

VISUALISING URBAN ENERGY USE: The use of LiDAR and remote sensing data in urban energy planning.

ABSTRACT: *This paper explores the potential for using remotely sensed data from a combination of commercial and open-sources, to improve the functionality, accuracy of energy-use calculations and visualisation of carbon emissions. We present a study demonstrating the use of LiDAR (Light Detection And Ranging) data and aerial imagery for a mixed-use inner urban area within the North East of England and how this can improve the quality of input data for modelling standardised energy uses and carbon emissions. We explore the scope of possible input data for both (1) building geometry and (2) building physics models from these sources.*

We explain the significance of improved data accuracy for the assessment of heat-loss parameters, orientation, and shading and renewable energy micro-generation. We also highlight the limitations around the sole use of remotely sensed data and how these concerns can be partially addressed through combinations with (1) open-source property data, such as age, occupancy, tenure and (2) existing stakeholder data sets, including building services and measured performance. We set out some of the technical challenges; addressed through data approximation (considering data quality and metadata protocols) and a combination of automated or manual processing; in the use, adaptation, and transferability of this data. We elucidate how the output can be visualised and be supported by many of industry-standard CAD, GIS, and BIM software applications hence, broadening the scope for real-world applications. We demonstrate the support of commercial interest and potential drawing evidence from primary market research regarding the principal applications, functionality, and output.

In summary, we conclude on the benefits in the use of remotely sensed data for improved accuracy in energy use and carbon emission calculations, the need for semantic integration of mixed data sources and the importance of output visualisation.

KEYWORDS: *Remote sensing, LiDAR, energy modelling, urban planning.*

1. INTRODUCTION

Accurate alternatives for collecting information that ease geometry models creation and calculation of energy performance at individual dwelling or at neighbourhood level are needed in order to improve quality of information at disposal for architects, urban planners and authorities. A number of building physics based models have been developed in the past and some of the notable include Building Research Establishment's Housing Model for Energy Studies (Shorrock and Dunster, 1997); UK Domestic Carbon Model (Boardman et al 2005) and Community Domestic Energy Model (Firth et al 2010). All these models have the same energy calculation engine which is BREDEM (Building Research Establishment Domestic Energy Model) and the Standard Assessment Procedure (SAP) which is recommended by the Department Of Business Energy And Industrial Strategy (BEIS) in the UK as the main tool to underpin BREDEM for assessing and comparing energy performance of dwellings. Accurate energy baselines for domestic buildings and neighbourhoods need that the models incorporate accurate raw data which collection can be expensive and time consuming. Generalised access to energy calculation models

35 requires a skillset which most of the urban planners haven't yet acquired, and energy assessment usually relies on
36 rough estimation of raw data making the energy calculation inaccurate. In this context, this paper addresses the
37 issue of raw data availability and accuracy through the development of new processes and techniques for data
38 collection and in particular the automated process of capturing dimensions and footprint of dwellings through the
39 combination of OSL (Ordnance Survey and Landmap) data and deployment of LiDAR and remote sensing as
40 means for aerial and terrestrial imagery. In addition, this captured geometrical data is further integrated with open-
41 source and publically available data for a faster and more accurate energy calculations integrating data from
42 available statistical sources, such as census data, deprivation and neighbourhood statistics data from ONS (Office
43 of National Statistics), HEED (Homes Energy Efficiency Database) and EHS (English Housing Survey). This is a
44 multi-source novel way of capturing and processing data for energy appraisal and visualisation. The remainder of
45 this paper discuss the main technique used to capture data, dealing with errors and data cleaning, integration with
46 other data bases and initial results from a case study.
47 The next section deals with remote sensing and LiDAR technology.

48 **2. REMOTE SENSING & LIDAR TECHNOLOGY**

49 **2.1 Introduction to LiDAR**

50 LiDAR is an active remote sensing technology. It allows acquiring topographical information over surfaces at high
51 Level of Detail (LoD), for large-scale urban areas. This data can be used for diverse aims, such as solar irradiance
52 estimation for PV (photovoltaic) calculation (Robinson and Stone, 2008, Lukač et al, 2013), energy heating
53 demand estimate (Tooke et al, 2014), and building type recognition and classification (Z. Lu et al, 2014) and this
54 might represent an important input for the SAP tool calculation. The potential use of this technology is growing in
55 line with the increased demand for accurate and updated data for energy calculation for dwellings and urban energy
56 planners and decision makers, in a way that overcomes the limitations of plot cadastral and statistical information
57 (Hermosilla et al, 2012).

