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A web-based visual analytics platform to explore smart houses energy data for stakeholders: A case study of houses in the area of Manchester

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ABSTRACT

Residential sector need quick and creative solutions since rising energy consumption poses serious risks to the economy and the environment. Information about residential houses is useful for promoting community well-being, protecting the environment, and fostering economic growth. By digging into the residential houses, we can accurately identify sudden spikes in energy consumption. Energy Performance Certificates (EPCs) play a critical role in reducing wasteful energy consumption by providing precise information about a home's energy efficiency. Unfortunately, inadequate EPC evaluations and suggestions contribute to the growing demand for energy. This research presents the creation of a smart web-based visual analytics platform that utilises data from cross-sectoral data to examine the effect of various variables on current house energy performance certificates (EPCs). In addition, our study illustrates a technique for mapping stakeholder assessments before offering substantial recommendations for refurbishments. To determine which smart home criteria are most important, we apply the Criterion Importance Through Intercriterion Correlation (CRITIC) method and weight the criteria based on their correlations. Finally, we sort smart house by their Energy Performance Certificate (EPC) ratings using the COmplex PRoportional ASsessment (COPRAS) technique.

1. Introduction

Over 40% of all direct and indirect GHG emissions come from the building industry, making it the single largest consumer of both energy and GHGs worldwide, which is a significant energy user worldwide [23]. Its domination causes considerable environmental issues and is a growing cause for concern. It is estimated that between 80 and 94% of a conventional building's total energy consumption happens during its actual use and operation. Hence, improving the energy efficiency of existing structures is essential for substantially lowering the building sector's negative environmental impact [3], [19]. Keeping an eye on how energy-efficient existing homes, especially private houses are regarded as a potential and cost-effective method for increasing the energy efficiency of structures. As part of an energy tracking plan, Building Information data like archetype, age, class, names in the form of longitude and latitude, owner, floor area, and air test are gradually updated and changed. However, a clear user-centric vision of smart house is indispensable due to overwhelmingly stress on just pushing the technology to advanced level and by ignoring the importance of sharing data among different sectors [15]. Pahl et al. [18] centred on energy visualisation, where they look at ways to lower energy use in buildings by fusing psychology concepts and clever methods.

Improving the efficiency of buildings requires knowledge of their energy consumption patterns and the installation of monitoring devices to identify and fix inefficiencies [13]. In fact, a number of building energy management systems have been created as visual analysis and monitoring in a variety of settings. Oh et al. [17] outlined a three-dimensional visualisation approach to building energy management that aimed to improve energy efficiency predictions made from energy use. One notable exception is the case [16] where a web application's design for visualising smart cities was put into practise. Furthermore, the solution is nearly always centred on a single structure rather than a large group of services spread out over a wide area. Therefore, on the above mentioned and other instances when the visualisation component of the solutions plays a static instructive role or is completely absent are common and they don't have a complex, intelligent model to aid in

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decision-making [5,31]. From the literature of data driven decision making, it is obvious that there is clear demand for collaborative visual analytics methods and techniques for future data based industries. Although, there are several visualization tools for group decision making in the market focus on interactive visualization for collaborative visualization challenges [10], designed preference visualizations for group decision making [2], abstractions for visualizing preferences in group decisions [6].

Data visualisation is a strong tool for effectively and interactively demonstrating important data findings. In this [22] paper, to fill the gap in our understanding of theoretical and analytical methodologies for optimising visualisation performance, we undertook an in-depth study of visualisation tools and approaches. Concerns for the future, both broad and narrow, are discussed, and potential avenues for further study are pointed out.

1.1. Problem statement and motivation

We have been proposed some research solutions in our previous findings [8,9]. The prime issues to investigate the hidden intelligence of multi domain data, knowledge and services from houses are threefold. First, the data collection is multi structured showing multilevel hierarchies. Secondly, the data analysis process includes subjective ratings of characteristics, which leads to the use of quantitative and fuzzy data to show the secret trends and patterns to the stakeholders in a way that is easy to understand. Thirdly, engagement of stakeholders to observe the visual charts, identify and understand the pattern to add their input for the selection of best alternative should be considered. An effective visualization platform is essential in promoting and supporting decision quality. Visualization become essential to promote the culture of co-thinking, co-creation and co-production in academia as well as in the industries. A cross disciplinary visual analytics could potentially support identifying and investigating the hidden intelligence by integrating data, knowledge and services from multiple domains which could add more values to the existing services. What needs to be further explored that what social, economic and environmental benefits could be achieved by fusing the services from multiple domains together and how they could be scaled up to the city as well as to the country level. However, this study designs the visualisation process to examine 20 smart houses in the Manchester area by involving multi domain stakeholders.

1.2. Research challenges

We have classified the research challenges of proposed framework into design challenges and technical decision making challenges. The design challenges investigate (1) the missing design methodology for collaborative visual analytics platform to support group decision making and (2) the knowledge gaps between stakeholders virtually and visually engagement in the group decision making process. (3) The technical challenges explore and investigate the specific group decision making scenarios that would be established with dashboard-based data driven platform. This research focuses on smart house attributes that will help to exploit, and visualise demographic, environmental, services, building, and energy data. Finding ways to increase a house's EPC rating is crucial. It's critical to investigate and comprehend how a smart home's attributes can significantly affect its EPC rating. This leads to the following research questions; How do the archetype and age of smart houses affect their EPC ratings? How visualization helps stakeholders to understand the affect of attributes on EPC rating? How do stakeholders weight the houses using visualization platform?

1.2.1. Design challenges

The reported visual design methodologies missed the specific requirement in the group decision making. First, specific data type of dashboard designing for collaborative decision making is not defined. Second, the visual mapping and integration of stakeholders with dashboard is not reported. Third, weighting process of stakeholders using visualization is not defined.

1.2.2. Technical challenges

Problem structuring process starts from the problem identification between the stakeholders to visual conceptualization, implementation, and evaluation for the group decision solution. There are several complex steps and stages which contribute to the whole group decision making process through interaction of visual analytical platform. It is an iterative process, which consists of several responses, opinions and feedback to reach a best possible decision. Visual engagement is one of the main technical challenges to engage multiple stakeholders and/or decision makers to observe, understand the selected tasks, and make data based well informed decisions visually and virtually.

1.3. Research contribution

In this proposed platform, a novel approach, that combining dashboard visual analytics and group decision-making process, is proposed to investigate the hidden trends and visualize the relevant information to stakeholders to improve and enhance the organizational decision-making process. This platform seeks to address the design and technical research challenges, with the following design and technical contributions:

1.3.1. Design contribution

The conceptual design contribution is the design of collaborative visual analytics platform, which addresses the challenge of design methodology for collaborative visual decision-making process. In order to design a dynamic dashboard, we need to map the dashboard with the stakeholders for the identification of actual problem, classification of goals and tasks. The design contribution is visually engagement of stakeholders in which the stakeholders are planned to be collaborated virtually integrated with dashboard and able to examine, investigate and weight the performance of selected goals visually.

1.3.2. Technical contribution

The technical contribution is to explore and investigate problem structuring from intelligence to visual analytics among stakeholders to visual conceptualization, implementation, and evaluation for the group decision solution. The technical contribution is to explore and investigate the data and related key performance indicators engaging various stakeholders.

