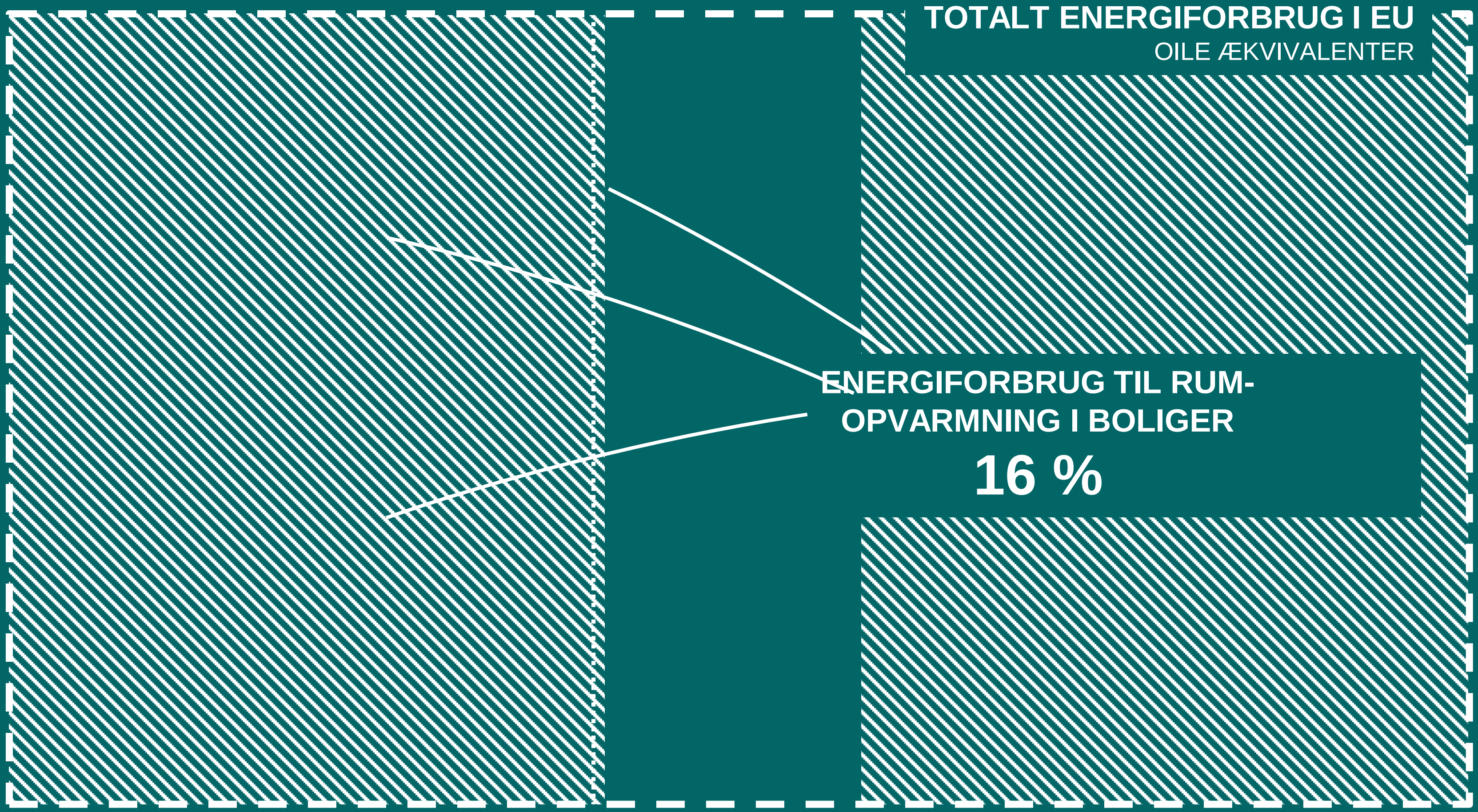
REBUS

RENOVATING BUILDINGS SUSTAINABLY

EMNE: Brug data til at bestemme bygningens termiske ydeevne

Christoffer Rasmussen, Postdoc
DTU Compute



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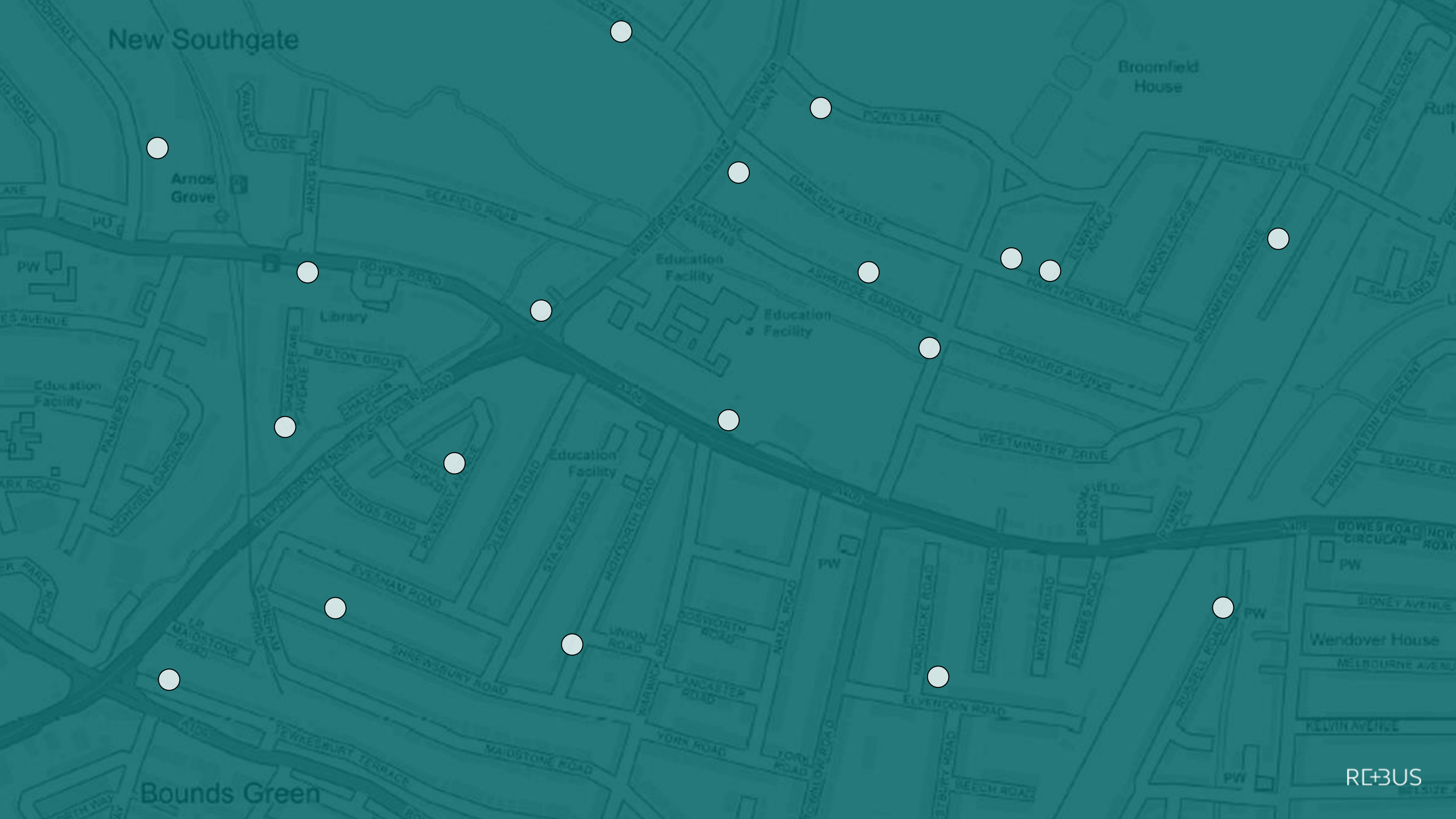
ENERGIFORBRUG TIL RUMOPVARMNING I BOLIGER

16 %

Eurostat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Westminster Drive
Broomfield Lane
Broomfield Avenue
Belmont Avenue
Elmwood Avenue
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Shrewsbury Road
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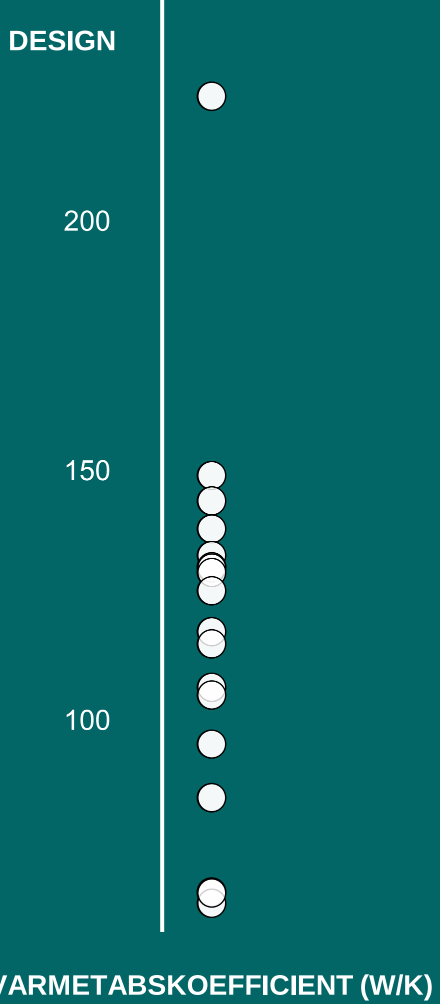

