ANNEX 86

EBC

Energy in Building and Communities Programme

D4 – Energy Efficient IAQ management strategies - applications

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Editor

Jakub Kolarik, Technical University of Denmark, Denmark

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www.iea-ebc.org

essu@iea-ebc.org

Preface

The International Energy Agency

The International Energy Agency (IEA) was established in 1974 within the framework of the Organisation for Economic Co-operation and Development (OECD) to implement an international energy programme. A basic aim of the IEA is to foster international cooperation among the 30 IEA participating countries and to increase energy security through energy research, development and demonstration in the fields of technologies for energy efficiency and renewable energy sources.

The IEA Energy in Buildings and Communities Programme

The IEA co-ordinates international energy research and development (R&D) activities through a comprehensive portfolio of Technology Collaboration Programmes (TCPs). The mission of the IEA Energy in Buildings and Communities (IEA EBC) TCP is to support the acceleration of the transformation of the built environment towards more energy efficient and sustainable buildings and communities, by the development and dissemination of knowledge, technologies and processes and other solutions through international collaborative research and open innovation. (Until 2013, the IEA EBC Programme was known as the IEA Energy Conservation in Buildings and Community Systems Programme, ECBCS.).

The high priority research themes in the EBC Strategic Plan 2019-2024 are based on research drivers, national programmes within the EBC participating countries, the Future Buildings Forum (FBF) Think Tank Workshop held in Singapore in October 2017 and a Strategy Planning Workshop held at the EBC Executive Committee Meeting in November 2017. The research themes represent a collective input of the Executive Committee members and Operating Agents to exploit technological and other opportunities to save energy in the buildings sector, and to remove technical obstacles to market penetration of new energy technologies, systems and processes. Future EBC collaborative research and innovation work should have its focus on these themes.

At the Strategy Planning Workshop in 2017, some 40 research themes were developed. From those 40 themes, 10 themes of special high priority have been extracted, taking into consideration a score that was given to each theme at the workshop. The 10 high priority themes can be separated in two types namely 'Objectives' and 'Means'. These two groups are distinguished for a better understanding of the different themes.

Objectives: The strategic objectives of the EBC TCP are as follows:

– reinforcing the technical and economic basis for refurbishment of existing buildings, including financing, engagement of stakeholders and promotion of co-benefits;
– improvement of planning, construction and management processes to reduce the performance gap between design stage assessments and real-world operation;
– the creation of 'low tech', robust and affordable technologies;
– the further development of energy efficient cooling in hot and humid, or dry climates, avoiding mechanical cooling if possible; the creation of holistic solution sets for district level systems taking into account energy grids, overall performance, business models, engagement of stakeholders, and transport energy system implications.

Means: The strategic objectives of the EBC TCP will be achieved by the means listed below:

– the creation of tools for supporting design and construction through to operations and maintenance, including building energy standards and life cycle analysis (LCA);
– benefitting from 'living labs' to provide experience of and overcome barriers to adoption of energy efficiency measures;
– improving smart control of building services technical installations, including occupant and operator interfaces;
– addressing data issues in buildings, including non-intrusive and secure data collection;
– the development of building information modelling (BIM) as a game changer, from design and construction through to operations and maintenance.

The themes in both groups can be the subject for new Annexes, but what distinguishes them is that the 'objectives' themes are final goals or solutions (or part of) for an energy efficient built environment, while the 'means' themes are instruments or enablers to reach such a goal. These themes are explained in more detail in the EBC Strategic Plan 2019-2024.

The Executive Committee

Overall control of the IEA EBC Programme is maintained by an Executive Committee, which not only monitors existing projects, but also identifies new strategic areas in which collaborative efforts may be beneficial. As the Programme is based on a contract with the IEA, the projects are legally established as Annexes to the IEA EBC Implementing Agreement. At the present time, the following projects have been initiated by the IEA EBC Executive Committee, with completed projects identified by (*) and joint projects with the IEA Solar Heating and Cooling Technology Collaboration Programme by (☼):

Annex 1: Load Energy Determination of Buildings (*)
Annex 2: Ekistics and Advanced Community Energy Systems (*)
Annex 3: Energy Conservation in Residential Buildings (*)
Annex 4: Glasgow Commercial Building Monitoring (*)
Annex 5: Air Infiltration and Ventilation Centre
Annex 6: Energy Systems and Design of Communities (*)
Annex 7: Local Government Energy Planning (*)
Annex 8: Inhabitants Behaviour with Regard to Ventilation (*)
Annex 9: Minimum Ventilation Rates (*)
Annex 10: Building HVAC System Simulation (*)
Annex 11: Energy Auditing (*)
Annex 12: Windows and Fenestration (*)
Annex 13: Energy Management in Hospitals (*)
Annex 14: Condensation and Energy (*)
Annex 15: Energy Efficiency in Schools (*)
Annex 16: BEMS 1- User Interfaces and System Integration (*)
Annex 17: BEMS 2- Evaluation and Emulation Techniques (*)
Annex 18: Demand Controlled Ventilation Systems (*)
Annex 19: Low Slope Roof Systems (*)
Annex 20: Air Flow Patterns within Buildings (*)
Annex 21: Thermal Modelling (*)
Annex 22: Energy Efficient Communities (*)
Annex 23: Multi Zone Air Flow Modelling (COMIS) (*)
Annex 24: Heat, Air and Moisture Transfer in Envelopes (*)
Annex 25: Real time HVAC Simulation (*)
Annex 26: Energy Efficient Ventilation of Large Enclosures (*)
Annex 27: Evaluation and Demonstration of Domestic Ventilation Systems (*)
Annex 28: Low Energy Cooling Systems (*)
Annex 29: ☼ Daylight in Buildings (*)
Annex 30: Bringing Simulation to Application (*)
Annex 31: Energy-Related Environmental Impact of Buildings (*)
Annex 32: Integral Building Envelope Performance Assessment (*)
Annex 33: Advanced Local Energy Planning (*)
Annex 34: Computer-Aided Evaluation of HVAC System Performance (*)
Annex 35: Design of Energy Efficient Hybrid Ventilation (HYBVENT) (*)
Annex 36: Retrofitting of Educational Buildings (*)
Annex 37: Low Exergy Systems for Heating and Cooling of Buildings (LowEx) (*)
Annex 38: ☼ Solar Sustainable Housing (*)
Annex 39: High Performance Insulation Systems (*)
Annex 40: Building Commissioning to Improve Energy Performance (*)
Annex 41: Whole Building Heat, Air and Moisture Response (MOIST-ENG) (*)
Annex 42: The Simulation of Building-Integrated Fuel Cell and Other Cogeneration Systems (FC+COGEN-SIM) (*)
Annex 43: ☼ Testing and Validation of Building Energy Simulation Tools (*)
Annex 44: Integrating Environmentally Responsive Elements in Buildings (*)
Annex 45: Energy Efficient Electric Lighting for Buildings (*)
Annex 46: Holistic Assessment Tool-kit on Energy Efficient Retrofit Measures for Government Buildings (EnERGo) (*)
Annex 47: Cost-Effective Commissioning for Existing and Low Energy Buildings (*)
Annex 48: Heat Pumping and Reversible Air Conditioning (*)
Annex 49: Low Exergy Systems for High Performance Buildings and Communities (*)
Annex 50: Prefabricated Systems for Low Energy Renovation of Residential Buildings (*)
Annex 51: Energy Efficient Communities (*)
Annex 52: ☼ Towards Net Zero Energy Solar Buildings (*)

Annex 53: Total Energy Use in Buildings: Analysis and Evaluation Methods (*)
Annex 54: Integration of Micro-Generation and Related Energy Technologies in Buildings (*)
Annex 55: Reliability of Energy Efficient Building Retrofitting - Probability Assessment of Performance and Cost (RAP-RETRO) (*)
Annex 56: Cost Effective Energy and CO_2 Emissions Optimization in Building Renovation (*)
Annex 57: Evaluation of Embodied Energy and CO_2 Equivalent Emissions for Building Construction (*)
Annex 58: Reliable Building Energy Performance Characterisation Based on Full Scale Dynamic Measurements (*)
Annex 59: High Temperature Cooling and Low Temperature Heating in Buildings (*)
Annex 60: New Generation Computational Tools for Building and Community Energy Systems (*)
Annex 61: Business and Technical Concepts for Deep Energy Retrofit of Public Buildings (*)
Annex 62: Ventilative Cooling (*)
Annex 63: Implementation of Energy Strategies in Communities (*)
Annex 64: LowEx Communities - Optimised Performance of Energy Supply Systems with Exergy Principles (*)
Annex 65: Long-Term Performance of Super-Insulating Materials in Building Components and Systems (*)
Annex 66: Definition and Simulation of Occupant Behavior in Buildings (*)
Annex 67: Energy Flexible Buildings (*)
Annex 68: Indoor Air Quality Design and Control in Low Energy Residential Buildings (*)
Annex 69: Strategy and Practice of Adaptive Thermal Comfort in Low Energy Buildings (*)
Annex 70: Energy Epidemiology: Analysis of Real Building Energy Use at Scale (*)
Annex 71: Building Energy Performance Assessment Based on In-situ Measurements (*)
Annex 72: Assessing Life Cycle Related Environmental Impacts Caused by Buildings (*)
Annex 73: Towards Net Zero Energy Resilient Public Communities (*)
Annex 74: Competition and Living Lab Platform (*)
Annex 75: Cost-effective Building Renovation at District Level Combining Energy Efficiency and Renewables (*)
Annex 76: ☼ Deep Renovation of Historic Buildings Towards Lowest Possible Energy Demand and CO_2 Emissions (*)
Annex 77: ☼ Integrated Solutions for Daylight and Electric Lighting (*)
Annex 78: Supplementing Ventilation with Gas-phase Air Cleaning, Implementation and Energy Implications (*)
Annex 79: Occupant-Centric Building Design and Operation (*)
Annex 80: Resilient Cooling (*)
Annex 81: Data-Driven Smart Buildings (*)
Annex 82: Energy Flexible Buildings Towards Resilient Low Carbon Energy Systems (*)
Annex 83: Positive Energy Districts
Annex 84: Demand Management of Buildings in Thermal Networks (*)
Annex 85: Indirect Evaporative Cooling
Annex 86: Energy Efficient Indoor Air Quality Management in Residential Buildings (*)
Annex 87: Energy and Indoor Environmental Quality Performance of Personalised Environmental Control Systems
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Annex 90: EBC Annex 90 / SHC Task 70 Low Carbon, High Comfort Integrated Lighting
Annex 91: Open BIM for Energy Efficient Buildings
Annex 92: Smart Materials for Energy-Efficient Heating, Cooling and IAQ Control in Residential Buildings
Annex 93: Energy Resilience of the Buildings in Remote Cold Regions
Annex 94: Validation and Verification of In-situ Building Energy Performance Measurement Techniques
Annex 95: Human-centric Building Design and Operation for a Changing Climate
Annex 96: Grid Integrated Control of Buildings
Annex 97: Sustainable Cooling in Cities
Annex 98: Flexibilization and Optimization of Heat Pump Systems in Existing Buildings through Secondary-Side Digitalization
Annex 99: Air Cleaning for Sustainable and Resilient Buildings

Working Group – Energy Efficiency in Educational Buildings (*)
Working Group – Indicators of Energy Efficiency in Cold Climate Buildings (*)
Working Group – Annex 36 Extension: The Energy Concept Adviser (*)
Working Group – HVAC Energy Calculation Methodologies for Non-residential Buildings (*)
Working Group – Cities and Communities (*)
Working Group – Building Energy Codes

Table of content

1. Introduction

This report presents a comprehensive summary of the work conducted under subtasks 2 to 5 of the IEA EBC Annex 86, focusing on case studies, demonstrations, and common exercises aimed at enhancing energy-efficient indoor air quality (IAQ) management strategies in residential buildings. The report documents collaborative efforts towards innovative approaches and practical applications that contribute to the advancement of IAQ management. IAQ management may be common in office and commercial buildings, but we do not see it that often in the residential sector. At the same time, future challenges call for IAQ management also in our homes. These challenges are climate change, increased pressure on both resource and energy efficiency as well as increased urbanization and lifestyle changes. IEA EBC Annex 86 addressed a broad range of issues related to IAQ management. The report offers an overview of some practical outcomes from the project. It does not have the ambition to serve as the ultimate guide to energy efficient IAQ management. It rather aims to serve as a “shop window” presenting the approaches, methods and solutions investigated within project’s subtasks.

A significant part of the report is dedicated to data processing and evaluation of ventilation strategies. It is obvious that effective IAQ management can only happen when reliable and solid data are available. The report presents an exploration of standardized statistical analysis and benchmarking of IAQ measurements, detailing the development and application of a specialized R package designed to facilitate the processing and comparison of IAQ data. Besides the work with measurement data, the report also deals with an analysis of pollutant loads from building envelope materials, utilizing the PANDORA database to evaluate formaldehyde emissions and their impact on IAQ. Such data is crucial for estimating performance of ventilation strategies during design by means of simulation tools. Further on, the report presents the methodology for evaluation of existing smart ventilation strategies by means of simulation. Here, the focus is on testing the usability of various performance indicators through a series of common exercises conducted by experts from multiple countries. It is not only ventilation that affects IAQ. The report introduces the use of metal-organic frameworks (MOFs) as a novel IAQ management strategy, showcasing their potential to selectively adsorb indoor pollutants like formaldehyde. Finally, the integration of big data and IAQ management is examined, summarizing insights from webinars that discuss the intersection of advanced data analytics, machine learning, and IAQ monitoring technologies. These discussions highlight the potential of leveraging big data to optimize ventilation systems and improve IAQ in residential settings.

This report is intended for researchers, practitioners, and policymakers involved in design and operation of residential buildings. It provides valuable insights and practical examples to support the development and implementation of energy-efficient IAQ management strategies, ultimately contributing to healthier and more sustainable living environments.

2. Standardized statistical analysis and benchmarking of IAQ measurements

Authors: Timm Freundorfer, Gabriel Rojas and Reto Stauffer

2.1. Introduction

The following report describes the application of the analysis framework developed within Subtask 2 (ST2) of IEA EBC Annex 86. Starting with the measurement data from an IAQ study a statistical analysis can be performed in a standardized way that allows direct and comprehensive benchmarking against the results of many other IAQ studies. The workflow is demonstrated using exemplary data from an Austrian measurement study. Note that the results from 21 IAQ studies, covering nearly 1.200 homes, analyzed with the herein presented analysis framework have been made available in a data repository (https://doi.org/10.5281/zenodo.14917724)(Freundorfer et al. 2025a). The combination of open data repository and the developed R package (https://github.com/IEA-EBC-Annex86/annex) (Freundorfer et al. 2025b) is intended to provide a valuable resource for future IAQ measurement analysis.

2.2. The "Annex" R package

R is a free programming language focused on statistical calculations and data visualization R Core Team (2025). It is convenient to use an integrated development environment (IDE) to program in R, in this case RStudio was chosen. First "base R" and then RStudio have to be installed, they can be downloaded from the following URL's: https://cran.r-project.org/bin/, https://posit.co/download/rstudio-desktop/.

Further details for the installation of R and RStudio can be found e.g. in Stauffer et al. (2025a).

