Mechanical ventilation performance assessment in several office buildings by means of Big Data techniques

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ABSTRACT

Mechanical ventilation performance is a key issue related both to energy efficiency and indoor air quality. There are several techniques for measuring ventilation rates in buildings, such as blower boor tests, flow hoods, VAV box measurements and tracer-gas techniques. From several decades ago, tracer-gas techniques are recognized as the most widely employed method to estimate air exchange rate in buildings. These methods are based on the study of the temporal evolution of the concentration of an injected gas. These methods are usually expensive and do not allow the occupancy of the building during the tests. This issue also limits severely the number of buildings to be evaluated. Despite the natural presence of CO_2 in the atmosphere, there has been a growing interest in using it as a tracer gas. It has been shown recently that it is possible to estimate the ventilation rates by means of the decay method using in-situ CO_2 measurements from transmitters available on the market.
On the other hand, there is a growing tendency to move to the smart paradigm, which usually implies to add more and more sensors to the buildings to achieve better controls, among other applications. Modern Building Energy Management Systems (BEMS) allow the access to a high quantity of data in different formats and resolutions, such as signals from sensors and actuators, set-point temperatures, schedules, digital switches, alarms, plots or reports.
In this work in-situ measurements are combined with data coming from BEMS to evaluate the mechanical ventilation performance of three different office buildings in different regions of Spain. Starting from metabolic CO_2 production from occupants of the buildings, a series of conditions are identified in to be able to evaluate the mechanical ventilation performance. Those conditions are translated into an algorithm, programmed in the Python language, which access the different sources of information to wrangle, cluster and finally calculate the mechanical ventilation performance. This operation is performed for five years of available experimental data and information in different formats, performing a search in more than 100 Gb. of information. This situation falls into the computational framework known as Big Data, as stated by the ICT community.
For the first of the buildings (located at Almería) the methodology is detailed and demonstrated through the complete series of five years of data. Thanks to the application of this technique, a mechanical ventilation rate is obtained in perfect agreement with the design values in different situations. The technique is then applied in two different buildings (located at Madrid and at Valladolid) to assess their respective ventilation rates.
Finally, some conclusions are summarised and possible improvements of the method are pointed out as future work.

KEYWORDS

Tracer-gas measurements, metabolic CO2, cheap ventilation rate assessment, Big Data, ventilation measurements during occupancy, two-point method.

1 INTRODUCTION

Ventilation performance assessment is a key issue regarding both energy efficiency and indoor air quality. Measuring ventilation rates in buildings is usually expensive and prevents from use during the testing periods, which difficult a continuous tracking of the system. On the other hand, there is a growing trend to use the so-called Big Data techniques in the context of smart buildings and cities. From the scientific point of view, there is no precise definition of what Big Data means. The first documented use of the term Big Data in the scientific context comes from NASA scientists (Cox and Ellsworth, 1997), describing a problem with computer graphics. Since then, different definitions have been provided, having all of them three common identified characteristics at the one-machine level: volume (amounts of data beyond the resources), variety (data coming from different sources and formats) and velocity (data needs to be stored in real time and processed in a brief interval). As can be seen, characteristics are still highly context dependent.

The exponential growth in streams of data sensing real world situations and human behaviors - including call detail records (CDRs), social media data (Twitter, Facebook, etc.), traffic data, spending data, government data, satellite data, and others - provides opportunities for carrying out new research and to deal with fundamental problems such as urban planning or healthy living, as stated recently by Antonelli et al. (2015). In the urban environment context, most of the works are related to ICT and mobility, such as that of De Domenico et al. al (2015), where big data is used to reduce the overall traffic in Milan by means of an adaptive routing strategy. Despite the high potential of big data in the field of energy efficiency assessment of the built environment, there are no studies up to the author's knowledge. In this work, it is explored the possibility to assess ventilation rates in buildings in the big data framework.

