

Article

Unlocking Insights: A Cloud Tool for Data Visualisation in a Smart Meter Project

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Abstract: Nowadays, the large amount of data generated by society has led to a dependency on data analysis and visualisation tools. Therefore, the objective of this research was to implement a cloud-based tool to improve the visualisation of data obtained from 4G network simulation on smart meters. Two stages were carried out in order to analyse and process the data using a cloud-based tool to support data visualisation and to understand and facilitate effective decision-making. This resulted in a remarkable 27.39% increase in average data quality, thanks to the authenticity and reliability of the data obtained through the 4G LTE network on smart meters. It also had a significant impact on the percentage of data read and displayed, with an increase of 63.70%. Finally, the percentage of useful data when applying the tool in the cloud also increased by 47.30%. This allows end users to visualise and understand the behaviour of electricity meters with an LTE network through a customised dashboard.

Keywords: data visualisation; smart cities; simulation; Universidad Nacional de Cañete



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1. Introduction

Nowadays, the exponential growth in the amount of data generated in different areas of society, known as the “big data” phenomenon, has given rise to the imperative need for efficient tools that enable the analysis and visualisation of this data in an accurate and comprehensible manner [1,2]. This avalanche of information poses significant challenges in terms of processing and understanding, and it is here that the sensible introduction of big data technologies becomes relevant in driving statistical analysis of data with greater depth and scope [3]. These technologies make it possible to process more complex information in a shorter time and to cover a wide range of content that was previously difficult to address. However, there are crucial challenges in data analysis and visualisation in the context of big data that include improving the accuracy of models, addressing interoperability, ensuring data privacy and security and dealing with high dimensionality and model interpretation. In this context, data analytics and visualisation are not only about presenting information but also about emphasising the integration of data with business processes and decision-making [4].

Data analysis has become a cornerstone of modern market economies. Through the analysis of real data and the construction of mathematical models based on economic principles, it is possible to uncover hidden problems, assess the feasibility of investment decisions, forecast future risks and returns and provide a sound basis for evidence-based decision-making [5,6]. While these techniques have proven to be effective in many respects, they also face notable limitations, such as accuracy in predicting extreme events, interpreting highly complex data and dealing with noisy or incomplete data. In this context, the use of cloud storage technologies and data visualisation tools has become a strategic priority for organisations seeking to extract valuable information and actionable insight from their

vast datasets [7]. To achieve this, an end-to-end solution is required to effectively explore and communicate data, facilitating informed decision-making. [8].

In this context, Quicksight emerges as an essential data visualisation and analysis tool. This tool provides real-time information, predictive analytics and a user-friendly interface that has transformed the way organisations manage their data and gain valuable insights [9]. As a result, it has become a strategic ally for businesses across all industries, enabling them to adapt nimbly to changing market demands and make informed decisions quickly in an information-driven world [10].

Such a tool must possess the ability to store and access data through cloud computing services, eliminating the need to rely exclusively on local resources [11,12]. This approach provides a flexible and scalable infrastructure that allows large volumes of data to be securely stored and accessed from any geographic location [13]. The benefits inherent in using the cloud are numerous and significant, including reduced operational costs, the ability to scale resources on demand and ease of access to data, which simplifies the analysis and processing of huge amounts of information [14,15]. In short, the cloud data analytics and visualisation paradigm has emerged as an essential catalyst for informed and strategic decision-making in an increasingly data-driven environment.

In that sense, a cloud-based solution emerges as a highly interesting proposal to optimise and enrich data visualisation, an essential process that involves the graphical representation of intricate information and data in a visually appealing and understandable way [16]. This approach involves the transformation of complex data into visual elements, such as elaborate graphs, descriptive charts and interactive maps, with the aim of simplifying and making more accessible the understanding of latent patterns, trends and relationships within the information [17,18]. For example, Quicksight is a data visualisation and analysis tool developed by Amazon Web Services (AWS). It is available as a cloud service and is intended to facilitate data exploration and understanding for both businesses and professionals. Although it offers a free version with limitations, it also provides scalable payment plans to meet the needs of users with varying levels of demand and complexity in their data analytics projects.

The undeniable effectiveness of this tool has been corroborated through various case studies, showing particular promise in contexts involving technological infrastructure projects aimed at building smart cities. This technology allows simulation and data management to be carried out, generating a positive impact on the understanding of results and the adoption of decisions backed by concrete information [19–22]. However, the question of how to effectively integrate this data visualised through cloud-based tools into the planning and development process of smart cities with the aim of maximising their potential in building advanced and sustainable urban environments is still at the heart of research. In this context, there is a pressing need to educate and empower citizens to take full advantage of the wealth of information provided by these visual measurement and analysis systems. In addition, it is crucial to explore more carefully and thoroughly the methods for a smooth integration of these technologies into the evolving urban environment. This task encompasses not only the technological dimension but also the consideration of sociocultural and regulatory factors that impact the adoption and success of these innovations within today's society.

