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Measurement and Analysis with KPIs based on an AMI system

Kevin Morgado[1], Álvaro Zambrano[2], Javier Rosero[3]
[1,2,3]Department of Electrical and Electronic Engineering, National University of Colombia, Colombia

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ABSTRACT

This paper presents the development of a series of Key Performance Indicators (KPIs) for the electrical system of the campus of the National University of Colombia based on the deployed smart metering infrastructure (AMI). To develop the proposed indicators, it was necessary to use different sources of information to complement the data provided by the AMI system. In the document, the formulation of the main indicators is presented alongside an analysis of the behavior obtained for each one. It was possible to observe how, based on the results obtained from the different indicators periods of inefficiency in electricity consumption. Finally, the main conclusion corresponds to the challenge of applying these KPIs to different conditions.

Corresponding Author:

Javier Rosero García,
Department of Electrical and Electronics Engineering,
National University of Colombia,
Carrera 30 # 45-03, ed. 453 - 208 Bogotá D.C., Colombia.
Email: jaroserog@unal.edu.co

1. INTRODUCTION

Currently, AMI systems have been deployed around the world demonstrating their great advantages for the management of electrical grids, allowing them to offer new services to users [1][2]. Thus, throughout these different deployments, several applications have been developed based on the data collected.

Initially, it is possible to identify works on the architecture in which AMI will be deployed that seek to ensure that the data can flow adequately and that they are distributed to the different stakeholders that require them to perform their functions [3][4]. Likewise, these architectures must guarantee their scalability and communications speed for the fulfillment of the most demanding applications that require analyzing data in real-time to offer advanced functionalities on the system [5][6][7]. Additionally, it has been observed how AMI can become an enabler for the integration of new functionalities around IoT [5][8].

Regarding the use of data, there are major trends to make the most of the data collected by this technology. On the one hand, different types of works are identified focused on performing demand prediction processes from historical data collected by AMIs. Although the focus of prediction methods varies according to the objectives pursued, it is evident that new techniques are constantly being tested to improve the accuracy of prediction models [9][10][11][12][13] and AMI data become a fundamental input for this development.

On the other hand, another trend focuses on the implementation of demand management programs, where the use of AMI data becomes a priority element to promote the use of all these programs [11]. The use of AMI data in such applications has a direct impact on the efficiency of distribution systems [14][15], becoming one of the most relevant applications for the use of AMI data.

Another use of AMI data is to characterize the different forms of demand from the measurements. This consists of applying Big Data techniques to AMI time series and determining the different clusters that describe demand behavior [16][17][18].

Additionally, the use of AMI data has been highlighted in terms of seeking efficiencies within distribution systems. The measurements obtained by AMI technology are used in algorithms that verify the energy balances constantly, thus obtaining points of inefficiency or losses that can be attacked [19][20][21].

Concerning the Key Performance Indicators (KPIs), in [22] indicators related to power quality were used for a system with a high penetration of Renewable resources. In the same way in [23] the KPIs were built to serve as a guide for stakeholders in a high scale power system, including specific formulations related to the end-users. Recently, the increase in the use of KPIs to help the end-user to make decisions in their near environment became an important tool in power systems, especially with power system variables such as power consumption and Demand Response [24][25].

In this article, the use of AMI data is proposed for the implementation of various Key Performance Indexes that seek to identify inefficient points of operation. These indicators were implemented using the AMI system implemented within the campus of the National University of Colombia in Bogotá. The AMI data was complemented with other sources of information and new index were proposed to monitor the electricity consumption. Based on the results of the indicators, it was possible to establish inefficient energy consumption points that could be reduced using energy demand management plans.

2. CASE OF STUDY

Currently, on the Campus of the National University of Colombia, the electrical system is divided into 33 electrical substations where each one has its own transformer with Dy5 connection and nominal power calculated according to the calculated demand. The nodes are connected in a ring topology, which has an approximate length of 3 km:

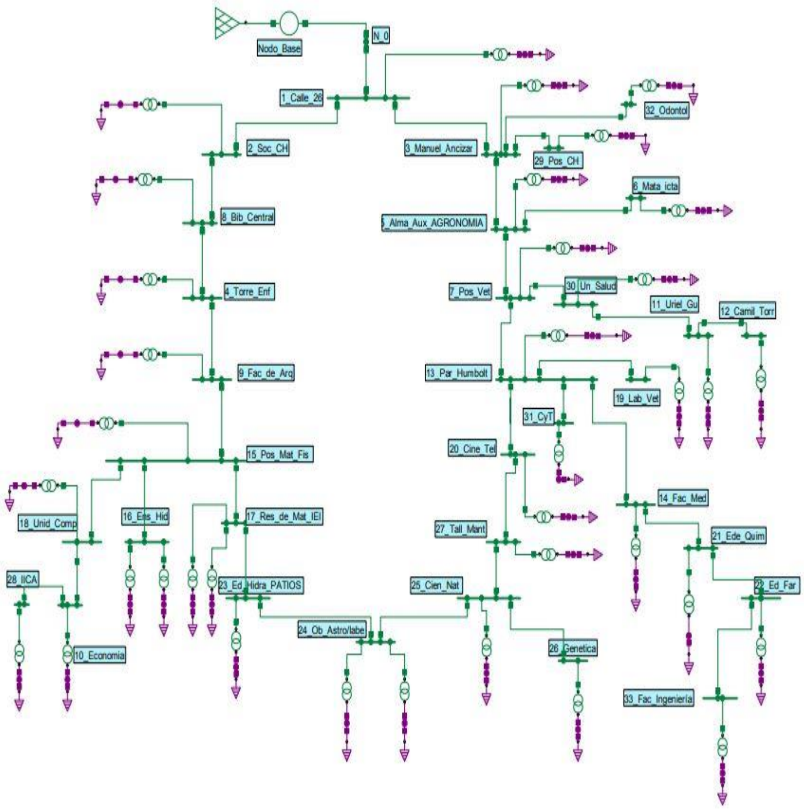

Figure 1. Medium voltage grid model of Bogota's campus [16]