There are several techniques for measuring ventilation rates in buildings, such as blower boor tests, flow hoods, VAV box measurements and tracer-gas techniques. From several decades ago, tracer-gas techniques are recognized as the most widely employed method to estimate air exchange rate in buildings as stated by Sherman (1989). These methods are based on the study of the temporal evolution of the concentration of a certain injected gas. The quantitative analysis is based on the solution of a mass balance equation for each zone under consideration. Each zone is supposed to be homogeneous (fluid properties such as density and tracer gas concentration are assumed to be the same at every point within the zone), isolated (the zone only exchanges with the "outside", an space whose concentration of tracer gas is unaffected by the zone) and perfectly mixed (the tracer gas becomes instantaneously and homogeneously dispersed within the zone). Assuming that there is no source or sink of air, the ventilation rate can be obtained as (Sherman, 1990):

$$Q = \frac{1}{T}\log\frac{C_{start}}{C_{end}}, \qquad (1)$$

Where Q stands for the ventilation flow of air (h^{-1}) C_{start} and C_{end} are the concentrations of the tracer gas at the start and the end of the testing period and T is the duration of the test. This calculation method assures an unbiased estimate of the average (Sherman, 1990).

Another major issue is the selection of the tracer gas. General characteristics for an adequate tracer gas can be drawn: easily measurable in terms of devices cost and non-reactive with the air. For applications involving occupied buildings issues related to toxicity and fire risk must also be taken into account. To meet perfect-mixing hypothesis a density close to the air is also desirable. In a recent study Cui et. al (2015) performed a brief review of the different tracer gases employed from several decades, to demonstrate that CO_2 can be a good candidate for tracer gas. In this paper metabolic CO_2 is used to estimate the ventilation rate of occupied offices from wall-mounted transmitters' measurements. Information related to the presence of the user and the state of the system is obtained from different sources.

A building located at Almería (Spain) is used to validate the methodology, which is applied to two different buildings located at Valladolid and Madrid.

2 METHODOLOGY VALIDATION

2.1. Experimental set-up and building description

A building located at the Plataforma Solar de Almería (PSA) facilities at the South East of Spain (37º 05' 28'' N, 2º 21' 19'' W) has been selected. The climatic conditions are those of a semi-arid zone with high daily thermal oscillations, hot and dry summers and cold winters. The building is an East-West axis longitudinal 1110 m^2 ground level construction. It was built under a Spanish energy efficiency and solar cooling project called PSE-ARFRISOL (www.arfrisol.es, in Spanish). The building was simulated by means of dynamic building energy simulation software to optimize thermal comfort, energy demand and final consumption. Parameters such as ventilation and infiltration rates or ground reflectance were obtained from Spanish Technical Codes and literature reviews. High thermal inertia south façades, low-emisitivy doble glazing, shadowing structures (including BIPV overhangs) and night ventilation were included in the building after simulation studies. In order to promote architectural integration a double wing structure was designed to allocate solar collectors and solar chimneys. Rooftop shading in summer is also provided form such structure. Heat from solar collector is used for space heating and cooling trough radiant floor systems, assisted by air conditioning. Other elements such as air to earth heat exchanger (buried pipes) and radiant coolers were also included.
With respect to ventilation systems, two air-handling units are operated during the day, with programmed schedules. Natural night ventilation in summer is promoted through solar chimneys.

Figure 1. Different views of the building under study, showing schematically the different bioclimatic strategies implemented. To the right, a floor plan with the fully monitored offices in blue.

Figure 1 shows the constructed building together with its floor plan. Representative rooms have been selected for the study, highlighted in blue. The building has been equipped with a multipurpose monitoring system to investigate different aspects such as HVAC systems performance, modelling of the thermal response of the fabric, thermal comfort assessment or IAQ assessment, among others (Jiménez et al., 2010). The software that manages the data acquisition system is reported by Ferre et al. (2010). The building has served for previous studies such as new methods to measure the ground reflectance by Enríquez et al. (2012a), simulation model calibration in the free running mode by Enríquez et al. (2012b), or the simulation of the performance of solar chimneys by Arce et al. (2013). In addition, the Building Energy Management System (BEMS) data is also accessible at real time through an OPC system or offline through a relational database.
For our purposes, the following measurements are selected for each room: Indoors and outdoors CO_2 concentration, state of door and window (closed/not closed) and recordings on the operation of the mechanical ventilation system (Boolean variable). Indoor CO_2 concentration sensors are wall-mounted at 1.5 m. height from floor. They provide a measurement range of 0 ... 2000 ppm, an accuracy of ±(50 ppm CO_2 + 3 % of reading) and a response time of 1 minute (Vaisala, GMW115). Outdoors CO_2 concentration sensor is located in the weather station at the top of the building, provide a measurement range of 0 ... 5000 ppm, an accuracy of ± 2.5% of reading and a response time of 30 seconds (Vaisala, GMP343).

