Introducing Innovative Energy Performance Metrics for High-Level Monitoring and Diagnosis of Telecommunication sites

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Abstract

This paper aims at deepening the theme of monitoring and energetic diagnosis of telecommunication (TLC) central offices, via the development and application of innovative performance parameters, whose objective is to detect the presence of anomalous energy absorption of the electronic equipment and cooling systems. Firstly, extensive energy analysis is conducted by using the degree days (DD) parameter, which is already consolidated in the field of efficient thermal management of data-centers. Secondly, properly designed indicators are added to this metric: the parameter of central utilization (PUC), which allows distinguishing the multi-use (e.g. combined TLC rooms and offices) from pure central offices; the index of cluster reliability (ICR), which evaluates the stability in time of the acquired data, and the reliability index (RI). The last parameter was specifically introduced to assess if a data center exhibits an unusual energy behavior with respect to a reference energy consumption benchmark, here defined for the group the site belongs to. The innovative contribution of the paper lies in the introduction and joint use of ICR and RI parameters, which can be set up as an effective diagnostic tool for telecommunications sites. The combined verification of current ICR and RI values allows outlining four possible scenarios, differentiated on the basis of the data reliability. Particularly, immediate determination of reliable and unreliable TLC sites is enabled, while the diagnostic potential is exploited to determine whether deeper investigation of energetic consumption trajectories is required. Specifically, the joint assessment of the ICR-RI pair was successfully applied to detecting the presence of anomalous TLC and cooling energy consumption data, as well as whether these abnormalities were due to inefficient thermal management or sensor malfunctioning.

Keywords: Energy intelligence; Telecommunication; Energy management; Monitoring and diagnosis; Thermal management

Nomenclature

CDD	Cooling degree days [°C]
CF_Y	Annual Comparison factor [/]
CF_{Yrif}	Annual reference Comparison factor [/]
CO	Central offices
DCiE	Data Center Infrastructure efficiency
DD	Degree days [°C]
ECLC	Climate control (Thermal management) energy quota [kWh]
EEI	Energy efficiency Index [/]
EMISC	Miscellaneous energy quota [kWh]
E_{TLC}	Telecommunication energy quota [kWh]
E_{TOT}	Total energy consumption [kWh]
FC	Free-Cooler
HDD	Heating degree days [°C]
ICR	Index of Cluster Reliability [/]
ICT	Information & Communication Technology
IT	Information Technology
KPI	Key performances indicators
MUC	Multi-use central offices
PUC	Parameter of utilization of Central [/]
PUE	Power usage effectiveness [/]
RI	Reliability index [/]
TLC	Telecommunication
WSN	Wireless Sensor Network

1 Introduction

Nowadays, the Information and Communication Technology systems (ICTs) are responsible for roughly 3% of the worldwide electricity consumption [1], with an upward trend of this rate because of the impetuous development of the Internet, smart services and mobile telephony. This technical innovation requires even more powerful infrastructure in terms of features and performance. Since the current way to meet the worldwide energy requirements primarily relies on fossil fuel, ICT systems cause 2% of global carbon emission, corresponding to 1/4 of the CO_2 emissions produced by passenger cars worldwide [1]. Furthermore, the ICT sector itself is expected to play a leading role in reducing the carbon footprint of industrial processes, by e.g. replacing current TLC equipment by innovative, more efficient devices,

as well as introducing intelligent energy management solutions, which could specifically rely on the above mentioned smart services to perform eco-friendly actions in any kind of industrial applications [2]. Such a need has been recently evaluated as one of the key actions~~,~~ to be undertaken in the framework of the 20–20–20 climate change plan ~~recently~~ ratified by the European Union [3]. In this overall framework, ICT companies already started monitoring their energy consumption with dedicated sensors, so as to ensure more efficient energy usage for all services and ancillary activities related to data center. Particularly, the telecommunication company TIM (Telecom Italia Mobile) has started, since 2006, a research activity aimed at the optimization and reduction of energy consumption of telecommunication sites. In order to do so, a middleware platform was set-up based on wireless sensor networks (WSN) for remote monitoring and diagnosis of TIM central offices. The WSN is based on ZigBee standard [4,5,6] and it is deployed in TLC switching plants to monitor environmental data (internal and external temperature and relative humidity), as well as the energy consumption of servers and storage systems, cooling and humidification systems, networking equipment and lighting/physical security. The wide availability of data provided by these monitoring platforms can enable the definition and application of innovative performance parameters aimed at energy intelligence [7] purposes, such as energy monitoring and diagnosis.

At international level, the energy performance of telecommunication sites is evaluated by the Power Usage Effectiveness (PUE) indicator, as introduced by the "The Green Grid" consortium in [8] and defined as in equation (2). The Green Grid, while recognizing [9] the importance of introducing indexes aimed at improving data centers sustainability, proposed the use of a new metric, namely the Carbon Usage Effectiveness (CUE), to well assess the effective carbon footprint of TLC sites. This indicator (see equation 3) considers the electric energy production method and estimates the CO_2 amount produced per each used kWh.

When CUE is used in combination with the power usage effectiveness (PUE) metric, data center operators can quickly assess the sustainability of their plants, as well as determine if any energy efficiency and sustainability improvement is eventually required. The family of xUE metrics is at the heart of many discussions, mainly because it is not effective when comparing different data centers. The use of the abovementioned metrics might involve the impossibility of accounting for external weather conditions, which directly affect TLC cooling energy demand. In [10] the energetic efficiency index (EEI), defined as the ratio between TLC equipment and overall plant energy demand, was used to evaluate the energetic performance of the plant. The knowledge of actual EEI, in conjunction with temperature monitoring, provided operators with useful information to improve energetic performance. Pelley et al. in [11] propose using total data center power to improve central offices energy efficiency; particularly, the development of specific power models for each critical data center component was proven effective in determining if: i) the energy management of existing hardware can be improved or ii) potentially costly hardware maintenance and/or ~~even~~ replacement are eventually needed.

