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Developing a meta-model for early-stage overheating risk assessment for new apartments in London

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ABSTRACT

The study presents a proposed approach towards developing the core engine for a simplified Rapid Overheating ASSessment Tool (ROASST), which is intended to help assist early-stage analysis of the risks of indoor overheating for apartments located in Greater London. Using a discrete number of plan forms selected from case studies, a virtual risk database was populated with the results of a large number of parametric dynamic thermal simulations based on the EnergyPlus calculation engine and including aspects such as location within Greater London, orientation, fenestration size and natural ventilation, which are associated with known overheating risk factors. Alternative statistical meta-models were developed with both explanatory and predictive purposes, correlating the simulation input with the overheating risk predictions expressed according to multiple metrics. Results from multiple linear regression analysis show that while all factors considered are relevant towards determining the propensity to overheating, window opening and natural ventilation capacity are by far the strongest predictors among those considered. The implementation of machine learning algorithms is shown to improve the accuracy of the meta-model, producing very high coefficients of determination (R^2) and lower prediction errors (RMSE). The development of a meta-model demonstrates the ability of returning accurate predictions with limited input, albeit with significant limitations. Possibilities of further improvements to the tool are briefly outlined, including the coupling with a User Interface for applicability in a design environment for early-stage design advice.

1. Introduction

1.1. Background: heat risk in a changing climate

Although ambitious actions have been taken globally to reduce greenhouse gas emissions (GHG), climate change impacts are projected to continue to increase globally [29]. In the UK evidence indicates that indoor overheating in residential buildings is particularly critical for Greater London and the South-East of England [11,12]. Evidence gathered over nearly two decades of research reveals a concerning growth in the occurrence of summertime overheating in naturally- and mechanically ventilated buildings, in climates that have been traditionally heating-dominated [31,57,58,21,50].

Several studies have investigated the inter-dependency of the multiple causes associated with this complex phenomenon. Studies by [1,32,35] mapped the vulnerability of the existing residential building stock in Greater London, identifying *layers* of risk associated with urban locations, building characteristics and occupancy behaviour and vulnerability. Building characteristics have been found to be strong determinants for propensity to indoor overheating. These include: *building age and space efficiency*, particularly post-1980s dwellings, as a result of reduced heat losses from higher energy-efficiency standards and lack of adequate natural ventilation for heat purge [41,6]. This is particularly problematic for single-aspect apartments [59,31]; *building form and orientation*, which impacts heat gains from solar radiation, such as for dwellings located at top floor and those oriented to the south [36,53], and to the west [4]. Furthermore, indoor overheating has a threefold link with building occupancy: exposure, linked to the amount of time occupants spend at home [53]; vulnerability to heat stress, often associated with the elderly and/or those with adverse health

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conditions [43,42]; behaviours (e.g. appliances use), which lead to high internal heat gains [33,35,34,31].

1.2. Assessing overheating: steady-state and dynamic thermal simulations

While understanding the main factors leading to overheating in the existing building stock is important, early risk assessment is crucial for informing the design of new buildings to minimise occupant heat-stress.

The Standard Assessment Procedure. As part of Part L of the Building Regulations [26] a mandatory overheating risk check exists, that is based on a simplified steady-state analysis method, described in *Appendix P* of the Standard Assessment Procedure (SAP) [9]. This was developed to identify the propensity of a dwelling to suffer from high internal temperatures, primarily with the purpose of minimising demand for cooling, rather than with a specific focus on thermal comfort. However, an overwhelming consensus exists in the building industry that robust and accurate overheating risk assessments can only be produced by using more complex methods and software tools based on Dynamic Thermal Simulations (DTS), rather than via simplified steady-state analysis [5,17].

CIBSE TM59. In recognition of the complexity and sensitivity of DTS output to modelling and input assumptions, CIBSE recently published Technical Memorandum 59, a standardised methodology for overheating risk predictions for residential buildings [17] that provides a common baseline based on tested and reviewed assumptions, enabling comparison between different designs. This has been adopted by industry professionals and policymakers as the standard methodology for overheating assessments at the design stage - as indicated in documents such as the New London Plan [38].

1.3. Limitations of current approaches and need for rapid risk assessment

The accuracy of DTS modelling requires specialist knowledge and considerable time and resources, depending on scale and complexity of the buildings to be assessed. For this reason, an approach that is typically adopted among industry professionals involves performing preliminary context checks, using expert judgement to qualitatively evaluate the susceptibility of a site to overheating, and to identify areas of greatest risk, which would require detailed modelling. While the combination of qualitative review and quantitative checks can be cost-effective and satisfactory in simple cases [58], often overheating assessments are performed late in the design process, when mitigation measures that rely on passive design strategies may no longer be feasible. Furthermore, limiting the DTS assessment to the *'worst-case scenarios'* can often result in superficial understanding of overheating propensity for all combinations of factors leading to lower yet non-marginal risk.

1.4. Aim of the study

The development of a 'Rapid Overheating ASsessment Tool' (ROASST) seeks to provide high accuracy of overheating risk assessment, at an early stage when critical passive design choices are still possible, with a focus on apartment design, as the building typology that previous research has identified to be at the highest risk [31]. The study here presented documents the development of the core engine of ROASST, as a physics-based tool that can express rapid early-stage risk estimates, with greater accuracy than steady-state analysis and close to full DTS assessments, and in line with the TM59 methodology. Building on a library of typical dwelling typologies provided by the industrial sponsor for the research, the work adopts standardised modelling assumptions and considers a small set of input parameters which correspond to choices made by building designers during conceptual design that are known to affect the risk of overheating [57,38]. More specifically, the study explores how the application of different techniques of surrogate (meta-) modelling to DTS output may permit to: (1) quantify the sensitivity of overheating risk estimates to the different risk factors considered (explanatory meta-modelling); (2) produce 'sufficiently accurate' risk estimates with reduced data, which can be available at the early-design stages (predictive meta-modelling).

2. Methods

The development of the core engine of the risk assessment tool was undertaken in three stages:

1. Selection of data input for the virtual model. This included the choice of relevant factors associated with early-stage design decisions corresponding to known overheating risk factors.
2. Physics-based assessment of the risk of overheating using dynamic thermal simulation (DTS), based on different combinations of the identified factors.
3. Statistical data analysis, looking at alternative meta-modelling techniques to develop a surrogate model on the data generated by means of DTS. This is intended to serve the purpose of both explanatory and predictive purposes, as detailed in the following section.

2.1. Selection of data input for the virtual model

The selection and categorisation of risk factors for the analysis was informed by previous studies that looked at residential stock modelling [36,47,44,33,52,34]. The following categories of risk factors were identified in previous literature: (1) location and weather; (2) dwelling or plan form; (3) built-up geometry; (4) thermal efficiency; (5) occupancy and internal heat gains. Given the scope of the present study, a parametric variation of parameters was considered for the first three categories only. As explained in more detail in Section 2.1.6, the impact of different occupancy profiles was not investigated as part of this study, with its focus being placed standard buildings for an healthy adult population.

2.1.1. Location and weather conditions

Given the focus on residential buildings in Greater London, input weather data was taken from those made available by the CIBSE TM49 publication *'Design Summer Years for London'* [16]. This includes data for three weather stations within Greater London, which offer a representation of the Urban Heat Island effect. Design Summer Year (DSY) weather files were used, containing hourly data and statistically-aggregated from multiple years' records to represent a year with a hot summer. The summer period is considered in the analysis, ranging 1 May to 30 September inclusive, for the 2020s, indicating a 30-year period representative of near future climate condition, in line with [16].

2.1.2. Plan forms: identifying representative types

Previous studies assessing and mapping indoor overheating risk for the London housing stock [44] used typical built forms from public databases. However, given the focus of the present study on contemporary dwelling typologies, the collaboration with the industrial sponsor ('PRP') - a practice specialised in residential building design - allowed access to more complete and relevant building data.

For the purpose of this study, different apartment types/ plan forms were considered from the PRP Dwelling Library, a large organised set of dwelling types gathered from different PRP projects and compliant with minimum space standards provisions [20], and adopted in The London Plan [37]. A set of plan forms were selected from PRP library of dwelling types, gathered from different PRP projects and compliant with minimum mandatory space standards provisions [20], and adopted in The London Plan [37]. The selected plan forms included four single-aspect layouts and four dual-aspect layouts, with windows on adjacent and opposite facades Fig. 1.

2.1.3. Built-up geometry

A number of geometric aspects related to the built form were grouped in this category, corresponding to design decisions that are typically influenced by architectural aspirations or constraints (e.g. massing and elevations treatment to recognise local architectural character) or by environmental drivers (e.g. daylight/sunlight access). The aspects of impacting thermal performance and the overheating risk are:

Floor. The distinction between ground-, mid- and top-floor accounts for the different boundary conditions that affect the thermal behaviour of the modelled spaces, more specifically heat losses [47].

Orientation. This determines the angle and intensity of solar radiation, which affects solar heat gains through the glazed surfaces. Eight variants of the rotation from north were considered in the study.