The occupants of the building are free to use the building at their own preferences; despite they have been encouraged to behave efficiently. The operation of the building is registered from 2009 and on-going, leading to a potential of five years of usable data recorded at a frequency of one minute. Data used in this study comes from two sources: a data acquisition system (DAS) and data coming from BEMS. The DAS stores signals in no-SQL csv-formatted files at a daily basis, reaching a total size of 1 Gb. at the moment of this study. Data coming from BEMS are stored in a relational database storing different kind of information: signals from more than eight thousand sensors and actuators, set-point temperatures, schedules, digital switches, alarms, plots and reports among others. The database is shared between four offices buildings and at the moment of this study reaches a size of 110 Gb. Under this context the problem can be classified in what the ICT community defines as the Big Data framework, with different sources of a big amount of data in different formats and places and in interaction with humans.

2.2. Data analysis and results

The analysis algorithm is now described. Data are separated by days which must fulfill the following criteria to be included: when the user leaves the workplace closes the door and the window (if not closed already) while the mechanical ventilation system is still in operation.
To select data to be included in the study a Python program has been developed, which has been shown to be an appropriate tool to apply under this framework. It is important to remark at this point that the computational efficiency of the algorithm is an issue to take care of, especially for scalability purposes. The following steps are applied, by order, for all the days included in the study (January, 1st, 2009 to February, 28th, 2015):

1. Check if csv-formatted data file contains all the registries (1440 minutes in one day). This can be seen as a very restricted quality filter which could be well relaxed, since one or two minutes can be interpolated. In the case under study, with five years of available data, it is more computationally efficient to discard directly those sets. For situations with less data the cost of the interpolation should be in trade-off with the lesser amount of information to process.
2. Check if the door was closed at the end of the day.
3. Check if the door was opened during the day. If so, store time series for Window/door state and indoor/outdoor CO2 concentration for that day.
4. For the days in which conditions 1-3 hold, query the database for the stop time of the mechanical ventilation. If mechanical ventilation stopped later than the closing door and window time, retrieve information of the ventilation operation and programmed schedule.

It is worth noticing at this point that with this procedure the queries to the database are optimized, which is seen as a bottleneck in many data wrangling applications. Table 1 show the statistics for the data under consideration, once the program is executed. This operation has been performed for the central office. Different offices will eventually offer different values, mainly due to door/window operation.
At the end, near 40% of the days are potentially useful for this study, leading to 1006 available sets of data. However, additional considerations must be done related to the conditions that both CO_2 concentration and mechanical ventilation must fulfil. CO_2 is present in the atmosphere, so in order to evaluate a perturbation a concentration baseline is to be selected. Two possibilities arise at this point as a reference: indoor or outdoor CO_2. Using outdoor as reference could seem, in principle, the most convenient choice. However, there are

issues such as shifting in the measurements due to different sensors and recirculation of air inside the building.

Table 1: Statistics for the data collected in the central office room for the five-years period

Data set	**Number of occurrences**	**Percentage**
Total number of days	2555	100 %
All registries	1950	76.3 %
Closed at the end of day	1768	61.2 %
Opened during the day	1093	42.7 %
Mechanical ventilation working after	1006	39.3 %

In this study both situations have been considered, and the results are presented in figure 2. The outdoors CO_2 reference concentration is taken as the daily mean of the outdoors CO2 concentration. The indoors CO_2 reference concentration has been taken as the mean for the two last hours of the day. It can be seen a bell shape centred around 4 air-changes per hour (ACH). For clarity purposes data are presented in the range 3-5 ACH, but long tail distribution appears up to the range 2-6 ACH. It should also be remarked that in many days (25% outdoors and 5% indoors) the reference concentration is higher than the measured indoors, leading to an error in eq. 1.

