Modelling Platform for Schools (MPS): The Development of an Automated One-By-One Framework for the Generation of Dynamic Thermal Simulation Models of Schools

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6 Abstract

The UK Government has recently committed to achieve net zero carbon status by year 2050.
Schools are responsible for around 2% of the UK's total energy consumption, and around 15%
of the UK public sector's carbon emissions. A detailed analysis of the English school building
stock's performance can help policymakers improve its energy efficiency and indoor
environmental quality.

Building stock modelling is a technique commonly used to quantify current and future energy demand or indoor environmental quality performance of large numbers of buildings at the neighbourhood, city, regional or national level. 'Building-by-building' stock modelling is a modelling technique whereby individual buildings within the stock are modelled and simulated, and performance results are aggregated and analysed at stock level

This paper presents the development of the Modelling Platform for Schools (MPS) – an automated generation of one-by-one thermal models of schools in England through the analysis and integration of a range of data (geometry, size, number of buildings within a school premises etc.) from multiple databases and tools (Edubase/Get Information About Schools, Property Data Survey Programme, Ordanance Survey and others). The study then presents an initial assessment and evaluation of the modelling procedure of the proposed platform.

The model evaluation has shown that out of 15,245 schools for which sufficient data were available, nearly 50% can be modelled in an automated manner having a high level of confidence of similarity with the actual buildings. Visual comparison between automaticallygenerated models and actual buildings has shown that around 70% of the models were, indeed, geometrically accurate.

28 Keywords: Stock modelling, Schools stock, Thermal simulation, Generative design

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1 1. Introduction

The UK Government has recently committed to achieving net zero carbon status by 2050 [1].
The built environment accounts for around 40% of the UK's carbon emissions [2]. Buildings,
therefore, will have an important role in achieving the government's carbon emission reduction

5 targets.

Schools are responsible for around 2% of the UK's total energy consumption [3], and 15% of
the UK's public sector's carbon emissions [4]. Given that two-thirds of the total English school
floor area was built before 1976 [5], there are great opportunities for significant improvements
of the school stock's energy performance.

10 Children spend around 30% of their lives at school, around 70% of which is in classrooms [6]. 11 As a building type, schools have a number of distinctive and unique features that impact on 12 energy performance: Schools typically have high and intermittent occupancy densities, which 13 can result in high and irregular internal heat gains and heating demand patterns [7]. 14 Classrooms are used in irregular patterns throughout the day and over the year, reflecting 15 academic use, but indoor conditions (e.g., lighting, environmental quality and thermal comfort) 16 need to be kept at appropriate levels. For these reasons, maintaining performance at a high 17 standard may be challenging in schools, especially in the context of climate change.

18 It is estimated that the UK school building stock has the potential to save 625,000 tonnes of
 19 CO₂ emissions annually [8]. A detailed analysis of the school stock's performance could,
 20 therefore, help policymakers improve its energy efficiency and indoor environmental quality.

Building stock modelling is a technique that enables an examination of a large number of buildings, which represent the entire building stock or a large proportion of it, aiming to evaluate a range of performance indicators (e.g., energy consumption, CO₂ emissions, Indoor Air Quality and others). Stock modelling is often used to examine current and future performance across large numbers of buildings at neighbourhood, city, regional or even national levels.

This paper aims to present the development of Modelling Platform for Schools (MPS) – a process of automatically generating and running one-by-one thermal models of the English school building stock. The platform offers a detailed representation of almost every school building (depending on data availability), enabling the impact of different improvement options or climate change scenarios to be evaluated while accounting for the diversity of the stock.

32 The objectives of this paper are to:

- present the individual components and data sources behind the development of MPS,
- describe the step-by-step procedure in the generation and simulation of the English
 school stock,
 - assess initial modelling results and evaluate the robustness and accuracy of MPS in describing the English school stock.
- 5 6

7 2. Background

8 9

2.1. Building stock and environmental performance

10 Schools have unique occupancy patterns: They often have high intermittent occupancy, 11 resulting in high internal heat gain peaks, high carbon dioxide (CO₂) levels, emissions of body 12 odours and other indoor pollutants. As school buildings are expected to maintain high levels 13 of performance under a wide range of environmental conditions, the design of schools can be 14 more complex and challenging than other building types.

Studies have explored a range of performance-related aspects in school buildings. These include the relationship between fresh air supply and mechanical ventilation [9], and indoor environmental quality and energy consumption [10, 11]. Other studies have investigated the impact of school environments on pupils' health, comfort and performance [12-14]. Some studies have explored the retrofitting of existing school buildings while dealing with risks such as overheating [15, 16].

It is, therefore, widely recognised that understanding the physical characteristics of school indoor environments is essential for understanding their performance as places for learning and wellbeing. This issue has greater importance in light of uncertainties due to potential changes in future climate change, and the increasing risk of overheating.

It is estimated that 75% of buildings that will be standing by the middle of the century have already been built [17]; as energy consumption and air control in existing buildings is typically higher than in new buildings, it is important to understand the conditions and performance of the current stock [18]. Evaluating the environmental performance of schools and exploring the impact of potential interventions at a stock level can help policy makers in taking informed actions for improving the stocks' performance.

31 It is acknowledged that previous work has been done in the area of estimating school 32 performance prediction. While many have shown interesting approaches, their main focus was 33 on establishing simulation platforms for non-professionals [19], or on urban-34 scale performance [20]. Such methods do not necessarily rely on stock data and historic records for evaluating the performance of the current stock, and are mostly focused onindividual buildings or blocks, rather than on a stock-level analysis.

