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Review

Building Energy Simulation and Monitoring: A Review of Graphical Data Representation

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Abstract: Data visualization has become relevant in the framework of the evolution of big data analysis. Being able to understand data collected in a dynamic, interactive, and personalized way allows for better decisions to be made when optimizing and improving performance. Although its importance is known, there is a gap in the research regarding its design, choice criteria, and uses in the field of building energy consumption. Therefore, this review discusses the state-of-the-art of visualization techniques used in the field of energy performance, in particular by considering two types of building analysis: simulation and monitoring. Likewise, data visualizations are categorized according to goals, level of detail and target users. Visualization tools published in the scientific literature, as well as those currently used in the IoT platforms and visualization software, were analyzed. This overview can be used as a starting point when choosing the most efficient data visualization for a specific type of building energy analysis.

Keywords: building energy analysis; building energy performance; data visualization; simulation; monitoring

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1. Introduction

The growing energy demands of buildings and their consequent environmental impacts motivate professionals and researchers in the field of building construction to seek out more sustainable ways to create built environments. To achieve energy efficiency, it is necessary to evaluate processes and consumption behavior. This building information not only allows the reduction in energy waste, but also the increase in energy savings, improving building efficiency [1]. Building Energy Simulation (BES), a computer-based analytical process, is one of the most used alternatives to understand the energy performance and environmental impact of buildings due to its variety of tools and retrofit alternatives [2]. BES could help in the identification of environmental issues in buildings, especially in the last stage of the design [3], and is mainly used in the prediction and analysis of building energy consumption [4]. Another useful alternative to control and monitor energy is the Building Energy Management System (BEMS), a technology which not only allows one to obtain updated and historical information on energy use, but also to predict consumption trends by means of appropriate models, thus promoting energy savings by controlling building loads [5].

Data obtained through BES or BEMS become relevant information when a data-driven analytic approach is used. This method allows for the interpretation and analysis of the data through their graphical representation [2,6], allowing these data to be processed, organized, and structured, gaining significance and purpose [7]. Currently, several tools may be used in the framework of this approach, among which are data visualization software and Internet of Things (IoT) platforms. These technologies could contribute to the efficient management of energy consumption, support the decision-making process and reduce costs while maintaining the required energy demand [8].

Due to the relevance of energy efficiency in this field of research and the importance of data visualization in the framework of the evolution of big data analysis [9], many companies have become interested in developing tools aimed at monitoring their energy metrics. When analyzing building energy simulation results, it is often necessary to combine different tools and software due to the large amount of data and various needs [10]. This limitation has led to companies developing their own visualization tools due to the complexity and advanced knowledge requirement for BES [3]. However, one of the recurring problems of specialized visualization is the lack of adaptability when the user is interested in relating different metrics and parameters [11]. Likewise, these dashboards do not have the ability to modify the charts according to particular purposes. Thus far, there is no data visualization tool that can analyze and compare scenarios based on custom parameters [10].

Being able to understand the metrics of the data collected in a dynamic, interactive, and personalized way allows for better decisions to be made when optimizing and improving performance [12–14], as well as for awareness and motivation/learning [15,16]. Additionally, there is currently a great variety of types of visualization, each of them having different levels of complexity. Therefore, several types of graphs, plots, and charts are used in the interdisciplinary field of data visualization in order to communicate information efficiently. Hence the characteristics of an effective graphical representation are: clarity, precision, and efficiency [17], considering that visual information should not only be useful but also meaningful [18–20].

Moreover, graph types can be organized in relation to: data dimensions (univariate or multivariate analysis), types of variables (numeric or categoric), as well as functional categories, such as comparison, relationship, distribution, and composition, among others. Likewise, their choice depends, above all, on the purpose of the analysis, the source and availability of the data, and the target user. Furthermore, in some cases, there is a need for simple and clean graphs in order to make quick decisions; in others, the users have more advanced knowledge and require personalized charts, with the possibility of creating their own data models [21]. Overall, these graphs can be used independently or they can increase their potential by being grouped into dashboards that provide a comprehensive overview of the current situation [22]. Although the importance of data visualization is known, there is a gap in the research regarding its design, choice criteria, and uses in the field of building energy analysis [9,13,15].

Intelligent energy control in buildings is an important aspect towards sustainability [23–25], and Internet of Things (IoT) technology is leading this transformation due to its ability to store, process, and exchange huge amounts of data [22,26]. By monitoring the target infrastructure through sensors and actuators, IoT technology gives an overview of the current situation of energy costs and consumption, allowing the user to have complete insight of the parameters at all times [24,27,28].

In many cases, these platforms include the graphical representation of data as an intrinsic feature; in others, they are supported by visualization software with a wide variety of charts. By providing an interface with the database and a Machine Learning (ML) tool for faster processing and improved efficiency, these platforms help users with no prior experience to better understand their information and data for future decision making. Although the opportunity to visualize data through dashboards is provided, Sarikaya et al. [29] emphasized the difficulty that exists when using pre-established dashboard tools, as they fail to reflect the multiple and varied needs of users, not allowing them to clearly interpret their data. It is important that visualization tools are adapted to the goals and intended scopes of the study [30] and become more "case-focused" [21].

Regarding this issue, the use of interactive tools capable of presenting complex information on a single display and making use of various types of visualization charts can be introduced [14,31]. In fact, several articles have already reviewed a great variety of visual analytics; however, the scientific literature is still lacking in organizing these visualizations into useful categories according to the types of building energy analysis and their levels-of-detail (LOD) of data.

On that respect, some research proposes new graphs, but the difference between their visual and functional design is clear, as these charts are often quite eye-catching, but due to the need to include as many variables as possible, they end up being complex and overloaded with information. The target of these visualizations is always a researcher, and the dialogue takes place, for the most part, between those in the same research field. On the contrary, other studies concentrate their efforts on testing graphics especially on occupants, i.e., people who do not have analytical data literacy. In order to study the effective understanding of data and the consequent impact on their behavior, typical and easy-to-understand graphs are compared, without developing new strategies or proposing new directions.

Existing data visualization reviews focus on presenting various types of graphs, cataloging them according to their ability to show variables or dimensions, but how should building energy performance be communicated for a better understanding of the trends, outliers and recurrences present in the data? How can both the consistency of data and the correct choice of parameters to be analyzed be verified? How should the information be displayed in regard to the analysis goal and the chosen design parameters? More specifically, under what criteria should professionals choose the most appropriate visualization to avoid misinterpretation and decision inaccuracy?

Therefore, the aim of the article is to review the current state-of-the-art in visualization techniques used in the field of building physics and energy systems, making a distinction between two types of building energy analysis: performance simulation (static inputs/prediction, mainly to support design purposes) and monitoring (changes in data over time, mainly for verification of buildings' actual energy performance). This overview can be used as a starting point when choosing the most efficient data visualization for a specific type of energy analysis.

The paper has been organized into four sections. Section 2 describes the research approach and methodology. Section 3 illustrates the research findings and outlines the literature gaps. Finally, Section 4 draws the conclusions and highlights possible future works for this line of research.

2. Method

The method consists of four phases. In the first phase, the visualization tools published in the scientific literature are analyzed, as well as the IoT platforms and visualization software currently used in the energy management of buildings. The literature enables the identification of the visualization techniques and tools used when analyzing the energy information of buildings, while the platforms and software cover the state-of-the-art in practice. In the second phase, the goals of the energy report analysis related to the target user are defined. Furthermore, in the next phase, the levels-of-detail (LOD) used to organize data presented in the literature are identified. Finally, in order to understand which graphs are the most used when carrying out a building energy analysis, two scopes are identified: building energy performance simulation and building energy monitoring.

2.1. Review

Relevant articles were searched for in the following scientific databases: Scopus, Web of Science, ScienceDirect, IEEE Xplore, MDPI, SpringerLink, ACM Digital Lib, and Taylor & Francis, while the most relevant IoT platforms and visualization software tools used for energy performance purposes were searched for using Google. The inclusion criteria for the selection of publications were:

- Types: Articles and conference papers;
- Period: published in the last 5 years (from 2017);
- Language: English;
- Keywords: ("energy efficiency" OR "energy consumption" OR "energy performance" OR "energy metrics") AND (building OR construction) AND "simul*" OR "moni-

tor*" AND ("data visualization" OR "data display" OR "dashboard" OR "graphical representation" OR "data representation" OR "visual analytics").

Due to the focus of the article, publications that did not have graphic results were discarded, as well as those focused on an urban scale. In addition, platforms or software covering scopes very different from building energy analysis or lacking in details and visualization examples were omitted.

These searches were updated on 18 February 2022. A total number of 48 relevant documents, 22 visualization tools and 28 IoT platforms, were selected. In addition, a review of the most important references of the selected articles was carried out, which led to a total of 48 results. These last articles were selected even though they do not meet the year of publication requirement.

2.2. Types of Graphical Representation of Energy Data

The types of visualization found in the scientific literature and in the IoT platforms are shown in Figure 1. In order to obtain an overview of the general pros and cons of each method, their main attributes and characteristics were analyzed (Figure 2). It is observed that graphs are limited to the most common types, relying on the combination of different types to deepen the analysis. A varied coverage of functionalities in the field of building energy performance is observed, comparison and distribution being the most recurrent categories.

