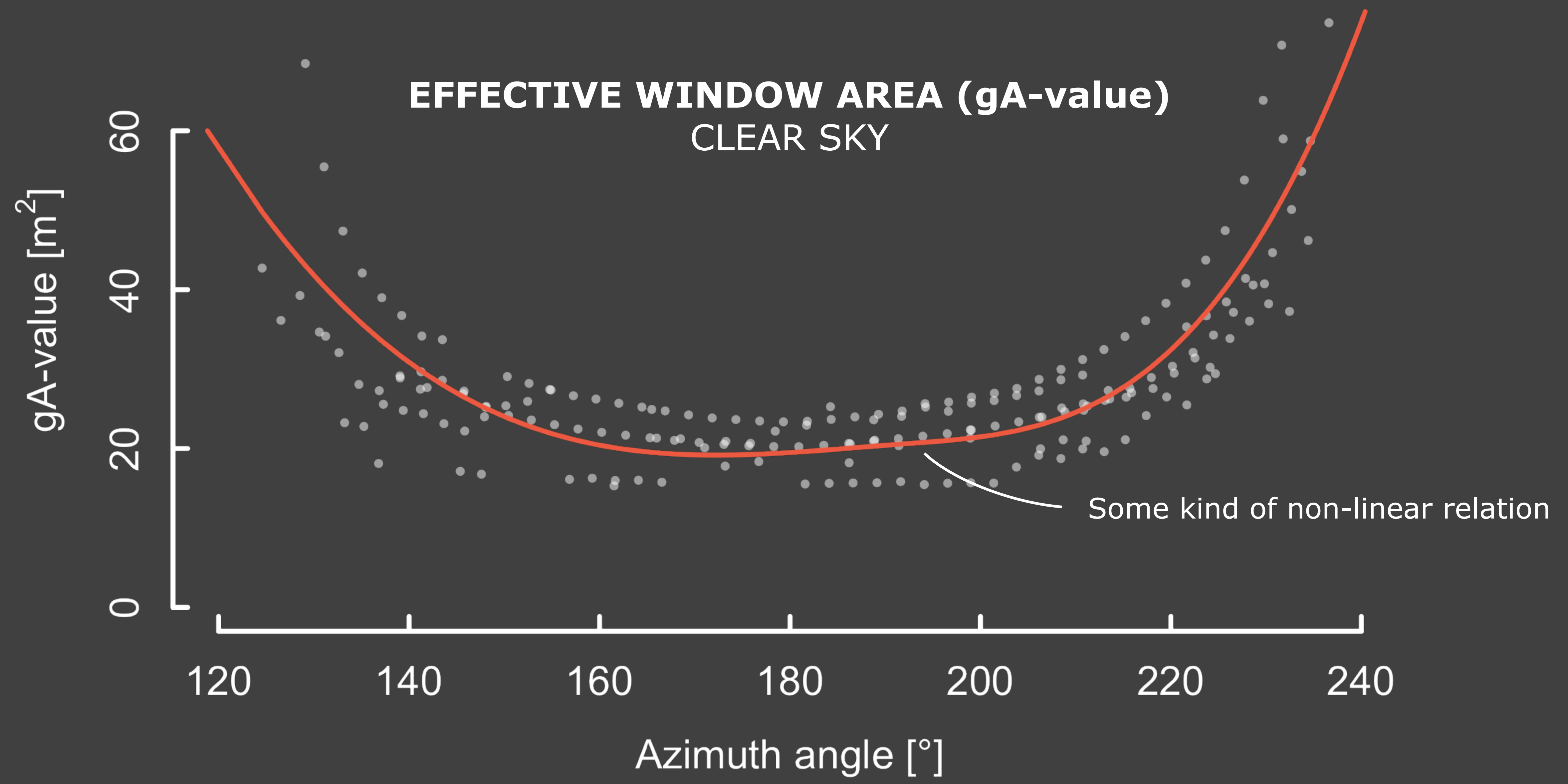
…WE CAN PREDICT THE SOLAR GAIN

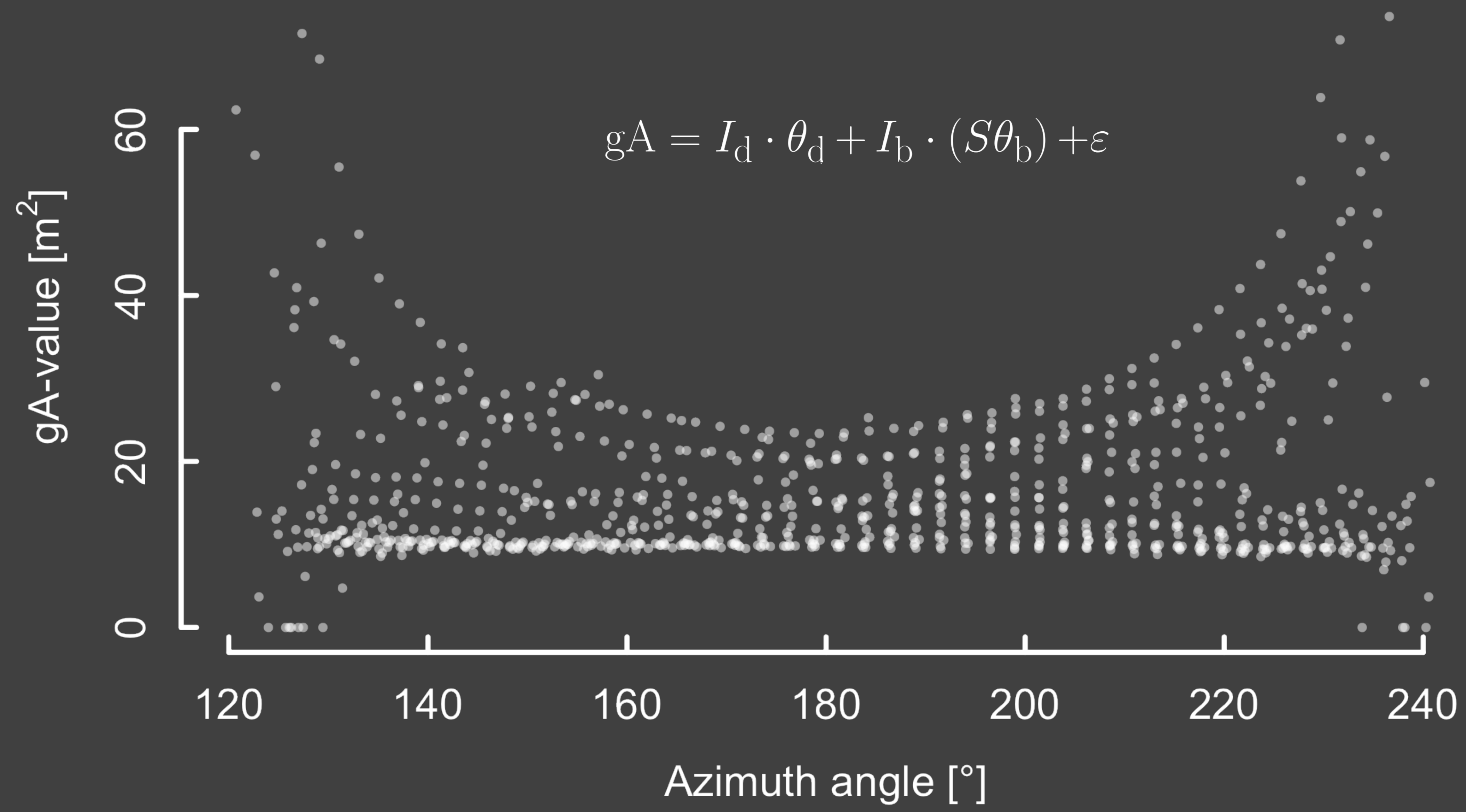

EFFECTIVE WINDOW AREA (gA-value)
ALL CONDITIONS
gA-value [m2]
0
20
40
60
120
140
160
180
200
220
240
Azimuth angle [°]

EFFECTIVE WINDOW AREA (gA-value)

