Simulated Versus Monitored Building Behaviours: Sample Demo Applications of a Perfomance Gap Detection Tool in a Northern Italian Climate

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Giacomo Chiesa, Francesca Fasano, and Paolo Grasso

Introduction

Sustainable and green energy solutions are progressively growing in consideration in the building sector for both new and retrofitted designs and actions. At a European level, the introduction of the EPBD (Energy Performance of Buildings Directive), since its initial 2002/91 version, has progressively supported Member States in introducing and/or upgrading energy and building regulations including the definition of minimal standards, e.g. U-values, supporting a progressive increase of the energy efficiency of the building stock. Furthermore, the EPBD is not a rigid instrument, since it has been improved over time, including the EPBD recast 2010 version and the 2018 one. Recently, the EU (European Union) funded a series of specific H2020 projects to support the 'next-generation of Energy Performance Assessment and Certification' approaches under the call LS-SC3-EE-5-2018-2019-2020. Among these projects, the E-DYCE (Energy Flexible Dynamic Building Certification) project [1] identified five main open issues connected to EBPD topics. These issues include [2] (i) free-running and passive technologies, (ii) smart readiness vision, (iii) energy metering and district network communication, (iv) dynamic hourly models and performance gap, and (v) renovation and operational roadmap. This paper outlines some initial outcomes of the E-DYCE project related to abovementioned issues i, ii and iv are focussing on two demonstrative buildings localized in Northwest Italy and illustrating a new approach for performance gap detection in semi-real time using a dynamic simulation platform which is under development by the authors.

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Chapter Objectives and Contents

As mentioned above, this chapter focusses on illustrating initial results of the application of a new underdevelopment dynamic simulation platform to detect building performance gap comparing simulated and monitored building behaviours under free-running conditions. Simulated buildings are based on verified models, while the simulation's operational inputs for performance gap are inputted by current standards, e.g. EN 16798-1:2019 [3]. Monitored data are based on a smart cloud-connected monitoring system, while weather data are retrieved from a cloud-connected meteorological station installed for the project. Tests were performed during the extended summer of 2021, also considering transitional periods from the late-spring to the beginning of autumn – from May to October. Additionally, the above-mentioned dynamic simulation platform is based on a Python tool named PREDYCE (Python semi-Realtime Energy DYnamics and Climate Evaluation) that is under implementation on the basis of different development actions, including the 'DYCE' action, based on the mentioned E-DYCE project, and a 'PRE' action, based on another project and adding additional functionalities. The 'DYCE' action includes a larger set of actions with respect to those presented in this chapter. The platform is based on EnergyPlus [4] that, among building energy dynamic simulation engines, is one of the most widely used and recognized [5]: its white box model algorithm to model building dynamics can give very accurate results in terms of both consumption and environmental variable trends, considering it is also used to support the validity of other software used for energy labelling, e.g [6]. This motivates the use of EnergyPlus in this chapter to detect the performance gap between simulated and monitored building behaviours and the increasing interest for both professionals and researchers in the past few years in developing libraries and tools supporting EnergyPlus input model editing and output analysis in a parametric and automatic vision, e.g [7, 8]. This chapter focusses on PREDYCE application scenarios that treat simulation and monitoring results together; see also section "Methodology and PREDYCE". The chapter is organized as follows: Section "Methodology and PREDYCE" shortly introduces the mentioned PREDYCE tool focussing on the 'DYCE' developing action contents and details the methodological pipeline used in this chapter. Section "Demo Building Applications and Results" focusses on two real-project demo applications of this methodology including model verification results and performance gap detection samples. Finally, Section "Conclusions" shortly concludes the chapter by mentioning main results, limitations, and future planned development steps.

