Analysis of building maintenance requests using a text mining approach: building services evaluation

End users' maintenance requests gathered from computerized maintenance management systems (CMMS) configure a rich source of information to evaluate the occupants' satisfaction and the building systems. Nevertheless, the non-standardized data gathered from CMMS makes it difficult to carry out analytics. This paper presents a text mining approach to extract information from end users' maintenance requests and an analysis of 6,830 maintenance requests derived from 46 buildings including offices, academic buildings and laboratories along two and a half years. The research results reveal that the most common maintenance requests during building operation and maintenance are related to problems in electrical and HVAC fixtures. Although the year of construction is not related to the occupants' maintenance requests, the type of building use and building property do influence them. The implementation of control and preventive strategies based on these results can increase facility managers' productivity and building systems' performance.

Keywords: Building operation; text mining; maintenance request; facility management

Introduction

The operations and maintenance costs of a built-asset represent 75-80% of the total annual facility operating costs (Madureira, Flores-Colen, Brito, & Pereira, 2017). The economic impact proves the importance of building maintenance management. A maintenance plan typically includes technical inspections, which consist of a type of preventive legal maintenance, where tasks are performed regularly to maintain an element or system in a safe and efficient operating condition (Sullivan, Pugh, Melendez, & Hunt, 2010).

Technical inspections are practical tools to analyse the condition of the main building elements (civil and architectural elements of the building), through the identification of defects. However, the condition of building systems (plumbing, electrical, HVAC, elevator and fire systems) are difficult to evaluate. Building systems generally require preventive maintenance, with statutory legal requirements and standards (RICS, 2009). Therefore, punctual inspection might give a wrong evaluation of the system condition. To assess the condition of building systems, the analysis of end users' maintenance requests provide a good source of information. Given that maintenance requests represent a perception that a feature or element of the building is underperforming (e.g., malfunctioning of some equipment), they relate to building performance in a very direct way (Goins & Moezzi, 2013).

The concept of building performance is related to building meeting the requirements of users in providing a conducive, safe, comfortable, healthy, and energy-efficient environment to carry out different activities (Bakens et al, 2005; Ibem et al., 2013). Therefore, the analysis of maintenance requests that reflect a perception of a malfunction of the services provided by the building can lead to the performance evaluation of the building systems.

End users' maintenance requests are generally managed and stored in computerized maintenance management systems (CMMS) (Becerik-Gerber, Jazizadeh, Li, & Calis, 2012). Although a CMMS contains descriptions of the requests, they often configures large, unstructured and amorphous datasets (Gunay, Shen, & Yang, 2018). Requests' details are frequently recorded inconsistently by different users or some details can simply be missing (Federspiel, 2001). Thus, although a CMMS dataset contains invaluable textual data to benchmark a facility's maintenance and operation performance, it is challenging to retrieve valuable and 'correct' information from these datasets quickly and efficiently (Hale, Arno, & Briggs, 1999).

With the development of text mining algorithms, that allow the extraction of useful information from datasets (Witten & Frank, 2011), it may be possible to find indications of the condition of building systems. Examples of such useful information in the context of the CMMS datasets is the identification of operational faults of systems to develop a component/equipment or building level failure rate models, and introduce faults and effects analysis tools for building systems (Otto et al., 2012; Yang, Chen, Shen, & Gunay, 2017). Therefore, the information extracted from CMMS datasets can be used to provide insights into operation systems performance.

The aim of this paper is to present a systematic text mining approach to analyse and extract information from end users' maintenance requests stored in CMMS datasets. The proposed approach consists of a method to classify and analyse maintenance requests and assess the condition of building systems. This approach is then used to analyse 6,830 maintenance requests derived from 46 buildings and determine the typical problems that end users complain about, the building system where these problems arose and their severity. Information about the building use (office, academic and laboratories), building property (public and private), gross floor area (GFA), number of floors and construction year are also evaluated. This analysis will provide information about the typical problems that occur during the building in use and maintenance, and determine if the characteristics of the building (type, age, etc.) are determinant in the maintenance requests submitted by end users. These results will provide invaluable knowledge about the areas where facility managers might deal with. Understanding the nature of problems within building systems can enable strategies for their reduction to be developed.