This paper aims to fill this gap by analysing the implementation of cloud tools in a smart building project, focusing on data visualisation and its influence on the understanding of results and decision-making. The aim is to improve the accessibility, clarity and effectiveness of data visualisation in the specific context of smart construction. Therefore, the aim of this research is to implement a cloud-based tool to improve the visualisation of data obtained from 4G network simulations on smart meters. This project is of significant importance as it focuses on the city of Cañete. It is a smart grid simulation that uses smart meters to calculate in real-time the electricity consumption of households in this locality. The choice of Cañete as a study scenario is not fortuitous, as it involves specific considerations and particular challenges that require a solution adapted to its context. In

order to implement this smart city model in Cañete, it is essential to carry out the necessary tests and calculations in a simulated environment, thus avoiding possible failures that could harm households in real life. This further highlights the relevance of this project in addressing the specific needs of the Cañete community and serving as a valuable example of innovation and improvement of the quality of life in this city.

In recent years, the problem of global energy scarcity has become increasingly prominent, which is a severe test for the sustainable development of mankind [23]. The contribution of this study lies in optimising the use of effective data visualisation tools for the purpose of improving the management of smart IT infrastructure projects. This approach is supported by the growing relevance of cloud computing, which provides advantages such as accessibility, high availability and security. Furthermore, this research is embedded in a broader context related to the Sustainable Development Goals by promoting the adoption of sustainable technologies and the search for greater energy efficiency in urban environments. The work is part of an effort to address crucial data and technology management issues in the current era, thus contributing to the advancement of more efficient and sustainable solutions in the field of technology infrastructure.

The article is organised as follows: In Section 2, a detailed description of the software implementation is given, including its main features and functionalities. Section 3 presents illustrative examples demonstrating the application and operation of the software in the data visualisation process. In Section 4, the impact of the software implementation on data quality and visualisation is analysed, as well as the percentage of useful data. Section 5 presents the conclusions of the study, summarising the main results and highlighting the implications of the work. Finally, Section 6 presents recommendations for future research in this field.

Relationship between cloud tools and data visualisation

Technological evolution has fundamentally transformed the way organisations store, process and analyse data. In this context, cloud tools have emerged as a comprehensive solution to address challenges in data management and visualisation. These cloud tools have not only facilitated accessibility and scalable storage but have also revolutionised the way data are presented and understood through visualisation.

Cloud tools have democratised access to data visualisation by enabling teams to access and collaborate in real time from geographically dispersed locations. Platforms such as Google Data Studio, Tableau Online and Microsoft Power BI have facilitated the creation of interactive dashboards and dynamic visualisations that can be shared and updated instantly. This has broken down barriers in terms of communication and collaboration, allowing teams to make informed decisions based on up-to-date and accurate visualisation of relevant data.

The advantages of AWS cloud computing for analytics and data warehousing are remarkable. First, it offers exceptional scalability, allowing resources to be scaled up or down according to user needs. The inherent scalability of cloud tools has addressed one of the biggest challenges in data visualisation: processing large volumes of information. Cloud platforms such as Amazon Web Services (AWS) and Microsoft Azure offer massive processing capabilities that enable efficient data manipulation and visualisation at any scale. This is especially valuable when dealing with real-time data, such as social media streams or sensor data, which must be instantly analysed and visualised to support real-time decision-making. In addition, the AWS Cloud provides a robust and secure infrastructure, ensuring data integrity and confidentiality. It also offers a wide range of data analytics-specific tools and services, simplifying the implementation of analytics projects. Flexibility and the ability to remotely access data from anywhere at any time are key features that make AWS an attractive option. In addition, its pay-as-you-go model is efficient and cost-effective. Finally, the ability to harness the power of the cloud for large-scale data processing and analytics is a significant advantage that facilitates large-scale projects.

Cloud tools have made it easier to integrate data from diverse sources, which in turn enriches the quality of visualisations. By connecting databases, applications and cloud

services, the tools enable data professionals to generate more complete and contextually relevant visualisations. This is especially relevant in an enterprise environment, where data often resides in dispersed systems. The ability to unify this data and represent it visually provides a more holistic perspective.

The integration of cloud tools with advanced analytics capabilities has led to the automation of visualisation generation and the inclusion of real-time predictive analytics. By leveraging machine learning and advanced data analytics, cloud platforms can identify patterns, trends and anomalies in data and represent them visually in the form of graphs, charts and interactive maps. This empowers users with actionable information, allowing them to make proactive decisions and respond to future events.

In short, the convergence of cloud tools and data visualisation has transformed the way organisations interact with their information. The accessibility, scalability and integration capabilities of these tools have expanded the possibilities for visualisation, enabling data professionals and businesses in general to make more informed and strategic decisions. As technology continues to advance, this relationship is likely to continue to evolve, offering innovative new ways to present and understand data.

2. Method

In this study, the hypothetic-deductive method was applied in order to analyse the theories related to the problems that exist in the data visualisation process. Based on the observations of this problem, hypotheses were formulated and corroborated throughout the research.

Type of research

This study is classified as applied research as it focuses on the practical application of the Quicksight cloud tool in the process of visualising data obtained from the smart cities: Cañete pilot plan with smart meters. Furthermore, it is considered experimental research since its main objective is to evaluate the results derived from the implementation of Quicksight in the data visualisation of this specific project. It also qualifies as explanatory research, as it seeks to analyse and understand the influence of Quicksight on the dimensions of data quality, interpretation and analysis in the context of the simulation of the 4G network in smart meters.

Research design: Pre-Experimental

Valderrama [24] reports that the pre-experimental design of a group consists of three stages:

1. Administering a pretest to measure the data visualisation process (dependent variable-process they perform manually).
2. Applying the experimental treatment, which is the Quicksight cloud tool, to the subjects.
3. Administering a post-test to re-measure the data visualisation process.