3 2.2. Building stock modelling approaches

Building stock modelling can assist stakeholders and design teams to better understand the
performance of a group of buildings. They have been widely used as an analysis technique
and supporting tools for decision making and policymakers [21, 22]. Stock level modelling,
unlike the modelling of individual buildings, requires a synthesis of the characteristics of a
group of buildings [23].

9

10 Building stock modelling approaches are typically classified into two main categories:

(i) *Top-down stock modelling* – works at an aggregated level, whereby the relationships
 between stock-level energy use and macro-economic factors are analyses and a model
 is built.

14 (ii) Bottom-up approach – where data of individual buildings is aggregated and analysed,
 15 and a stock model is built. The bottom-up approaches can be further divided into
 16 'archetype approaches' and 'building-by-building' sub-categories.

17 - Archetype approach: where buildings are classified by a set of building properties 18 (e.g., form, construction age, location etc.) to statistically represent buildings with 19 similar features. The stock-level performance under the archetype approach can be 20 estimated by simulating a relatively small number of models in a relatively short time. 21 and then, by taking into account the frequency of occurrence of each archetype 22 within the stock, aggregated at larger geographic units (neighbourhood, regional or 23 national level). On the other hand, archetype models are generic and represent 24 'average' buildings rather than specific ones, which means it cannot predict the 25 performance of individual buildings. Stocks with a small sample size could also be 26 challenging for archetype approach, as individual 'outlier' buildings within the small 27 sample may have higher impact on the archetype than they should.

Building-by-building' approach: where data on individual buildings is used. In this
 approach, data is gathered for each individual building in the stock. Based on these
 data, individual buildings are modelled and simulated, and performance results are
 aggregated and analysed at a stock level. While the building-by-building approach
 can reflect the heterogeneity of a building stock, it may also take significantly longer
 to model and simulate.

While the archetype modelling approach has been used quite extensively in the literature [59], recent years have seen the increasing availability of large datasets and advances in

computational capability, which have contributed to the development of building-by-building
 stock modelling frameworks.

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- 4

2.3. Applications and Challenges in Building-by-building Stock Modelling

5 Building-by-building school building stock modelling is highly reliant on the availability of 6 accurate school building data. Obtaining and processing of the required input data, however, 7 is a key challenge, as multiple layers of data may be required for the building-by-building stock 8 model. These may include external environmental data (e.g., geography, external climate and 9 pollution levels), or building level data (e.g., building construction materials, geometry and 10 layout).

11 Estimating building stock performance using the building-by-building approach may be a 12 computer-intensive process [24]: As each thermal model requires one CPU thread to perform 13 the simulation, the simulation of individual buildings may take a significant amount of time for 14 large stocks. Cloud-based computing technologies (also called High Performance Computing 15 - HPC) offer a solution for batch simulation in a relatively quick and efficient way. A study by 16 Symonds et al. (2016) [25] used HPC, which enabled simulations of a large set of models in 17 parallel. Chen et al. (2017) [26] described the development of City Building Energy Saver 18 (CityBES) – a web-based tool that can model building stocks at an urban level and simulate 19 their performance in parallel, using cloud computing. Batch simulations and cloud computing 20 can, therefore, boost the building-by-building stock modelling approaches at large scales and 21 significantly reduce the simulation time.

22 The building-by-building approach has been in used primarily for estimating and assessing 23 energy performance at the urban scale: Zucker et al. (2016) [27] proposed a dynamic co-24 simulation of the residential building stock in a German neighbourhood at the city of 25 Gothenburg. The model was used to assess peak energy demand and the local district heating 26 plant. Romero Rodríguez et al., (2017) [28] used the building-by-building approach to explore 27 the benefits of using photovoltaics for each building of the Ludwigsburg County in south-west 28 Germany. Österbring et al. (2016) [29] used a building-by-building stock model to investigate 29 the energy demand of heating for buildings in the city of Gothenburg, to support policy-making 30 for estimating a set of environmental impacts of buildings in the city.

One important limitation of thermal simulations – which is also reflected in the one-by-one building stock modelling – is the validity of simulated energy consumption results due to issues such as the performance gap. The validation of one-by-one stock models is often based on a comparison between modelled data and measured performance data, which can be retrieved from the stock [29]. Nageler et al. (2017) [30] compared modelled and measured energy consumption of 69 buildings in Gleisdorf (Austria) and showed a good approximation between
the two, with a mean deviation of 0.98%.

While these trends in building-by-building stock modelling seem to be promising, most reviewed studies have investigated residential buildings. To the knowledge of the authors, building-by-building stock modelling has not yet been applied to school building stocks in a systematic manner.

7 3. Methodology

8 In recognizing advancements and gaps in existing building stock modelling approaches, this 9 paper presents Modelling Platform for Schools (MPS) – a platform that characterises the 10 English school building stock performance and predicts the impact of improved building 11 regulations, technology enhancements and refurbishment interventions on the stock's energy 12 efficiency, indoor environment and cognitive performance of students. The features of MPS 13 and its structure are outlined below.

14 3.1. Introducing Modelling Platform for Schools (MPS)

The main characteristic of MPS is the use of individual dynamic building energy simulation models automatically generated for each building in the English school stock. In contrast to models that rely on building archetypes, this fully disaggregated approach accounts for the heterogeneity within the stock by explicitly modelling each individual school building. MPS considers key characteristics for each building, such as geometry, geolocation, surroundings, building fabric characteristics and occupancy patterns.