Background

The operational phase of a built-asset is the main contributor to the building lifecycle cost (Kassem et al., 2014). Buildings require continuous operating expenses, including maintenance actions on a periodic basis to keep them in appropriate condition for use and to meet a minimum standard or level of performance (Grussing & Liu, 2014). Although software systems have been introduced to support maintenance processes, facilities data and information is fragmented (Becerik-gerber et al., 2012). Buildings may have many sophisticated sensors and computerized systems capable of delivering data about the status and performance of its systems. However, building systems' condition are difficult to evaluate (Das & Chew, 2011; Douglas, Ransom, & Ransom, 2013). Few studies have analysed the major problems within building systems and there is little to no practical use regarding most of data collected from computerized systems (Pärn, Edwards, & Sing, 2017).

Different techniques to identify building condition have been used by previous studies. Among them, Failure Mode and Effect Analysis (FMEA) is a technique used to identify and eliminate known or potential failures, in order to enhance the reliability and safety of complex systems (Liu, Liu, & Liu, 2013). The results of an FMEA can help analysts to identify and correct the failure that have a detrimental effect on the system and improve its performance. FMEA may be followed by a criticality analysis which defines the importance of each failure mode, qualitatively, semi-qualitatively, or quantitatively (ISO 31010:2009). Existing studies used FMEA in different applications, including HVAC systems, in order to provide a solution for HVAC prognostics (Yang, Shen, Chen, & Gunay, 2018).

Automated fault detection and diagnosis (FDD) is a process related with automating the detection of faults and their causes in physical systems (Katipamula & Brambley, 2005). The main objective of an FDD system is early detection of faults and diagnosis of their causes, allowing correction of the faults before additional damage to the system or loss of service occurs (Katipamula & Brambley, 2005). This is accomplished by continuously monitoring the operations of a system, using FDD to detect and diagnose abnormal conditions and the faults associated with them, then evaluating the significance of the detected faults, and deciding how to respond.

Recently, text mining has been proposed as an approach to identify problems in systems by analysing maintenance requests (Gunay et al., 2018). The purpose of text mining is to transform text into numeric attributes that can then be used in data mining algorithms (Witten & Frank, 2011). Modern building operations generate a large number of maintenance requests from end users in routine daily basis. These maintenance requests are treated as work-orders by the building manager or facility manager. Work-orders can be generated by occupants, who report a complaint about a malfunction, and by maintenance staffs who report faults in a daily operation and maintenance of the building. Typically, work-orders are managed by CMMS and contain some valuable information, including dates, fault symptoms, fault types, problem descriptions, actions taken to fix the problems, fault locations, and causes (Yang et al., 2018).

Existing text mining research has focused on methods of classifying documents and extracting information from datasets. A recent work (Gunay et al., 2018) focused on the identification of HVAC faults using text mining. Unfortunately, in the reviewed literature, there were not any publications regarding the analysis of maintenance requests to evaluate the condition of the different systems of a building.

Research methodology

The research methodology employed three main steps. First, a classification system of building system problems was proposed based on the results of literature review and questionnaire survey from (Bortolini & Forcada, 2018). The survey was conducted with fifty-three international experts on the topic of building performance and the results included the identification of the main problems within the building elements and systems. The results were then used to develop an objective and standardized building inspection system to evaluate the technical performance of existing buildings.

In the second step, a text mining approach to systematize the analysis of maintenance requests from CMMS was developed and 6,830 maintenance requests within 46 buildings were analysed. The buildings are located in the Mediterranean climate of Spain. The sample included office, academic buildings, and laboratories. Table 1 summarizes the main characteristics of these buildings.

Insert Table 1. Main characteristics of the analysed buildings

To enable analysis of the data and the extraction of conclusions, maintenance requests were classified by type and severity. The building characteristics (GFA, number of floors, construction year, type of building use, type of property) where these maintenance requests come from were also collected.

The data was analysed using the Statistical Package for the Social Sciences (SPSS) for Windows (version 17.00). Buildings that had missing data were eliminated from the analysis. SPSS was used to test the associations between the quantitative variables by computing Pearson’s correlation coefficient. This identified variables that had significant correlations at the 95 and 99% confidence intervals. SPSS was also used to identify whether there were any differences between samples (i.e., building property (public and private), type of building use (office, academic and laboratories)) (qualitative vs. quantitative variables) by means of a t-test or ANOVA for normal distributions and equal variances of the groups. The normality of the sample was tested using the Shapiro-Wilkinson test. The homogeneity of variance was tested using Levene's test.