In R, additional packages can be installed to extend the base functionality. To process and standardize indoor air quality data from multiple sources, a specialized package, entitled "annex", was developed. Installation of this package requires first installing the 'remotes' library, followed by using the 'install_github' function. The following code sample demonstrates this process:

```
> install.packages('remotes') # installs remote package
> library('remotes') # loads in remote package
> install_github("IEA-EBC-Annex86/annex") # installs the annex package from github
> library('annex') # loads the annex package
```

The annex package consists of multiple core functions to process the input data. Full documentation of these functions is found in Stauffer et al. (2025b). An illustration of the workflow is shown in Figure 2-1: Schema of the processing workflow for the functions developed in the R package "annex"Figure 2-1.

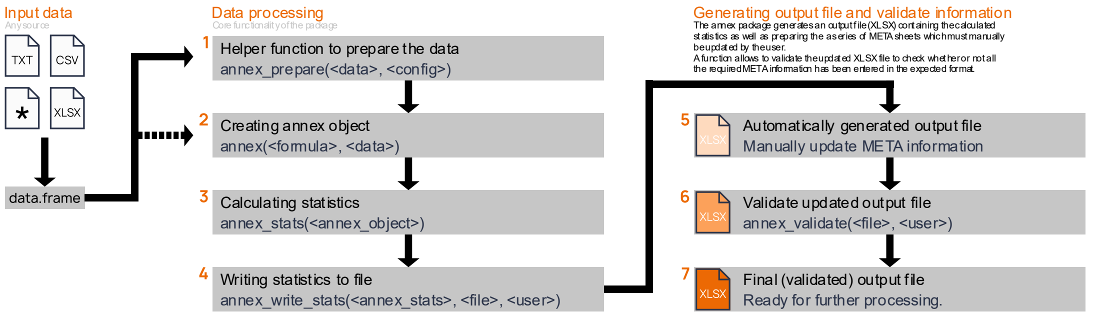


Figure 2-1: Schema of the processing workflow for the functions developed in the R package "annex"

Data from the study "Lodenareal" (Rojas et al., 2015) will be used as an example to illustrate the process. This study focused on analysis of the measured indoor environmental data collected during long-term monitoring of a social housing project built to the Passive House standard. The indoor temperature, CO2 concentration and relative humidity levels were continuously logged in 18 of the 354-apartment complex built in 2008. The volatile organic compound concentrations were also measured before the tenants moved in. Furthermore, a survey using questionnaires and interviews was performed providing assessment of satisfaction levels. A more detailed guide to load in the data can be found at https://iea-ebc-annex86.github.io/annex/articles/from_xlsx.html.

The following script was used to apply the functions from the annex package to this exemplary dataset. Its content is described in more detail in the following section.

```
> # Reading measurement data
> raw_df <- read_excel("ExampleData.xlsm", sheet = "Rohdaten")
> # Read and prepare config object
> config <- read_excel("ExampleData.xlsm", sheet = "annex_configuration")
> # Prepare annex object
> annex_check_config(config) #optional check
> prepared_df <- annex_prepare(raw_df, config, quiet = TRUE)
> annex_df <- annex(RH + T + CO2 + Other + SolRad ~ datetime | study + home + room,
  data = prepared_df, tz = "Europe/Berlin")
> stats  <- annex_stats(annex_df, format = "wide")
> annex_write_stats(stats, file = "ExampleData_output.xlsx", user = 999)
> # fill out meta information directly in Excel and validate
> check <- annex_validate("ExampleData_output.xlsx", user = 999)
```

To start, the original measurement data must be loaded into R. Additionally, a configuration file must be created to allow the correct identification and interpretation. The annex package needs to know which columns in the original data set correspond to which variable of interest (pollutants for most cases). There are six mandatory columns that have to be defined in the *config* file, see https://iea-ebc-annex86.github.io/annex/articles/lookupfunctions.html.

For example, the *config* "file" for the Lodenareal data was manually created in an own sheet of the Excel data file. The original measurement data from Lodenareal has a five minute resolution (with some data gaps), so that there is a data column for each of the three relevant variables (T, RH, CO2) for each home (W1/W2/W3 ..) and for each room in that home (WZ/SZ for bedroom/living room), Figure 2-2.

The configuration table (Figure 2-2) consists of 84 rows, where the three main variables of interest (T/RH/CO2) are listed for each room and each home plus additional variables like ambient temperature (T), duct flow velocity (Other) or solar radiation (SolRad). In this example, those additional variables were assigned to the home "General". The other 18 homes were labelled "W1" through "W18". Note that here the optional column "process" (True/False) was defined, to define which of the variables/columns that annex package should process and which it should ignore. To check if the config file/table is defined correctly one can run the function *annex_check_config()*, once the config file has been loaded into R.

	Zeitraum ab	T-WZ_W1 [°C] avg	rH-WZ_W1 [% rH] avg	CO2-WZ_W1 [ppm] avg	T-WZ_W2 [°C]
1	2010-01-01 00:05:00	23.51	39.6	1376	
2	2010-01-01 00:10:00	23.47	39.5	1341	
3	2010-01-01 00:15:00	23.46	39.5	1326	
4	2010-01-01 00:20:00	23.42	39.5	1296	
5	2010-01-01 00:25:00	23.44	39.5	1307	
6	2010-01-01 00:30:00	23.34	39.7	1348	
7	2010-01-01 00:35:00	23.38	39.9	1395	
8	2010-01-01 00:40:00	23.41	39.9	1422	
9	2010-01-01 00:45:00	23.48	40.4	1430	
10	2010-01-01 00:50:00	23.53	40.4	1408	

Showing 1 to 10 of 100,662 entries, 277 total columns

	process	column	variable	unit	study	home	room
71	TRUE	CO2-SZ_W12 [ppm] avg	CO2	ppm	Lodenareal	W12	BED1
72	TRUE	CO2_SZ_W15 [ppm] avg	CO2	ppm	Lodenareal	W15	BED1
73	TRUE	CO2_SZ_W18 [ppm] avg	CO2	ppm	Lodenareal	W18	BED1
74	TRUE	Pyro [W/m2] avg	SolRad	W/m2	Lodenareal	General	AMB
75	TRUE	T-AUSSEN [°C] avg	T	C	Lodenareal	General	AMB
76	TRUE	rH-AUSSEN [% rH] avg	rH	%	Lodenareal	General	AMB
77	TRUE	T_ZL [°C] avg	T	C	Lodenareal	General	SUP
78	TRUE	rH_ZL [% rH] avg	rH	%	Lodenareal	General	SUP
79	TRUE	C_ZL [ppm] avg	CO2	ppm	Lodenareal	General	SUP
80	TRUE	V_FRILU [m/s] avg	Other	NA	Lodenareal	General	ODA
81	TRUE	T_ABL [°C] avg	T	C	Lodenareal	General	ETA

Showing 71 to 81 of 84 entries, 7 total columns

Figure 2-2: Left: Screen shot of the original dataset loaded into R as a data frame. Right: Screen shot of the data frame containing the configuration table which defines how the original data is to be interpreted for further processing.

2.3. Conducting the analysis

Step 1:

After loading the original dataset and the configuration file, those two "data frames" (that's how those data tables are called in R) are passed into the function *annex_prepare()*. It produces a new data frame. At this point one has to make sure that the timestamp of each measurement row is interpreted correctly (including time zone), see https://iea-ebc-annex86.github.io/annex/articles/prepare_xtra.html.

Part of the resulting data frame for the Lodenareal data is shown in Figure 2-3 (left). Now there is one row per timestep, home, and room, with the corresponding measurement values in different columns.

	datetime	study	home	room	RH	SolRad	T	CO2	Other
512960	2010-02-03 12:10:00	Lodenareal	W6	BED1	24.6	NA	22.10	611	NA
512961	2010-02-03 12:15:00	Lodenareal	W6	BED1	24.8	NA	22.15	599	NA
512962	2010-02-03 12:20:00	Lodenareal	W6	BED1	24.8	NA	22.20	598	NA
512963	2010-02-03 12:25:00	Lodenareal	W6	BED1	24.9	NA	22.25	588	NA
512964	2010-02-03 12:30:00	Lodenareal	W6	BED1	24.8	NA	22.28	588	NA
512965	2010-02-03 12:35:00	Lodenareal	W6	BED1	24.8	NA	22.33	583	NA
512966	2010-02-03 12:40:00	Lodenareal	W6	BED1	24.8	NA	22.36	577	NA
512967	2010-02-03 12:45:00	Lodenareal	W6	BED1	24.8	NA	22.37	571	NA
512968	2010-02-03 12:50:00	Lodenareal	W6	BED1	24.8	NA	22.40	568	NA
512969	2010-02-03 12:55:00	Lodenareal	W6	BED1	24.7	NA	22.44	561	NA

Showing 512,960 to 512,970 of 2,919,198 entries, 9 total columns

	study	home	room	year	month	tod	variable	quality_lower	quality_upper
3736	Lodenareal	W13	LIV	2010	1	07-23	CO2	0.00	
3738	Lodenareal	W13	LIV	2010	1	07-23	RH	0.00	
3740	Lodenareal	W13	LIV	2010	1	07-23	T	0.00	
3741	Lodenareal	W13	LIV	2010	1	23-07	CO2	0.00	
3743	Lodenareal	W13	LIV	2010	1	23-07	RH	0.00	
3745	Lodenareal	W13	LIV	2010	1	23-07	T	0.00	
3746	Lodenareal	W13	LIV	2010	10	07-23	CO2	0.00	
3748	Lodenareal	W13	LIV	2010	10	07-23	RH	0.00	
3750	Lodenareal	W13	LIV	2010	10	07-23	T	0.00	
3751	Lodenareal	W13	LIV	2010	10	23-07	CO2	0.00	

Showing 2,134 to 2,143 of 3,486 entries, 127 total columns

Figure 2-3: Left: Screen shot of the data frame after the function annex_prepare() was applied to the dataset (left). Right Screen shot of the data frame containing the results of the statistical analysis (actual statistics like mean, standard deviation, percentiles are cut off and not shown).

Step 2:

This newly created data frame is passed into the *annex()* function together with a formula-expression specifying the relationship between analyzed variables and the time zone information (of the measurement location). It prepares a data object, which can be interpreted by the statistical analysis function, annex_stats, described in the next step. It adds the columns *year*, *month*, *tod* (time of day: night or daytime), which is used for aggregation during the statistical analysis. The formula-expression defines which variables should be included in the statistical analysis like for the definition of regression models; it has to be in the form of *<variables to be processed> ~ <time variable>* | *<grouping variables>*. In general, the time and grouping variables will always stay the same, so that only the variables to be processed need adaptation. For the example here, it is defined as *RH + T + CO2 + Other + SolRad ~ datetime* | *study + home + room*. Note that the variables *Other* and *SolRad* define some of the beforementioned additional variables and are only available for the home "General" (entire apartment building). For more details see https://iea-ebc-annex86.github.io/annex/articles/calculate_stats.html.

Step 3:

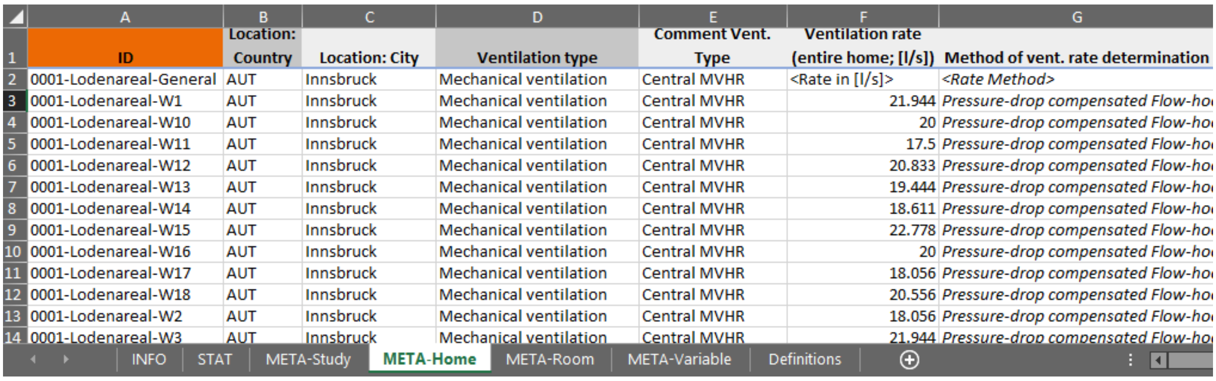
The annex data frame is passed into the function annex_stats (object, format), which performs the statistical analysis and returns a data frame with the results, see Figure 2-3 (right). The original data has now been aggregated to monthly data while distinguishing between the day- and night-time. Therefore, each row contains the statistics for each study (usually only one processed at a time), home, room, year, month, time of day and variable. To retain as much information as possible, the statistical output includes (in addition to the mean and standard deviation) the percentiles in 1%-increments, so that the empirical probability distribution is available for each month (and tod). Additionally, quality indicators and useful information are also provided for each data point (row), e.g. number of datapoints, sampling interval, share of datapoints being outside a predefined plausibility threshold (e.g. CO2<350 ppm), etc.

Steps 4-6:

The results are then written to an Excel sheet using the function *annex_write_stats()*. Now, the meta information about the study, homes, rooms and sensors can be added directly in Excel or the corresponding sheets can be loaded into R and filled with a customized R script. In particular for studies with many homes, and where the relevant meta information is available electronically, it will be worthwhile (semi)automatizing this step. The following shows a summary of the necessary commands in R to manipulate the Excel files generated via the annex package:

```
> library(openxlsx)                                              # Load the library openxslx
> wb <- loadWorkbook(path)                                       # Load in the xlsx file from path
> meta.room <- readWorkbook(wb, sheet="META-Room")               # Load in the desired sheet
> meta.room$ `Occupancy: Number` <- "enter relevant meta information"    # Change the meta information
> writeData(wb=wb, sheet = "META-Room", x = meta.room,
  rowNames = FALSE, colNames = FALSE, startRow = 2, startCol = 1)        # Write the data to the workbook
> saveWorkbook(wb, path, overwrite = TRUE)                               # Save the xlsx file to path
```

After adding the meta information, the meta-information-enhanced Excel sheet can be validated with the function annex_validate(). It will return error messages if some critical checks are not fulfilled or return warnings if, for example, meta information is missing. Note that for most studies not all meta-information asked in the meta-sheets will be available. The only obligatory meta-information is classification of the ventilation type. The final output of this annex package and workflow will be an Excel file containing the monthly (and tod) statistics as well as the most relevant meta information. For the presented example case the "Meta-Home" sheet will look like depicted in Figure 2-4. It is structured in a database-like format, for easier processing if many of such output files are to be analyzed jointly, i.e. for meta-analysis including many IAQ studies or benchmarking of an individual study compared to many others. The latter application will be outlined in the following section.