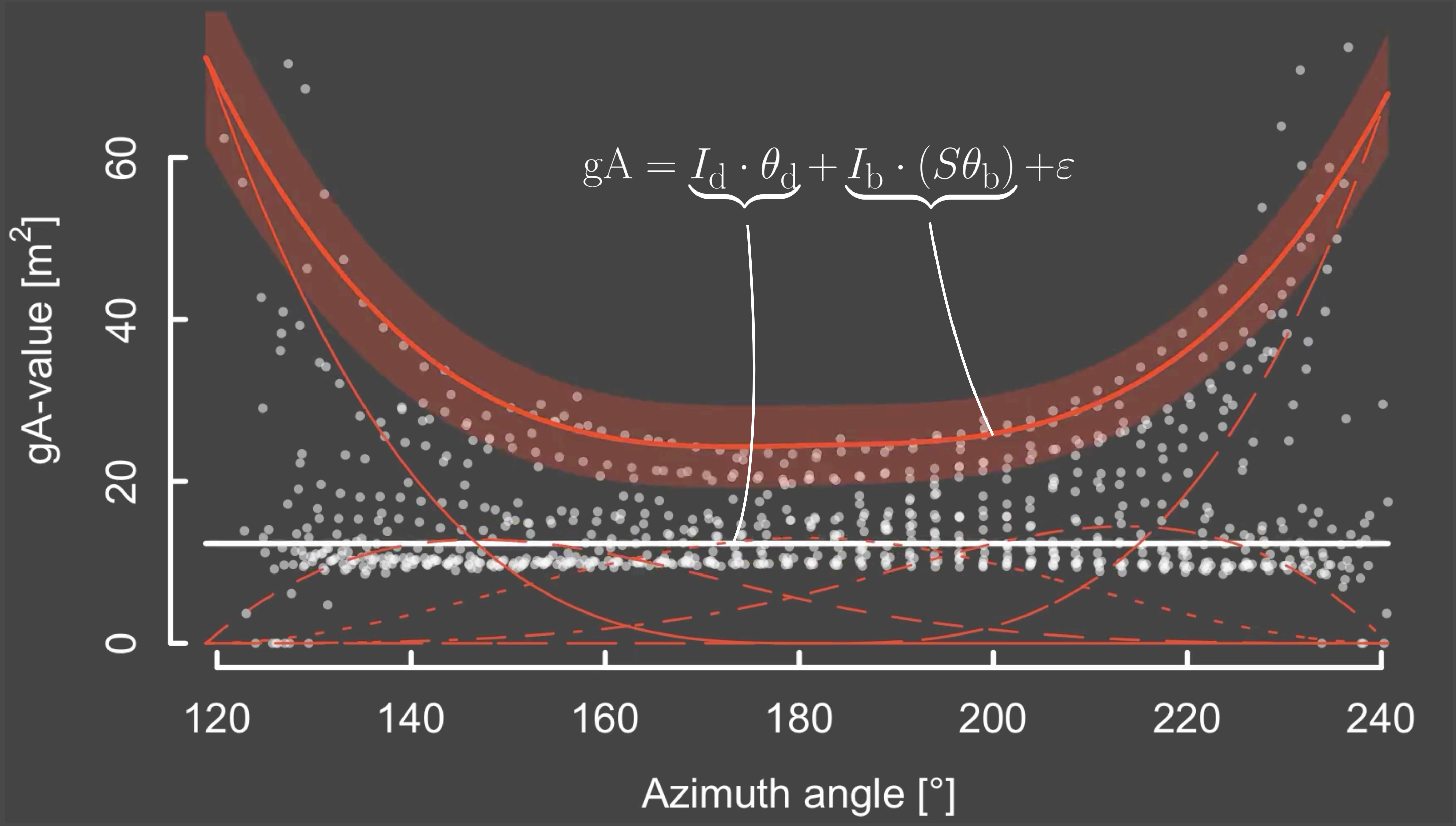
CLOUDY SKY




EFFECTIVE WINDOW AREA (gA-value)
CLEAR SKY
gA-value [m2]
0
20
40
60
120
140
160
180
200
220
240
Azimuth angle [°]
Some kind of non-linear relation



$\mathrm{gA} = I_\mathrm{d} \cdot \theta_\mathrm{d} + I_\mathrm{b} \cdot (S\theta_\mathrm{b}) + \varepsilon$
gA-value [m2]
0
20
40
60
120
140
160
180
200
220
240
Azimuth angle [°]



$\mathrm{gA} = \underbrace{I_\mathrm{d} \cdot \theta_\mathrm{d}} + \underbrace{I_\mathrm{b} \cdot (S\theta_\mathrm{b})} + \varepsilon$
gA-value [m^2]
0
20
40
60
120
140
160
180
200
220
240
Azimuth angle [°]

energies

MDPI

Article

Method for Scalable and Automatised Thermal Building Performance Documentation and Screening