21 Input data for MPS is drawn from various sources, in particular Edubase/Get Information About 22 Schools [31], Property Data Survey Programme (PDSP) [5], Ordanance Survey (OS) [32] 23 Display Energy Certificates (DEC) [1] and National Modelling Methodology (NCM) [33]. MPS 24 checks, validates, and then matches datapoints across the different datasets and generates 25 a thermal model in an EnergyPlus format – a thermal modelling and simulation tool. Models 26 are generated for each school, independently. This approach enables a detailed investigation 27 of a range of environmental performance indicators at the individual school level, but also 28 allows the results to be aggregated to assess the impact on a stock level.

29 3.2. Input Databases

30 MPS has been developed by combining data from multiple sources, described below. Each

31 database holds valuable information that can feed into a thermal model, however, none of the

32 databases are complete:

- <u>Edubase/Get Information About Schools</u> Edubase is a centralised database on the
 school stock for school workers and parents/guardians. This includes information on
 several key variables, including the phase of education (primary, secondary, etc.), the
 capacity (number of pupils), and the use characteristics (boarding facilities,
 establishment type, etc.). Edubase was used as the 'spine' of school data for MPS,
 onto which each of the other datasets was matched.
- PDSP (Property Data Survey Programme) The PDSP database includes information gathered between 2012 and 2014 in a large-scale survey of the English school building stock [34]. Covering 85% of the total school estate of England, this database includes a number of important parameters for building thermal simulation models, including construction age, and glazing ratio. Detailed information on building geometry is not covered within PDSP. However, it does include summary data on building geometry, such as floor area and building height (in m² and storeys respectively).
- 14 OS (Ordnance Survey) – OS provides several GIS-based datasets on the geometric 15 description of the building stock of Britain. This covers not only buildings, but also other 16 physical structures, such as sheds, parking garages, and shading surfaces. 2D polygons of these entities are included in the OS MasterMap 'Topography' dataset [35] 17 18 which also includes the average height of each entity. Since OS data covers all building types, not just schools, the OS MasterMap 'Sites' layer [35] has been used to identify 19 20 those structures within school sites, and for matching the OS data to Edubase. The 21 OS 'Code-Point with Polygons' dataset [36] which shows the shape of every postcode 22 unit in Great Britain, was also used for OS matching purposes.
- 23

Figure 1 shows an example of the OS 2D data: The dark-grey polygon shows the school site. Blue lines are the postcode boundaries. Physical entities, as defined by OS, which lay within the school site, are presented with light-grey filled polygons. Enumerated elements in the figure represent 'Built Islands' – which are either a single structure or a group of joined structures.

29 30



Figure 1: An example of the OS 2D data inputs. Schools site (Dark-grey polygon), Postcode
boundaries (Blue lines) and Physical entities (Light-grey-filled polygons).

DEC (Display Energy Certificates) - Since 2008, large public buildings in the UK 4 5 frequently visited by the public are required to produce a DEC [1]. While DEC include 6 normalised benchmarks of performance ('Operational Ratings'), crucially unlike Energy 7 Performance Certificates (EPC), they also include raw annual energy consumption 8 data. These are presented as 'electricity' and 'fossil-thermal' use. In addition to 9 performance data, DEC also include information on building systems (the main indoor 10 HVAC (Heating, Ventilation and Air Conditioning) type, main heating fuel and any 11 renewable technologies). As a source of disaggregate empirical data on building 12 performance, several studies have analysed DECs, to understand the performance of 13 the non-domestic building stock [37-39].

In addition to the four sources of detailed data on the school stock listed above, several further
data sources were used in MPS. These provide information on typical building characteristics
and occupancy behaviour for the energy models and are described below.

- 17 NCM (National Modelling Methodology) – NCM [33] is a modelling guide for buildings 18 other than dwellings in England, for demonstrating compliance with UK Building 19 Regulations, and calculating operational performance as part of the production of Non 20 Domestic Energy Performance Certificates (NDEPC). The NCM provides a set of 21 standardised energy-use-related variables and internal gains patterns for typical 22 building uses (e.g., typical light loads in classrooms, typical occupancy in school gymnasiums, etc.). In MPS, these are used as input parameters for the school 23 24 modelling.
- <u>Thermal Properties</u> Where available, information on the building envelope characteristics of the schools have been extracted from the PDSP database. This includes a mix of quantitative and qualitative data (e.g. window-to-wall ratios) as well as data that could work as a proxy for building fabric characteristics (e.g. building

- construction age). These variables have been converted into thermal properties for
 modelling (e.g. U-values), using the assumptions based on previous studies [38], as
 shown in Table 1.
- 4 Table 1: Build-ups and U-values (W/m²/k)

Building surface	Pre-1919	Inter war	1945	1965	1976
External Wall	1.80	1.80	1.70	1.70	0.83
Roof (Flat)	1.87	1.87	1.87	1.13	0.57
Roof (Pitched)	2.90	2.90	1.85	1.25	0.54
Ground floor	1.50	1.50	1.40	1.40	0.94
Windows	5.70	5.70	5.70	5.70	5.70

6 <u>Weather files</u> – Test Reference Year (TRY) weather files from the Chartered Institution • 7 of Building Services Engineers (CIBSE) were used in this study [41]. TRY files are 8 used for plant sizing (based on conditions of a typical year) and represent typical 9 weather conditions based on 30-year measurements (1984 – 2013) in 13 cities around 10 the UK and are used for assessing compliance with Building Regulations. These files 11 have been applied to the school stock using the degree-day regions defined in the CIBSE methodology [42]. Table 2 shows the list of climate regions and the associated 12 13 CIBSE TRY weather files that were used. Note that the reference to 'Wales' 14 corresponds with schools that have been matched to the Wales climate region but are 15 still physically located within England.