	A	B	C	D	E	F	G
1	ID	Location: Country	Location: City	Ventilation type	Comment Vent. Type	Ventilation rate (entire home; [l/s])	Method of vent. rate determination
2	0001-Lodenareal-General	AUT	Innsbruck	Mechanical ventilation	Central MVHR	<Rate in [l/s]>	<Rate Method>
3	0001-Lodenareal-W1	AUT	Innsbruck	Mechanical ventilation	Central MVHR	21.944	Pressure-drop compensated Flow-ho
4	0001-Lodenareal-W10	AUT	Innsbruck	Mechanical ventilation	Central MVHR	20	Pressure-drop compensated Flow-ho
5	0001-Lodenareal-W11	AUT	Innsbruck	Mechanical ventilation	Central MVHR	17.5	Pressure-drop compensated Flow-ho
6	0001-Lodenareal-W12	AUT	Innsbruck	Mechanical ventilation	Central MVHR	20.833	Pressure-drop compensated Flow-ho
7	0001-Lodenareal-W13	AUT	Innsbruck	Mechanical ventilation	Central MVHR	19.444	Pressure-drop compensated Flow-ho
8	0001-Lodenareal-W14	AUT	Innsbruck	Mechanical ventilation	Central MVHR	18.611	Pressure-drop compensated Flow-ho
9	0001-Lodenareal-W15	AUT	Innsbruck	Mechanical ventilation	Central MVHR	22.778	Pressure-drop compensated Flow-ho
10	0001-Lodenareal-W16	AUT	Innsbruck	Mechanical ventilation	Central MVHR	20	Pressure-drop compensated Flow-ho
11	0001-Lodenareal-W17	AUT	Innsbruck	Mechanical ventilation	Central MVHR	18.056	Pressure-drop compensated Flow-ho
12	0001-Lodenareal-W18	AUT	Innsbruck	Mechanical ventilation	Central MVHR	20.556	Pressure-drop compensated Flow-ho
13	0001-Lodenareal-W2	AUT	Innsbruck	Mechanical ventilation	Central MVHR	18.056	Pressure-drop compensated Flow-ho
14	0001-Lodenareal-W3	AUT	Innsbruck	Mechanical ventilation	Central MVHR	21.944	Pressure-drop compensated Flow-ho

Figure 2-4: Screen shot of the Excel file produced with the annex package and the presented workflow for an exemplary study. Note that the statistical output is stored in the sheet "STAT", while the shown sheet contains the meta information for each measured home.

2.4. Comparison/ benchmark

The intention of this section is to outline an example of how the R package, and the underlying standardized analysis procedure, can be used for benchmarking the results of a particular study against many other studies that have been analysed applying the presented "annex" package. It will be outlined with the same exemplary study "Lodenareal". The data containing all the studies processed within the project IEA EBC Annex 86 are available in the data repository https://doi.org/10.5281/zenodo.14917724 (Freundorfer et al. 2025a). The R scripts to perform the following benchmark will be made available in this git repository: https://github.com/IEA-EBC-Annex86/ST2analysis (Freundorfer et al. 2025b).

The meta-analysis / benchmarking script is structured in several sections, which are outlined below.

Section 1 deals with loading and preparing the data. All the necessary sheets, statistics and the meta information get loaded into one data frame. The data is checked for consistency, and a basic cleaning (removing NA's, empty entries, etc.) is performed. Additional cleaning, e.g. removing entries which don't fulfil certain quality criteria is also performed here, e.g. remove rows (monthly aggregation) where share of measurements with CO2 < 350 ppm is above 1% and remove rows with less than 30 data points (from the original time series). Depending on the needs the data can be further enriched or homogenized at this stage, e.g. extracting numerical values from the "free text" meta information, e.g. extract room area.

Section 2 the data as required for the benchmarking. The postprocessed data has a column called 'tod', short for time of day, with data for daytime, nighttime and the whole daily period. The relevant filter for this exemplary evaluation consists of filtering for CO_2 concentration in bedrooms at night during the winter months. This filter is applied to the example study and the bulk data (of all other studies) and can include filtering for homes or rooms of certain characteristics, e.g. homes with mechanical ventilation, homes from certain countries, rooms with certain area or measurements with specific sensors, just to mention a few examples. In this example the focus is to benchmark the CO_2 concentrations from the Lodenareal study with other mechanically ventilated bedrooms.

The next section deals with various statistical tests for the data, like ANOVA or fitting linear regressions for different subsets of the dataset, e.g. in the benchmarking case, checking if there is a significant difference between the specific study and all the other studies.

Section 3 aggregates the data over time to have one row per room and calculates aggregated distribution functions (probability density functions: PDFs and/or cumulative distribution functions: CDFs). They give a comprehensive overview of the time distribution of pollutant concentration in the investigated rooms/homes. They represent the time distribution, i.e. not a distribution of the aggregated mean or median values but for the original time series measurements. That way non-linear exposure effects can be accounted in further analysis. Now the CDFs (or PDFs) of the rooms of the example study can be compared to those from other studies.

The next section aggregates the data further into one single CDF/PDF per study, which can then be used to directly compare different studies. Or new subsets filtered for ventilation type can be created, aggregated and compared directly. In this example the time distribution of nighttime CO_2 concentration during the colder time of the year (October through May) measured in the Austrian study "Lodenareal" is compared to the mixed distribution of all the other studies (differentiated between mechanical ventilation and non-mechanical ventilation), see Figure 2-5.

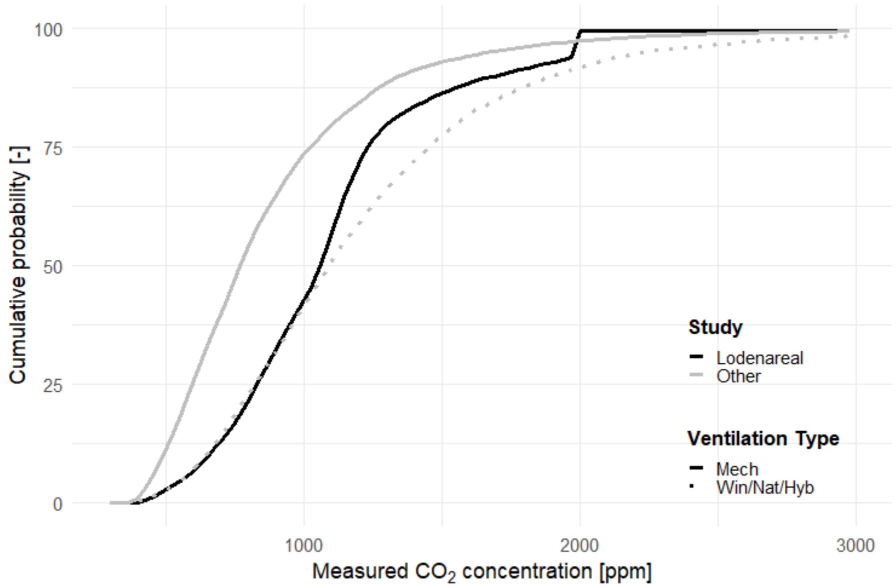


Figure 2-5: Empirical cumulative distribution function of the CO_2 concentration measured in bedrooms during nighttime hours (23-07) in the months October through May for the measurement study "Lodenareal" and for the measurements in all other studies analyzed within IEA EBC Annex 86, while differentiating between mechanically (Mech) and window aired, naturally (Nat) or with hybrid solutions (Hyb) ventilated homes.

2.5. References

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3. Pollutant Load from Building Envelope Materials for Indoor Air Quality Modelling

Authors: Raïssa Andrade, Gaëlle Guyot, Marc Abadie, Gabriel Rojas-Kopeinig

3.1. Objective and methods

The objective of this analysis is to illustrate the use of PANDORA database to evaluate the pollutant loads from the building envelope materials in the case of a residential building. We intend to calculate the Emission Rates (ER) of formaldehyde in each room of a single-family house.

The case study is based on a real two-story low-energy brick detached house (Poirier et al., 2021). The house has four bedrooms (called BR1, BR2, BR3, BR4), two bathrooms (Bath 1 and 2), two toilets (WC 1 and 2), a mezzanine (Mezz), a kitchen open on the living room (K+LR) and a hall, as shown in Figure 3-1.

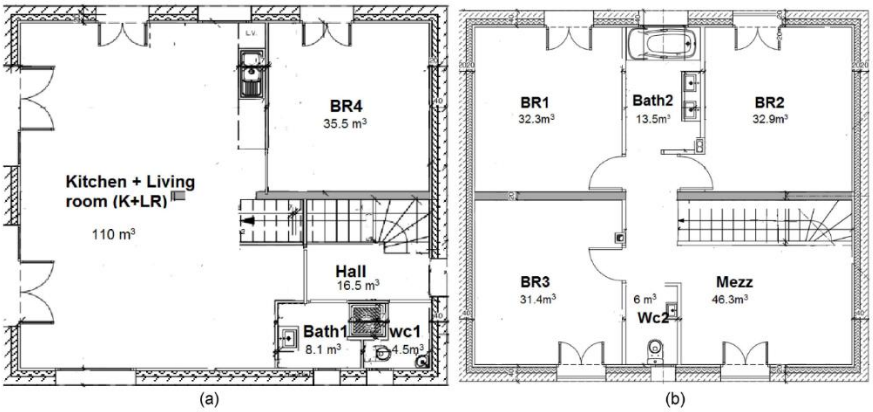

Figure 3-1: Plan of the house studied: (a) ground floor; (b) first floor (Poirier et al., 2021).

The PANDORA (a com**P**il**A**tion of i**ND**o**OR A**ir pollutant emissions) database is used to evaluate the Specific Emission Rates (SER) of the walls, floor and ceiling. Since its creation in 2009 (Abadie and Blondeau, 2011), the database systematically compiles available data on the emission rates of both gaseous and particulate pollutants, providing valuable information for IAQ modelers to set up their indoor sources input values. In 2021, a significant development transformed the original downloadable MS Access file into an internet-based database accessible on all devices, including phones, tablets, and desktops, through the dedicated website https://db-pandora.univ-lr.fr/ (Abadie, M., Blondeau, P. (2021). Additionally, participants of Annex 86 Subtask 2 identified new data through a literature review for integration into the database. As a result, approximately 1,000 new entries were added in 2024 to the 9,000 that already existed.

Regarding the pollutant emission rates from construction and decoration materials, i.e., the constituents of building envelopes that emit Volatile Organic Compounds (VOCs) to the indoor air, statistical calculations have been performed for some selected pollutants (formaldehyde, benzene and TVOC) so that modelers can have access to aggregated data, enabling more informed decision-making than arbitrarily picking one specific data from the database. Those statistical data can be accessed through the "Data Analysis" page of the PANDORA database by clicking on the link labeled "PANDORA Statistical Analysis". Figure 3-2 presents the data for the Finishes subcategory that includes different kinds of water- or oil-based paints, waxes and varnishes. The left graph gives ER after different periods in the experimental chamber used to measure the SER. Those periods can be seen as the elapsed time from the installation of new materials in a building. In the present case, only 7 ER are available for 3 days and 6 for 28 days. No data is available after one year. The graph on Figure 3-2 (right) presents the same data but according to the year of publication of the scientific paper or report that evaluates the SER i.e. about the year of material construction. It is worth noting that a decrease in formaldehyde emissions based on the manufacturing date of products is expected, as many countries have gradually introduced legislation since the 2000s to limit VOC emissions from construction and decorative products.

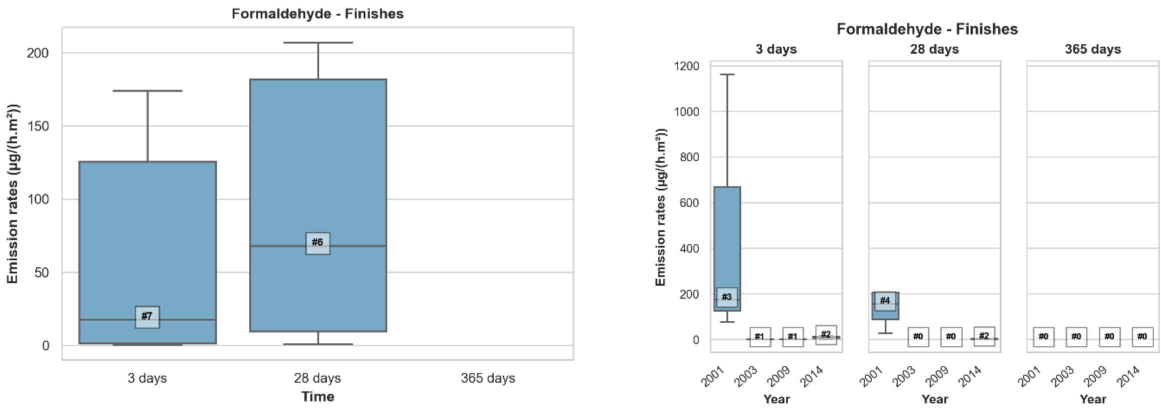

Figure 3-2: Statistics of emission rates of formaldehyde for Finishes after 3, 28 and 365 days (left: all data; right: separated by the year of publication).

3.2. Results

The PANDORA database was used to select formaldehyde emissions in low, medium and high exposure scenarios, considering data after 28-day period as it is usually done in labeling system regarding VOCs emission. We only use the SER from Finishes to simplify this illustrative example, but each surface could have been defined differently to account for the presence of carpets, wood flooring, wallpaper, furniture, etc.

In the present calculation, three levels scenarios have been defined: low, medium and high formaldehyde emission from “finishes”:

- For the low-level scenario, the values considered are the minimal SER and emissions from 5 walls (4 vertical walls and ceiling) are considered.
- In contrast, the high-level scenario considered Percentile 25 (p25 i.e. 1st quartile) and emissions from 5 walls (4 vertical walls and ceiling) are considered. One could ask why not use the maximal value or P75. It comes from the fact that those values (and the median and average to some extent) tend to be very high because of the limited data and the fact that potentially high emitting materials have been preferentially tested in literature (instead of testing materials according to their actual recurrence in indoor environments). As recommended in Cony Renaud Salis (2020), p25 should be considered as a high emission SER of formaldehyde for Finishes. Statistical levels will take on greater significance as SER from materials commonly found in buildings are integrated into the database.
- For the medium-level scenario, p25 was also used, but it was necessary to make some assumptions to get intermediate values between the low and high -level scenarios. The idea here is to account for both emission-free surfaces such as windows or tiled walls (in bathrooms and kitchen) and the presence obstructions that lower/suppress the pollutant emission from the walls such as closets, paintings, posters… Three assumptions were therefore evaluated:
    - Assumption 1: There are no emissions from floors or ceilings in any of the rooms. In addition, there is one emission-free wall in each room to account for.
    - Assumption 2: In the bathrooms and toilets, the walls are tiled, so there are only emissions from the ceiling. In the living room with kitchen and in the bedrooms, there are no emissions from the floor or one tiled wall. Nor are there any emissions from one wall in the bedrooms.
    - Assumption 3: Same as assumption 2, except that each bedroom has 2 emission-free walls.

Table 3-1 presents the formaldehyde SER related to the floor area that accounts for the different configurations. As expected, only the medium level varies with the three-assumption giving intermediate values that are between the lowest SER of 4.5 (µg/h)/m²$_{floor}$ and the highest one of 48.4 (µg/h)/m²$_{floor}$.

Zhao et al. (2022) reported formaldehyde emission rate for a whole dwelling using field-measured, time-resolved formaldehyde concentrations, air exchange rates, and indoor environmental parameters in 63 California single family houses built between 2011 and 2017 (Table 3-1) that are all post-date California requirements for lower emission rates (CARB, 2007). The calculations using the database lie within the range of the SER evaluated from Californian houses.