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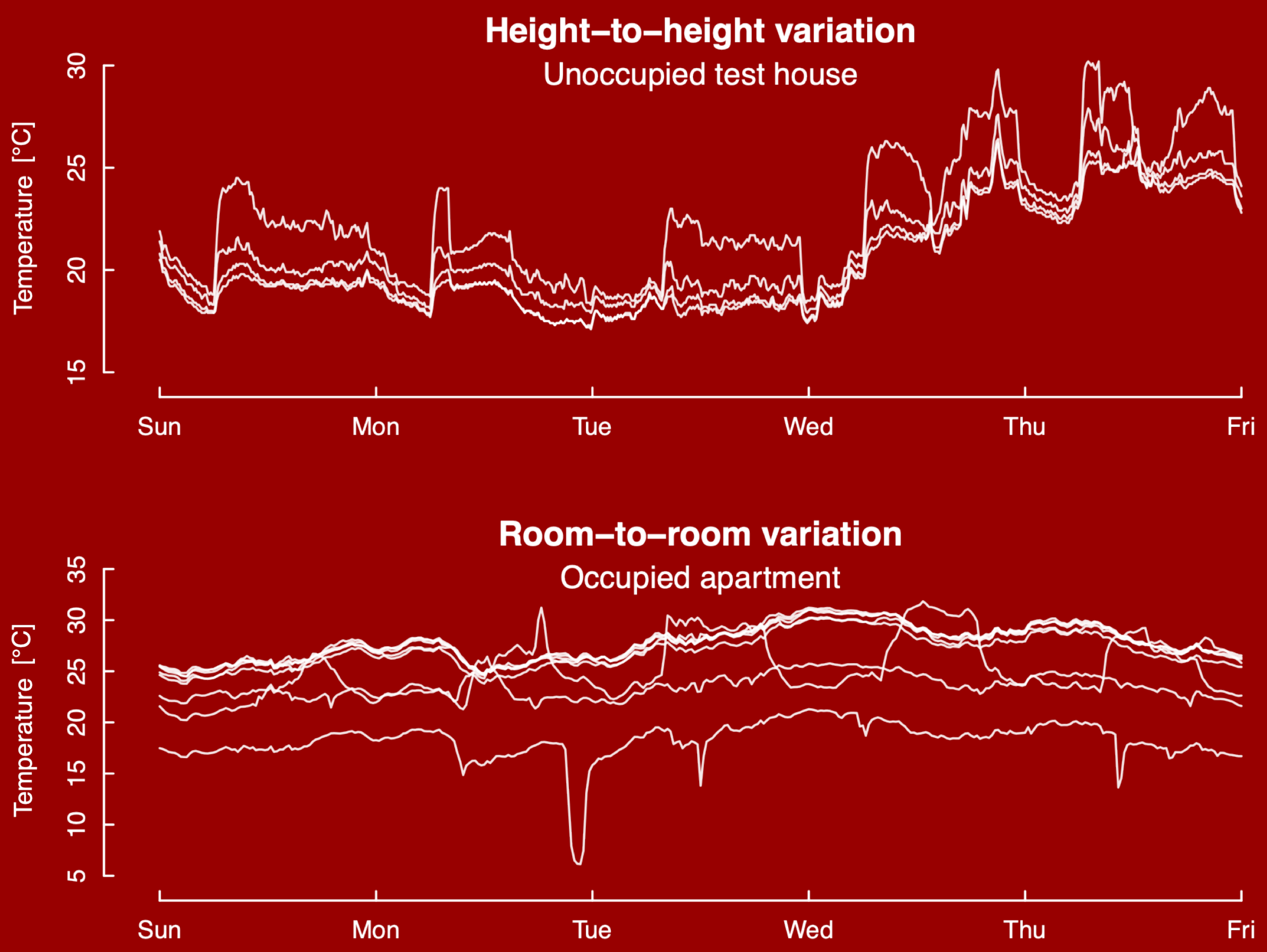
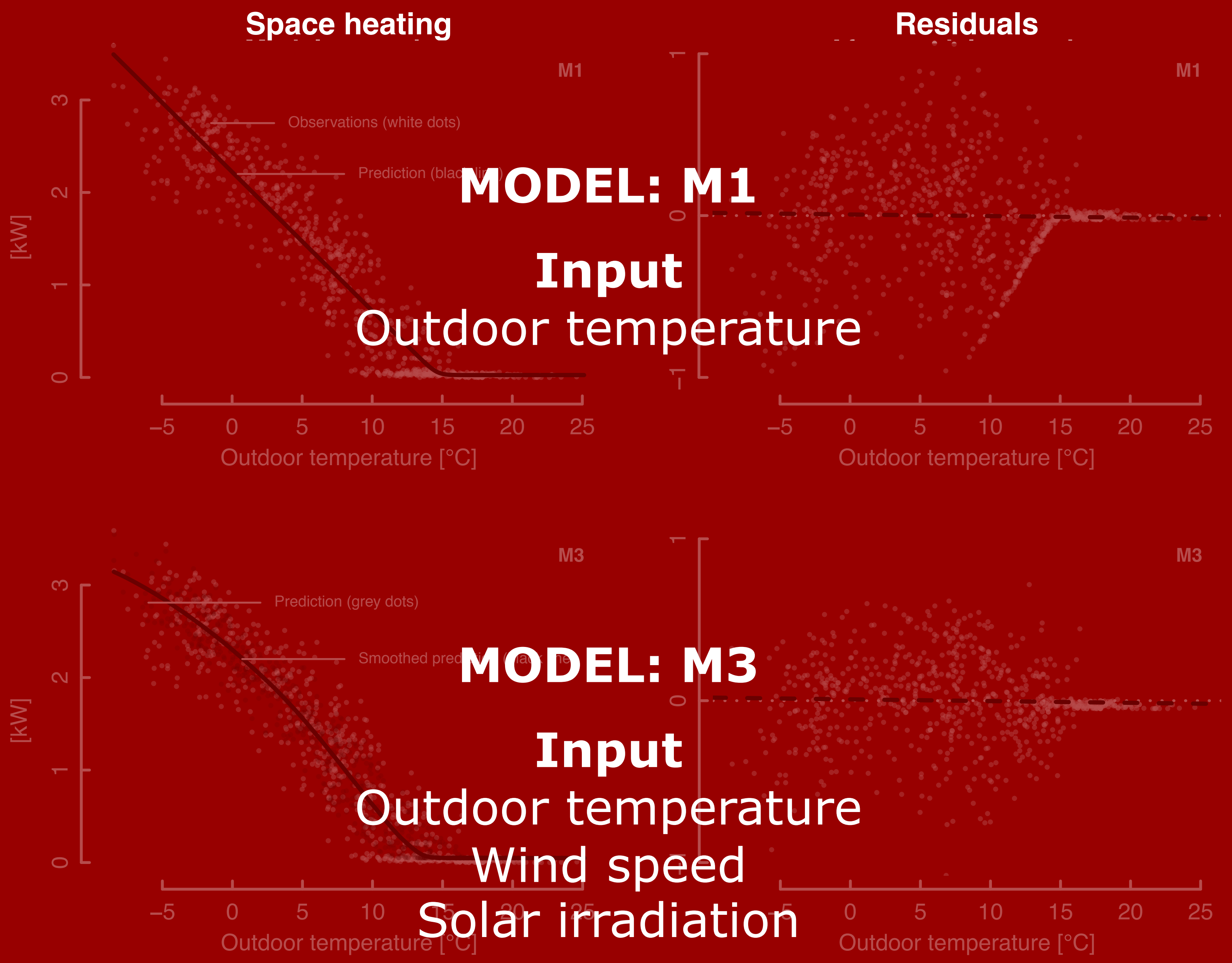
check for updates