16 Table 2: Climate regions and their weather files [41]

	Climate	CIBSE weather file
	region	(TRY)
1	Thames	London
-	Valley	
2	South-	London
_	eastern	
3	Southern	Southampton
4	South-	Plymouth
т	western	2
5	Severn Valley	Swindon Brize Norton
6	Midland	Birmingham
7	West	Manchester
	Pennines	
8	North-	Newcastle
v	western	
9	Borders	Newcastle

10	North-	Leeds
	eastern	
11	East	Nottingham
	Pennines	_
12	East Anglia	Norwich
13	Wales	Cardiff

2 3.3. MPS Structure

The successful application of one-by-one dynamic building energy simulation depends largely on the available data used for the automatic generation of individual school models. A summary of the MPS method is provided below and can be read in conjunction with Figure 2, which illustrates the main components of the platform, the input data, and the processes undertaken by each component.

8



9 Figure 2: The main components of Modelling Platform for Schools (Input data in grey).

10 MPS is comprised of a number of processes. Input data processing and school geometrical

- 11 analysis, generation of full thermal model and a stock-level simulation.
- 12 3.3.1 Step A: Data processing and geometrical representation

13 Step A of MPS involved producing a unified database of the school stock with sufficient

- 14 building, system, and building form data for step B (the generation of thermal models for each
- 15 school). Input data describing the building stock comes from a range of sources, as shown in
- 16 Figure 2. These include building geometry data (OS), databases that provide building-level

1 inputs (e.g., construction year and systems) on specific school estates (PDSP), measured 2 energy consumption (DEC) and assumptions on internal conditions and occupancy behaviour 3 (NCM). Reflecting the overall data requirements of MPS, schools included in the analysis were 4 selected on the basis of having data available from a number of sources: Building age and 5 form, for instance, are required for producing thermal models so schools without reliable data 6 from PDSP and OS could not be included. Similarly, those without actual electricity and fossil-7 thermal use data from DECs could not have their modelling results compared, so were 8 similarly excluded. Thus, schools without reliable data from any of the sources previously listed 9 - due to gaps in the original files (e.g. not all schools have lodged DECs), or reflecting the 10 processing (e.g. incomplete address-matching, or spurious data while processing) - were 11 excluded from the analysis.

12 The OS, Edubase, DEC and PDSP datasets were processed and address-matched to 13 produce a unified set of inputs for each individual school building. As the main database of the 14 national school stock, Edubase (currently called 'Get Information About Schools') was used 15 as the central spine onto which each other dataset was matched. Edubase includes a 16 referencing system (the Unique Reference Number, URN) for each building, which is also 17 used in PDSP, hence these datasets were matched directly. The DEC database does not 18 include URNs, so these entries were address-matched using the available school's name and 19 address fields. Considerable processing was carried out on the PDSP and DEC files. This 20 included checking for invalid and unlikely datapoints (e.g. DECs with default values, or 21 unusually small floor area), scaling variables originally collected at an element level to school 22 blocks (e.g. the overall HVAC system for each school was aggregated from floor area 23 breakdowns from the PDSP data), and identifying schools with incomplete or 'unknown' data. 24 Following these steps, the processed schools data covered approximately 80% of all open 25 primary schools and 50% of all open secondary schools in England. Comparison of the 26 schools with and without energy data found very similar characteristics between the samples, 27 although the sample does not include any schools built since 2004 since these were excluded 28 from the PDSP survey. Full information on this process is provided elsewhere [43]. However, 29 the use of individual school OS form data is new for this study, and is, therefore, presented in 30 detail below.

31 a. Matching PDSP school entries with OS school sites

Each school record in Edubase holds, among others, the following information: school name,
phase of education (primary, secondary, etc.), street address with postcode and geographic
Cartesian coordinates of northing and easting. Similarly, for education facilities, the OS
MasterMap Sites Layer provides for each site; function (primary, secondary, etc.), distinctive

name and a polygon representing the school site. Unfortunately, the Edubase school names
and OS education site distinctive names do not always match directly. As a result, 4 phases
of matching were applied, each associated with a different match quality between Edubase
and OS:

Phase 1: In the first phase, schools for which the Edubase coordinates are within one
(or more) OS site boundaries were identified. This matching was ranked as 'Excellent'.
In a few cases, the coordinates were within multiple OS site boundaries. That was
usually the case when there were multiple overlapping sites, such as primary and
secondary school under the same establishment. There were also instances where
multiple school records had the same coordinates. For schools where an OS match
could not be found following phase 1, these were then passed to phase 2.

- Phase 2: The second phase identified schools for which the postcode polygon (based
 on the postcode in PDSP data) intersected only one OS site boundary. In these cases,
 the matching was ranked as 'Good'.
- Phase 3: The third phase identified school sites for schools in which the postcode
 polygon intersected several OS site boundaries. In these cases, the matching was
 assumed to be to the site closest to the school coordinates. Matching outputs from the
 third phase was also ranked as 'Good'.
- Phase 4: Last, the next matching rank of 'Poor' matches was based on identifying the
 nearest OS school site (distance from school coordinates) for schools which had no
 postcode polygon in the database, or those of which the postcode polygon did not
 intersect any OS school site.

A summary of the matching process can be found in Table 3, including the match quality and overview of any matching issues. Over 85% of schools achieved an 'Excellent' match, although a total of 4.5% of the stock had some matching issues (i.e., multiple schools sharing the same site or schools in overlapping sites). Less than 13% of the schools had a 'Good' match, while around 1.5% of the schools had matching issues (such as postcode polygon and school sites intersections, or multiple schools that share the same site). Only around 2% of the schools were ranked as 'Poor' matches.