In order to fully exploit the potential of the above-introduced WSN data acquisition platform, properly designed indicators are added to these consolidated metrics. Indeed, previous works were already devoted to propose metrics specifically aimed at improving cooling performance in TLC rooms [12, 13]. Although these latter metrics were proven effective in assessing the efficacy of adopted cooling devices, none of them can be deployed to perform the above-mentioned high-level energy monitoring tasks. Thereby, the main aim of this paper is to propose energetic performance metrics suitable to characterize TLC sites and collect them in homogeneous groups, on one hand, and, on the other, enable energy monitoring tasks aimed at verifying the reliability of acquired data both in the time and space domain. Successful comparative analyses would be enabled between homogeneous sites, thus providing a significant contribution towards the establishment of long-lasting energy intelligence policies [14] in telecommunication environments. More specifically, the innovative metrics proposed later on, namely the index of cluster reliability ICR and reliability index RI, are conceived in such a way as to account for the impact of cooling load demand, thus resulting in a twofold benefit: i) assessing how efficient are the thermal management strategies adopted in the TLC site under-investigation and ii) providing fast and trustable feedbacks on the reliability of the data acquisition system (i.e. the WSN). Particularly, the above introduced possible exploitations shall be considered highly valuable towards deep valorization of the large amount of data acquired and provided by the WSN, mainly aiming at successfully accomplishing the control and diagnostic tasks within a comprehensive energy intelligence protocol [14]. This is a key advantage with respect to available metrics, such as the above introduced xUEs, which are mostly useful at the monitoring level of the mentioned energy intelligence policy or, eventually, for energy audit purposes.

The paper is structured as follows: in Section 2 the energy balance to be associated to a generic central office, as well as the main performance metrics with their use and application are presented. Section 3 presents both the TLC sites characterization, based on DD, PUC and EEI, and possible scenarios that may result from the joint analysis of ICR-RI metrics values. In the conclusions the potential areas of application of proposed performance metrics are presented and discussed.

2 Monitoring and diagnosis of telecommunication sites

This section introduces the main performance metrics, which are then proven suitable to introduce strategic energy intelligence strategies within telecommunication sites. In the following, particular relevance is given to the cooling energy demand, as a consequence of the significant and recently increasing efforts made by researchers and Telecom operators to optimize thermal management in telecommunication systems and data centers [15, 16, 17], with the final aim of substantially reducing its impact on the energy bills of TLC companies.

2.1 Energy balance

In telecommunication sites two categories of energy consumption can be detected: the direct one, due to the current absorption by the electronic equipment (E_{TLC}) and indirect ones, which are primarily associated to miscellaneous absorption of auxiliary systems (E_{MISC}) and cooling systems (E_{CLC}), the latter being necessary to remove the thermal energy dissipated by the TLC equipment [18, 19]. Figure 1 provides a schematic representation of the energy balance expressed by equation (1).

$$E_{TLC} + E_{CLC} + E_{MISC} = E_{TOT} \tag{1}$$

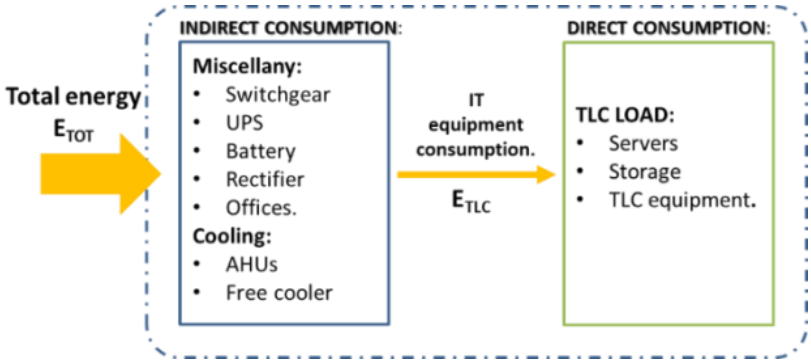


Figure 1: Energy balance in TLC sites.

Hereinafter all energy variables, expressed in kWh, are computed on a year time-base. Therefore, the afore-mentioned State of the Art metrics PUE and CUE can be estimated as function of the energy consumptions introduced by equation (1), as follows:

$$PUE = \frac{E_{TOT}}{E_{TLC}} \tag{2}$$

$$CUE = \frac{Total\,CO_2\ emissions\,caused\,by\,Total\,Data\,Center\,Energy}{E_{TLC}} \tag{3}$$

It is worth noting here that equation 2 holds valid when the yearly average PUE value shall be estimated.

2.2 Performance metrics

The use of performance parameters aims at supporting IT companies in determining if the energy management strategies of an existing central office must ~~shall~~ be improved. First of all, Heating Degree Days (DD) allow classifying TLC sites as a function of climate conditions. Data centers with high DD are located in cold climatic zones. The resulting beneficial effect on climate control task is twofold: on one hand, the range of use of free coolers (which are less energy demanding as compared to the traditional HVAC) increases; on the other hand, the natural thermal exchange between the inside and the outside enhances switching rooms cooling. Therefore, if DD are high (2101-3001), the TLC site is most likely classifiable as a less energy intensive site.

Properly designed indicators are added to the DD metrics. The parameter of utilization of centrals (PUC) allows distinguishing the pure central offices (CO, i.e., composed by switching rooms only), from multi-use central offices (MUC), composed by both switching rooms and offices. The PUC parameter can be calculated as shown in equation (4).

$$PUC = \frac{E_{TLC}}{E_{TLC} + E_{MISC}} \tag{4}$$

Since the miscellaneous energy contribution is not easy to recognize, it is possible to obtain an indirect estimate of PUC parameter by referring to the energy balance expressed by equation (1). Thus, the following alternative formulation can be obtained for PUC:

$$PUC = \frac{E_{TLC}}{E_{TLC} + \left(E_{TOT} - E_{TLC} - E_{CLC}\right)} = \frac{E_{TLC}}{E_{TOT} - E_{CLC}} \tag{5}$$

PUC values vary from zero to one. When PUC tends towards the unity, the miscellaneous energy is negligible and the plant can be classified as central office. On the other hand, if PUC is significantly lower than one (e.g. at least normalized PUC shall be lower than 0.9, as shown in Figure 5), energy contributions are not closely related to the TLC equipment: the plant is thus classified as multi-use (i.e. TLC site is composed by switching rooms and offices), as shown in Figure 2.

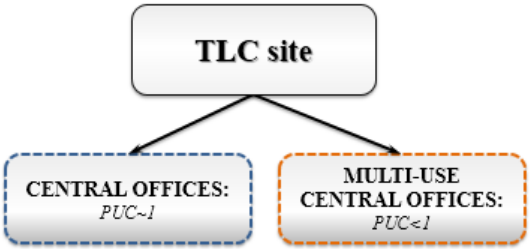


Figure 2: PUC-based classification, which was here adopted to distinguish between pure (i.e. consisting of TLC rooms only) and multi-use (i.e. consisting of both TLC rooms and offices) central offices.