In this study, we applied the pre-experimental research design because we intend to analyse the data visualisation process before and after applying the Quicksight cloud tool.

Data analysis and processing stage

The intention behind the development of analysis and visualisation technologies is to explore methods for converting the physical world into actionable data that is incorporated by various commands and executed by an actuator (or other hardware components used to manipulate the physical world) [25]. Data collection is a precondition for analysis. The wide application of IoT in industrial production provides convenience for data acquisition [26].

In this section, we describe the process for analysing and processing the data obtained in the smart cities simulation project, with the aim of visualising it in a cloud environment. Figure 1 presents a graphical representation of the steps to be followed in this process. The ETL (extract, transform and load) process is shown below with the help of various tools that are currently known.

1. The first step is to obtain the data in CSV format generated from the smart cities simulation project. These data contain relevant information about the behaviour of the smart meters in the simulation, showing the performance of the 4G LTE network in the smart meters, which are: name, type, module, attrname, attrvalue, value, vectime and vecvalue, which are related to the communication between meters, sending and receiving packets, packet loss, response time, meter and meter group identifier, data type and values.
2. Once the data are obtained, we import it into an Excel spreadsheet to start with the data processing.
3. It is necessary to have them in orderly cells to be able to manipulate them optimally, with cleanliness and accuracy to facilitate the reading in the cloud, so they are imported into an Excel spreadsheet to perform the aforementioned treatment and then saved in CSV format.
4. The Amazon Web Services (AWS) page is then accessed via the Chrome browser.
5. Log in with the AWS account previously created. This allows you to use the cloud services.
6. AWS cloud computing offers a simple and well-documented http-based interface for computing and storage services [27]. We look for the S3 service to upload the data in CSV format and host it in a secure repository called a bucket.
7. To establish the connection between S3 and Quicksight services, a manifest file is set up in a notepad and then saved with the JSON extension. JSON manifest files are used to specify the Amazon S3 files to be imported into Amazon QuickSight. Configure the S3 bucket URIs, prefixes and global settings for the file to import.
8. Next, access the main AWS dashboard to search for and select the Quicksight service. This tool, integrated into the AWS platform, offers advanced data analysis and visualisation functionalities in an intuitive and easy-to-use environment.
9. Finally, a new analysis is initiated in Quicksight using the data hosted in the S3 service, and the previously configured manifest file is used. This stage marks the beginning of the data analysis and visualisation process, where patterns, trends and relationships are explored for valuable information that can support informed decision-making.

Visualisation Stage and its forms of sharing

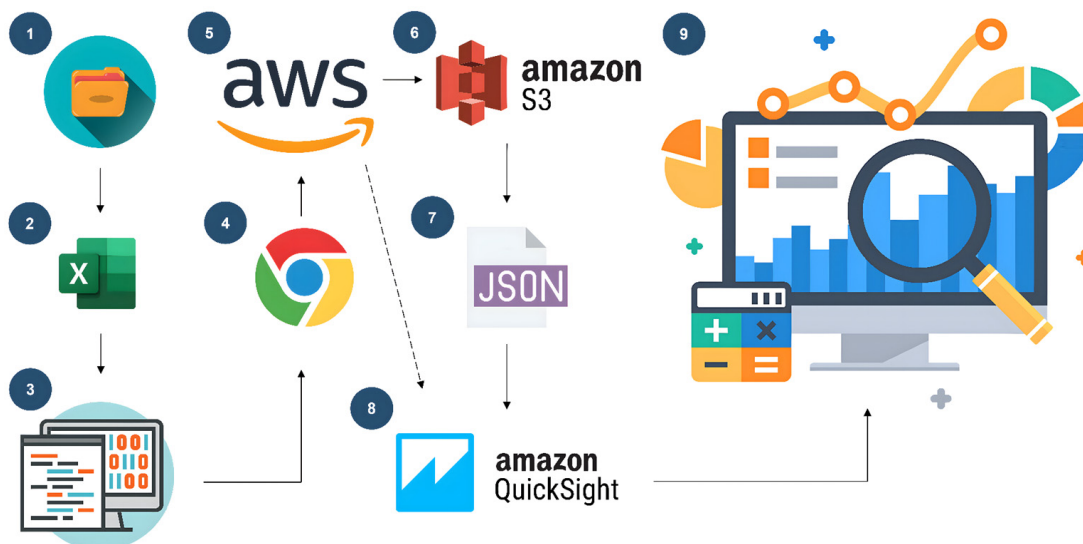


Figure 1. Steps for data analysis and processing.

In this section, the different visualisation and sharing modes offered by the Quicksight tool are explored. Figure 2 illustrates these options, which allow the results obtained from the analysis of the imported data to be communicated effectively.