Abstract: In Europe, more and more data on building energy use will be collected in the future as a result of the energy performance of buildings directive (EPBD), issued by the European Union. Moreover, both at European level and globally it became evident that the real energy performance of new buildings and the existing building stock needs to be documented better. Such documentation can, for example, be done with data-driven methods based on mathematical and statistical approaches. Even though the methods to extract energy performance characteristics of buildings are numerous, they are of varying reliability and often associated with a significant amount of human labour, making them hard to apply on a large scale. A classical approach to identify certain thermal



Height–to–height variation
Unoccupied test house
Temperature [°C]
15
20
25
30
Sun
Mon
Tue
Wed
Thu
Fri
Room–to–room variation
Occupied apartment
Temperature [°C]
5
10
15
20
25
30
35
Sun
Mon
Tue
Wed
Thu
Fri



MODEL: M1

Input

Outdoor temperature

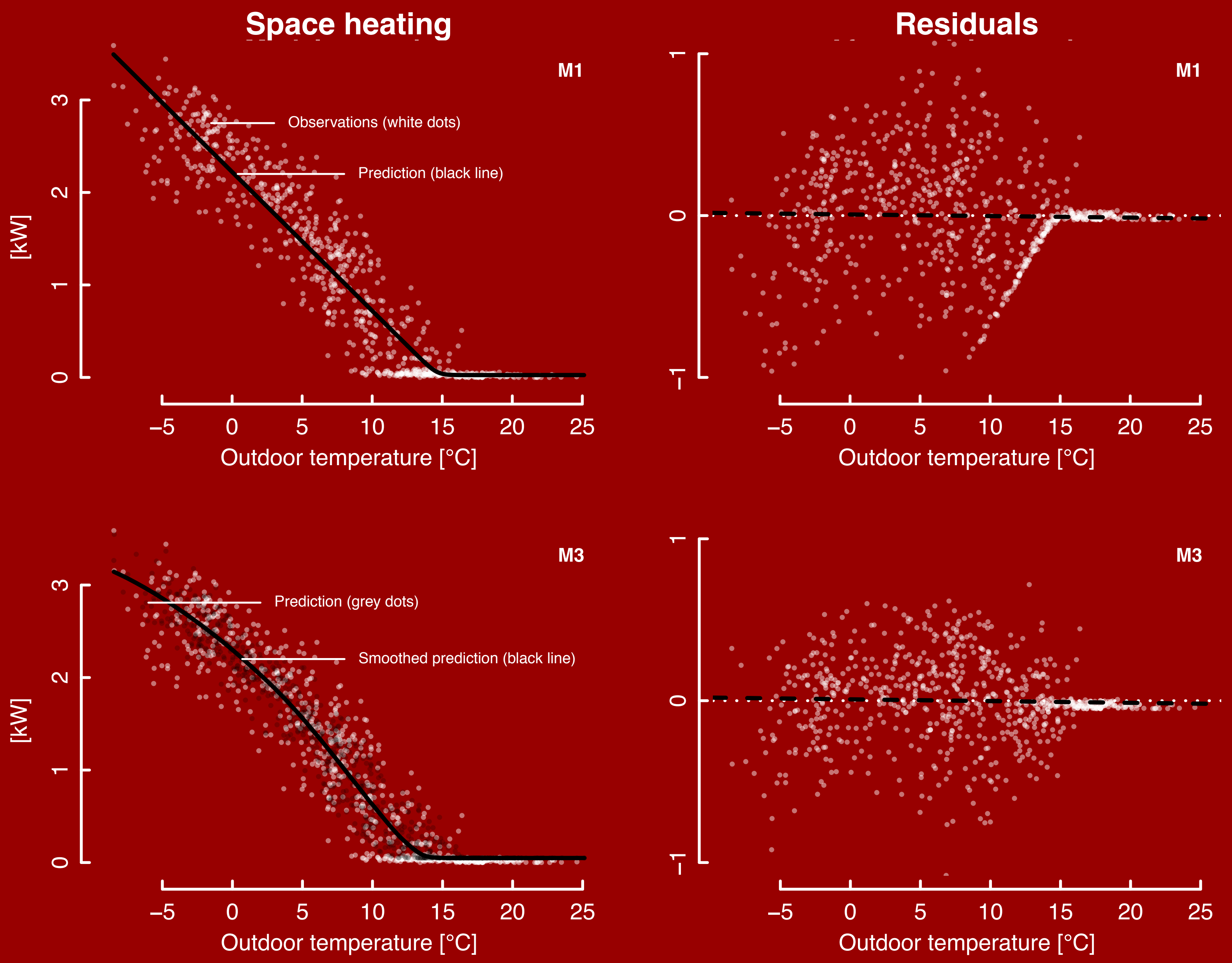
MODEL: M3

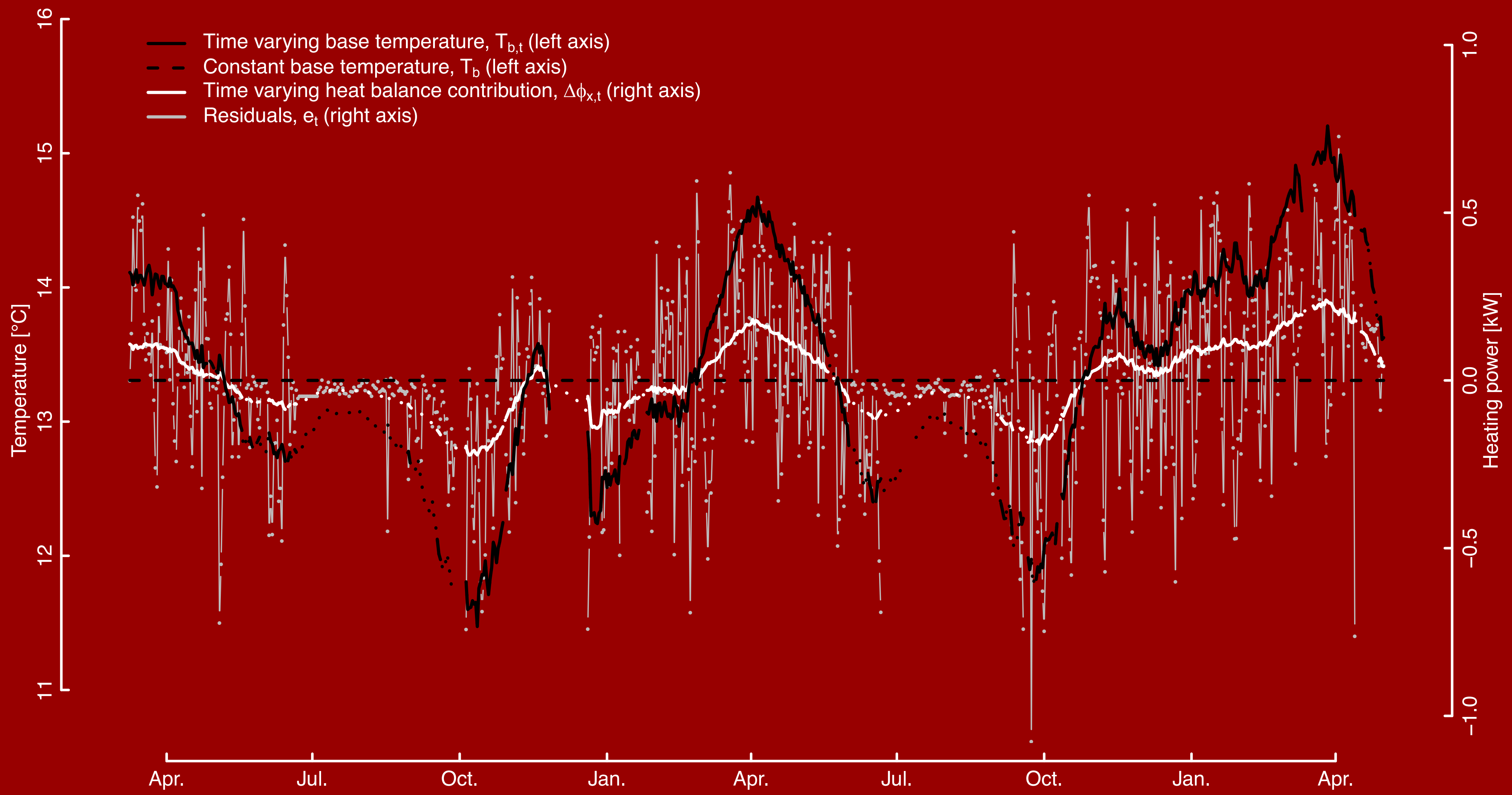
Input

Outdoor temperature

Wind speed

Solar irradiation


Space heating
Residuals
M1
Observations (white dots)
Prediction (black line)
[kW]
Outdoor temperature [°C]
M3
Prediction (grey dots)
Smoothed prediction (black line)