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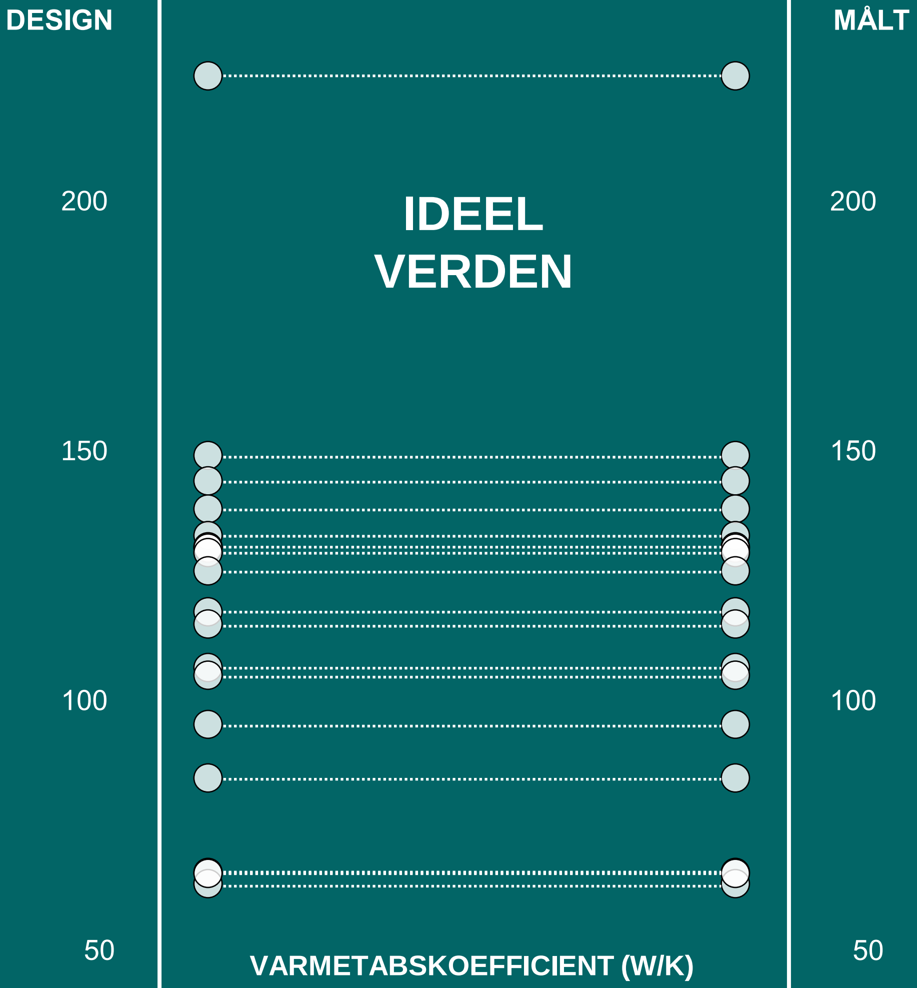
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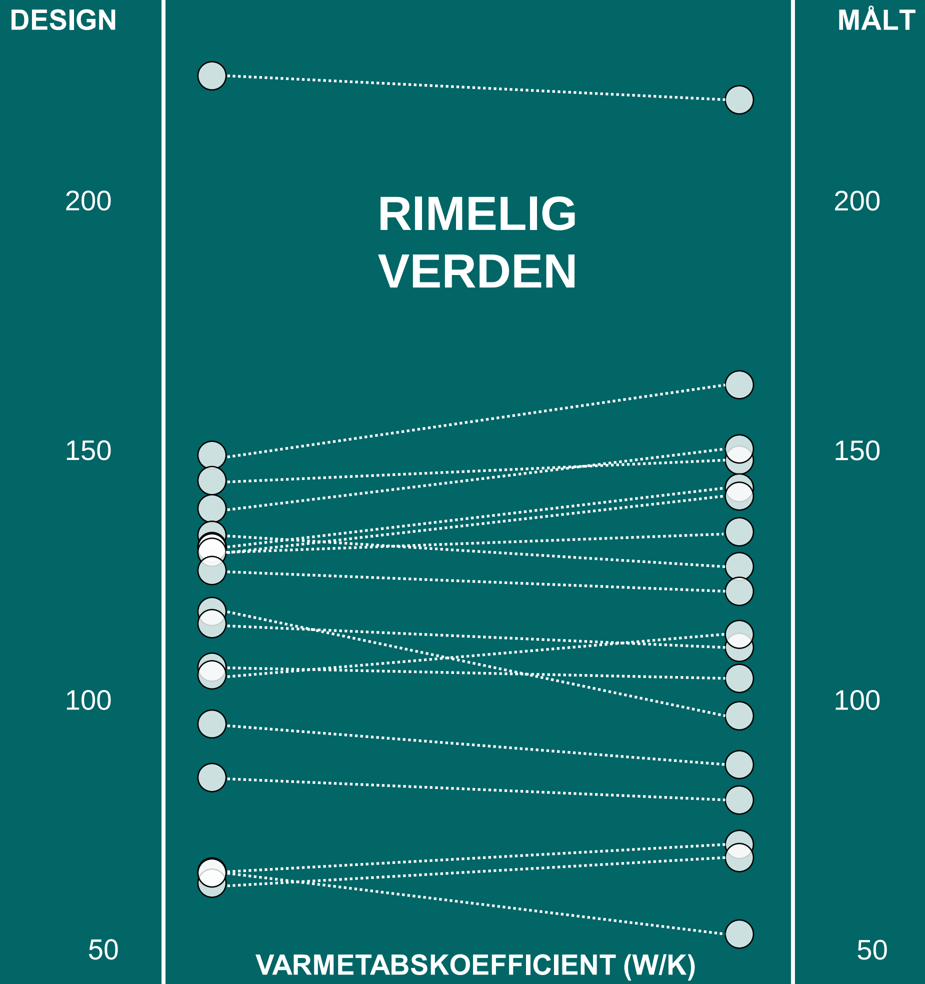

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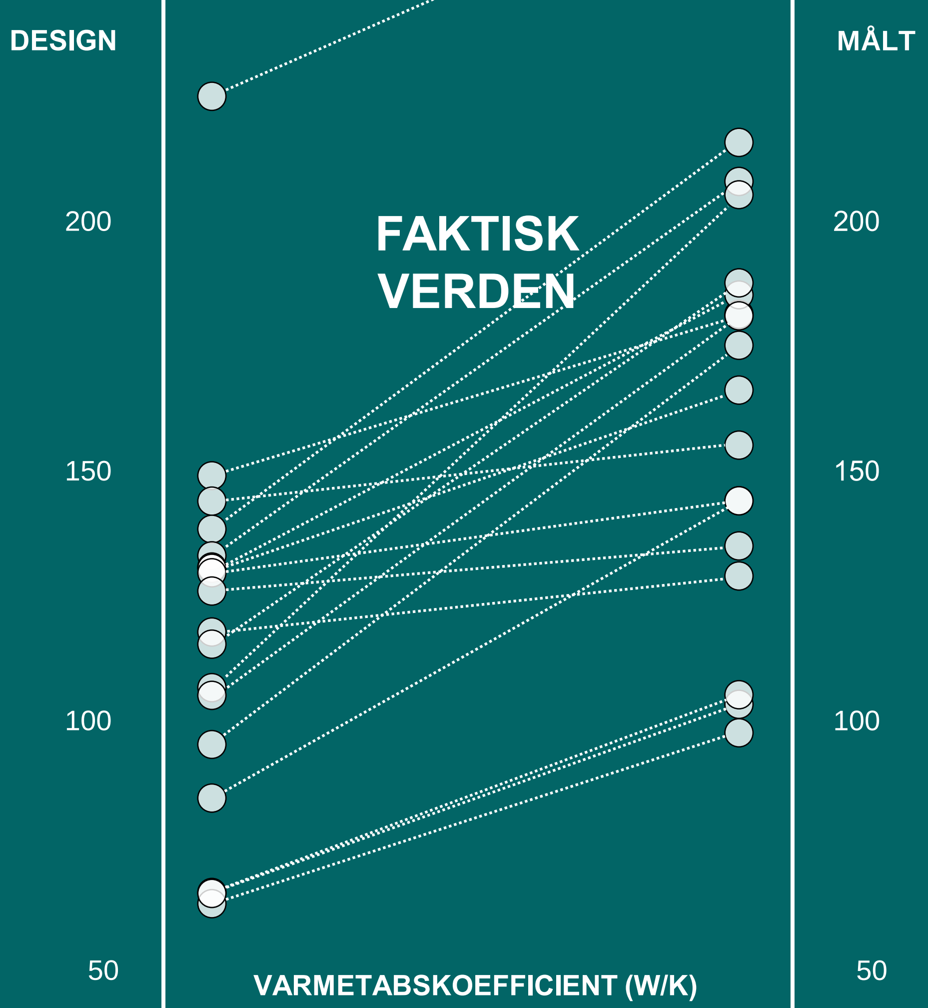

J. Wingfield et al., 2011

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Det bedste fra to verdener:

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HVAD BRUGER VI GREY-BOX MODELLER TIL?

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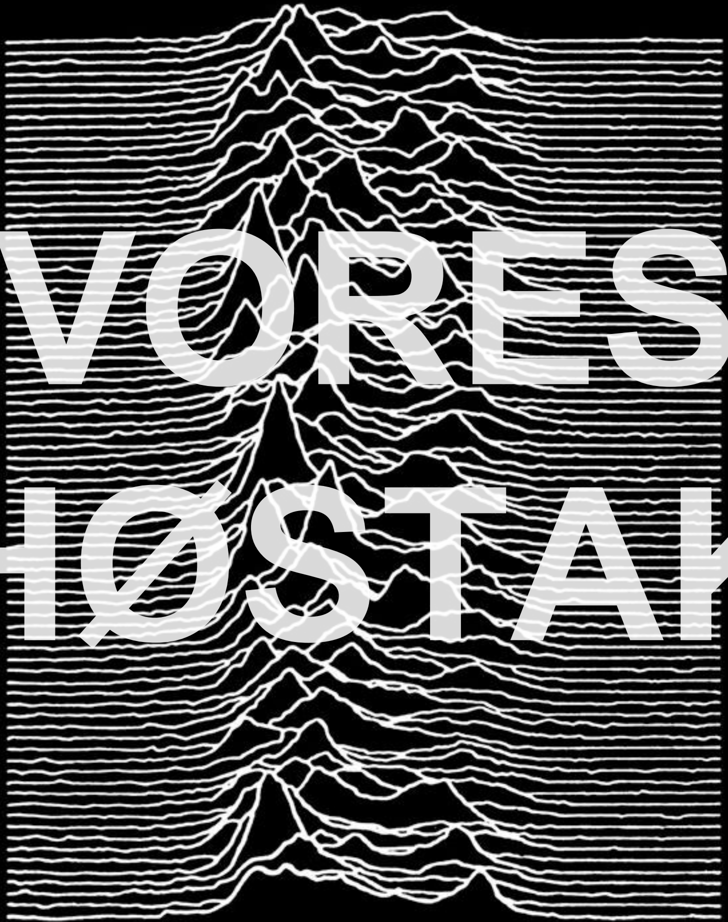
Sven Sachsalber, Palais de Tokyo, 2014



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Joy Division, Unknown Pleasures, 1979

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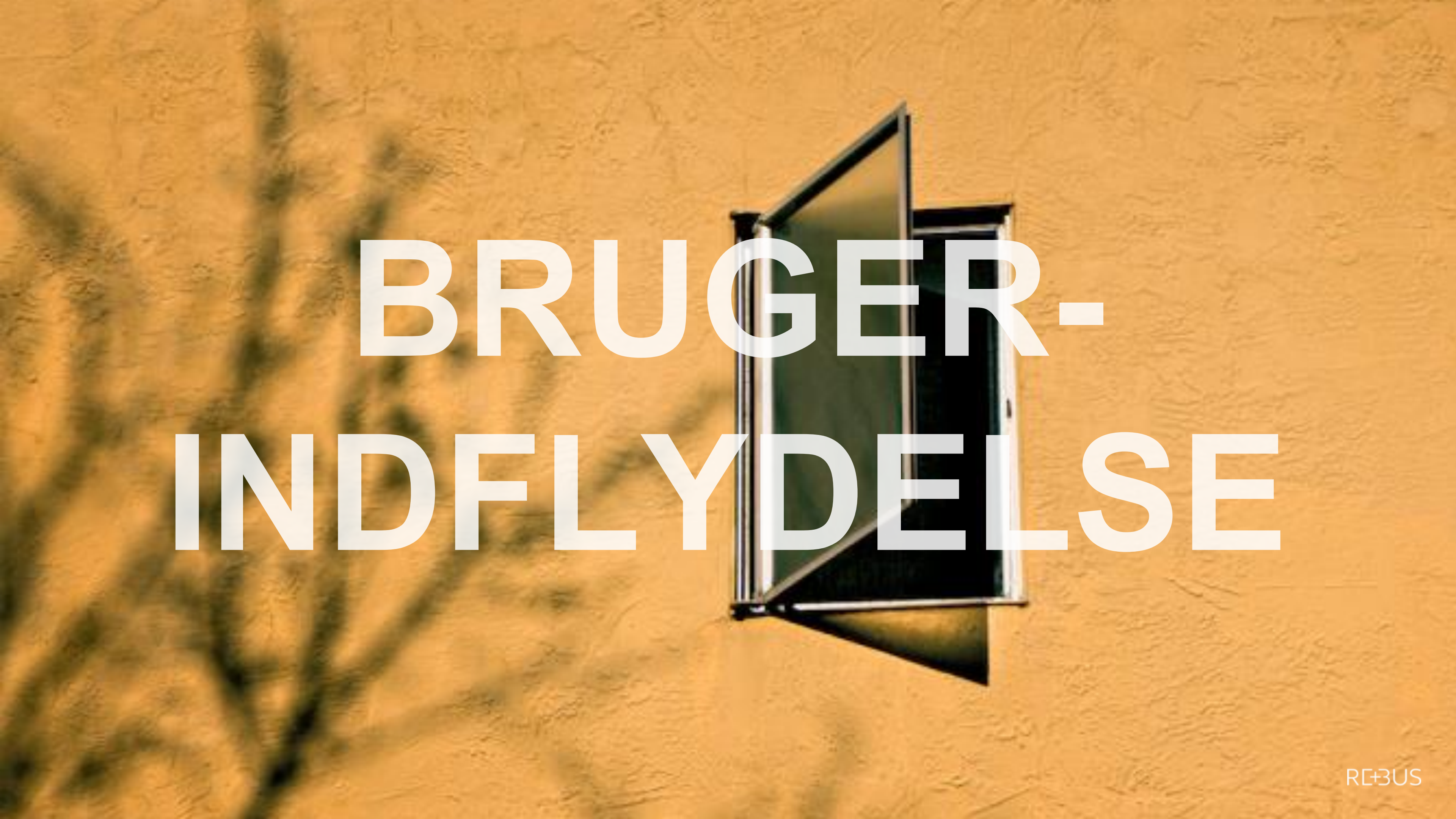