Balconies. A provision for balconies was also included for the dwellings considered, to align with the GLA *Housing Design Quality and Standards* [39], specifically with Policy C4.2.1 (*"A minimum of 5 sqm of private outside space should be provided for one-to-two person dwellings and an extra 1 sqm should be provided for each additional occupant.*"). Balconies were modelled to be as wide as the room they serve, ad with a depth of 1.5 m, in compliance with Policy C4.2.2 (ibid). Multi scenarios were considered, including: (1) balcony on kitchen/living room; (2) balcony on main bedroom only; (3) balconies on both kitchen/living and main bedroom. Being modelled as objects with no thermal properties, these intended to account for the beneficial impact of reduction to solar radiation due to shading (for each dwelling, the balcony/ies of a fictional dwelling above were modelled).

Fenestration size, window opening factor and air-flow rates. The size of windows affects both the heat losses through the building envelope, as glazed constructions tend to have much lower thermal transmittance than opaque constructions and, most notably, the heat gains due to solar radiation.

The *'free area'* describes how well air can travel through an opening (i.e. an external window) for the purposes of natural ventilation [30]. The Window Opening Factor (*wof*) parameter is introduced in the P-DTS, as shown in Fig. 2, and considered for each orientation. Ranging between 0 and 1, the parameter defines the percentage of the gross window area that is available for ventilation and it is used by the DTS software tools to derive the *free area*, which in turn is used to calculate natural ventilation air-flow rates. In line with the methodology developed by [17], the modelling assumed that windows would be opened upon reaching 22 °C.

2.1.4. Other parameters affecting air-flow rates: wind direction and pressure

The authors are aware that parameters like orientation can have a dramatic impact on airflow due to pressure differences driven by wind patterns. With reference to AM10 guidance [14], and as indicated in Eq. 1, for a general opening i a linear relationship exists between the flow rate through the opening q_i $[m^3/s]$ and the opening area A_i $[m^2]$, when the boundary conditions defined by pressure difference Δp_i [Pa], the air density ρ $[kg/m^3]$ and the discharge coefficient C_d are constant.

$$q_i = C_{di} \cdot A_i \cdot \sqrt{\frac{2 \cdot |\Delta p_i|}{\rho}} \tag{1}$$

The impact of different orientations on wind direction and pressure was not explicitly considered as a dedicated parameter in this study, but was implicitly accounted for in the weather data used as input for the DTS modelling for the three locations considered. The wind rose diagrams shown in Fig. 3 indicate a variable wind direction during the summer period, with a general predominance of south-west winds. The authors are aware of the limitations associated with a simplified consideration of wind turbulence and wind-driven pressure differences for single-sided and cross ventilation respectively. This is further discussed in Section 7.

Fig. 1. Plan forms selected from the PRP Dwelling Library selected as input for the development of ROASST.

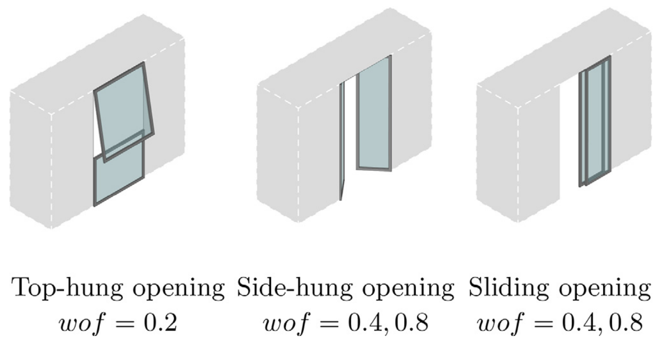

Fig. 2. Graphic representation of the *wof* parameter used in the parametric DTS. (*wof* = window opening factor).

2.1.5. Thermal efficiency

The choice of building fabric thermal properties has an impact on both heat gains/losses and on thermal mass capacity. While these aspects are generally relevant from a building physics perspective and in the context of summer thermal performance and overheating risk, they were excluded from the scope of this study, given to the focus on a very homogeneous set of dwelling types and age (i.e. new urban apartments). Only one set of building envelope thermal characteristic was considered, in compliance with *'Part L1A'* of the Building Regulations 2013 for England and Wales. This is presented in Table 1. The authors are aware that this may limit the flexibility and applicability of the ROASST tool built on the engine described in this study, particularly with regards to window properties and solar heat gains. This is discussed in Section 7.

2.1.6. Occupancy and internal heat gains

While occupancy is a key factor impacting on the risk of overheating, the alignment with the TM59 methodology [17], placed the focus of the study on the link between overheating risk and buildings characteristics, rather than occupant behaviour. It has to be noted that despite the extension to 24-h occupancy for bedrooms, introduced to overcome the limitations of the previous TM52 [15], the TM59 considers early morning and late evening occupancy for living areas (kitchen, living room etc.). This is tailored for working-age healthy adults and does not adequately capture the prolonged exposure to high temperatures which is associated to considerable health impacts for vulnerable people (i.e. elderly and disabled people) who are likely to spend most of the day at home. Given the full alignment with the TM59, the present study also focuses on housing provision for an adult healthy population (Fig. 4).

Table 1
Thermal characteristics of the building envelope considered for the development of ROASST.

Description	U-value (W/m^{2}K)	G-value
Exposed Floor	0.22	-
Internal Ceiling/Floor	1.09	-
Roof	0.18	-
External Wall	0.12	-
Internal Wall	1.79	-
External Window	1.40	0.63

Previous studies [40] have critiqued the deterministic approach to occupancy assumptions adopted by the TM59, suggesting that multiple or probabilistic occupancy scenarios could more adequately represent complex relationship between occupancy patterns and overheating propensity that has been observed in real-world scenarios.

2.2. Physics-based assessment and Parametric Dynamic Thermal Simulation workflow

In order to carry out a physics-based assessment of the risk of overheating based on DTS and consider the contribution of the risk factors identified, a custom workflow was devised. The assessment was based on the EnergyPlus simulation engine, an open-source whole-building energy modelling software package which has been extensively tested and validated using industry standard methods [55,56].

The first stage of work involved producing virtual thermal models of the chosen dwelling archetypes and assigning baseline characteristics to these, using DesignBuilder [22]. The second stage of work involved the assessment of all unique combinations of each of the variants of the identified risk factors. A parametric DTS (P-DTS) work-flow was implemented to manage the large number of iterations to be considered. This included using bespoke scripts to manipulate the baseline thermal models, using the Eppy Python library [46] and a simulation manager jEPlus [60], allowing to store input and output data systematically and permitting replicability of the parametric exercise. The variants considered are listed in Table 2. The calculation of air flow rates resulting from the different window opening options was made out using EnergyPlus Air-Flow Network (AFN) [8].

2.3. Criteria for measuring indoor overheating

The following output metrics were used to measure overheating on the output of the physics-based DTS assessment using EnergyPlus, aligned with CIBSE TM59.

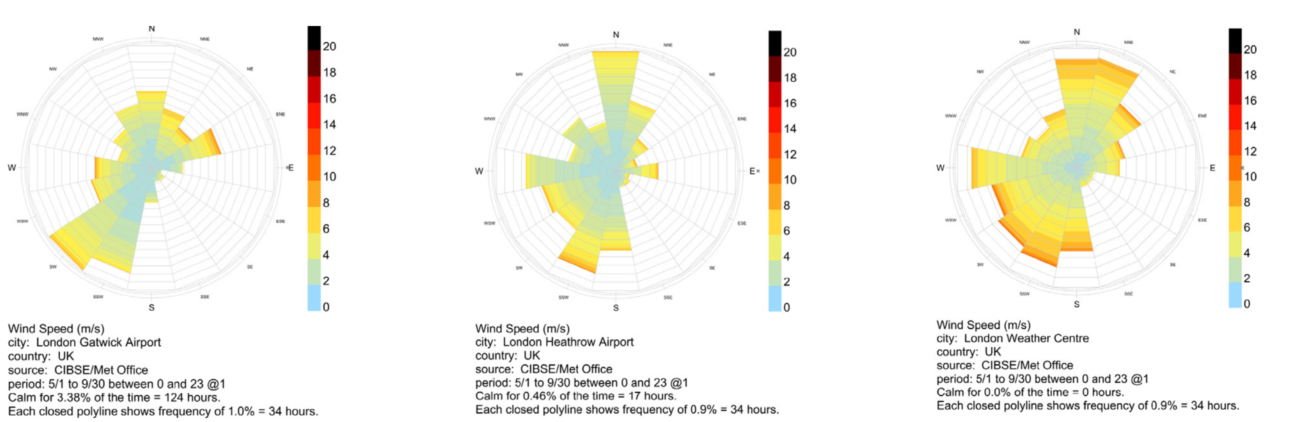

Fig. 3. Wind rose for summer period (May to September) for the three weather locations within Greater London considered in the study. From left to right: LGW, LHR, LWC.