In each building or node, there are connected different measuring devices that send data to the main server through the OSIsoft PI System interface and related programs such as NEPLAN [26] for analyzing the data at the same time as forecasts are developed. In parallel, the current system installed in the server on the campus [26] allows to make different types of analysis with the data obtained and it has the option to add information from elements that come from other databases of the core measuring devices, being the last ones related to the measurements of most of the electrical variables such as Power and Voltage. For this reason, to analyze this document, specific buildings were chosen as they have different uses. They are shown in Table 1:

Table 1. Substations and their main use

Substation	Building Category
Calle 26 (Campus)	Main Substation
Odontology	Laboratories and Classroom
Leon de Greif Auditorium	Conferences
Chemistry	Laboratories and Classroom
Uriel Gutierrez	Offices
Unisalud	Health facility

3. INTERFACE

The system developed by the Laboratory of Smart Grids (LAB+i) of the National University of Colombia is divided into the following categories:

a) *Physical Processes:* This section covers the processes to be monitored. In this case, the energy and power consumption were considered, along with the data that would help to represent the behavior of campus users, such as the number of Internet connections and quantity of students in classes in each building.
b) *Meeting Interfaces:* It corresponds to the devices that allow the measurement of the variables of interest in how this data is sent to the management server. Most of them can communicate via Modbus TCP/IP protocol to the main server, where their configuration could be changed according to the research requirements [26].
c) *Communication:* It refers to the equipment that allows data transmission from the source to the storage server. In other words, after the data processing, this is sent to the main server using different communication protocols via Ethernet Cable, which is associated with a Wi-Fi Modem [26].
d) *Management System in Real Time:* It refers to the equipment that allows data transmission from the source to the storage server. In other words, after the data processing, this is sent to the main server using different communication protocols via Ethernet Cable, which is associated with a Wi-Fi Modem [26].
e) *Visualization and Analysis:* This is the last stage, where the information can be processed through calculations implemented in code or to make corrections related to server problems. At the same time, the tools that are used to visualize the results of the KPIs in real-time with plots and images are located here.

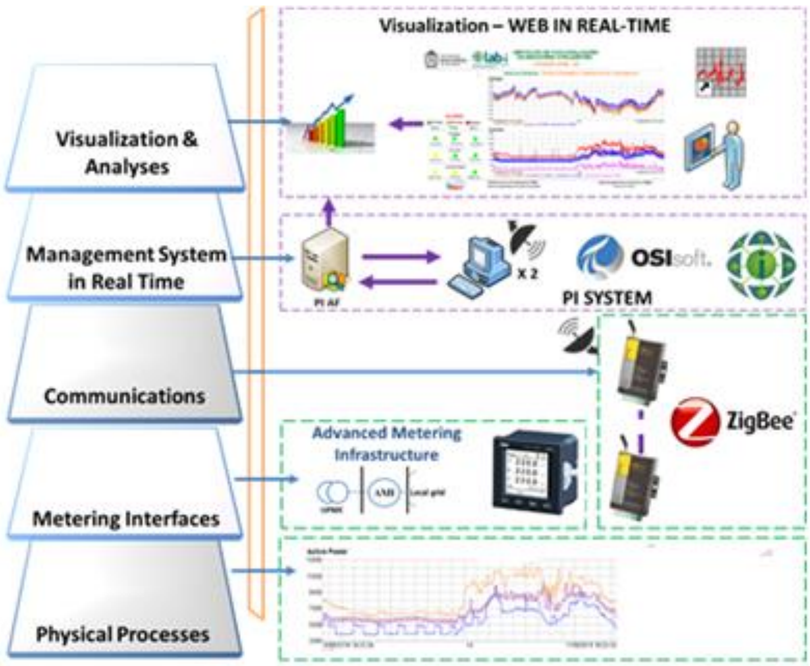

Figure 2. Simplified Data Processing Structure [26]

4. KPI'S STRUCTURE AND TYPES

Firstly, a Key Performance Indicator (KPI) is an evaluation index of an event that is related to the strategic objectives of an organization, and it is a way of expressing the results of an implemented strategy or behavior [27] [28]. Nowadays, they are used to assess performance aspects of the electric grid, especially by grid operators, such as [29]:

- Network efficiency
- Renewable generation integration
- Reactive power flow reduction
- Greenhouse gasses emission

This can be done by analyzing in real-time different measuring devices that are installed on the grid. However, these KPIs can be used as building blocks of more complex KPIs. For example, the integration between those and metrics is defined as any data provided by an EMS (energy measurements) [31]. Using this procedure, the KPIs were designed, using grid parameters such as power and energy consumption with information that is not used in the analysis of electrical efficiency in real-time related to the data communication and users' behavior [32].

In this paper, the interface shown in Figure 3 was implemented to obtain and analyze the 4 main KPIs considering that the main objective of them is to give data to make possible the implementation of saving campaigns and infrastructure changes that would allow the decrease of the waste of energy in the Campus of the National University of Colombia, especially when there are no users in the buildings:

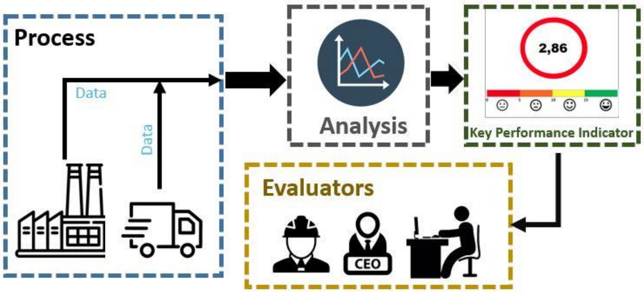

Figure 3. Main structure of the KPI Analysis

a) *Process:* Process: The set of programs that conforms PI System was used for obtaining the data from different sources such as power consumption. Firstly, there is the main server where all the data is sent and stored for later uses. These values could come from the measuring devices that are installed on Campus' Buildings or developed by an operator. It was mainly used the programming language C# for organizing the values and at the same time being able to compare the data in the form of KPIs.
b) *Analysis:* Process: The set of programs that conforms PI System was used for obtaining the data from different sources such as power consumption. Firstly, there is the main server where all the data is sent and stored for later uses. These values could come from the measuring devices that are installed on Campus' Buildings or developed by an operator. It was mainly used the programming language C# for organizing the values and at the same time being able to compare the data in the form of KPIs.
c) *KPI:* Process: The set of programs that conforms PI System was used for obtaining the data from different sources such as power consumption. Firstly, there is the main server where all the data is sent and stored for later uses. These values could come from the measuring devices that are installed on Campus' Buildings or developed by an operator. It was mainly used the programming language C# for organizing the values and at the same time being able to compare the data in the form of KPIs.
d) *Evaluators:* Process: The set of programs that conforms PI System was used for obtaining the data from different sources such as power consumption. Firstly, there is the main server where all the data is sent and stored for later uses. These values could come from the measuring devices that are installed on Campus' Buildings or developed by an operator. It was mainly used the programming language C# for organizing the values and at the same time being able to compare the data in the form of KPIs.

Then, the holidays in Colombia were considered alongside the working hours of the employees to make the KPIs easier to understand and, in some cases, use those restrictions for the calculation of the indicators that depend directly on the user's behavior in those time intervals:

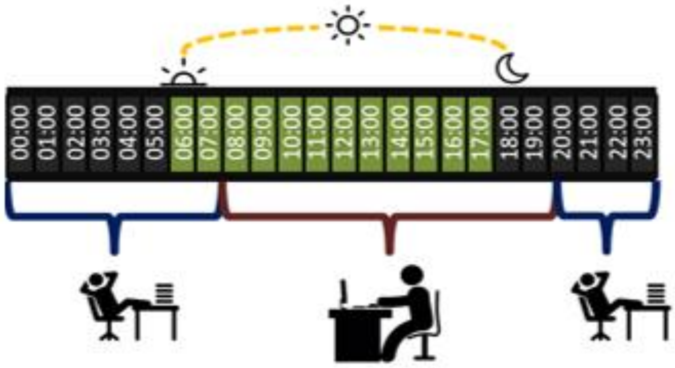

Figure 4. Hours Intervals in an office day

After that, the KPIs were chosen according to the data availability and the analyses that were required. The development of KPIs shown in the document unlike those referenced would allow for the identification of the users' behavior at the site and how it is related to the efficient use of the energy and a way to identify the waste of electrical usage. In the same way, they can be linked with other KPIs for showing to both final users and persons in charge ways of identifying the efficient use of energy, an important aspect of smart systems development because their overall efficiency is linked with people's behavior using the different services. Finally, they also could be used to design forecasts.

4.1. Students per kW

This indicator depends on two measures. The first one is the power consumed in real-time (given in kW), which is taken from the measuring devices located on the campus. At the same time, the data of the number of students per hour that was registered in the System of Academic Information (SIA) of the University is sent to the server through an excel file that organizes all this data according to the different Campus buildings. Then this data is filtered according to the academic schedule and Colombian holidays, filling it with a value of 0 when it is not a working or studying day. In Figure 5 the values of the total of students in an office day and the Campus power consumption per hour are shown, with a maximum of 37500 students and 2000 kW of consumed power.

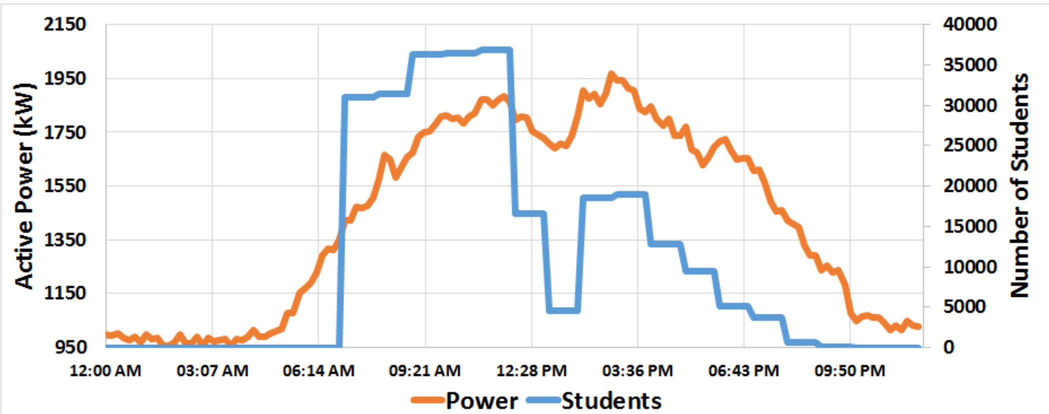

Figure 5. Comparison of Students and Power consumption on Campus

With the data, the KPI divides the number of students between active power to obtain the indicator value, i.e., It can be known how many students represent 1 kW of power in real-time.

$$KPI_{St} = \frac{\#Students}{kW} \tag{1}$$

For categorization, the historic data was used for creating 4 categories that classify in real time the efficiency of used energy, in the case of Figure 6 the scale of the University Campus, where the maximum registered corresponds to 20 students per kW. In other words, a high value means that there are more students consuming energy and vice versa.