The uniqueness of this classification is undermined by the fact that the miscellaneous energy not only contemplates the load associated to the offices, but also contains the energy consumption related to ancillary devices and the rate of dissipation due to the current rectification. Nevertheless, for the sake of simplicity, the PUC can be safely considered as a suitable parameter in distinguishing between CO and MUC plants.

In order to evaluate the energetic performance of TLC sites, the energy efficiency index (EEI) is used by Telecom Italia operators. The EEI parameter is defined as the ratio between TLC equipment (E_{TLC}) and overall plant demanded energy (E_{TOT}), as shown in equation (6):

$$EEI = \frac{E_{TLC}}{E_{TOT}} \tag{6}$$

The EEI indicator is also known in literature as DCiE. This parameter, originally introduced by the "The Green Grid" consortium in [8] and defined as the reciprocal of PUE, belongs to the family of xUE metrics. Since EEI values vary from zero to one, when EEI tends towards unity, the TLC site shows high energetic performance. If EEI value is low, energy efficiency actions are required to optimize the energy consumption relating to conditioning and auxiliary systems. Hereinafter, since Telecom operators deem it more effective than PUE in the establishment of long-lasting energy intelligence policy in telecommunication environments, the EEI index is preferred.
The above-introduced metrics (i.e. PUC and EEI) are very effective in synthesizing the huge amount of data provided by the available WSN [4-6], thus complying with the general guidelines of TLC energy intelligence policies [7]. Moreover, TLC energy intelligence also entails setting-up effective monitoring and diagnostic procedures. Therefore, further metrics shall be defined to enable, on one hand, accurate evaluation of current cooling control strategies and, on the other, the detection of faulty functioning of cooling devices, as well as the eventual loss of data acquisition by the WSN. Therefore, the comparison factor (CF_Y) is firstly introduced, which will be shown later to be propaedeutic to the introduction of more monitoring- and diagnostic-oriented indexes. The CF_Y index, shown in equation (7), is defined as the ratio between the annual energetic demand for climate control and the annual energetic demand of TLC equipment, both expressed in kWh.

$$CF_Y = \frac{\int_0^{365\cdot 24} P_{CLC}(t)dt}{\int_0^{365\cdot 24} P_{TLC}(t)dt} \tag{7}$$

For the purpose of evaluating if a plant exhibits an unusual behavior with respect to a reference energy consumption trend, the reliability index is introduced:

$$RI = \frac{CF_Y}{CF_{Yref}} \tag{8}$$

In order to calculate the RI parameter, in accordance with equation (8), it is necessary to identify the reference Comparison Factor value (i.e. CF_{Yref}). The CF_{Yref} is representative of typical behavior, regarding energy management, and it is specifically defined for the group the plant is expected to belong to. The identification of the reference comparison factor should account for the relationship between energetic demand for climate control and external environment parameters. To this end, following the indications provided in [20], central offices are divided into three distinctive groups, determined as a function of heating degree days (HDD) ranges (see Table 1):

Table 1: HDD-based grouping, with reference temperature being set to 20 °C. Column 1 resumes the outcomes of HDD based-zone classification.

1	2	3
	HDD range [°C]	CDD range [°C]
Low Degree days (hot zones)	<1401	>750
Medium Degree days (mild climate zones)	[1401-2100]	[651-750]
High Degree days (cold zones)	>2100	<651

It is worth noting here that HDD-based climatic zone classification of TLC sites can be based on larger DD ranges. This is the reason why HDD were preferred to cooling degree days (CDD), which still provide useful classification ranges, although narrower and, thus, potentially less reliable when comparing one year to another, due to higher sensitivity to average temperature oscillations. Figure 3 shows the comparison factor statistical distributions associated to each group, as determined upon application of Table 1 ranges to available TLC sites database. Afterwards, the reference comparison factors are estimated through a suitable statistical processing of the data [21] shown in Figure 3 (see Equations 9, 10 and 11).

$$CF_{Yref} = \frac{\sum_{i=1}^{n_{classes}} x_{G_i} \cdot A_i}{A_T} \tag{9}$$

$$A_T = \sum_{i=1}^{n_{classes}} A_i \tag{10}$$

$$n_{classes} = \sqrt{n_{elements}} \tag{11}$$

In equations (9) and (10), x_{Gi} is the coordinate of each class centroid, whereas A_i is the i-th class geometric area. The weighted average is the most suitable statistical index to calculate the CF_{Yref} parameter; other positioning indexes have been tested and return much worse results. Indeed, the arithmetic average would make relevant, to the identification of CF_{Yref}, singular values of CF_Y that are positioned at the domain extremes. Instead, the statistical mode (?) would have given relevance to a very small number of plants, whose CF_Y values converge into a single class; the results were thus not representative of the entire data set. The median is not able to take into account the climatic effect on CF_{Yref}. After the identification of the CF_{Yref} parameter, for each period subject to analysis, the RI index can be calculated. Such an indicator is particularly suitable to assess the space uniformity of the central offices under investigation, as it will be discussed in detail later.

With the purpose to evaluate the time data stability, the index of cluster reliability (ICR), mathematically defined in the equation (12), can be introduced.

$$ICR = \frac{CF_{Y1}}{CF_{Y2}} \tag{12}$$

The subscripts Y1 and Y2 (see equation 12) refer to two different time periods, in the specific case the years 2013 and 2014. The ICR index is able to give preventive information about the deviation of measured data during analyzed periods. Therefore, the indicator is useful to evaluate the time stability of the measurements obtained via the acquisition network. In case such time stability is not guaranteed, and the central office under investigation shall be removed from a data-base destined to perform clustering analyses, e.g. aimed at classifying central offices as a function of climatic and energy efficiency features.