30 Table 3: Summary of schools' database matching.

Matching ranking	Number of Schools (%)	
Excellent	14,892 (85.3%)	
	Raised warnings:	
	2 schools share the same site: 600 (3.4%)	
	2 schools share 2 overlapping sites: 128 (0.7%)	
	school in 2 overlapping sites: 44 (0.2%)	
	3 schools share the same site: 15 (0.1)	

Good	2,194 (12.5%)
	Raised warnings:
	postcode polygon intersects 2 multiple sites: 108 (0.6%)
	selected site is not the nearest one: 93 (0.5%)
	2 schools share the same site: 36 (0.21%)
	postcode polygon intersects 3 multiple sites: 11 (0.1%)
	postcode polygon intersects 4 multiple sites: 1 (0.01%)
Poor	377 (2.2%)
Total	17,463 (100%)

2 b. Matching PDSP and OS school buildings

3 A key task for MPS was to automatically detect the 'true' buildings in the OS database and 4 match them with the appropriate entries from the PDSP data: While PDSP, OS and DEC 5 databases hold some information at building level, the number of entries in each database, in 6 many cases, can differ. E.g., a particular school might have 2 buildings (entries) in PDSP data, 7 while showing 5 geometrical entities (polygons) on the OS database. This is because OS 8 database holds each and every detectable physical entity within the school premise (i.e., 9 buildings, but also sheds, storage spaces etc.), whereas PDSP only holds information about 10 habitable space blocks.

11 The reversed phenomenon can be observed too – i.e., when schools may have a higher 12 number of buildings (entries) in the PDSP data, compared to the OS data. This may occur 13 when polygons on OS – which are in fact independent but adjacent buildings - are aggregated 14 into a single built entity, or a 'built island'.

Since for both polygons in OS and entries in DEC, the 'area' entry can be obtained, the
matching procedure searches for a combination of polygons and DEC entries that can match.
The buildings matching procedure is described below:

- Step 1: 'Unrealistic entities' in the OS data (polygons with a footprint smaller than 30 m² or head-height lower than 2.5 m) were filtered out.
- Step 2: In OS data, per each build island, all possible buildings combinations based
 on building footprint area were found.
- Step 3: In the PDSP data, per each school, all possible buildings combinations based
 on building footprint area were found.
- Step 4: The OS area combinations were compared to those of PDSP area
 combinations.
- Step 5: A 'combination matching score' was calculated by evaluating the similarities
 of each area combination, per school, and each combination was ranked accordingly.
- 28 3.3.2. Step B: SimStock Thermal models generation

1 Once all buildings in a school site were identified, the relevant use patterns and thermal 2 attributes were assigned to them and a dynamic thermal simulation file, in the form of 3 EnergyPlus idf, was generated by SimStock – a platform that automates the generation of 4 dynamic thermal simulation models. Generated models are formatted to align with the 5 EnergyPlus [44] simulation programme requirements.

Each thermal model contains a geometrical description of the school, but also details on the
building's fabric, internal loads, use patterns and other thermal-related properties. Following
the matching procedure, each school building is modelled: the number of storeys is taken from
the PDSP and OS databases, where each floor is modelled as an individual thermal zone.

Window dimensions are determined by the synthesis of PDSP and OS data and is represented as window-to-wall-ratio (WWR). In the modelling procedure, windows are placed at the centre of an external wall and are sized as a percentage of the wall's surface area. It is acknowledged that placing a window in the centre of a wall might not be an accurate representation of the wall's position in the actual building, and that this might impact on the accuracy in simulating buildings with off-centred windows.

- In conjunction with school building thermal properties data (which were collected through an
 analysis of PDSP and DEC), information about the local climate (i.e., CIBSE weather files [42],
 and building use schedules and loads (based on NCM [33]), the pre-processed inputs were
 passed to SimStock,
- 20 3.3.3. Step C: Stock-level simulation

Once all thermal models were set up and a stock was defined – the models were subsequently simulated. Since EnergyPlus is designed to analyse a single building or a limited, small, number of buildings at a time, which can be computing-intensive process, MPS makes use of a High-Performance Computing (HPC) [45] platform, which enables simulations of multiple models simultaneously. This has been found to be a quicker method for simulating the stock when the number of schools and scenarios being assessed is large.

27 **3.4.** MPS – innovative approach

MPS includes advanced features for the analysis of the performance of school buildings.These include:

Automated process – School building geometry is often very complex, composed of large
 exterior surfaces. Features such as courtyards (i.e., a hole inside a building polygon) and
 modifications, such as extensions, might contribute to a building's complexity. The modelling

platform automatically represents the three-dimensional geometry of selected buildings,
 based on data drawn from multiple sources.

3 Height detection – Height of the 3D structures is obtained by crossing and matching data 4 between PDSP and OS databases. These data further increase the accuracy of school models 5 by differentiating multiple and aggregated buildings (such as extensions or demolitions -6 rebuilt) which often share a single footprint in the digital map data. It is not an uncommon 7 condition in schools where part of the school is rebuilt, for example with a different height, or 8 an additional floor is built on top of a small part of the original structure. Crossing these 9 independent databases enables MPS to detect built additions and increases the overall 10 accuracy of the thermal model.

Building and model attributes detection – The generation of dynamic thermal simulation models requires the identification of various building attributes. Variables that are related to a building's thermal properties, its services and system are particularly important. Many of these crucial input parameters are associated with the school construction age. Therefore, to increase modelling accuracy, construction age is used to estimate thermal performance when generating the thermal model. Where schools have multiple buildings constructed at different periods, the age of each individual buildings is used.