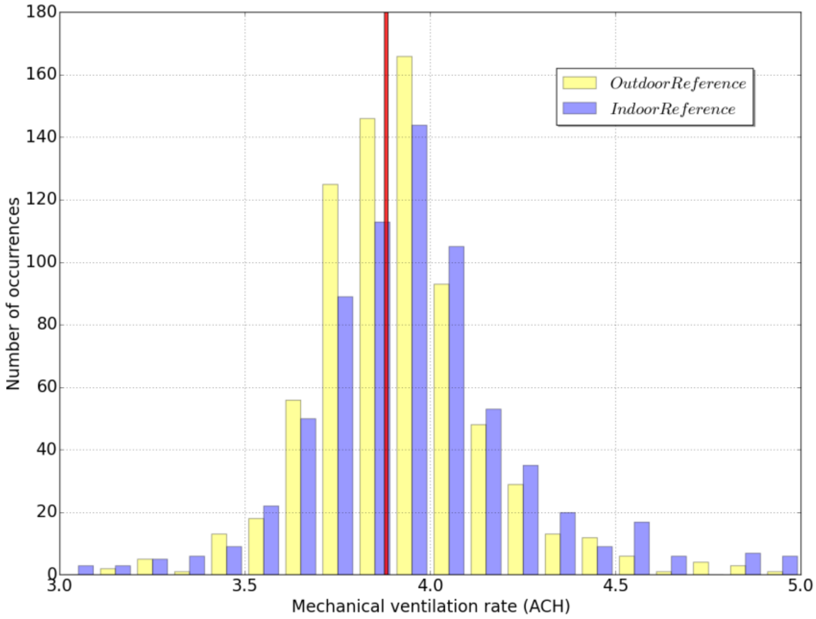

Figure 2. Mechanical ventilation rates estimates taking indoors and outdoors CO2 concentration as references. Some values appear up to 6 ACH and 2 ACH (not shown in the picture). The red bar represents the ventilation rate as designed.

To avoid these situations (long tail distribution and 25% outdoors errors) a new filter is applied to the data. Data are included only if initial indoor CO_2 concentration is 200 ppm higher than the reference one. From sensor technical data and the range of measurements performed the accuracy of the sensor is near 50 ppm. By taking a minimum of 200 ppm of difference for both measurements, initial and reference, will be far distant from accidental difference. In addition, data is considered for the study if mechanical ventilation is in operation after at least three hours since the door was lastly closed. Again, this condition can be relaxed in studies with less available data. Once filtered, outdoors CO_2 concentration reference data are near one half the data for indoors CO_2 concentration reference. Both of them are bell-shaped centred and around 4 ACH. To estimate the value for each series a Gaussian fit has been performed to the data. Table 2 resumes the parameters obtained.

Table 2. Parameters obtained from the gaussian fit for the vetilation rate, together with the design value.

Data series	Mean	Deviation
Outdoors reference	3.96	0.11
Indoors reference	4.01	0.12
Indoors, corner office	3.85	0.15
Design value	3.88	-

It can be seen that outdoors and indoors are close to the design value for the mechanical ventilation system. Both methods give accurate estimates, moreover when variance is taken into account. Due to the accuracy of the sensors, an uncertainty is associated with every value, and can be calculated by means of eq. 3. A mean uncertainty of near 0.2 ACH is obtained when sensor accuracy is considered. It is worth noting at this point that both series and the design values are indistinguishable from this point of view.
Up to now it has been shown that big data analysis techniques and indoors CO_2 concentration measurements derived from metabolic activity can be used to estimate accurately the ventilation rate of an office. It has also been shown that outdoors or indoors CO_2 concentration can be used as reference values for the calculation with similar precision.

2.3. Cross-validation

The indoors CO_2 concentration reference is of particular interest, since it is a cheaper measurement that requires less sensors. In order to check the validity of the method a different office has been selected to check this. The office selected is that of the corner (see figure 1). Due to problems with the wall-mounted sensor, it was substituted for one of the same kind of the outdoors, so the time series is shorter. The same methodology has been applied taking indoor CO_2 concentration as the reference value. Gaussian fits for both offices are presented in figure 3. Table 2 also includes the results for the Gaussian fit, labelled as corner office.