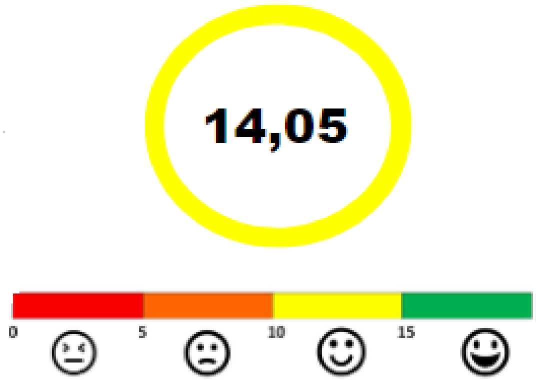

Figure 6. Reference values for Students per kW on the University Campus

4.2. kW per Internet Users

In this second indicator, the users connected to the university's internet network are obtained from a website designed by the Office of Technology and Communications of the National University where they place on a table the quantity of connections to the internet for each of the buildings, that is measured directly from the installed Wi-Fi modems, which have the record of the total connections. These values are updated every 5 minutes, but that time could be changed related to the overall internet connection.

In the same way as the previous KPI, the power consumption was used to calculate this indicator that shows the relation between the number of users connected in each of the buildings and the consumption as seen in Figure 7, where the total users and power consumption are plotted in an office day in the University Campus.

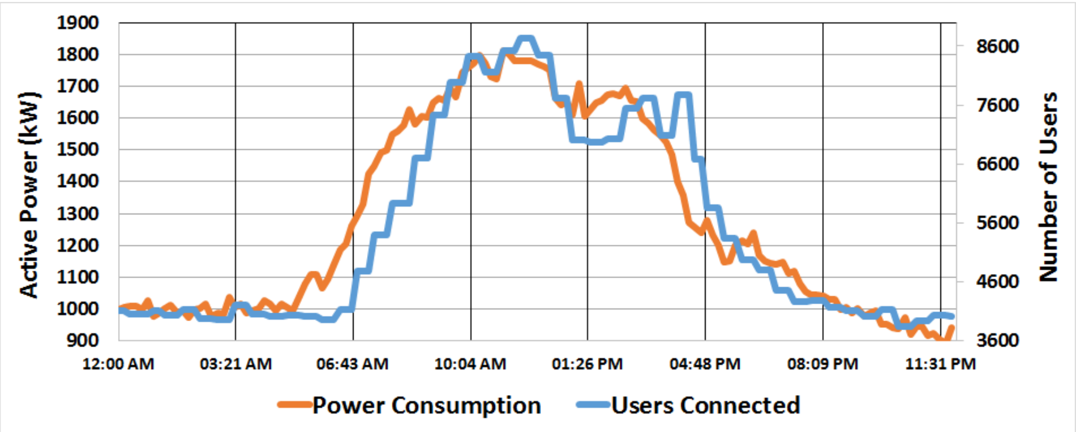

Figure 7. Comparison of users connected and power consumption on Campus

Then it was divided the power and the number of connections for analyzing how many kW are consumed per internet user.

$$KPI_{Us} = \frac{kW}{\#Connections} \qquad (2)$$

However, unlike the previous KPI, it is better to have a lower value which represents that there are more users consuming energy but sometimes there aren't people using the Internet and the energy is still being consumed, showing problems in the overall campus efficiency. As on the previous indicator, the scales were built related to the historical values of each of the buildings, choosing in this case only three.

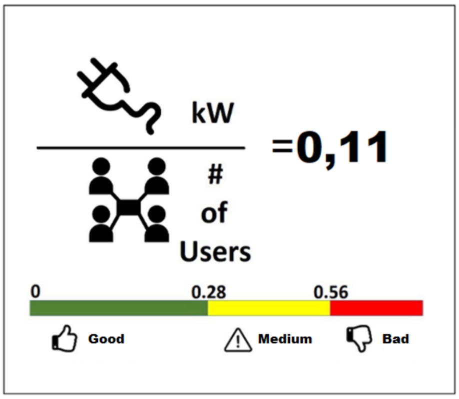

Figure 8. kW per Internet Users for University Campus

4.3. Consumption in office hours

Firstly, it is necessary to define which hours are going to be considered working hours and at the same time consider the holiday. For this reason, it was decided that the hours where the energy is going to be registered will be considered are the ones shown in Table 2.

Table 2. Office time per day

Day	Starting Hour	End Hour
Monday to Thursday	7:00	18:00
Friday and Saturday	7:00	14:00
Sunday and Holidays	7:00	14:00

With these restrictions, the measurement of energy consumed in each of the chosen buildings was analyzed during these periods and it was stored in a System variable. Each of the visualizations has the bar length related to the historical maximum consumption of each of the periods as presented in Figure 9:

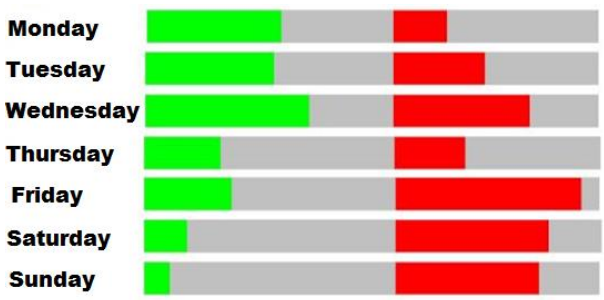

Figure 9. Visualization of energy consumption in PI Software

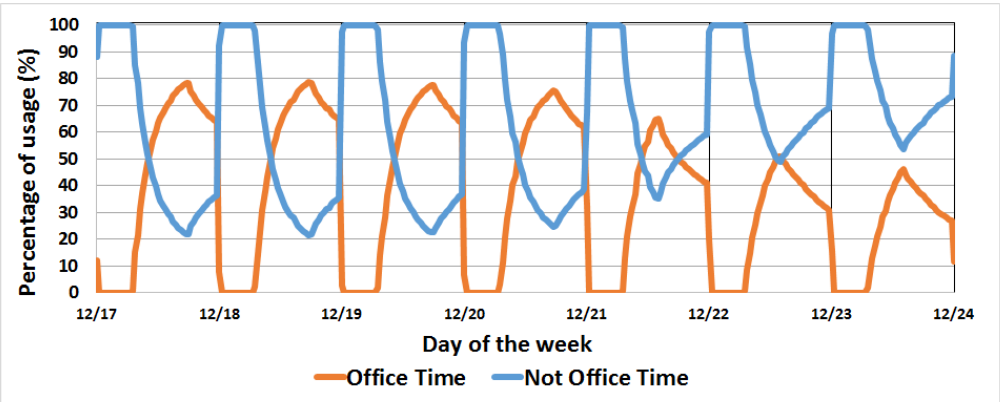

Figure 10. Energy percentage in a week of University Campus

This data was used to make a comparison between the consumption during office and not office hours considering the use of the buildings as laboratories or classrooms. For example, in Figure 10 through the afternoon the used energy corresponds to office hours.