Surrounding context – Considering the surrounding context when conducting an analysis at an individual school level is of particular importance in highly dense urban areas, where nearby buildings can create overshadowing. This can potentially reduce daylight access and benefits from solar gains during the heating season. In addition, although rarely, school buildings are adjacent to other buildings, in which case the model makes possible the identification of party walls.

24 4. Results Analysis

An analysis of MPS outputs is presented below. This section mainly focuses on the evaluation
of the capability of the automated processes behind MPS in generating robust thermal models
that accurately represents the English school building stock.

28 **4.1. Initial full stock-model assessment**

MPS was first tested for its full-stock generation capabilities. The study carried out an analysis of all the schools that MPS currently has data for and is capable of generating a model of. Following data processing, a database of around 15,000 schools was created with the necessary data to feed into MPS, as detailed in [43]. This analysis holds information about each school – based on their URN (Unique Reference Number linked to the PDSP database) and the school's name. A 5-grade 'traffic-light' system was then developed, to express the predicted 'matching robustness' (i.e., the likelihood that the automated data merging procedures were accurate), for each school. In the traffic-light grading-scale, each label represents a certain matching percentage range, which is based on a comparison between the inputs of school buildings polygons' area in the different databases.

As seen in Table 4, of the 15,245 schools, 48.2% achieved 'excellent' or 'very good'
robustness levels. 28,3% achieved medium robustness and 13.7% had low confidence levels
in results. 9.8% of the schools had missing data (e.g., unrealistic 'height' parameter) or issues
of miss-matched data (e.g., significant differences in number of entities in a school site).

In addition, as schools can vary in shape, size, floor area and number of buildings, large numbers of buildings within a school site can significantly increase the complexity of the model generation procedure. As a result, the likelihood of the data merging and matching procedure being accurate is significantly reduced. Overall, the analysis has shown that around 6% of the examined schools had more than 8 buildings within the school premise. These schools would be classified under the 'Red' (very low) category in Table 4. Figure 3 shows an example of such school.

18 Table 4: Stock-level model generation evaluation



High - An accurate match is highly likely. Very good match between the OS and PDSP buildings.

Moderate - Matching is likely, but there might be small discrepancies between OS and PDSP floor area.

Medium - Some buildings might mismatch, or, there might be some discrepancies between the OS and PDSP buildings' floor area.

Low – Big differences between the matched data, due to significant discrepancies between the databases, missing or incomplete data.

Very low – Data is missing or too detailed at the source databases. Unable to generate a model.



Figure 3: A school containing a large number of buildings, which contributes to the uncertainty
of the model generation procedure.

4 4.2. Visual model matching

5 Following the automated model-assessment procedure, a visual inspection of a sample of 6 models was carried, to ensure the models were generated accurately. This was done in order 7 to visually assess the resemblance between the geometries of the EnergyPlus models and 8 the corresponding actual buildings they represent.

- 9 A sample of 200 school models across England were randomly selected.
- 10 Their models' geometry was imported to Sketchup [46] using the Legacy Open Studio plug-in 11 [47] and compared with the schools' 3D images as viewed in Google Maps and Google Street 12 View [48]. Google Maps provides satellite or high-resolution aerial imagery of areas in the UK, 13 with top-down and 'bird's eye' views. Google Street View is a component of Google Maps that 14 offers interactive panorama views from eye-level perspective. Fast locating places featured in 15 Google Maps allows the actual school buildings to be easily found simply by typing their 16 postcodes or addresses. However, not all schools have records in Google Maps or Google 17 Street view. Therefore, different evaluation strategies were applied as follows:
- (1) Most schools had records in 3D Google Maps (Figure 4), and the entire schools could
 be viewed using 45-degree aerial imagery. In these cases, the inspection of the
 schools' configuration, numbers of floors and buildings layouts was straightforward.
- (2) Some schools (e.g., Figure 5), only had top-down satellite images on Google Maps. In
 these cases, Google Street View was used for the photos of the schools' elevation, to
 record the number of floors and their configurations.
- (3) For a small number of schools (Figure 6), only the top-down satellite images were
 recorded on Google Maps. In these cases, only the schools' layouts could be viewed.

26





Figure 4: Screen grab of a school's 3D view via Google Maps [48]



Figure 5: Screen grab of a school's elevation and top views via Google Maps and Street view [48]





Figure 6: Screen grab of a school's top views via Google Maps [48]

Similarly to the building stock model matching evaluation system, a traffic-light evaluation
criterion was developed to rank school models based on their quality of building geometry
representation:

- 5 High quality Excellent match between modelled and simulated buildings
- 6 Medium quality There are minor mismatches in the school layout, the number of floors,
- 7 or building heights.

- 1 Low quality Both school layout and the number of floors or their heights are poorly
- 2 matched.



Figure 7: The quality of EnergyPlus school models, based on a visual comparison to
actual schools

6

As Figure 7 shows, 64% of the examined models achieved excellent geometrical similarity,
and 28% had minor mismatching. Only around 8% models were poorly matched, where the
models had differed in number of floors and layouts, compared to the actual buildings.

10 **4.3. IDF Model generations – complex model testing and simulation**

To examine the potential limitations of MPS under worst case scenarios, the platform was tested by producing potential energy consumption to be compared with measured energy demand found in complex, atypical school campuses. The aim of this exercise was not exact replication but to demonstrate a basis could be provided for quantifying the performance gap, and discussing its attribution to different sources (such as design, construction and operational factors) [49].