To finish, the French VOC emission labelling regulation (French decree, 2011) was published on 25 March 2011 regarding a mandatory labelling of construction products installed indoors, floor and wall coverings, paints and lacquers with their emission classes based on emission testing. Table 3-1 presents the formaldehyde emission rates considering 5 emitting walls (4 vertical walls and ceiling). The low and medium -level assumption leads to SER representative of A+ class while the high-level is related to the A one.

Table 3-1. Specific Emission Rates ((µg/h)/m^2_{floor}) of formaldehyde (the surface area is the total floor area).

	Present study			Zhao et al. (2022)			French 2011 VOC emission label for constructive and decorative materials			
Scenario	**Low**	**Medium**	**High**	**Min.**	**Mean**	**Max**	**A+**	**A**	**B**	**C**
Assumption 1	4.5	29.0	48.4	3.3 ± 1.4	19.6 ± 10.4	58.9 ± 10.0	≤ 32.5	≤ 195	≤ 390	> 390
Assumption 2	4.5	29.2	48.4							
Assumption 3	4.5	24.1	48.4							

This simple example aims at exemplifying the use of the statistics from the PANDORA database produced in the frame of the Annex 86 for the construction and decorative materials for selected pollutants. Other specific emission rates from other sources are available regarding furniture, occupants' activity, cleaning products, and electrical equipment. Almost ten thousand emission rates (ER) from literature have been integrated so far, formaldehyde is currently the most cited pollutant with 336 ER, followed by TVOC (311), particles (173) and benzene (150). These data serve as inputs for simulation tools, like those used in the calculations of Annex 86 Subtask 4.

3.3. References

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4. Smart materials as an IAQ management strategy - Common Exercises

Editors: Menghao Qin, Jianshun J. Zhang

Authors: Nicolas Sadovnik, Doyun Won, Zhenlei Liu, Weihui Liang, Jinzhe Nie, Jialei Shen, Rui Zhang, Marco Daturi, Christian Serre

4.1. Common Exercise Structure

The common exercise consists of three parts: 1A (basic) is mandatory for all participants, while 1B and 1C (advanced) are optional but encouraged for capable participants to provide data.

Common Exercise 1A (basic) - mandatory for all participants

1) Perform a small-scale chamber test to investigate the capacity of the materials for VOC adsorption.
2) Perform a small-scale chamber test to characterize the removal rate per unit exposure surface as a function of time.
3) Determine the empirical sorption function $M_s(C_s)$, where $M_s(C_s)$ is the mass of VOC adsorbed on (or removed by) the material.
4) Perform a n-decane emission test to estimate convective mass transfer coefficient over the material's surface.

Common Exercise 1B (advanced) – optional

5) Investigate the impact of relative humidity on VOCs adsorption on the novel material's surface.

Common Exercise 1C (advanced) - optional

6) Investigate the impact of temperature on VOCs adsorption on the novel material's surface.

The Annex 86 project team fabricated multiple MOF-based (Metal-Organic Frameworks) paper membranes (>20 × 20 cm) for distribution to collaborating laboratories, enabling comprehensive testing under various real-world conditions. Key performance metrics, including airflow, temperature, humidity, formaldehyde concentration, and coexisting pollutants, were evaluated. This section presents experimental results concerning testing duration, formaldehyde concentration, and the effects of relative humidity.

4.2. Experimental Implementation of Common Exercise 1

4.2.1. Chamber test setup

Syracuse University (SU) and the National Research Council of Canada (NRC) performed experiments using 50-liter stainless steel chambers. NRC placed two Al-3,5-PDA paper membranes (22.5 × 20 cm; adsorption capacity: 4.44 mmol/g) with single-sided exposure at the bottom of the chamber (Figure 4-1a), whereas SU suspended a single substrate with double-sided exposure on a rack (Figure 4-1b).

The NRC's baseline test conditions consisted of an air exchange rate of 1 h^{-1}, temperature of 23°C, 50% relative humidity (RH), and formaldehyde concentration of approximately 50 μg/m³, with a 7-day adsorption phase followed by 4-day desorption. Extended long-term tests (28 days) examined two formaldehyde concentrations (~50 and 500 μg/m³), while varying RH levels (10%, 30%, 50%, 70%) were applied to assess interference effects. SU conducted 28-day adsorption tests at concentrations of 115 and 321 μg/m³ followed by 7-day desorption to investigate re-emission characteristics.

MOF paper activation involved both static and dynamic vacuum drying protocols. The static protocol comprised: (1) immersion in distilled water (4 L per sheet) for 24 h, (2) air-drying for 12–24 h, and (3) 5 h under vacuum (110°C, −700 to −970 mbar). Dynamic drying utilized a vacuum oven (Across International, ~50 L capacity) at 100°C and −200 mbar with 3 L/min air circulation for 16 h. While NRC primarily employed static drying for material regeneration due to its superior reproducibility, SU utilized activating new sheets at 104–107°C and −700 mbar for 4 h.

Formaldehyde gas (HCHO) was generated by a calibrated gas generator equipped with paraformaldehyde permeation tubes (VICI Metronics). Periodic analysis was performed using DNPH (2,4-dinitrophenylhydrazine) adsorption tubes coupled with HPLC. Additionally, Tenax TA thermal desorption tubes were employed for GC/MS analysis to identify potential MOF-derived byproducts.

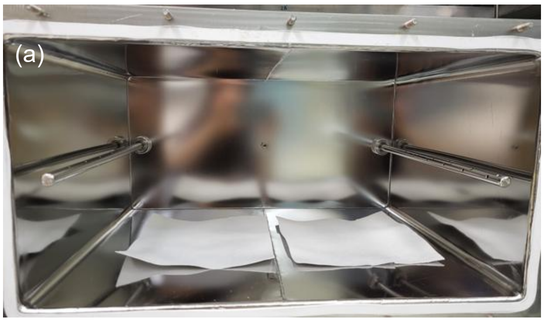


Figure 4-1 Al-3,5-PDA MOF paper sheets in a chamber at NRC (a) and SU (b)

4.2.2. Formaldehyde Removal Efficiency Analysis

Formaldehyde removal efficiency (RE) was calculated as:

$$RE = (1 - \frac{C_{out}}{C_{in}}) \times 100\%$$

Equation 4-1

where C_{in} and C_{out} represent the inlet and outlet concentrations, respectively.

4.2.3. Experiment Results and Discussion

4.2.3.1. Comparative Analysis of Formaldehyde Chamber Concentrations with/without MOF paper sheet (Based on 7-Day Adsorption Experiment)

Figure 4-2 presents comparative results of formaldehyde concentration change over time at the chamber inlet and outlet under two experimental conditions in NRC's tests: (a) control, empty chamber and (b) with MOF paper sheet. The control test results (Figure 4-2a) showed nearly identical inlet and outlet concentrations, confirming the absence of inherent adsorption effects in the test system. In contrast, when MOF paper sheet was placed in the chamber (Figure 4-2b), the outlet concentration decreased by an average of 87.5%.

Following termination of formaldehyde injection, the outlet concentration in the control test rapidly declined to near-zero levels within 2 hours (Figure 4-2a). Conversely, the experimental chamber (with MOF material) exhibited significantly slower concentration reduction, maintaining a residual concentration of 2.3 μg/m³ even at the end of experiment (Day 11). This persistent residual concentration indicates the occurrence of minor formaldehyde re-emission from the MOF material.

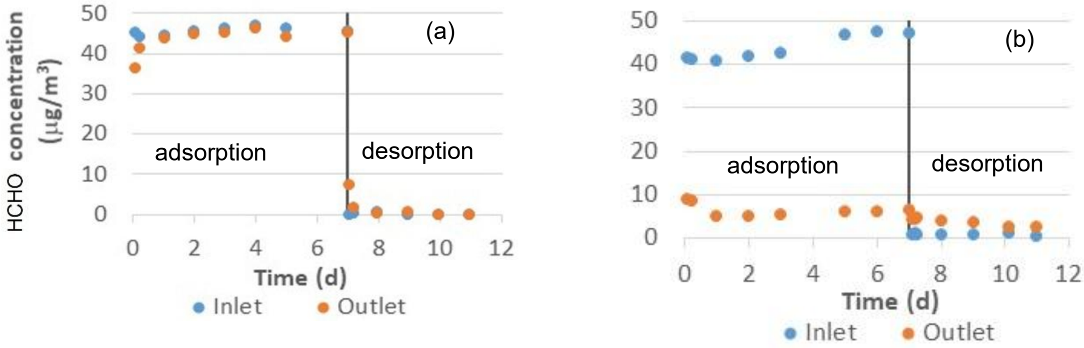


Figure 4-2 Measured inlet and outlet HCHO concentrations - without (a) and with (b) MOF paper sheets at NRC

4.2.3.2. Effect of HCHO concentration and long-term performance

This Common Exercise conducted a 28-day continuous test under four formaldehyde concentration conditions (~50, 115, 321, and 500 µg/m³) by NRC and SU. As shown in Figure 4-3a, the long-term removal efficiency trends observed by NRC demonstrated relatively stable efficiency during the initial 7-14 days, followed by a consistent weekly decline of approximately 7%. Notably, no significant difference in removal efficiency was observed between the two concentration conditions (~50 µg/m³ vs. 500 µg/m³).

SU's 28-day test data (Figure 4-3b) revealed that at an initial concentration of 115 µg/m³, the removal efficiency decreased from 72% to 49% during test period, while under 321 µg/m³ conditions, the efficiency declined from 77% to 55%. Overall, SU's test results were slightly lower than NRC's data. The observed discrepancies between NRC (70-90%) and SU (49-72% and 55-77%) may be attributed to several factors. There are slight differences between the regeneration methods employed before the test. The test conditions differed between the two labs, including inlet formaldehyde concentration, sample placement configuration, and exposed surface area. The primary discrepancy was that NRC employed two curved MOF membranes (effective exposed area: 0.117 m²), whereas SU used a single double-sided exposed membrane (measured areas: 0.0900/0.0892 m²). The double-side adsorption configuration may alter diffusion depth, thereby affecting physical adsorption kinetics. Although chemical adsorption remains the dominant mechanism, differences in physical adsorption site accessibility may contribute to the observed variations in results.

Both NRC and SU's 28-day long-term tests showed a gradual decline in removal efficiency to approximately 55-70%. While the efficiency remains relatively high, theoretical calculations suggest that cellulose-composite MOF materials could have a service life of several years. Therefore, extended testing is necessary to evaluate performance degradation under practical usage conditions.

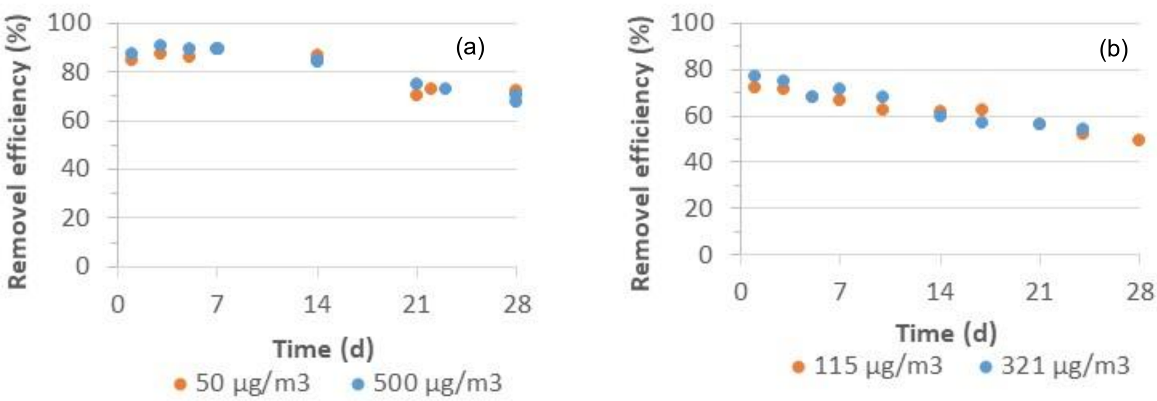


Figure 4-3 HCHO removal efficiencies at different HCHO concentrations during a long-term test (28 days) at (a) NRC and (b) SU

4.2.3.3. Formaldehyde Re-emission Phenomenon and By-products

Initial evidence of formaldehyde re-emission was observed during a 7-day test at 50 µg/m³ concentration (Figure 4-4b). To validate this phenomenon, NRC and SU conducted a 28-day adsorption experiment under various formaldehyde concentration levels followed by a 7-day desorption tests. As shown in NRC's results (Figure 4a), the chamber formaldehyde concentration did not decline to zero but stabilized at 70% of the final adsorption phase concentration, confirming re-emission behavior from the MOF paper sheet. SU independently replicated this observation during their 28-day long-term testing (Figure 4-4b).

The combined experimental results from both institutions demonstrate that re-emission occurs consistently across 50-500 µg/m³ concentration ranges, residual formaldehyde levels remain significant (70% of saturation concentration), and the phenomenon is reproducible under different experimental configurations.

According to collaborative research by Sadovnik et al. (2024), formaldehyde is chemically adsorbed into Al-3,5-PDA pores through reactions with pyrazole groups in the ligands, achieving zero leakage. The observed re-emission after both 7-day and 28-day tests is more likely attributable to physical adsorption by the cellulose paper substrate. This hypothesis requires verification through comparative experiments using pure cellulose paper without Al-3,5-PDA. These findings have important practical implications, suggesting that MOF-based filtration materials may require periodic regeneration or replacement to maintain optimal performance.

Chemical analysis by NRC using Tenax TA and DNPH sampling methods detected VOCs (e.g., acetone, toluene, acetophenone) and other aldehydes (e.g., acetaldehyde, butyraldehyde) at concentrations comparable to background levels. Similarly, SU's analysis of Tenax adsorbent samples collected at multiple time points (background, Day 1, Day 3, and Day 21) revealed no byproduct generation. All concentration fluctuations observed during the adsorption phase remained within measurement uncertainty ranges, demonstrating that the MOF paper sheet produced no detectable degradation byproducts during testing.