This research, particularly, articulates how smart house attributes can exploit, and visualise demographic, environmental, services, building, and energy data to improve EPC rating. Finding ways to increase a house's EPC rating is crucial. Therefore, stakeholders can better understand how their houses use energy and pinpoint areas for improvement by displaying the data gathered by smart house features. This may result in greater energy-conscious behaviour, lower energy costs, and higher EPC rankings. This study also helps researchers and policymakers better understand each other's perspectives and work together to make well-informed decisions.

As proof of concept, an intelligent web-based visual analytics platform is designed and implemented to incorporate cross sectoral data and to analyse the impact of various factors on a particular case study. The case studies selected in this work, further, reveal the pivotal role of cross sectoral research attributes and the importance of visually analysing energy consumption patterns by cross-referencing the results with their dependant variables (Fig. 1).

Rest of the paper is structured as; Section 2 articulates the case study description and stakeholders; section 3 explains and evaluates the smart houses criteria; section 4 describes solution of the problem and the decision making process; that is required to comprehend stakeholders' requirements; At the end, this research work is concluded with some future visionary augmentation of the work in section 5.

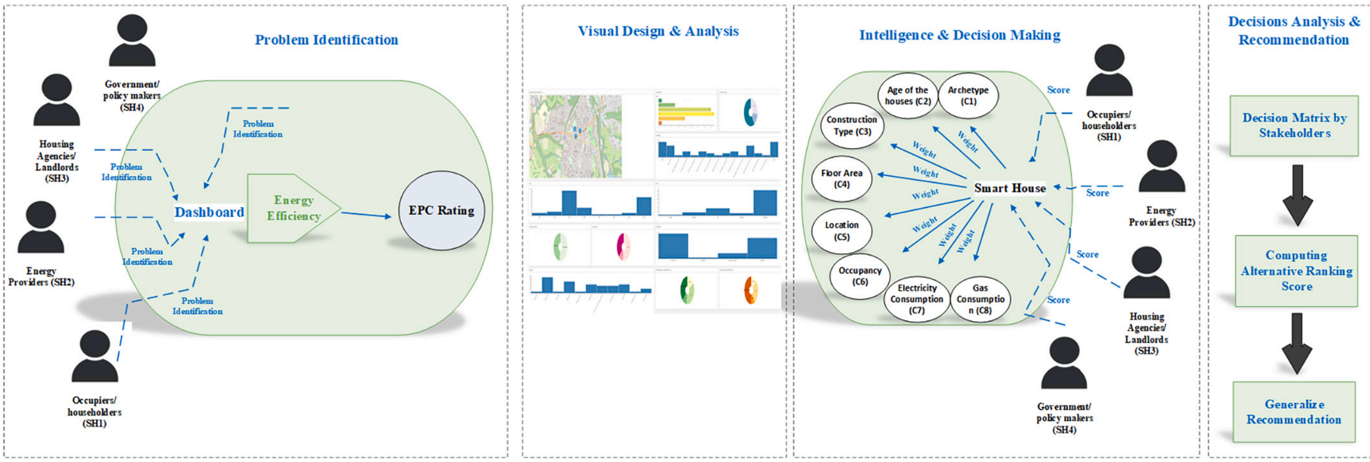


Fig. 1. Framework for Visual Analytics Platform to explore smart house data.

2. Problem description (case study)

The data ecosystem of a smart house includes all conceivable data concepts that can benefit many stakeholders on a social, environmental, and economic level. The capabilities of a traditional database model are insufficient to record important elements of a domain based complex system. To automate house services, it is therefore prioritised to have a semantic representation of a specific domain that includes precise description of the key ideas and how they relate to one another. These procedures improve the ability to process data and promote data integration, interoperability, and analysis.

Data of 20 houses in the Greater Manchester area are obtained for this exploratory study. Information on building types, ages, locations (in the form of longitude and latitude), building classes, construction methods, building owners, square footage, and air quality tests are all part of the Building Information domain. There were 15 distinct building types discovered in the BISF region. Solid as a brick, Brick and block detached 1980s, solid wall end terrace pre-1919, wimpy no-finess non-trad flat Wates, semi-detached, pre-1800 brick, terraced, and semi-detached all pre-1919 solid walls; mid-terrace, pre-1919 solid walls; semi-detached, 1919 solid walls; semi-detached, 1920s; semi-detached, 1930s; semi-detached, 1970s; semi-detached, pre-1800 brick; and terraced, 1919 solid walls. The era in which a structure was constructed is classified as either the 1920s, 1930s, 1950s, 1960s, 1970s, 1980s, 1800s, or before 1919. Detached, End Terraced, Flats, Mid Terraced, and Semi-detached are the different types of housing available. Both conventional and nonconventional building methods are recognised. Little (less than fifty square metres), medium (fifty to one hundred square metres), and large (more than one hundred square metres) are the three categories for floor space. The air leakage test results are broken down into three categories based on the air permeability values found: (5 m3/(m2.h)), (5-10 m3/(m2.h), and (>10 m3/(m2.h)).

Age, gender, family make-up, and health status are all examples of demographic information that falls under the Human Information umbrella. Additional family types that are acknowledged include: singles, couples who are both working, small families of two or three, families of four, families of five, families of six, retired individuals, retired couples, families of five that include retired individuals, and short-term tenants with special requirements. KWH/m2 annual power and gas consumption data is collected in the Services domain. Gas consumption data is likewise broken down into three groups: (120 Kilowatt hour), (120-140 Kilowatt hour), and (>140 Kilowatt hour). Similarly, electricity consumption data is broken down into three groups: (35 Kilowatt hour), (35-40 Kilowatt hour), and (>40 Kilowatt hour).

2.1. Smart house stakeholders

Table 1 articulates types of stakeholders those are key players in smart houses. Stakeholders are integrated to a digital energy management platform to get optimal benefits to achieve energy efficiency. Those measures that share an equal importance from all potential stakeholders are narrated as; user friendliness, enhanced interactivity, instant feedbacks with possible recommendations, advanced data visualization techniques and web-based portal.

Therefore, the importance of each stakeholder depends on the specific goals, tasks, and constraints of the relative smart house activities. Each stakeholder is assigned weights based on their relative importance, and to balance their interests and needs to achieve the best overall outcome. The following are the key stakeholders of smart houses and their related roles and activities.

2.1.1. Occupiers/householders (SH1)

The primary stakeholders of a smart house are the homeowners who live in the house and benefit from the convenience, security, and energy efficiency provided by smart home technologies. Occupiers/householders are likely to be the most important stakeholder as they are the primary users of the smart house technology and will be most affected by its benefits and drawbacks.

2.1.2. Energy providers (SH2)

Energy companies that provide energy and other services to house can benefit from smart home technologies that help customers use energy more efficiently. Energy companies are important stakeholders as they may be able to provide incentives or discounts for smart house technology that promotes energy efficiency and conservation.

2.1.3. Housing Agencies/Landlords (SH3)

Housing Agencies/Landlords are important stakeholders as they provide support for the installation, maintenance, and troubleshooting of the smart house technology, ensuring that it operates reliably and effectively.

2.1.4. Government/policy makers (SH4)

Government agencies that regulate building codes and energy usage may also be stakeholders in the smart home market, as they seek to promote more efficient and sustainable housing. Government agencies are important stakeholders as they may regulate the use of smart house technology, especially in areas related to building codes, safety, and energy efficiency.