4.4. Consumption per Month

In this last indicator, the consumption of energy is measured and registered for each month of the year. Afterward, the magnitudes of each of the values were compared related to the people moving on the campus.

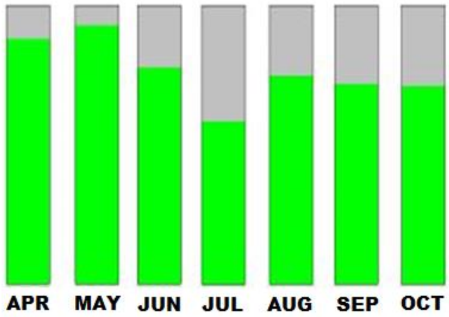

Figure 11. Month comparison template

Lastly, for the implementation of these indicators is important to assure that the information sent from the measuring devices is continuous and that each visualization is adapted to the historical values of measurements and updated in real-time. However, it is common to have communication problems that could be solved by changing the calculation parameters of the KPIs. Simultaneously, the data that represents the behavior of the campus users must be available, especially as this data is measured by other university institutions and it is important to assure that these variables could be updated at a similar rate to the ones that come from the measuring devices.

5. RESULTS

5.1. Consumption per Month

Firstly, it is shown in Figure 12 the plot of power consumption per user of the university campus, the chemistry building, and Uriel Gutierrez in an Office Day (24h). On the campus and in the Chemistry building, there is a maximum value of 0.4 kW per user between 6 and 7 o'clock because the consumption of electrical energy starts to increase because of the arrival of users to the Campus, but that surge is greater than the increase of internet connections.

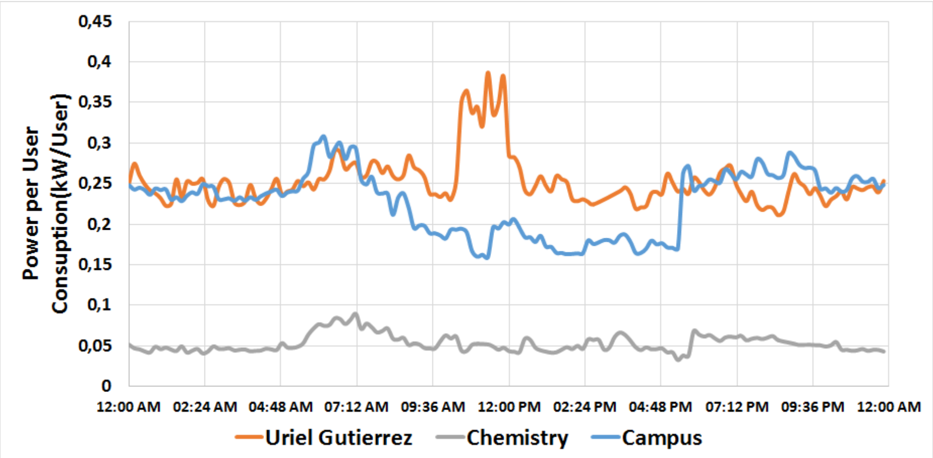

Figure 12. Result of kW per users connected

Then the KPI's value starts to decrease according to more users connecting their devices to the network as the hours between 8 a.m. and 4 p.m. are the time lapse when these buildings have the largest number of programmed activities. In Figure 12, there was a reduction of 30% of the KPI from 7 a.m. to 11 a.m. on the university Campus, while the other maintain different trends.

Afterward, there was another peak of a maximum of 30% increase between 4 and 6 o'clock in the three cases, because the number of Internet users decreases associated with the ending of most of the academic and work activities on the Campus. Nonetheless, before 6 a.m. and after 6 p.m. the value remains constant, being that the most expected behavior would be a great increase of this KPI as there is only the security personnel and the critical devices as research equipment. However, the Uriel Gutierrez Building has a different behavior as there is only one peak between 11 and 12 o'clock that corresponds to the lunch hour of the workers while most of the computers and other work items remain connected to the electrical grid without using the internet services.

At the same time, the KPI's performance could be analyzed in another way. There were plotted the values of power consumption versus the number of users connected to each building, as shown in Figure 13, Figure 14, and Figure 15. For each one, an approximation through polynomial regression was calculated.