A chi-square (x2) test was used to determine the dependence between samples and levels of severity (low, medium and high) (qualitative variables). This test allows a comparison to be made of the observed and expected frequencies. For a chi-square test, the null hypothesis is that the two sets of frequencies (i.e., observed and expected) are equal. The alternative hypothesis is that they are unequal. To identify those variables with significant correlations at the 95% confidence intervals, the asymptotic significance should be less than 0.05.

Text mining approach

The method to evaluate the condition of building systems starts with the extraction of the maintenance requests from the CMMS, creating a dataset in a *.csv* format, for example. Using scripts of *Python* programming language in a text editor (e.g., Notepad++), all punctuation marks and spaces need to removed, so only individual words are considered. The dataset is then encoded into a standard format (e.g., UTF-8) to ensure the correct removal of diacritical marks, reducing the complexity of dealing with a multilingual dataset. Finally, all words are converted to lower-case, therefore the letter case is not differentiated (e.g., Doors and doors are considered the same word).

To classify the maintenance requests in ‘categories’, the most frequent words of each problem type category are found using the *MapReduce algorithm* (Dean & Ghemawat, 2008). The most frequent words are then used to define a set of keywords for each category. For instance, the components of each system (e.g., boiler, chiller, light, pipes) are the most frequent words used to classify the problem type in a category. To classify the problem, adjectives that describe the characteristics of the systems (e.g., temperature, hot, cold, burnt) and the action needed to address the request (e.g., clean, check, inspect) are used. A stemming algorithm is employed to obtain the root words associated with each problem and then maximize word finding (e.g., window instead of windows). Then, the requests not labelled in any category and the ones mislabelled are reviewed and assigned with the correct category manually, improving the set of keywords.

The next step is to define the keywords that represent each ‘problem type’ for each category. The most important problems for each building system defined by (Bortolini & Forcada, 2018) are used in this step (Table 2). The same process for obtaining the most frequent words using the *MapReduce algorithm* is employed (e.g., failure, leakage). Then, root words for each defect type are established using the stemming algorithm (e.g., crack instead of cracking).

Insert Table 2. Problem type in systems (Bortolini & Forcada, 2018)

After the classification of the problem types, they are classified in three levels of severity (low, medium and high). The most frequent words related to high severity are the ones that the end user or the facility management (FM) team use when an immediate repair or action is required (e.g., urgent, safety, emergency, alarm, fire). The words related to low severity are the ones that the end user or the FM team use when a repair or action can be postponed and planned (e.g., have a look, change, verify, clean, paint). The requests not classified in any of the previous categories are defined as medium severity.

The next step is the creation of a dictionary in *Python*. For each building, a key is created to count the number of maintenance requests with a given set of characteristics in the dataset. After that, different statistics can be performed, including the frequency of problems by type, by year, by day, among others. Moreover, patterns can be identified seasonally.

To evaluate the condition of each building system, the magnitude of each problem type should be assessed using the following equation:

$$\text{Magnitude} = \frac{(\text{№ of low sev. prob. x 1}) + (\text{№ of medium sev prob. x 3}) + (\text{№ of high sev. prob. x 5})}{\text{A}}$$

Where *A* is the area of the building under analysis. For the problems in elevators, the *A* is referred to the number of elevators in the building.

For each system, with exception of elevators, a 100 plant square meter was defined and the ranges used to define the magnitude is presented in Table 3. This was used to standardize the results and be able to compare buildings using a standard measure.

Insert Table 3. Ranges to determine the magnitude of each problem type

Analysis of maintenance requests

Data collection

Data was collected from end users' maintenance requests from 46 buildings located in the Mediterranean climate of the metropolitan area of Barcelona, Spain (see Table 1). The sample included offices, academic buildings and laboratories. The majority of them were built in the 90s, so the systems are much related to this period of construction. The buildings are managed jointly in three groups by three distinct FM organizations. The dataset consists of 6,830 maintenance requests gathered from the CMMSs used by the FM organizations. All requests were submitted between 2015 and 2017 by the end users and the FM team through an intranet application linked to the CMMS. The information gathered was limited to the information provided by the requester (name, e-mail), date, description of the problem, problem type category (predefined labels) and the location of the room/building. The problem type categories that were analysed included: HVAC maintenance, electricity maintenance, plumbing maintenance, fire system maintenance and elevators maintenance.