58 This paper incorporates and extends on the methodology already established in Mhalas et al. (2014), where a
59 framework that integrates visual systems, databases and a decision support system to rapidly evaluate energy
60 performance of the dwellings is described. For this purpose, the Standard Assessment Procedure (SAP) was
61 selected as a main element of the proof-of-concept. This paper focuses on the accuracy and availability of
62 information that will be used for energy use using SAP as a methodology for energy calculation. Therefor the main
63 thrust of this paper is on data gathering, cleaning, processing and use for accurate energy calculation.

64 The remainder of this section discusses the methods and techniques used in previous literature to pre-process, filter,
65 noise reduction and conversion of the acquired LiDAR data and open source databases into usable object based
66 formats in Geographical Information Systems (GIS) software tools ready to be used by energy calculation tools.

67 **2.2 Previous literature in LiDAR data processing**

68 Blaschke and Tomljenovic (2010) reviewed the state of the art of remote sensing technologies for Object Based
69 Image Analysis (OBIA). The review highlighted the utilities, main limitations, as well as problems to be solved
70 and where the main research has been focused, namely the high definition of images transformation through Fuzzy
71 and Neural algorithm and other techniques. Tomljenovic et al.

72 (2016) further develops the concept of use of LiDAR for 2D and 2,5D model extraction.
73 The use of LiDAR, within the urban built and energy related environment, has been mostly used to collect building
74 physical features, assessment of the potential PV installation on rooftops and energy demand related studies
75 (Lukac et al, 2013, Santos et al, 2014). Tooke et al. (2014) developed a methodology to utilise LiDAR data to
76 aggregate a range of residential building energy and urban parameters and incorporate them with additional spatial
77 data in order to calculate baseline estimates for energy demand for neighbouring regions within urban areas (see
78 fig. 1). The 3D shapes and the year of construction are incorporated within the statistically established energy
79 performance data. Finally, both of the boundary conditions are considered, physical and environmental. The aim
80 of the research is, based on this methodology, to systematically estimate the global energy demand for thermal
81 uses in complete urban areas which is at the moment based on rough estimates.

82
83 *Fig 1: Schema and workflow of Tooke et al. approach (2014)*
84

85 Lukač et al (2013, 2014) developed a methodology for determining a rating list of roofs' surfaces in relation to
86 their solar potential and suitability for installing PV systems. LiDAR data from the urban environment has been
87 used to obtain a 3D representation of the roofs. This data, along with irradiance historical files, have been used to
88 estimate accurately the time dependent electricity generation from Photovoltaic Modules (PVMs) and the solar
89 inverter, taking into consideration the non-linearity of the process and the accurate shadowing calculation inferred
90 by the topological map created for the whole of urban area. These estimates are then compared with measurements
91 obtained from a monitored PV plant. Jochem et al, 2009, Heinzel et al. and 2011, Mongus et al., 2012 presented
92 methodology for the pre-processing of the LiDAR data using State of the Art classification methods. The obtained
93 cloud points from LiDAR capture are converted into the urban elements and buildings' rooftops surfaces, with a
94 twofold objective; firstly, to be able to accurately estimate the slopes and orientation of the PVM on the rooftops,
95 and secondly, to calculate the instant shadowing during a whole year period (Lukač et al., 2013, Yuan et al., 2011).
96 Lu et al (2014) developed a methodology to generate a building information accurate geodatabase, which solves
97 the limitations of obtaining data from parcel datasets that are often not reliable and up to date. Apart from the
98 directly inferred geometrical data, the approach eases building and boundary area classification. The process
99 includes three main tasks: (1) to delineate the boundaries of buildings and elements within the data, (2) to separate
100 building data and (3) to classify the buildings into pre-established types.