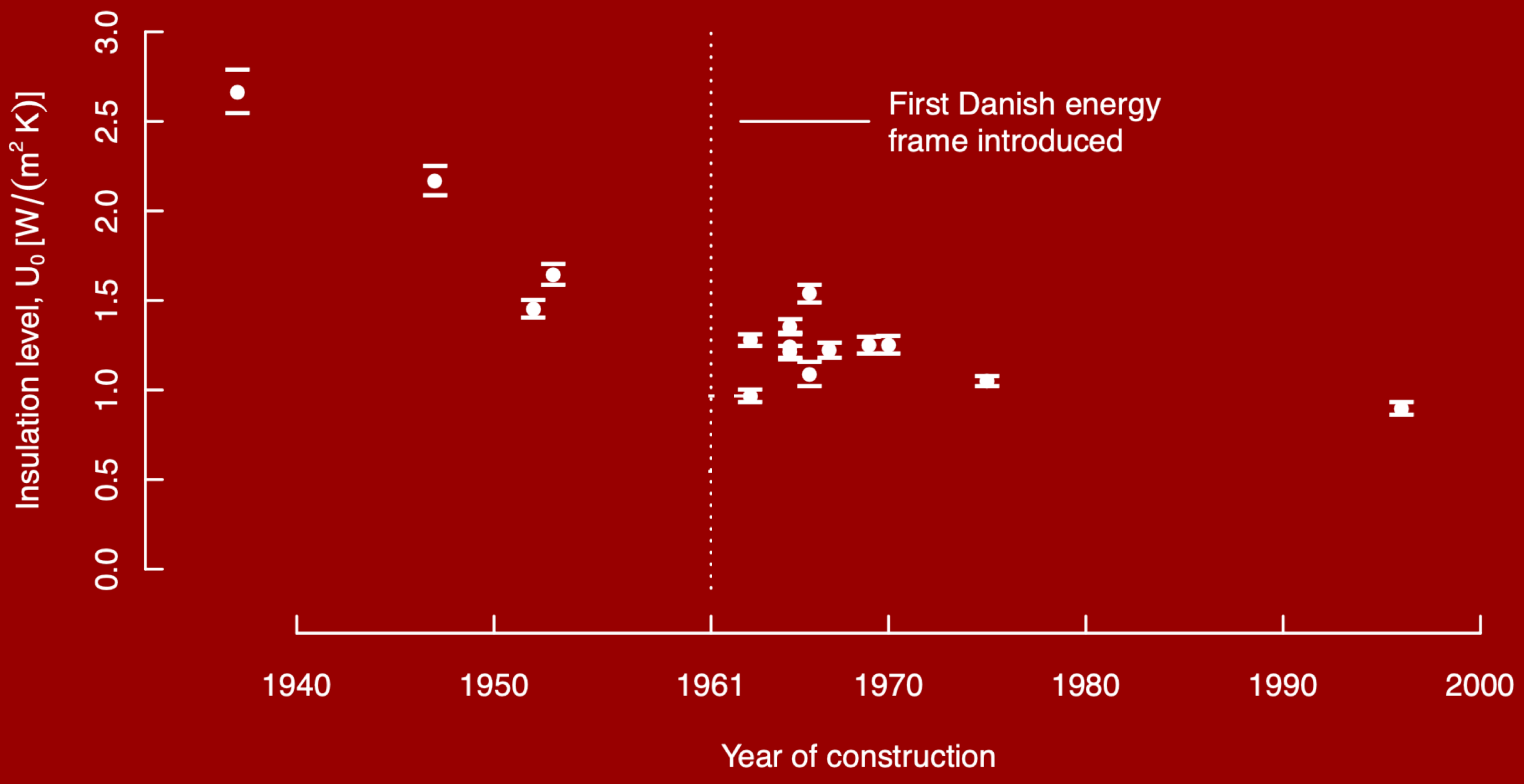


Time varying base temperature, $T_{b,t}$ (left axis)
Constant base temperature, T_b (left axis)
Time varying heat balance contribution, $\Delta\phi_{x,t}$ (right axis)
Residuals, e_t (right axis)
Temperature [°C]
Heating power [kW]
16
15
14
13
12
11
1.0
0.5
0.0
−0.5
−1.0
Apr.
Jul.
Oct.
Jan.
Apr.
Jul.
Oct.
Jan.
Apr.

House	Year	Floor Area $[m^2]$	U_0 $[W/(K\,m^2)]$	UA_0 [W/K]	UA_W [W/K per m/s]	gA $[m^2]$	Φ_0 [W]	T_b [°C]	$T_{transition}$ [°C]	$\overline{\Phi}_{x,t} \mid T_i = 20\,°C$ [W]	$\sigma_{\Phi_{x,t}}$ [W]
1	1970	151	1.25 (0.03) *	189 (4) *	58 (7) *	2.5 (0.3) *	676 (84) *	16.5 (0.5)	12.1–21.0	702	157
2	1969	163	1.25 (0.02) *	204 (4) *	39 (8) *	3.7 (0.3) *	340 (47) *	14.2 (0.4) *	9.5–18.9	1246	194
3	1963	140	1.28 (0.02) *	179 (2) *	32 (5) *	2.5 (0.1) *	141 (30) *	15.7 (0.2) *	11.9–19.5	810	103
4	1952	86	1.45 (0.03) *	125 (2) *	41 (5) *	1.5 (0.2) *	215 (19) *	12.8 (0.3) *	10.2–15.4	971	118
5	1966	111	1.54 (0.03) *	171 (3) *	61 (7) *	1.6 (0.2) *	110 (63)	16.6 (0.3)	9.6–23.6	643	155
6	1963	119	0.97 (0.02) *	115 (2) *	65 (6) *	2.8 (0.2) *	47 (19) *	13.3 (0.3) *	10.2–16.4	880	129