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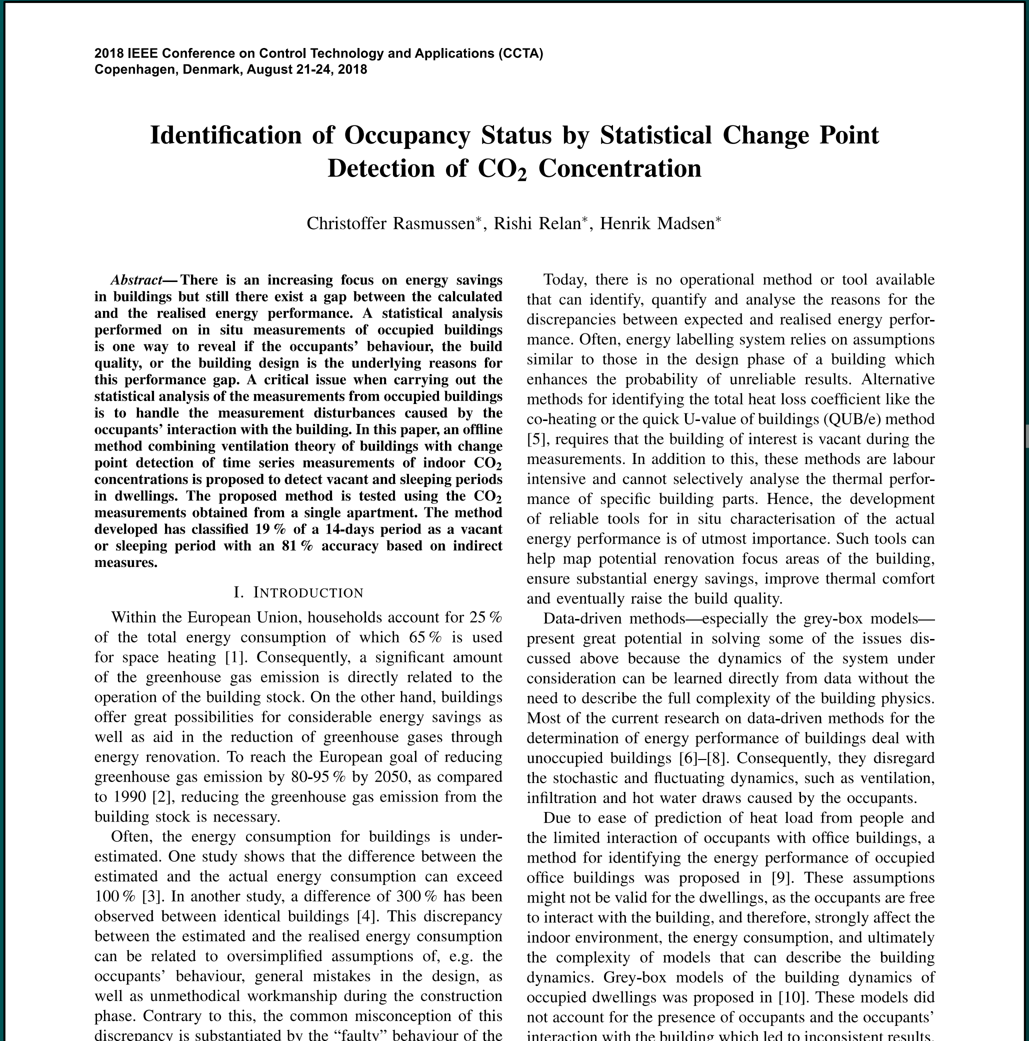

2018 IEEE Conference on Control Technology and Applications (CCTA)
Copenhagen, Denmark, August 21-24, 2018

Identification of Occupancy Status by Statistical Change Point Detection of CO_2 Concentration

Christoffer Rasmussen*, Rishi Relan*, Henrik Madsen*

Abstract— **There is an increasing focus on energy savings in buildings but still there exist a gap between the calculated and the realised energy performance. A statistical analysis performed on in situ measurements of occupied buildings is one way to reveal if the occupants' behaviour, the build quality, or the building design is the underlying reasons for this performance gap. A critical issue when carrying out the statistical analysis of the measurements from occupied buildings is to handle the measurement disturbances caused by the occupants' interaction with the building. In this paper, an offline method combining ventilation theory of buildings with change point detection of time series measurements of indoor CO_2 concentrations is proposed to detect vacant and sleeping periods in dwellings. The proposed method is tested using the CO_2 measurements obtained from a single apartment. The method developed has classified 19 % of a 14-days period as a vacant or sleeping period with an 81 % accuracy based on indirect measures.**

I. INTRODUCTION

Within the European Union, households account for 25 % of the total energy consumption of which 65 % is used for space heating [1]. Consequently, a significant amount of the greenhouse gas emission is directly related to the operation of the building stock. On the other hand, buildings offer great possibilities for considerable energy savings as well as aid in the reduction of greenhouse gases through energy renovation. To reach the European goal of reducing greenhouse gas emission by 80-95 % by 2050, as compared to 1990 [2], reducing the greenhouse gas emission from the building stock is necessary.

Often, the energy consumption for buildings is underestimated. One study shows that the difference between the estimated and the actual energy consumption can exceed 100 % [3]. In another study, a difference of 300 % has been observed between identical buildings [4]. This discrepancy between the estimated and the realised energy consumption can be related to oversimplified assumptions of, e.g. the occupants' behaviour, general mistakes in the design, as well as unmethodical workmanship during the construction phase. Contrary to this, the common misconception of this discrepancy is substantiated by the “faulty” behaviour of the

Today, there is no operational method or tool available that can identify, quantify and analyse the reasons for the discrepancies between expected and realised energy performance. Often, energy labelling system relies on assumptions similar to those in the design phase of a building which enhances the probability of unreliable results. Alternative methods for identifying the total heat loss coefficient like the co-heating or the quick U-value of buildings (QUB/e) method [5], requires that the building of interest is vacant during the measurements. In addition to this, these methods are labour intensive and cannot selectively analyse the thermal performance of specific building parts. Hence, the development of reliable tools for in situ characterisation of the actual energy performance is of utmost importance. Such tools can help map potential renovation focus areas of the building, ensure substantial energy savings, improve thermal comfort and eventually raise the build quality.

Data-driven methods—especially the grey-box models—present great potential in solving some of the issues discussed above because the dynamics of the system under consideration can be learned directly from data without the need to describe the full complexity of the building physics. Most of the current research on data-driven methods for the determination of energy performance of buildings deal with unoccupied buildings [6]–[8]. Consequently, they disregard the stochastic and fluctuating dynamics, such as ventilation, infiltration and hot water draws caused by the occupants.

Due to ease of prediction of heat load from people and the limited interaction of occupants with office buildings, a method for identifying the energy performance of occupied office buildings was proposed in [9]. These assumptions might not be valid for the dwellings, as the occupants are free to interact with the building, and therefore, strongly affect the indoor environment, the energy consumption, and ultimately the complexity of models that can describe the building dynamics. Grey-box models of the building dynamics of occupied dwellings was proposed in [10]. These models did not account for the presence of occupants and the occupants' interaction with the building which led to inconsistent results.

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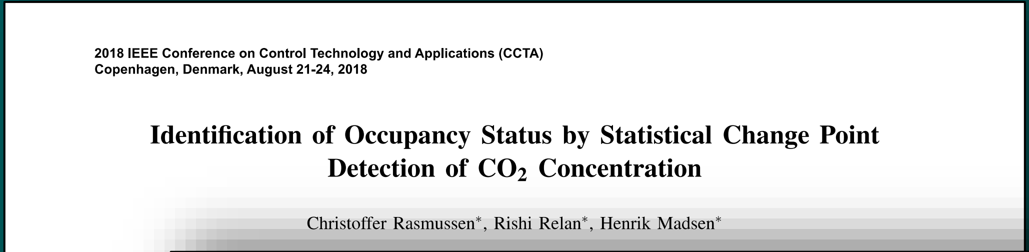

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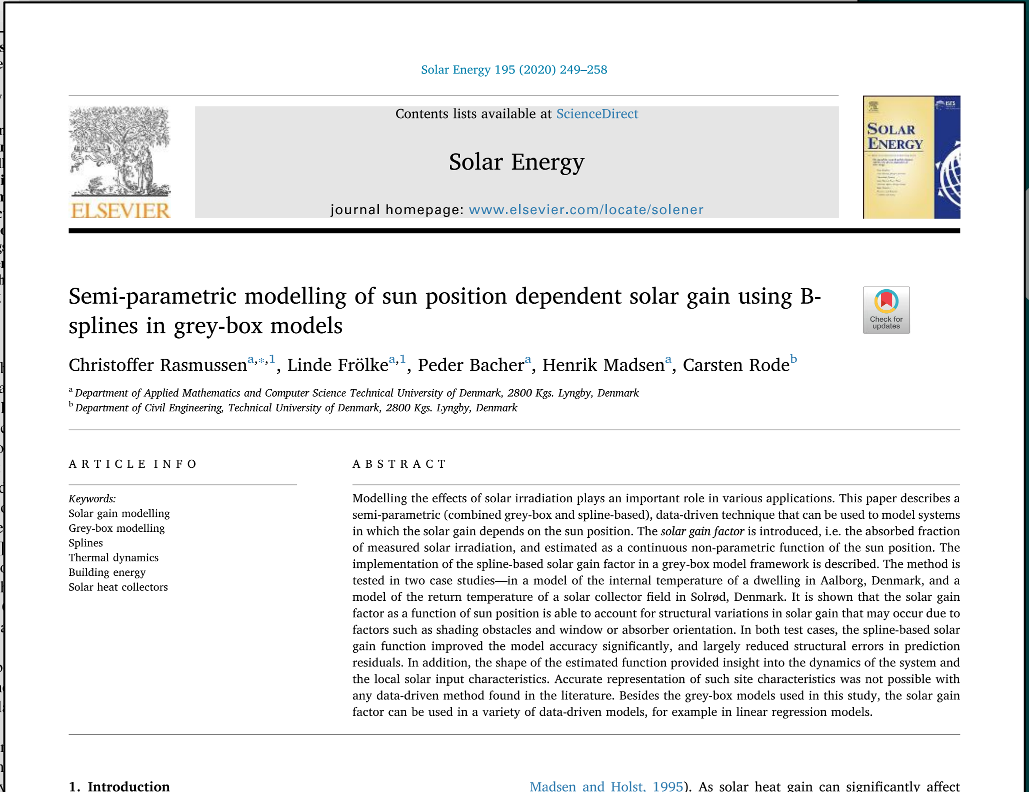

Solar Energy 195 (2020) 249–258

Contents lists available at ScienceDirect

Solar Energy

journal homepage: www.elsevier.com/locate/solener

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SOLAR ENERGY

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

Check for updates

Christoffer Rasmussen[a,*,1], Linde Frölke[a,1], Peder Bacher[a], Henrik Madsen[a], Carsten Rode[b]

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ARTICLE INFO

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

ABSTRACT

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 any data-driven method found in the literature. Besides the grey-box models used in this study, the solar gain factor can be used in a variety of data-driven models, for example in linear regression models.