Table 1
Smart house Data Description: Data Domains, Classes and Sub-classes.

Smart house Domain: Building Information														
Archetype	BISF	Brick and block	Detached 1980s brick and block	End terrace with a solid wall before 1939	Separate 1980s block and brick building	Flat no-fitness and non-traditional	Mid terrace pre 1919 solid wall	Semi-detached pre 1919 solid wall	Semi-detached 1919 solid wall	Semi-detached 1920s solid wall	Semi-detached 1930s solid wall	Semi-detached 1970s brick and block cavity	Semi-detached pre 1800 brick	Terraced pre 1919 solid wall and Wates
Building Age	1920s		1930s	1950s		1960s		1970s	1980s	pre 1919			pre 1800	
Building Classes	Detached			End-terraced			Flats		Mid-Terraced			Semi-detached		
EPC Rating	A			B			C		D	E		F		
Construction type				Traditional							Non-traditional			
Floor area			Small (<50 meter sq.),			Medium (50-100 meter sq.)					Large (>100 meter sq.)			
Air leakage test			(<5 meter cube/(meter sq.hour))			(5-10 meter cube/(meter sq.hour))					(>10 meter cube/(meter sq.hour))			
Smart house Domain: Services														
Electricity Data	<35 (Kilowatt hour/year/m2)			35-40 Kilowatt hour)							>40 (Kilowatt hour/year/m2)			
Gas Data	<120 (Kilowatt hour/year/m2)			120-140 (Kilowatt hour/year/m2)							<140(Kilowatt hour/year/m2)			

3. Smart house criteria analysis

Evaluation of smart houses needs to be performed under multiple conflicting criteria. A visualization platform is developed to visualize the performance of eight key criteria that influence the assessment of smart houses for energy efficiency optimization and management. The importance of each criteria is justified and grouped into Building Information data, Demographic Information, Services domain data.

3.1. Building information data

3.1.1. Archetype (C1)

In that region, known as BISF, sixteen distinct building types were discovered. Solid as a brick, Independent 1980s brick and block, The pre-1919 solid wall at the end of the terrace, Nontraditional flat wimpy, Solid wall, mid-terrace, built before 1919. Separated house with solid walls before 1919, Solid-wall detached houses built after 1919, 1920s, and 1930s; brick and block cavity detached houses built in the 1970s; 1970s semi-detached detached houses, Wates, semi-detached, and terraced house built before 1919 use brick from the 1800s.

3.1.2. Age of the houses (C2)

The buildings are separated into nine different decades, beginning with the 1920s and ending with the 1980s. There are structures from as early as 1800 and as late as the 1980s, as well as those from the 1920s, 1930s, 1950s, 1960s, 1970s, and 1980s.

3.1.3. Construction type (C3)

Houses are classified as detached, end-terraced, flats, mid-terraced, or semi-detached. Conventional and nonstandard construction practises are both recognised categories.

3.1.4. Floor area (C4)

Small (less than 50 m2), medium (between 50 and 100 m2), and large (more than 100 m2) are the three sizes of floor area. The air permeability test findings are categorised as follows: (5 m3/(m2.h) or less), (5-10 m3/(m2.h) or more), and (>10 m3/(m2.h) or more).

3.1.5. Location (C5)

Age, sex, family make-up, and health status are all examples of demographic information that falls within the Human Information umbrella.

3.2. Demographic data

3.2.1. Occupancy (C6)

Other recognised family configurations include: singles, couples without children, families of two, families of three, families of four, families of five, and families of six. Single retirees, couples, families of five including retirees, and temporary residents with special requirements.

3.3. Services domain data

3.3.1. Electricity consumption (C7)

Electricity and gas consumption is measured in Kilowatt hour/m2 year for a whole year in the Services sector. There are three distinct groups of information for electricity use: (35 Kilowatt hour/year/m2), (35-40 Kilowatt hour/year/m2), and (>40 Kilowatt hour/year/m2).

3.3.2. Gas consumption (C8)

There are additionally three groups of gas data represented by the ranges (120 Kilowatt hour/year/m2), (120-140 Kilowatt hour/year/m2), and (>140 Kilowatt hour/year/m2).

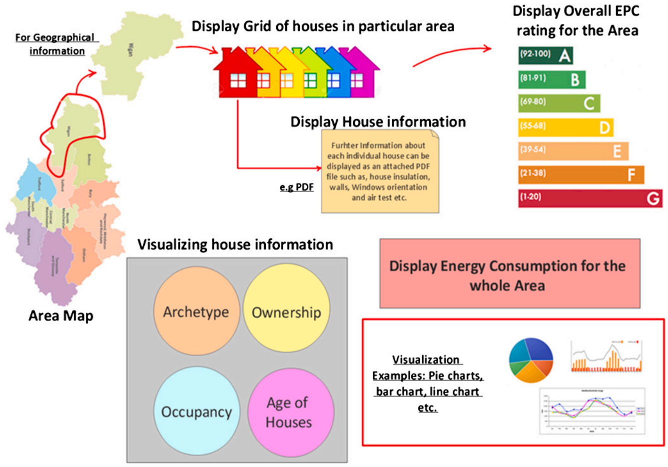


Fig. 2. Blueprint of web-based visual analytics platform to explore energy data. (For interpretation of the colours in the figure(s), the reader is referred to the web version of this article.)

4. Problem solution

4.1. Design of visualization platform

The proposed design framework, in Fig. 2, provides a platform for interdisciplinary investigation into energy-efficient smart buildings, which is often necessary for the design of context-aware, environmentally-driven, and intelligently monitored smart services. This framework defines the energy performance certificate research paradigm for energy-efficient smart house with respect to eight critical factors that should be taken into account to maximise efficiency and minimise consumption. To understand and enjoy the interesting and useful patterns of energy use, you need to know about the problems with global warming, social behaviour, economic output, and the modelling of very large energy datasets.

Our secondary research and interviews with different stakeholders to understand their requirements for the design and development of web-based graphical interface to explore smart houses' energy data let us create the first blueprint of the proposed platform. We want to make an interactive platform with analytical and visualisation features that will let us see how different smart house variables relate to the energy performance certificate (EPC), which gives houses a grade between A and G based on how well they use energy. Fig. 3, demonstrates our initial design blueprint for the implementation of a visual analytics platform to explore energy datasets. At first, we used MEAN.JS2 framework to design a web framework to implement our idea. To create a dynamic dashboard, MEAN.js provides a full-stack JavaScript framework that is freely available to the public. The four components that make up the MEAN stack are the database MongoDB, the web framework Express, the frontend framework AngularJS, and the server platform Node.js. The R framework's output was imported into this environment for graphical exploration.

However, the real challenge was to interact with the maps and graphical artefacts and to explore the impact of different variables on each other by cross-referencing the information and provide the EPC rating. To incorporate interactivity into this framework, we used D3.JS and Cross Filter which are JavaScript open source libraries. This brings more dynamic and interactive features to our platform that would be demonstrated in the later sections. 4, demonstrates web based visual analytics platform that has been implemented to explore smart house energy datasets. In the next section, different case studies will be explored using this web framework to understand areas and houses with higher or lowers energy consumption rates and their possible reason of using that energy (Fig. 5).