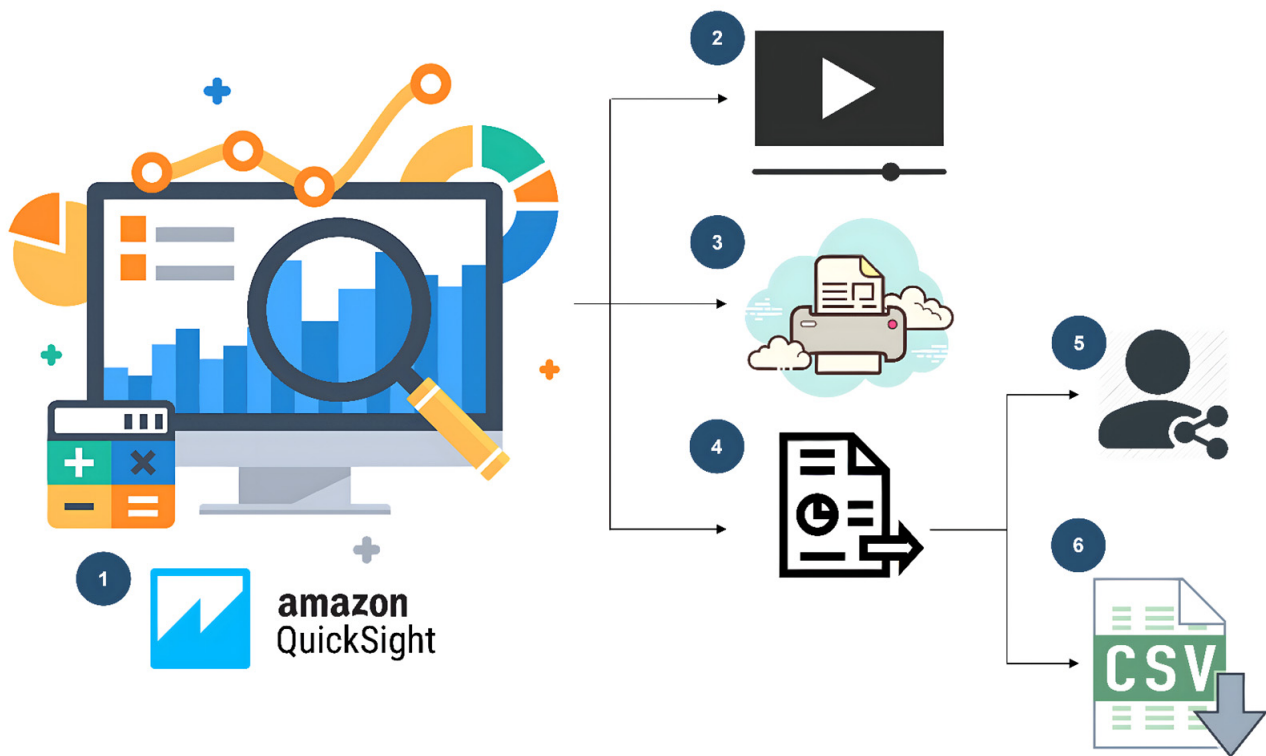


Figure 2. Forms of visualisation and their forms of sharing.

1. Once the analysis of the imported data has been performed, it is then represented in a graphical form using a variety of graph types available in Quicksight. The behaviour of the LTE network on the meters should be visualised and analysed, observing if there is good performance of the meters on the network. These graphs are carefully selected to clearly and accurately communicate relevant and necessary information for decision-making. The aim is to achieve a dashboard that is composed of individual visualisations that are coherent and thematically related to each other. They are widely used in organisations for the analysis of sets of variables and decision-making. For example, analysis of data graphs can reveal where the highest price of a house is located in a city, while analysis of a patient's medical history can facilitate early detection of a disease, allowing timely decisions to be made at an early stage [28].
2. Once the analysis is complete, it is possible to capture the results or transfer them to a multimedia format provided by Quicksight. These results can be exported to the History section, where they are stored as "Scene 1" by default. This facilitates presentations on the analysis performed, allowing effective sharing of the findings.
3. In addition, this tool offers the option to print the graphs directly from the cloud. It is possible to configure the type of sheet and orientation according to specific needs. This option allows physical copies of the visualisations to be obtained for later reference or distribution.
4. Another way to share the results is through the publication of a dashboard. This is achieved by selecting the "Share" option and then "Publish panel". A name is assigned to the new dashboard, and the actions and visual options are configured in the advanced settings. Clicking on "Publish" creates the dashboard and enables sharing.
5. Once the dashboard is created, a window is displayed that allows you to share it with other users of the tool. However, it is important to note that these dashboards can only be shared with other AWS users for security reasons. The root user has the control to manage access to the dashboard, delegate permissions and perform other necessary actions.

6. Finally, it is possible to download the analysis in CSV format. At the top right of the graph, there is an options bar that includes the export to CSV function. This option allows you to obtain a copy of the analysed data in a widely used format that is compatible with other tools and systems.

3. Results

Quicksight allows several dashboards to be produced once the data has been uploaded and preprocessed for analysis and visualisation. Figure 3 shows a dashboard made from the different insights offered by the cloud tool, focused on the objective of the project, which is to visualise the information on the performance of the LTE network in smart meters. We can see in the figure some KPIs with information on the total data, total simulated modules with their IDs, the total measurements that were made in the meters during the simulation, bar charts with the number of packets sent and received and a pie chart with the types of data that were obtained from each meter in the simulation. This dashboard helps a lot to make decisions when moving the simulated project to the real world. We can see how feasible it will be to implement these smart meters in the homes of the people of the city of Cañete. It also allows us to review if you need to adjust some methodologies or tools to save time and money in order to achieve the goal of transforming the city of Cañete into a smart city.