1. Introduction

Madsen and Holst, 1995). As solar heat gain can significantly affect

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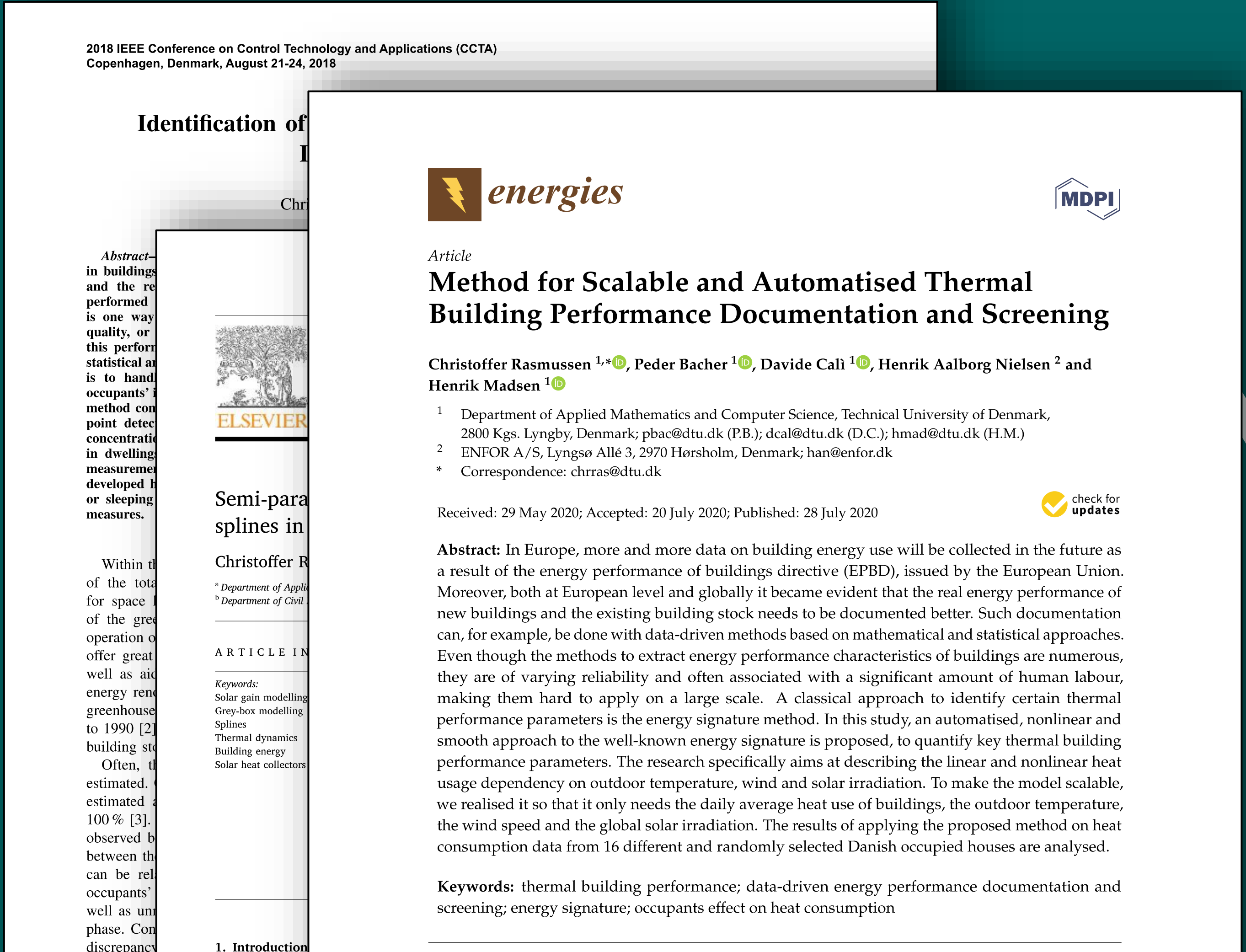

2018 IEEE Conference on Control Technology and Applications (CCTA)
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[a] *Department of Appli*
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ARTICLE IN

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

1. Introduction

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Article

Method for Scalable and Automatised Thermal Building Performance Documentation and Screening

Christoffer Rasmussen [1,*], Peder Bacher [1], Davide Calì [1], Henrik Aalborg Nielsen [2] and Henrik Madsen [1]

[1] Department of Applied Mathematics and Computer Science, Technical University of Denmark, 2800 Kgs. Lyngby, Denmark; pbac@dtu.dk (P.B.); dcal@dtu.dk (D.C.); hmad@dtu.dk (H.M.)
[2] ENFOR A/S, Lyngsø Allé 3, 2970 Hørsholm, Denmark; han@enfor.dk
[*] Correspondence: chrras@dtu.dk

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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 performance parameters is the energy signature method. In this study, an automatised, nonlinear and smooth approach to the well-known energy signature is proposed, to quantify key thermal building performance parameters. The research specifically aims at describing the linear and nonlinear heat usage dependency on outdoor temperature, wind and solar irradiation. To make the model scalable, we realised it so that it only needs the daily average heat use of buildings, the outdoor temperature, the wind speed and the global solar irradiation. The results of applying the proposed method on heat consumption data from 16 different and randomly selected Danish occupied houses are analysed.

Keywords: thermal building performance; data-driven energy performance documentation and screening; energy signature; occupants effect on heat consumption

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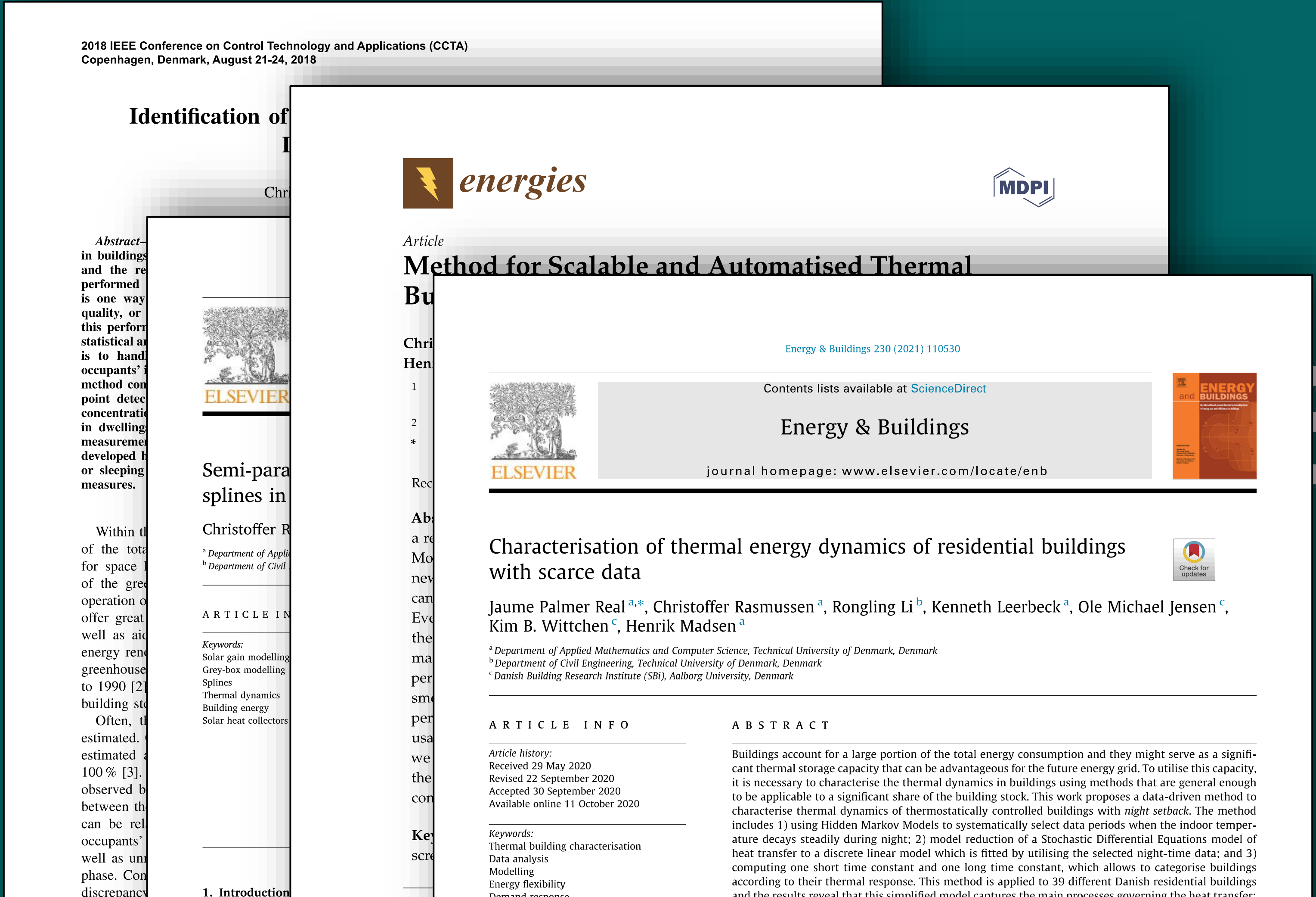

2018 IEEE Conference on Control Technology and Applications (CCTA)
Copenhagen, Denmark, August 21-24, 2018

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Keywords:
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Solar heat collectors

1. Introduction

Energy & Buildings 230 (2021) 110530

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Characterisation of thermal energy dynamics of residential buildings with scarce data

Jaume Palmer Real [a,*], Christoffer Rasmussen [a], Rongling Li [b], Kenneth Leerbeck [a], Ole Michael Jensen [c], Kim B. Wittchen [c], Henrik Madsen [a]

[a] *Department of Applied Mathematics and Computer Science, Technical University of Denmark, Denmark*
[b] *Department of Civil Engineering, Technical University of Denmark, Denmark*
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Thermal building characterisation
Data analysis
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ABSTRACT

Buildings account for a large portion of the total energy consumption and they might serve as a significant thermal storage capacity that can be advantageous for the future energy grid. To utilise this capacity, it is necessary to characterise the thermal dynamics in buildings using methods that are general enough to be applicable to a significant share of the building stock. This work proposes a data-driven method to characterise thermal dynamics of thermostatically controlled buildings with *night setback*. The method includes 1) using Hidden Markov Models to systematically select data periods when the indoor temperature decays steadily during night; 2) model reduction of a Stochastic Differential Equations model of heat transfer to a discrete linear model which is fitted by utilising the selected night-time data; and 3) computing one short time constant and one long time constant, which allows to categorise buildings according to their thermal response. This method is applied to 39 different Danish residential buildings