Research findings

The keywords that represent the elements' names were used to retrieve the maintenance requests from the dataset and classify the problems by type. Figure 1 illustrates the most frequent terms within the maintenance requests using the MapReduce algorithm (Dean & Ghemawat, 2008). The size of the terms in the word-cloud represents its relative frequency in the dataset.

Insert Figure 1. Results of the maintenance requests analysis: word-cloud of the most frequent terms

Then, the problems detected through the maintenance requests were categorized by severity. Low severity problems included terms linked to those regular actions about maintenance activities that could be planned for a reasonable period of time, such as check, adjust, clean, among others. High severity problems included terms linked to an urgent action, and related to safety of end users. Figure 2 illustrates the most frequent terms within the maintenance requests to classify low and high severity problems.

Insert Figure 2. Word-cloud of the most frequent terms: (a) low severity problems and (b) high severity problems

Table 4 shows the number of maintenance requests by type of problem and the percentage of problems by severity. Operational problems with electrical and HVAC fixtures were the most frequent within the maintenance requests, with 36.50% and 30.48%, respectively.

Results revealed that many electrical fixture operation problems were related to plugs, switches and hand dryers not working, lights burnt or blinking, lights or equipment without electrical supply and problems with the automatic lighting control. While the HVAC operational problems were mainly related to terminal units (radiators, fan-coils or splits) out of order or not working properly, problems with the thermostat and temperature control. In fact, maintenance requests about hot and cold are typically the most frequently problem type reported by occupants (Federspiel, 2001). Other problems were linked to regulation such as valves, actuators, or stopcocks, leaks in fan-coils, noise from equipment, etc. However, the severity of problems linked to these maintenance requests were found to be minor or moderate.

Those minor problems were related to burnt lights. However, the electrical and the HVAC fixtures are the systems most directly related to the end user, with an immediate day-to-day interaction. Maintenance requests linked to occupants' comfort such as thermostat regulation, fan coils or plugs not working, etc. which can affect the wellbeing of occupants impairing their performance at work are found to be moderate. Finally, problems related to safety such as ventilation in datacenters or laboratories, although being low, are considered highly severe.

Although leakage problems being not very numerous (only 8.87% of the total maintenance requests), the severity of some of these problems were found to be important (54.29% of the plumbing leakage on fixtures were found to be moderate). Leakage problems included those found in the HVAC system such as fan-coils and splits and those found in the cold and hot water stopcocks, taps, boilers, accumulators, etc. Moderate and high severe leakage problems were related to leaks in taps and toilet that can cause floods and subsequently cause other serious problems.

Results also revealed that problems in fire system, elevators and electrical supply were not relevant since the preventive maintenance legislation are compulsory for these building systems. However, when these problems occur they are moderate and highly severe.

Insert Table 4. Results of the analysis of systems problems by type

Influence of building characteristics on the type of maintenance requests

Building characteristics such as GFA, construction age and the number of floors might influence the quantity and severity of building system problems and thus maintenance requests. In parametric tests such as Pearson's (r) correlation, Anova or Student's t-test, samples should be normally distributed. Consequently, the Shapiro–Wilkinson test was used to determine the type of distribution of the maintenance requests. The p-value of this test for a normal distribution was higher than 0.05, assuming that maintenance requests were normally distributed.

Pearson's (r) correlation was computed to test whether there existed a significant relationship between the different maintenance requests in system types, the GFA, the construction age and the number of floors. A positive Pearson's (r) correlation value indicates that when a variable increases, so does the related variable. In contrast, a negative Pearson's (r) correlation value indicates that when a variable increases, the related variable decreases.

According to the results, the correlation coefficients for the data revealed that the GFA and the number of floors were significantly related to maintenance requests in all systems. None of the building systems maintenance requests were correlated with the year of construction. The year of construction affects basically the building construction elements such as the structure, envelope, interior partitions, etc. However, the majority of maintenance requests were related to building system equipment (fan-coil, lights, etc.) which were replaced once they do not work properly.