5. Decision-making method

5.1. CRITIC method

The CRITIC methodology, initially introduced by Diakoulaki et al. [4], is primarily employed for attribute weight determination. The current approach ensures attribute consistency and utilizes the decision matrix (DiMx) to establish attribute weights. The technique is utilized for automated areal matching of characteristics [7,25], healthcare quality evaluation [26,30], prioritization of machining procedures [12,11] and many more [20,14].

Step 1:
As illustrated in Equation (1), the DiMx is based on inputting the technique and expressing the alternatives and characteristics depending on the information obtained from the decision maker.

$$X=\begin{bmatrix} \lambda_{11} & \cdots & \lambda_{1j} & \cdots & \lambda_{1n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \lambda_{i1} & \cdots & \lambda_{ij} & \cdots & \lambda_{in} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \lambda_{m1} & \cdots & \lambda_{mj} & \cdots & \lambda_{mn} \end{bmatrix}_{m\times n} \tag{1}$$

$i=1,\dots,m, j=1,\dots,n,$
where λ_{ij} indicates the element of the DiMx for ith alternative in jth attribute.

Step 2:
The normalized DiMx is developed in during this stage. In order to normalize the positive and negative attributes of the DiMx, Equation (2) and Equation (3) are used, respectively.

$$\daleth_{ij}=\frac{\lambda_{ij}-\lambda_i^-}{\lambda_i^+-\lambda_i^-};\quad i=1,\dots,m, j=1,\dots,n \tag{2}$$

$$\daleth_{ij}=\frac{\lambda_{ij}-\lambda_i^+}{\lambda_i^--\lambda_i^+};\quad i=1,\dots,m, j=1,\dots,n \tag{3}$$

where $\daleth_{ij}$ represents a normalized value of the DiMx for ith alternative in jth attribute and $\lambda_i^+=\max\left(\lambda_1,\lambda_2,\dots,\lambda_{\mathrm{m}}\right)$ and $\lambda_i^-=\min\left(\lambda_1,\lambda_2,\dots,\lambda_{\mathrm{m}}\right)$.

Step 3: The determination of the correlation coefficient among attributes is achieved through the use of Equation (4).

$$\rho_{jk}=\frac{\sum_{i=1}^{m}\left(\daleth_{ij}-\bar{x}_j\right)\left(\daleth_{ik}-\bar{x}_k\right)}{\sqrt{\sum_{i=1}^{m}\left(\daleth_{ij}-\bar{x}_j\right)^2\sum_{i=1}^{m}\left(\daleth_{ik}-\bar{x}_k\right)^2}} \tag{4}$$

where $barx_j$ and $barx_k$ show the average of the jth and kth traits, respectively. Equation (5) is used to figure out $barx_j$. In the same way, it can be found for $barx_k$. Also, rho_jk is the correlation coefficient between qualities j and k.

$$\bar{x}_j=\frac{1}{n}\sum_{j=1}^{n}\daleth_{ij};\quad i=1,\dots,m \tag{5}$$

Step 4: At first, the following Equation (6) is used to figure out an estimate of the standard deviation for each characteristic.

$$\sigma_j=\sqrt{\frac{1}{n-1}\sum_{j=1}^{n}\left(\daleth_{ij}-\bar{x}_j\right)^2};\quad i=1,\dots,m \tag{6}$$

Then, the index (C) is calculated using Equation (7).

$$C_j=\sigma_j\sum_{k=1}^{n}\left(1-\rho_{jk}\right);\quad j=1,\dots,n \tag{7}$$

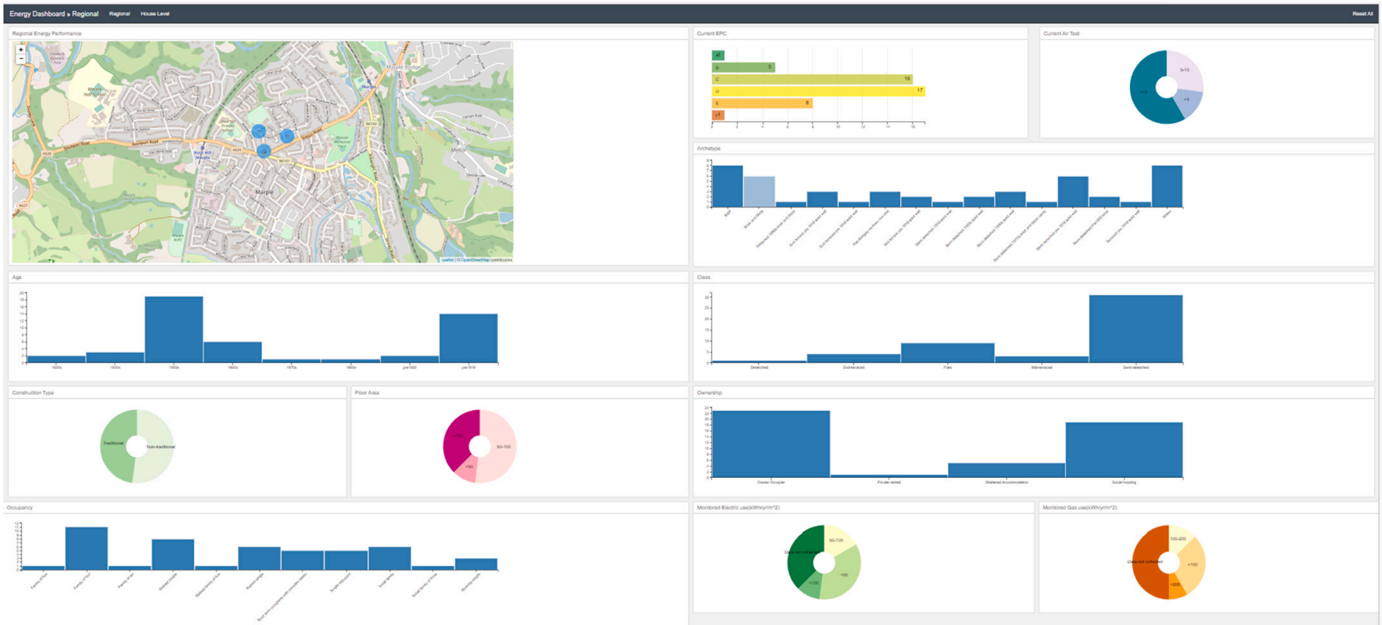
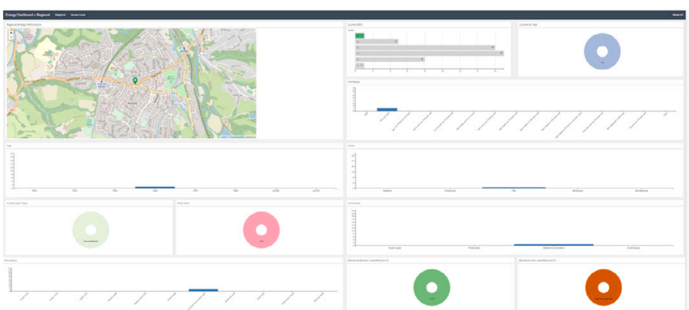
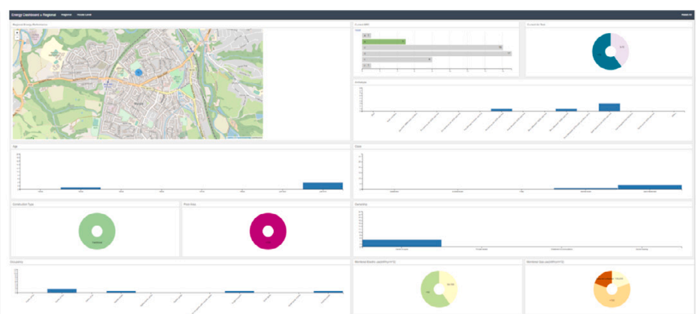