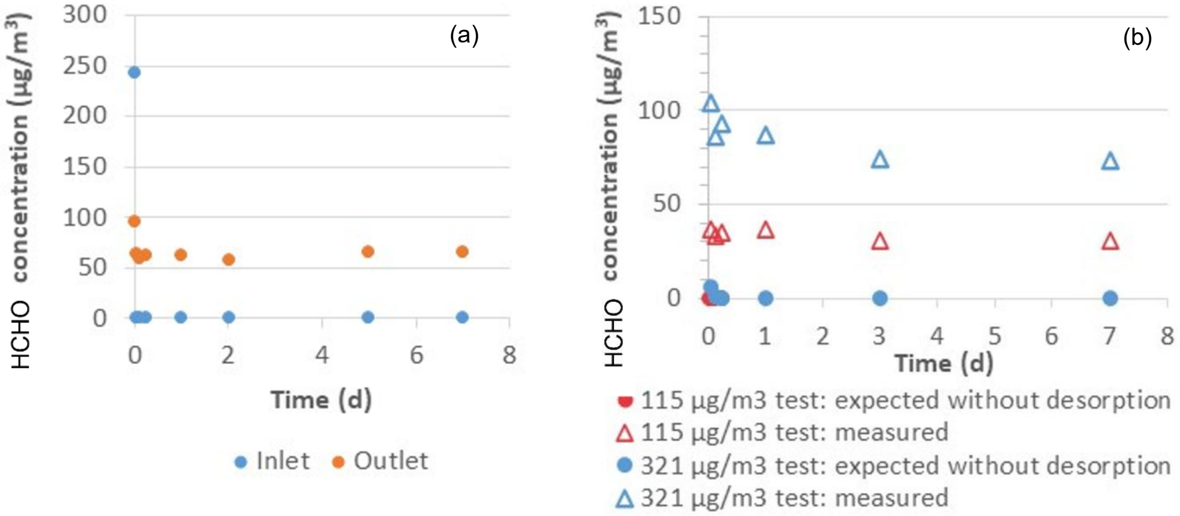


Figure 4-4 HCHO concentrations during a 7-day desorption test after long-term adsorption tests for 28 days at (a) NRC and (b) SU

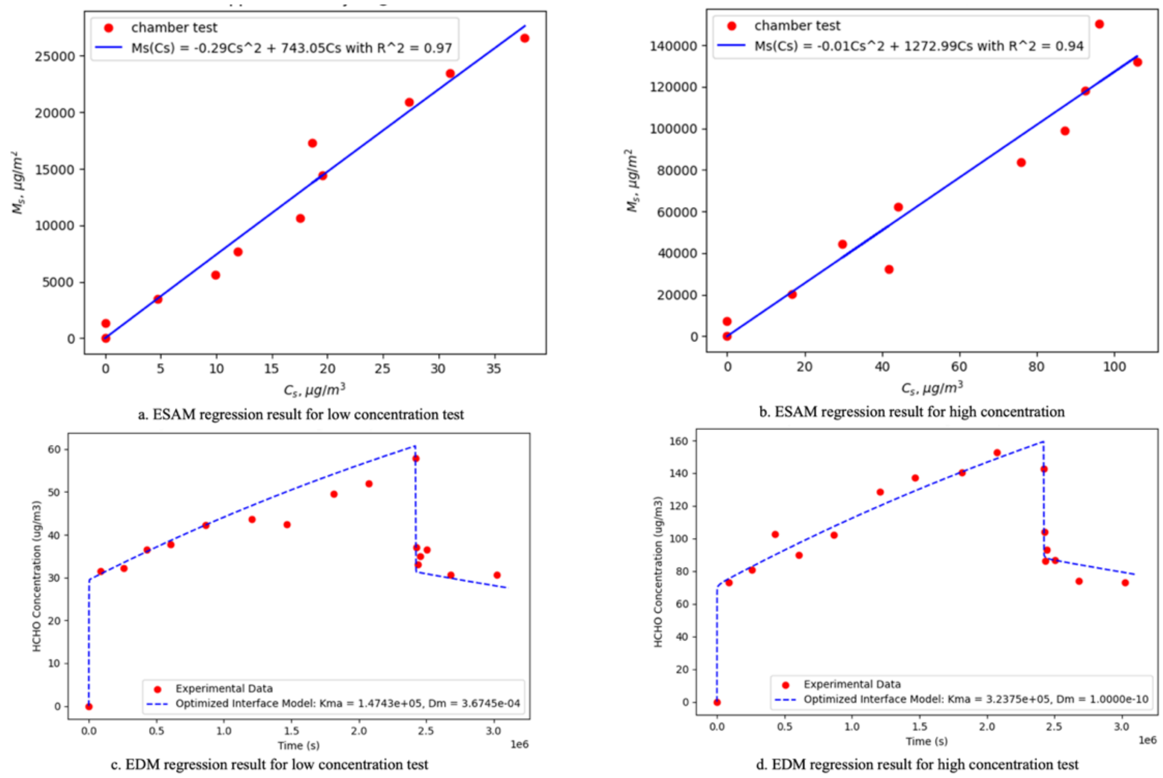
4.2.4. Mechanistic Insights and Model Validation of Common Exercise 1A

4.2.4.1. Model Parameter Estimation and Adsorption Process Analysis

The 28-day adsorption tests confirmed that the MOF material had not reached saturation capacity. Considering the experimental duration and associated costs, this Common Exercise adopted a combined experimental and simulation approach. The following section presents the model parameters derived from the test results and evaluates the effectiveness of different models in characterizing formaldehyde adsorption on Al-3,5-PDA. Detailed methodologies for parameter estimation by regression analysis can be found in Annex86 ST3 Report Section 5.

For the EDM, parameters K_{ma} and D_m were determined through regression analysis. The results revealed that K_{ma} values for EDM under 115 µg/m³ and 321 µg/m³ tests were 1.47×10^5 and 3.24×10^5 respectively, indicating a significant surface adsorption effect compared with conventional building materials. These findings aligned with the observation that adsorption primarily occurred at the surface due to chemical reactions, leading to a thin adsorbed layer with high capacity. While the D_m values showed a significant difference between the low and high concentration tests, this suggested that the assumed diffusion process did not accurately reflect the actual adsorption behavior. Furthermore, this indicated that, compared with the surface effect, in-material diffusion was not the dominant process governing formaldehyde adsorption on Al-3,5-PDA. Overall, the EDM effectively represented the chamber tests in both the adsorption and desorption phases (Figure 4-5).

For the ESAM, parameters M_s and C_s were calculated based on chamber test data. The results indicated that parameter a was significantly smaller than b, suggesting that the first-order adsorption-desorption model effectively described early-stage adsorption behavior (Figure 4-5). The equilibrium constant $K_e=M_s/C_s$ remained relatively constant over the 28-day test period, implying a steady-state condition where adsorption and desorption processes reached the dynamic equilibrium.



a. ESAM regression result for low concentration test

b. ESAM regression result for high concentration

c. EDM regression result for low concentration test

d. EDM regression result for high concentration test

Figure 4-5 Regression test results of the ESAM and the EDM under low and high formaldehyde concentration tests. (a) Results for ESAM under low concentration test. (b) Results for ESAM under high concentration test. (c) Results for EDM under low concentration test. (d) Results for EDM under high concentration test.

4.2.4.2. Saturation Condition Analysis by Simulation

Given the high cost of year-long experimental testing, we utilized EDM to simulate long-term formaldehyde adsorption dynamics. Figure 4-6 presents the temporal concentration profiles under two SU's exposure scenarios, revealing that the adsorption process followed a characteristic curve where formaldehyde concentration increased over time and approached saturation. Regardless of the initial exposure level, the adsorption exhibited rapid uptake initially, followed by a slower approach towards equilibrium. The findings indicated that both low- and high-exposure concentration conditions led to saturation within approximately one year. These results validated the applicability of diffusion models for long-term predictions and provided valuable insights into practical applications without costly experimental testing. The ability to simulate extended exposure scenarios aided in assessing the long-term effectiveness of adsorptive materials.

For ESAM, saturation conditions can be determined by solving a quadratic function. The highest surface concentration was achieved at the peak point. By analyzing the total amount of formaldehyde injected, the time required to reach saturation could also be estimated. For 115 μg/m³ formaldehyde test, this time was approximately 300 days, aligning with EDM results of about one year. However, for 321 μg/m³ concentrations, ESAM suggested a much longer time of around 13 years, which conflicted with EDM findings. This discrepancy may arise from the limitations of short-term tests in accurately estimating long-term conditions over a year. Further investigation was needed to reconcile these differences and ensure accurate modeling of adsorption processes over various timescales.

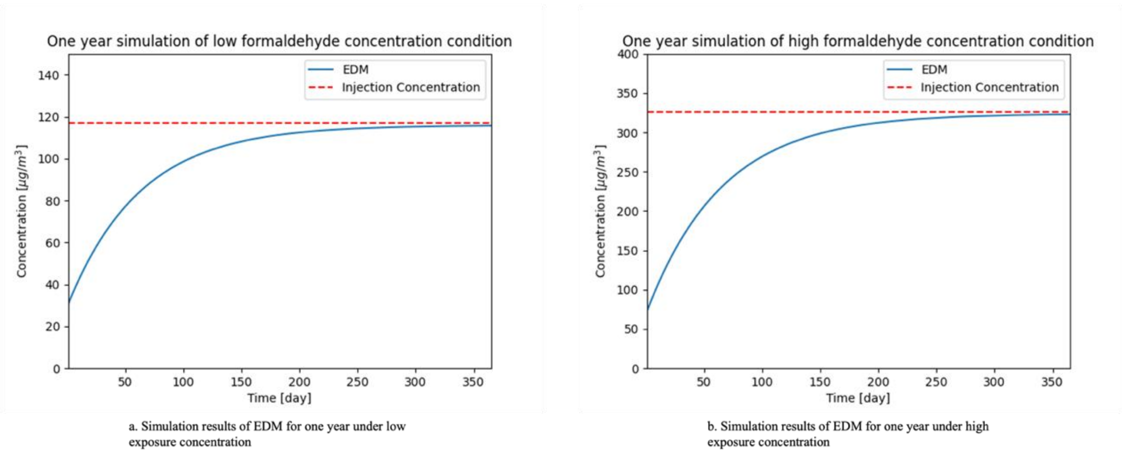


Figure 4-6 One-year simulation by EDM of formaldehyde adsorption under low and high concentration.

4.3. Experiment Results of Common Exercise 1B

4.3.1. Effect of Relative Humidity

To investigate the formaldehyde adsorption effectiveness in the present of water, NRC conducted chamber tests under various relative humidity (RH) conditions. As shown in Figure 4-7, the formaldehyde concentration profile was measured over 7 days under 4 different RH conditions. During the 7-day test period, the removal efficiency (RE) remained relatively stable. The test results indicate that when the ambient RH increased from 10% to 50%, the RE of formaldehyde decreased slightly from 92.8% to 87.5%. However, when the RH further increased to 70%, the RE rose to 89.5%. The variations in RE under different RH levels were within in the standard deviation, suggesting that Al-3,5-PDA's RE stability was unaffected by RH changes.

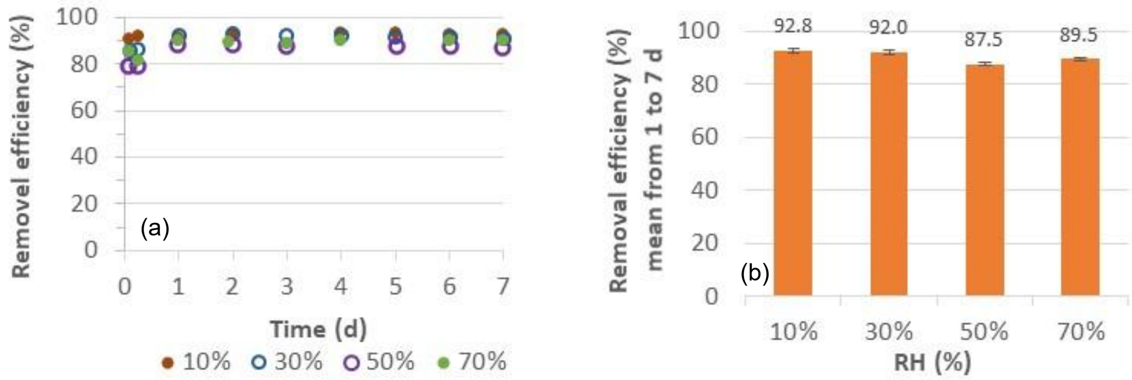


Figure 4-7 HCHO removal efficiencies at different RH levels: time-variant (a) and mean values (b).

4.4. Conclusion of Common Exercise

The Annex86 ST3 Common Exercise 1 systematically evaluated the performance of Al-3,5-PDA paper membranes for formaldehyde removal through collaborative experiments conducted by Syracuse University and the National Research Council of Canada. Mandatory tests (1A) demonstrated the material's high initial removal efficiency (87.5% average reduction) and stability over 28 days, although with gradual efficiency declines (~7% weekly) and observable formaldehyde re-emission during desorption phases. Advanced investigations (1B) revealed relative humidity (10–70% RH) had minimal impact on removal efficiency, confirming the material's robustness under varying environmental conditions. Mechanistic analyses highlighted chemical adsorption via MOF ligands as the dominant process, though physical adsorption by the cellulose substrate contributed to re-emission phenomena. Model simulations (EDM and ESAM) provided insights into long-term saturation dynamics, predicting material saturation within ~1 year in 115 μg/m³ and 321 μg/m³ formaldehyde concentration levels. These findings underscore the material's potential for real-world passive formaldehyde control and air purification applications while emphasizing the need for periodic regeneration protocols and extended durability testing. The consistent results across institutions validate the experimental framework and highlight critical considerations for optimizing MOF-based filtration systems, including configuration design, regeneration methods, and long-term performance monitoring under practical operating conditions.

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5. Rating existing smart ventilation strategies – testing usability of performance indicators

Authors: Baptiste Poirier, Jakub Kolarik, Douaa Al Assad, Quinten Carton, Hilde Breesch, Klaas De Longe, Jelle Laverge, Markus Wirnsberger, Gabriel Rojas, Marcos Batistella, Daniela Mortari, Nathan Mendes, Annamaria Belleri, Irene Laraibeas, Evangelos Belias, Dusan Licina, Gaëlle Guyot

5.1. Introduction and background

Evaluating the performance of smart ventilation systems involves several approaches (Guyot et al., 2019; Poirier et al., 2021). One common approach is the use of performance-based metrics, which assess the system's ability to maintain IAQ. In most cases, the ability of the system to provide simultaneous minimization of energy consumption is also assessed. Key metrics include the concentration of indoor air pollutants, mostly represented by CO_2 (although the CO_2 is not really a pollutant, but rather an indicator of outdoor air supply relative to occupancy), volatile organic compounds, air humidity levels, and energy use. Additionally, the concept of "equivalent ventilation" can be employed, which allows for the anticipation of future ventilation needs and retroactive compensation for previous ventilation needs (BSR/ASHRAE, 2016; ASHRAE 2023). According to (Wang et al., 2024), evaluating the effectiveness of smart ventilation systems under various conditions happens mostly using computer simulations. Utilization of experiments or combination of experiments with simulations is rare.

Despite the promising benefits, smart ventilation systems face several challenges. One of the most important challenges is the fact that the regulatory landscape for smart ventilation is still evolving, and there is a need for standardized guidelines and performance criteria to ensure consistent and effective implementation (Guyot et al., 2019).

One of the key objectives of the collaborative research project entitled “Energy Efficient Indoor Air Quality Management in Residential Buildings”, performed under the framework of the International Energy Agency (IEA), IEA EBC Annex 86, has been to build an internationally based performance-based approach for assessing smart ventilation multicriteria performance, to allow the generalization of such promising solutions in residential buildings.

The present report demonstrates the application of an internationally applicable performance-based approach for the assessment of residential ventilation performance, including smart as well as traditional ventilation strategies. First, we aim to create a generally acceptable rating scheme- a set of performance indicators for assessment of residential ventilation. Secondly, we investigate its applicability with a common exercise conducted by experts in six countries (France, Denmark, Belgium, Italy, Austria, and Brazil) with different design contexts, simulation software, smart ventilation strategies, building geometries. The analysis of results shows: (1) how a performance-based approach using different performance indicators can be used to assess the performance of smart ventilation strategies in different countries and (2) how these smart strategies perform compared to standard ones.