101 It was concluded from previous efforts and approaches in building and neighbourhood energy modelling, that
102 integration of information coming from various data sources is one of the greatest obstacles to tackle for application
103 of LiDAR data in urban and city planning and operation. There is a challenge of managing urban change within
104 the paradigm of the 'information city' (Kraemer & King 1988). Municipalities and their partners require a
105 supporting information infrastructure that supports a broad range of urban stakeholders to mutually understand
106 and reinforce geophysical communities within urban neighbourhoods and localities (Doheny-Farina 1996). The
107 city map and urban model remain the most intuitive ways of structuring and accessing this urban information.
108 Appropriate and accurate data is crucial for understanding the viability of substantive urban energy systems and
109 decision-making procedural systems that manage the urban system (Grossmann & Watt 1992). In effect, there are

110 complementary requirements from both technical and non-expert urban stakeholders in the use of urban energy
111 information, its collection, analysis, sharing, and visualisation. Here, there is real potential for LiDAR data
112 collected remotely at neighbourhood or city scale to simultaneously contribute to both, the technical and political
113 decision-making requirements for better data. Initially it is ideal for information directly relating to building
114 geometry. This geometry or ‘property-based’ data can be the basis for integration with wider and ‘softer’ aspects
115 of urban planning and sustainability.

116 As summary from the previous literature review, it is possible to generate an estimation of an individual property
117 energy use based on the attributes of the building supported, but not limited to cadastral plots (age / method of
118 construction, geometry and services) and ‘standardised’ behaviour of the typical occupants. It is these property
119 attributes that are well suited to the integration of LiDAR data on geometry with other open-source and publically
120 available data sets that record the building performance characteristics. For example, the use of open-source
121 database on the age of construction of the property, the use of stakeholders’ own asset management database,
122 systems upgrades to social housing as part of ‘decent homes programme’.

123 This research presents a case study using a similar approach to the techniques demonstrated in Tooke et al (2014).
124 It presents the process to collect and pre-process data with the aim of estimating more accurately, the global energy
125 demand for thermal uses in complete urban areas. Unlike in the Tooke’s approach, the calculation for the baseline
126 estimates of energy demand is based on SAP methodology shown in Mhalas et al. (2014). Database and
127 assumptions are adapted to the case study. Visualisation and integration of the generated data offers a wider range
128 of possibilities compared to the aforementioned approaches, combining and merging the results of the model with
129 open source GoogleMaps and GoogleEarth. Figure 2 shows the workflow of the proposed approach for estimating
130 Energy Demand, integrating different data sources.

131

132 *Fig.2: Baseline Energy Performance Assessment process map*

133

134 The next section introduces the case study that was conducted in this research to demonstrate the techniques and
135 methodologies used to process data for energy calculation.

136 **3. Capturing Geometry Data: A Case Study**

137 The objective of this section is to introduce a real life case study to demonstrate the procedure of capturing,
138 processing and using LiDAR information. A case study is selected in the inner area of west end of Newcastle upon-
139 Tyne in the UK. This case study was part of **SEMANTCO** (Semantic Tools for Carbon Reduction in Urban
140 Planning), a European project co-funded by the European Commission within the 7th Framework Programme
141 (<http://semanco-project.eu/>). The case study is based on an area which contains a variety of housing typologies,
142 including significant multi-story and multi-occupancy properties for a mix of different ownership patterns and
143 tenures. The research project presented in this paper commissioned the LiDAR scanning of the project area for the
144 purpose of calculating energy rating and ways in which these ratings can be improved through a more informed
145 refurbishment programmes. The rationale was to overcome some of the costs and technical limitations of existing
146 two-dimensional spatial data sets; for example, Ordnance Survey Landline / Master map that only held building

147 ground floor footprints and no accurate building heights. Moreover, for the purpose of energy calculation and to
148 augment the geometric information from LiDAR. This research has investigated the potential use of a variety of
149 publically accessible and open-source data sets such as age of property, construction methods, type and age of
150 boilers, etc.