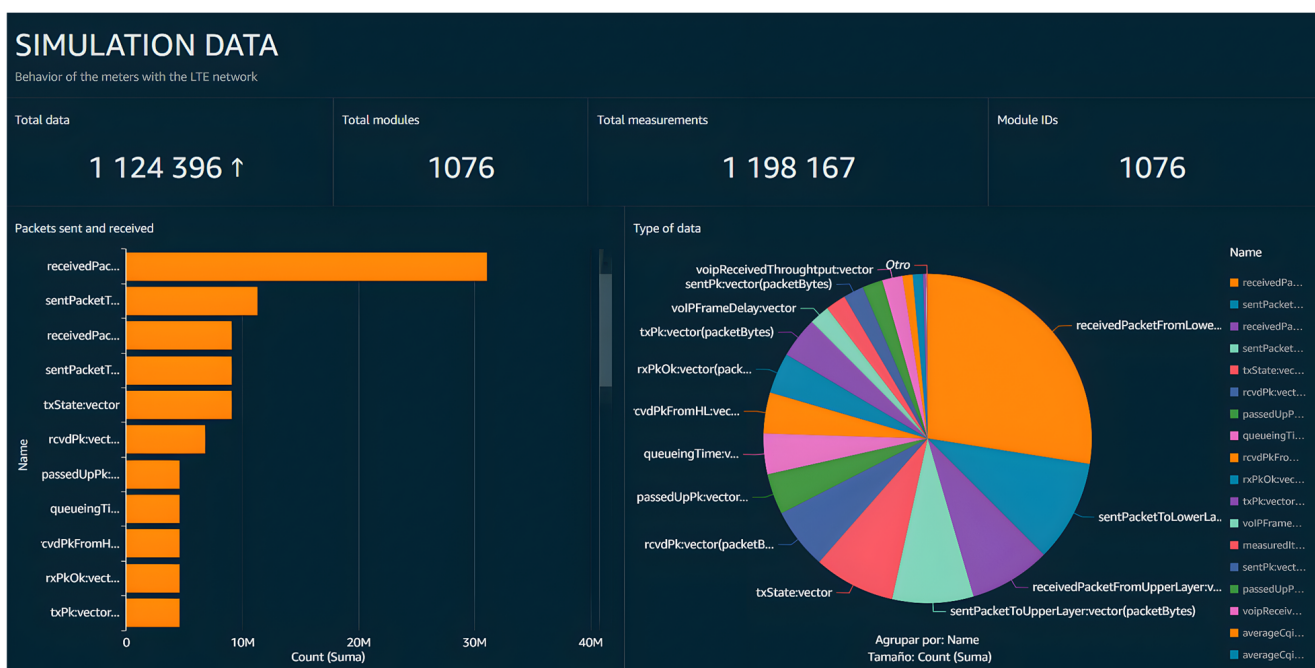


Figure 3. Dashboard in Quicksight.

Next, Figure 4 shows another type of graph that can be used for analysis and visualisation, as well as other models that can be applied to observe which one is best suited for the work to be carried out. This is a bar graph where information is displayed on the maximum and minimum salaries of some collaborators, and the legend indicates which city it belongs to, related to the colour of the bar that is represented. We observe a graph that we use to make reports on the salary rhythm that the company manages and of each sector where it belongs to, for decision-making in the areas of human resources, accounting and treasury.

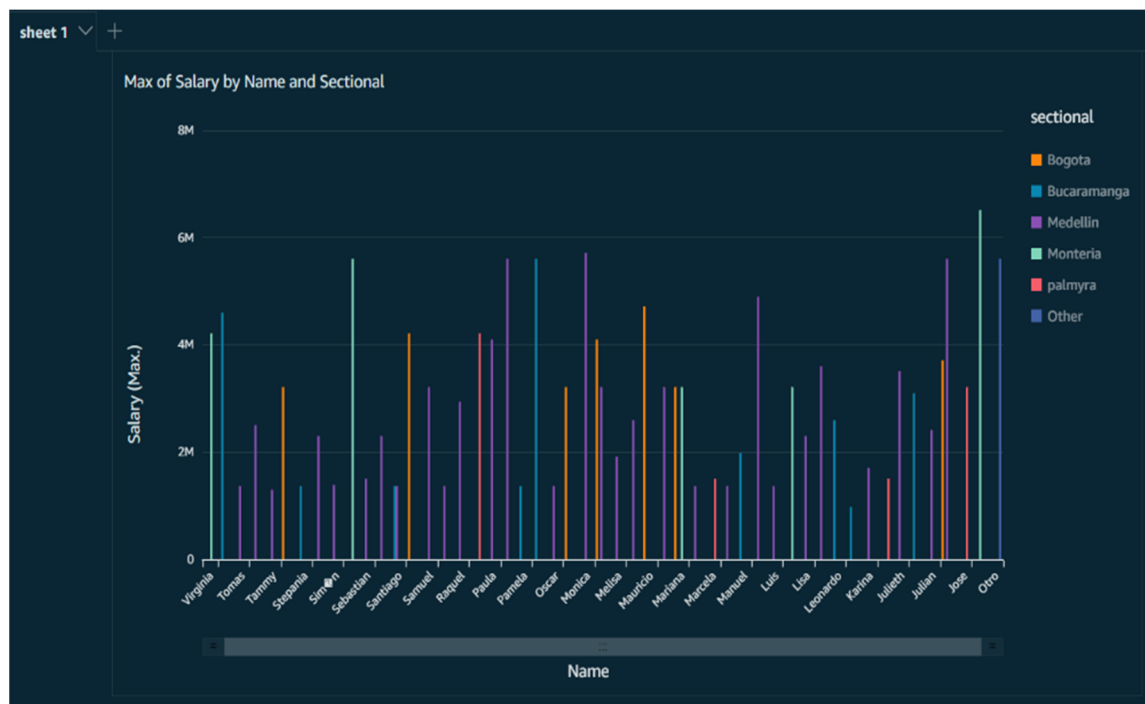


Figure 4. Example of another visualisation.