5.2. Methods

5.2.1. A general method in two steps – Construction and applicability

The first step consisted in the build of an internationally based “rating scheme” or “performance-based approach”. Before the second meeting in Athens, a “homework” questionnaire was sent to all Annex 86 participants to identify the relevant performance indicators to use and the identified barriers. Eight experts send an answer from seven countries (UIBK-Austria, SINTEF-Norway, Buildwise-Belgium, KU Leuven-Belgium, CETIAT-France, LBNL – USA, TUe-The Netherlands, CSIC-Spain). During a series of meetings and workshops, an international consensus was obtained with the selection of a set of performance indicators, using the available literature as well as an expertise of the team members and the work performed during the IEA-EBC Annex 68 project (Abadie and Wargocki, 2017; Cony Renaud Salis et al., 2017; Cony-Renaud-Salis et al., 2019). Then, a work group was set up to create a common description of the simulation study to be conducted by each of the participants. The description included description of the workflow, to be obeyed by each participant, list of target contaminants to be simulated and description of the required output data. Besides the output data, each participant had to fill out forms collecting the standard simulation input information (e.g. occupancy schedules, pollutant emission rates and information about simulated ventilation control strategies).

The second step consisted in testing this rating scheme in different national or regional contexts. The project participants from seven research institutions in six countries agreed to participate in this common exercise. The participants were free to use an existing simulation case including building geometry, type of simulation software, weather data, etc. The task was to conduct a performance analysis of the different ventilation strategies for the case, with both standard and smart approaches to control and use the predefined set of performance indicators to assess these strategies. We gave the participants a free choice to select the case as well as the ventilation strategies studied. The only condition was that they provided all the required information and that they selected one strategy, preferably standard (not smart), as a reference. The common set of performance indicators constituted the framework for the analysis which looked at the data from two main angles:

- Usability of the indicators to describe a relation between the smart ventilation strategies and a "reference case", which had a country specific relevance.
- A general qualitative analysis of the usability of the performance indicators. This analysis comprised of a synthesis of experiences, observations, identified barriers and challenges reported by all involved participants in a dedicated formular.

5.2.2. Target contaminants and collected data

Table 5-1 summarizes contaminants to be included in the simulation studies of performance of ventilation. There were four obligatory contaminants and one optional contaminant.

Table 5-1 Contaminants/parameters to be included in the simulations

Contaminant/parameter	Reasoning behind the choice of the contaminant
Carbon dioxide (CO_2)	Emitted by humans and pets, indicates emission of bioeffluents, if the bioeffluents dominate the indoor emission can be used as a surrogate for IAQ, indicator of ventilation. In limited amount emitter also by indoor combustions (e.g. gas cookers).
Relative humidity	Emitted by humans and pets as well as occupancy related activities and processes. Low relative humidity leads to irritation of mucous membranes, discomfort and increased transport of viruses. High relative humidity can result in condensation on constructions and consequent mould growth.
Particulate matter $PM_{2.5}$	Main indoor sources of particles include combustion of all kinds, printing, use of cosmetics (lacquers, sprays), erosion of coating materials, presence of occupants and occupants' activities. Cooking emissions cannot be reduced and are major sources. Health impact of $PM_{2.5}$ has been demonstrated on major among other pollutants in indoor environments (Jones, 2023; Logue et al., 2011a; Poirier et al., 2021). $PM_{2.5}$ emissions are rather localized in time and in location. In some locations, outdoor air can also be a source of $PM_{2.5}$.
Formaldehyde	Formaldehyde is a common pollutant found in almost all residential buildings and its health impact is important among other pollutants in indoor environments (Jones, 2023; Logue et al., 2011a; Poirier et al., 2021). Formaldehyde emissions are rather evenly distributed in time and in location, when they are due to buildings materials, products and furniture.
Fictive pollutant (optional). constantly and continuously emitted in each zone	The procedure is being developed for the new version of ASHRAE 62.2 standard and in the French national framework, it can be complimentary to the 4 other parameters.

The following data were collected with a time-step which must stay in the range 10-15 min:

The concentrations raw time-series data, at least for CO_2 and relative humidity, in all rooms

- The exposure concentrations raw time-series data, at least for $PM_{2.5}$ and formaldehyde and for two occupants (as occupants should differ in their presence patterns in particular rooms).

The calculation period has been defined as the entire period of ventilation operation, depending on the context: either the typical heating period when there is no cooling with outside air supply - the heating period can extend to the "fee floating" period when neither heating nor cooling is used; or the whole year if there is a cooling system with outside air supply and a heating system, or the typical cooling period in countries where there is no heating period.

5.2.3. Selection of performance indicators

All the ventilation strategies must be evaluated by the performance indicators described in Table 5-2.

Table 5-2 Description of selected performance indicators

Performance Indicator	Unit	Description
DALY	[years.10^5]$^{(*)}$	The total population health impact is the sum of all DALYs (Dynamic Disability-adjusted life years) (Final Report ST1, 2025). The calculation was based on approach by (De Jonge and Laverge, 2022).
E_{CO2}	[ppm.h]	Normalized cumulative exposure when concentrations are higher than 1000 ppm in a room.
P_{CO2}	[ppm]	95^{th} percentile of the CO_2 exposure concentrations.
T_{RH}	[%]	Percentage of time spent out of the humidity range of 25-60% (EN 16798 category II)
E_{HCHO}	[µg m^{-3}. h]	Cumulative formaldehyde occupant exposure.
$E_{fictive}$	[µg m^{-3}. h]	Cumulative fictive occupant exposure.
$E_{PM2.5}$	[µg m^{-3}. h]	Cumulative $PM_{2.5}$ occupant exposure.
E_{HCHO_acute}	[µg m^{-3}. h]	Maximum of the formaldehyde cumulative occupant exposure over 1h.
$E_{fictive\_acute}$	[µg m^{-3}. h]	Maximum of the fictive cumulative occupant exposure over 1h.
$E_{PM2.5\_acute}$	[µg m^{-3}. h]	Maximum of $PM_{2.5}$ cumulative occupant exposure over 1h.
ACH	[h^{-1}]	Average building air changes per hour due to ventilation.
E_{losses}	[kJ]	Ventilation heat loss
E_{elec}	[kJ]	Energy consumption of the fan(s)

(*) Disability-adjusted life years (DALYs) lost in a group of 100 000 people.

5.2.4. Collection of input data and modelling assumptions

Every participant must describe all the entry data and assumptions used to calculate the selected performance indicators. This includes entry data: detailed occupancy patterns and emission scenarios (multizone) for CO_2, humidity, formaldehyde, $PM_{2.5}$, fictive pollutant, weather files, simulation period, and outdoor pollution data. This includes the modelling assumptions and data, notably on moisture absorption/desorption, PM deposition/resuspension, air leakage values and distributions, position of internal doors and windows and associated models, penetration factors for PM, formaldehyde emission rate dependences (on temperature, moisture and ventilation), wind pressure / microclimate around the building, etc.

5.2.5. Description of smart and reference ventilation strategies

Eleven smart ventilation systems were selected for the simulations, which could be classified into 3 categories:

- Humidity controlled mechanical exhaust-only ventilation (**MEV-rh**).
- Mechanical, balanced ventilation with heat recovery and humidity control at the apartment level (**MVHR-rh**).
- Mechanical balanced ventilation with heat recovery and humidity + another parameter (CO_2 or VOC generally) control at the room level (**MVHR-rb;** rb = "room based")

For each category (MEV-rh, MVHR-rh and MVHR-rb) there are several systems with different types of sensors, and/or location of sensors, and/or setpoints, and/or airflows.

We decided to use the constant airflow ventilation strategies (**-cav**) for each contributor separately as the reference systems. Again, despite the identical name (MEV-cav or MVHR-cav), the reference system is different for each participant.

Table 5-3 Description of the studied smart ventilation strategies and associated reference ventilation strategies for every participant to the common exercise

Contributor	Smart ventilation system	Reference system
Cerema	MVHR_rb	MVHR_cav
	MEV_rh, MEV_rb	MEV_cav
DTU	MVHR_rb, MVHR_rb1	MVHR_cav
	MEV_rh, MEV_rh1	MEV_cav
KUL	MVHR_rb	MVHR_cav
	MEV_rb	MEV_cav
PUCPR	MEV_rb	MEV_cav
UGENT	MVHR_rb	MVHR_cav
UIBK	MVHR_rb	MVHR_cav
EURAC	MEV_rb	MEV_cav

5.2.6. Analysis of data - new criteria for normalizing the results

All the output performance indicators calculated by the contributors were regrouped and homogenized. The units of the results were checked carefully to ensure that the assessed performance can be correctly compared. Because every contributor used a different reference ventilation system/strategy as well as boundary conditions, it was not the intention to perform a direct comparison among the cases from different contributors. Instead, the trends represented by particular ventilation strategies for individual contributors were studied. In some cases, there were huge differences in the order of magnitude of performance indicators. This made it difficult to represent the absolute results data on the same scale. To tackle these issues, we proposed to calculate a relative direction of the indicators with a new criterion named Indicator's Relative Direction (IRD). This criterion allows us to focus on the relative performance of a smart ventilation system in comparison to a reference ventilation system.

$$IRD_{sys} = 100.\frac{I_{sys} - I_{ref}}{I_{sys} + I_{ref}}$$

Equation 5-1

With IRD, in percentage [%], the relative direction of ventilation system- *sys,* for a given performance indicator *I,* in comparison to the reference ventilation system- *ref*.

5.3. Results

The comparison of the performance results between all the contributors is not straightforward due to the number of performance indicators and the diversity of modelled ventilation systems. We divided the results analysis into three short sections. Firstly, a general overview of all the data is provided, followed by the data detailed by contributor and lastly by performance indicator.

5.3.1. Overview of results data – participants, strategies, basic data

Figure 5-1 presents all the results provided by the contributors across the 13 performance indicators. Each contributor corresponds to a unique colour: EURAC (light green), UIBK (purple), UGent (blue), PUCPR (blue green), KUL (yellow), Cerema (orange), and DTU (red). The marker is different depending on the ventilation system.

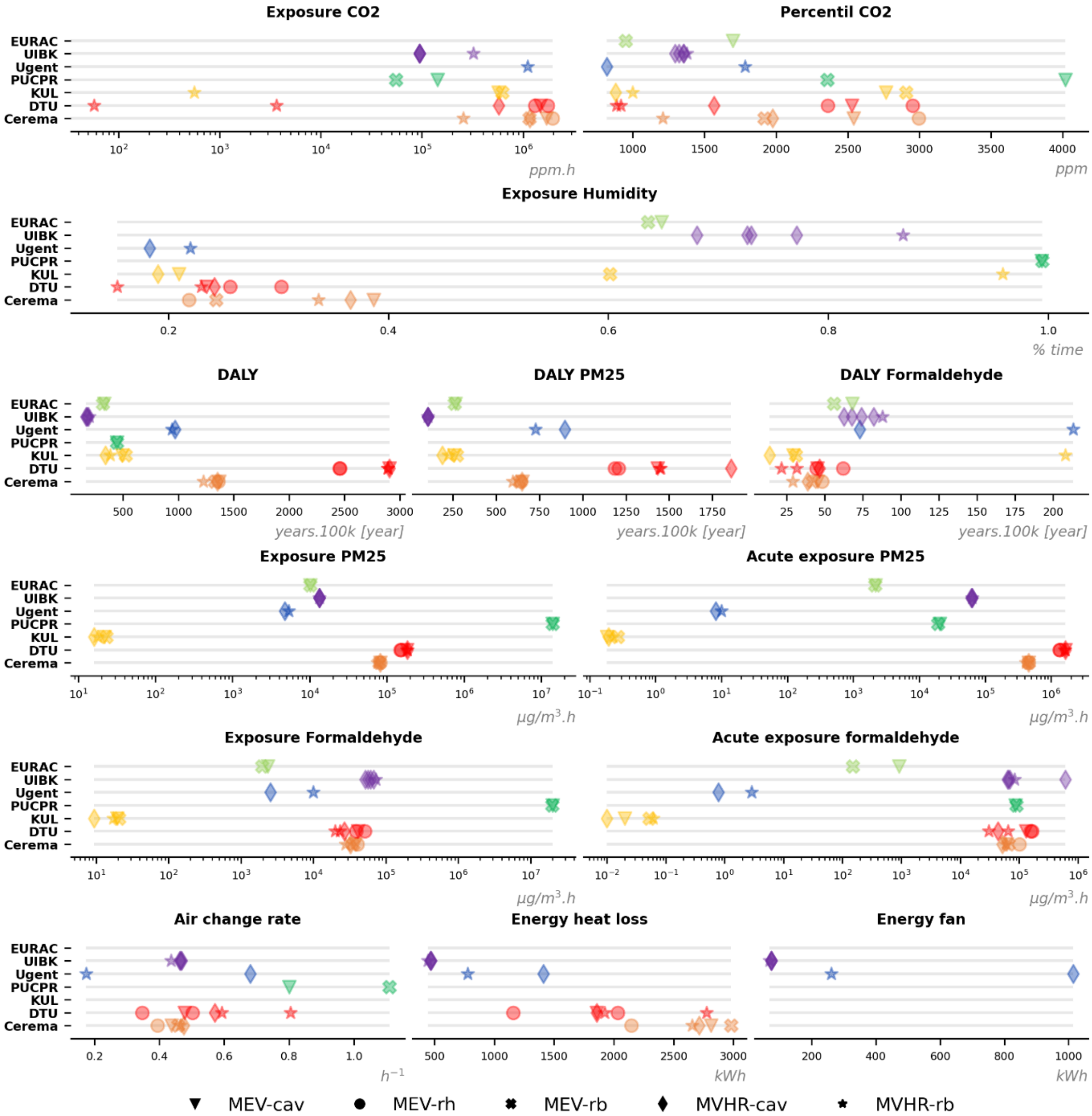

Figure 5-1 : Overview of all data provided by the contributors

The results for CO_2 exposure range between 10^2 and 10^7 . The cases from DTU and Cerema present the highest values. The second indicator, 95th percentile of exposure concentrations ranges, for most cases, between 1000 – 3000 ppm with MEV systems representing the highest values. Higher levels were observed only for PUCPR with MEV-cav, with results over 4000 ppm and we can observe that KUL MVHR system performed better than KUL MEV. Regarding RH, UGent, DTU and Cerema were between 20% and 40 % of the time out of the [25% - 60%] range, while EURAC, UIBK and PUCPR were out 60-100% of the time, PUCPR, 100% of the time. The results of KUL cover the whole range between 2% to almost 100% of the time out of the [25% - 60%] range. The total DALY results are similar for EURAC, PUCPR and KUL between 300 to 600 DALYs.100k people, UIBK has the lowest values under 200 DALYs.100k people where UGent and Cerema have higher results between 1000 and 1440 DALYs.100k. Lastly, DTU results are the highest ones with values over 2300 DALYs.100k people. Almost the same patterns can be observed between the contributors results for the pollutant exposure indicators to formaldehyde and PM. KUL have the lowest exposures results, EURAC, UIBK, UGent are mostly in the middle range and PUCPR, CEREMA and DTU have the highest ones.