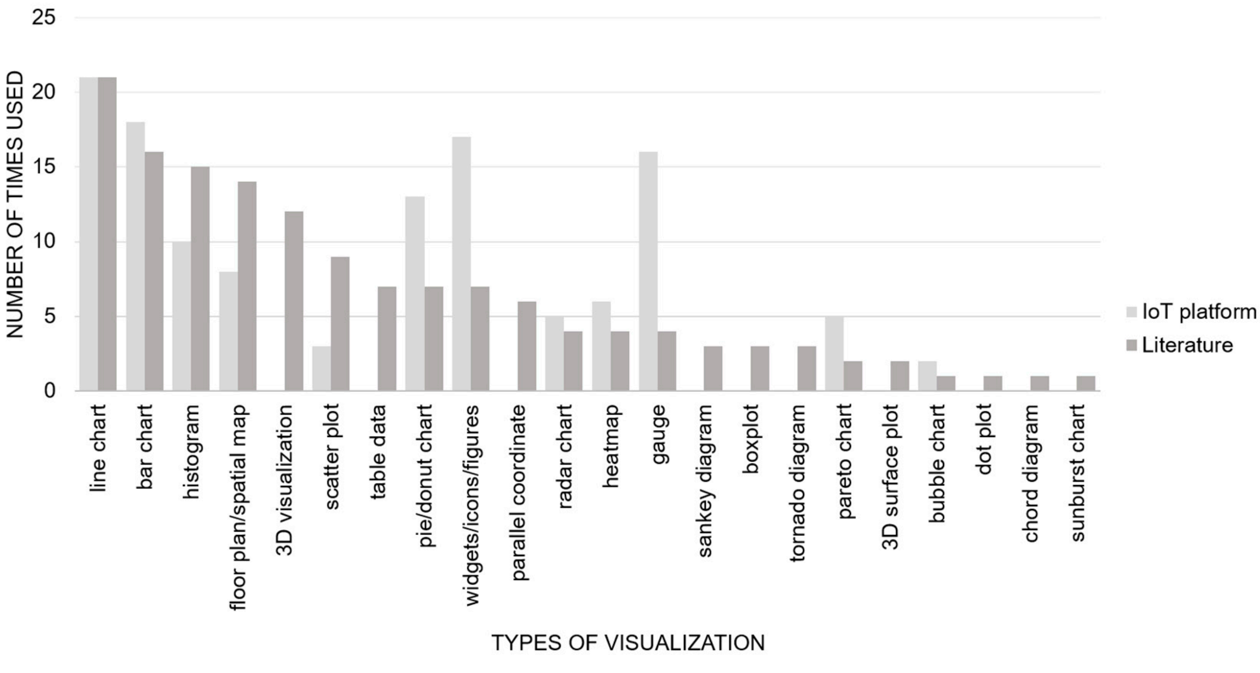

Figure 1. Visualization types found in scientific literature and IoT platform review.

There is a propensity to use graphs that allow data to be grouped while maintaining accurate values. These visualizations tend to be clear, simple, and functional, rather than aesthetic. This result is presumed to be because 90% of these graphs are primarily intended for an expert user.

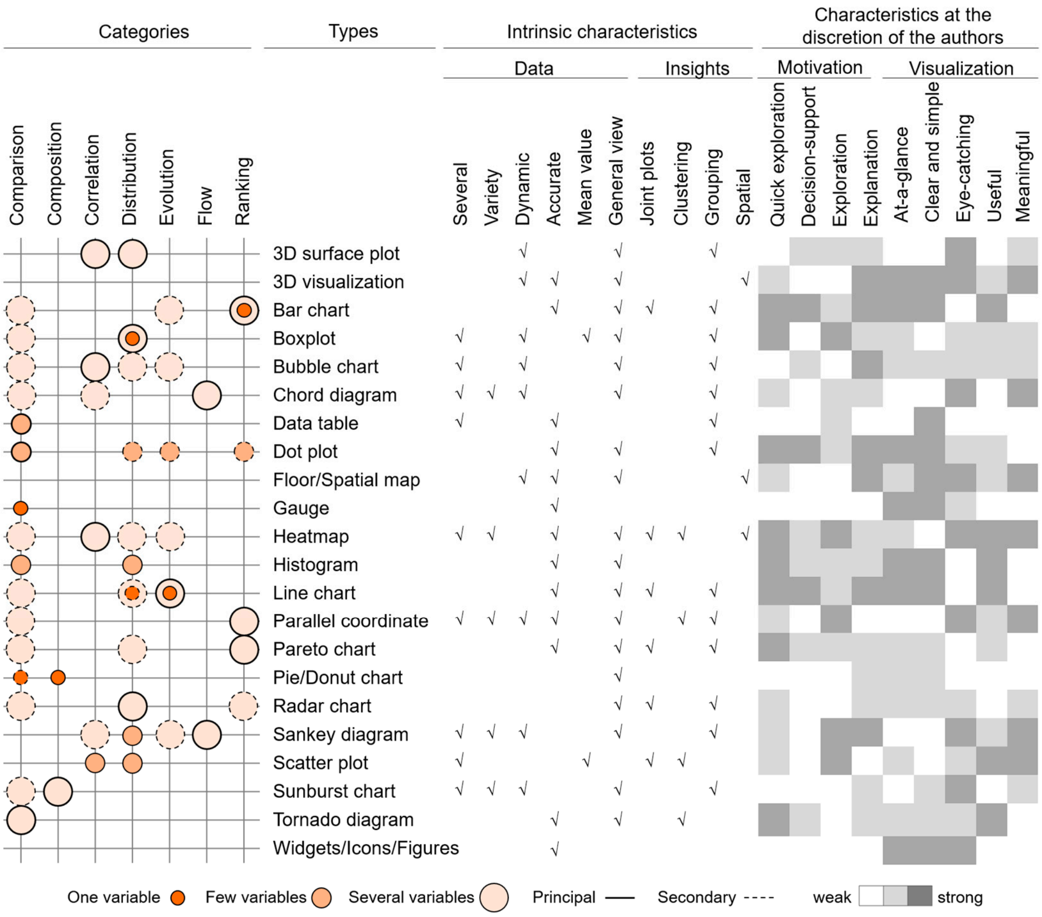

Figure 2. Most commonly used types of graphical representation of data in scientific literature, IoT platforms, and visualization software in relation to functional categories and characteristics.

2.3. Goals of the Energy Report Analysis

Based on the literature reviewed and the experience of the authors, the indicators of a building's energy performance as well as their variables were grouped according to the following categories: environment perception (temperature/comfort, relative humidity, air quality, daylight/luminance/glare, ventilation, and noise values), building geometry and thermal performance (geometry, envelope, occupancy, HVAC equipment), and energy consumption (general consumption, equipment, lighting, heating and cooling).

In addition, three key goals, with a strong relation to the target user, were identified when interpreting energy data:

- Decision making. The visualization technique used to display data, as well as the choice of metrics, can affect and influence decision-making processes [10,29,30]. These graphs must be able to communicate information clearly and effectively. In this situation, visualization should help in identifying key metrics, hotspots, risks, and trends in order to optimize operations. Two levels of decision making are identified in this category: operational and strategic. The visualization techniques used in the operational field are quantitative and informative, describe the current and recent situation and enable the execution of short-term processes. On the other hand, strategic decisions are qualitative and proactive, and have a broader time vision. In this case, metrics of different levels of detail are combined, thus allowing long-term decisions with global consequences to be made. For this goal, it is recommended to use at-a-glance graphics where the most important and critical information is prioritized and prominently displayed, as well as to use alerts or benchmarks to identify trends and insights [29]. Users interested in achieving this goal are expert professionals in the field, such as architects, engineers, operators, developers, and building managers, among others.

- Awareness. Being aware of the information behind data and of the importance of metrics is of great interest when making decisions, whether for expert users or occupants without prior knowledge. For this goal, graphics are usually static and display short-term information in operational dashboards [29].
- Motivation and behavior-addressing. User's behavior drastically influences the energy consumption of a building [32–34]. As a result, the identification of the most efficient method to visualize energy performance, which helps in motivating and educating users, has become a recurring research topic [35–37]. For this goal, narrative becomes essential, and the logical and temporal order must be maintained.

2.4. Levels of Detail (LOD) of Data Analysis

To facilitate the analysis of information, it is necessary to know how to choose and present the adequate amount of data and parameters without saturating and cluttering the graphs [30]. The complexity of the visualization can limit the understanding and lead to a misleading interpretation [14,38]. Visualization tools are more accurate when information is subdivided into levels of analysis [39]. Therefore, to catalog the different types of visualization used in the building energy report, the following LOD of data analysis proposed by Gadelhak et al. [10] are used in this paper:

- Design space overview and exploration. In this first level, a general exploration of the largest number of available parameters is proposed, among which it is possible to choose and filter the information according to objectives, giving to the user the control of their data [40]. Additionally, a 3D space visualization and/or floor plans of the building should be shown to contextualize the information.
- Sensitivity analysis and parameter relations. At this LOD, it is recommended to select and analyze the relationship between two or more variables in order to obtain specific information relevant to the user. Here, the graphical representation of multidimensional data is necessary, being easier to understand when performing correlations [12].
- Detailed results and comparison between options. The last level should present the detailed data of the chosen parameters and should enable the comparison between performance optimization alternatives (i.e., two or more design options of energy consumption due to the choice of one material instead of another, of a specific Heating, Ventilation, and Air-Conditioning (HVAC) system, etc.).

2.5. Types of Building Energy Analysis

There are two alternatives in the study of building energy analysis:

- Simulating the performance. One of the main objectives of building energy analysis is to be able to optimize performance. In order to improve the process, it is necessary to understand its operation and quantify relevant aspects [41]. BES tools, by modeling the project and incorporating the necessary inputs, provide the possibility to simulate realistic behavior and to compare design alternatives [42].
- Monitoring the performance. Data can be collected and stored through sensors, IoT devices and smart meters in existing buildings. An optimal visualization of data from real-time monitoring may allow the facility manager to quickly identify problems and provide corrections.

3. Results and Discussion

The choice of the most appropriate type of data visualization is generally given through the workflow detailed in Figure 3. The method starts from the user's need, specifying the scope and objectives of the energy report analysis.