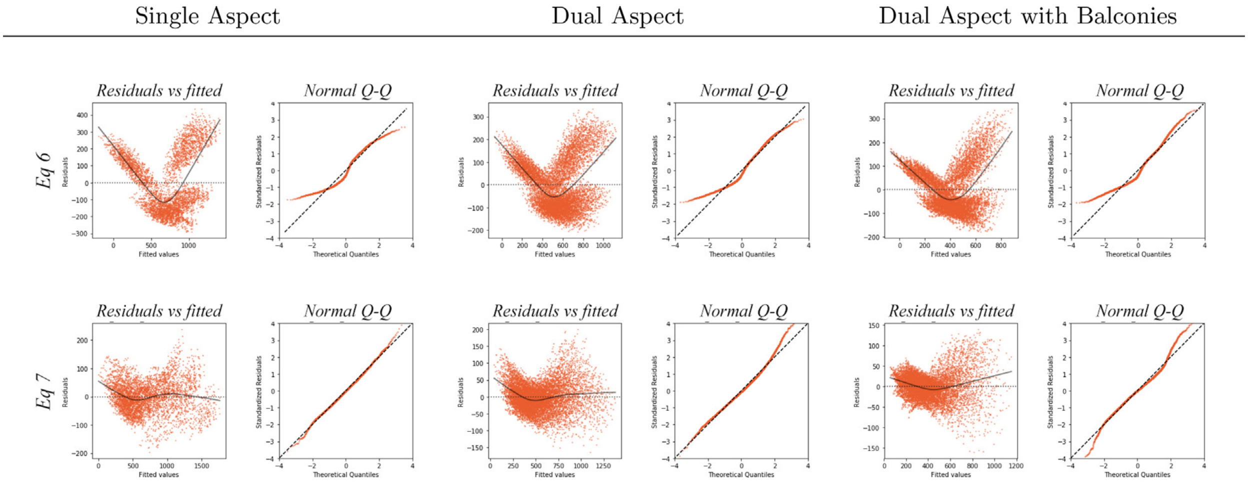

Fig. 4. Comparison of 'Residuals-vs-Fitted' and 'Normal Q-Q' plots for Eq. 6 and Eq. 7 for the three data-sets considered, for the Kitchen/Living area and .metric *KLA*.

Table 2
Parameters used in the Parametric DTS.

Short name	Input variable	Variants	
		No.	Values (*unit*)
dwe	Dwelling/ Plan Form	12	4 single-, 4 dual-aspect, 4 balcony layouts
wea	Weather File	3	[LGW, LHR, LWC]
flo	Floor	3	ground, mid, top floor
north	Angle from north (main facade)	8	[0, 45, ..., 315] (*degrees*)
wwidth_kl	Window size for Kitchen/Living (KL)	2	[1, 2] (*m*) with height = 2.4 m
wwidth_bd	Window size for Bedrooms (BD)	2	[1, 2] (*m*) with height = 2.4 m
wof	Window Opening Factor	4	[0.1, 0.2, 0.4, 0.8]

Criterion A (TM59_A) or *Hours of Exceedance* (*He*) records the number of hours in which the difference between the operative temperature and the maximum acceptable temperature is greater than 1 degree, expressed as a percentage of the total occupied hours during a summer season (1st May to 30th September).

$$(a)tm59\_a = He = \frac{\sum_1^s hr_i}{hr_s} where hr_i = \begin{cases} 1, & \text{if } \Delta T > 1K \\ 0, & \text{otherwise} \end{cases} \quad (2)$$

where: $\Delta T = T_{op} - T_{max}$. The criterion is considered to be failed (i.e. overheating) if $He \geqslant 3\%$ total occupied summer hours. It is based on the adaptive comfort temperature threshold T_{max}, introduced with the BS EN 15251:2007 and later embedded in TM52 and TM59 ([17]). This can be expressed as:

$$T_{max}\ (^{\circ}C) = 0.33 \cdot T_{rm} + 21.8 \quad (3)$$

where: T_{rm} is the exponentially weighted running mean temperature.

Criterion B (TM59_B) *Night-time Hours of Exceedance* (*NHe*) records the number of hours during which the operative temperature in bedrooms exceeds 26 °C at night:

$$(b)tm59\_b = NHe = \Sigma hr_n \quad (10pm - 7am) \quad when\ T_{op} \geqslant 26^{\circ}C \quad (4)$$

The criterion fails if $NHe \geqslant 32 = 1\%$ *annual night − time hours.*

3. Preliminary analysis of DTS output

Table 3 shows the pass rates for the kitchen/living areas (TM59 Criterion A) for all iterations and all the variants of the risk parameters considered. A few observations can be made from these results. Firstly, the impact of the weather and floor parameters appear to be similar for all single aspect dwellings considered. The variation within each of these two parameters appeared to be noticeable but not significant, with ground-floor location (GF) and London Weather Centre weather file (LWC) being associated with higher pass rates, i.e. lower overheating risk. More pronounced variations can be observed with orientation, and particularly with 225°(south-west) and 270°(west) orientations presenting the lower pass rates for the single aspect dwellings. A more complex picture emerges for the dual aspects dwellings, as due to internal layout these are not fully characterised by one single angle from north.

Finally, it can be observed that the most significant variations are associated with the *wof* parameter, whereby 10% opening area ($wof = 0.1$) results in certain failure of both TM59 criteria (pass rate 0–2%). The pass rate increases significantly for every increase of *wof*. At the lower values of *wof* the step is more pronounced for dual aspect dwellings than for single aspect ones, as a result of a greater potential for cross ventilation driven by pressure difference between different facades. The increase in pass rates are presented in Table 3 as a function of various parameters.

4. Developing a meta-model for explanatory modelling

4.1. Introduction

The present and following sections presents the analysis carried out to provide an insight into the data produced by means of P-DTS, applying traditional statistical as well as more recent machine learning techniques. The purpose of the explanatory modelling was to gain an understanding of the relative impact of each factor on the resulting risk of overheating, according to the two metrics considered.

Three data-sets were considered: (1) single-aspect dwellings; (2) dual-aspect dwellings and (3) a chosen dwelling with different balconies arrangements. This sub-division reflects the importance of natural ventilation - single versus dual dwellings - and the impact of alternative shading configurations as provided by the balcony arrangements, as explained further in this section. Multiple linear regression was deployed to determine the strength of the relationships between risk of overheating (*response variable*) and the multiple explanatory variables (*predictors*). The coefficients of the model were estimated using Ordinary Least- Squares (OLS). Simple graphical diagnostics on regression residuals were pro-

Table 3
Distribution(%) of simulations passing overheating criterion *tm59_a* for the open plan kitchen/living area. (GTW = Gatwick Airport, LHR = Heathrow Airport, LWC = London Weather Centre; GF = Ground Floor, MF = Mid Floor, TF = Top Floor).

	weather			*floor*			*anglefromnorth* (orientation)								*wof*			
Dwelling	GTW	LHR	LWC	GF	MF	TF	0(N)	45(NE)	90(E)	135(SE)	180(S)	225(SW)	270(W)	315(NW)	0.1	0.2	0.4	0.8
SINGLE ASPECT																		
P1201	38	22	41	41	30	29	26	20	13	10	10	4	3	12	1	6	32	61
P1202	37	23	40	40	30	29	25	19	14	11	11	4	4	13	1	8	32	59
P2302	36	27	37	47	31	23	24	19	13	11	12	4	4	13	2	11	32	56
P2401	37	24	39	51	29	20	28	20	13	10	11	4	3	12	1	8	30	62
ALL	37	24	39	45	30	25	26	19	13	11	11	4	4	12	1	9	31	59
DUAL ASPECT																		
P1203	40	22	38	34	33	32	21	10	7	13	19	9	6	14	1	13	35	51
P1204A	37	16	48	37	32	30	25	17	11	1	2	4	16	24	0	13	33	54
P1205	38	19	43	35	33	32	12	28	26	15	10	5	3	2	1	13	35	51
P2303	38	14	48	33	34	33	33	16	10	3	0	1	8	30	0	10	35	55
ALL	39	19	43	35	33	32	21	17	13	10	10	5	8	15	0	12	35	52

duced, including *'Residuals vs Fitted'* and *'Normal Q-Q'* plots [28], to verify the four main assumptions underlying the use of linear regression models, that is: linearity and additivity of the relationships between dependent and independent variables; statistical independence of the errors; homoscedasticity of the errors; normality of the error distribution. A check on the Variation Inflation Factor (VIF) was carried out on the continuous variables to test for multi-collinearity issues, which may be associated to artificial and inherently-biased data, such as that generated by P-DTSM involving an arbitrary choices of input parameters considered.

4.2. Transformation of predictors and definition of a polynomial regression model

Introduction of a new predictor to better account for solar radiation. In order to test the ability of the meta-model to capture a wider range of design scenarios, including the beneficial impact of solar shading from external balconies, a transformation of predictors was carried out in two steps.

Firstly, a measurement of solar radiation was introduced as a proxy for orientation, replacing the angle from the north. Secondly, for each of the thermal zones (rooms), the contribution of solar radiation received by all windows of that zone was considered. For all main rooms, the Room Mean Solar Radiation Rate (*rmsrr*) was calculated as:

$$rmsrr = \sum_{i=1}^{n} wmsrr_{W_i} = \sum_{i=1}^{n} (A_{W_i} \cdot msrr_{W_i}) \quad (5)$$

where:A_{W_i} : Area of the window W_i [m^2];$wmsrr_{W_i}$: Mean Solar Radiation Rate received on the surface of the window W_i over the analysis period [W];$msrr_{W_i}$: Mean Solar Radiation Rate received on the surface of the window W_i, measured per unit area [W/m^2]. The value of new predictor depends on the mean solar radiation rate on the facade where the window is located, on the area of the window and on the geometry of balconies from dwellings above (acting as shading devices), where present. Table 4 shows the calculated values of *wrmsrr* associated with different orientations, which are used to calculate *rmsrr*.