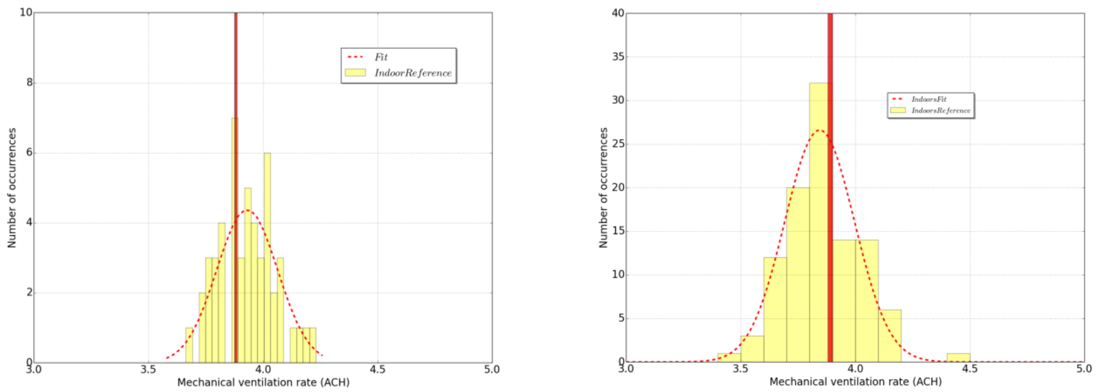

Figure 3. Mechanical ventilation rates estimates taking indoors CO_2 concentration as reference. Left: center office. Right: corner office. Gaussian fit as a red dotted line. The red bar represents the ventilation rate as designed.

It can be seen a good agreement with the situation previously described for the centred office. The ventilation rate estimate is 3.85 ACH, the closest to the design value. Again, the variance of the series and the uncertainty derived from the accuracy of the sensor makes the estimated value and the designed one indistinguishable. Additionally, it should be noticed also that a more accurate sensor is not necessary, since the uncertainty and the variance are quite similar.
It has been proven, then, in two different rooms with data series from five years that ventilation rate of a building can be estimated by means of measurements of indoors CO_2 concentration due to metabolic activity. The methodology employed need to apply techniques coming from the new Big Data field.
The question that arises at this point is that of the optimal size of the sample to estimate the ventilation rate in a confident enough way. From the statistical point of view the previous problem is that of the estimation of the mean for a Gaussian distribution. In the case under study every point can be considered an independent measurement, so a good approximation for the standard deviation of the population is the half of the uncertainty of one single measurement, which can be assessed by error propagation in eq 1.
At a confidence interval of 95% if the error estimation of the mean is to be reduced by a factor k it can be shown, after common algebraic manipulations, that minimum sample size is k^2. In the case under consideration, the uncertainty of one single measurement is close to 0.6 ACH. It can be easily seen that an uncertainty of 0.3 ACH will be reached for a sample of 4 days, 0.2 ACH for a sample of 9 days, 0.15 ACH for a sample of 16 days and so on. On the other hand, if a 0.03 ACH uncertainty should be desired, it can also easily seen that a minimum sample size of 400 would be needed. However, such accuracy is not needed for the most common commissioning applications, and a sample of 16 days is enough for tracking the ventilation rate in a reliable way. Once the ventilation rate has been estimated for the first time, samples of four to nine days can be enough for testing periodically the building ventilation performance.
Scheduling testing time with the help of the user will reduce dramatically the testing time required. In mechanically ventilated office buildings, for example, user collaboration can be solicited and HVAC programmed properly. In the residential sector, smart meters can be incorporated and user collaboration can also be requested by means of ICT or mobile phone applications. Infiltration and natural ventilation can also be estimated, the only difference will be the selection of the CO_2 decay time according to the lower ventilation rate.