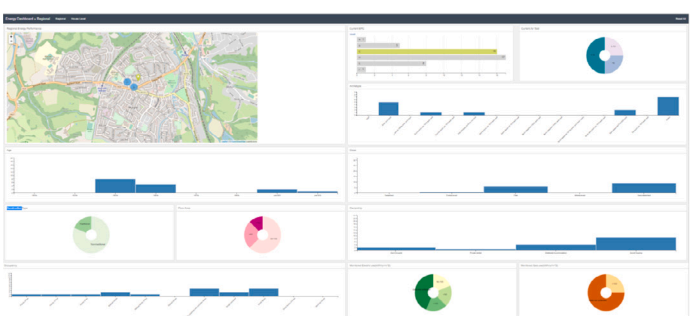
Fig. 3. Web-based Visual Analytics for Investigating EPC Rating.



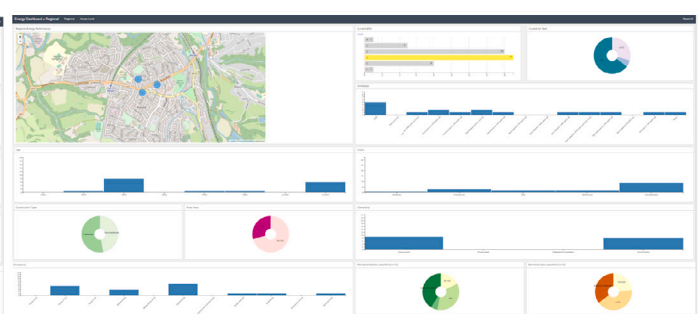
(a) Web-based Visual Analytics for EPC A



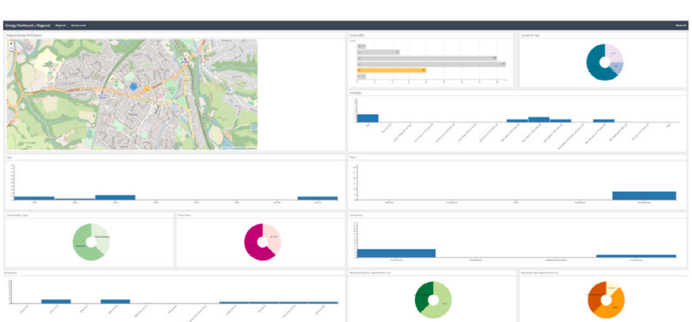
(b) Web-based Visual Analytics for EPC B



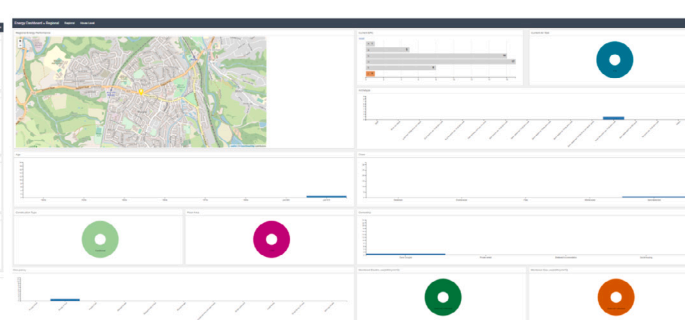
(c) Web-based Visual Analytics for EPC C



(d) Web-based Visual Analytics for EPC D



(e) Web-based Visual Analytics for EPC E



(f) Web-based Visual Analytics for EPC F

Fig. 4. Web-based Visual Analytics of EPCs with Attributes.

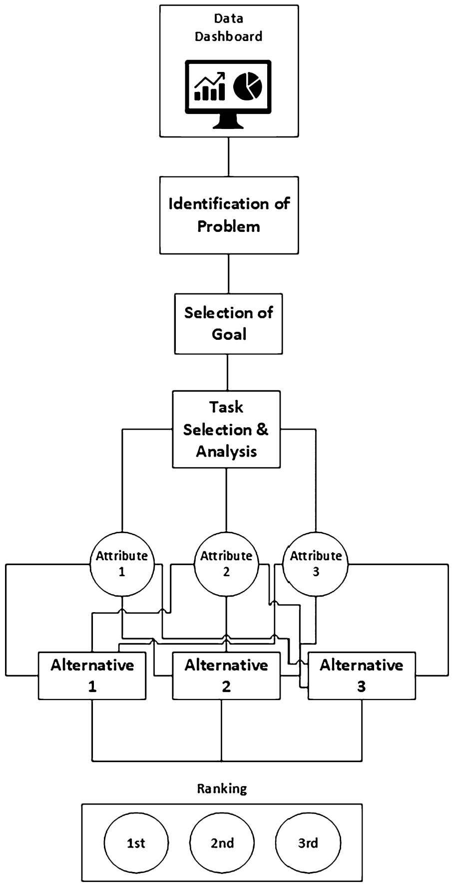


Fig. 5. Decision Making Framework.

Step 5: Equation (8) is used to figure out how much each trait should be worth (Fig. 6).

$$w_j = \frac{C_j}{\sum_{j=1}^{n} C_j}; \quad j = 1, \dots, n \tag{8}$$

5.2. COPRAS method

The COPRAS methodology was first introduced by Zagorskas et al. [27]. This approach is utilized to evaluate the maximizing and minimizing index values, with a separate consideration given to the impact of maximizing and minimizing attribute indexes on the assessment of outcomes. The COPRAS methodology finds application in various domains, including but not limited to risk assessment [28], investment project selection [29], material selection [1] and many more [24,21]. The following features are being taken into consideration for this method:

Step 1: In this technique, the DiMx is formed based on the information received from decision maker in Equation (9).

$$X = \begin{bmatrix} \lambda_{11} & \cdots & \lambda_{1j} & \cdots & \lambda_{1n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \lambda_{i1} & \cdots & \lambda_{ij} & \cdots & \lambda_{in} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \lambda_{m1} & \cdots & \lambda_{mj} & \cdots & \lambda_{mn} \end{bmatrix}_{m\times n} \tag{9}$$

$i = 1, \dots, m, \quad j = 1, \dots, n.$

In Equation (9), λ_{ij} is the element of DiMx for ith alternative in jth attribute. On the other hand, decision maker provides the weight of the attribute $[w_1, w_2, \dots, w_n]$.