In Table 1, indicator I indicates that the data quality when using Quicksight is approximately 27.39% better compared to not using Quicksight. Regarding indicator II, the results show that the ability to read and display data is significantly better (+63.70%) when using Quicksight compared to not using it. Finally, indicator III suggests that the proportion of useful data is 47.30% higher when using Quicksight compared to not using it. A substantial improvement in data quality, reading and reporting efficiency, as well as in the proportion of useful data is evident.

Table 1. Descriptive data according to the implementation of the Quicksight cloud tool.

Indicators	Control	M	CVM
(I) Percentage of data quality	With Quicksight	75.5	+27.39%
	Without Quicksight	51	
(II) Percentage of data reading and display	With Quicksight	80.5	+63.70%
	Without Quicksight	30.5	
(III) Percentage of useful data	With Quicksight	79.8	+47.30%
	Without Quicksight	39.8	

Note: N = 10; M = mean; CVM = coefficient of variation of means.

3.1. Percentage of Data Quality

To obtain the percentage of data quality, it was observed that the data obtained maintain their integrity and legitimacy and show real data of the 4G LTE network performance in smart meters, which are: name, type, module, attrname, attrvalue, value, vectime and vecvalue. These data must be related to their respective values; otherwise, they would not be quality data as they would be useless data. The data quality value is obtained by dividing the number of readings per person by the number of simulations performed multiplied by 100, then averaging them and comparing them with the quality index references in Table 2 to achieve the purpose of this research.

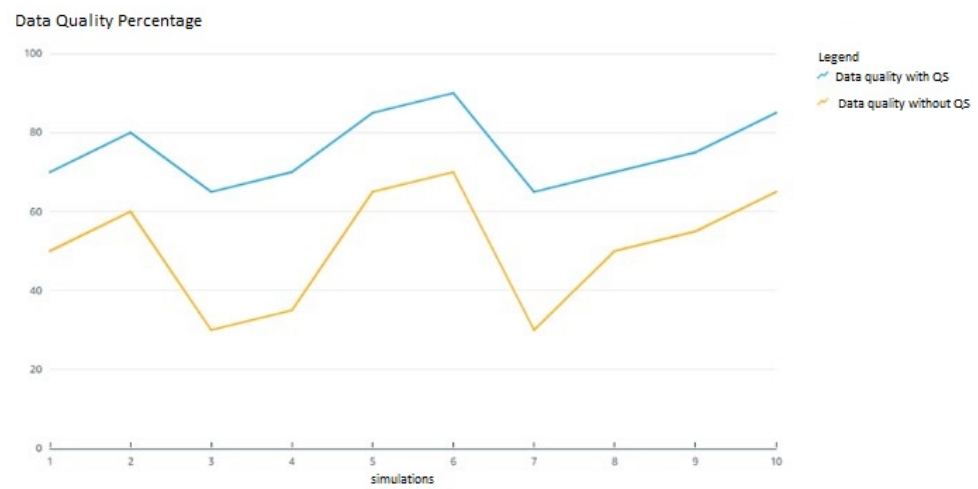
$$\text{Dataquality} = \frac{n^{\circ} \text{ reading perperson}}{n^{\circ} \text{ of simulations}} * 100$$

Table 2. Quality index reference range.

Reference Margin	Quality Index
≈ 100	Excellent
≥ 50	Good
≤ 49	Bad

The number of readings per person is rated on a scale of 1 to 10.

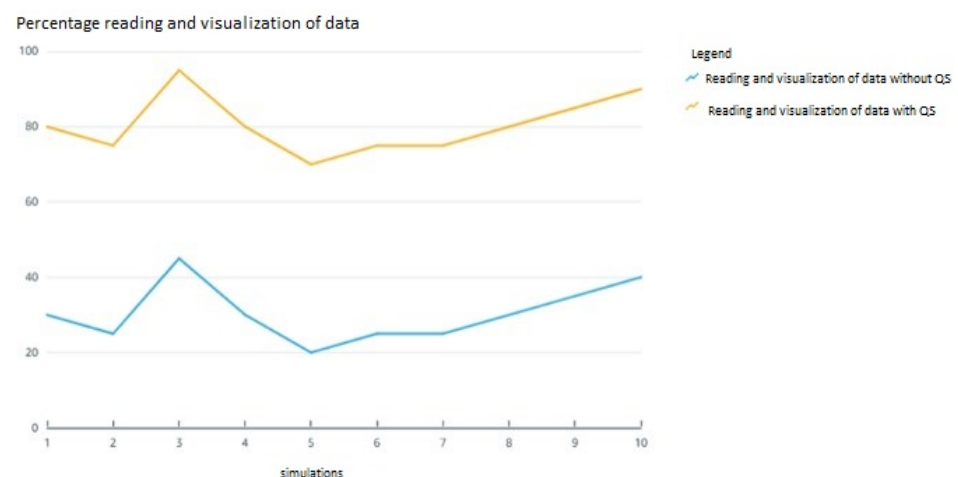
In Figure 5, we can see how the percentage of data quality increases by applying the cloud tool, having a great impact on the 10 simulations.