The results revealed that the problems in “faulty operation of electrical fixtures” and “electrical operational distribution problems” were significantly related [$r = +0.421$, $n = 46$, $p < 0.01$, two tails, and $r2 = +0.25$ (25%)]. When electrical fixture operation problems occur these affect the distribution operation. The most common faulty operation of electrical fixtures were found to be plugs, switches and hand dryers not working, lights blinking, lights or equipment without electrical supply and problems with the automatic lighting control. These problems were found to be related to those “electrical operational distribution problems” which in general include cuts in the electrical boards and/or blowing protections (thermal magnetic circuit breaker and thermal overload relay). The majority of the minor fixture operation problems might affect the electrical line and the board where its protections are located. Then, from a small incident in an electrical fixture, a big electrical cut or dysfunction might occur. While some maintenance works cannot be prevented, a lot can however be minimised through a preventive maintenance program (Balaras & Argiriou, 2002). Preventive maintenance in electrical fixtures such as lights, plugs, switches and small equipment might reduce considerably big distribution electrical problems. This is to avoid necessary disruption of work and potentially hazardous problems. Basic checks and inspections can help minimize the most common and frequent problems pertaining to electrical systems (Balaras & Argiriou, 2002).

The results also revealed that problems in “Faulty operation of electrical supply” and “HVAC operational production problems” were significantly related [$r = +0.745$, $n = 46$, $p < 0.01$, two tails, and $r2 = +0.56$ (56%)]. Since the majority of the HVAC production equipment (boilers and chillers) and other related equipment such as pumps and fans, require electricity supply those problems in electrical supply do considerably affect the HVAC production. The results of the Chi-square analysis also revealed that the level of severity problems in “Faulty operation of electrical supply” and “HVAC operational production problems” were also not independent ($p<0.05$) (Table 5). This result indicates that when problems in electrical supply are severe, such as power disturbance, (changes in power voltage, current, or frequency), these interfere with the normal operation of electrical equipment, such as HVAC production equipment provoking sever HVAC functioning problems.

Insert Table 5. Chi-square test of independence: “Faulty operation of electrical supply” and “HVAC operational production problems”

Results also found that the problems in “plumbing leakage” and “plumbing supply” were significantly related [$r = +0.702$, $n = 46$, $p < 0.01$, two tails, and $r2 = +0.49$ (49%)]. Plumbing supply problems included under or over pressure problems due to malfunctioning of pumps. These problems can provoke malfunctioning of fixtures which can end up with leakages. Implementing building automation system (BAS) and building management system (BMS) to control the water flow, pressure, temperature, etc. in plumbing production can avoid distribution plumbing problems to occur and reduce the number of maintenance requests. Although the detection of problems in building systems is difficult, BAS/BMS allow automatic fault detection, and thus preventive maintenance can be planned (Domingues, Carreira, Vieira, & Kastner, 2015). Alarm events capture a problem in a device, and the information pertaining to an alarm indicates the apparent source of the problem (Domingues, Carreira, Vieira, & Kastner, 2015).

Analysis of maintenance requests by type of building

An analysis of whether public and private buildings behaved differently was carried out.

The significance of the Shapiro-Wilkinson test for a normal distribution was not less than or equal to 0.05 in either sample (public and private). Therefore, one can assume that both groups had a normal distribution. Then, a t-test was performed to determine whether the building system problems varied between public and private buildings. Levene's test for homogeneity of variance was violated for the HVAC fixture problems ($p=0.00<0.05$), which indicates that population variances were different in each group and the Welch-Satterthwaite test for testing the means should be performed. This test revealed that at the 95% confidence level, the HVAC fixture maintenance requests varied by public and private buildings ($p=0.026<0.05$; IC 95% -92.810÷-8.169) (Table 6).

Insert Table 6. t-Test for the HVAC fixture maintenance to compare Public and Private buildings

However, the Chi-square analysis revealed that the severity of HVAC fixture problems was independent to the property of the building (public or private) ($p=0.138>0.05$) (Table 7).