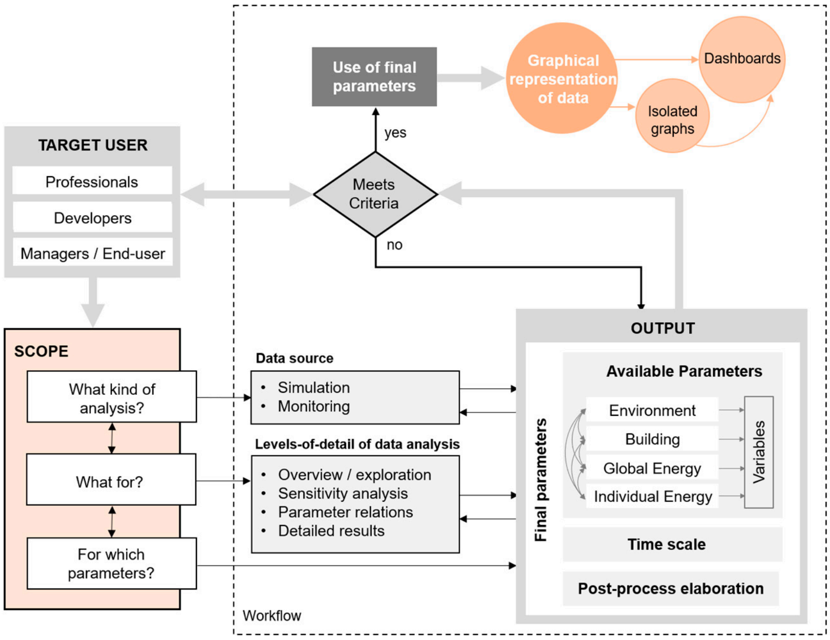

Figure 3. Workflow to identify the most suitable graphical representation of data.

In order to define the LOD of data analysis, it is necessary to identify the type of building energy analysis performed, whether it is simulated or monitored, to determine data granularity, available parameters, and time-scales. After a post-processing procedure, where data are refined to improve the accuracy of the acquired insights [43], the final available parameters are obtained. If this result meets the given criteria, data can be graphically displayed; otherwise, it is necessary to recalibrate the preceding process. Graphs can be presented in an isolated way or in a dynamic process, such as dashboards.

3.1. Scientific Literature

The complete list of tools reviewed in the scientific literature is shown in Table 1. These tools were analyzed by considering four features:

1. Visualization technique. More than half of the tools (53%) present energy results in isolated and unrelated visualizations, while the other half (47%) have designed a dashboard-like interface that allows for exploring data in an organized way, contextualizing the information and hierarchizing graphics. In the latter case, the interface allows the user to interact with the information [44–50], choose parameters [10,33,51–57], and analyze the context through 3D visualizations [10,50–52,56–58] or floor plans of the building [10,44,53,56,58]. It is also noted that the dynamic capacity of data visualization is an underutilized feature in the tools. This attribute is aimed at expert users and is related to other parameters within dashboards [10,47,51,54,58].
2. LOD of data analysis. The information may be explored through different levels of detail, thus presenting the possibility to choose comparable parameters. A fundamental need to initially show global consumption values is observed in most of the tools. This possibility allows users to have an overview of the variables and parameters that influence the performance of the building. At the next LOD, 36% of the tools enable the analysis and comparison of variables according to the user's objective (i.e., subdivide the building's energy use by categories and/or areas to identify the error in the performance if one is present or study the frequency of particular events), even comparing design alternatives in search of performance optimization strategies [10,51,59]. Regarding the third LOD of data analysis, 40% of the tools allow the user to delve into the specific value and, through interactions such as clicks, identify the variables that influence the metrics according to time periods [2,53,59,60]. Moreover, they allow the association of these variables with consumption ranges [1,55,59,61], presenting data divided by zones or

environments [33,53,58] and parameters or categories [44–46,49]. Likewise, at this same level, it is possible to compare metrics to a performance time-scale [47,48,51,55,59,61,62], showing values by seasons, months, days, hours, and sub-hours.

3. Tool testing, either using data from a real case or testing the tool with users through interviews or focus groups. Most of the tools (95%) have validated the data presented in the graphs since they are derived from real case studies of buildings whose performance has been simulated or monitored for a certain period of time. The only exceptions found respond to a purely graphic exploration of data [49] and to a presentation focused on the BIM-GIS integration systems where only the display mechanisms are explained [50]. By contrast, only 33% of tools have been validated with their target user; this is a problem that many authors indicated as a limitation and a future research topic [2,10,44,46,50,52,63,64].
4. Guiding system. Having a system that guides the reading of graphs could help users with poor analytical literacy to comprehend the information displayed [15,21,29,62]. Even so, in this review, only five tools have guidelines, and this is only due to the use of interviews or focus groups that require them [16,35,45,54,65].

Table 1. Summary of the main characteristics of the visualization tools considered in this review.

	Dashboard			Levels of Detail (LOD) of Data Analysis					Tool Testing		
				Design Space Overview and Exploration		Sensitivity Analysis and Parameter Relations	Detailed Results Comparison between Options				
Reference to Paper	**Visual Interface**	**Dynamic**	**Interactive: Click (c) Pan (p), Zoom (z) Rotate (r), Export (e)**	**Context (C) and Parameters (P)**	**Exploration**	**Variable-Objective Analysis**	**Comparison between Options**	**Detailed Results**	**Building Data**	**Users**	**Guiding System**
[10]	√	√	c, p, z	C, P (*)	√ (*)	√ (*)	√ (*)	√ (*)	√		
[1]		√		C (*)	√		√ (*)	√	√		
[62]						√	√		√	√	
[66]						√	√		√		
[35]			c	C, P	√				√	√	√
[67]				C, P					√		
[44]	√		c	P	√			√	√		
[63]			c		√ (*)	√			√		
[16]					√				√	√	√
[68]					√			√	√		
[69]	√		c, p, z		√		√		√		
[38]					√				√	√	
[45]	√		c		√			√	√	√	√
[33]	√		c	C, P	√		√	√	√	√	
[34]			c, p, z	C, P	√		√	√	√		
[58]	√	√		C, P	√		√		√	√	
[60]				C	√			√	√		
[46]	√		c	C	√	√		√	√		
[47]	√	√	c, p, r		√ (*)		√		√	√	
[48]	√		c		√ (*)		√		√	√	
[70]					√	√	√	√	√		
[51]	√	√	c, r	C, P	√		√		√	√	
[71]			c, z, p		√	√			√		
[52]	√		c	C, P	√	√			√		
[64]		√	c, p, z, r		√	√			√		
[72]					√	√	√	√	√		
[61]				C	√	√	√	√	√		
[49]	√		c, p, z		√ (*)	√ (*)	√ (*)	√ (*)			
[53]	√		c, p, z	C, P	√		√	√ (*)	√		
[2]			c, p, z, r, e		√	√	√	√	√		
[59]			c, p, z, r, e		√	√	√	√	√		
[50]	√		c	C	√						
[73]	√	√	c, p, z, r, e	C, P	√	√		√	√	√	
[54]	√	√	c	P	√	√	√		√	√	√

Table 1. *Cont.*

	Dashboard			Levels of Detail (LOD) of Data Analysis					Tool Testing		
				Design Space Overview and Exploration		Sensitivity Analysis and Parameter Relations	Detailed Results Comparison between Options				
Reference to Paper	Visual Interface	Dynamic	Interactive: Click (c) Pan (p), Zoom (z) Rotate (r), Export (e)	Context (C) and Parameters (P)	Exploration	Variable-Objective Analysis	Comparison between Options	Detailed Results	Building Data	Users	Guiding System
[65]					√		√		√	√	√
[74]				C	√		√		√		
[75]					√		√		√		
[76]					√	√	√	√	√		
[37]	√		c, p	P	√	√	√	√	√		
[77]					√	√	√	√	√		
[55]	√			P (*)	√		√	√ (*)	√		
[56]	√		c, p, z, e	P (*)	√				√		
[78]			c		√			√	√		
[42]				C	√	√		√	√		
[57]	√		c, p, z, e	C, P	√				√		
[79]	√	√	c, p, z, e	P	√	√		√	√		
[80]					√				√		
[81]				C, P	√	√		√	√		

Note: (*) customizable.

3.1.1. Types of Visualization Used in Relation to the Goal of the Analysis

When choosing the best way to visualize energy data, more than one graph can be used at the same time, but these types are the same ones being used constantly. Line and bar charts are the most used graphs, having been identified in 26 and 20 scientific papers, respectively. Likewise, it is observed that more complex graphs, which offer the possibility of analyzing multiple data dimensions or attributes (e.g., bubble charts and boxplots) and hierarchical graphs (e.g., sunbursts) are used less frequently. Furthermore, 3D visualizations and floor plans are used in a large number of tools as a visual and contextual support, thus reinforcing the presentation of quantitative graphics [82].

In relation to the goal of energy report analysis, authors predominantly focus their visualizations on a professional/expert user in the field of energy management (Table 2). These users need to be aware of the building's energy performance in order to make informed decisions. Among the charts aimed at this purpose, in addition to the typical lines and bars, histograms, scatter plots, parallel coordinates, as well as pie charts and their variations were found. In most cases, these graphs complement data tables that present the same numerical information [1,10,51,57,58,63,64], giving the expert user the opportunity to interpret data under different possible relationships between variables.

The literature focused on energy performance visualization presents a wide variety of types of presentations and techniques of use. Literature presenting case studies as the main goal use common graphs, such as line, bar, and pie charts. Moreover, some papers present information with just one type of chart in which the time-scale and variables change, and these can be presented in isolation or as a composition. Some examples of graphs used in these papers are Sankey diagrams [62], heatmaps [66], radar charts [53], parallel coordinates [63,71], scatter plots [78], and sunbursts [75].

Even though many authors focus on the simulation of building energy performance, not much difference is observed between graphs used for this purpose or for real-time monitoring. However, an important difference is observed between the use of line and bar charts and other types of visualizations when monitoring performance: these graphs are frequently used in the scientific literature and are considered the most effective visualizations not only for experts who need to identify benchmarks or hotspots, but also for occupants who are interested in knowing peak consumption and understanding its origin [13,16,65].

Furthermore, for this group of non-expert users, the use of widgets, icons, and/or figures is a constant [16,33,45,58,65]. This strategy could help at-a-glance interpretation and improve data comprehension [29,54].

Table 2. Number of occurrences per visualization type, per goal of the energy report, per user, and type of building energy analysis.