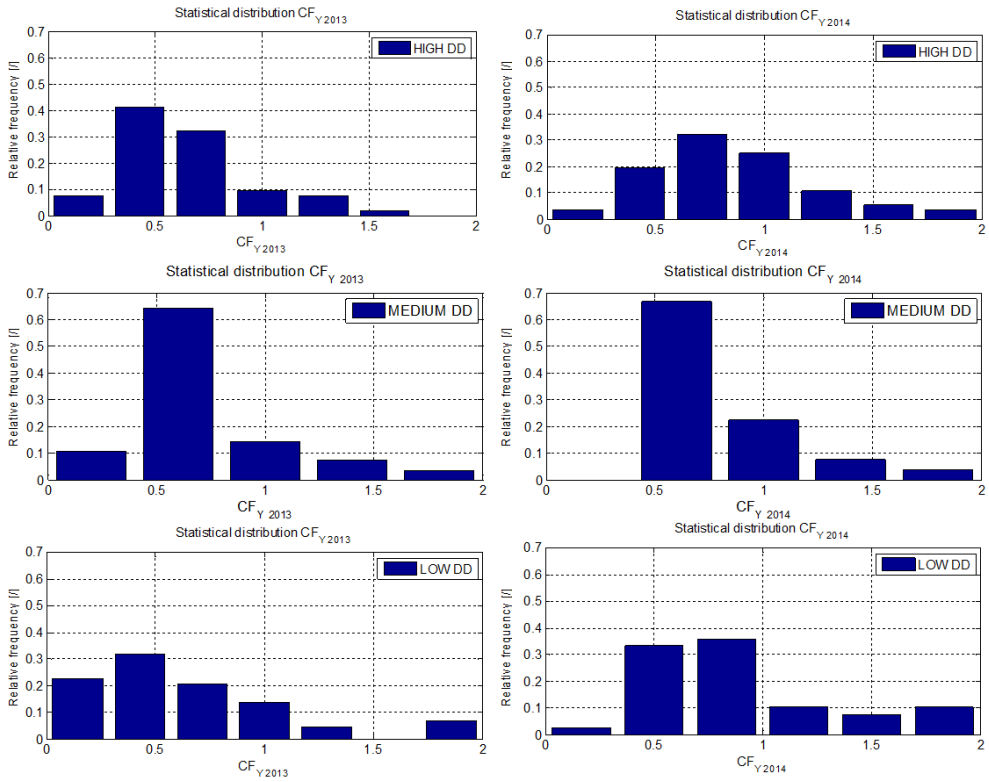


Figure 3: Statistical distribution of CF_Y values. Such comparison factor and related relative frequency values were evaluated by applying equations (7-11) to the available data-set of TLC sites, as detailed in Table 2.

2.3 Combined check of parameters

The combined check of the performance parameters ICR and RI is an effective diagnostic tool, which can be integrated within advanced energy intelligence protocol to be deployed in TLC contexts. The check provides a criterion both to assess the reliability in terms of time analysis of the sensors network, used for monitoring purposes, as well as to evaluate how differently from its class a given central office behaves. Firstly, the energy diagnosis of TLC sites is carried out by observing the ICR parameter. If this metric value is far from the unit, time instability in the measured data is detected. Secondly, RI is computed for each year subject to analysis. The period corresponding to the highest discrepancy from the unit identifies data whose behavior is not compatible with the reference pattern (see equations 9-11). The combined check of the diagnostic parameters consisted in evaluating the following inequalities:

$$|ICR - 1| < \varepsilon_1 \tag{13}$$

$$|RI - 1| < \varepsilon_2 \tag{14}$$

Experimentally, it was found that ICR and RI values higher/lower than the 1+/-ε_i tolerance interval (with ε_1 and ε_2 both equal to 0.5) indicate unreliable TLC sites. It is worth noting that both ε_1 and ε_2 are purely mathematical threshold levels, specifically introduced to account for the unavoidable distance from the unit value, as resulting from the application of the ICR and RI formulas (see equations 8-12) to the entire and highly diverse TLC sites data-base.

3 Results and discussions

This section will introduce the main results and discussions about the energy analysis conducted on the available experimental data. The KPIs (Key Performance Indexes) defined above allow monitoring the TLC sites behavior during the examined period, as well as performing the energy diagnosis on the basis of the theoretical principles suggested by the Energy Intelligence concept [7]. The analysis of collected data is developed mainly along two lines: the evaluation of energy performance indicators in order to characterize plants energetically and the combined analysis of diagnostic parameters to check the reliability of the measures. In the following, the performance parameters defined above are applied to a sample of 20 data center over the years 2013 and 2014, as detailed in Table 2. It is worth remarking that the opportunity of relying on highly affordable data, such as the ETOT values retrieved from energy bills, allowed selecting the central offices that are more consistent with respect to the energy balance expressed by equation (1). This way it was possible to perform reliable assessment of proposed innovative metrics-based energy diagnosis of TLC sites, as discussed later on in this paper.

Table 2: Input data set and selected TLC sites.

Years	2013 and 2014
Data acquired by TIM WSN [4]	E_{TLC} [kWh·month^{-1}] and E_{CLC} [kWh·month^{-1}]

Data retrieved from energy bills (i.e. provided by the electricity	E_{TOT} [kWh·month^{-1}]
Number of sites (see Table 1) in hot (A), mild climate (B) and cold (C)	A=7, B=3, C=10

3.1 TLC sites characterization

The analyzed TLC sites are located in different geographical areas; therefore, it is useful to split them according to the climatic characteristics of the place they are located in. The central offices under current investigation, here assigned to the six climate zones, were divided into three groups, as shown in Figure 4, as a function of corresponding heating degree days' values ranges (see Table 1).

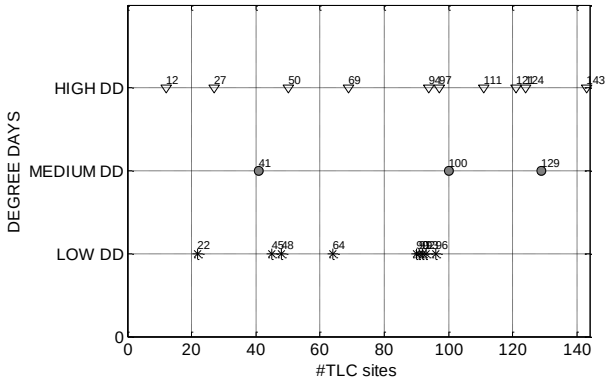


Figure 4: DD-based grouping of TLC sites.

The most rigid external climatic conditions are favorable for reducing the energy consumption due to the air conditioning. On one hand, low external temperature causes (?) the range of use of the free-cooling systems (whose cost impact is much less than traditional air handling units), while, on the other hand, enhances the natural heat exchange between the internal rooms and external environment. Therefore, plants placed in geographical areas with high DD are candidates to be more energy efficient with regard to climate control consumption. In Figure 5, TLC sites are divided in two groups by using the PUC parameter: central offices and multiuse central offices. Figure 6 presents the classification of TLC sites in three groups, differentiated on the basis of EEI values evaluated for each period subject to analysis.