Insert Table 7. Chi-square test of independence: "HVAC fixture problems" and "Building property"

Preventive maintenance on the electrical, fire and elevators systems is compulsory, so the problems in these systems are found to be the same in both samples. However, preventive maintenance within HVAC systems are only compulsory in water systems. Figure 3 shows that private buildings incur higher HVAC fixture problems than public buildings. This might suggest that maintenance within HVAC systems in private buildings is mainly corrective. However, these results support the opinion of FM experts which declared that end users accept different performance levels depending on whether the building is private or public (Bortolini & Forcada, 2019). Generally, public buildings managed by the government are restricted by budget limits and conditioned by political issues, consequently the quality of services provided by public buildings is different from that of private buildings (Alonso et al. 2015). End users are aware of this fact and accept different levels of performance depending on the services available in the building. These differences on the acceptance level is called “forgiveness factors” (Leaman & Bordass, 2007). End users in private buildings might have a higher expectation in relation to the thermal environmental conditions and thus require better services.

Insert Figure 3. Box plot: HVAC fixture maintenance requests vs. Type of property

Regarding the type of building (office, academic or laboratory), the significance of the Shapiro-Wilkinson test for a normal distribution was not less than or equal to 0.05 for any sample. It can thus be assumed that all sample groups have a normal distribution. An ANOVA was performed to determine whether the building system problems varied among building types. The only difference between maintenance requests among different building types was found in HVAC fixtures ($F = 3.617$, $p = .035$) (Table 8). Office buildings, academic buildings and laboratories are very different in nature. In office and laboratory buildings end users tend to spend all the workday in the same room and generally the occupancy ratio is low. Then, end users have a better thermal control of their rooms but a higher level of exigency. In contrary, in academic buildings, end users move among classrooms and the occupancy ratio is higher. Difficulties on reaching an agreement on the comfort temperature among all end users and the fact of being in different rooms along the day might reduce the thermal comfort exigency of these buildings.

Insert Table 8. Anova test to compare HVAC fixture problems among building types

Discussion and Conclusions

Occupants dissatisfaction related to building systems represent a common problem in the building operation. Determining an approach to identify the most relevant problems is the first step toward addressing such a problem. If FM and building owners can effectively formulate prevention strategies based on the common use and maintenance problems, buildings will perform better, occupants will be more satisfied and building operational cost will be minimized.

Within the operational phase, valuable data regarding maintenance requests is generated. There is usually little analysis of these data due to the amorphous and unstructured datasets. Therefore, methods to analyse maintenance requests datasets are of great value for facility managers.

This paper presented a text mining approach based on Python programming language to analyse maintenance requests related of building systems. The text mining approach was then used to evaluate 6,830 maintenance requests derived from 46 buildings to identify the crucial maintenance issues and direct the improvement of maintenance strategic planning.

The analysed dataset represented the typical maintenance requests of buildings located in the Mediterranean climate, which is characterized by the four seasons, with dry and hot summers and cool or mild winters. Therefore, buildings generally require both heating and cooling systems to acclimatize and achieve comfort requirements. In addition, the type of services provided by the buildings are also related to the climatic zone and, therefore, to the type of maintenance requests. For instance, in subarctic climates only heating is required. Radiant systems, which are simpler than air water systems, are then normally implemented in this climatic regions, resulting in lower problems detected by end users.

The detailed analysis concluded that the most common end users' maintenance requests were related to electrical and HVAC fixtures. Although considered minor problems, "electrical fixture problems" were found to be significantly related to "electrical distribution problems" such as cuts in lines and boards. These problems have a bigger repercussion on the services provided, so preventive maintenance in fixtures might improve considerably end user maintenance requests and thus end user satisfaction.

According to the results, "HVAC production problems" were significantly related to "electrical production problems". Implementing management systems such as BMS can then detect and prevent those production problems that might then affect other system problems. A BMS can control and monitor the building's mechanical and electrical equipment, enabling the early detection of problems (Domingues, Carreira, Vieira, & Kastner, 2015). The results of the automatic fault detection can then be used to plan corrective maintenance actions.