151 The key intention for LiDAR data use was to support the estimation of urban energy use where there is a
152 requirement for a high degree of accuracy in the building geometry. In addition, the commissioned LiDAR data
153 included the necessary permission to integrate it with other data sets as part of an online energy modelling and
154 decision-support tool. The rights to share this data and demonstrate the potential functionality when it linked to
155 other data sets, is one of the initial outputs of this research work. Effectively, it allowed the research team to
156 maintain an open-ended approach to the use and adaptation of the data set without being time-limited or legally
157 restricted to the scope of use.

158 **3.1 Data Specification and Data Collection**

159 The supply and collection of the LiDAR data was performed by a professional commercial provider (Blue Sky
160 Company PLC). However, many factors and issues are realised regarding the specification of the data collection.
161 Most significantly is the lack of any standard specification for the format, resolution and cleaning of the data, the
162 following section discusses this.

163 **3.2 Data conversion and input**

164 The provided data used CityGML (City Geography Markup Language) and COLLADA (COLLABorative Design
165 Activity) formats that are readable within many different standard software packages. Inner city is surveyed over
166 a square kilometre using two separate scans that provided a terrain model and ‘partially’ auto-rectified structures.
167 Typically, LiDAR data contained more than required details of specification in certain areas and significant gaps
168 regarding surface materials and varied dimensions of these solid / opaque surfaces. There are some recent
169 demonstrations of the application around the detail available and transferring or ‘tracing’ (Kimpton et al 2010)
170 CAD polylines over a polygon surface model / point cloud data. This is effectively a manual task to reduce the
171 level of detail within the model. It turns a set of point cloud data into closed polygons – polygons with properties
172 suitable for adding attributes and for visualisation. A similar approach is required for the neighbourhood scale to
173 make the data usable for the purpose of estimating the energy use for individual properties.

174 The process of inferring 2D and 2.5D-classified information from the point cloud data through processing is time
175 consuming and depends greatly on technical skills. However, the use of software such as ArcGIS (a complete,
176 cloud based mapping platform) can automate these tasks easily through the implementation as modules, to obtain
177 the features as the building footprint, height and shape. However, there is sparse development of this semi-
178 automatic data processing, which depends a great deal on the density of points for the images at disposal.
179 According to Henn et al, (2013) in the UK, the density is 0.5 points/m², 1 points/m² for Germany and 8 points/m²
180 for the Netherlands. In the latest years, resolution available data has improved considerably, but at the time the
181 survey was done, the density of data at disposal was at first instance not enough to conduct accurate identification.
182 That can be the case in a majority of cases. Combination of usual 5x5 m² resolution files with LiDAR 4 points/
183 m², as for the conducted survey in the case study, means a significant improvement in accuracy and data

184 consistency. Ultimately, the data has two significant geometry values that need to be maintained as input
185 measurements into a Reduced data Standard Assessment Procedure (RdSAP) or estimated SAP calculation process
186 as the normal UK energy model. The input geometry is (a) the shape of the property; measured as the gross external
187 footprint of the individual dwelling unit; and (b) the height of the property. Together, these input parameters allow
188 an accurate calculation of heat-loss parameters around the extent of internal heated living space relative to the
189 exposed surface areas as made up from the ground floor, external walls and roof. While there are limited
190 opportunities for changing the shape (simplifying) and size (reducing) of homes to affect the heat loss parameters
191 (Friedman 2005), building fabric interventions (typically internal or external insulation) can improve the thermal
192 efficiency of specific building elements to reduce the heat loss. In most cases, improvement work to the building
193 fabric will also be dependent upon the same geometry in terms of cost of treatment per square metre. Further
194 interventions relate to possible upgrades to building services or the provision and connection to renewable and /
195 or decentralized energy systems. These can likewise be attached as attributes to the property-based data that is
196 consistent with similar scoping and qualitative assessments of stakeholder requirements (National Refurbishment
197 Centre 2012) and those responsible for property management and maintenance, there is a practical focus on cost-
198 effective and technically trusted approaches to refurbishment that requires good evidence base on accurate data.
199 In order to reach the point of using accurate building geometry data we need to identify any significant errors
200 inherent within the original format of the commercially provided data and implement some data editing. Most of
201 the errors reflect to inconsistencies of the polygons, differences to cadastral existing information, vegetation and
202 unrecorded elements and structures. Figure 3 shows key steps in data handling processes .