Transformation of wof to resolve quadratic relationships. A further transformation of predictors was carried out, as the independent variable *wof* was replaced with the square of its natural logarithm $(ln(wof))^2$. This aimed at addressing the quadratic relationships initially identified through diagnostic plots and to improve the model goodness-of-fit. While the quadratic relationship can be partly attributed to the choice of discrete values of *wof* as a geometric sequence - $0.1, 0.2, 0.4, 0.8$ - which aimed to better reflect real-case window opening scenarios, the authors are aware of issues of non linearity in the relationships between heat losses from natural ventilation air-flow and indoor temperatures, as defined by EnergyPlus heat-balance algorithms [54]. The usage of Window Opening Factor *wof* as a proxy for natural ventilation capacity is a critical assumption for this study, and the limitation deriving from this are discussed in Section as well as in the final discussion. The transformation of predictors allowed to move from Eqs. 6 to Eq. 7.

$$y_i = a_0 + a_1 \cdot wea + a_2 \cdot flo + a_3 \cdot dwe + a_4 \cdot wof + a_5 \cdot north + a_6 \cdot wwidth\_kl + a_7 \cdot wwidth\_bd \quad (6)$$

$$y_i = a_0 + a_1 \cdot wea + a_2 \cdot flo + a_3 \cdot dwe + a_4 \cdot (ln(wof))^2 + a_5 \cdot kl\_rmsrr + a_6 \cdot bd\_rmsrr \quad (7)$$

For each dataset, regression coefficients were estimated using 70% of the data (*training set*) and tested on the remaining 30% of the data (*test set*), deriving *RMSE* for each of the metrics considered.

Table 4
Values of *msrr* and *wmsrr* for eight different orientations, three locations in Greater London and two shading scenarios (w*msrr* = Mean Solar Radiation Rate on an entire window, *msrr* = Mean Solar Radiation Rate, per unit area).

Angle from the North	*msrr* [W/m^2]			*wmsrr* [W]	
	LGW	LHR	LWC	un-shaded window (1 m x 2.4 m)	with balcony above (1.5 m deep)
0	66.57	66.53	66.51	159.62	135.36
45	95.61	95.75	95.37	228.89	179.42
90	132.44	132.83	132.37	317.69	240.67
135	142.27	142.92	142.71	342.50	228.41
180	130.12	130.83	130.98	314.35	162.72
225	131.99	132.17	132.52	318.05	211.42
270	120.33	120.01	120.44	289.06	219.22
315	88.77	88.39	88.69	212.86	168.53

Table 5
Summary statistics of all tested linear regression models for the three datasets.

Equation		Single Aspect		Dual Aspect		Balconies	
		R^2	*rmse*	R^2	*rmse*	R^2	*rmse*
Eq. 6	kl a	0.52	11	0.47	6.6	0.41	4.3
	bd a	0.5	6.4	0.46	3.5	0.37	2.7
	bd b	0.46	88.7	0.49	53.1	0.46	42.8
Eq. 7	kl a	0.91	4.7	0.86	3.4	0.87	2.1
	bd a	0.9	2.5	0.87	1.6	0.85	1.4
	bd b	0.79	48.8	0.82	31.2	0.82	25.7

Table 6
Standardised regression coefficients for Eq. 7 for overheating metrics A, B considered. (*wea* = weather, *flo* = floor, *dwe* = dwelling type/layout, *wof* = window opening factor, *rmsrr* = room mean solar radiation rate, *kl* = kitchen/living, *bd* = bedroom).

	Single Aspect			Dual Aspect			Dual Aspect with Bal.		
	KL	BD		KL	BD		KL	BD	
Param.	A	A	B	A	A	B	A	A	B
wea	0.02	0.03	0.27	−0.01	0.01	0.30	0.02	0.02	0.31
flo	0.14	0.09	0.17	−0.04	−0.01	0.09	−0.01	0.01	0.1
dwe	0.02	−0.08	−0.06	−0.02	0.03	−0.02	0.01	0.01	0.01
$ln(wof)^2$	0.77	0.73	0.76	0.70	0.70	0.78	0.64	0.57	0.74
kl_rmsrr	0.33	0.14	0.09	0.50	0.15	0.12	0.47	0.17	0.14
bd1_rmsrr	0.19	0.41	0.20	0.13	0.44	0.19	0.15	0.49	0.22

Table 7
Binary classification of predicted and actual values to be used in logistic regression.

Metric	SingleAspect			DualAspect			Balconies		
	sens	spec	prec	sens	spec	prec	sens	spec	prec
kl A	0.77	0.92	0.80	0.68	0.92	0.74	0.91	0.87	0.90
bd A	0.84	0.87	0.86	0.89	0.80	0.86	0.95	0.81	0.94
bd B	0.97	0.92	0.92	0.97	0.95	0.96	0.95	0.90	0.93
All	0.76	0.93	0.79	0.67	0.94	0.76	0.89	0.89	0.88

4.3. Establishing a hierarchy of risk factors

A better understanding of the relative importance of the risk factors can be gained by examining the coefficients of the different linear regression models that were developed, in accordance with the model described by Eq. 7. The data were standardised and centred, transforming all independent and dependent variables to have a mean of 0 ($\mu = 0$) and standard deviation 1 ($\sigma = 1$). This allowed to express the regression coefficients on comparable scale, ranging from 0 to 1, in such a way to facilitate a comparison of their relative importance. This is presented in Table 6.

Discussion. It can be observed that, for all three data-sets, the replacement of a categorical variable (*north*) with ordinal ones (*rmsrr*) and the transition to polynomial regression with the introduction of the quadratic logarithmic term $ln(wof)^2$ allow significant improvements of the meta-model's fitness and accuracy to be achieved. These are indicated by higher coefficients of determination (R^2), and a lower Root Mean Square Error (*rmse*) indicated in Table 5 (Table 7).

Coefficients indicate that the overheating metrics considered are weakly correlated with both *weather* and *floor* parameters. The *weather* parameter appears to be moderately correlated with metrics *kl_a* and *bd_a*, but more strongly with overheating metric *bd_b*. This can be attributed to the increase of night-time temperature, resulting from the Urban Heat Island effect which is reflected in the weather data from London Weather Centre (LWC). The *floor* parameter is a rather weak predictor of the risk of overheating, with values ranging 0.01–0.11 and peaking for metric b for single aspect dwellings at 0.17.

The *dwelling* parameters is the weakest predictor of all those considered, with coefficients always below 0.08. This would appear to suggest that the choice of plan form – with respect to variations of internal layout (including minor variations of room depth, size and shape of non-regularly occupied ancillary rooms etc.) – would have marginal impact on the propensity of overheating once key parameters are considered, which can adequately characterise heat gains and losses. An example of how these parameters are considered is the grouping dwelling types into single and dual aspect, that is excluding or allowing possibility for cross ventilation which is the stronger driver of heat losses.

The sample of plan forms, informed by data provided by the industrial sponsor, chosen as input for the development of the research work should not be deemed representative of all design variations that can be produced for single and dual aspect apartments in London. The authors are aware that the discretionary choice of plan forms is a limitation of the present study, and this is further discussed in Section 7.

For the balconies dataset, where the variation of the *dwelling* parameter solely indicates a different balcony arrangement for the same flat archetype, this means that the *kl_rmsrr* and *bd_rmsrr* parameters are a much stronger predictor of the risk of overheating and are able to capture the presence of solar shading resulting from balconies. Furthermore, the coefficients for *kl_rmsrr* and *bd_rmsrr* appear to have similar relative importance for dual aspect and balconies data-sets when criteria kl_a is considered (i.e. 0.45–0.51 for kitchen living and 0.38–0.49). This confirms that the choice of the derived metric is suitable to capture the influence of different external shading scenarios.

The window opening factor (*wof*) is the most significant impact among all predictors considered. Coefficients range between 0.73 to 0.87 for single aspect dwellings, 0.70 to 0.82 for dual aspect dwellings, 0.57 to 0.77 for different balcony arrangements on a dual aspect dwelling, when the tranformed predictor $ln(wof)^2$ is considered, according to Eq. 7. The significance of *wof* for all datasets reveals the extent to which limitations on '*free areas*' for ventilation ($wof = 0.1, 0.2$) is associated with the risk of overheating.

5. Developing a meta-model for predictive modelling by means of logistic regression

5.1. Moving from a linear to a logistic regression model

The present section documents the development of an alternative meta-model for predictive purposes. The intention is here to build a surrogate model, using the data obtained by means of P-DTS, in order to formulate rapid risk estimates against standards and metrics described in Section 2.3 with limited input, such as the case in early design stages.

While the expression of the risk of overheating risk by means of an ordinal score against TM59 Criteria was appropriate to gain an understanding of the hierarchy of risk factors by means of multiple linear regression analysis, the industry-standard approach set by CIBSE ultimately pivots around a binary pass or fail with respect to the thresholds set for TM59 A and B. For this purpose, logistic regression was identified as a valid statistical technique to model a binary dependent variable [3].