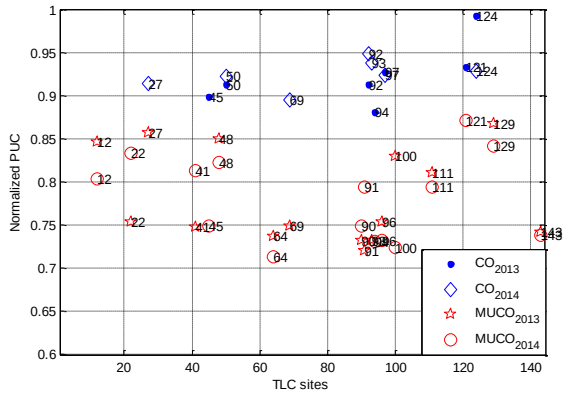


Figure 5: PUC-based grouping of TLC sites.

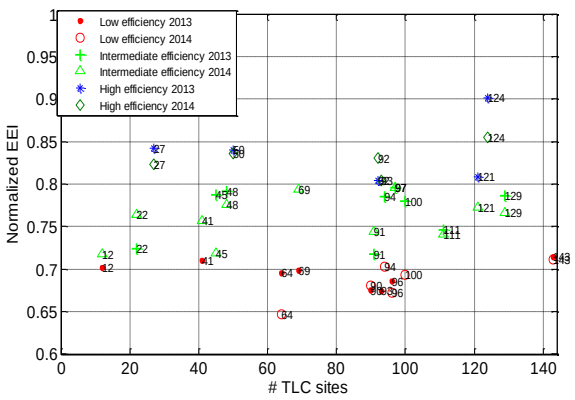


Figure 6 : EEI-based grouping TLC sites.

The PUC and EEI evaluation can result into a discordant characterization in different periods, due to possible anomalies in energy consumption measures. Therefore, the diagnostic phase becomes fundamental to identify the most critical period in terms of data reliability.

3.2 TLC sites diagnosis

Below, the results related to the energy diagnosis procedures described in paragraph 2.3 are presented. The CF dependent parameters (i.e. RI assesses if class compliancy is verified, whereas ICR evaluates time data stability) allow making energy intelligence analysis, particularly monitoring in time (ICR) and diagnosis in space (RI). By combining them, it is possible to perform simultaneous monitoring and diagnosis for energy audit purposes of TLC sites [14]. The combined check of the diagnostic parameters (ICR and RI) allows outlining four possible scenarios, presented in Figure 7 and differentiated on the basis of the data reliability. The activity carried out is a high-level diagnosis, being independent on deviation's quantitative evaluation from the expected operation. Therefore, this activity is propaedeutic to the execution of reliable clustering analyses, as discussed earlier in this paper. Indeed, the inclusion of TLC sites with uncertain data could have a negative impact on the identification of the average or reference behavior of each cluster.

If both metrics assume values close to unity, the data would appear reliable. They would be unreliable, instead, in case of values quite different from one. It can also occur the case in which the ICR value is close to unity, while RI exhibits values significantly different from one for all analyzed periods; in such a case class compliancy does not occur and anomalies in measured data, protracted over time, are expected. Less frequent is the case in which only the RI value is close to unity. The main case studies, representative of the scenario described in Figure 7, are presented below.

RELIABILITY INDEX \ INDEX OF CLUSTER RELIABILITY	RI/ICR	$\lvert ICR-1\rvert > 0,5$	$ICR \sim 1$
	$\lvert RI-1\rvert > 0,5$	UNRELIABLE DATA TIME INSTABILITY & NON COMPLIANCE	DATA SUBJECT TO VERIFICATION NON COMPLIANCE
	$RI \sim 1$	DATA SUBJECT TO VERIFICATION TIME INSTABILITY	RELIABLE DATA

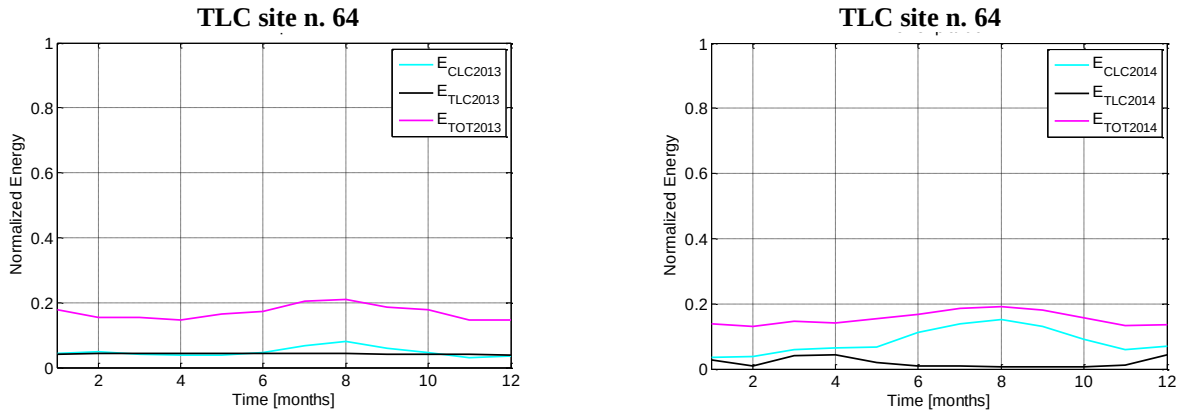
Figure 7: Possible scenarios that may result from the joint analysis of ICR&RI values.

3.2.1 Scenario 1: unreliable data

$$\lvert ICR-1\rvert > 0.5 \tag{a}$$

$$\lvert RI_{2013}-1\rvert > 0.5 \cup \lvert RI_{2014}-1\rvert > 0.5 \tag{b}$$

The data are unstable over time, in accordance with the above condition (a), and disagree with the reference behavior (see condition (b)). Figure 2 resumes the diagnostic parameters values obtained for TLC site n. 64, which is one of the 7 TLC sites located in hot climate zones (see Table 2). The synthetic values expressed in Table 3 are nothing but the results of an elaboration, obtained via equations (7-12), of the consumptions associated to the individual energy quotas (i.e. see Figure 1) characterizing the TLC site under investigation.
The conclusions suggested by the joint RI&ICR analysis is confirmed by the analysis of energy consumption trends shown in Figure 8. The anomalous behavior of 2014 TLC energy trajectory is underlined by the high $RI_{2014,}$ as shown in Table 3. Therefore, the energetic trend is non-compliant with its space domain (i.e. class compliancy not verified).



(a) (b)

Figure 8: (a) Energy consumptions trends in 2013, (b) Energy consumptions trends in 2014, TLC site n. 64.