To improve building systems' performance and thus end users' satisfaction, preventive maintenance in electrical and the HVAC fixtures, which are the systems most directly related to the end user, should be put in place. Preventive maintenance should focus on HVAC terminal units, electrical plugs, switches and small equipment and the inspection of pipes and fixtures to detect potential leakage problems. Detecting potential fixtures problems through preventive maintenance, entails a reduction of electrical and water distribution problems which are more severe and difficult to solve. Some of these severe problems might not be prevented but minimised.

Interestingly, the results showed that the construction year does not affect the end users' maintenance requests. The majority of the buildings analysed were built in the 90s when energy efficient standards and performance based regulation were not compulsory in Spain.

The research presented in this paper also determined the different behaviours in terms of end user satisfaction within different types of building uses and building properties. The study revealed that the type of building use and the type of building property are decisive on the end user satisfaction. Forgiveness factors are probably influencing this result. End users accept different performance levels depending on whether the building is private or public, which is related to the resources that are available for the building. Generally, buildings managed by the government are restricted by budget limits and conditioned by political issues, consequently the quality of services provided by public buildings is different from that of private buildings. Thus, forgiveness is lower when high quality services are present in a building. For instance, people working in air-conditioned spaces are isolated from the outdoor environment, therefore they expect their buildings to provide consistent thermal environmental conditions regardless of outdoor weather conditions (Kim & De Dear, 2012). End users of naturally conditioned buildings turn out to be more active in thermoregulatory adaptation through changes in activity level and clothing (behavioural adaptation), and tend to be more tolerant to a wider range of temperatures (psychological adaptation) (Van Hoof & Hensen, 2007). When analysing technical data, researchers should take into account those human and psychological factors that might affect statistical results.

This study provides evidence that the special characteristics of the building management, with FM dealing with many different systems (mechanical, electrical, etc.), building types and building properties, low compulsory preventive regulations and low implementation of BMS contribute to end user maintenance requests. Facility management regulation and certification exists. However, adaptation of these regulations to the real needs of the sector, emphasizing the analysis of end user satisfaction are needed to improve the quality of the building services provided.

These results could make it possible to put strategies in place prior to maintenance requests and, thus, improve productivity and performance.

Although the findings of this research are revealing, it is clear that future research is required to further investigate the building performance situation through maintenance requests in greater depth. Future research will focus on determining the costs of corrective maintenance request, which will enable preventive measures to be identified, as well as demonstrate to owners the impact of implementing preventive strategies on their overall profitability.

In summary, this research contributes to a better understanding of maintenance requests and thus, building systems performance.

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Table 1. Main characteristics of the analysed buildings.

Building	Type of building	Building property	Year of Construction/ Rehabilitation	GFA (m^2)	Number of floors	Number of maintenance requests
1	Academic	Public	1990	3,967	5	83
2	Academic	Public	1990	3,886	5	217
3	Academic	Public	1991	3,783	5	203
4	Academic	Public	1991	3,795	5	176
5	Academic	Public	1992	3,886	5	101
6	Academic	Public	1992	4,216	5	472
7	Offices	Public	1989	2,867	5	137
8	Academic	Public	1990	1,318	5	162
9	Offices	Public	1993	2,263	7	159
10	Offices	Public	1994	5,919	7	124
11	Offices	Public	1995	2,337	7	101
12	Offices	Public	1986	4,895	5	248
13	Offices	Public	1989	2,124	5	135
14	Laboratories	Public	1993	4,755	7	365
15	Offices	Public	1995	4,790	5	205
16	Offices	Public	1994	5,280	7	268
17	Offices	Public	1995	4,753	5	210
18	Laboratories	Public	1986	5,208	5	121
19	Offices	Public	1989	2,971	5	113
20	Offices	Public	1989	2,969	5	167
21	Laboratories	Public	1990	3,049	5	148
22	Offices	Public	1991	3,011	5	90
23	Offices	Public	1993	3,048	5	101
24	Academic	Public	1904/1995	9,429	3	233
25	Academic	Public	1904/1994	2,940	3	51
26	Academic	Public	1904/1993	2,577	2	7
27	Academic	Public	1960/1997	7,626	5	88
28	Academic	Public	1960/2002	3,143	5	40