The logistic regression model sought to evaluate the relationship between the binary pass/fail outcome for TM59 Criterion A, B and the group of independent variables considered as part of the multiple linear regression meta-modelling. In order to carry out logistic regressions, the values of $kl\_tm59\_a, bd\_tm59\_a, bd\_tm59\_b$ - expressed on a continuous scale - were converted into binary values, in line with TM59 guidance.

$$y_a = \begin{cases} 1, & \text{if } tm59\_a \leqslant 3(pass) \\ 0, & \text{otherwise } (fail) \end{cases} \tag{8}$$

$$y_b = \begin{cases} 1, & \text{if } tm59\_b \leqslant 32(pass) \\ 0, & \text{otherwise } (fail) \end{cases} \tag{9}$$

This allowed to develop a logistic regression model based on the following equation:

$$log\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 \cdot wea + \beta_2 \cdot flo + \beta_3 \cdot dwe + \beta_4 \cdot ln(wof)^2 + \beta_5 \cdot kl\_rmsrr + \beta_6 \cdot bd\_rmsrr \tag{10}$$

where: y: outcome variable indicating binary score ($0 = fail, 1 = pass$); $p = prob(y = 1)$: probability of y to be 1 (*pass*); $x_1, \ldots, x_n$: set of predictor variables; $\beta_1, \ldots, \beta_n$: coefficients associated with likelihood predictions.

5.2. Binary classification and logistic model metrics

A classification was carried out to assess the meta-model capability of predicting the risk of overheating assessed with DTS, in terms of passing/failing the TM59 criteria. *True* indicates agreement (and *False* disagreement) between the meta-model (MM) (*predicted*) and the DTS assessment (*simulated*), whereas *Positive* and *Negative* indicate the meta-model prediction of passing or failing TM59 criteria. Hence, *True Positives* are data points predicted as positive (MM pass), which are measured positive (DTS pass); *False Negatives* are data points predicted as negative (MM fail), which are actually positive (DTS pass); *False Positives* are data points predicted as positive (MM pass), which are actually negative (DTS fail); *True Negatives* are data points predicted as negative (MM fail), and measured as negative (DTS fail).

The following metrics were used to test the outcome of the regressions in terms of relevance: *sensitivity* expresses the number of iterations passing TM59 criteria ($tp + fn$) that are correctly predicted by the meta-model (tp); *specificity* indicates the number of iterations predicted to fail TM59 by the meta-model (tn), that actually do fail in the DTS assessment ($tn + fp$); *precision* indicates, out of all iterations flagged as a TM59 'pass' by the meta-model ($tp + fp$), those that pass the DTS assessment as well (tp).

$$sensitivity = \frac{tp}{tp + fn} \tag{11}$$

$$specificity = \frac{tn}{tn + fp} \tag{12}$$

$$precision = \frac{tp}{tp + fp} \tag{13}$$

where: $tp = true\ positives, fp = false\ positives, fn = false\ negatives, tn = true\ negatives$.

5.3. Results and discussion

The *sensitivity* parameters indicate how many iterations passing TM59 are correctly identified by the meta-model. The results show values typically above 0.75 for all metrics and data-sets considered. The lowest values are obtained when all metrics are considered, with sensitivity of 0.76 and 0.67 for single and dual aspect, respectively. The sensitivity of the model decreases for dual aspect dwellings and the metric *klA* showing the most significant reductions. This is attributed to the greater heterogeneity of room physical layout for dual aspect dwellings, that affects heat gains due to exposed glazed area and, most importantly, heat losses associated with natural ventilation. This should be read together with the greater homogeneity of results obtained for *bdB*, where conversely a lower variation in room layout and a linear overheating threshold ($26^\circ C$) appears to allow a better alignment between meta-model predictions and DTS assessment.

Overall, it is important to observe how, both when the TM59 metrics are considered individually and all together, the model appears to be more specific than sensitive. In overheating terms, this means that the meta-model is very good at predicting the 'risky' cases, i.e. capturing the iterations that fail TM59, and it is better at doing that than capturing the iterations that pass TM59. It follows that the meta-model slightly overestimates the overheating risk of the data considered. The equations defining the probabilistic risk expressed by the surrogate model are listed in Table 9.

6. Developing a meta-model for predictive modelling by means of machine learning

6.1. A machine learning approach to predictive overheating modelling

While the linear regression analysis presented in earlier section was presented as a method to define a hierarchy of risk factors, it can be used for predictive purposes too. The figures presented in Table 5, however, appeared to indicate an insufficient predictive accuracy, specifically with a *rmse* appearing too high when compared to the TM59 pass/fail thresholds (3).

This section seeks to investigate whether machine learning models, formulated as regression problems, can allow to predict overheating risk with higher accuracy, that is with lower *rmse* and higher R^2 than the linear regression models generated previously. To our knowledge, there is only one example in the literature of similar type of work, that is the indoor overheating and air polluting risk modelled by [51], based on the EnergyPlus simulations, and using Support Vector Machines (SVMs) and Neural Networks (NN). The authors concluded that NN had a better performance in terms of R^2; this was included between 0.80 and 0.97, depending on the configuration of the network. Among the limitations pointed out by the authors, it was recognised that the meta-model did not include information on building layout and geometry. This information is included in the meta-model proposed in this work.

From a machine learning perspective, the prediction of overheating risk can be formulated as a regression problem. Given a set of features and a measure of overheating risk, the objective is to train a machine learning algorithm such that the Root Mean Squared Error (*rmse*), calculated based on the output values of the model and the target values, is minimised. This type of problem can be addressed by a multiplicity of machine learning algorithms.

In this work, four approaches are compared and evaluated in terms of their prediction capability: Support Vector Regression Machines, Long-Short Term Neural Networks and two ensemble approaches: Random Forest and Extreme Gradient Boost. The ensemble machine learning methods consists of the combination of several machine learning methods. As pointed out by [23], there are several approaches to combine the results of a number of classifiers. The Random Forest is a typical example of *bagging* predictor. This means that several samples with replacement are considered to train *weak* classifiers (i.e. Decision trees). The XGBoost, is a *boosting* method, meaning that each classifier is built sequentially thus trying to correct the errors committed by the previous classifier. In both cases, the result is a *strong* classifier or predictor. The Support Vector Machines have been initially proposed by [19] to solve binary classification problems. The objective of the binary classification problem is to find the optimal hyperplane that divides the space in two subspaces to separate the observations in two distinct groups. The optimal hyperplane is the one with the maximum margin, which is thus able to generalise the regression or classification problem. SVR works in a similar way, as explained by [49]. Here, the objective is to fit the error within a certain threshold. In SVR, the optimal hyperplane is the one with the highest number of observations included within the margins. Long-Short Term Memory Networks (LSTM) are a special type of Recurrent Neural Networks (RNN) to model time sequences. LSTM have been proposed by [27] to model long term time sequences. Random forest (RF) have been proposed by [10] to reduce the problem of over-fitting. The main innovation of the method consists of creating several decision trees based on a sample of observations and features with replacement. The RF can also be deployed to assess the importance of features based on the Information Gain or the Gini Impurity Index which are the metrics that measure the quality of the split during the creation of each Decision Tree.

6.2. Evaluation of features importance

The features importance evaluated based on the Random Forest, using the Gini Impurity Index, by considering the target variable *bd1_tm59_a* is reported in Fig. 5. The figure shows that *wof* is the most important feature to predict overheating risk, followed by the variable *bd1_rmsrr*. All the other variables are less important for the prediction problem. Although the contribution of *wwidth_kl* and *wwidth_b* is nearly zero, they have been included in the model as they improve the prediction results. eXtreme Gradient Boosting (XGBoost), proposed by [13], has been selected because has shown high performance on a wide range of problems. The XGBoost, proposed by [24], is based on the Gradient Boosting (GB) approach which consists of training several models sequentially thus allowing to identify the shortcomings of each model based on the gradient of the loss function. The value of the loss function, which indicates how well the model fits the data, is then utilised in the second stage to improve the next learner.

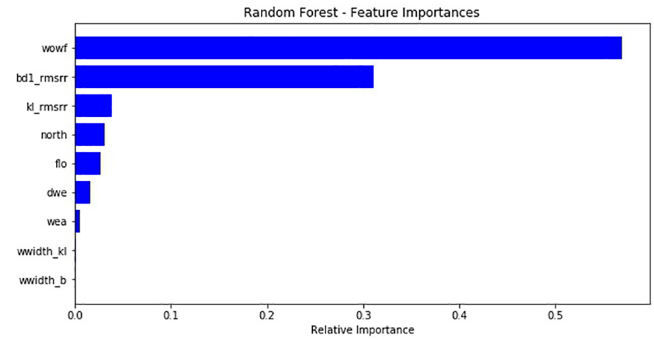

Fig. 5. Random Forest - Features importance with reference to target variable *bd1_tm59_a*.

6.3. Results and discussion

The optimal parameters of the four machine learning algorithms have been identified using the Random Search with 3-fold cross-validation. Where the cross-validation consists of testing each configuration of parameters on three different subset of data. As [7] have shown, the Random Search performs well in a reasonable amount of time. In this work, the combination of parameters to be tested in the Random Search framework are sampled from a uniform distribution.