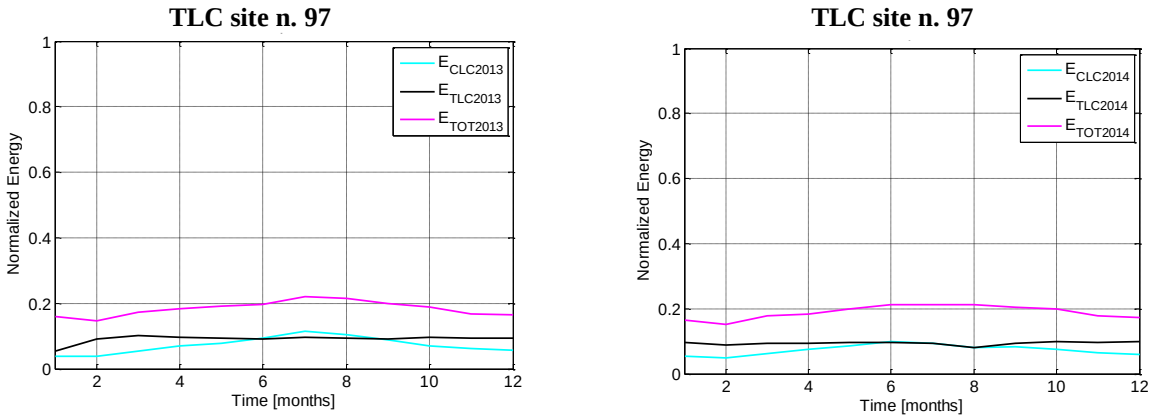
Table 4 shows the TLC sites characterization, here carried-out on the basis of the performance parameters introduced in chapter 2 (i.e. HDD, PUC and EEI). In the examined case, the site classification appears quite reliable, although the differences in 2013 and 2014 PUC and EEI values well justify the outcomes resulting from Table 3 and Figure 8, as discussed above. Particularly, the significant differences in the energy trajectories recorded in the 2 considered consecutive years, as underlined by the high ICR value (see Table 3 in correspondence of site n. 64 row), makes this TLC site useless for subsequent energetic analyses. This specific site shall be thus removed from the whole available data-set for the execution of e.g. clustering analyses (see section 2.2). Moreover, it is worth remarking how the combined use of proposed diagnostic parameters enables reliable and fast detection of abnormal data acquisitions, thus avoiding the execution of time-consuming detailed analyses of each energy consumption quota trend. Such an aspect is highly strategic in the framework of energy intelligence policies to be deployed across an entire TLC company.

3.2.2 Scenario 2: reliable data

$$ICR \approx 1 \tag{c}$$

$$RI_{2013} \approx 1 \cup RI_{2014} \approx 1 \quad \text{(d)}$$

The data are stable over time according to the above condition (c) and agree with the average behavior (condition (d), class compliancy). This case corresponds to TLC site 97, as indicated in Table 3. The diagnostic procedure does not manifest any abnormality, in agreement with what can be observed experimentally in the energy consumption profiles shown in Figure 9.



(a) (b)

Figure 9: (a) Energy consumption trends in 2013, (b) Energy consumption trends in 2014, TLC site n. 97.

The TLC site 97 is one of the 10 TLC sites located in cold climate zones (see Table 2); as previously observed, the rigid external climatic conditions allow substantially reducing cooling energy consumption (i.e. E_{CLC}), mainly relying on a larger range of use of FCs. Consequently, sites such as the 97 are natural candidates to be more energy efficient with regard to climate control consumption, as confirmed by the energy trajectories shown in Figure 9. Particularly, it emerges how in this case the cooling energy consumption is comparable to TLC absorption for each analyzed period. Moreover, Table 3 underlines how the TLC site 97 is a pure data center: auxiliaries do not require a huge amount of energy (PUC-based characterization in Figure 5). Consistently with the above observations, EEI achieves relatively high values (see Table 4), thus leading to classify TLC site 97 as an intermediate efficiency one (refer to Figure 6). It is worth remarking here that site n. 97 falls in between intermediate and high efficiency groups; this aspect, beyond indicating the need of adequately selecting threshold values to correctly classify TLC sites, also confirms that the decision maker should rely on reliable data. As for the outcomes of the combined use of ICR and RI pair, it confirms once again its suitability to automatically select (without requiring the energy managers to go too much into the details of the acquired energy trajectories) a TLC site reliable enough for subsequent clustering analyses, as well as establishing long-lasting energy intelligence policy in telecommunication environments.

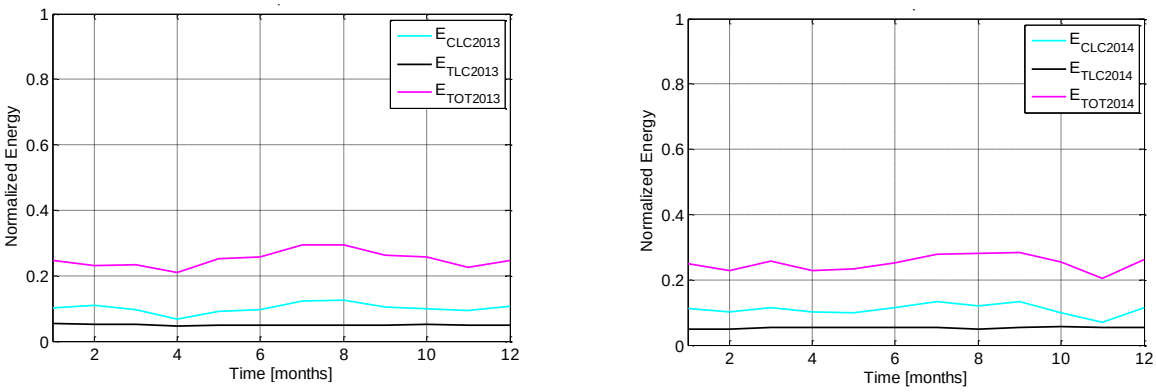
3.2.3 Scenario 3: data subject to verification - not class compliant

$$ICR \approx 1 \quad \text{(e)}$$

$$\left|RI_{2013} - 1\right| > 0.5 \cup \left|RI_{2014} - 1\right| > 0.5 \quad \text{(f)}$$

The data are stable over time according to condition (e), but the TLC site energy behavior disagrees with the reference one (see condition (f)). The data center n. 90 is representative of this condition (see corresponding values in Table 3, where the high RI values indicate that class compliancy is not verified, while stability over time is guaranteed). In this particular case, data anomalies were not found (E_{TOT} compatible with the sum of E_{TLC} and E_{CLC}, as shown in Figure 10); therefore, TLC site classification based on PUC and EEI values is reliable over time.