		Line Chart	Bar Chart	Floor Plan/Maps	3D Visualization	Histogram	Scatter plot	Data Table	Pie/Donut Chart	Parallel Coordinate	Widgets/Icons/Figures	Radar Chart	Heatmap	Tornado Diagram	Gauge	Sankey Diagram	Boxplot	Pareto Chart	3D Surface Plot	Dot Plot	Chord Diagram	Bubble Chart	Sunburst Chart
Result goal	Decision making	18	15	13	11	14	9	7	6	6	4	4	4	3	3	3	3	2	2	1	1	1	1
	Awareness	9	6	6	5	6	0	2	4	1	5	2	1	0	3	0	1	0	0	0	0	1	0
	Addressing Motivation/ Behavior	3	2	3	1	2	0	0	1	0	3	1	0	0	1	0	1	0	0	0	0	0	0
User	Pro/Expert	18	15	13	11	14	9	7	6	6	4	4	4	3	3	3	3	2	2	1	1	1	1
	Occupant	5	4	4	2	3	0	2	3	0	4	2	1	0	2	0	1	0	0	0	0	1	0
Analysis	Simulation	13	12	12	8	11	7	5	6	6	4	4	4	2	3	3	3	2	2	1	1	1	1
	Monitoring	11	4	5	4	8	2	3	2	0	5	1	0	1	2	0	1	0	0	0	0	0	0

Note: Some types of visualization have been considered in more than one alternative due to their capacity for multiple goals or intentions indicated by the authors. The values indicated do not represent the number of articles reviewed, but rather the number of times each technique has been used for this purpose.

3.1.2. Types of Visualization Used in Relation to Performance Indicators

The types of visualization found in the reviewed literature have been analyzed in relation to the energy data they display: performance indicators, time-scales and units of measurement (Figure 4).

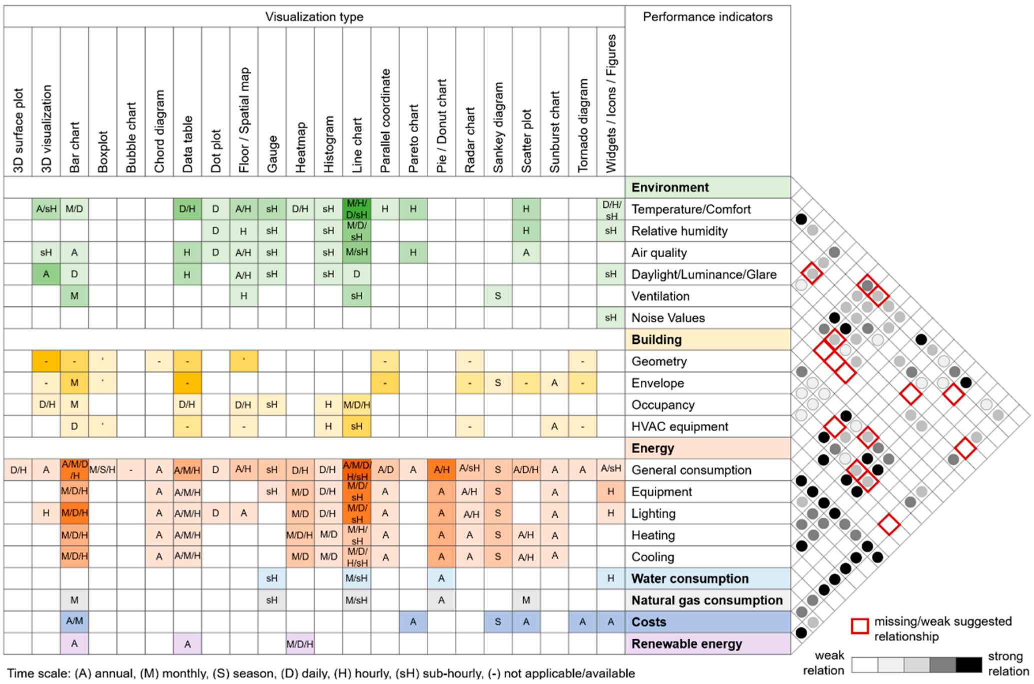

Figure 4. Visualization types in relation to building performance indicators and time-scale.

All graphs were analyzed according to the following categories:

1. Environment perception. Temperature/comfort and relative humidity are the most recurrent variables and generally presented in a single graph. When the data source is a simulation, the time-scale is predominantly monthly and daily; when it comes to monitoring data, the main scales are hourly and sub-hourly. Generally, the graph

chosen in these cases is a line chart. In relation to daylight/luminance/glare, a trend towards its relationship with geometry variable is observed. This is presented by means of 3D visualizations and/or floor plans at an annual time-scale, when the analysis is simulated, and sub-hourly when it is monitored. Although air quality and ventilation are closely related variables, a weak relationship has been observed in the analyzed graphs. Ventilation is usually associated with temperature/comfort and presented as a line graph on an hourly scale.

2. Building geometry and thermal performance. Geometric data are usually shown through 3D visualizations and floor plans, often accompanied by a data table that deepens the information displayed. Although the geometry and envelope variables play an important role in the internal temperature/comfort of the building, no strong relationship has been observed between these parameters. When the geometry and envelope of the building are associated, bar charts, parallel coordinates, radar charts, and tornado diagrams are regularly used. When analyzing building occupancy through simulations, line and bar charts with daily and hourly time-scales are preferred; when monitoring, 3D visualizations, floor plans, and gauges are additionally used. Some graphs have been prevalently used to represent air quality in relation to occupancy, but in no case has occupancy been associated with noise values. This may be due to the fact that this review focuses on the energy domain rather than comfort.
3. General energy consumption. There are several types of visualization used in the field of energy consumption. Among the most representative, line, bar, pie/donut, and radar charts have been notably used to show general consumption in simulations with annual, daily, and hourly time-scales. In relation to monitoring, in addition to those already mentioned, gauges and widgets/icons/figures were identified when at-a-glance and eye-catching visualizations are needed. Heatmaps have been used to visualize average demands over a given time [77,78] and compare performance between individual consumption patterns [73]. However, this graph gains even more relevance when data are visualized spatially with the support of 3D visualizations or floor plans [29,40,53,64,67]. Likewise, the use of Sankey diagrams to visualize energy flows [61,74] and associate them with costs [62], using colors to compare values and differentiate flow levels, has been identified as useful for professional/expert users. In the latter case, the author specified that such information does not necessarily facilitate the identification of problematic operations and that inexperienced users could have difficulty considering the values as efficient or not. Tornado diagrams and radar charts are used when energy performance is simulated and display information on an annual scale. The first one is used to visualize the influence of design variables in relation to its performance [2], load factors [59], and costs [54], while the second is used to compare design alternatives in relation to energy savings [10], as well as multiple variables and key performance indicators [46,53].
4. Individual energy consumption. Line, bar, and histogram charts are chosen to display monthly, daily and hourly lighting consumption, while pie/donut charts show just annual data. No relation is observed between lighting and daylight/luminance/glare parameters, despite the fact that their association often derives from cause–consequence analysis. Furthermore, it is noted that the lighting–geometry relation is not as strong as expected. Although papers focus on the final energy consumption rather than analyzing the underlying causes, it would be useful to show data of both variables in a single graph to study the correlation. Regarding heating and cooling consumption—the most studied parameters in the field—sunburst charts, parallel coordinates, and chord diagrams are the common visualization types chosen to present annual data as an overview, while bar and line charts, heatmaps, histograms, and scatter plots are preferred when the aim is to understand behavior over shorter periods of time. Parallel coordinates, in most cases, show interrelated design variables and attributes [10,52,71], allowing one to identify the impact generated by the design alternatives in general consumption and achieve a "direct reading key" between input and output [63]. Fur-

thermore, the use of the pie/donut chart and its variations is observed in the following cases: when showing the total consumption and its subdivisions by category, e.g., heating, cooling, lighting, and hot water [51]; when comparing consumption between spaces [1] and equipment [45]; and when monitoring [48,50] and predicting [61] minimum and maximum consumption, with the help of color differentiation. In addition to the typical line and bar charts, which seem to have the ability to adapt to all parameters and purposes, scatter plots and histograms are the most versatile visualizations. Scatter plots are used when different variables must be related to one or more objectives [2,10,55]. It offers the possibility to identify patterns [78] or separate clusters [71] in search of anomalies and allows for the analysis of design performance according to different alternatives [54]. Histograms have proven useful when comparing hourly and daily consumption [55,62,64], as well as weekly and monthly variations [44,47,60,61]. Historical performance and design variables can also be plotted using this graph [38,54].

5. Water and natural gas consumption. For the study of these parameters, line and bar charts associated with widgets/icons/figures, data tables, or gauges were identified when data monitoring activities are being displayed. Scatter plots are used in simulations on a monthly scale, mainly due to the availability of water and gas bills.
6. Costs and renewable energy. Costs related to consumption are represented annually by means of bars, scatter plots, Pareto charts, and tornado diagrams. Likewise, presentations of renewable energy use are always related to cost and general consumption and thus use bar charts and heatmaps. It is noted that this information is not commonly displayed and is not related to other parameters.

In relation to measurement units, it was found that the kW was the most used unit to measure electrical consumption, being associated with geometry and users, as well as annual divisions of the building's total consumption (%). Meanwhile, to evaluate energy performance, the energy use intensity (EUI) and the energy efficiency index (EEI) were the most used indicators to summarize information and emphasize results (Figure 5). These measurements have been identified in clear and simple graphs (e.g., line and bar charts, radars, histograms, heatmaps, and data tables), supported by interactions and commonly associated with other plots to deepen the presented information (Figure 6).