3 METHODOLOGY APPLICATION

In order to further check the usefulness of the methodology two new buildings are considered. Both of them have being designed under high energy efficiency criteria. The first one is located in Madrid and it is mechanically ventilated by means of air handling unit. It was constructed under the same research project that the previously described, so it implements the same monitoring system. The interested reader can obtain complete description of the building and associate studies in Soutullo et al. (2014) and Castillo et al. (2014). One office is selected to estimate the ventilation rate in analogous conditions to the one studied in the previous section.
Table 3 summarizes the data gathered. It can be seen that more than one half of the days the office was occupied and door and windows were closed when user(s) left the room. However, for the decay period selected there are no days where the indoors CO_2 difference is bigger than four times the uncertainty associated with one single measurement. This condition needs to be relaxed in order to have data enough. Several CO_2 differences have been chosen as filter, such as 150 ppm (10 days), 100 ppm (67 days) and 75 ppm (137 days). As it was expected, the lesser the difference the more days included. 100 ppm is selected as a trade-off between the number of days and the amplitude of the decay. It represents about twice the

uncertainty of one single measurement and being below that number would compromise the reliability of the method. From the 67 days, 2 of them occur when mechanical ventilation is off, which opens the possibility to estimate natural ventilation (infiltration included).

Table 3: Statistics for the data collected in Madrid's building

Data set	Number of occurrences	Percentage
Total number of days	2526	100 %
All registries	2202	87.17 %
Closed at the end of day	1635	64.73 %
Opened during the day	1508	59.70 %
Ventilation on (100 ppm)	65	2.57 %
Ventilation off (100 ppm)	2	0.08 %

The mechanical ventilation rate obtained from experimental data is close to 3.9 ACH, physically compatible with the designed value for the installation (3.82 ACH). However, these data present variance of 1.4 ACH, which takes into account the fact that the decay amplitude was not as good as desired. If the 75 ppm where to be used, the variance would grow until 2 ACH approximately. When ventilation is off 1.06 ACH is obtained for the two days under consideration. Due to the lack of statistics enough this value should not be considered since its associated error is too big. Anyway, it suggest that under appropriate conditions such as scheduled measurement campaigns in collaboration with users different regimes could also be explored.

The second building is located in Valladolid and also implements passive strategies. Among them: vegetation open areas under offices and a gardened roof, natural ventilation system composed by a grid system, and distributed lucernaires coupled to the air exchange system. Again, the interested reader is referred to Soutullo et al. (2015) to find a more detailed description.

Table 4: Statistics for the data collected in Valladolid's building

Data set	Number of occurrences	Percentage
Total number of days	1825	100 %
All registries	1146	62.8 %
Closed at the end of day	177	9.6 %
Opened during the day	108	5.9 %
100 ppm CO_2 difference	40	2.2 %

Table 4 summarizes the relevant data related to this building. It is a newer building than the previous two and it was monitored from the very early unoccupied stages, so only a 6% is, in principle, suitable. From the 108 days, 40 hold an indoor CO_2 decay bigger than 100 ppm. The air exchange rate estimate for this dataset is 1.29 ACH with a variance of 1.58 ACH, far from the designed value. When inspected carefully, the data showed that the information of the control system was not being recorded properly.

When applying this methodology, the ventilation rate estimation fail can be seen as a benefit. It helped to identify system malfunctions, a common source of energy waste in a complex environment.

4 CONCLUSIONS

The metabolic CO_2 has been identified as an opportunity tracer-gas to estimate ventilation rate in buildings. Big Data techniques have been identified as a necessary tool to deal with volume, variety of sources and human interaction.

Ventilation rate is identified successfully in two different offices of the same building and the methodology is elaborated, assessing its uncertainty and the minimum testing time required. The methodology is tested against five years of data to get statistics enough. It has been shown that user interaction can enhance the method, opening the gate to non-invasive scheduled testing periods.

Once the methodology has been validated it has been applied in two additional cases. In the first case the ventilation rate is identified successfully, with a high variance due to the statistics. Once more, ICT user interaction can lead to scheduled non-invasive ventilation testing periods. The possibility to study different regimes is also identified in this building. In the second case, the ventilation rate estimation fails. This fact is revealed as a benefit, helping to detect system malfunctioning and could be used as ventilation tracking system.

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6 REFERENCES

Antonelli et al. 2015. Fabrizio Antonelli, Bruno Lepri, Alex 'Sandy' Pentland, Fabio Pianesi. Making Big Data work: Smart, Sustainable, and Safe Cities, EPJ Data Science article collections, 28 January 2015.