TLC site n. 90 **TLC site n. 90**

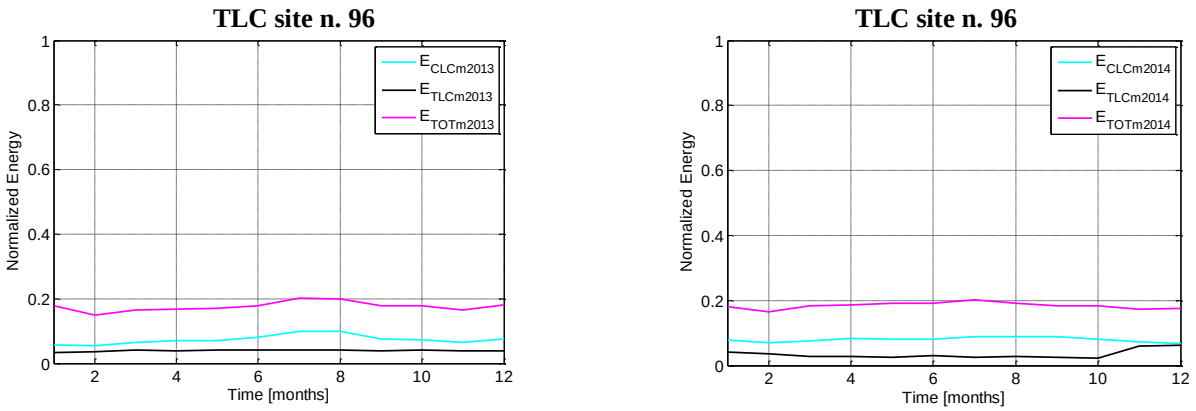


(a) (b)

Figure 10: (a) Energy consumption trends in 2013, (b) Energy consumption trends in 2014, TLC site n. 90.

Being located in hot climate zones (see Table 2), the TLC site n. 90 is candidate to be less energy efficient with regard to climate control consumption. Such hypothesis is confirmed by the application of the EEI-based classification criterion (see Figure 6) to the site under-investigation, here classified as lowly efficient for each period subject to analysis. Deeper analyses are thus required to understand if inefficient thermal management strategies are adopted. Moreover, in this case the decision maker plays a key role: he may still remove the TLC site from the whole available set of TLC sites, to avoid including too extremal elements in the cluster identification procedure.

The TLC site 96 is also included in this scenario: the ICR parameters, shown in Table 3, assure the time stability; moreover, no class migrations occur moving from 2013 to 2014, as shown in Table 4. On the other hand, similarly to what was verified for TLC site number 90, the corresponding RI values exhibit a behavior that drifts from the low DD reference one. Nevertheless, the careful analysis of 2013 and 2014 energy trajectories (see Figure 11) indicate that this time, differently than site n. 90, the noticed abnormalities are not due to inefficient thermal management, but rather to unreliable TLC energy data acquisition from January 2013 until November 2014. Therefore, this case study underlines the need of combining time stability evaluation with class compliancy verification, so as to ensure the correct TLC site characterization and the required redundancy level are achieved for safely performing high-level diagnosis of central offices.



(a) (b)

Figure 11: (a) Energy consumption trends in 2013, (b) Energy consumption trends in 2014, TLC site n. 96.

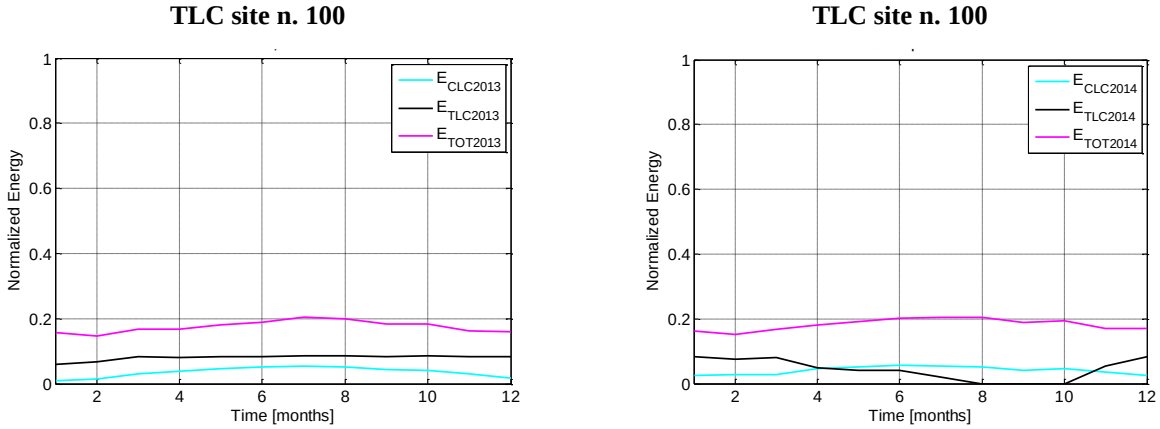
It is finally worth remarking that the analysis of TLC sites 90 and 96 in the scenario 3 associates the same symptoms on performance and diagnosis parameters to different causes: the non-class compliancy for TLC site 90 suggests sub-efficient energy management is performed, whereas the behavior of TLC site 96 indicates WSN abnormalities. In this case the deployment of the ICR&RI based diagnostic analysis was proven effective in determining whether to deepen or not the verification of energy trajectories acquired in those TLC sites, whose behavior does not exhibit significant anomalies in terms of energy performance parameters (i.e. PUC and EEI, as shown in Table 4). This is an added value with respect to the benefits previously discussed in sections 3.2.1 and 3.2.3: indeed, in this case the ICR&RI pair addresses the energy managers to perform further analyses, whereas in the previous cases it allowed saving time when aiming at classifying a TLC site reliable or not from a data-acquisition point of view.

3.2.4 Scenario 4: data subject to verification - time instability

$$|ICR-1|>0.5 \qquad \text{(g)}$$

$$RI_{2013} \approx 1 \cup RI_{2014} \approx 1 \quad \text{(h)}$$

The time data stability is not verified, in accordance with condition (g), but class compliancy is verified (see condition (h)). The TLC site n. 100 is representative of this condition. The joint analysis of Table 3 and Figure 12, as in the previous cases, enables deep understanding of energy and monitoring tasks performance.



(a) (b)

Figure 12: (a) Energy consumption trends in 2013, (b) Energy consumption trends in 2014, TLC site 100.