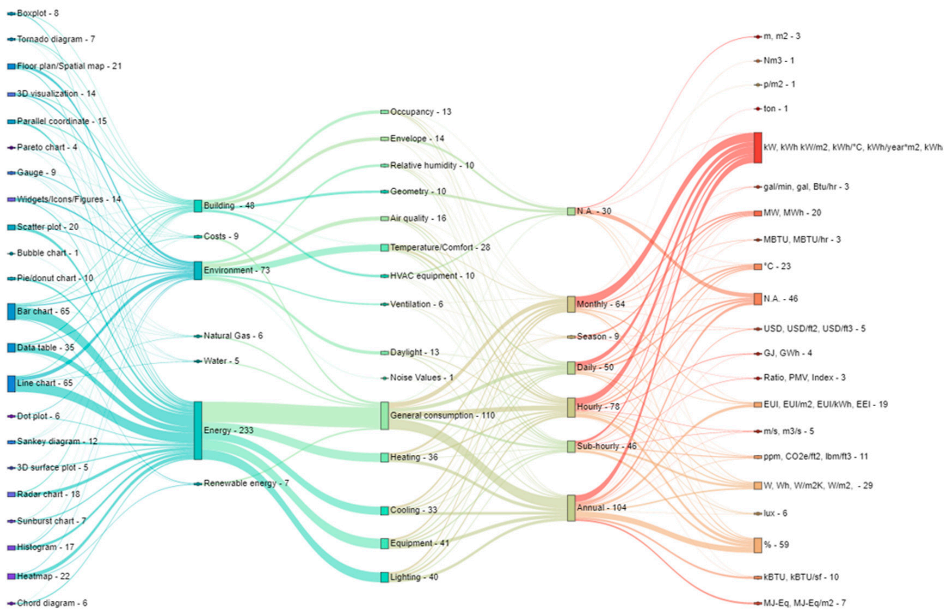

Figure 5. Relationship and trends between visualization types, energy performance indicators, time-scale, and units of measurement. The values indicate the number of occurrences found.

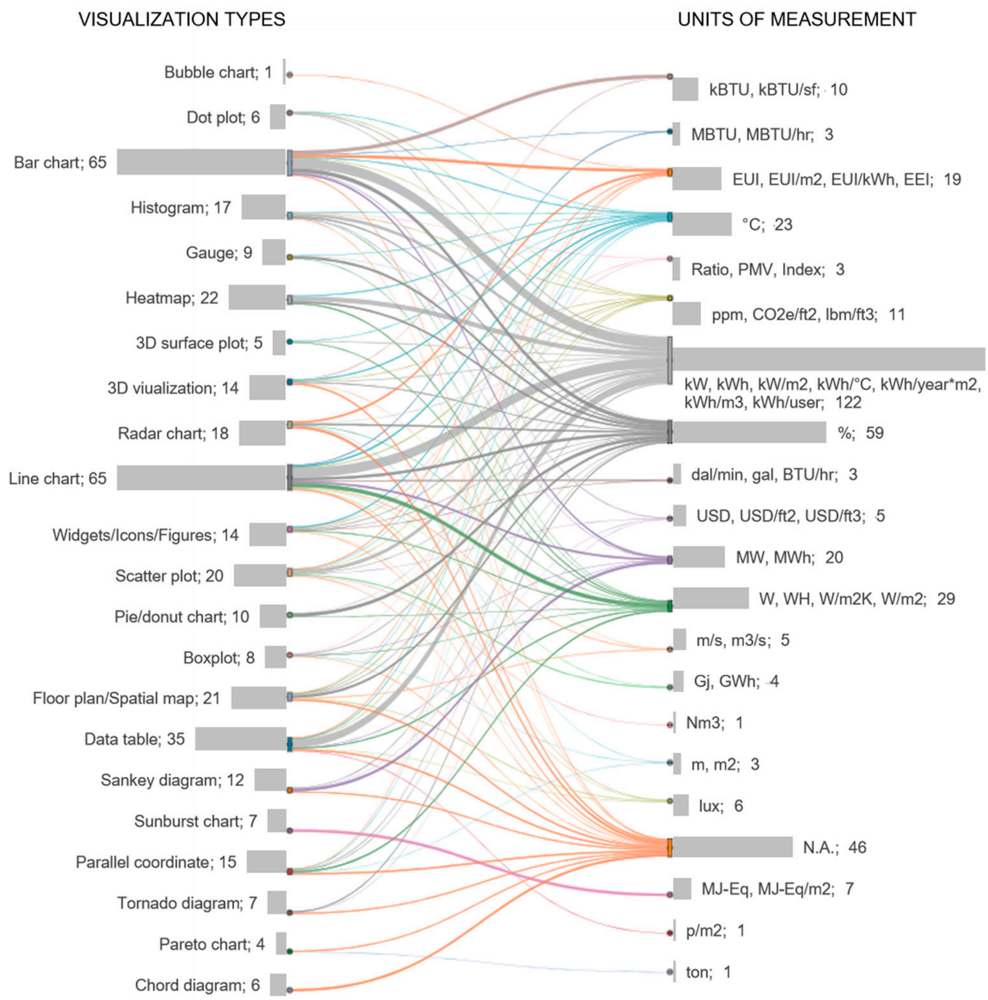

Figure 6. Relationships and trends between visualization types and their units of measurement. The values indicate the number of occurrences found.

3.1.3. Synthesis of Visualizations According to the Type of Building Energy Analysis

The results of the analysis of data visualization types are summarized in Figure 7. In order to understand which graphical representations are the most used according to the type of building energy analysis, a subdivision by categories is presented. On the left side of the table, the types are related to the goals of the interpretation phase, while the LOD of the data analysis is shown at the top. The visualizations are color-coded to differentiate the number of times each graphic is used in the scientific literature. The red color indicates that the use of the graphic has been identified many times, yellow indicates less use, while the gray color indicates its use only once.

Having noticed that awareness is a shared goal between professionals/experts and occupants, users were divided according to two main purposes: decision making and motivation/learning. This classification allows the identification of the most used types for each of the LODs.

In the initial exploration phase, eight charts were identified as the most used graphics when making decisions in both types of performance analysis (i.e., simulations and monitoring): line charts, histograms, bar charts, pie/donut charts, scatter plots, data tables, and radar charts. When displaying combined simulation results, parallel coordinates is a recurring option, followed by boxplots, Pareto charts, and heatmaps. By contrast, when monitoring data, widgets/icons/figures are used for detecting hotspots. Dynamisms such as alerts allow trends to be identified and for mitigating measures to be taken. Furthermore, when the goal is to motivate and educate the occupant, the use of contextualized charts, such as 3D visualizations and floor plans/maps, is a trending strategy, aiming to help a non-expert user to better understand the metrics. Their use is observed mainly in simulations, taking advantage of the model previously elaborated in the preceding phase.

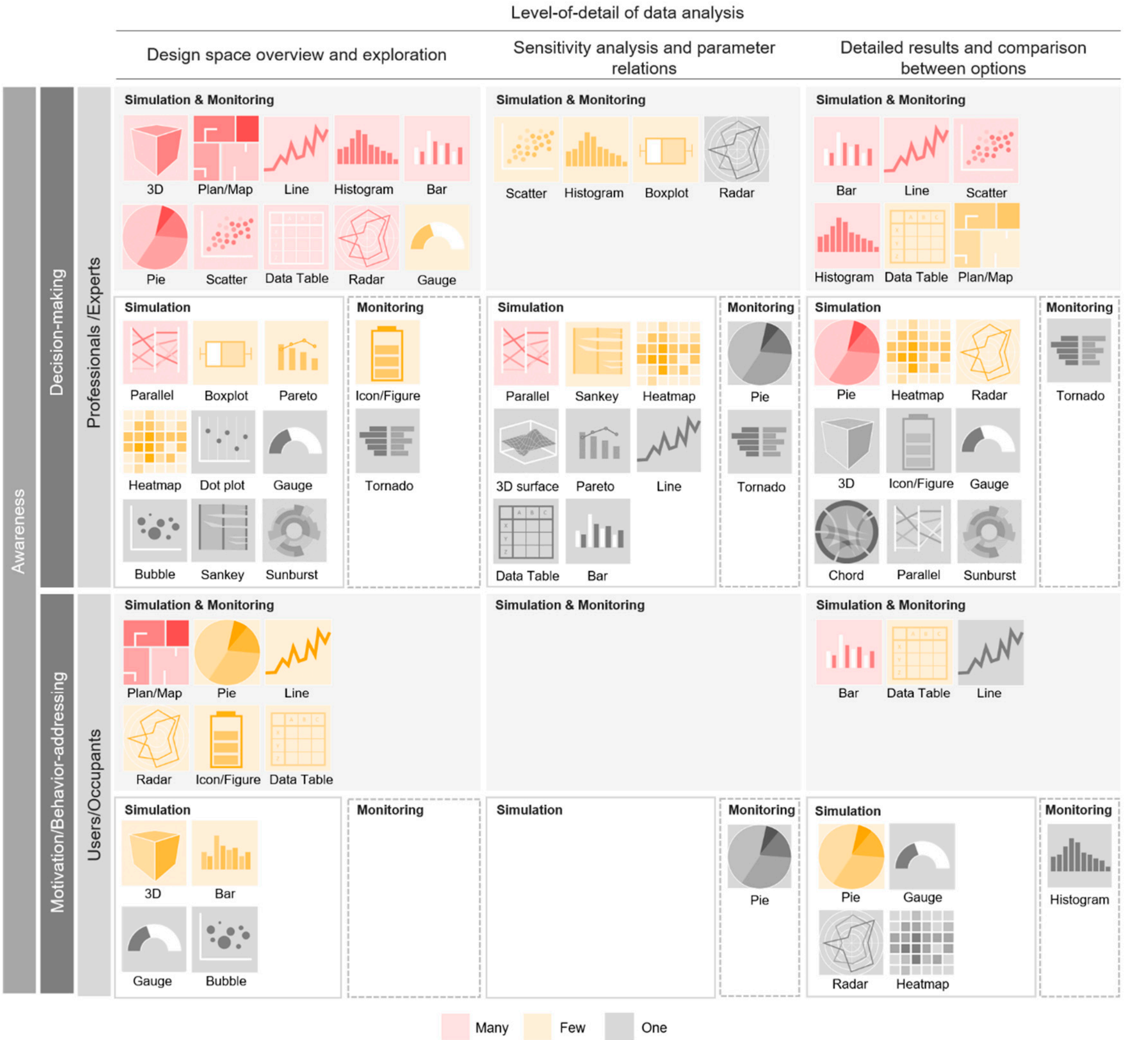

Figure 7. Graphical representations per type of building energy and level of detail of data analysis in relation to users.