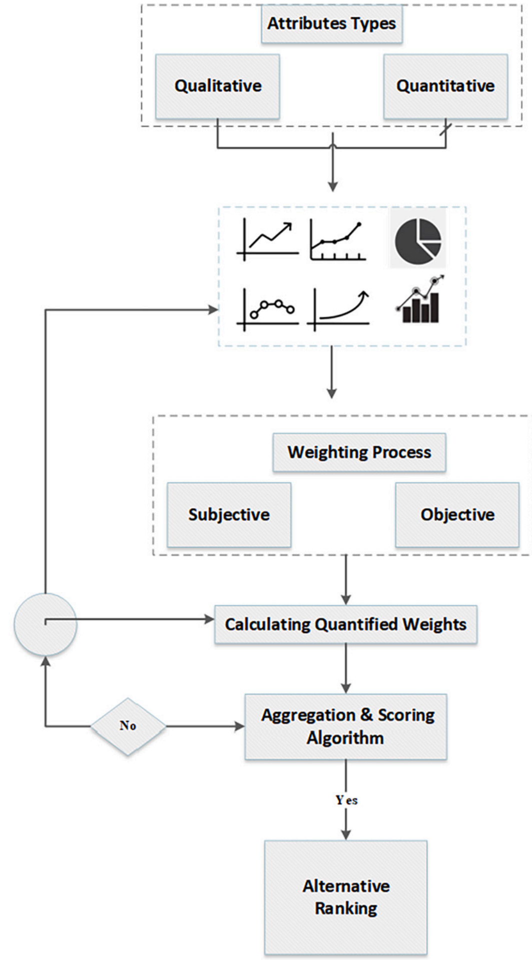


Fig. 6. Criteria Analysis.

Step 2: The normalized DiMx is obtained by using Equation (10).

$$\lambda^*_{ij} = \frac{\lambda_{ij}}{\sum_{i=1}^{m} \lambda_{ij}}; \quad j = 1, \dots, n \tag{10}$$

Here, λ^*_{ij} indicates the normalized value of the DiMx of ith alternative in jth attribute.

Step 3: The weighted normalized DiMx is obtained by using Equation (11).

$$\hat{r}_{ij} = \lambda^*_{ij} \cdot w_j; \quad i = 1, \dots, m, \quad j = 1, \dots, n \tag{11}$$

In Equation (11), w_j is the weight of attribute $[w_1, w_2, \dots, w_n]$ which is obtained by CRITIC method.

Step 4: Given the negative or positive type of attributes, the maximizing and minimizing indexes of each attribute are obtained by Equation (12) and Equation (13).

$$S_{+i} = \sum_{j=1}^{g} \hat{r}_{ij}; \quad i = 1, \dots, m \tag{12}$$

$$S_{-i} = \sum_{j=g+1}^{n} \hat{r}_{ij}; \quad i = 1, \dots, m \tag{13}$$

where g indicates the number of positive attributes and $n - g$ represents the number of negative attributes, and S_i describes the maximizing and minimizing indexes of ith at tribute, according to the type of it.

Table 2
Criterion for Evaluation.

	Criteria
C1	Archetype
C2	Age of the houses
C3	Construction Type
C4	Floor Area
C5	Location
C6	Occupancy
C7	Electricity Consumption
C8	Gas Consumption

Step 5: The relative significance value of each alternative is calculated through Equation (14) or Equation (15).

$$Q_i = S_{+i} + \frac{\min_i S_{-i} \sum_{i=1}^{m} S_{-i}}{S_{-i} \sum_{i=1}^{m} \frac{\min_i S_{-i}}{S_{-i}}} \tag{14}$$

$$Q_i = S_{+i} + \frac{\sum_{i=1}^{m} S_{-i}}{S_{-i} \sum_{i=1}^{m} \frac{1}{S_{-i}}} \tag{15}$$

Step 6: On the basis of their relative significance values, the alternatives are ranked in descending order, with the highest ultimate value receiving the highest position.

5.3. *Decision making assessment*

Data is collected for 20 different houses in the area of Manchester in different domains to evaluate which house is more energy efficient. In this regard, the criteria such as Archetype (C1), Age of the houses (C2), Construction Type (C3), Floor Area (C4), Location (C5), Occupancy (C6), Electricity Consumption (C7), Gas Consumption (C8) were specified by stakeholders. They can be shown in Table 2. The qualitative criteria were quantified by the stakeholders using a visualization platform. Four stakeholders (SHs) were involved in the case study that was given. Table 3 shows how the linguistic scale was used on the SHs. The table had a weighted list of smart houses based on how important each of the criteria was.

Using linguistic terms given in Table 3 SHs gave their views regarding to each alternative. These views are given in Table 4. The final values of each criterion correspond to the importance of its contribution towards energy efficiency given in Table 5. After constructing the normalized DiMx, the correlation coefficients are found which are given in Fig. 7. Following an evaluation of the standard deviation and index, the final weights and ranking of criteria are presented in Table 6.

A pictorial view of final weights and ranking of criteria can be seen in Fig. 8. After determining the cumulative weights of criteria using the CRITIC method, the COPRAS method is used to determine the final ranking of alternatives. By applying the COPRAS method final ranking of alternatives is given in Table 7 and the pictorial view of alternatives ranking can be seen in Fig. 9.

6. Discussion

We split the discussion section into two parts.

6.1. *Visual task investigation*

Identify all the houses and display it on the map where users have consumed higher amount of energy and identify relevant factors that have direct or indirect influence on higher EPC grade.

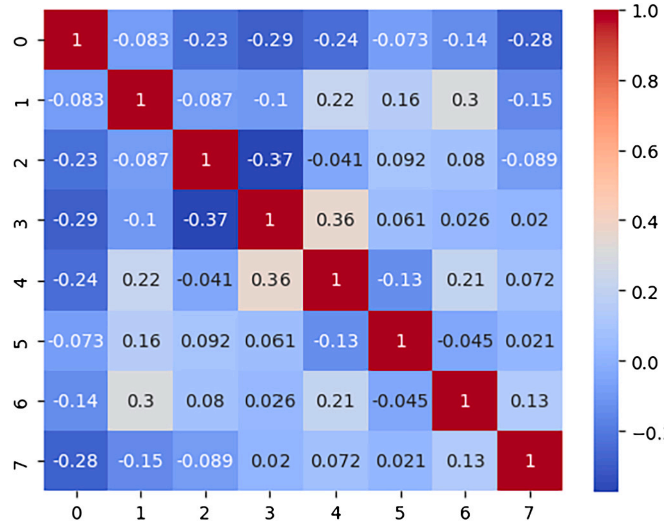


Fig. 7. Correlation Coefficient.

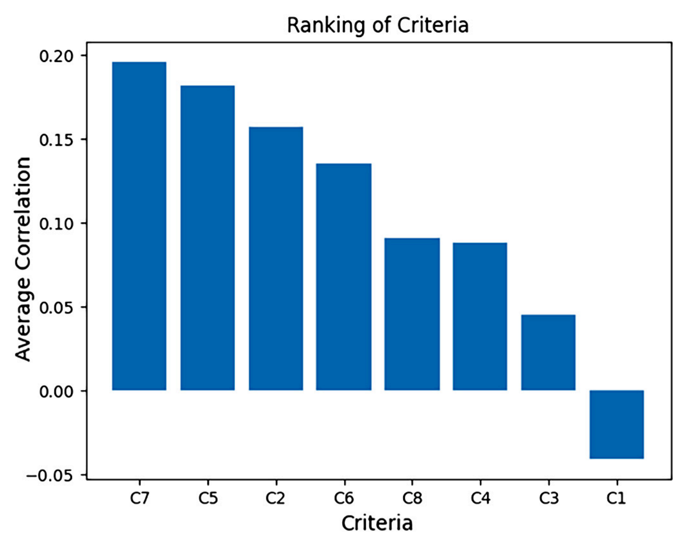


Fig. 8. Ranking Criteria.