29	Academic	Public	1960/1995	11,492	5	252
30	Offices	Public	1998	2,344	4	21
31	Laboratories	Public	1960	2,624	4	56
32	Academic	Public	1992	6,446	4	74
33	Academic	Public	1996	2,393	2	121
34	Offices	Public	1996	2,218	4	100
35	Academic	Public	1997	2,779	4	63
36	Laboratories	Public	2001	3,198	6	75
37	Laboratories	Public	2011	7,378	5	76
38	Offices	Public	1945/1994	1,350	1	18
39	Offices	Private	1996	9,835	13	400
40	Offices	Private	1986	1,755	10	237
41	Offices	Private	1986	4,464	10	103
42	Offices	Private	1989/2018	5,000	9	64
43	Offices	Private	1999	8,622	14	160
44	Offices	Private	2015	5,480	5	117
45	Offices	Private	2015	5,480	5	108
46	Offices	Private	2015	8,394	5	259

Table 2. Problem type in systems (Bortolini & Forcada, 2018).

System	Problem type
Electrical	Faulty operation of electrical fixtures
	Faulty operation of electrical distribution elements
	Faulty operation of electrical supply elements
Plumbing	Leakage in water distribution elements
	Faulty operation of water supply elements
	Corrosion in water distribution elements
HVAC	Faulty operation of HVAC production elements
	Faulty operation of HVAC fixtures elements
Fire	Faulty operation of fire fixtures
	Faulty operation of electrical fire fixtures
	Faulty operation of water supply elements
Elevator	Electrical faulty operation
	Mechanical faulty operation

Table 3. Ranges to determine the magnitude of each problem type.

Building systems	Magnitude ranges	Level of severity
Problems in the HVAC production, plumbing and electrical supply and distribution	<0.30	Low
	from 0.31 to 0.50	Medium
	>0.51	High
Problems in the HVAC and electrical fixtures	<1.0	Low
	from 1.1 to 2.0	Medium
	>2.1	High
Problems in the fire system	<0.10	Low
	from 0.11 to 0.20	Medium
	>0.21	High
Problems in the elevator system	<3.0	Low
	from 3.1 to 10.0	Medium
	>10.1	High

Table 4. Results of the analysis of systems problems by type.

System	Problem type	Number of problems	% of the total	% low severity	% moderate severity	% high severity
Electrical	Operational fixtures problems	2493	36.50	52.35	44.00	3.65
	Operational distribution problems	212	3.10	68.40	28.30	3.30
	Operational supply problems	82	1.20	65.85	30.49	3.66
Plumbing	Leakage on fixtures	606	8.87	37.29	54.29	8.42
	Operational supply problems	420	6.15	68.81	28.81	2.38
HVAC	Operational production problems	434	6.35	69.12	21.66	9.22
	Operational fixtures problems	2082	30.48	49.33	46.35	4.32
Fire	Electrical operational fixtures problems	63	0.92	23.81	69.84	6.35
Elevator	Operational mechanical problems	372	5.45	11.29	76.88	11.83
	Operational electrical problems	66	0.97	28.79	69.70	1.52
	Total	6830	100			

Table 5. Chi-square test of independence: “Faulty operation of electrical supply” and “HVAC operational production problems”.

	Value	df	Asymp. sig (2-tailed)
Pearson chi-square	15,319	2	,000
Likelihood ratio	5,902	2	,052
No. of valid cases	48		

Table 6. t-Test for the HVAC fixture maintenance to compare Public and Private buildings.

	Levene's test for equality of variances		t-test for equality of means					95% Confidence interval of difference	
	F	Sig.	t	Df	Sig. (2-ailed)	Mean differen ce	Standar d error differe nce	Lower	Upper
Equal variances not assumed*	16,06 9	,00 0	- 2,809	7,14 9	,02 6	- 50,48 947	17,97 319	- 92,81013	- 8,16 881

* Welch-Satterthwaite test

Table 7. Chi-square test of independence: “HVAC fixture problems” and “Building property”.

	Value	df	Asymp. sig (2-tailed)
Pearson chi-square	3,960	2	,138
Likelihood ratio	4,123	2	,127
No. of valid cases	48		

Table 8. Anova test to compare HVAC fixture problems among building types.

	Sum of squares	gl	Mean square	F	Sig.
Between groups	5690,450	2	2845,225	3,617	,035
Within groups	33826,427	43	786,661		
Total	39516,877	45			