The use of scatter plots, histograms, and boxplots is observed in the second LOD. These graphs, focused on an expert user, allow multiple variables to be related at the same time and facilitate the analysis of sensitive data. Specifically for combined simulation analysis, the tendency to use parallel coordinates is once again observed, but for monitoring, no predilections were identified. In this case, pie/donut charts and tornado diagrams were used to subdivide and present data by annual categories. The only chart aimed at occupants was the pie chart, most likely because this graph allows one to observe data in real time by dividing the total consumption by services.

The use of line and bar charts, scatter plots, and histograms was mainly observed when analyzing results in detail and comparing the performance between design options. The visualization of this kind of information is intended for energy experts with decision making power. Among those chosen for occupants, pie/donut charts were again prioritized for simulation, while for monitoring time-series, histograms were chosen due to their ability to show frequency distributions.

In order to deepen the analysis and prioritize expert users, such as professionals, developers, managers, and end-users, the graphical representations in relation to the types of building energy analysis, whether simulation (Figure 8) or monitoring (Figure 9), are presented.

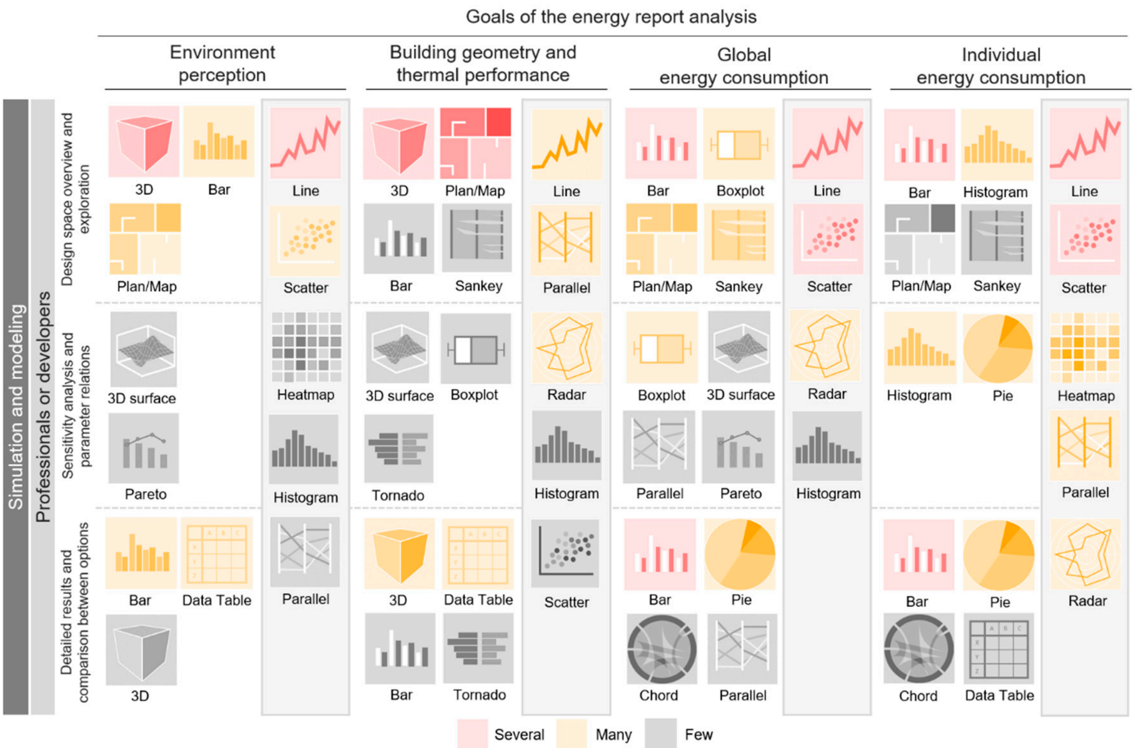

Figure 8. Graphical representations per goals and level of detail of data analysis for simulation and modeling.

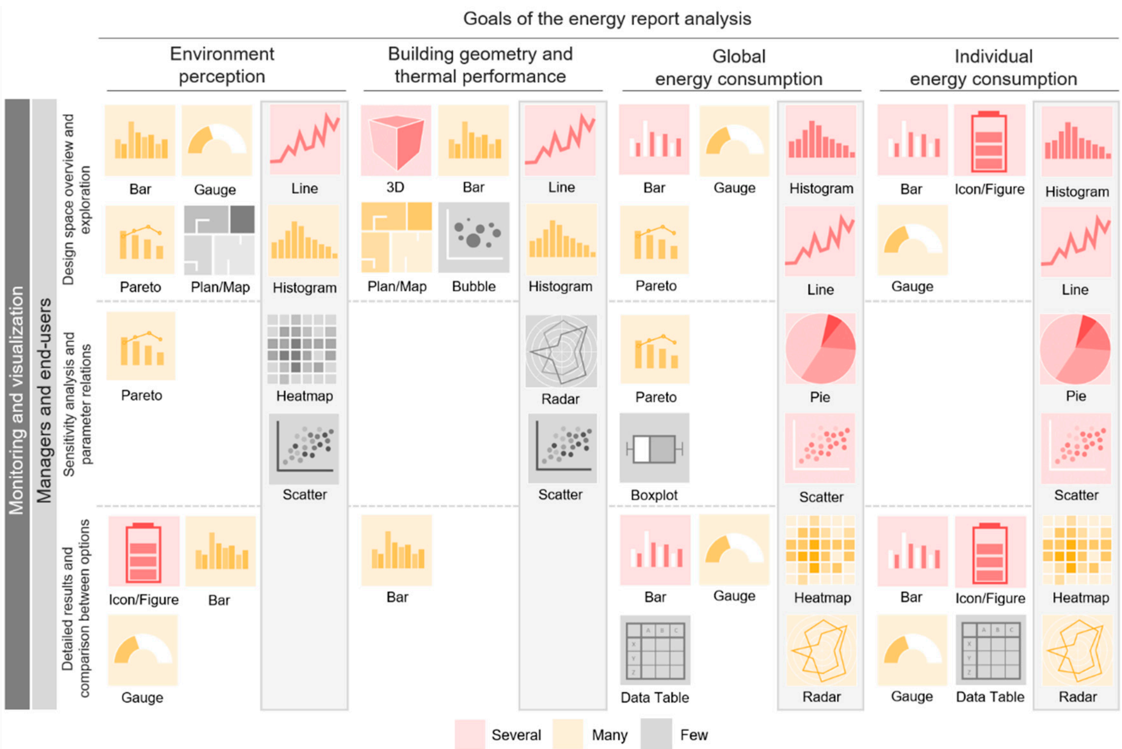

Figure 9. Graphical representations per goals and level of detail of data analysis for monitoring and visualization.

BEPS are developed and analyzed by highly trained professionals in the energy field capable of obtaining relevant information from collected data. Performance monitoring and visualization, on the other hand, could also be analyzed by managers and end-users. Certain trends and preferences were identified when analyzing these two types of energy analysis in relation to the goals and LOD of the data:

- When an expert wants to simulate energy performance, the 3D visualization used in the modeling phase is still useful in the exploratory and overview phases. Such visualization makes it possible to understand the building in its entirety—its orientation, geometry, and thermal performance due to materials, as well as having a spatial perception of the interior and exterior environment. Then, to delve into the energy analysis of specific sectors or areas of study, floor plans, line and bar charts, and scatter plots are included to display trends of custom variables, as well as understand flows in greater detail through Sankey diagrams. At the next LOD, experts tend to carry out a sensitivity analysis, studying changes generated in one or more variables when certain variations are introduced in the original model in order to understand the limitations and scopes of any decision made in this regard. In this context, boxplots, parallel coordinates, heatmaps, and histograms are identified as the most used graphs for this purpose, being subsequently associated with radar and pie/donut charts as summary displays. When a rigorous analysis of the results is necessary, it is observed that data tables are used to review data in depth, while bar charts are usually used to compare possible options/scenarios. Likewise, the trend/need to prioritize interactions in graphic visualizations is observed as it allows for magnifying, hiding, showing, and isolating metrics to deepen a specific analysis.
- By contrast, a user who needs to visualize and monitor the building's energy performance in real-time, in addition to the typical line and bar charts, requires dynamic, at-a-glance, and eye-catching visualizations. Under this scenario, it can be inferred that gauges, widgets/icons/figures, pie/donut charts, and radar charts gain unexpected relevance as a result. In this specific type of analysis, 3D visualizations and floor plans are useful to contextualize the information, but not as exploratory means. The need to display graphs that are not only interactive but dynamic, with automatic updates, flexible interfaces, and the ability to use and prioritize different graphs in the same display, is observed almost exclusively in this type of analysis. Hence, there is a tendency to create dashboards through visualization software (Table 3) or use pre-established templates on IoT platforms (Table 4).

3.1.4. Interactive Dashboards as a Supporting Strategy for Decision Making

Energy results, whether derived from simulation or monitoring, need graphical representations in order to be understood effectively. In this research, it was found that the choice of the most appropriate graph depends on key factors: data source and availability, goals of the energy analysis, and target user. Likewise, prioritizing a single graph without context, without explanation of the findings or situational comparisons, restricts the scope of interpretation and limits decision-making. For this reason, the fluid integration of different types of graph, where the user is allowed to explore and control the information, is necessary [31,40]. The graphs must complement each other and be presented with a certain hierarchy, prioritizing some of them and emphasizing important results [83].

In this regard, some examples of dashboards have been identified. These cases take advantage of the visual and functional aspect of the interfaces, providing an interactive display that allows the "monitoring of dynamically updating data" [29].

Following a hierarchical approach, Gadelhak et al. [10] proposed an interface that allows an overview of the building situation as well as detailed data through different types of graphs. Each one of these panels is interrelated, and the information is dynamically updated according to the user's interaction (Figure 10). With another approach, Stavropoulos et al. [53] presented energy results using color-coded radar charts in relation to floor plans, allowing the information to be contextualized (Figure 11). This interface is not dynamic, but it allows the user to interact with the graph by displaying screens simultaneously. In the same direction, Lin et al. [52] presented a dashboard developed for SketchUp, where it is possible to identify issues and optimize the building performance through 3D visualizations (Figure 12).