For this purpose, three schools in Camden area in London were selected for the automatedgeneration of models. These schools were selected for the following reasons:

- All three schools had high levels of complexity in modelling, in terms of multiple
 construction era buildings and new extensions.
- All three schools are local authority run and hence have had requirements to submit
 DECs.
- All three are located within 400 m of each other, which made it easier to verify their
 actual building construction characteristics through physical visit and inspection, and
 any discrepancies due to weather dependency (i.e., the climate conditions are the
 same, therefore the impact of other variables can be isolated).

3

2 Figure 8 shows the automatically generated EnergyPlus models of the three selected schools.



4 Figure 8: Dynamic building energy simulation models of three Camden schools generated by

5 MPS: (a) La Sainte Catholic school, (b) Parliament Hill school and (c) William Ellis school

To examine the quality of the predicted energy consumption, annual simulation was carried
out for each model, and then compared to measured energy consumption data. The models
were simulated using the following methodology:

- The NCM was used to define Lighting, Equipment and heating loads and schedules,
 as well as percentage areas for various activities within each model for classrooms,
 offices, catering, etc. The NCM assumed values for classrooms only (constituting 28%
 of the school site by area) are shown in Table 4. Note also that occupancy level has
 been derived from reported pupil numbers from DfE reported figures [50] divided by
 model floorspace.
- Ideal loads HVAC systems were used in each model to represent the optimum sizing
 of equipment required to provide heating and air flow in volumes required. Necessarily
 this means that there is a significant underprediction in required heating
- 3. The Gatwick test reference year (TRY) weather file [51] was used to simulate an
 average year for all four models since the selected schools lie within 25 miles of this
 site.
- 21 Table 4: Assumptions used in model simulation of Camden schools (classrooms only)

Parameter	Setpoint	School day (Classroom – D1 Edu Class Room from NCM)
Occupancy	0.08- 0.12 /	100% (10am-noon, 2-4pm), 0% (6pm-7am) with
	m ²	50% (noon-2pm, 4-6pm) and 10%-25%-75% (7-10am)
Lighting	280 lux	100% (7am to 6pm), 5% (6pm-7am)
Equipment	4.7 W/m2	100% (7am to 9pm), 5% (9pm-7am)
Infiltration	0.35 ac/h	Constant throughout
Fresh air	10/I/s/student	Dependent on occupancy
Heat setpoint	18° C	5am to 6pm – heat to heat setpoint if required
Setback temperature	12° C	6pm-5am - heat to setback temperature if required
Cooling setpoint	23° C	5am to 6pm - cool to cooling setpoint if required

- Annual thermal and electrical energy use intensity was collected from each school's available DECs and plotted against the simulated data. For the La Sainte Catholic school, DECs were created for the individual buildings described in the DECs as the "Main Block" and "Upper School" separately. Models were, therefore, generated and run as separate EnergyPlus files for these two entities.
- 6 It is also important to acknowledge that in one case (Parliament Hill school) there was a large
- 7 discrepancy in the floorspace recorded in the DEC and the actual footprint of the site derived
- 8 from checking the site on Google Maps.
- 9 Having considered these factors, calculated heating and electrical demand, derived by the
- 10 simulation are compared against measured data, as seen in Figure 9 below:





12 Figure 9: Simulated and Measured electrical and thermal fuel usage.

13 It is worth noting the following:

14 1) As mentioned above, Figure 9 does not represent a like for like comparison, since the 15 models' use of generic data on occupancy, heating and other electrical systems is based on 16 NCM default assumptions rather than actual use in practice. Services, such as domestic hot 17 water, for which there is no specific data on operation within the study schools, were fixed at a low and constant rate. As such the modelled results represent asset performance, which 18 19 could be seen as the potential operation of the school given idealised conditions. This is 20 reflected in the DEC data, which represents the operational performance of the school, in 21 terms of both annual electrical and heating demand, generally being higher than the calculated 22 annual electrical and heating demand, respectively. While within the NCM there is a domestic 23 hot water requirement for classrooms of 1.35 l/day/m² floorspace (classroom), data about the percentage of class areas within a school area is lacking. For this reason, hot water was set
at a nominally low value, until data about classroom area as a percentage of the school site is
available.

2) Discrepancies were identified between the DECs and PDSP for two of the case studies.
Specifically, the floorspace reported for the entire Parliament Hill Site was reported as 7,940
m², whereas an inspection of the site revealed a floorspace in the order of the model's
floorspace of 15,015 m². Both Parliament Hill and La Sainte schools had a few smaller
buildings contained within their polygons, and it was unclear which of those, if any, were
included in the DECs. This highlights the challenges generating models using MPS faces,
when there are discrepancies between the input data sources.

11 **5. Summary**

12 5.1. Discussion & Conclusions

13 This paper presents the principles underlying the development of a new Modelling Platform 14 for Schools – the MPS – a stock model that can represent the school stock more accurately 15 than traditional approaches. Other methods for estimating the school stock performance (e.g., 16 archetype modelling or energy audits) are either overly simplified or time consuming and 17 complex. Furthermore, while archetype models are limited in terms of accurate representation 18 of the stock, audits only reflect the state of the current-stock performance, and do not provide 19 the opportunity to estimate stock-level performance under certain interventions or climate-20 change scenarios. It is hoped that MPS - which has the capability to generate individual 21 schools within the English school building stock – will enable analysis and evaluation of the 22 future impact of a range of school-performance issues (e.g., assessing refurbishment 23 packages, stock-resilience under changing climate, integration of renewables and more).