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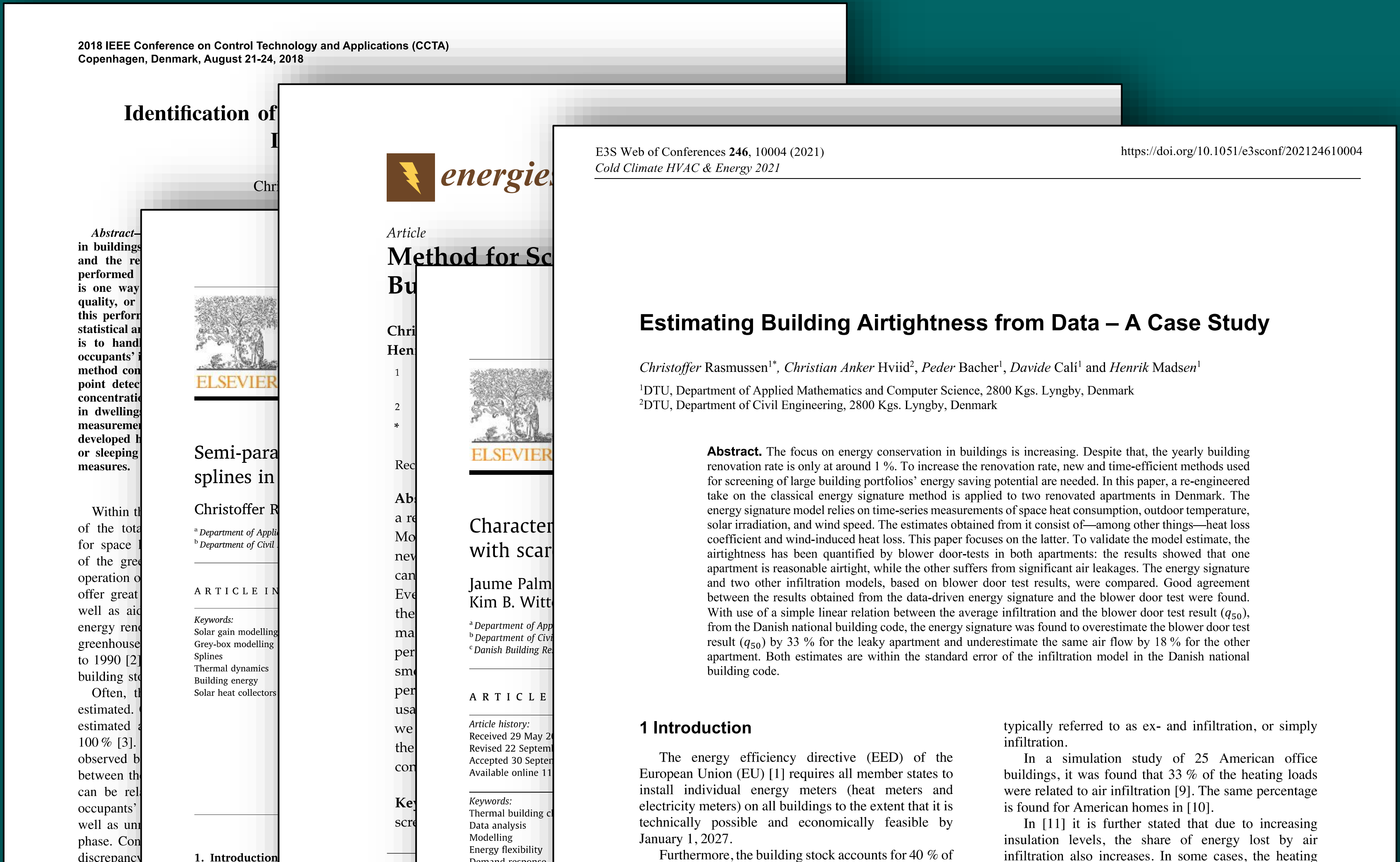

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1. Introduction

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E3S Web of Conferences **246**, 10004 (2021) https://doi.org/10.1051/e3sconf/202124610004
Cold Climate HVAC & Energy 2021

Estimating Building Airtightness from Data – A Case Study

Christoffer Rasmussen[1*], *Christian Anker* Hviid[2], *Peder* Bacher[1], *Davide* Calí[1] and *Henrik* Madsen[1]

[1]DTU, Department of Applied Mathematics and Computer Science, 2800 Kgs. Lyngby, Denmark
[2]DTU, Department of Civil Engineering, 2800 Kgs. Lyngby, Denmark

Abstract. The focus on energy conservation in buildings is increasing. Despite that, the yearly building renovation rate is only at around 1 %. To increase the renovation rate, new and time-efficient methods used for screening of large building portfolios' energy saving potential are needed. In this paper, a re-engineered take on the classical energy signature method is applied to two renovated apartments in Denmark. The energy signature model relies on time-series measurements of space heat consumption, outdoor temperature, solar irradiation, and wind speed. The estimates obtained from it consist of—among other things—heat loss coefficient and wind-induced heat loss. This paper focuses on the latter. To validate the model estimate, the airtightness has been quantified by blower door-tests in both apartments: the results showed that one apartment is reasonable airtight, while the other suffers from significant air leakages. The energy signature and two other infiltration models, based on blower door test results, were compared. Good agreement between the results obtained from the data-driven energy signature and the blower door test were found. With use of a simple linear relation between the average infiltration and the blower door test result (q_{50}), from the Danish national building code, the energy signature was found to overestimate the blower door test result (q_{50}) by 33 % for the leaky apartment and underestimate the same air flow by 18 % for the other apartment. Both estimates are within the standard error of the infiltration model in the Danish national building code.

1 Introduction

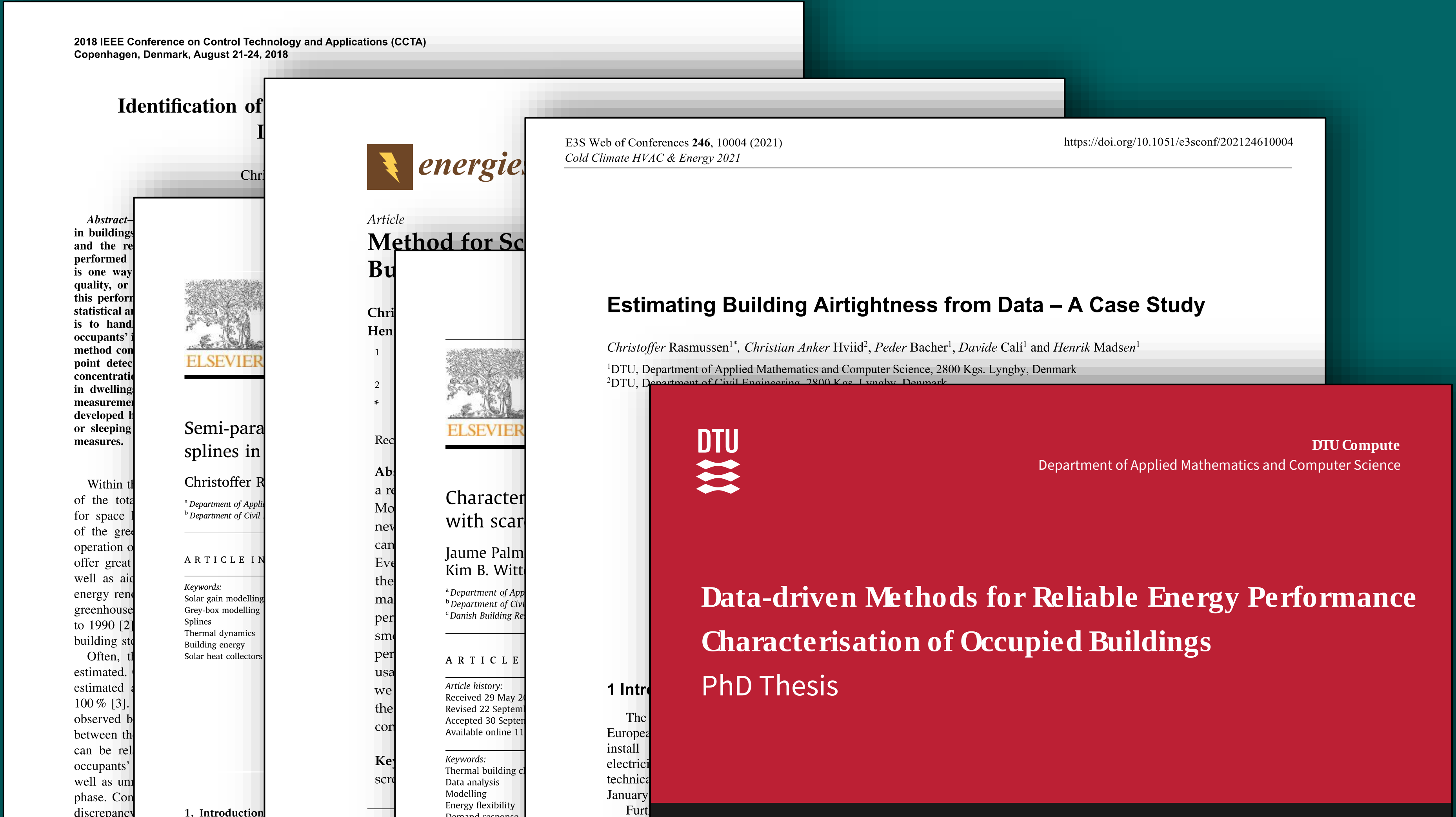
The energy efficiency directive (EED) of the European Union (EU) [1] requires all member states to install individual energy meters (heat meters and electricity meters) on all buildings to the extent that it is technically possible and economically feasible by January 1, 2027.

Furthermore, the building stock accounts for 40 % of

typically referred to as ex- and infiltration, or simply infiltration.

In a simulation study of 25 American office buildings, it was found that 33 % of the heating loads were related to air infiltration [9]. The same percentage is found for American homes in [10].