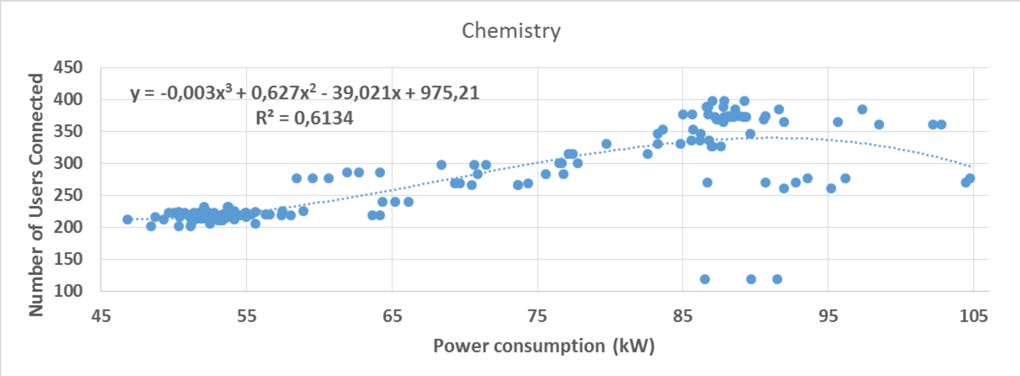

Figure 13. Power consumption vs. number of users connected in Chemistry building

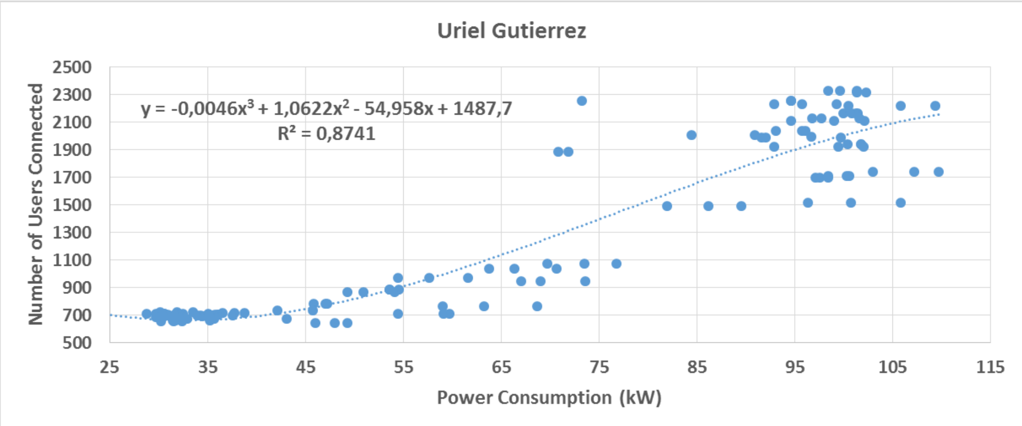

Figure 14. Power consumption vs. number of users connected in Uriel Gutierrez building

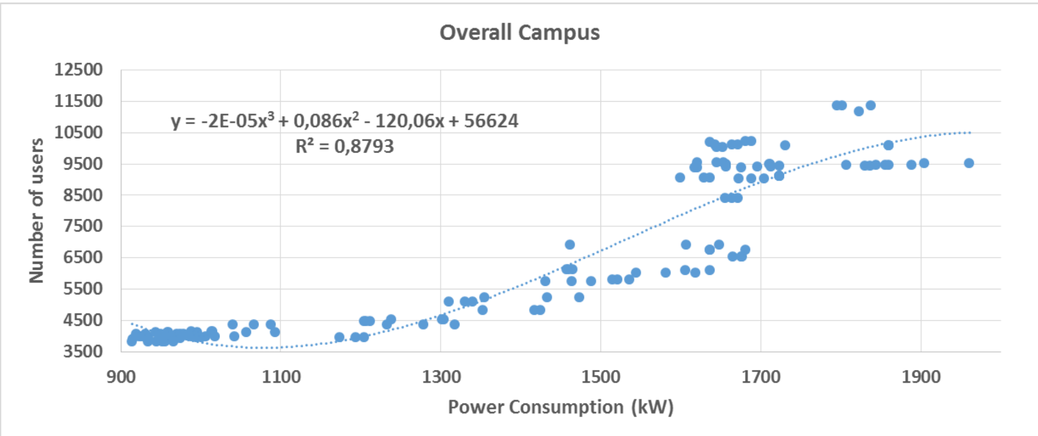

Figure 15. Power consumption vs. number of users connected in the Campus

With a data sample taken every 20 minutes in a 24h span for both power consumption and the number of users connected it was made a polynomial regression where correlation can be seen more easily. For example, the Campus and the Uriel Gutierrez buildings have an R^2 value of 0.87, showing a high correlation between the power consumption and the number of users of the regression, probing that this KPI could be used to recognize similar users' behavior in different places of the University.

However, that is not the case in the Chemistry building seen in Figure 13, in which the relation of the two data is different with an R^2 of 0.613, mostly because of the hybrid use of that building as a classroom and laboratory. In all graphs when the power consumption is the lowest, the number of users remains almost the same as it represents the time in the day when there are the fewest people on the Campus and when Internet connections are made by the computers or other systems that must be connected continuously.

5.2. Consumption in office hours

There was taken data from 2 different buildings and the Campus for comparing the difference between the percentages of energy consumption in each of the frames. Tables 3 and 4 show the respective data for each of the days of the week. The data correspond to one week where there were classes and Monday wasn't a holiday.

Table 3. Percentage of energy consumption on office time

Element	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
Univ. Campus	58,5	57,6	58,9	59	42,4	36,3	30,9
Odon. Building	75,1	76,3	67,1	80	53,1	46,5	42,1
Uriel G. Building	68,8	67	70,6	66,7	46,3	34,2	28,1

Table 4. Percentage of energy consumption on no office time

Element	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
Univ. Campus	41,4	42,3	41,1	41	57,5	63,6	69,1
Odon. Building	24,9	23,6	32,8	20	46,9	53,4	57,8
Uriel G. Building	31,1	33	29,4	33,2	53,7	65,8	71,8

As seen in table 3, on weekdays regardless of Fridays, more than 59% of energy is consumed during Office Hours because there are students in classes and workers. However, this value also varies with use. For example, the percentage of energy consumed in Odontology and Uriel Gutierrez buildings during those intervals is higher than the campus, 75% and 67% on average, because the first two have a big movement of people and the Campus indicator gathers all the University's buildings.

At the same time on Fridays, all the campus' activities last until 4:00 p.m., making this the main reason for the increase of consumption in not Office Hours with a maximum of 57% registered on the University Campus. Then on Saturday and Sunday, most of the electricity is consumed during not office hours and the KPI also shows that with few campus users, according to the programmed activities, the consumption is higher on no office hours.

5.3. Students per kW

Firstly, Figure 16 shows the behavior of the Students per kW KPI on an Office Day of the first semester in an academic year, taking into account the schedule delivered by the SIA of the National University of Colombia, obtaining a similar trend for each of the cases.