**Figure 5.** Percentage of data quality.

3.2. Percentage of Reading and Display of Data

In the pretest, it was only calculated by expert judgement, as the tool was not applied, and therefore there was only structured data with a low percentage of reading and no graphical visualisation. In the post-test, the same tool shows us the total number and percentage of rows imported and read by its SPICE data analysis engine, which is why in the pretest it is not possible to obtain this indicator because the tool is not applied.

In Figure 6, we can see how there was an improvement in the percentage of reading and visualisation of data. This is due to the fact that in the pretest, the Quicksight tool was not applied, and the data were only shown in tables with a low reading rate and no graphical visualisation.

**Figure 6.** Percentage of data reading and visualisation.

3.3. Percentage of Useful Data

Based on the PowerData reference [25], we take the objectives and requirements of the company into account to obtain the percentage of useful data. That is, we take the data that will allow us to see the performance of the smart meters through the 4G LTE network, which are: name, value, vectime and vecvalue. We must take into account the origin of the data, detailing the origins of the data, the processes and the methods by which they are produced. Data integrity is defined as the degree to which all data are complete, consistent, accurate and reliable throughout the data life cycle [29].

In the pretest, the percentage was low because all the data were unprocessed and without visualisation, making it more difficult for experts to use it for decision-making.

Figure 7 shows how the Quicksight tool had a positive impact on the percentage of useful data. Thanks to visualisation, the best decisions can be made in the organisation.

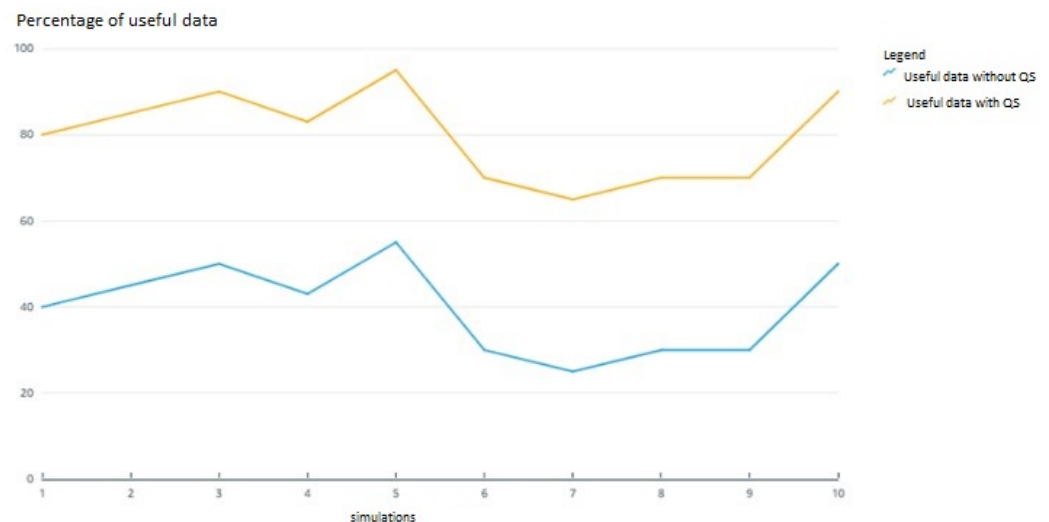


Figure 7. Percentage of useful data.

4. Discussion

The purpose of this research was to determine the influence of the Quicksight cloud tool for the visualisation of data obtained from the smart cities project: Cañete pilot plan with smart meters. These results were contrasted with previously cited research. By applying this tool, it was possible to increase the percentage of quality data, corroborated through questionnaires applied to those involved in the smart cities project who claimed to obtain clean data of good quality to achieve visualisation. These results are consistent with Salazar's research in 2017, which highlighted the satisfaction of users with having access to high-quality information stored in the cloud and presented in a graphical way, thus facilitating decision-making. In addition, it evaluated the quality of the information through user surveys, obtaining an 85% affirmation of the improvement in quality, allowing for improved decision-making in the applied company [30]. By applying the cloud tool to measure the percentage of data reading and visualisation, it was possible to import 80% of the data with 431 rows for the data visualisation process, thanks to the SPICE analysis engine, which, by cleaning some null data, saved the memory consumption, which is a maximum of 1 GB in the free layer, and helped to avoid manual verification that would take a long time to find the null data. These results are congruent with those of Peralta, 2019, who achieved the visual representation of 210 million data points through heat maps (graphical representation of data) using different evaluated queries that have great importance when interpreting data and that are of vital importance in data visualisation [31,32]. This is aligned with the use of tools in the cloud, where large amounts of data can be processed to bring them to visualisation, as well as the use of heat maps. In this research, a dashboard is used for the purposes of the project. By obtaining different insights with the cloud tool, it

was possible to generate important information from useful data, as these results can be visualised in different ways, helping to make good decisions focused on the objectives and goals of the company or organisation. It was also possible to obtain knowledge about how to work in the AWS cloud, as well as the connection that can be achieved between its different tools and the high availability and security that it has for information. And by having different insights, it is possible to analyse the information from different perspectives for decision-making [33]. These results are congruent with the results of Rodríguez, 2017, who stated that the availability of information and its visualisation support decision-making in the agro-industrial chain [34]. This is because the availability of information and its graphical representation are key factors that support and strengthen decision-making in the agro-industrial chain.