203
204 *Fig 3: Key steps in data handling processes in Lukač et al, 2013.*

206 **3.3 Errors within data collection**

207 To acquire useful data sets for energy monitoring, several types of initial data errors needed to be dealt with in
208 advance. These errors relates to almost exclusively issues of ‘bad geometry’ arising from a combination of the
209 angle of scanning of the terrain and properties together with the level of ‘noise’ within the LiDAR data. The ‘noise’
210 included errors from building overhangs, shadows, trees / vegetation and became more pronounced in areas where
211 there were more complex geometries and structures. Figure 4 highlights some of LiDAR data issues and errors.

212
213 *Fig 4: Highlighting the initial LiDAR data errors.*

214
215 The best strategy in dealing with the various geometry errors is to create two separate data sets that hold discrete
216 input data. The first deals with building footprints and the second with building heights. This strategy has proven
217 most effective in a more complex process. Brenner et al (2016) showed a process for which data is processed in
218 three steps, from coarse Digital Surface Model (DSM) to fine DSM and making use of the close range domain
219 given by the fine Digital Terrain Model (DTM) and the LiDAR points cloud. This information is checked against
220 CityGML to obtain the final polygonal information in a 2.5D data file. The approach taken in this case study
221 consists of checking the polygonal information from both 2D footprint and 3D height information, check for

222 inconsistencies and solve clashes of information. Figure 5 depict a flow chart for cross data and inconstancies
223 correcting and figure 6 shows an example of data error correction.

224 *Fig 5: Flowchart of the process for correcting polygonal inconsistencies.*

225
226

227 *Fig 6: Examples of correction of data errors.*

228

229 **3.4 Data cleaning and editing**

230 The first step in handling data is to pre-treat data by eliminating any basic errors/ outliers. Editing is carried out
231 using the edit functions within ESRI's ArcGIS (see Figure 6).

232 Overlapping polygons in the commercial data set are cleared of errors as they represent two properties occupying
233 the same building footprint. These are merged and then split along an estimated property boundary. Furthermore,
234 there were issues with sections such as disconnected polygons or 'gaps' in between terrace properties. These had
235 their vertices snapped to match.

236 There are several instances of vertices existing within polygons that seemingly picked up variations in roof
237 structures, chimneys / ventilation or in some instances in larger multi occupancy properties and non-residential
238 units mechanical and engineering services plant on the roof. These are merged into single polygons with all
239 extraneous vertices deleted. The result represents an accurate footprint data set.

240 **3.5 Identifying individual properties**

241 The next step was to separate the contiguous polygons / structures into individual properties. It is useful that the
242 LiDAR data is effective in picking up changes in external building heights. In an area of exaggerated topography
243 in the west end of Newcastle where contiguous properties / terraced housing step up and down the slope, this
244 suggests division between properties. However, in looking at the details, it failed to make a distinction between
245 property boundaries because this boundary is in reality the thickness of a party wall between the individual
246 properties. The change in roof heights coincided with the end (or in some instances the roof overlap) of the party
247 wall and not the middle of the party wall. This becomes apparent when rear extensions have to be attributed to a
248 particular property polygon. This could only be corrected manually using 'best-guess' information (Figure 7) based
249 on equidistant polygons to create properties of equal sizes as a typical property typology or using external
250 information to property boundaries.

251 *Fig. 7 Data editing to create individual property polygons*

252 It is accepted that additional errors are re-introduced at each of these discrete stages within data cleaning and
253 editing. Maintaining two separate data sets holding the footprint and height details separately is the best strategy
254 to reduce the number of stages in data handling and thus reducing the potential of re-introducing any new errors
255 when handling data.

256 4. INTEGRATION WITH OTHER DATA SETS

257 Thinking around the value of city models is rapidly changing in response to the power of computing but more
258 significantly, the quantum of big data that now exists digitally.