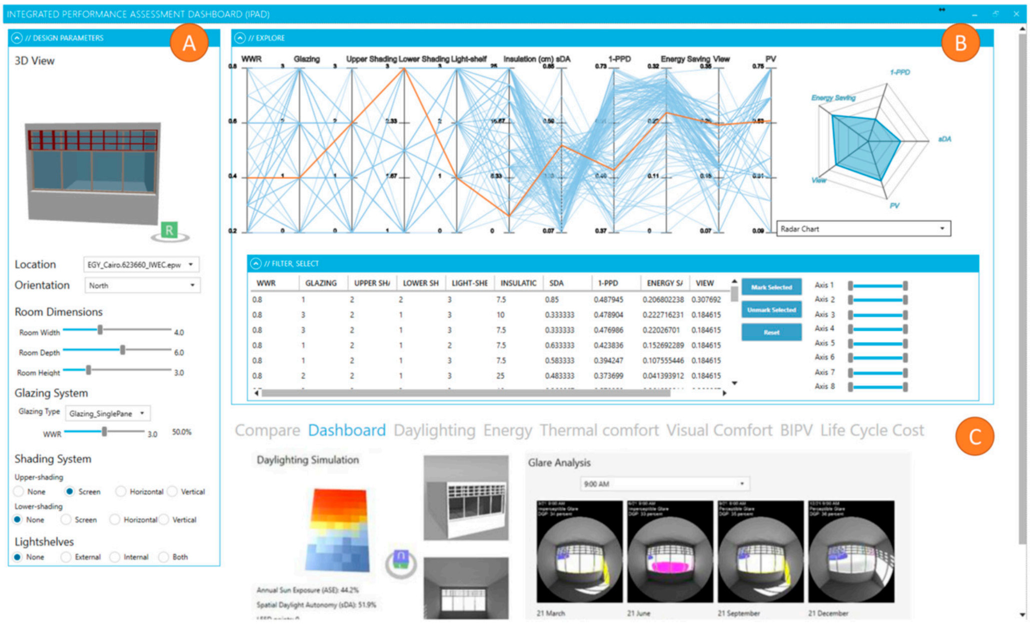

Figure 10. Visualization interface: (**A**) context and design parameters panel, (**B**) explorer panel, and (**C**) integrated dashboard. © (2017) eCAADe 35 conference proceedings, from Gadelhak et al. [10].

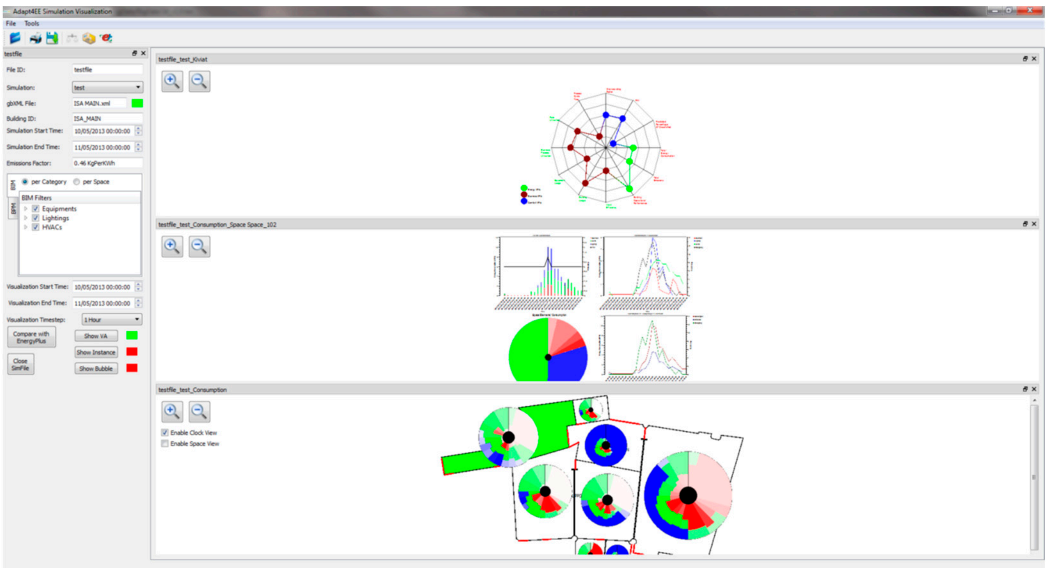

Figure 11. Visual analytics application. The tool gives the possibility to view multiple screens simultaneously. © (2022) IEEE. Reprinted, with permission, from Stavropoulos et al. [53].

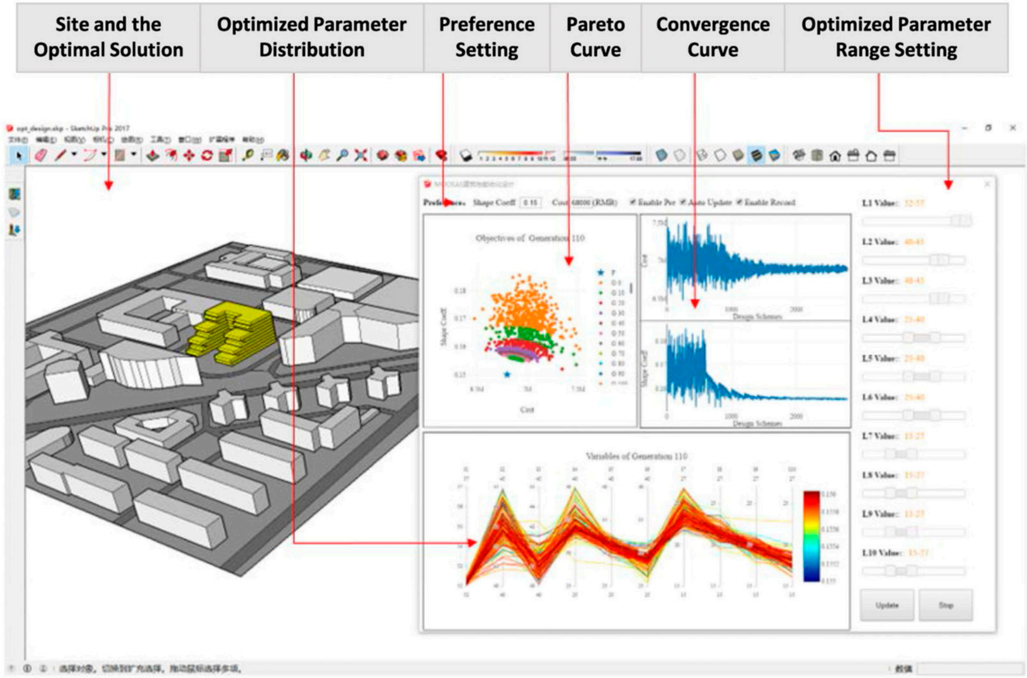

Figure 12. Building Performance Optimization (BPO) application developed on SketchUp. Reprinted by permission from Springer Nature License: Building Simulation, A preference-based multi-objective building performance optimization method for early design stage, B. Lin et al. [52], © (2022).

Dashboards allow different scenarios to be seen simultaneously, offering the possibility to simplify visualizations or detailing them according to the user's need [30,68]. This interaction between user and data is subject of constant study, and technological advances, such as virtual-reality/augmented-reality (VR/AR) could accentuate this connection [84,85]. Shen at al. [64] presented an intuitive virtual interface capable of displaying energy performance results directly on the built environment. This new way of visualizing metrics in "near real-time" could make it easier to interpret results and enable more effective optimization measures. The virtual building approach could have a high communicative potential and its future studies could help to reduce the gap between users with diverse data analytics literacy [86].

3.2. Data Visualization Tools and Platforms

3.2.1. Software Development Tools

When processing large data sets and interpreting the information is an immediate need, automating these processes can help significantly. Table 3 shows tools that have been identified as highly useful and versatile in the field of building energy analysis. Their characteristics and potentials are pointed out, as well as the variety of chart types offered.

These tools have a few things in common. Although some of them require a high knowledge of programming, most have developed an intuitive interface that is easy to use, with tutorials and blogs that allow for interaction between users and exchanges of information. Another practical feature of these tools is the management of multiple data sets that can be viewed on a single screen as a dashboard. These visualizations are often accompanied by dynamic graphics and give the user the opportunity to interact with their data. Additionally, the possibility of customizing the charts, changing colors, labels, positions, and parameters is a capability that all these tools provide. On the contrary, historical or predictive data analyses, as well as the management of detection processes through alerts according to benchmarks, are qualities that are not fully exploited.

It is interesting to observe that, even though tools that specialize in a few types of visualizations tend to have better-quality graphics (e.g., ChartBlocks, Charts.js, Chartist.js), those that present a greater variety are preferred (e.g., Tableau, Google Charts, Grafana).

Moreover, it has been noticed that, although the possibility of choosing between several visualizations is given, in the field of buildings' energy efficiency, the chosen charts are always the same: line, bar, and pie/donut charts; histograms; data tables; tree maps; tornado diagrams; and sunburst charts. Comparably to the scientific literature, it is observed that scatter plots, Sankey diagrams, and parallel coordinates are used when prior knowledge of energy data literacy and/or programming language is assumed. As a result, these charts are usually associated with other simpler one-dimensional charts, such as line and bar charts.

Table 3. Data visualization software development tools.