The paper discussed the different steps in the stock-modelling procedure and presented the databases MPS relies on. The study presented outputs of the MPS modelling procedure and evaluated both the generation of individual schools and that of the entire stock through a series of tests.

An automated 'traffic light' matching evaluation mechanism was developed to evaluate the accuracy and robustness of individual school buildings models. Based on this evaluation procedure, nearly 50% of the examined English school building models that were generated by MPS achieved 'excellent' or 'very good' score. This means that for almost half the schools in the stock, there is an excellent match between building characteristics, as recorded in the different databases that were used for generating the models. It is highly likely, therefore, that those schools' models will accurately describe the actual buildings they represent. In practical terms, this means that half of the school stock – thousands of schools - could be generated accurately in an automated manner in a matter of hours, saving many hours of work. The matching evaluation mechanism was tested and validated through a visual inspection of 200 schools in London and achieved satisfactory results.

Nonetheless, nearly 25% of the examined schools had achieved 'low' or 'very low' matching scores (13.7 and 9.8%, respectively). The main reasons for these discrepancies are inaccuracies in the initial input databases, significant discrepancies between the input databases, or entirely missing data. The promising results of MPS in generating schools with accurate data implies that once input data quality is improved – the stock model's accuracy will be improved too.

12 MPS could potentially be used for:

- Analysing policy makers and other stake holders (school communities, local authorities etc.) on the efficacy of a wide range of retrofit measures applied to an individual school, such as improved insulation, replacing existing lighting with more efficient LED lighting, glazing replacement, or improved HVAC (heating, ventilating and air-conditioning) systems' control strategies.
- Testing the potential for integrating renewable technologies on an individual school
 building level.
- Assessing daylight availability and quality, by taking into account the surrounding
 context. This would enable the identification of schools, or zones within schools, which
 are likely to experience poor daylighting quality.
- Estimating the overheating risk of individual schools. This is of particular interest in
 schools with no air-conditioning which, due to applied refurbishment measures or
 climate change, might be more predisposed to experience severe overheating.
- Identifying schools, mainly in dense urban areas, which are under a risk of decreased
 Indoor Air Quality (IAQ). MPS can evaluate possible scenarios, such as reduced
 potential for passive cooling through natural ventilation due to higher ambient
 temperatures as a result of the Urban Heat Island (UHI) effect, increased particulate
 pollution due to poor ventilation or external air pollution, and exposure to nitrogen
 oxides (NOx) from traffic due to proximity to major roads.
- 32
- 33 **5.2.** Future work

Further examination of the schools that received 'medium', 'low' and 'very low' assessments found that a main contributor to that low score were significant discrepancies between school buildings' height between the databases, or unrealistic height figures. Furthermore, some schools were excluded from the analysis at the initial stage – primarily due to missing height data.

As the main limitation of MPS is inaccurate data inputs, the next steps in developing MPS will
be focused on collecting accurate and meaningful data that describes the stock in a more
comprehensive manner. These include:

9 *CDC Data* – Between 2017 and 2019, the Condition Data Collection (CDC) survey was 10 undertaken, the successor to PDSP [52]. This survey included some school types excluded 11 from the former programme (e.g. modern schools), and included more detailed information 12 covering a larger number of variables. Work is currently underway to incorporate the improved 13 data available within CDC into the MPS platform.

14 LiDAR - It is noted that while the overall models' resemblance is satisfactory, even models 15 that achieved a 'high-quality' rating are not always an identical replica of the actual buildings. 16 This is especially true for schools with pitched roofs, as the shape of the roof had not been 17 considered at this stage of MPS. This may have an impact on the simulation results, while this 18 is still a current limitation of MPS and the automated model generation procedure. Light 19 Detection and Ranging (LiDAR) data publicly available through the Department for 20 Environment, Food & Rural Affairs (DEFRA) can hugely improve the buildings height 21 assumption. LiDAR technique accurately measures both the terrain and objects on the surface 22 heights. Overlapping the OS polygon data with the LiDAR point cloud, where each cloud point 23 holds X, Y and Z (height) location coordinates among other attributes, makes possible the 24 identification of portion of structures with different height sharing the same footprint polygon 25 as well as the creation of models with actual roof geometry replacing the flat roofs.

Crowdsourcing-based data collection - A data crowdsourcing exercise is being carried out in the Greater London Authority (GLA) school stock to investigate supplementing the fabric and geometry inputs. Two types of questionnaire have been sent, to evaluate building users' willingness to participate:

- Generic questionnaire: schools have been emailed access to a generic questionnaire
 confirming fabric and refurbishments, and requesting data on basic school layout,
 heating schedules and setpoints (2,512 schools).

Bespoke questionnaire: In addition to the generic questionnaire, 685 schools have
 been emailed access to a bespoke questionnaire, which included autogenerated
 models from MPS. This questionnaire contains more specific questions on buildings
 use (for teaching, office, catering etc.).

It is hoped that such data could allow parts of the stock to be updated from NCM assumptionsto more realistic occupancy and building service usage.

7 The proposed method is based on data which does not record any interventions and 8 refurbishments in the existing school stock. While it is acknowledged that this is a data and 9 modelling limitation, MPS has been built in a flexible manner, so that more detailed, granulatar 10 data can be integrated in the modelling generation procedure in the future. It is hoped that 11 with more accurate description of the stock, the MPS framework could better represent the 12 school stock.

Lastly, while the majority of 'poor' models were the result of poor input data, the study has also showed that one important limitation of MPS is analysing and generating schools that have more than 8 buildings. While an analysis has shown that only 6% of the English schools' stock fall within this category, future work will factor in such complex cases too.

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