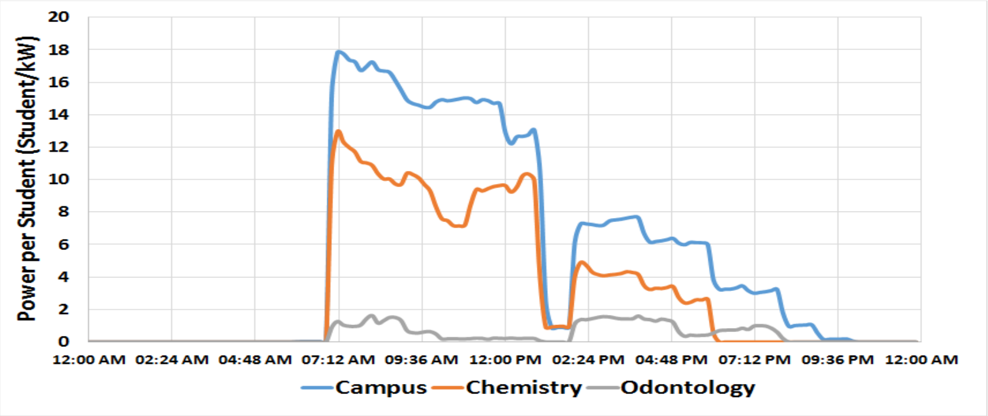

Figure 16. Result of students per kW

At lunchtime, which is scheduled at 1 p.m., there is an important decrease in the students in classes, which makes the KPIs have a value close to 0. At the same time, the maximum value was recorded at 7 a.m.

with 18 students per kWh, when students start to arrive at the buildings and power consumption is on a rising trend. Later, this value starts to decrease, with a reduction of 20% in the Chemistry building because power consumption increases at a lower rate than that of the students. Then at 2 p.m., the decreasing trend repeats until the end of the day. However, there are some differences between the KPIs on each of the buildings.

For example, in the Odontology building, the value of the KPI compared to the other with a peak of fewer than 2 students per kWh, showing the similitude between the increase of power consumption and the number of students, considering the use of laboratories. On the other hand, the Chemistry building's KPI has the same behavioral tendency as the Campus with a reduction of 20% in the frame of 11 a.m. to 1 p.m. because of the use of the laboratories at the same time as classrooms.

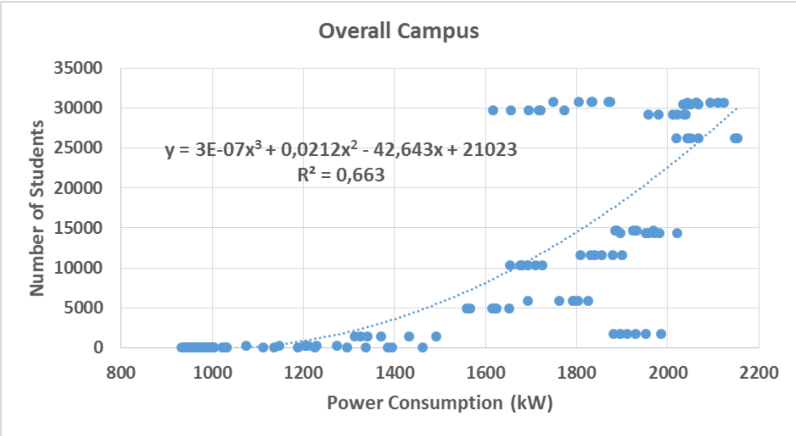

Figure 17. Power consumption vs. number of students in Campus

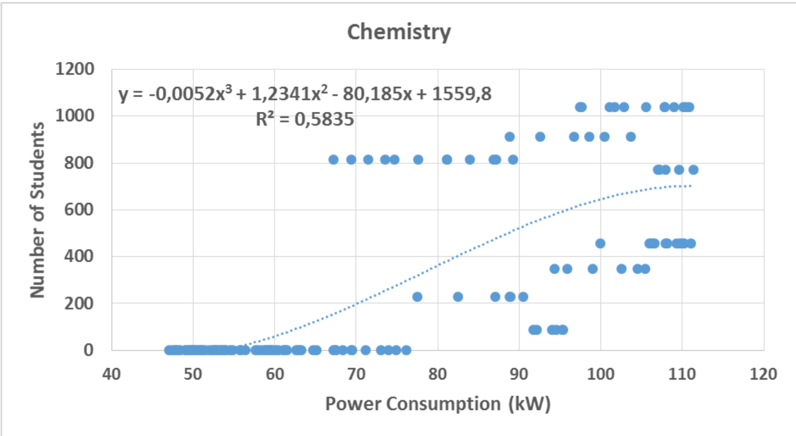

Figure 18. Power consumption vs. number of students in Chemistry building

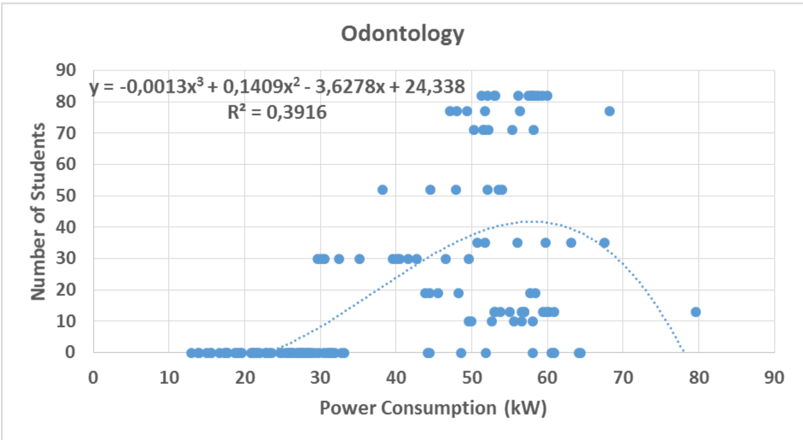

Figure 19. Power consumption vs. number of students in Odontology building

Finally, there was plotted Power Consumption versus the number of students, graphs shown in Figure 17, Figure 18, and Figure 19. With the same polynomial regression as with the previous indicator, the R2 value decreases to a minimum of 0.3916.