Once the optimal hyper-parameters are identified, the machine learning algorithms are trained on the 70% of the dataset to predict the overheating risk based on three measures of overheating and on three dataset representing different flat configuration (Single Aspect, Dual Aspect and Dual Aspect with Balcony). The experiments were performed using `scikit-learn` package to implement Random Forest, Support Vector Regression and to optimize the hyper-parameters based on the Random Search with cross-validation approach. The `keras` package with `tensorflow` backend was deployed for the experiments performed with the Long-Short Term Neural Networks and the `xgboost` library to implement the XGBoost. The prediction capability of the model is assessed on the test set thanks to the 10-fold cross-validation. The Root Mean Squared Error (RMSE) is calculated as the average prediction errors measured on ten different subsets of the test set. The coefficient of determination, R^2 is thus the average of those calculated for the 10 subsets.

Table 8 shows the results obtained thanks to the implementation of four machine learning approaches and the linear regression. The results are presented in terms of two indicators: the R^2 and the Root Mean Squared Error (rmse). While the R^2 is a measure of adaptation to the model, the *rmse* measures the prediction errors. Overall, the XBoost is the method that allows to obtain an almost perfect fit of the model and a considerable reduction of the prediction error compared to the other machine learning approaches. The linear regression allows to obtain better results compared to the SVR, while the Random Forest, the LSTM and the XBoost perform

Table 8
Results of machine learning predictions on the three data-sets.

Data-set	Lin. Reg.		XBoost		RF		LSTM		SVR	
Single Aspect	R^2	*rmse*	R^2	*rmse*	R^2	*rmse*	R^2	*rmse*	R^2	*rmse*
kl a	0.91	4.7	1.00	0.53	0.98	1.10	0.94	3.84	0.69	7.07
bd a	0.90	2.5	1.00	0.22	0.99	0.55	0.84	3.32	0.71	4.11
bd b	0.79	48.8	1.00	3.47	0.98	9.04	0.94	28.07	0.31	94.28
Dual Aspect	R^2	*rmse*	R^2	*rmse*	R^2	*rmse*	R^2	*rmse*	R^2	*rmse*
kl a	0.86	3.4	1.00	0.50	0.97	1.04	0.94	2.16	0.69	7.08
bd a	0.87	1.6	1.00	0.24	0.98	0.42	0.88	1.64	0.70	3.71
bd b	0.82	31.2	1.00	3.18	0.98	6.42	0.97	13.19	0.31	88.98
Dual with Balcony	R^2	*rmse*	R^2	*rmse*	R^2	*rmse*	R^2	*rmse*	R^2	*rmse*
kl a	0.87	2.1	0.99	0.26	0.97	0.58	0.97	1.01	0.67	2.98
bd a	0.85	1.4	1.00	0.12	0.99	0.21	0.96	0.66	0.70	1.84
bd b	0.82	25.7	1.00	1.77	0.99	4.32	0.97	11.03	0.47	42.05

Table 9
Coefficients for the Eq. 14 defining the probabilistic meta-model obtained using logistic regression for single and dual aspect dwellings and for the three TM59 metrics considered (A,B = TM59 criteria, *kl*= kitchen/living, *bd* = bedroom).

Metric	β_0	β_1	β_2	β_3	β_4	β_5	β_6
Single Aspect Dwellings							
kl A	+7.380	+0.207	−0.868	+0.005	−1.618	−0.009	−0.004
bd A	+7.490	−0.020	−0.324	+0.394	−1.357	−0.003	−0.010
bd B	+13.118	−2.211	−1.079	+0.475	−2.375	−0.002	−0.006
all	+5.993	+0.027	−0.626	+0.118	−1.645	−0.006	−0.005
Dual Aspect Dwellings							
kl A	+6.68	+0.241	−0.088	+0.045	−1.226	−0.005	−0.003
bd A	+9.532	+0.17	+0.083	−0.196	−1.322	−0.001	−0.011
bd B	+16.177	−2.836	−0.67	+0.169	−2.79	−0.001	−0.006
all	+7.439	−0.107	−0.092	+0.029	−1.548	−0.005	−0.004

all better than the linear regression. Overall, it can be concluded that boosting *approaches* might have a better performance compare to the implementation of a single machine learning method. This seams reasonable because the sequential machine learning approaches allow to improve the results by learning from previous implementations.

7. Discussion and limitations

As part of the development of the core engine for a simplified Rapid Overheating ASSessment Tool (ROASST), this study had the objective to try and develop surrogate models that could condense the complexity of dynamic thermal simulations into discrete equations. A number of alternative approaches to meta-modelling were investigated, both for explanatory and predictive purposes, and that led to a number of useful findings.

Importance of window design for natural ventilation. One of the key findings of this study is the importance of heat losses associated with natural ventilation the risk of indoor overheating.

Standing the grouping of dwellings into single and dual aspect data sets, the choice of the window opening factor (*wof*) appeared the be the most significant among all risk factors considered. This was indicated by the explanatory meta-modelling using multiple (polynomial) linear regression, where the 'hierarchy' of risk factors revealed by the standardised regression coefficients indicated a clear predominance of the *wof* predictor. This was confirmed when features importance was evaluated using the Random Forest machine learning technique for regression and classification problems.

This revealed that any limitation to the natural ventilation potential of dwellings to purge built-up heat, such as the choice of single-sided ventilation and/or the installation of window restrictors limiting the 'free area', is the single most crucial factor on the risk of overheating.

Limitations to indoor air-flow modelling. The authors are aware that the consideration of *wof* as the main proxy for natural ventilation potential represents a substantial simplification of the phenomena that regulate real-world natural ventilation, as well as of the algorithms used by the EnergyPlus to simulate indoor air-flow [54]. Detailed natural ventilation modelling and further considerations of this in the development of the meta-models could have better accounted for the impact of orientation and wind data for:

- wind turbulence, the main driving force for natural ventilation in absence of significant density differences driven by indoor-outdoor temperature gradients or stack effects, as it is the case for the single aspect dwellings and the summer period considered [14];
- wind-driven cross ventilation, and specifically the pressure differentials between openings on different facades resulting from different wind speeds and directions.

The present study also did not include a detailed exploration of factors impacting wind pressure coefficients on openings, such as height from the ground plane, obstructions, building shape and aspect ratio among others. These do affect pressure differentials, which in turn determine indoor air-flow through openings as indicated Eq. Eq. 1. Wind pressure coefficients for the present study were based on the assumptions of low- and medium-rise buildings in urban environments and were calculated by EnergyPlus as defined in [54], and based on the Handbook Fundamentals by [2]. This has been identified by previous studies as one of the key sources of uncertainty in DTS [18], and further work to couple the

Computational Fluid Dynamics (CFD) with thermal modelling would be appropriate to approximate real-case scenarios.

Impact of dwelling types and internal layout. As the meta-modelling indicated that the *dwelling* parameter is the weakest predictor of all those considered, this was interpreted as the indication that variations of internal layout (including minor variations of room depth, size and shape of non-regularly occupied ancillary rooms etc.) would not have a significant impact on the overheating propensity once other parameters are considered, which can adequately characterise solar heat gains and heat losses through natural ventilation (such as for example the grouping of dwellings into single and dual aspect to account for cross ventilation potential).

The authors are aware that this appears to contradict empirical findings [40] and common rules of thumbs, such as on aspects like the impact of internal partitions on indoor air-flow. Single-room and zonal/network models - such as those used in this study - are typically capable of returning macroscopic information on thermal and flow parameters (that is one sensor per thermal space and one node per opening). More detailed investigation of indoor air-flow would require Computational Fluid Dynamics (CFD), which involves far greater complexity and is beyond the scope of this article.

Impact of fabric and glazing thermal characteristics. The authors are aware that the choice of one set of building envelope characteristics can be seen as a limitation to the capability and usefulness of a rapid overheating risk tool that use the algorithms developed with the meta-modelling methods described in this study. This was justified by the intention to develop a tool that could provide quick feedback in early, conceptual design stages, when detailed information of building fabric is typically not yet considered by architectural designers.

For that reason, measures introduced to mitigate the risk of indoor overheating, that is design features that may be specifically implemented for the purpose of reducing heat gains, such as for instance improvement in window thermal performance or solar shading devices, were not considered in this study. The value of allowing perspective users to test a greater rage of options including those mitigating the overheating risk early in the design, is however recognised and further work is suggested to expand the tool capability.

Value of introducing new predictors to better account for solar radiation. The introduction of a the Room Mean Solar Radiation Rate (*rmsrr*) as a proxy for orientation, replacing the angle from the north and window size parameters, calculated for all windows belonging to each of the key thermal zones (rooms) under analysis, achieved notable improvement in the quality of the meta-models.

Moreover, using the *rmsrr* parameter in the equations defining the surrogate model permit to de-couple the calculation of incident solar radiation from the DTS simulation, in such a way to allow for that to calculated separately using rapid software tools like the Ladybug Tools [48] and/or to derive these *rmsrr* by interpolation from tabular values, in a way similar to what done in Table 4. This approach in intended to allow for the ROASST tool to assess the risk of overheating based on a range of fenestration size and external shading configurations scenarios beyond than those included in the analyses.