In relation to the research question: How does the cloud-based tool Quicksight influence the visualisation of the data obtained from the smart cities simulation: Cañete pilot plan with smart meters? The research shows that the implementation of this tool improves the level of reliability of the data obtained, as these data are stored in the cloud and only specific users with the appropriate permissions can manipulate it. Furthermore, with the help of the SPICE engine, there is a more reliable analysis, which helps to improve the analysis, interpretation and decision-making based on statistical graphs (insights) of the percentage of data quality, the percentage of reading and visualisation, as well as the percentage of useful data, optimising the way of interpreting the information in different ways for decision-making. Finally, from the study of Cardenas [35], it is possible to obtain data on the performance of the LTE network in smart meters through simulations, citing that his research would be helpful for future work with cloud computing, where it is corroborated in our research that it is possible, since we could take the data obtained from a similar simulation to visualisation with the help of the proposed cloud tool. It also talks about the security of cloud computing, where it could be confirmed that it is efficient, since the visualisation elements are private and to access them, an AWS account is needed with the respective permission granted by the creator of the visual element, who grants the necessary permissions to specific users to work with the information [36].

Cardenas' study on the LTE network in smart meters sheds light on how data obtained through similar simulations can be effectively visualised using the proposed cloud tool. His research not only validates the feasibility of carrying out this data transfer to a cloud environment but also underlines the importance of security in this context. The assertion that visualisation elements are private and require access through an AWS account with specific permissions granted by the creator highlights the efficiency of security measures implemented in cloud computing. These findings suggest a promising horizon for future work seeking to harness the power of the cloud for data analysis and visualisation in LTE networks and cloud computing.

The incorporation of the Quicksight tool in our smart cities simulation has brought significant improvements in the reliability of the data obtained. Thanks to its ability to visualise and analyse data in real time, we have achieved more accurate monitoring of electricity consumption in households in the city of Cañete. This has enabled faster identification of possible anomalies or fluctuations in supply. In terms of analysis, Quicksight has greatly simplified the task of processing large volumes of data generated by the smart meters. Its interactive charting and graphing capabilities made it easier to identify patterns and trends, which in turn streamlined the interpretation of results. Ultimately, these improvements in data reliability and streamlined analysis and interpretation processes have had a significant impact on decision-making. We can now take more informed and timely action in response to changing conditions in the simulated power grid.

5. Conclusions

The results obtained in this research demonstrate the positive influence of the Quicksight cloud tool on the visualisation of the data obtained from the smart cities project: Cañete pilot plan with smart electricity meters. A significant increase was observed in

the average percentage of data quality, data reading and visualisation, as well as in the percentage of useful data.

By applying this tool, an increase of 27.39% in the average percentage of data quality was achieved, which is attributed to the integrity and legitimacy of the data obtained from the 4G LTE network in the smart meters. The tool was able to identify and eliminate useless data, ensuring that the data used was of high quality. These results are in line with previous research highlighting the improvement in information quality and decision-making through data visualisation. The tool also had a significant impact on the percentage of data reading and visualisation, with an increase of 63.70%. In the pretest, where the cloud tool was not applied, the reading rate was low and there was no graphical visualisation. However, when using the tool, 80.5% of the data were imported and read, allowing for more effective visualisation, thanks to the SPICE analysis engine. These results are consistent with previous research highlighting the importance of visualisation in data interpretation and informed decision-making. In addition, a 47.30% increase in the percentage of useful data was observed when applying the cloud-based tool. The tool enabled the identification of relevant data to assess the performance of smart meters across the 4G LTE network. In the pretest, the data were not processed or visualised, which made it difficult to make it useful. However, the tool facilitated the identification and presentation of relevant data, improving decision-making.

These results reinforce the effectiveness of cloud tools in improving data visualisation and analysis in projects such as smart cities, providing valuable insights that support informed decision-making and performance improvement in different application areas.

6. Future Research

In terms of future research, despite the benefits evidenced in this research on data visualisation using the Quicksight cloud tool in the smart cities project, there are several areas that could be the subject of future research to extend and improve the results. These areas include the optimisation of this tool and exploring more efficient algorithms and additional functionalities to improve its performance and analysis capabilities. Currently, high-quality data sharing leads to misuse or data leaks with the use of machine learning, mostly in cases involving financial technology, which merits cybersecurity studies in the cloud to respond to any attacks [33]. In addition, it would be interesting to make comparisons with other available cloud tools to determine which offers the best results in terms of quality, performance and ease of use. Furthermore, the integration of real-time data from smart meters would allow for continuous monitoring and real-time decision-making. It would also be valuable to investigate the application of advanced data analytics techniques, such as machine learning and data mining, in conjunction with Quicksight to identify hidden patterns and relationships, as well as accurate anomaly detection in the same cloud to save time and resources used in processing and decision-making, safeguarding data and tools from cyber threats emerging on the web [34].

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