In [11] it is further stated that due to increasing insulation levels, the share of energy lost by air infiltration also increases. In some cases, the heating



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1. Introduction

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ARTICLE

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Cold Climate HVAC & Energy 2021

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Christoffer Rasmussen[1*], *Christian Anker* Hviid[2], *Peder* Bacher[1], *Davide* Calí[1] and *Henrik* Madsen[1]

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[2]DTU, Department of Civil Engineering, 2800 Kgs. Lyngby, Denmark

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Data-driven Methods for Reliable Energy Performance Characterisation of Occupied Buildings

PhD Thesis

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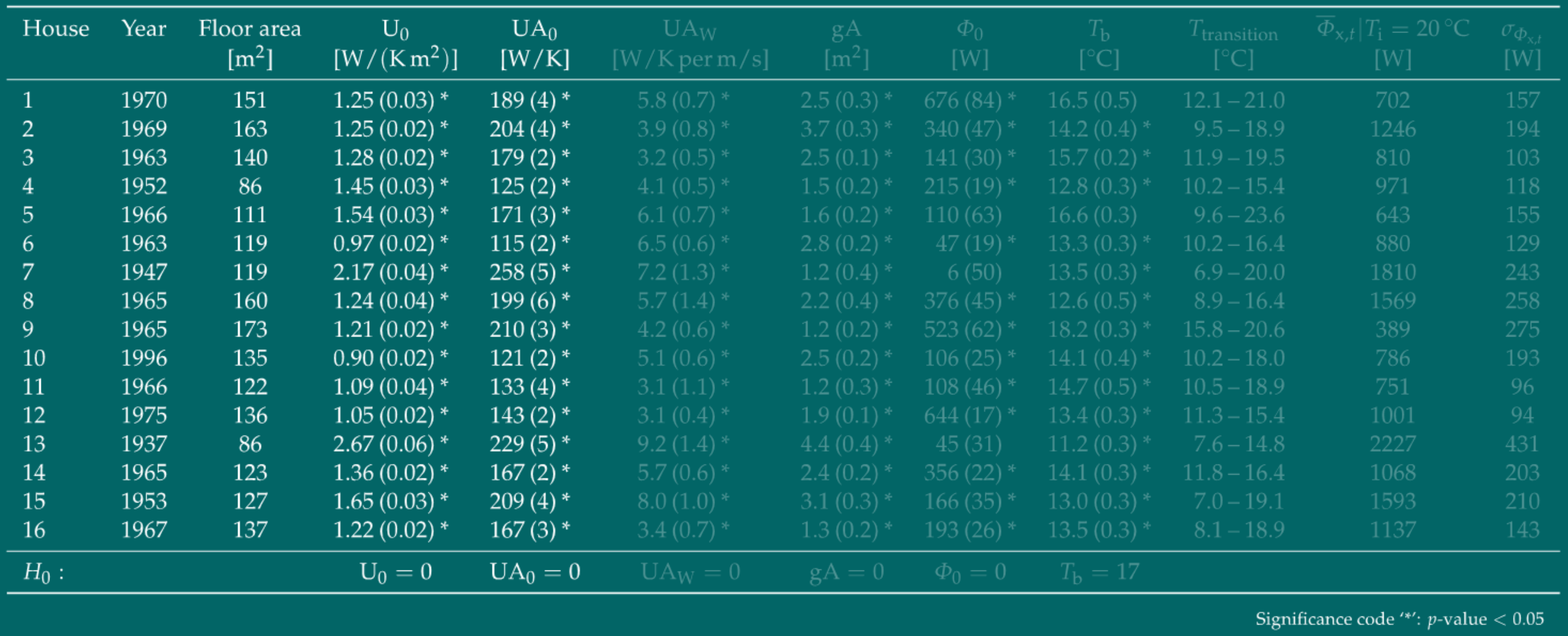
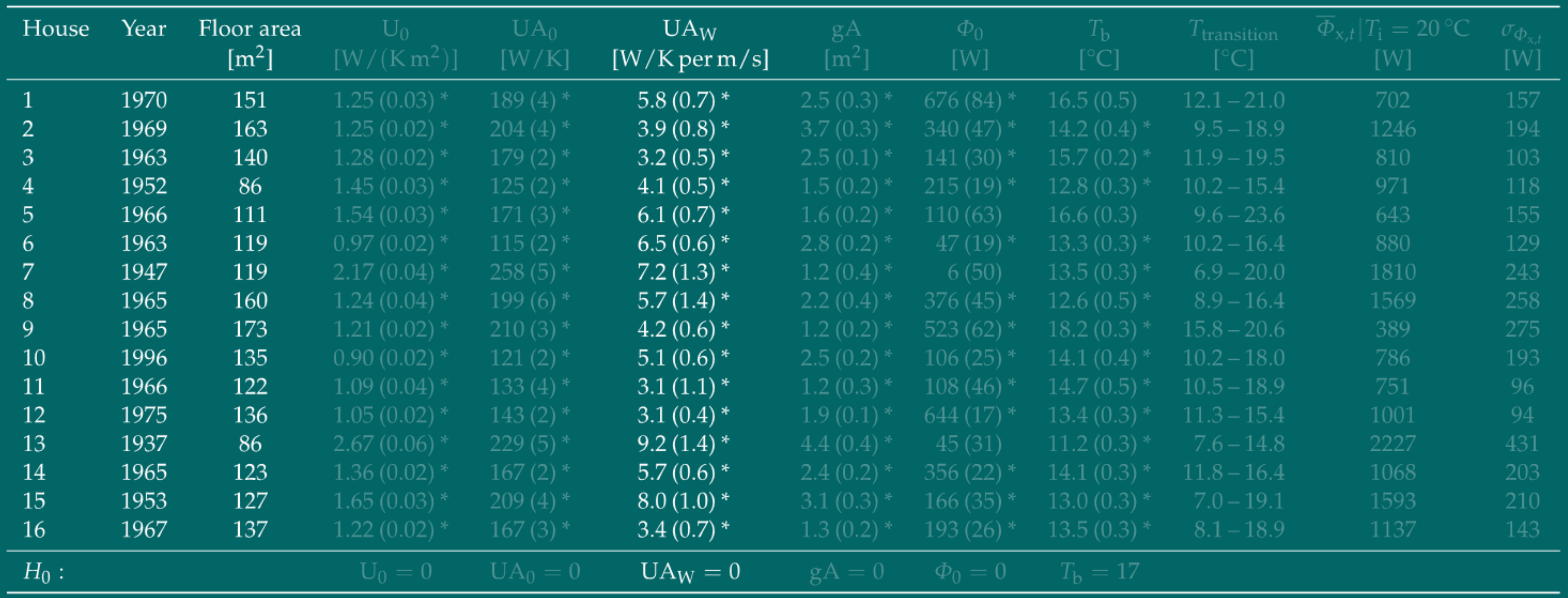


House	Year	Floor area [m^2]	U_0 [W/(K m^2)]	UA_0 [W/K]	UA_W [W/K per m/s]	gA [m^2]	Φ_0 [W]	T_b [°C]	$T_{transition}$ [°C]	$\overline{\Phi}_{x,t} \vert T_i = 20\,°C$ [W]	$\sigma_{\Phi_{x,t}}$ [W]
1	1970	151	1.25 (0.03) *	189 (4) *	5.8 (0.7) *	2.5 (0.3) *	676 (84) *	16.5 (0.5)	12.1 – 21.0	702	157
2	1969	163	1.25 (0.02) *	204 (4) *	3.9 (0.8) *	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) *	3.2 (0.5) *	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) *	4.1 (0.5) *	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) *	6.1 (0.7) *	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) *	6.5 (0.6) *	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) *	7.2 (1.3) *	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) *	5.7 (1.4) *	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) *	4.2 (0.6) *	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) *	5.1 (0.6) *	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) *	3.1 (1.1) *	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) *	3.1 (0.4) *	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) *	9.2 (1.4) *	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) *	5.7 (0.6) *	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) *	8.0 (1.0) *	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) *	3.4 (0.7) *	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

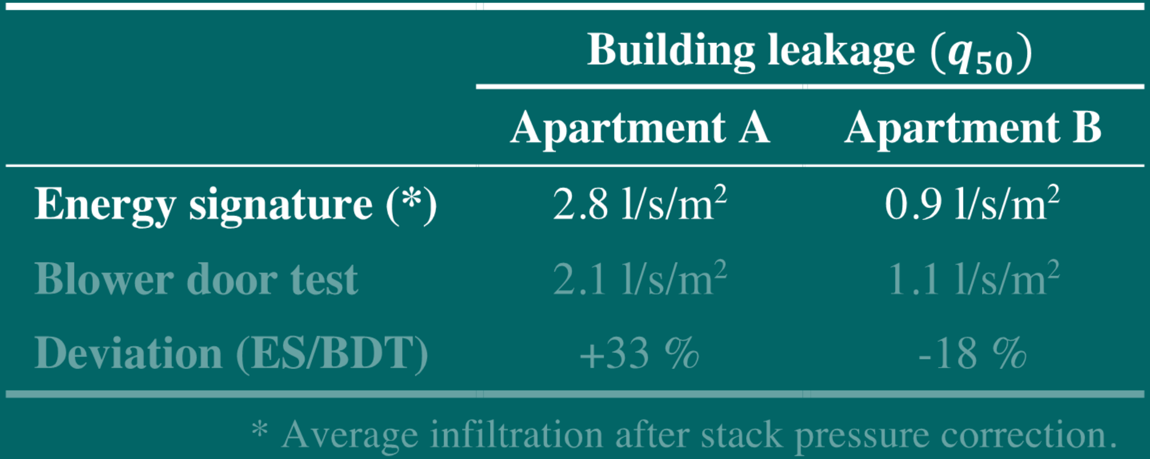
KORTLÆGNING AF TERMISKE EGENSKABER I 16 DANSKE BOLIGER



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) *	5.8 (0.7) *	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) *	3.9 (0.8) *	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) *	3.2 (0.5) *	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) *	4.1 (0.5) *	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) *	6.1 (0.7) *	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) *	6.5 (0.6) *	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) *	7.2 (1.3) *	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) *	5.7 (1.4) *	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) *	4.2 (0.6) *	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) *	5.1 (0.6) *	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) *	3.1 (1.1) *	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) *	3.1 (0.4) *	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) *	9.2 (1.4) *	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) *	5.7 (0.6) *	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) *	8.0 (1.0) *	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) *	3.4 (0.7) *	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

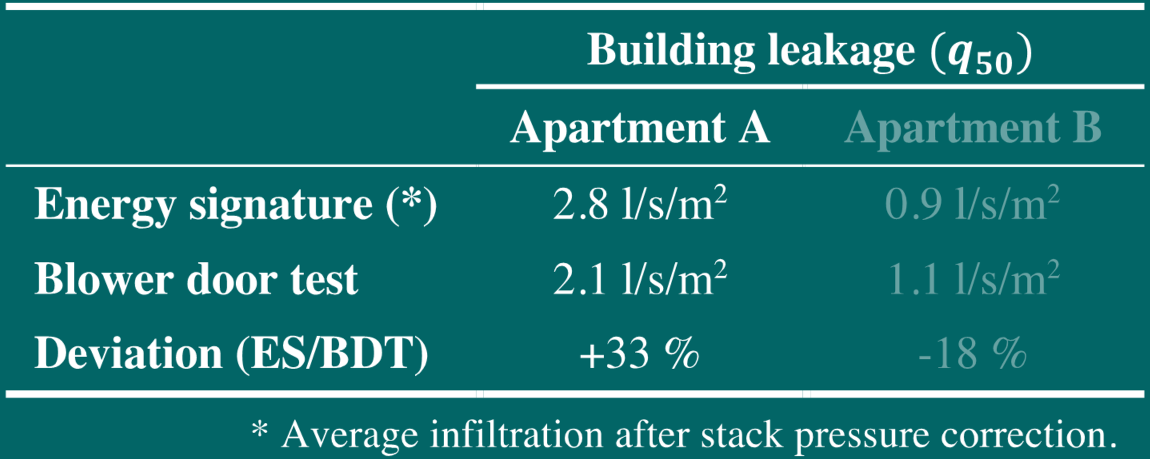
ESTIMERET BLOWER DOOR RESULTAT MED DATA



	Building leakage (q_{50})	
	Apartment A	**Apartment B**
Energy signature (*)	2.8 l/s/m^2	0.9 l/s/m^2
Blower door test	2.1 l/s/m^2	1.1 l/s/m^2
Deviation (ES/BDT)	+33 %	-18 %

* Average infiltration after stack pressure correction.