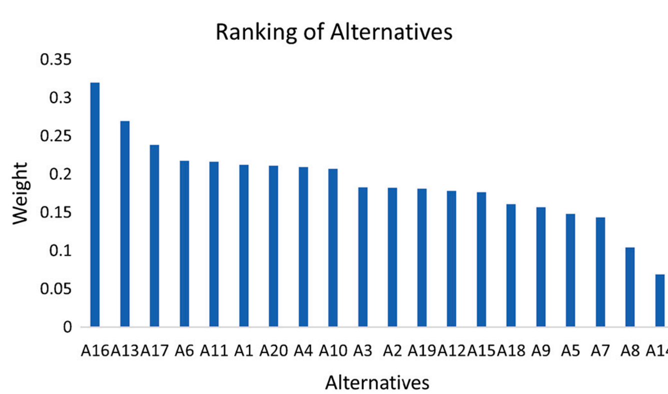


Fig. 9. Ranking of alternative.

6.1.1. *System's anticipation*

The proposed system allows user to choose the required attributes from a well-organized interactive user interface. As soon as user selects an attribute, the system responds immediately to reconfigure the data values and their corresponding visual autonomously with reference to the selected attributes and updates them in the interface. For each single selection of the variable in the interface, the system keeps

Table 3
Linguistic scale.

Extremely Very Important (EVI)	Very Important (VI)	Important (I)	Medium Important (MI)	Not Important (NI)
0.95	**0.8**	**0.65**	**0.45**	**0.10**

Table 4
Stakeholders matrix using linguistic scale.

Alternatives	Criteria							
	C1	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**	**C8**
A1	EVI	I	MI	EVI	VI	I	NI	VI
A2	I	MI	NI	EVI	VI	I	VI	EVI
A3	NI	MI	EVI	I	I	EVI	VI	MI
A4	MI	I	VI	NI	VI	EVI	VI	EVI
A5	NI	I	EVI	I	VI	MI	VI	NI
A6	MI	MI	VI	EVI	I	NI	EVI	NI
A7	VI	EVI	I	I	MI	NI	VI	NI
A8	NI	MI	VI	I	EVI	EVI	NI	NI
A9	MI	I	VI	EVI	VI	NI	MI	NI
A10	EVI	I	EVI	MI	VI	I	NI	NI
A11	NI	MI	EVI	VI	I	I	VI	I
A12	EVI	MI	VI	I	EVI	VI	NI	I
A13	MI	I	NI	I	EVI	VI	MI	MI
A14	EVI	I	MI	EVI	NI	VI	I	EVI
A15	I	MI	I	NI	I	EVI	VI	VI
A16	MI	NI	NI	MI	EVI	VI	I	MI
A17	VI	NI	VI	EVI	I	MI	I	NI
A18	VI	I	EVI	MI	I	NI	VI	I
A19	EVI	EVI	VI	I	NI	MI	I	NI
A20	EVI	NI	VI	MI	VI	I	I	MI

Table 5
Stakeholders DiMx using linguistic scale.

Alternatives	Criteria							
	C1	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**	**C8**
A1	0.95	0.65	0.45	0.95	0.80	0.65	0.10	0.80
A2	0.65	0.45	0.10	0.95	0.80	0.65	0.80	0.95
A3	0.10	0.45	0.95	0.65	0.65	0.95	0.80	0.45
A4	0.45	0.65	0.80	0.10	0.80	0.95	0.80	0.95
A5	0.10	0.65	0.95	0.65	0.80	0.45	0.80	0.10
A6	0.45	0.45	0.80	0.95	0.65	0.10	0.95	0.10
A7	0.80	0.95	0.65	0.65	0.45	0.10	0.80	0.10
A8	0.10	0.45	0.80	0.65	0.95	0.95	0.10	0.10
A9	0.45	0.65	0.80	0.95	0.80	0.10	0.45	0.10
A10	0.95	0.65	0.95	0.45	0.80	0.65	0.10	0.10
A11	0.10	0.45	0.95	0.80	0.65	0.65	0.80	0.65
A12	0.95	0.45	0.80	0.65	0.95	0.80	0.10	0.65
A13	0.45	0.65	0.10	0.65	0.95	0.80	0.45	0.45
A14	0.95	0.65	0.45	0.95	0.10	0.80	0.65	0.95
A15	0.65	0.45	0.65	0.10	0.65	0.95	0.80	0.80
A16	0.45	0.10	0.10	0.45	0.95	0.80	0.65	0.45
A17	0.80	0.10	0.80	0.95	0.65	0.45	0.65	0.10
A18	0.80	0.65	0.95	0.45	0.65	0.10	0.80	0.65
A19	0.95	0.95	0.80	0.65	0.10	0.45	0.65	0.10
A20	0.95	0.10	0.80	0.45	0.80	0.65	0.65	0.45

Table 6
Final weights and ranking of criterion.

Criteria	Weight	Average Correlation	Ranking
C1	-0.047904	0.195863	**8**
C2	0.184376	0.18139	**3**
C3	0.052376	0.157314	**7**
C4	0.103539	0.135539	**6**
C5	0.212593	0.090964	**2**
C6	0.158854	0.088342	**4**
C7	0.229555	0.044689	**1**
C8	0.106611	-0.040873	**5**

Table 7
Final ranking of alternatives.

Alternative	Weight	Ranking
A16	**0.319943**	**1**
A13	**0.269749**	**2**
A17	**0.238722**	**3**
A6	**0.217993**	**4**
A11	**0.216684**	**5**
A1	**0.212633**	**6**
A20	**0.211233**	**7**
A4	**0.209514**	**8**
A10	**0.207227**	**9**
A3	**0.183016**	**10**
A2	**0.182236**	**11**
A19	**0.181305**	**12**
A12	**0.178277**	**13**
A15	**0.176702**	**14**
A18	**0.161347**	**15**
A9	**0.156922**	**16**
A5	**0.148159**	**17**
A7	**0.143604**	**18**
A8	**0.104483**	**19**
A14	**0.069384**	**20**

responding to the user's commands and reconfigures the data and the corresponding visuals for each single input it receives from the user. In this particular case, once user selects the variables; Monitored Electric Use >40, Floor Area = Large, and Age = Pre1919, system identifies total 6 houses that fulfil the anticipated use case requirements and displays them on the map as demonstrated in Fig. 4. The system also fetches the dependent variables data from different domains, recalculates the data values based on user's commands and reflects the results back to the user interface.

Fig. 4, demonstrates that once user selects the required variables in the interface the values of the corresponding dependent variables also changes. For instance, user selects the higher electricity range that belongs to Services domain with greater floor area and the building age that belongs to the Building Information domain. However, the system recalculates the values from other domains such as house occupant's information from the Human Information domain, Ownership detail, Construction Type, House Class, and Archetype data from Buildings Information domain and gas usage value from Services domain. This clearly reflects that there is a significant dependency among these variables across different domains that could help us to understand higher electricity usage in these houses. This also verifies that only few variables cannot justify a house marked as defected until we understand other data dependencies that relate to the problem. For instance, in this particular use case 2 houses have 4 occupants, 1 occupies a retired couple, 1 belongs to a retired single and 1 belongs to a single occupant. Similarly, out of these 6 houses 1 belongs to End-Terraced, 2 to Mid-Terraced, and 2 to Semi-detached. In relation to Archetype of the buildings, 3 houses belong to Semi-detached pre 1919 solid wall, 1 belongs to End terrace pre 1919 solid wall, 1 to Mid terrace pre 1919 solid wall and the last 1 to terrace pre 1919 solid wall. For air leakage test 4 houses have (>10 m3/(m2.h)) values and 2 falls to (5-10 m3/(m2.h)) values. All this information would be revealed by hovering over the visuals in the interface. These results reveal that higher electricity usage is normal for all those houses with either large number of occupants or where there retired people are living in the houses since they stay at home most of the day. However, only one house where only one occupant is living needs further investigation. Selecting that particular house in the interface further reveals that this is a traditionally built, Mid-Terraced house, occupied by the owner himself, with Mid terrace pre 1919 solid wall Archetype. Results also reveal that Air leakage test result for this particular house is (>10 m3/(m2.h)) which could be a possible reason for higher electricity usage. Furthermore, these results also help to identify the possible retrofitting activities that need to be carried out in a particular house to overcome the problems.