259 We are entering into a world where everything is data. Planning has to deal with the scope of different sources of
260 supporting evidence each using a variety of methodologies. There has to be an understanding of limits,
261 unpredictability and allied to this are the procedural issues around irrationality, objectivity and political / cultural
262 perceptions and definitions of qualitative aspects of behaviour, knowledge, attitudes and perceptions. Maps are
263 clearly a useful way to explore data. Nonetheless, ultimately they are didactic tools. They are abstractions of reality
264 and are designed primarily for exploration and understanding at strategic scales and early stages of decision-
265 making. They will contain errors and have to be treated as tools for understanding rather than predicting energy
266 usage.

267 Porter & Neale (2000) acknowledged the development of the ‘map’ or ‘model’ from physical to digital, a paradigm
268 shift in urban design and planning ‘... that hold(s) the potential for allowing the designer to move directly from
269 concept to full scale construction’. In order to achieve this, the development of new methodologies to support the
270 analysis and integration of large data sets has to be implemented (Aiden & Jean-Baptiste 2013). Real ‘big data’
271 can be considered a replacement for intuition or guesswork where there are strategies in place for harvesting and
272 mining every possible source (Baumgartner et al 2012).

273 4.1 LiDAR data use for energy performance evaluation with SAP engine

274 Precise image data and aerial imagery is needed in order to conduct accurate neighbourhood energy performance
275 evaluation. As well, use of published databases such as Homes Energy Efficiency Database (HEED), household
276 surveys such as English House Condition Survey (EHCS), census and the Office of National Statistics (ONS) are
277 used as data sources for input for the core SAP calculation engine as detailed in Mhalas et al. (2014).

278 Basing on this research, we realised that one major condition for the city model development, i.e. Newcastle
279 Cruddas Park building areas (fig. 10) included in the use case, was that it should support the demonstration of the
280 baseline energy modelling SAP based software tool, with the variety of building and dwelling archetypes. To do
281 that, accurate individual geometries of buildings needed to be put in place, in order to allow correct identification
282 when geo-referencing and establishing links to the cadastral and other Database information sources. In the first
283 instance, due to the resolution and also potentially the nature of the conveyed drive-by surveys, available data was
284 not sufficiently consistent for these purposes, raising concerns related to the data processing regime and date of
285 data capture, i.e. a number of buildings were missing from the map; the height of some buildings appeared to be
286 updated in the Ordinance Survey (2010); some of the extruded 3D blocks did not correspond to buildings at all.
287 Additionally knowledge of the site, images and visual inspection analysis allowed the recognition of other
288 discrepancies, which meant a barrier for the definition of the energy performance map.

289 The selected process followed to generate and classify the individual building geometries according to the
290 predefined archetypes is found in the IDEF0 map (figure 8), evolved from previous research found in Mhalas et
291 al. (2014). The use of LiDAR was of help in resolving the aforementioned definition barriers in the Geometry and
292 Physics components in figure 7. It allows the correct identification of individual buildings and a georeferenced

293 location of them, granting integration of the COLLADA files with CityGML and open-source resources as Google
294 Earth Pro. Both SHP vector files and CityGML files are superimposed on aerial map adding a layer to the open-
295 sourced one.

296

297

Fig. 8: Dwelling Objects Creation

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299 This precise imagery serves as input for the SAP sub-models for the specific building. This consists of extracting
300 information for footprint, floor height, exposed perimeter wall area, and roof-area as well as opaque and window
301 area and materials (U-values). Once the LiDAR file for a specific neighbourhood is in place, we use OS MasterMap
302 layer and OS MasterMapTopography Layer to identify the buildings, and Visual Basic for Applications (VBA) to
303 add information related to building physics and usage. ArcGIS features attribute replication for different buildings.
304 Once the different buildings units and attributes have been defined ArcGIS developer allows SAP algorithms to
305 be formulated into calculation tools, which will result in energy demand, heating and cooling demand, electricity
306 demand, PV and Thermal solar generation. The process to obtain neighbourhood Baseline Energy Performance
307 Assessment integrating the LiDAR data is shown in figure 2.