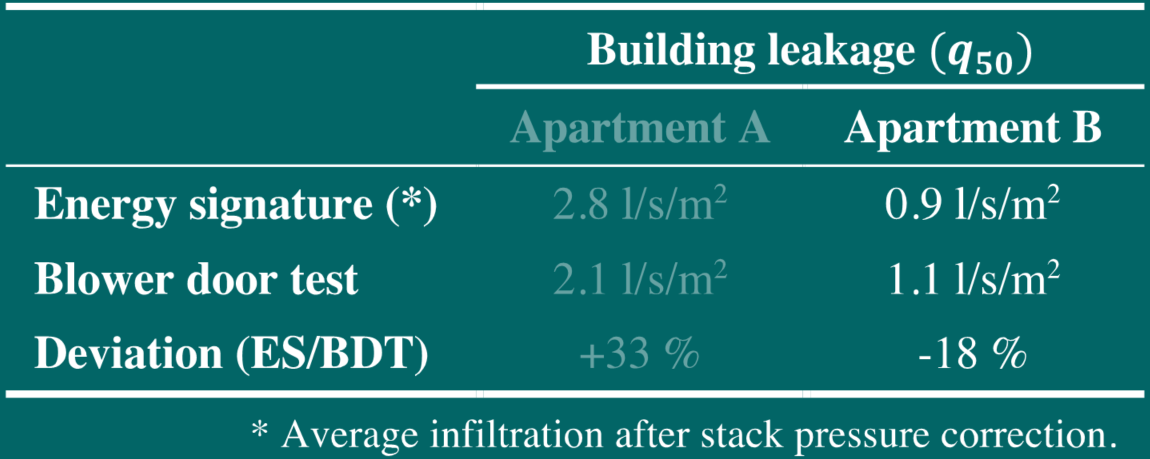
ESTIMERET BLOWER DOOR RESULTAT MED DATA



	Building leakage (q_{50})	
	Apartment A	**Apartment B**
Energy signature (*)	2.8 l/s/m^2	0.9 l/s/m^2
Blower door test	2.1 l/s/m^2	1.1 l/s/m^2
Deviation (ES/BDT)	+33 %	-18 %

* Average infiltration after stack pressure correction.

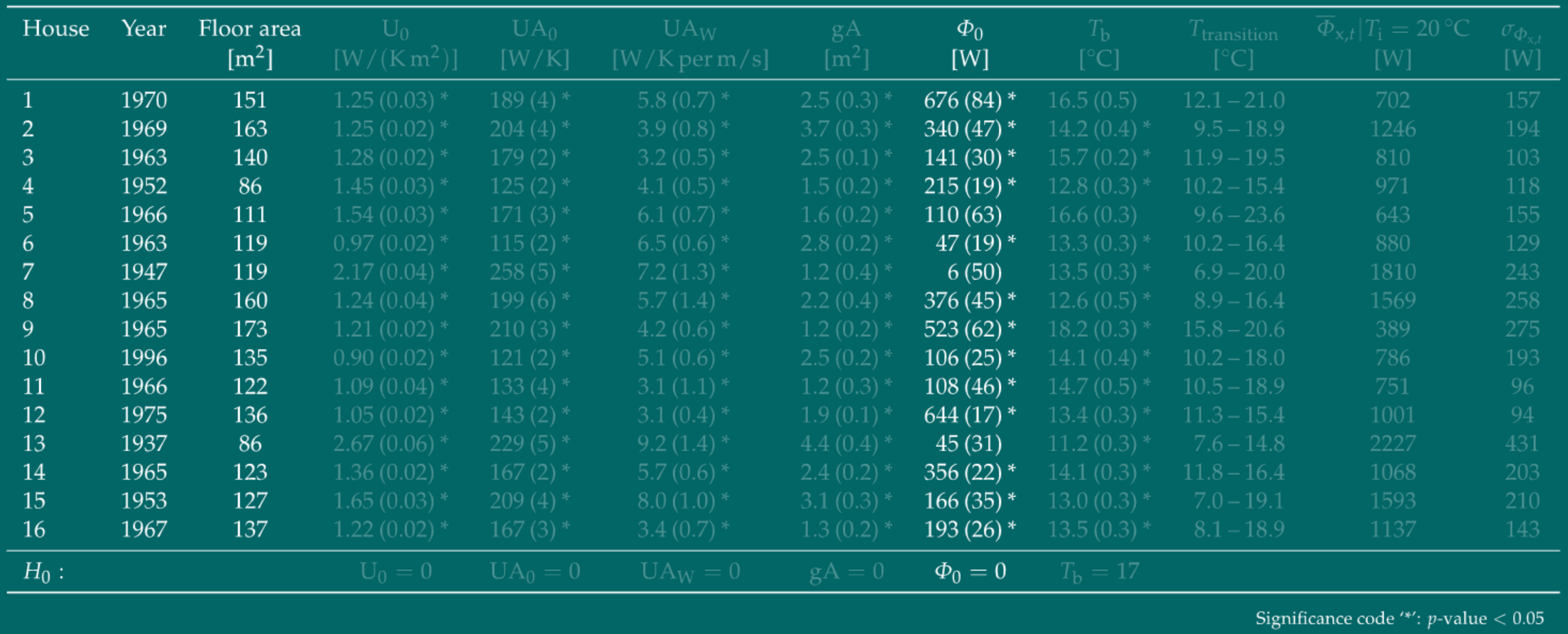
ESTIMERET BLOWER DOOR RESULTAT MED DATA



	Building leakage (q_{50})	
	Apartment A	**Apartment B**
Energy signature (*)	2.8 l/s/m^2	0.9 l/s/m^2
Blower door test	2.1 l/s/m^2	1.1 l/s/m^2
Deviation (ES/BDT)	+33 %	-18 %

* Average infiltration after stack pressure correction.

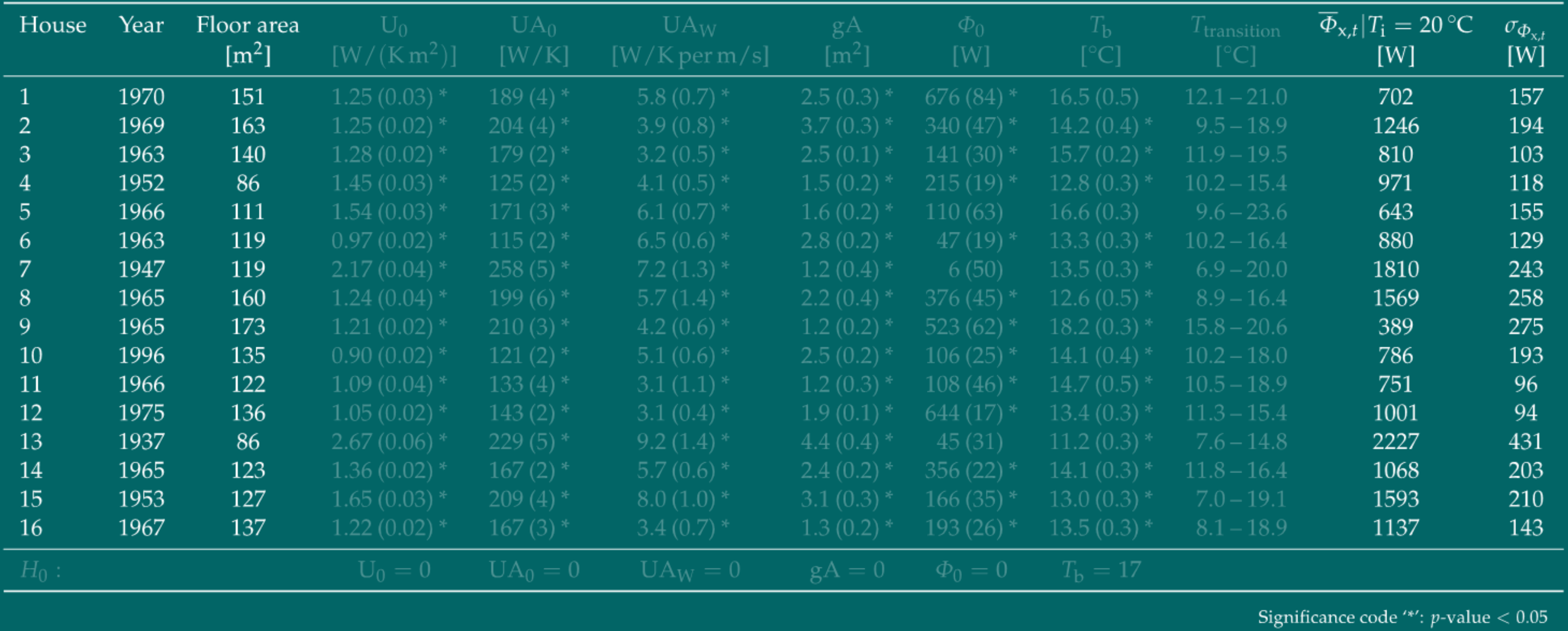
KORTLÆGNING AF TERMISKE EGENSKABER I 16 DANSKE BOLIGER



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]	$\overline{\Phi}_{x,t} \| T_i = 20\,°C$ [W]	$\sigma_{\Phi_{x,t}}$ [W]
1	1970	151	1.25 (0.03) *	189 (4) *	5.8 (0.7) *	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) *	3.9 (0.8) *	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) *	3.2 (0.5) *	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) *	4.1 (0.5) *	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) *	6.1 (0.7) *	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) *	6.5 (0.6) *	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) *	7.2 (1.3) *	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) *	5.7 (1.4) *	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) *	4.2 (0.6) *	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) *	5.1 (0.6) *	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) *	3.1 (1.1) *	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) *	3.1 (0.4) *	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) *	9.2 (1.4) *	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) *	5.7 (0.6) *	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) *	8.0 (1.0) *	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) *	3.4 (0.7) *	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

KORTLÆGNING AF TERMISKE EGENSKABER I 16 DANSKE BOLIGER



House	Year	Floor area $[\mathrm{m}^2]$	U_0 $[\mathrm{W/(K\,m^2)}]$	UA_0 $[\mathrm{W/K}]$	UA_W $[\mathrm{W/K\,per\,m/s}]$	gA $[\mathrm{m}^2]$	Φ_0 [W]	T_b [°C]	$T_\mathrm{transition}$ [°C]	$\overline{\Phi}_{\mathrm{x},t} \| T_\mathrm{i} = 20\,°\mathrm{C}$ [W]	$\sigma_{\Phi_{\mathrm{x},t}}$ [W]
1	1970	151	1.25 (0.03) *	189 (4) *	5.8 (0.7) *	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) *	3.9 (0.8) *	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) *	3.2 (0.5) *	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) *	4.1 (0.5) *	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) *	6.1 (0.7) *	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) *	6.5 (0.6) *	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) *	7.2 (1.3) *	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) *	5.7 (1.4) *	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) *	4.2 (0.6) *	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) *	5.1 (0.6) *	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) *	3.1 (1.1) *	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) *	3.1 (0.4) *	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) *	9.2 (1.4) *	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) *	5.7 (0.6) *	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) *	8.0 (1.0) *	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) *	3.4 (0.7) *	1.3 (0.2) *	193 (26) *	13.5 (0.3) *	8.1 – 18.9	1137	143
H_0 :			$\mathrm{U}_0 = 0$	$\mathrm{UA}_0 = 0$	$\mathrm{UA}_\mathrm{W} = 0$	$\mathrm{gA} = 0$	$\Phi_0 = 0$	$T_\mathrm{b} = 17$			