6.2. Platform evaluation

The proposed system has been evaluated for its usability and functionality testing with set of 16 questionnaires. For system evaluation, stakeholders were invited from multiagency teams who were also involved in providing requirement specifications of the system. In a preliminary evaluation phase seven different stakeholders from multi agency teams and 8 Engineering and Computer Science students were involved. The questionnaires were divided into two sets. First set of questionnaires focused on users' satisfaction testing. 78% of the users found system very useful and easy to navigate to explore different case studies. 10% users especially from housing agency couldn't find analysis for all of their anticipated case studies. We found that one of the reasons of this analysis is the limited amount of data that we have used for this work. However, 2% users wanted the user interface more simple.

For the second set of questionnaires where we asked users to provide their feedback for further improvements, we found very interesting and useful suggestions. Mostly the feedback was to extend the system from region to house level where energy consumption could be visualized at different times of the day throughout a month and a year. Some of the users also suggested that instead of interpreting the results ourselves, system should explain the results and also some future recommendations based on analysis.

Algorithm for CRITIC

Require: DiMx D of size $m \times n$, where m is the number of alternatives and n is the number of criteria. Importance weights w of size $n \times 1$, where each element represents the importance of the corresponding criterion.
Ensure: A list of criteria importance values c of size $n \times 1$, where each element represents the importance of the corresponding criterion.

function CRITIC(D, w)
    Normalize the DiMx D to obtain a normalized DiMx D_{norm}:
    for $i \leftarrow 1$ to n **do**
        Calculate the sum S_i of the values in column i.
    end for
    for $i \leftarrow 1$ to m **do**
        for $j \leftarrow 1$ to n **do**
            Divide D_{ij} by S_i.
        end for
    end for
    Calculate the intercriteria correlation matrix R of size $n \times n$:
    for $i \leftarrow 1$ to n **do**
        for $j \leftarrow 1$ to n **do**
            Calculate the Pearson correlation coefficient λ_{ij} between the corresponding columns in D_{norm}.
        end for
        Fill the diagonal of R with 1.

end for
Calculate the weights of criteria W of size $n \times 1$:
for $i \leftarrow 1$ to n **do**
Calculate the sum S_i of the absolute values of the correlation coefficients in row i of R.
Calculate the weight W_i as the product of w_i and S_i.
end for
Calculate the criteria importance values c of size $n \times 1$:
Calculate the sum S of the weights in W.
for $i \leftarrow 1$ to n **do**
Calculate the criteria importance value c_i as the ratio of the weight W_i to the sum S.
end for
Normalize c to obtain a vector of values that sum to 1.
return c
end function

Algorithm for COPRAS

Require: DiMx D of size $m \times n$, where m is the number of alternatives and n is the number of criteria. Importance weights w of size $n \times 1$, where each element represents the importance of the corresponding criterion. A reference point R of size $1 \times n$, where each element represents the ideal value for the corresponding criterion.
Ensure: A list of alternative rankings λ_k of size $m \times 1$, where $\lambda_k(i)$ represents the ranking of alternative i.
function COPRAS(D, w, R)
Normalize the DiMx D to obtain a normalized DiMx D_{norm}:
for $i \leftarrow 1$ to m **do**
for $j \leftarrow 1$ to n **do**
Divide D_{ij} by the corresponding element in R.
end for
end for
Calculate the concordance matrix C of size $m \times m$:
for $i \leftarrow 1$ to m **do**
for $j \leftarrow 1$ to m **do**
Calculate the concordance index c_{ij} between alternative i and alternative j as follows:
Set $c_{ij} \leftarrow 0$.
for $k \leftarrow 1$ to n **do**
if $D_{ik} \leq D_{jk}$ **then**
$c_{ij} \leftarrow c_{ij} + w_k$.
end if
end for
end for
end for
Calculate the discordance matrix D of size $m \times m$:
for $i \leftarrow 1$ to m **do**
for $j \leftarrow 1$ to m **do**
Calculate the discordance index d_{ij} between alternative i and alternative j as follows:
Set $d_{ij} \leftarrow 0$.
for $k \leftarrow 1$ to n **do**
if $D_{ik} > D_{jk}$ **then**
$d_{ij} \leftarrow \max(d_{ij}, \frac{D_{ik}}{D_{jk}})$.
end if
end for
end for
end for
Calculate the net concordance matrix N of size $m \times m$:
Set $N \leftarrow C - D$.
Calculate the aggregated net concordance matrix A of size $m \times 1$:
For each row i of N, calculate A_i as the sum of the elements in that row.
Calculate the ranking vector λ_k of size $m \times 1$:
Sort the alternatives in decreasing order of their values in A to obtain the ranking vector λ_k.
return λ_k
end function

7. Conclusion and future work

The increasing demand of energy in residential and commercial buildings over the past several years has had a negative impact on our planet's natural energy supplies and ecology as a whole. To reduce the increasing energy consumption of buildings, innovative and efficient solutions are needed. Furthermore, in the area of energy-efficient smart buildings, the relevance of establishing a cross-sectoral research paradigm is generally overlooked in the existing literature. The goal of this study was to offer a cross-sector multidisciplinary framework for the design and development of sustainable energy-efficient smart buildings. In order to implement policies that effectively enhance energy efficiency, this framework also includes the collaboration model for sharing knowledge across various stakeholders and knowledge specialists. For the purpose of developing an auto-filtering web-based visual analytics platform, this paper analyses case studies to determine the needs of various stakeholders. Initial blueprint was first modelled to initiate brain storming sessions to implement such interactive system. This research work proposed ontologies as big data structuring model to capture, store, analyze and visualize multi-dimensional complex energy datasets. At first, MEAN.JS framework is chosen to implement the system, however, this lacked interactive features. Later, cross filtering features were added in the system to cross reference the information among different variables to understand the impact of a particular case study. This system later evaluated and tested with different stakeholders. The outcomes of this research work are appreciated by multiagency teams by suggesting few advance features to be incorporated to improve the system further.

As part of future work, we intend to visualize the impact of weather datasets along with exiting demographic as well as building datasets to explore its impact on the energy consumption patterns in a given area. Moreover, we aim at extending the system to visualize energy consumption at lower granular level to understand energy consumption in a given house at different times of the day and at different house spaces such as living room, bedroom, hallway and kitchen. We also would like to visualize the energy that is consumed by different appliances that are integrated in a particular house such as boiler, refrigerator, TV, and heating/cooling systems.

Declaration of competing interest

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

Data availability

Data will be made available on request.

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