7	1947	119	2.17 (0.04) *	258 (5) *	72 (13) *	1.2 (0.4) *	6 (50)	13.5 (0.3) *	6.9–20.0	1810	243
8	1965	160	1.24 (0.04) *	199 (6) *	57 (14) *	2.2 (0.4) *	376 (45) *	12.6 (0.5) *	8.9–16.4	1569	258
9	1965	173	1.21 (0.02) *	210 (3) *	42 (6) *	1.2 (0.2) *	523 (62) *	18.2 (0.3) *	15.8–20.6	389	275
10	1996	135	0.90 (0.02) *	121 (2) *	51 (6) *	2.5 (0.2) *	106 (25) *	14.1 (0.4) *	10.2–18.0	786	193
11	1966	122	1.09 (0.04) *	133 (4) *	31 (11) *	1.2 (0.3) *	108 (46) *	14.7 (0.5) *	10.5–18.9	751	96
12	1975	136	1.05 (0.02) *	143 (2) *	31 (4) *	1.9 (0.1) *	644 (17) *	13.4 (0.3) *	11.3–15.4	1001	94
13	1937	86	2.67 (0.06) *	229 (5) *	92 (14) *	4.4 (0.4) *	45 (31)	11.2 (0.3) *	7.6–14.8	2227	431
14	1965	123	1.36 (0.02) *	167 (2) *	57 (6) *	2.4 (0.2) *	356 (22) *	14.1 (0.3) *	11.8–16.4	1068	203
15	1953	127	1.65 (0.03) *	209 (4) *	80 (10) *	3.1 (0.3) *	166 (35) *	13.0 (0.3) *	7.0–19.1	1593	210
16	1967	137	1.22 (0.02) *	167 (3) *	34 (7) *	1.3 (0.2) *	193 (26) *	13.5 (0.3) *	8.1–18.9	1137	143
H_0 :			$U_0 = 0$	$UA_0 = 0$	$UA_W = 0$	$gA = 0$	$\Phi_0 = 0$	$T_b = 17$			

Significance code '*': p-value < 0.05.

ESTIMATED INSULATION LEVEL



THANK YOU!

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