The average air change rate is mostly between 0.3h^{-1} and 0.8h^{-1} except for UGent (MVHR–rb) which performs the lowest rate at 0.17h^{-1} and PUCPR (MEV-rb) the highest one at 1.1h^{-1}. It shows that smart ventilation strategies can provide a quite large range of air change rates depending on the systems. For an ACH of the same order of magnitude, Cerema has the highest heat losses, while UIBK achieves the lowest. The heat losses of DTU and UGent are intermediate and comparable, slightly lower for UGent. These differences can be explained by different weather and climate conditions and/or the temperature set point in the heating system. Lastly, some results were obtained on yearly fan energy consumption.

5.3.2. Relative performance direction-IRD by contributor

Figure 5-2 represents the IRD (Equation 5-1) by contributor, for all indicators. The color of the plotted result indicates if the relative direction is negative (better performance in comparison to the reference) in green, or positive in red (worst performance in comparison to the reference). Boxplots represent the median, 1st quartile, 3rd quartile and outliers (detailed in Table 5-4). The boxplot serves solely as a comparison of the spread of IRD across the different contributors. In general, we can conclude that smart ventilation strategies have:

- **Always better performance** for EURAC simulations with results in average -7.9 %.
- **Generally, the performance** of the Cerema, DTU, PUCPR, and UIBK simulations was better, with results between -2.3 % and -5.5 %.
- **Generally, the worst performance** was for the UGent and PUCPR simulations, with results on average 9.14% higher.
- **Always the worst performance** for the KUL simulations, with an average of 15.5 % higher results.

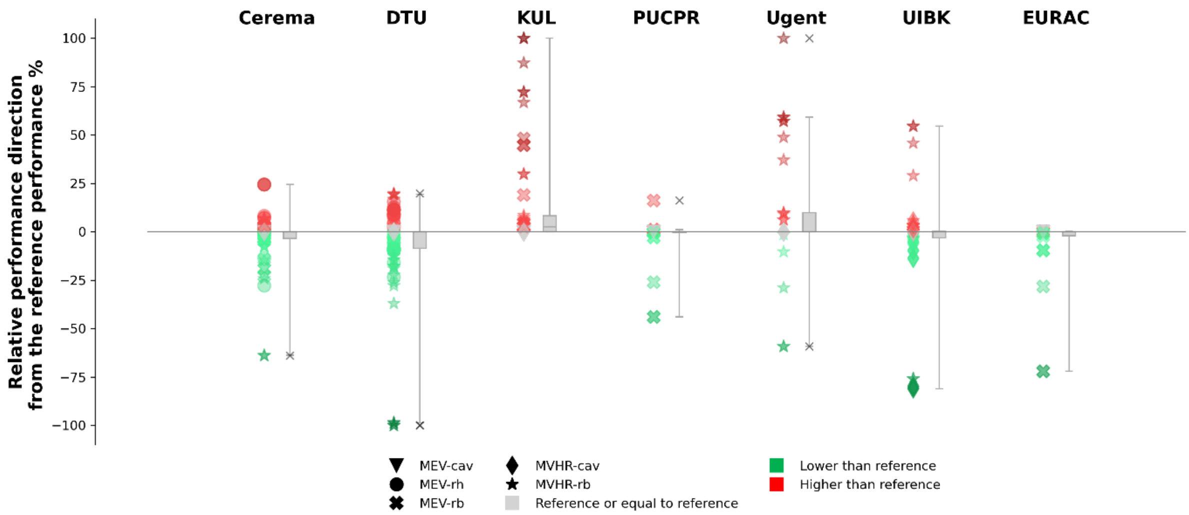

Figure 5-2. "Relative performance direction-IRD" by contributor

Table 5-4 Detailed statistical results for IRD

	Cerema	DTU	KUL	PUCPR	Ugent	UIBK	EURAC
count	95.00	114.00	50.00	28.00	33.00	100.00	26.00
mean	-2.31	-5.17	15.54	-3.67	9.14	-5.48	-7.91
std	11.95	20.50	28.33	12.84	32.06	24.15	19.81

min	-63.91	-100.00	0.00	-43.97	-59.20	-81.13	-71.95
25%	-3.38	-8.51	0.00	-0.36	0.00	-3.10	-1.97
50%	0.00	0.00	2.52	0.00	0.00	0.00	0.00
75%	0.00	0.00	8.28	0.00	9.86	0.27	0.00
max	24.57	19.82	100.00	16.23	100.00	54.72	0.17

5.3.3. Relative performance direction-IRD by performance indicator

The plotted points in Figure 5-3 are the relative performance direction named IRD (Equation 5-1), already plotted in Figure 5-2, but classified by indicators separately for all the contributions.

We can observe that:

- The CO_2 exposure and 95th percentile indicator give rather similar indications, but the exposure has the ability to highlight the frequency of high concentrations ($CO_2 > 1000$ ppm).
- There is a reduction of the total DALY indicator for smart ventilation in main cases except for KUL results, as already discussed in the previous part. It shows potential benefits of such strategies to improve the IAQ in comparison with their reference constant airflows strategies.
- In detail, the total DALY as well as the DALY form $PM_{2.5}$ and DALY from HCHO result in the same ranking as given by $PM_{2.5}$/HCHO exposure indicators. The color and relative direction are the same. Only the $PM_{2.5}$/HCHO acute exposure indicators highlight different tendencies, in comparison with the DALY indicator.
- Air change rates and energy benefits give the same ranking in all cases.

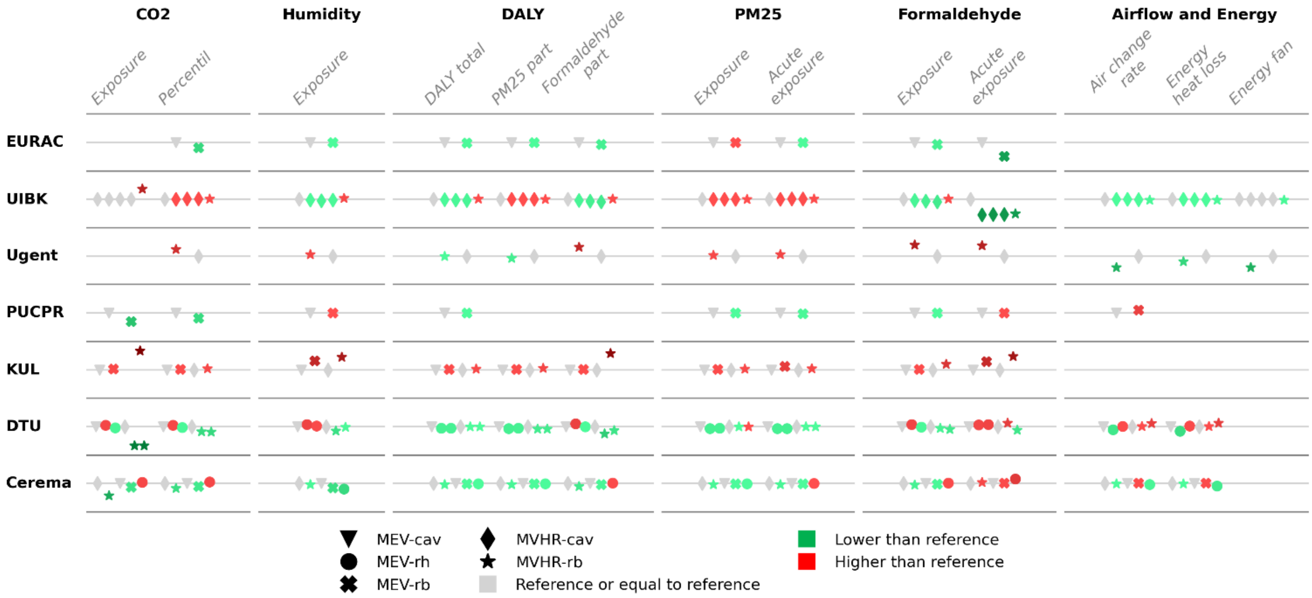

Figure 5-3. “Relative performance direction-IRD” by performance indicator

It is clear that IDR with its color code (green and red) could be used for a decision-making process. For each specific context of the contributor, we can easily observe the performance of a system depending on which aspect of the performance is prioritized. For example, the MVHR-rb system of UGent shows good relative performance for energy-based indicators (green) and offers high IAQ regarding the total DALY indicator. This good performance is, however, contradicted by worse relative performance (red) for CO_2 and humidity-based indicators, and for $PM_{2.5}$/HCHO exposures. In opposition, the MVHR-rb system of Cerema and DTU offers good relative performance (green) on IAQ based on CO_2, total DALY, but with higher energy losses/demands for DTU (and not for Cerema).

5.4. Conclusions and perspectives

An internationally based performance-based approach has been developed for assessing smart ventilation performance using multicriteria approach. This approach was tested and used in a common exercise conducted by experts in six countries with different design contexts, simulation software, smart ventilation strategies and building geometries. The analysis of results performed by indicator and by contributor show in different countries: (1) how a performance-based approach using different performance indicators can be used to assess performance of smart ventilation strategies and (2) how these smart strategies perform compared to standard ones.

With respect to the usability of the indicators, our results show that not all indicators need to be used. For example, the DALY and exposure indicators point in the same direction and therefore only one of them could be used. The same can be concluded about air change rate indicator and the energy demand indicators. It must be confirmed by more simulations in future work.

Another step of analysis in this common exercise is being conducted using more standardized conditions to compare performance of these different smart strategies under different climatic and boundary conditions, using identical building model and modelling tools.

Despite the promising benefits, smart ventilation systems face several other technical challenges such as the reliability and accuracy of sensors used to monitor airflows and/or contaminants. Current pollutant sensors, for instance, are not always robust or accurate enough for reliable residential ventilation control. There are also concerns regarding potential system malfunctions (e.g. zero-drift, lack of calibration), which can lead to suboptimal performance (Zhao et al., 2022) and regarding the long-term performance of sensors and systems in general.

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6. Annex 86 webinars - big data, IAQ and ventilation

Author: Jakub Kolarik

6.1. Introduction

The following chapter summarizes the webinar series “Big Data, IAQ, and Ventilation” organized by Subtask 5 of the Annex 86 in cooperation with AIVC. The series included two webinars organized on April 13th and April 21st, 2021. The webinars brought together leading experts to discuss the intersection of big data, indoor air quality (IAQ), and ventilation. The aim was to explore innovative approaches to managing IAQ in residential buildings, leveraging the latest advancements in technology, data analytics, and machine learning. The speakers at the webinars were leading experts in the fields of IAQ, big data, and smart building technologies. They included researchers from prestigious universities and professionals from innovative companies. Industry speakers brought practical insights into the application of advanced technologies in real-world settings. They emphasized the importance of collaboration, data quality, and the potential of advanced technologies to revolutionize IAQ management. Their presentations highlighted the practical implementation of IAQ monitoring systems and the use of connected systems to transform data into actionable insights. The webinars have provided a platform for researchers, industry professionals, and academics to share their insights and findings, fostering a collaborative environment for advancing the field.

The first webinar focused on the integration of big data and IAQ management, featuring presentations on energy-efficient IAQ management, the use of predictive twins, personal IAQ monitoring, and the integration of smart building data. The discussions highlighted the importance of data calibration, the challenges of linking various data sources, and the potential of wearable sensors and citizen science projects to enhance IAQ monitoring. The first presentation emphasized the collaborative nature of Annex 86, which includes 42 institutes from 24 countries, and outlined its structure, divided into six subtasks focusing on different aspects of IAQ management. Another presentation explored the use of predictive twins to optimize building performance and improve IAQ, discussing the integration of building information modeling (BIM) with sensor data. The use of wearable and fixed sensors for personal IAQ monitoring was also explored, highlighting the challenges of data quality and the variability of individual behavior. Additionally, the integration of various data sources to create comprehensive descriptions of buildings was discussed, using linked data and semantic web technologies.

The important part of every webinar was the Q&A session giving the audience opportunity to interact with the speakers and discuss topics of interest. Q&A of the first webinar addressed key topics such as data calibration for building automation systems, the practical implementation of research work, the accuracy of fixed sensors, and the challenges of linking data through APIs. The importance of selecting the right training data, the potential of hybrid models, and the need for accurate self-reported behavior data were emphasized.

The second webinar in the series continued the exploration of big data and IAQ, featuring presentations on data analytics for ventilation systems, the role of CO_2 as an indicator for ventilation standards, remote data logging, and the use of sensors and machine learning to improve Heating, Ventilation and Air Conditioning (HVAC) control. One industry presentation highlighted a company's shift towards digital innovation, using connected systems to stream real-time data and transform it into actionable insights. Another presentation explained the importance of CO_2 sensors in identifying poorly ventilated rooms and discussed the impact of the COVID-19 pandemic on raising awareness about CO_2 levels. The introduction of a mobile app for conducting air tightness tests was also discussed, emphasizing the benefits of cloud storage and remote data logging. Additionally, the development of a service that uses an AI agent to optimize HVAC settings and improve air quality was presented.

The Q&A session of the second webinar covered topics such as sensor calibration, the relationship between Volatile Organic Compounds (VOC) and CO_2, the development of comfort indices, data privacy, and the effectiveness of IAQ monitoring in naturally ventilated buildings. The discussions underscored the need for automated systems for long-term air quality improvement and the importance of feedback mechanisms to engage users.

The Subtask 5 webinars have provided valuable insights into the future of IAQ management, showcasing the potential of big data, IoT, and machine learning to revolutionize the field. The following summaries offer a detailed account of the presentations and discussions, highlighting the key takeaways and innovative approaches presented by the experts.

6.2. Annex 86 & AIVC webinar "Big data, IAQ and ventilation – part 1", April 13th, 2021

The webinar series on smart building data and indoor air quality (IAQ) management featured a series of presentations by experts in the field. The speakers included Marc Delghust from Ghent University, Wouter Borsboom from TNO, Benjamin Hanoune from the University of Lille, and Pieter Pauwels from Eindhoven University of Technology. The session concluded with a Q&A segment where the speakers addressed questions from the audience.

6.2.1. Presentations

Marc Delghust from Ghent University introduced the webinar, emphasizing its focus on energy-efficient IAQ management in relation to big data and IoT. He provided an overview of Annex 86, which aims to improve the energy efficiency of IAQ management in residential buildings. Annex 86 includes 42 institutes from 24 countries and is open to new partners, including research institutes and private companies. Marc highlighted the importance of collaboration and the potential for new partners to join the initiative. He outlined the structure of Annex 86, which is divided into six subtasks focusing on different aspects of IAQ management, from underlying methodologies to applications of technology and new opportunities from IoT and big data.

Wouter Borsboom from TNO, Netherlands, presented on "Improving IAQ with BIM-based Predictive Twins," focusing on the use of predictive twins to enhance indoor air quality. He discussed the integration of building information modeling (BIM) with sensor data to create digital replicas of physical buildings. These predictive twins help in optimizing building performance and improving IAQ. Wouter emphasized the importance of data calibration and the use of hybrid models to achieve accurate predictions. Calibration is a separate process from the model part of a digital twin and can be done manually or automatically using system dynamics. He highlighted the challenges of data quality and the need for high-quality data to make accurate predictions. Wouter provided examples of how predictive twins can be used in practice, such as monitoring the performance of HVAC systems and assessing the energy efficiency of buildings.