Software Tools	Source	Free Version	Dashboard	Dynamic	Interactive	Customizable	Historical Analytics	Predictive Analytics	Data Alert	Chart Types
Bokeh [87]	open	available	√	√	√	√	-	-	-	M
ChartBlocks [88]	open	available	√	n/a	√	√	n/a	n/a		F
Chartist.js [89]	open	available	√	√	n/a	√	-	-	-	F
Charts.js [90]	open	available	√	√	√	√	-	-	-	F
D3.js [91]	open	available	√	√	√	√	-	-	-	M
DataHero [92]	n/a		√	n/a	n/a	√	n/a	n/a	n/a	F
Datapine [93]	closed		√	√	√	√	√	√	√	S
Dundas BI [94]	n/a		√	√	√	√	√	√	√	S
Dygraphs [95]	open	available	√	√	√	√	-	-	-	M
FusionCharts [96]	open		√	√	√	√	-	-	-	M
Google Charts [97]	open	available	√	√	√	√	n/a			S
Grafana [98]	open	available	√	√	√	√			√	M
Infogram [99]	n/a	available	√	√	√	√	n/a			S
Klipfolio [100]	n/a	available	√	√	√	√	n/a	n/a	n/a	S
Looker [101]	n/a		√	√	√	√	√	√	√	S
Matplotlib [102]	open	available	-	√	√	√	-	-	-	M
Plotly [103]	open	available	√	√	√	√	-	-	-	S
Power BI [104]	closed	available	√	√	√	√		√	√	S
Qlikview [105]	closed	available	√	√	√	√	√	√	√	S
Sisense [106]	open		√	√	√	√	√	√	√	F
Tableau [107]	open	available	√	√	√	√	√	√	√	M
Zoho Analytics [108]	open	available	√	√	√	√	n/a	√	√	S

Note: "-" it does not apply, "n/a" information not available, "M" many, "S" several, "F" few.

3.2.2. IoT Platforms

Visualization tools provide a wide variety of charts to present information. In relation to the reviewed tools, it has been observed that, although they make displaying graphics in a dynamic and interactive interface possible, they do not seem to have sufficiently flexible attributes to meet the multiple needs of users [21,83]. Likewise, the need to expand the customization options, extend the functionalities of the tools and hierarchize the graphs has been identified as fundamental [29]. These improvements could allow variables and parameters to be modified instantly, as well as organize and prioritize graphs according to the metrics and goals established by users. In this context, IoT platforms could be positioned as key tools in energy data management [109] by allowing the use and creation of personalized interfaces.

The complete list of reviewed IoT platforms is shown in Table 4. The systems were analyzed in relation to four categories of metric performances: thermal and energy data and water and gas values. In addition, the table indicates if visualizing graphical information as well as customization is a possibility. As a final consideration, it was reviewed whether these platforms offer the possibility of analyzing historical information.

Despite the fact that all platforms support data visualization, only 68% allow for customization. Correspondingly, the same number of platforms (19) allow data to be analyzed historically. Upon closer examination, it is observed that the personalization of graphics requires a greater mastery over the system, as well as a demand for additional time to program the interface. Even though in all cases the tools present guides and blogs that seek to resolve user's problems, this does not align with the automatic and agile characteristics that the same platforms want to sell.

IoT platforms offer a wide variety of very useful charts for the industrial, business, health and transport sectors, while for the energy consumption of buildings, this offer decreases. As a consequence, the same types of graphs identified in the scientific literature were found. Although some software and platforms allow users to create and/or choose between visually captivating graph options, it seems that familiar charts provide some security and avoid possible confusion around data interpretation caused by less used ones.

Table 4. IoT platforms.

IoT Platform	Source	Scale	Thermal	Energy	Water	Gas	Visualization	Customizable	Historical Analysis	Chart Types
Adafruit IO [110]	open	all	-	-	-	-	√	√		F
Al Faruque and Vatanparvar [27]	open	home	√	√			√			F
Ali-Ali et al. [8]	closed	home	√	√			√		√	F
Arduino IoT [111]	open	all	-	-	-	-	√	√	√	F
Azure IoT [112]	closed	all		√			√	√	√	F
Blynk [113]	open	all	-	-	-	-	√	√	√	F
Cayenne [114]	open	all	-	-	-	-	√	√	√	F
CREST [115]	closed	home		√			√			S
Device Hive [116]	open	all	√	√			√	√		M
Empower [117]	closed	home	√	√			√		√	S
GridPoint [118]	closed	all	√	√			√	√	√	S
HEMS [119]	closed	home		√			√			F
Honeywell [120]	closed	all	√	√			√	n/a	n/a	S
Initial state [121]	open	all	-	-	-	-	√	√	√	S
Kaa IoT [122]	open	all	√	√	√	√	√	√	√	F
LoBEMS [48]	closed	all	√	√			√		n/a	S
Open Remote [123]	open	all	-	-	-	-	√	√	√	F
Sisense [106]	open	all	-	-	-	-	√	√	√	S
Tera4Buildings [124]	closed	all	√	√			√	√	√	F
Thethings [125]	open	all	-	-	-	-	√	√	√	F
Thinger [126]	open	all	-	-	-	-	√	√	√	S
Thingsboard [127]	open	all	-	-	-	-	√	√	√	F
ThingSpeak [128]	open	all	-	-	-	-	√	√	√	S
Ubidots [129]	open	all	-	-	-	-	√	√	√	M
WattsOn [130]	closed	home		√			√			F
Wibeee [131]	closed	home & business		√			√	√	√	S
WSo2 [132]	open	all	-	-	-	-	√	√	√	M
SEM [133]	closed	home	√	√			√			F

Note: "-" it does not apply, "n/a" information not available, "M" many, "S" several, "F" few.

These findings are supported by surveys and interviews with experts/professionals in energy monitoring and analysis as well as users/occupants of the buildings. Lehrer and Vasudev [36] conducted a survey involving 70 professionals and confirmed that data analysis remains an intense process, where 27% "still relay on data exported and manipulated in spreadsheet programs". Francisco et al. [35] used a user survey (200 people with no previous experience with visualization tools) to validate some spatial and color-coding techniques in BIM, corroborating that 2D visualizations facilitate the understanding of results better in comparison to common charts and technical units. In a survey of 25 undergraduate and graduate students with backgrounds in energy efficiency, Nimbarte et al. [45] compared different types of dashboard designs. The use of gauges, pie charts, and widgets produced quicker responses and higher engagement and interest. Masoodian et al. [37] conducted a user study to compare the effectiveness of different charts. It was found that time-stack visualization is more accurate when comparing energy usage data. Furthermore, Herrmann et al. [16] conducted a laboratory experiment (n = 43 university students) where they confirmed that the combination of simple visualizations makes the information easy to understand and motivates responses from users.

4. Conclusions

Building energy data require accurate graphical representations in order to be understood effectively. These visualizations could provide useful and meaningful information in the decision-making process for the improvement and optimization of a building's energy performance. This paper presents a review of the state-of-the-art visualization techniques used in the field of energy performance, making a distinction between two types of building energy analysis: simulation and monitoring. Visualization tools published in the scientific literature, as well as those currently used in IoT platforms and software developments, were analyzed. The review showed that most tools use common graph options, such as line and bar charts, to display energy consumption data. In the same way, when there is a need to compare parameters or analyze sensitive data, the use of scatter plots, parallel coordinates, histograms, and radar charts are preferred due to their ability to analyze multidimensional data or attributes.

There is a tendency to use and combine common and well-known graphs instead of using more complex options or creating new forms of representation, even though the inclusion of more variables and features could help to discover hidden insights. From this perspective, it could be assumed that the information is displayed through these graphs due to convenience, as they are the easiest to create and interpret [78]. Graphs such as boxplots, heatmaps, parallel coordinates, and scatter plots are intended mainly for professionals/experts since it is particularly challenging to represent and interpret plots containing more than two variables. In view of the fact that understanding the origin of energy consumption and the relationship between its parameters is of interest to all users, these complex graphs are often associated with 3D visualizations and floor plans in order to contextualize the information and facilitate its comprehension.

When simulating building energy performance, charts such as heatmaps, scatter plots, and parallel coordinates are consistently used to analyze high-dimensional datasets and visualize distributions, potential relationships, patterns, and/or correlations, prioritizing color codes for at-a-glance communication. Likewise, there is a tendency for joining plots and multidimensional graphs with one data variable, such as histograms and density or bar plots, to quickly visualize relationships and individual distributions on the same plot. In the specific case of monitoring, due to the need to visualize dynamically updated data, clear and simple graphs, such as line and bar charts, are preferred, mostly accompanied by disaggregated charts such as pie/donut charts, radar charts, and tornado diagrams. These visualizations provide an insight into energy usage by dividing the data into areas, categories, and variables. Moreover, in this type of analysis, the use of data tables as a means to expand information and delve into metrics and parameters is observed. Widgets, icons, and figures complement the presentation, especially for non-expert users.

Building energy performance data can be communicated in different time scales. The most used temporal frequency is the monthly one, often being subdivided in days and hours. Such a time scale allows users to understand the seasonal performance and its fluctuation. In the specific case of monitoring, the sub-hourly time scale becomes important, mainly due to the availability of detailed data from the used sensors.

In comparison with isolated graphs, dashboards could be the most effective tool to analyze results, but only if they have been designed in a personalized way and with a clear purpose and goal. In this regard, the association of contextual graphics, such as 3D visualizations and floor plans, as well as exploratory graphics should be enabled by these interfaces.

In addition, the selection of more detailed charts, for example, scatter plots, parallel coordinates, and histograms, should be observed on the same display through interactions.

The differences found in data visualization techniques reflect the need for more flexible and customized functions in relation to the user's visualization and analytic literacy and the objective of the analysis [13,29]. It is also necessary to delve into the relationship between aesthetics and functionality in terms of visual impact and effectiveness [13]. In this context, the creation of templates, organized according to goals and types of energy analysis, could help identify anomalies and trends with greater accuracy.

It seems clear that with the evolution of technology and the constant need to process big data, visualization techniques have become a relevant subject of study. Although having a clear analysis goal, choosing the necessary level of detail and knowing the target-user are helpful in designing an effective tool, choosing an appropriate visualization technique remains a challenge due to the lack of guidelines and successful user-tested case studies. In consequence, future steps for this research will be directed towards (1) the comparison of these results with surveys and interviews of professionals/experts and users/occupants; (2) the development of robust dashboard tools for different application scenarios and target users; (3) the validation of developed tools by focus groups; and (4) the proposal of guidelines for the development and application of data visualization techniques. Additionally, future works could analyze more case studies and application tests to evaluate the support of graphical data representation in the design, simulation and monitoring processes.

It is hoped that the present review will provide a foundation on which future research on the graphical representation of building energy reports can be developed.

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