Methodology and PREDYCE

PREDYCE Introduction and Use Scenarios

PREDYCE is a newly developed Python library composed of three main modules able to manage EnergyPlus input files (IDFs) in a parametric and automatic mode, executing multiple parallel simulation runs and handling the obtained results. Moreover, additional modules have been developed to manage other important aspects linked to EnergyPlus simulations, e.g. to compile EPW input weather files starting from monitored data from weather stations. A detailed PREDYCE library scheme is illustrated in [9] and in [10, 11]: its architecture is based on the previously mentioned main modules, i.e. (i) an IDF editor module, (ii) an EnergyPlus running module, and (iii) a KPI calculator module. Each module has been built to work harmoniously with the others but also independently in tailored scripts, thus guaranteeing high flexibility and modularity in terms of, for example, data sources for a KPI calculator module, whose input can accept both simulation results and structured monitored data, allowing the development and testing of new methodologies. Similarly, the IDF automatic editing module is able to modify numerous building aspects such as activities, simplified HVAC systems, and envelope materials. The provided set of Python methods for IDF editing and KPIs computation, combined with the integrated EnergyPlus launcher, can help in performing different tasks like sensitivity analysis, retrofitting suggestions, performance gap analysis, or model verification, either automatically or semi-automatically.

The different tasks, which exploit all PREDYCE functionalities, are organized in separate scripts (herein referred to as use scenarios), easily executable by command line or also through a dedicated web service. Thanks to future actions, each script could be treated as a pre-built use scenario through a common application. In particular, the basic PREDYCE scenario is devoted to perform sensitivity analysis allowing parametrization of numerous building characteristics and computation of many possible KPIs according to the most recent European standards. Based on this more general use scenario, two other scenarios have been developed to introduce monitored data in the automatic loop: one is devoted to help in model verification phases, while the other aims to compare KPIs computed on calibrated building models and on monitored data, in order to highlight potential gaps in performance. Each scenario takes in input files and generates output files that are structured in the same way, as shown in Fig. 1. In particular, the main inputs are the building model in IDF format and the weather data in EPW format, which are needed to feed an EnergyPlus simulation; an input JSON file used to personalize the parametric request and apply preliminary modifications to the building model if needed; and finally, a CSV of environmental monitored data if required by the chosen application scenario, e.g. the performance gap one. Main outputs, instead, include a CSV file named *data_res* containing aggregated KPI results for the considered time period; a CSV file named *data_res_timeseries* containing timeseries KPI results with definable timestep resolution (hourly by default) for each performed

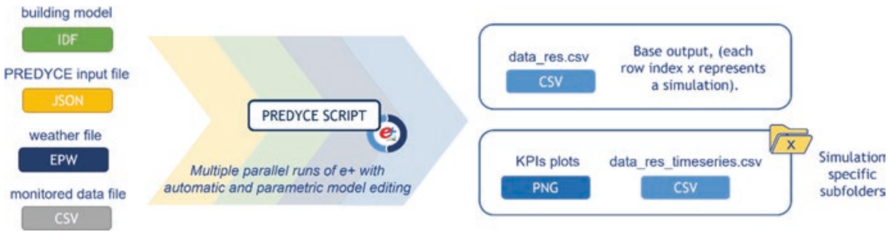

Fig. 1 PREDYCE scenario generic input/output workflow

```
{
  "building_name": "MainBlock",
  "preliminary_actions": {
      "change_runperiod": {
          "start": "01-05",
          "end": "30-09",
          "fmt": "%d-%m"}},
  "actions": {
      "change_ach": {
          "ach": [0, 0.2, 0.4],
          "ach_type": ["infiltration"]},
      "add_ceiling_insulation_tilted_roof": {
          "ins_data": ["MW Glass Wool (rolls)"],
          "Thickness": [0.3]}},
  "kpi": {
      "Q_c": {},
      "Q_h": {}}
}
```

Fig. 2 Example of input JSON file for PREDYCE

simulation; and finally, plots (e.g. carpet plots, energy signature) allowing us to deepen the meaning of KPIs.