An unintended consequence of the predictor transformation, however, is the loss of information on orientation and linkage between solar radiation and outdoor temperature. Similar amounts of solar radiation may have a very different impact on indoor overheating depending on when they occur during the day, and this is due to ability to lose heat via natural ventilation, whose effectiveness heavily relies on outdoor temperatures being cooler than indoor temperatures, as well as on other factors discussed above.

The inclusion of an explicit parameter defining orientation (*angle from north*) captured the circadian profiles of outdoor temperature and this is reflected in the TM59 pass rates indicated in Table 3, whereby the south-west and west orientations are associated with higher risk than those at east and south-east, despite comparable solar radiation.

Limitations of the TM59 methodology and simplified modelling assumptions. It is important to recognise that while building physics models serve as approximations to reality, validating the underlying physics algorithms against real-world data is essential for fine-tuning thermal performance models. [40] compared simulated and monitored data for newly built flats in central London, and found significant discrepancies between simulated and monitored data, highlighting the limitations of the prescriptive approach adopted by CIBSE TM59 methodology when attempting to capture the complexity of real world conditions. They recommend replacing the TM59 binary risk predictions based on a discrete number of deterministic scenarios with confidence intervals, which could better reflect uncertainties associated both with DTS modelling assumptions and real-world scenarios.

The probabilistic risk estimates expressed via the surrogate model built on logistic regressions presented as part of this work goes in a similar direction, however further work based and fail This could be a viable approach for further.

Value of predictive meta-modelling and potential integration with user interface. While basing the Parametric DTS workflow on robust and extensively validated engines for thermal calculations, the authors recognise the bias and limitations associated to the discretionary choice of input parameters/ predictors. While any validation of the building physics algorithms for calculating heat transfer carried out by other studies [45] are beyond the scope of the present work, the usage of classic statistical techniques such as multiple linear regression to characterise correlations between a small sample simulation inputs and outputs can be regarded as reductive, as noted by [34] Establishing an acceptable trade-off between accuracy, completeness and rapidity presented itself as the most crucial challenge for this work and the surrogate models built on logistic regression and using Random Forest techniques showed a good ability to predict the pass or fail/rate against the TM59 criteria, with reduced input. Machine learning models, formulated as regression problems, show a good capacity to predict overheating risk with low *rmse* and with very high R^2. The ensemble approaches perform better compared to SVR and Neural Networks. The RF allows to assess the relative importance of features, it is thus possible to determine that *wof* is the most important variable in the prediction problem, followed by *kl_rmsrr* and *bd_rmsrr*.

The meta-model shows variable fitness for the three data-sets (single-, dual-aspect and dual-aspect with balconies), but broadly speaking it appeared to be very sensitive and extremely specific. This means that it showed a very good capability to predict both combination of risk factors passing TM59 and those failing TM59 in the DTS assessment, with a slight overestimation of the risk assessed by means of building physics.

The possibility of producing reasonably accurate early-stage probabilistic risk predictions with limited input, which was targeted by the development of a predictive meta-model using logistic regression analysis, allowed to explore alternative options for integration with a user interface targeting building designers and sustainability consultants. The equations shown in Table 9 permit the integration with spreadsheets or web applications to allow perspective users to input design parameters and obtain rapid overheating risk feedback. Further work will look at developing a suitable user interface, with reference to existing tools such as the simple checklist developed by the Good Homes Alliance [25].

This is not further discussed as it sits outside the scope of the current study.

8. Conclusions

Minimising the risk of indoor overheating in residential buildings is a key priority within the context of climate change adaptation. The high accuracy of Dynamic Thermal Simulation (DTS) modelling tools is crucial to capture the complexity that robust overheating risk assessments require, but DTS is not suitable for routine early-stage assessments. Design decisions taken at the early stage may however have a high impact on the risk of overheating. The paper sets out the methodology for a new tool intended to address these issues. The meta-model was developed using data from the specific case of new build apartments in London, reflecting one important category of residential building design, in a major city which is facing growing overheating risk issues. The model developed balances accuracy with ease of operation, reflecting the realities of commercial practice, and was found to provide acceptable fit with results using more detailed simulation methods for the case studied. However, as discussed above, there are numerous opportunities to refine and extend the method. The paper shows that reasonably accurate early-stage probabilistic risk predictions can be made with limited input, based on a predictive meta-model using logistic regression analysis, which could integrate via a user interface targeting building designers and sustainability consultants. The equations shown in Table 9 permit the integration with spreadsheets or web applications that facilitate users to input design parameters and obtain rapid overheating risk feedback. Future work will look at developing a suitable user interface, with reference to existing tools such as the simple checklist developed by the Good Homes Alliance (GHA, 2019).

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A

Given the probability p, the logit of the probability $log(p/(1-p))$, also defined as the natural logarithm of the odds, characterises the meta-model developed using logistic regression analysis can be expressed as:

$$log\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 \cdot wea + \beta_2 \cdot flo + \beta_3 \cdot dwe + \beta_4 \cdot (ln(wowf))^2 + \beta_5 \cdot kl\_rmsrr + \beta_6 \cdot bd\_rmsrr \qquad (14)$$

References

[1] ARUP, 2014. Reducing urban heat risk. Technical Report. ARUP. London. http://publications.arup.com/Publications/R/Reducing_urban_heat_risk.aspx..

[2] ASHRAE, 2017. ASHRAE Handbook Fundamentals 2017. Technical Report. ASHRAE..

[3] G. Aurélien, Hands-on machine learning with Scikit-Learn and TensorFlow: concepts, tools, and techniques to build intelligent systems, O'Reilly Media, Sebastopol, California, 2017.

[4] Baborska-Narozny, M., Stevenson, F., Chatterton, P., 2016. Temperature in housing: stratification and contextual factors. Proceedings of the Institution of Civil Engineers - Engineering Sustainability 169, 125–137. http://www.icevirtuallibrary.com/doi/10.1680/ensu.14.00054, DOI: 10.1680/ensu.14.00054..

[5] A. Bateson, Comparison of CIBSE thermal comfort assessments with SAP overheating assessments and implications for designers, Building Services Engineering Research and Technology 37 (2016) 243–251, https://doi.org/10.1177/0143624416631133.

[6] A. Beizaee, K. Lomas, S. Firth, National survey of summertime temperatures and overheating risk in English homes, Building and Environment 65 (2013) 1–17, https://doi.org/10.1016/j.buildenv.2013.03.011, http://www.sciencedirect.com/science/article/pii/S0360132313000917.

[7] J. Bergstra, Y. Bengio, Random search for hyper-parameter optimization, Journal of Machine Learning Research 13 (2012) 281–305, http://dl.acm.org/citation.cfm?id=2188385.2188395.

[8] BigLadderSoftware, 2016. Airflow Network: Input Output Reference - EnergyPlus 8.6. https://bigladdersoftware.com/epx/docs/8-6/input-output-reference/group-airflow-network.html#group-airflow-network..

[9] BRE, 2014. SAP 2012 - The Government' s Standard Assessment Proceedure for Energy Rating of Dwellings. Technical Report rev June 2014. Buiding Research Establishment (on behalf of DECC). Watford. http://www.bre.co.uk/filelibrary/SAP/2012/SAP-2012_9-92.pdf..

[10] L. Breiman, Random forests, Machine Learning 45 (2001) 5–32, https://doi.org/10.1023/A:1010933404324, DOI: 10.1023/A:1010933404324.

[11] CCC, 2016. UK Climate Change - Risk Assessment 2017. Technical Report January. Committee on Climate Change. London. https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/584281/uk-climate-change-risk-assess-2017.pdf..

[12] CCC, 2019. UK housing: Fit for the future? Technical Report February. Committee on Climate Change. London. www.theccc.org.uk/publications..

[13] Chen, T., Guestrin, C., 2016. Xgboost: A scalable tree boosting system, in: Proceedings of the 22Nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, ACM, New York, NY, USA. pp. 785–794. http://doi.acm.org/10.1145/2939672.2939785, 10.1145/2939672.2939785.

[14] CIBSE, 2005. Natural ventilation in non-domestic buildings. Technical Report. CIBSE. London. 10.1002/9781119951773..

[15] CIBSE, 2013. The limits of thermal comfort: avoiding overheating in European buildings. Technical Report. CIBSE. Norwich. 10.1017/CBO9781107415324.004, arXiv:arXiv:1011.1669v3..

[16] CIBSE, 2014. TM49: Design Summer Years for London. Technical Report. CIBSE..

[17] CIBSE, 2017. TM59: Design methodology for the assessment of overheating risk in homes. Technical Report. CIBSE. London. CIBSE TM59: 2017..

[18] D. Có Stola, B. Blocken, J.L.M. Hensen, Overview of pressure coefficient data in building energy simulation and airflow network programs, Building and Environment 44 (2009) 2027–2036, https://doi.org/10.1016/j.buildenv.2009.02.006, http://www.wind.ttu.edu/.

[19] C. Cortes, V. Vapnik, Support-vector networks, Machine Learning 20 (1995) 273–297, https://doi.org/10.1007/BF00994018.

[20] DCLG, 2015. Technical housing standards - nationally described space standard. Technical Report. Department for Communities and Local Government. London..

[21] Dengel, A.D., Swainson, M., 2013. Assessment of MVHR systems and air quality in zero carbon homes. Technical Report. NHBC Foundation..