308 Visualisation of this data can be either be obtained with the aerial survey map, creating tailored layers to show the
309 different output values, or integrate them into open-source platform layers as GoogleMaps or GoogleEarth. Both
310 options need to create the layers using the KML layer creation. In that way visualisation of neighbourhood
311 extended attributes becomes available for the platform users, and becomes a valuable source of information for
312 urban planners, architects, and public services.

313 **4.2 Stakeholder data and user-defined mapping**

314 Big data tends to have veracity as well as volume, velocity, and variety. One of the key support tasks is to organise,
315 structure and make sense of data. This is generally accomplished using one or more of the industry standard
316 software packages, ArcGIS, AutoCAD, Sketchup and to a lesser degree, Google Earth. Additionally, there is an
317 open-source mapping software and data, for example in the ESRI sponsored crowd-sourced mapping (Medeiros,
318 2013). Building energy data is just another element of this big data. Building energy use and carbon emissions
319 have to be understood in the wider policy context and the complexity of the real world. There is a requirement to
320 provide for users the ability to export, import, and connect with their own datasets to build on the functionality of
321 the basic building geometry. Moreover, the significance of having remotely sensed data is that it provides accurate
322 building geometry and other information. While initially, this geometry has value as input data for the calculation
323 of the energy efficiency of buildings, this can be modified to incorporate a range of additional functionalities when
324 data is shared online and is linked to the individual property addresses for a more accurate measurement. For
325 example, for the calculation of property refurbishment and renovation costs, building geometry is linked to a cost
326 database or cost estimations.

327

328

Fig. 9: Data visualization integration into GoogleEarth KML layer.

329

330 Furthermore, the availability of an open-source three-dimensional data is both limited and controlled and
331 remarkably the same case study area of Newcastle is represented in Google Earth and effectively uses the same
332 data from the same commercial supplier (see figure 9). Yet the functionality of this is limited to basic visualisation
333 and the virtual exploration of the urban environment. The export functions, if any, are limited to two-dimensional
334 aerial imagery, creating a level of frustration in achieving the level of accuracy, which is available through open-
335 source data compared to the knowledge of the existence of accurate geometry. Yet this data is still currently just a
336 collection of shapes without any property specific tagging. However, looking beyond the visualisation of the data
337 are extractable geometry models that can be used for a variety of purposes, including acting as input data for more
338 detailed urban design and architectural modelling.
339

340 **5. DISCUSSION ON THE IMPORTANCE OF VISUALISING ENERGY DATA AND** 341 **FUTURE WORK**

342 Urban planning and regeneration is complex as it brings together a broad range of stakeholders, as a mix of
343 technical professionals and many different non-expert stakeholders that have their own personal and organizational
344 experiences. Urban planning and management has become a two-way educational mutual learning process (Wals,
345 1996) that have connections between many consultation / participation exercises. These urban planning processes
346 require the development of evidence base and information provision that is accessible and understandable to the
347 broad scope of project stakeholders and in particular visual energy use. Indeed, Castells (2000) suggested that the
348 appropriate sharing of urban data assists with the reform and legitimization of local democracy and governance.
349 Data, including energy data, with all of its errors is best shared in a manner that is accessible to multiple
350 stakeholders and is understandable to non-technical users, extractable and editable for technical users.
351 The SEMANCO project reported in this paper has provided an online platform that provides access to widely
352 dispersed energy related data about cities stored by many organisations. Thus, the platform supports improved
353 energy analysis based on the assessment of existing data rather than estimates. This is performed using semantic
354 data modelling that uses information stored in different places with different formats to create a multi-level energy
355 model of an urban area. This can be further used to analyse the energy performance of individual buildings,
356 neighbourhoods, districts and regions. Figure 10 shows a screen shot of the developed SEMANTIC tool for the
357 Urban Energy Model.

358

359

Fig. 10: Developed SEMANTIC tool for Urban Energy Model

360

361 The SEMANCO platform includes a set of tools to visualise and analyse a city's energy data. The visualisation
362 combines interactive 3D models, tables and diagrams to display energy related data. Madrazo et al (2013) stressed
363 the importance of the visual three-dimensional interface as a common language for a range of stakeholders
364 becomes more apparent.