This case could be representative of modified climate control strategies over time, or dramatic differences in external environment conditions moving from 2013 to 2014. A further reason can be that acquired data were not reliable in one year. The latter was the exact justification for the anomalous ICR computed for TLC site n. 100 (see E_{TLC} trend between months 6 and 10 in Figure 12.b). It is worth noting that RI values computed over 2013 and 2014 also are remarkably different from each other; nevertheless, the loss of information was limited in time, thus resulting in mitigating the effect of such an anomaly in the RI comparison exercise. Overall, the case of TLC site n. 100 confirms the need of combining time stability evaluation with class compliancy verification, so as to ensure the required redundancy level is achieved for safely performing high-level diagnosis of central offices.

The time data instability is also highlighted by the performance parameter values (see Figure 5 and Figure 6): PUC and EEI values evaluated in 2013 and 2014 are significantly different. Table 4 particularly underlines (see site 100 row) that EEI-based classification results in group changing moving from 2013 to 2014; indeed, both PUC and EEI 2014 values significantly decreased with respect to 2013, thus providing a further reliable warning of E_{TLC} data loss in 2014. It is finally worth remarking that all scenario analyses discussed above, in sub-sections 3.2.1 through 3.2.4, highlighted how the evaluation of the ICR&RI parameters pair enables immediate and quite automatic assessment of acquired data reliability. This is true both in the time and space domain, thus demonstrating that the most relevant targets of this research were successfully accomplished, namely the development of an automatic innovative metrics-based procedure, which quickly and accurately reports on acquired data reliability, as well as the adoption of inefficient energy management in the TLC site under current investigation. Such application potentialities are expected to provide TLC operators with key and strategic information without requiring high-level knowledge and expertise, while also avoiding conducting detailed and time-consuming analysis of main energy consumption trajectories throughout the observed year.

Finally, it is worth synthesizing how the proposed energy metrics can be deployed in the framework of monitoring and control activities to be conducted within a comprehensive energy intelligence protocol [14]. First, the information content held by PUC and EEI parameters shall be exploited to the maximum extent. For all those cases (see TLC sites number 90, 96 and 97 in Table 4) exhibiting quasi-constant values comparing one year to another, there is no need of estimating ICR, as the sole evaluation of RI was proven sufficient to verify actual energy behavior of the specific TLC site. Whenever either PUC or EEI changes significantly (see cases 64 and 100 in Table 4), the joint ICR&RI-based monitoring task becomes mandatory.

Table 3: ICR&RI joint analysis.

ICR&RI joint analysis	TLC site	ICR(value) [/]	RI_{2013}(value) [/]	RI_{2014}(value) [/]
Unreliable data	64	5.07	1.8	4.84
Subject to verification	90	0.99	3.24	2.31
Subject to verification	96	0.81	2.95	2.58
Reliable data	97	1.01	1.24	0.92
Subject to verification	100	0.48	0.63	1.17

Table 4: TLC sites characterization.

ICR&RI joint analysis	TLC site	Climatic zone/HDD [°C][1]	PUC_{2013} (value) [/]	PUC_{2014} (value) [/]	EEI_{2013} (value) [/]	EEI_{2014} (value) [/]
Unreliable data	64	Hot zone/LOW	MUCO (0.74)	MUCO (0.71)	LOW EFFICIENCY (0.7)	LOW EFFICIENCY (0.65)
Subject to verification	90	Hot zone/LOW	MUCO (0.73)	MUCO (0.75)	LOW EFFICIENCY (0.68)	LOW EFFICIENCY (0.68)
Subject to verification	96	Hot zone/LOW	MUCO (0.76)	MUCO (0.73)	LOW EFFICIENCY (0.69)	LOW EFFICIENCY (0.67)
Reliable data	97	Cold zone/HIGH	CO (0.93)	CO (0.93)	INTERMEDIATE EFFICIENCY (0.8)	INTERMEDIATE EFFICIENCY (0.8)
Subject to verification	100	Mild climate zone/Medium	MUCO (0.83)	MUCO (0.72)	INTERMEDIATE EFFICIENCY (0.78)	LOW EFFICIENCY (0.69)

4 Conclusions

In this paper, several metrics are analyzed and discussed in view of their potential deployment within TLC energy intelligence policies. The results obtained by applying the proposed monitoring and diagnostic procedures particularly highlight the opportunity of differentiating between central offices and multiuse central offices, or to monitor the efficiency of adopted thermal management strategies in TLC sites. Another effective application is the possibility to identify fault in TLC and cooling energy consumption measurements. The activity carried out is a high-level analysis, being independent on deviation's quantitative evaluation from the expected operation. Therefore, it is propaedeutic to the execution of an effective clustering analysis. Indeed, ICR monitoring parameter can be deployed to cleanse the initial TLC site data-base, by removing those plants that would cause distortive effects, thus resulting in a more reliable sub-set for subsequent clustering analyses. Abnormal data, not imputable to sub-efficient thermal management, would destabilize the reliability of the reference centroid identification procedure for each cluster. At the same time, the use of ICR and RI pair is an effective diagnostic tool for TLC sites and provides a criterion to demonstrate the time reliability of the sensors used for the above-mentioned monitoring process, as well as to assess if proper energy and thermal management of the TLC site under investigation is performed. The possibility to evaluate both the time and space stability (joint analysis of ICR&RI indexes) introduces a greater redundancy when the objective is to clean up the TLC site data-base, on which to perform clustering analyses. Such joint analysis also fulfills one of the key requirements of energy intelligence, namely to find instruments to valorize the wide availability of experimental data, with the specific aim of reducing company energy bills and improving thermal management. This valorization must lead to the synthesis of the huge amount of data, in this case obtained by means of specific energy performance indexes, here deployed to assess the effectiveness of the strategies and hardware equipment used for TLC sites thermal management. ICR and RI indicators are also considered useful for ISO-50001 certification. The proposed methodology is indeed expected to play a strategic role and decisively support the successful implementation of innovative energy intelligence protocols across an entire telecommunication company. Particularly, pursuing energy efficiency, as addressed by the afore-mentioned ISO-50001 rule, shall always be intended as a continuous improvement process. It is thus not sufficient to evaluate the energy saving achieved through a dedicated action, but it is rather preferable to constantly monitor and verify if the supposedly improved performance keep as such over time; if this is not verified it becomes very important to get aware of it in due time. Therefore, the proposed metrics-based methodology is deemed suitable to initially set-up a reference baseline, then establish a reference trajectory to be reproduced and finally track energetic performance evolution over time.

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[1] The DD based-grouping is based on the splitting criteria shown in Table 1.

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