Arce et al. al, 2013. J. Arce, J. Xamán, G. Álvarez, M.J. Jiménez, R. Enríquez, M.R. Heras, 2013. "A simulation of the thermal performance of a small solar chimney already installed in a building”. Journal of Solar Energy Engineering, Transactions of the ASME. 135(1), art. no. 11005.

Castillo et al., 2014. L. Castillo, R. Enríquez, M.J. Jiménez, M.R. Heras, Dynamic integrated method based on regression and averages, applied to estimate the thermal parameters of a room in an occupied office building in Madrid, Energy and Buildings, Volume 81, October 2014, Pages 337-362.

Cox and Ellsworth, 1997. Michael Cox and David Ellsworth, Application-controlled demand paging for out-of-core visualization Proceeding. VIS '97 Proceedings of the 8th conference on Visualization '97, Pages 235-ff. IEEE Computer Society Press Los Alamitos, CA, USA ©1997.

Cui et al. al, 2015. Shuqing Cui, Michaël Cohen, Pascal Stabat, Dominique Marchio, CO2 tracer gas concentration decay method for measuring air change rate, Building and Environment, Volume 84, January 2015, Pages 162-169.

De Domenico et al. 2015. Personalized routing for multitudes in smart cities. Manlio De Domenico, Antonio Lima, Marta C González and Alex Arenas. EPJ Data Science 2015, 4:1 doi:10.1140/epjds/s13688-015-0038-0.

Enríquez et al. 2012a. R. Enríquez, L. Zarzalejo, M.J. Jiménez, M.R. Heras. 2012. “Ground reflectance estimation by means of horizontal and vertical radiation measurements”. Solar Energy. 86(11), pp. 3216-3226.

Enríquez et al., 2012b. R. Enríquez, M.J. Jiménez, M.R. Heras. 2012. “Analysis of a solar office building at the South of Spain through simulation model calibration”. Energy procedia. 30, pp. 580-589.

Ferre et al., 2010. J.A. Ferre, M. Pasamontes, M. Castilla, M. Berenguel, M.J. Jiménez, D. Bravo, M. Pérez. 2010. In Spanish. “Desarrollo de un sistema de monitorización y control para edificios bioclimáticos en el marco del proyecto ARFRISOL”. Presented at “I Congreso sobre Arquitectura Bioclimática y Frío Solar”. Aguadulce, Almería, Spain. 23-26 March 2010. ISBN: 978-84-693-5141-3.

Jiménez et al., 2010. M. J. Jiménez, R. Enríquez, R. Olmedo, N. Sánchez, M.R. Heras. 2010. In Spanish. “Monitorización energética de los C-DdIs del PSE-ARFRISOL. Diseño experimental”. Presented at congress: “I Congreso sobre Arquitectura Bioclimática y Frío Solar”. Aguadulce, Almería, Spain. 23-26 March 2010. ISBN: 978-84-693-5141-3.

Sherman, 1989. M.H. Sherman, On the estimation of multizone ventilation rates from tracer gas measurements, Building and Environment, Volume 24, Issue 4, 1989, Pages 355-362, ISSN 0360-1323, http://dx.doi.org/10.1016/0360-1323(89)90030-9.

Sherman, 1990. M.H. Sherman, Tracer-gas techniques for measuring ventilation in a single zone, Building and Environment, Volume 25, Issue 4, 1990, Pages 365-374.

Soutullo et al., 2014. Soutullo, S.; Enríquez, R.; Jímenez, M.J.; Heras, M.R. (2014). Thermal comfort evaluation in a mechanically ventilated office building located in a continental climate. *Energy and Buildings,*81*, 424-429.*

Soutullo et al., 2015. Silvia Soutullo, Mª Nuria Sánchez, Ricardo Enríquez, Mª José Jiménez and Mª Rosario Heras, Thermal comfort assessment in a sustainable designed office building. Contribution accepted in AIVC 2015.

Vaisala, GMP343. Vaisala, Technical Data Sheet. GMP343 Carbon Dioxide Probe for Demanding Measurements Ref. B210641en rev. A.

Vaisala, GMW115. Vaisala, Technical Data Sheet. GMW115 Carbon Dioxide Transmitter for Demand-controlled Ventilation. Ref. B210568EN-A 2006-03.