This data was sampled every 20 minutes for a full day for each of the buildings. However, unlike the KPI of users connected to the Internet this regression has problems as the number of students is a fixed value that initially doesn't show a direct relationship with the increase of power consumption, represented by the R2 values.

The plots in Figure 17 and Figure 18 show similar behavior as the campus reunites all types of buildings, almost representing the behavior of the Chemistry Building, being this a way to identify that the KPI is performing as expected but it is important to remark that there is a difference in the Odontology building's trend as the regression shows a decreasing behavior as shown in Figure 17. In the end, it could be seen that the values of zero students are related to lower consumption in all buildings, an aspect that was expected to happen.

5.4. Consumption per Month

Table 5 contains the consumption data for 2018, obtaining missing values in April and May because of blackouts that affected the connection between measuring devices and the Internet network. Each scenario has a different behavior related mainly to the total kWh.

Table 5. Consumption in the 3 main scenarios (kWh)

Month	Campus	Odontology	Unisalud
January	709102	10550	13891
February	864936	20237	13588
March	906733	18729	14276
April	974762	22472	-
May	-	-	14147
June	819612	15101	13396
July	738525	10565	13798
August	936322	17410	14435
September	885598	17154	13740
October	959123	11862	14242
November	942094	14166	13960
December	724176	15189	8849

Firstly, the energy use in the Unisalud building, which is used as a health service building for members of the National University, is the same with a mean of 14000 kWh per month all the year but December, when the number of users decreased to a minimum of 8849 kWh. On the other hand, Odontology building has an energy consumption that is during the vacation months (January, July, and October) with the lowest value of 10550 kWh. At the same time, the months of classes have a higher consumption of electricity except in October, when the value is 11862 kWh because of problems with the measurement devices.

Finally, the Odontology building follows the same trend as the Campus that groups all the substations. Specifically, it is seen that in February, June, and September there is a decrease of consumption of 15% related to the maximum registers because these months have Office and not Office weeks, which correspond to the end of the semester and the administrative holidays.

5.5. Malfunction and Restrictions of KPIs

In the KPIs' development, there were identified different problems located in parts of the implemented system. Firstly, not all buildings have the data availability that is required to create the indicators. At the same time, some of the KPIs didn't show a pattern that would allow showing the users' behavior, mainly the office buildings where is common to keep the computers connected and making the proposed KPIs useless as they couldn't make visible a relation between the users and the energy consumption. Moreover, the number of students in classes in the buildings is obtained from a source that can't register the real quantity of people that assist to the university. Finally, it was very common to have problems with the data available in the server as some data that comes from measuring devices is lost before arriving at the data server or is changed by a misreading of the electrical devices.

6. CONCLUSIONS

The different KPIs are a tool for analyzing the behavior of the electrical energy consumption in the National University of Colombia Campus in Bogota related to the users' habits. At the same time, there were recognized ways to reduce the waste of energy usage with awareness-raising campaigns that could change those habits, divided into the different KPIs:

- In the KPI of kW per Internet User, there is a direct relationship between the power consumption and the connections to the internet network, even when there are no people on the Campus because most of the workers and laboratories' users don't turn off the computers, turning into in a waste of energy and money in the long run.

- The KPI of consumption during office hours shows that a building's use is related to how much energy is spent in specific frames. Also, it gives information about the waste of energy on the not office hours because there are no users or workers but there is a significant consumption.

- The KPI of students per kW shows that energy efficiency can be measured in the number of users that use electricity in real-time. However, it also shows the inefficient use of energy in the hours when this indicator has its lowest values. Moreover, this data is not enough to make a full analysis of the efficiency.

- The last KPI shows that there is a consumption pattern related to the month of the year and the academic calendar. Also, there is a relation between the use of the building and electricity usage, especially in places that must be opened every day or have loads that cannot be disconnected but are very difficult to have reliable data as problems could happen in the communications and exactitude of the total consumption calculation.

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BIOGRAPHY OF AUTHORS

Kevin Morgado. He was born in Bogotá, Colombia in 1997; he obtained his bachelor's degree in electrical engineering in 2019 and his master's degree in 2022 from the National University of Colombia. Since 2019, he is a researcher at the Electrical Machines and Drives group of the National University of Colombia. From 2021, he is a researcher on the project Energetica2030. His research interest is power systems, renewable energies, optimization, machine learning, and smart grids.

Electrical Engineer from Universidad Distrital Francisco Jose de Caldas and Master's degree in electrical engineering from Universidad Nacional de Colombia with knowledge in quality power, modeling of electrical power systems, reliability in power systems and Smart grids. Interested in demand side management for energy efficiency, phasor measurement units, renewable energy integration and Software development.

Javier Rosero Garcia was born in Potosi, Colombia, in 1978. He received his BSC in Electrical Engineering from the Universidad of Valle, Cali, Colombia, in 2002. He worked for construction and maintenance of power systems and substations in Bogotá, Colombia, between 2002 and 2004. He received a PhD degree from the Technical University of Catalonia (UPC) in 2007 and Master in Administration from National University of Colombia, in 2020. Dr Rosero received IEEE Senior Member and the IEEE AESS Harry Rowe Mimno award for excellence in technical communications for 2007 from the Aerospace and Electronic Systems Society (AESS) IEEE 2007. He worked with Asea Brown Boveri (ABB), Barcelona, Spain, from 2007 to 2009 providing service and technical support for drives for industrial and windmill systems. He is currently a Full Professor in the Universidad Nacional de Colombia's Electrical and Electronic Engineering Department in Bogota. Dr. Rosero has published more than 100 referred journal and conference papers.

His research interests are focused on the areas of modelling, diagnosis and control of electrical machines and drives, electric mobility and smart grids.