[22] DesignBuilder, 2019. DesignBuilder Software. https://designbuilder.co.uk/..

[23] T. Dietterich, Ensemble methods in machine learning, in: Multiple Classifier Systems, Springer Berlin Heidelberg, Berlin, Heidelberg, 2000, pp. 1–15.

[24] J. Friedman, Greedy function approximation: A gradient boosting machine, The Annals of Statistics 29 (2001) 1189–1232, http://www.jstor.org/stable/2699986.

[25] GHA, 2019. Overheating in new homes. Tool and guidance for identifying and mitigating early stage overheating risks in new homes. Technical Report July. Good Homes Alliance..

[26] HMGovernment, 2013. The Building Regulations, Conservation of fuel and power Approved Document Part L1A (2013 version). Technical Report. HMGovernment. London. http://www.planningportal.gov.uk/uploads/br/BR_PDF_AD_L1A_2013.pdf..

[27] S. Hochreiter, J. Schmidhuber, Long short-term memory, Neural Comput. 9 (1997) 1735–1780, https://doi.org/10.1162/neco.1997.9.8.1735, DOI: 10.1162/neco.1997.9.8.1735.

[28] G. Hutcheson, Ordinary Least-Squares Regression, The Multivariate Social Scientist, 4PU. chapter 3, SAGE Publications Ltd, 6 Bonhill Street, London EC2A, 1999, pp. 56–113, https://doi.org/10.4135/9780857028075.d49.

[29] IPCC, 2018. Global warming of 1.5C. Technical Report October. IPCC. www.environmentalgraphiti.org.

[30] B.M. Jones, M.J. Cook, S.D. Fitzgerald, C.R. Iddon, A review of ventilation opening area terminology, Energy and Buildings 118 (2016) 249–258, https://doi.org/10.1016/j.enbuild.2016.02.053.

[31] K.J. Lomas, S.M. Porritt, Overheating in buildings: lessons from research, Building Research and Information 45 (2017) 1–18, https://doi.org/10.1080/09613218.2017.1256136.

[32] A. Mavrogianni, M. Davies, Z. Chalabi, P. Wilkinson, M. Kolokotroni, J. Milner, Space heating demand and heatwave vulnerability: London domestic stock, Building Research & Information 3218 (2009) 583–597, https://doi.org/10.1080/09613210903162597, http://discovery.ucl.ac.uk/139435/.

[33] A. Mavrogianni, M. Davies, J. Taylor, Z. Chalabi, P. Biddulph, E. Oikonomou, P. Das, B. Jones, The impact of occupancy patterns, occupant-controlled

ventilation and shading on indoor overheating risk in domestic environments, Building and Environment 78 (2014) 183–198, https://doi.org/10.1016/j.buildenv.2014.04.008.
[34] A. Mavrogianni, A. Pathan, E. Oikonomou, P. Biddulph, P. Symonds, M. Davies, Inhabitant actions and summer overheating risk in London dwellings, Building Research and Information 45 (1–2) (2017) 119–142, https://doi.org/10.1080/09613218.2016.1208431.
[35] Mavrogianni, A., Taylor, J., Thoua, C., Davies, M., Kolm-murray, J., 2014b. A coupled summer thermal comfort and indoor air quality model of urban high-rise housing, in: Counting the Cost of Comfort in a changing world, Network for Comfort and Energy Use in Buildings, Windsor. p. 17..
[36] A. Mavrogianni, P. Wilkinson, M. Davies, P. Biddulph, E. Oikonomou, Building characteristics as determinants of propensity to high indoor summer temperatures in London dwellings, Building and Environment 55 (2012) 117–130, https://doi.org/10.1016/j.buildenv.2011.12.003.
[37] Mayor of London, 2016. Housing Standards - Minor Alterations To the London Plan. Technical Report. Mayor of London..
[38] Mayor of London, 2019. The Draft New London Plan. Technical Report. Mayor of London..
[39] Mayor of London, 2020. Housing Design Quality and Standards - Supplementary Planning Guidance. Technical Report. Mayor of London..
[40] K. Mourkos, R.S. McLeod, C.J. Hopfe, C. Goodier, M. Swainson, Assessing the application and limitations of a standardised overheating risk-assessment methodology in a real-world context, Building and Environment 181 (2020), https://doi.org/10.1016/j.buildenv.2020.107070, https://reader.elsevier.com/reader/sd/pii/S0360132320304509?token=28C3DF612B66032725A 1912C7C2E398 DE32A8B63EBA704F3 9F414A3C5080B FF2551206FD 87FB7D8CC1256E6 43210B4F6&originRegion=eu-west-1&originCreation=20210903092028.
[41] NHBC, 2012. Understanding overheating - where to start: An introduction for house builders and designers. Technical Report. NHBC Foundation. Milton Keynes..
[42] NHS, 2015. Heatwave Plan for England. Technical Report May. Public Health England. London. https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/429384/Heatwave_Main_Plan_2015.pdf..
[43] ODPM, 2006. Housing Health and Safety Rating System (HHSRS) - Operating Guidance. Technical Report. Office of the Deputy Prime Minister (ODPM). London. http://www.sholland.gov.uk/housing/privatesector/Housing+Health+and+Safety+Rating+System.htm..
[44] E. Oikonomou, M. Davies, A. Mavrogianni, P. Biddulph, P. Wilkinson, M. Kolokotroni, Modelling the relative importance of the urban heat island and the thermal quality of dwellings for overheating in London, Building and Environment 57 (2012) 223–238, https://doi.org/10.1016/j.buildenv.2012.04.002.
[45] G. Petrou, A. Mavrogianni, P. Symonds, A. Mylona, D. Virk, R. Raslan, M. Davies, Can the choice of building performance simulation tool significantly alter the level of predicted indoor overheating risk in London flats?, Building Services Engineering Research and Technology 40 (2019) 30–46, https://doiorg/10.1177/0143624418792340.
[46] Philip, S., 2013. Eppy 0.4.6.4 documentation. http://eppy.readthedocs.io/en/latest/..
[47] Porritt, S.M., 2012. Adapting UK Dwellings for Heat Waves. Ph.D. thesis. De Montfort University. http://hdl.handle.net/2086/6327..
[48] Roudsari, M.S., 2021. Ladybug Tools. https://www.ladybug.tools/..
[49] A. Smola, B. Schölkopf, A tutorial on support vector regression, Statistics and Computing 14 (2004) 199–222, https://doi.org/10.1023/B:STCO.0000035301.49549.88.
[50] F. Stevenson, M. Baborska-Narozny, P. Chatterton, Building Research & Information Resilience, redundancy and low-carbon living: co-producing individual and community learning Resilience, redundancy and low-carbon living: co-producing individual and community learning, Building Research & Information (2016), https://doi.org/10.1080/09613218.2016.1207371, https://www.tandfonline.com/action/journalInformation?journalCode=rbri20.
[51] P. Symonds, J. Taylor, Z. Chalabi, A. Mavrogianni, M. Davies, I. Hamilton, S. Vardoulakis, C. Heaviside, H. Macintyre, Development of an England-wide indoor overheating and air pollution model using artificial neural networks, Journal of Building Performance Simulation 9 (2016) 606–619, https://doi.org/10.1080/19401493.2016.1166265.
[52] J. Taylor, M. Davies, A. Mavrogianni, C. Shrubsole, I. Hamilton, P. Das, B. Jones, E. Oikonomou, P. Biddulph, Mapping indoor overheating and air pollution risk modification across Great Britain: A modelling study, Building and Environment 99 (2016) 1–12, https://doi.org/10.1016/j.buildenv.2016.01.010, http://linkinghub.elsevier.com/retrieve/pii/S0360132316300105.
[53] Taylor, M., 2014. Preventing Overheating. Technical Report. Good Homes Alliance. London. http://goodhomes.org.uk/wp-content/uploads/2017/08/REPORT-GHA-Preventing-Overheating-FINAL-140217-2.pdf..
[54] US DoE, 2016. Engineering Reference - EnergyPlus 8.5. Technical Report. US Department of Energy. https://bigladdersoftware.com/epx/docs/8-5/engineering-reference/ http://scholar.google.com/scholar?hl=en&btnG=Search&q=intitle:EnergyPlus+Engineering+Reference,+The+Reference+to+EnergyPlus+Calculations#1, citeulike-article-id:10579266..
[55] US DoE, 2018a. EnergyPlus energy simulation software..
[56] US DoE, 2018b. EnergyPlus. Testing and Validation. https://energyplus.net/testing..
[57] Zero Carbon Hub, 2015a. Overheating in Homes: the big picture. Technical Report. Zero Carbon Hub. London..
[58] Zero Carbon Hub, 2015b. Overheating Risk Mapping - Evidence Review. Technical Report. Zero Carbon Hub. London..
[59] Zero Carbon Hub, 2016. Solutions to Overheating in Homes, Evidence Review. Zero Carbon Hub, London. http://www.zerocarbonhub.org/sites/default/files/resources/reports/ZCH-OverheatingEvidenceReview.pdf..
[60] Y. Zhang, Parallel EnergyPlus and the development of a parametric analysis tool, in, in: Proceedings of the 11th International IBPSA Building Simulation Conference, International Building Performance Simulation Association (IBPSA) Glasgow, 2009, pp. 1382–1388.