Significance code '*': p-value < 0.05

LIVET EFTER REBUS

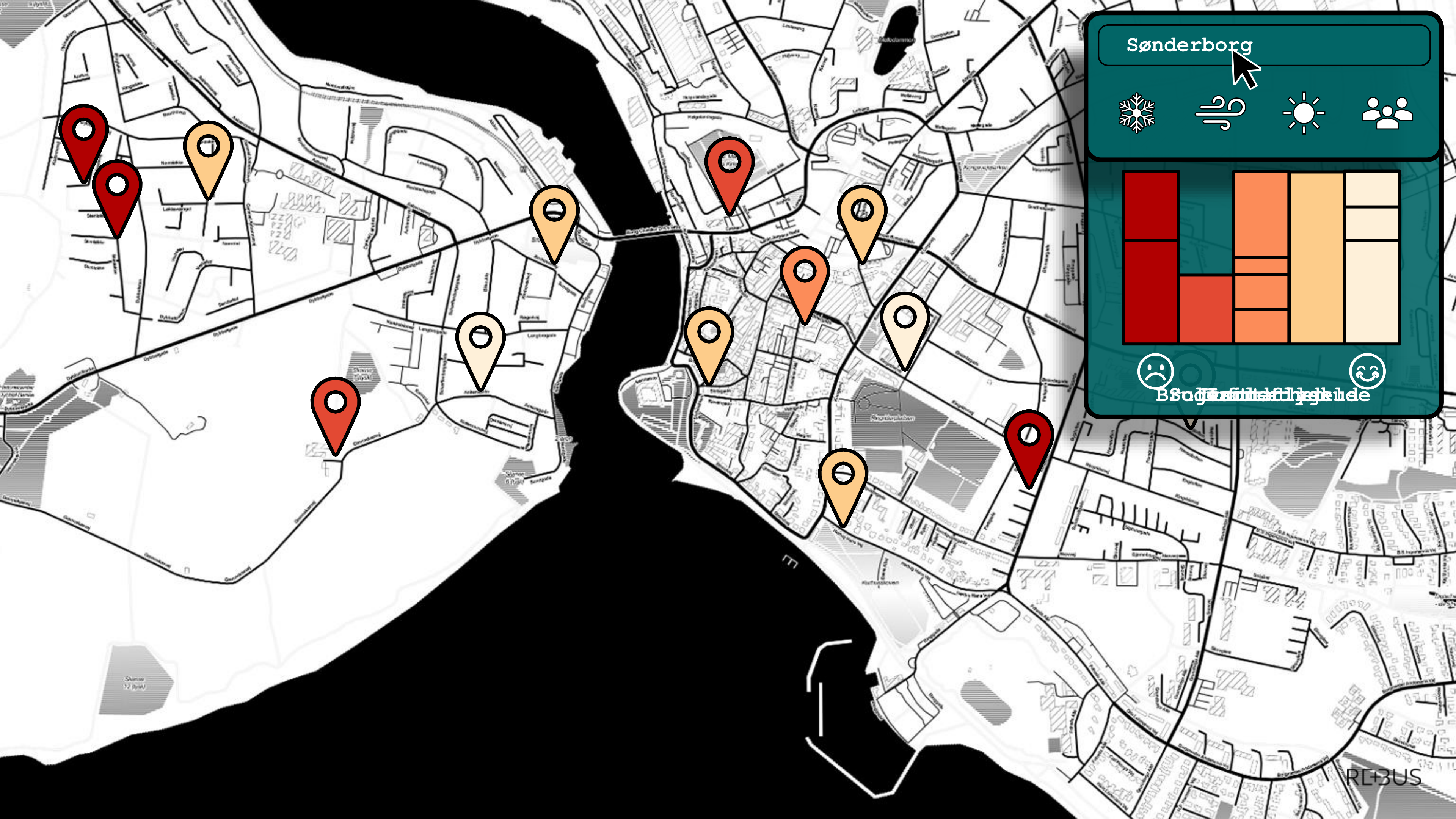
PLANLÆGNINGS- OG DRIFTVÆRKTØJ

INTERREG PROJEKT (2020-2022)

SMART CITY ACCELERATOR+

PARTNERE:

Københavns Almene Boliger (KAB), Lyngby-Taarbæk Kommune, Københavns Kommune, Danmarks Teknisk Universitet, Hørsholm Kommune, Sustainable Business Hub Scandinavia, Lunds Universitetet, Malmö stad, E.ON Energilösningar, E.ON Energidistribution


Sønderborg
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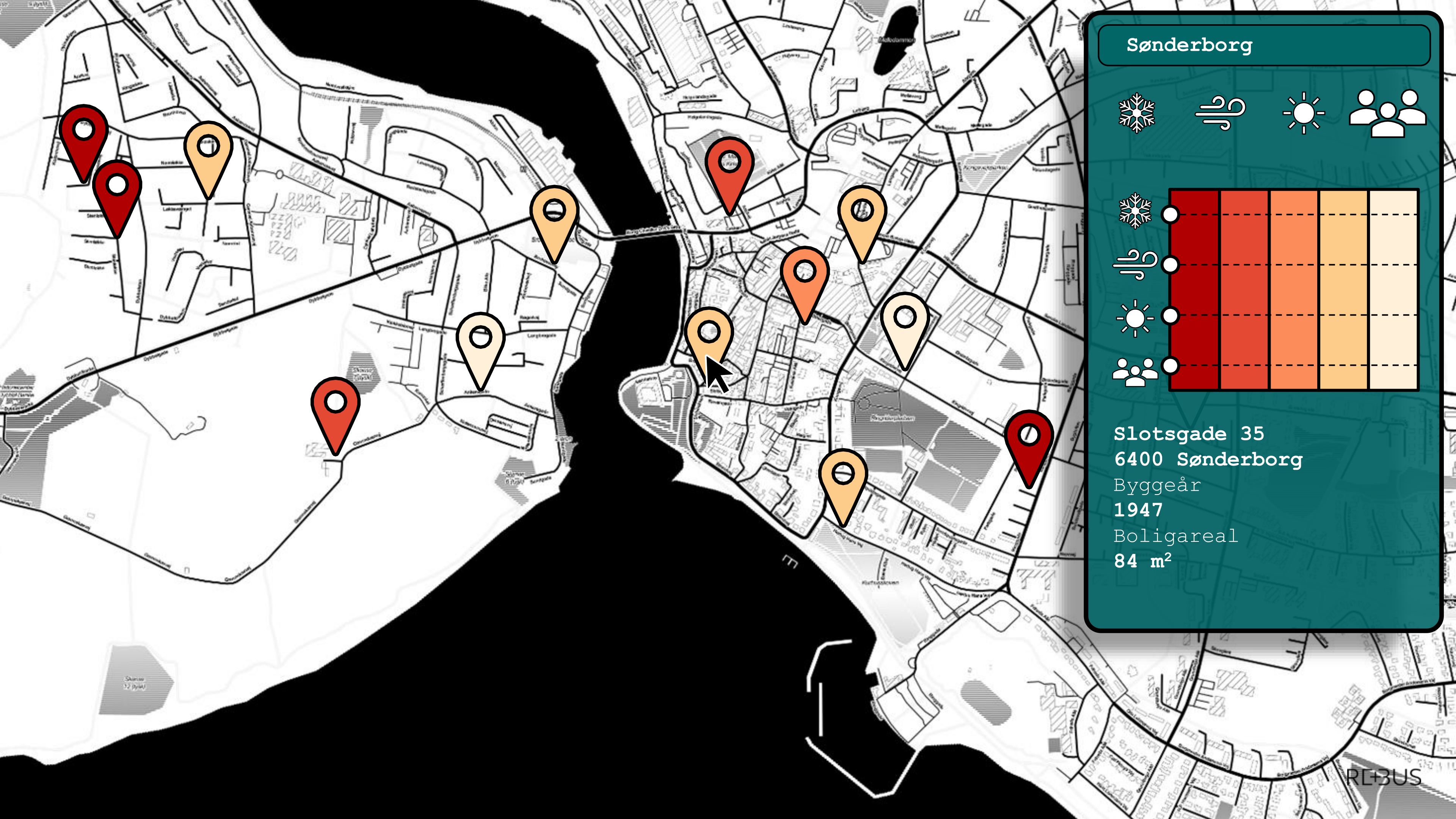
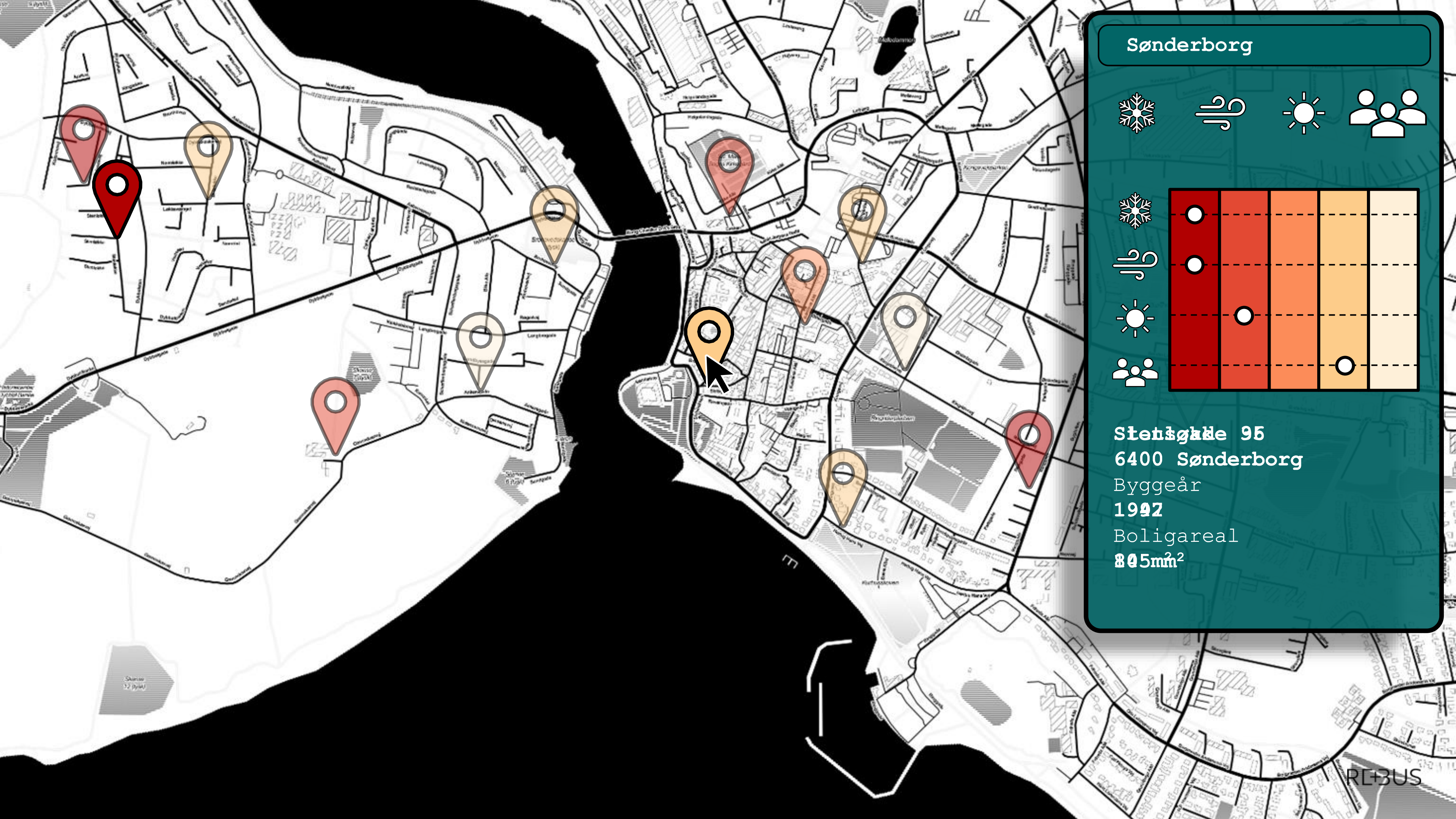


Sønderborg

Slotsgade 35
6400 Sønderborg
Byggeår
1947
Boligareal
84 m^2


Sønderborg
[illegible]
6400 Sønderborg
Byggeår
[illegible]
Boligareal
[illegible]

TAK!

Christoffer Rasmussen, Postdoc
DTU Compute – Dynamical Systems
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