Benjamin Hanoune from the University of Lille, France, presented on "Online Personal IAQ Monitoring," discussing the use of wearable and fixed sensors to monitor personal exposure to indoor air pollutants. He highlighted the challenges of data quality, sensor placement, and the variability of individual behavior. Benjamin emphasized the importance of constructing chemical signatures of activities to recognize pollution events and the need for accurate self-reported behavior data. Wearable sensors provide data on both indoor and outdoor exposure, while fixed sensors measure pollution levels in specific locations. He discussed the challenges of distinguishing between indoor and outdoor environments and the importance of understanding the time and space variability of pollution. Benjamin also highlighted the need for large-scale data collection and the potential of citizen science projects to gather data from a wide range of environments.

Pieter Pauwels from Eindhoven University of Technology, Netherlands, presented on "Brains for Buildings: Where to Find All the Relevant Smart Building Data?" focusing on the integration of various data sources, including BIM data, sensor data, and geospatial data. He discussed the use of linked data and semantic web technologies to create a comprehensive description of buildings. Pieter highlighted the challenges of linking data through APIs and maintaining data consistency over time. Linked data initiatives aim to connect data across different servers, making it more accessible and useful. He provided examples of how linked data can be used in practice, such as integrating sensor data with 3D geometry to improve user understanding. Pieter also discussed the importance of using incoming data from BIM models for existing buildings and the challenges of maintaining data links over time.

6.2.2. Discussion and Q&A

The Q&A session addressed several key topics. One of the main discussions focused on data calibration for building automation systems, exploring how to calibrate data for HVAC control and the advantages or disadvantages of using a digital twin for calibration. Calibration is a separate process from the model part of a digital twin and can be done manually or automatically using system dynamics. The importance of selecting the right training data and the potential of using hybrid models to achieve accurate predictions was emphasized. Another significant topic was the practical implementation of research work, particularly for small residential buildings. The feasibility of implementation depends on the quality of data and the specific goals. The complexity of the model is influenced by the quality of data and the specific predictions needed. Examples were provided of how predictive twins can be used in practice, such as monitoring the performance of HVAC systems and assessing the energy efficiency of buildings.

The accuracy of fixed sensors and how to deal with the gap between sensor placement and where the person is was also discussed. Fixed sensors measure pollution levels but do not indicate if people are close to the sensor. The presence of people and their activities can influence pollution levels. The challenges of distinguishing between indoor and outdoor environments and the importance of understanding the time and space variability of pollution were highlighted.

The accuracy of occupant self-reported behavior for events like cooking was another topic of interest. Volunteers may miss one or two events per day, often due to forgetting or not realizing certain activities produce pollution. There is a bias in what people think causes pollution. The importance of constructing chemical signatures of activities to recognize pollution events and the need for accurate self-reported behavior data was emphasized. A concrete example of an application where linking geometry and sensor data is crucial was provided. Integrating sensor data with 3D geometry in the browser helps in better understanding by the user. The importance of using incoming data from BIM models for existing buildings and the challenges of maintaining data links over time were discussed.

Finally, the main challenges in linking data through APIs were addressed. Handling data within the software where it is stored and linking data from different databases requires matching identifiers, which is more difficult than it sounds. Maintaining data consistency over time and using linked data and semantic web technologies to create a comprehensive description of buildings were highlighted as key challenges.

The webinar concluded with a discussion on the importance of defining goals and methods for data collection and analysis. The speakers emphasized the need for collaboration across different fields of research and the importance of finding the right balance between data collection and analysis to avoid being overwhelmed by a "tsunami of data." They also highlighted the potential of predictive twins, wearable sensors, and linked data to improve IAQ management and building performance.

6.3. Annex 86 & AIVC webinar "Big data, IAQ and ventilation – part 2", April 21st, 2021

Benjamin Hanoune opened the second joint Annex 86 & AIVC webinar. He provided an overview of Annex 86, which focuses on energy-efficient indoor air quality (IAQ) management for residential buildings. The goal is to improve energy efficiencies and IAQ through various subtasks, including methodology, technology applications, and the use of IoT and big data. He emphasized the importance of collaboration among academic institutions and private companies to achieve these goals.

6.3.1. Presentations

Steven Delrue presenting on “Data Analytics at Renson: From Airflows to Dataflows” discussed Renson's evolution from a hardware production company to a provider of complete concepts in ventilation, sun protection, and outdoor living. He highlighted Renson's innovative mindset and the shift towards digital innovation. Renson is a family-owned company based in Waregem, Belgium, known for its innovative approach to product development. The company has moved from selling individual products to offering integrated concepts in ventilation, sun protection, and outdoor living. Renson has embraced digital innovation by developing connected systems like the L-box ventilation system, which streams real-time data to the cloud (Figure 6-1). The data analytics team focuses on transforming data into actionable insights to improve products and services. They use a data platform for real-time and historical data analysis. Historical data is used to demonstrate product quality and functionality, presented in papers and journal articles. Connected devices and apps create touchpoints with end-users, providing real-time advice and increasing awareness. Data is used for predictive maintenance and optimizing installation processes.

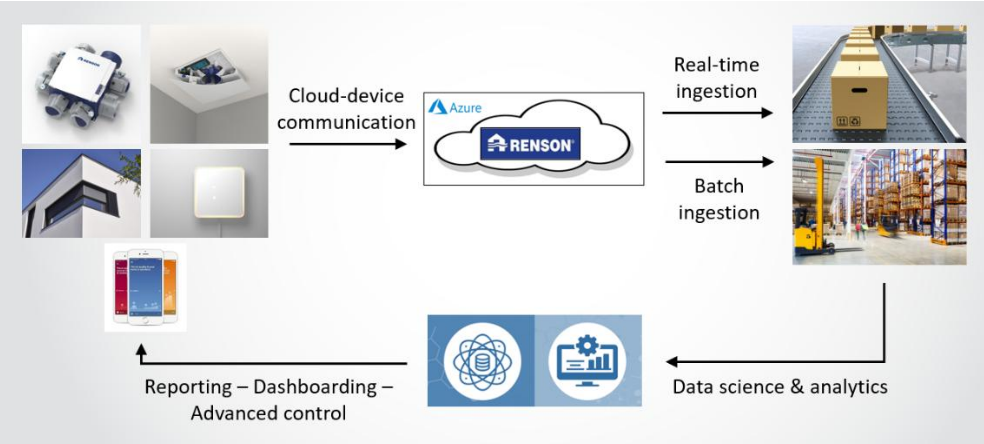

Figure 6-1 Example of a ventilation data platform (image credit: Steven Delrue, Renson)

In the second presentation, Sandra Chochod from Netatmo, France, presented on “CO_2: A Reference Point for Ventilation Standards.” She explained the importance of CO_2 as an indicator of indoor air quality. Presentation discussed the use of CO_2 sensors in Netatmo products and the relevance of CO_2 in identifying poorly ventilated rooms. The company chose to include CO_2 sensors in their products to measure indoor air quality. Other sensors, such as those for VOCs and PM2.5, are also available on the market. CO_2 is a reliable indicator of air "stiffness" and helps evaluate the balance between air exchange rates and room occupancy. High CO_2 levels indicate poor ventilation and potential health risks. The pandemic has raised awareness about CO2 levels, leading to new legislation and increased consideration of CO_2 as an important indicator. While CO_2 is useful, it is not sufficient on its own. Other pollutants can be present even if CO_2 levels are low. Activities like cleaning or painting can introduce chemical pollutants that CO_2 sensors won't detect. Netatmo's data shows that around 22-23% of European households experience poor indoor air quality at least once per day, with CO_2 levels exceeding 1000 ppm.

In his presentation on “Remote Data Logging with Retrotec DM32 SmartGauges and Leveraging rCloud”, Ben Walker from Retrotec, USA, introduced company’s rCloud application, a mobile app for conducting air tightness (blower door) tests in buildings. He explained how the app uses GPS to verify the user's location and collects data on house characteristics and weather conditions. The app is designed to conduct air tightness tests and leverage cloud storage for data collection. An example test was conducted at a rental house near Retrotec's manufacturing facility, capturing data such as square footage and weather conditions. The app supports various standards from around the world and provides step-by-step instructions for each test. Users can choose between single-point or multi-point tests. A new feature allows for remote data logging with digital pressure gauges, enabling real-time logging to Microsoft Azure.

In his presentation on “Using Sensors and Machine Learning to Improve HVAC Control”, Inouk Bourgon from Foobot, Luxembourg, discussed company's approach to improving HVAC control. He described the development of the Smart Air Building service, which optimizes HVAC systems to reduce carbon footprint and improve air quality. Foobot's first product attracted significant interest from the academic world, resulting in several research papers. Integrating sensors with the Nest thermostat allowed for improved indoor air quality without increasing ventilation, resulting in energy savings. The service uses an AI agent to determine optimal HVAC settings every 15 minutes, gathering external data such as weather forecasts and outdoor air pollution. The AI agent is trained using a digital replica of the building, allowing it to be ready from day one without weeks of data collection. The first deployment in a large building in Denmark resulted in 52% energy savings and maintained 99% thermal comfort. The indoor air quality was kept below acceptable thresholds 100% of the time.

6.3.2. Discussion and Q&A

The Q&A session addressed various technical and general questions from the audience. Discussions covered sensor calibration, VOCs and CO_2, comfort indices, data analysis, emergency warnings, natural ventilation, and feedback mechanisms. Calibration procedures for CO_2 and PM sensors were emphasized, highlighting the importance of factory calibration and ongoing adjustments. The relationship between VOCs and CO_2 was explored, noting that both can indicate occupancy and air quality but serve different purposes. The challenge of measuring comfort indices for individuals versus entire buildings was highlighted, with a preference for developing indices at the dwelling or room level. The importance of privacy and internal analysis of collected data was discussed, with a focus on not publishing results due to privacy concerns. The distinction between IAQ monitoring sensors and detection of life-threatening conditions was clarified, emphasizing that the sensors discussed are for monitoring environments, not emergency situations. The effectiveness of IAQ monitoring in naturally ventilated buildings was addressed, stressing the need for automated systems for long-term air quality improvement. The development of feedback mechanisms to interact with users and provide actionable advice was discussed, with plans to add such mechanisms to improve user engagement.

6.4. Conclusion and future research directions

The Subtask 5 webinars co-organized with AIVC have highlighted significant advancements and ongoing challenges in the field of indoor air quality management. The presentations from both webinars underscored the critical role of data analytics, predictive modeling, and advanced sensor technologies in enhancing IAQ and energy efficiency in residential buildings. However, several key areas for future research have emerged from these discussions.

Firstly, there is a need for improved data calibration techniques. Accurate calibration of sensors and predictive models is essential for reliable IAQ management. Future research should focus on developing standardized calibration protocols and exploring the use of hybrid models that combine different data sources to enhance prediction accuracy. Secondly, the integration of various data sources remains a challenge. The use of linked data and semantic web technologies to create comprehensive descriptions of buildings is promising but maintaining data consistency over time and linking data from different databases require further investigation. Research should aim to develop robust methods for data integration and ensure the interoperability of different data systems. Thirdly, the variability of individual behavior and its impact on IAQ needs more attention. Wearable sensors and personal IAQ monitoring have shown potential but distinguishing between indoor and outdoor environments and understanding the time and space variability of pollution are complex tasks. Large-scale data collection and citizen science projects could provide valuable insights, but there is a need for more sophisticated methods to analyze and interpret this data.

Additionally, the practical implementation of IAQ management technologies in small residential buildings poses unique challenges. Research should explore cost-effective solutions and scalable models that can be easily adopted in various residential settings. The development of user-friendly interfaces and feedback mechanisms to engage occupants and encourage proactive behavior is also crucial. Finally, the role of automated systems in long-term IAQ management cannot be overstated. Future research should focus on enhancing the capabilities of AI agents and machine learning algorithms to optimize HVAC settings and improve air quality continuously. The potential of predictive twins and digital replicas of buildings to simulate and predict IAQ scenarios should be further explored. In conclusion, while significant progress has been made, the need for interdisciplinary collaboration and innovative research remains crucial.

6.5. Other Annex 86 webinars

Besides the above summarized webinars focused on big data, the Annex 86 arranged also two other webinars focused on metrics for IAQ and ventilation and effects of ventilation on SARS-CoV-2 transmission respectively. The first webinar discussed the road towards a robust comprehensive IAQ metric for the assessment of the performance of ventilation. The three speakers first looked at the open issues that remained after the work in IEA EBC Annex 68, then explored methodological updates, future potential and limitations for the DALY method included in the suite of metrics proposed by that annex and finally discussed the newly proposed TAIL rating scheme. The second webinar addressed the potential mitigating role of building ventilation in the spread of the COVID-19 pandemic. In the first part of the webinar, the focus was at building ventilation as one of the mechanisms that affects exposure to infectious aerosols and the uncertainty in relating exposure to airborne transmission of viruses. In the second part of the webinar, the airflow in real indoor environments was in focus. This included results from field experiments with aerosol sources and the use of pressure differences in buildings to control the spread of aerosols.

6.6. Access to IEA EBC ANNEX 86 webinars

All webinars organized by the Annex 86 can be accessed via AIVC webpage.

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8. Authors

Authors in alphabetical order:

Annamaria Belleri, EURAC Research, Italy

Baptiste Poirier, Cerema, France

Christian Serre, Institut des Matériaux Poreux de Paris, ESPCI Paris, Ecole Normale Supérieure, CNRS, PSL University, Paris, France

Daniela Mortari, Cerema, France / PUCPR-Pontifícia Universidade Católica do Paraná, Brazil

Douaa Al Assad, KU Leuven, Belgium

Doyun Won, National Research Council Canada, Ottawa, Canada

Evangelos Belias, EPFL, Switzerland

Gabriel Rojas, University of Innsbruck, Austria

Gaëlle Guyot, Cerema, France

Hilde Breesch, KU Leuven, Belgium

Irene Laraibeas, EURAC Research, Italy

Jakub Kolarik, DTU- Technical University of Denmark, Denmark

Jelle Laverge, UGent, Belgium

Jialei Shen, Department of Civil Construction and Environment Engineering, The University of Alabama at Birmingham, Birmingham, USA

Jinzhe Nie, Beijing University of Architecture and Civil Engineering, China

Klaas De Longe, UGent, Belgium

Marc Abadie, LaSIE - La Rochelle University, France

Marco Daturi, Normandie University, ENSICAEN, UNICAEN, CNRS, Laboratoire Catalyse et Spectrochimie, Caen, France

Marcos Batistella, PUCPR-Pontifícia Universidade Católica do Paraná, Brazil

Markus Wirnsberger, University of Innsbruck, Austria and TH Rosenheim, Germany

Menghao Quin, Technical University of Denmark, Denmark

Nathan Mendes, PUCPR-Pontifícia Universidade Católica do Paraná, Brazil

Nicolas Sadovnik, Normandie University, ENSICAEN, UNICAEN, CNRS, Laboratoire Catalyse et Spectrochimie, Caen, France

Quinten Carton, KU Leuven, Belgium

Raïssa Andrade, Cerema, France

Reto Stauffer, University of Innsbruck, Austria

Rui Zhang, GTI Energy, Des Plaines, USA

Timm Freundorfer, University of Innsbruck, Austria

Weihui Liang, Nanjing University, China

Zhenlei Liu, Building Performance Lab, City University of New York, New York, USA

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