365 Although it is a significant way short of BIM standards, this is potentially the next step in the use of LiDAR
366 information. Format and specifications in line with Construction Operations Building Information Exchange

367 (COBie) and can be useful at the earliest stages of a design or construction plan of works. At present ISO 1006-2
368 sets the specification standards for ICT in construction projects and includes a detailed ontology for construction
369 and building elements. This standard also sets out the design responsibilities between different professional
370 stakeholders and the minimum requirements for technical / digital information change between the professionals.
371 The standards overlap with COBie standards for data exchange, which sets out the specification of element
372 properties in the form of an industry standard data language with specification properties. For the SEMANCO
373 project, strategies are consigned to convert LiDAR datasets into accurate urban consistent information data to be
374 used in COBie compliant BIM tools as well as specific energy related information fields have been merged to
375 obtain an energy related ontology (Corrado et al, 2015). This is achieved by creating a formal vocabulary according
376 to the Ontology Web Language specifications to assess the energy performance of an urban area.

377 As an increasing range of software packages use COBie standards for data input and integration, the challenge is
378 to allow the use of remotely sensed LiDAR data on building geometry to be useful and timesaving as input data
379 into these design software packages. Here the best versions are mostly automated from Revit or similar SOLIBRI
380 compliance checking software. When remotely sensed data can be used with confidence at an early project stage
381 and form part of the initial information exchange it will have significant new functionality. It has to be remembered
382 that while most design packages and protocols are intended for new construction, around 80% of all construction
383 projects still include existing structures for renovation, refurbishment, adaptation, or conversion (Itard & Meijer
384 2009). An accurate representation of existing structures with a usable database containing the attributes and
385 parameters of these structures will be hugely valuable addition to the initial business planning stages of many
386 urban planning and regeneration projects.

387 It is also valuable to address compatibility of this methodology to parallel efforts in the direction of the W3C and
388 Linked Building Data group to generate city models integrating data from disparate data sources such as LiDAR,
389 photogrammetry and other survey methods considering OWL (Web Ontology Language). This points out the
390 direction to follow, going beyond the building bound COBie and IFC models.

391 **6. CONCLUSION**

392 This paper presents a methodology to integrate remote sensing methodology and LiDAR techniques to visualise
393 and calculate urban energy use in neighbourhoods, making use of proprietary and open source software tools. The
394 paper emphasises the process to improve consistency of data for the assessment of energy use and calculation in
395 urban settings and analyses the different barriers and problems raised in the undertaken research and solutions to
396 them. The paper highlights the limitations around the current ways in which neighbourhood energy analysis and
397 calculations are conducted and how these can be addressed through combinations with open-source property data
398 and existing stakeholder data sets, including building services and measured performance. The paper shows how
399 remote sensing data and LiDAR information can be captured, cleaned, processed and used.

400 This paper puts the thrust in ways to ease city models generation integrating LiDAR survey maps, especially
401 considering neighbourhood energy analysis and benchmarking. In sum, the process improves the aspects of the
402 model generation, process, analysis and visualisation, making use of widespread cloud based software tools.
403 Unlike existing approaches, the possibilities open by the research shown in this paper enhances the use and

404 handling of neighbourhood energy analysis and the integration with other visualisation tools enables not proficient
405 users to access tailored and versatile information.

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496 **List of Abbreviations**

497 BIM, (Building Information Modelling)

498 BREDAM (Building Research Establishment Domestic energy Model),

499 CAD, (Computer Aided Design)

500 CityGML (City Geography Markup Language),

501 COLLADA (COLLABorative Design Activity),

502 COBie (Construction Operations Building Information Exchange),

503 DSM (Digital Surface Model)

504 DTM (Digital Terrain Model),

505 GIS, (Geographical Information System)

506 LoD (Level of Detail)

507 LiDAR (Light Detection And Ranging),

508 OBIA (Object Based Image Analysis),

509 PVMs (Photovoltaic Modules), 5

510 PV (photovoltaic), 4

511 RdSAP (Reduced data Standard Assessment Procedure),

512 SEMANCO (Semantic Tools for Carbon Reduction in Urban Planning),

513 SAP (Standard Assessment Procedure),

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