Figure 2 shows a simple example of a standard PREDYCE JSON input file, in order to explain its structure and general potential. It is made by keywords, which are later used by the scenario scripts to understand how to execute a simulation, and values, which can contain names of IDF objects to be added or modified in the model or values to be set. IDF editing actions, in accordance with specific materials or object names, are made possible by the presence of internal databases of IDF objects that are hidden to the final user. Looking at the main keywords in Fig. 2, the *building name* is the name of the main block of the IDF which is utilized by the tool to know which zone elements need to be edited and then perform calculations on it; the *preliminary actions* are the actions which are executed only once before running the simulations such that all simulated buildings have in common the same modifications listed in this section (e.g. changing the run period or also activating/deactivating the HVAC system); the *actions* are the parametric modifications that have to be applied to the building (e.g. changing infiltration through windows or adding an insulation layer to the ceiling, eventually filtering based on the building's thermal zones); and finally, the *KPI* section includes the key performance indicators that are computed at the end of each simulation (in the example, *Q_c* and *Q_h* are the primary energy needs for cooling and heating in the building).

Considering the PREDYCE scenarios that involve comparisons between monitored and simulated data, a structured nomenclature of both sensors located in the building and the IDF model thermal zones is necessary to obtain a correct and automatic spatial association within the tool without the need of an intermediate translator, such that spatial aggregations for KPI analysis correspond. Consequently, the following nomenclature has been adopted for sensors: *building name_block name_thermal zone name_sensor identifier_type of variable*. The naming part preceding the sensor identifier (e.g. MAC address) follows the IDF model naming structure, which always includes the building name, the block name, and the thermal zone name. To apply this nomenclature, the mentioned naming scheme must be used both within the building model – when initially creating it through an interface, e.g. DesignBuilder or OpenStudio – and on sensor ID. This coherence allows a strict spatial correspondence, making it possible to aggregate analyses and results at both the building and block level. Moreover, at the end of the naming structure, the name of the measured variable must be included. The variable name is then used inside each KPI calculator methodology to recognize which CSV columns need to be included in the computation. The proposed scheme leaves freedom to build the IDF model as desired (e.g. following a multi-zone or a mono-zone approach), allowing different thermal zone aggregations, without impacting the matching. In this chapter, two sample applications of both the performance gap scenario and the model verification scenario are shown assuming preliminary data of two demonstration buildings of the E-DYCE project; see section "Demo Building Applications and Results".

PREDYCE Model Verification Scenario

The PREDYCE semi-automatic model verification scenario has been used previously to the performance gap scenario execution in order to adjust the considered building models to the real indoor air temperature trend, speeding up the manual procedures usually adopted for this purpose. Temperature is adopted as a target verification variable, given that this chapter focused on summer free-running conditions. The following IDF editing values were varied to try aligning the simulated trend to actual building behaviour: U-value of the walls and roof; U-value and SHGC (solar heat gain coefficient) of the windows; internal mass and equipment gains in each thermal zone; and ACH (air changes per hour) ventilation and infiltration. Model verification is made possible by PREDYCE's ability to handle both simulation results and monitored data. The adopted model verification methodology is inspired by [12] and consists in optimizing a combined error measure which includes RMSE (root mean square error) and MBE (mean bias error) (see Eq. (1))

on a given variable or combination of variables, which is in this case represented by the indoor dry bulb temperature.

$$\mathrm{Error}_{\mathrm{tot}} = \sqrt{\mathrm{RMSE}^2 + \mathrm{MBE}^2} \tag{1}$$

The calibration signature described in [12] is computed according to Eq. (2), considering indoor dry bulb temperature an objective variable.

$$\text{Calibration signature} = \frac{\text{measured}\,T_{\mathrm{db}}^{\mathrm{i}} - \text{simulated}\,T_{\mathrm{db}}^{\mathrm{i}}}{\max \text{measured}\,T_{\mathrm{db}}^{\mathrm{i}}} \cdot 100\% \tag{2}$$

The different IDF editing actions allow the user to shift the curve (e.g. acting on ACH, equipment gains), change coefficient and inclination, and modify amplitude variations – e.g. acting on internal mass – thus reaching a flat line within a 5% error range, which corresponds to reference suggestions for model calibration (see also ASHRAE Guideline 14-2014 for calibration criteria) [13]. Figure 3 shows an example of calibration signature plots before and after the calibration of one of the considered buildings.

The model verification scenario is currently considered to be semi-automatic since. In order to minimize the number of performed simulations, it requires observation of calibration signature plots and at the CSV of aggregated total error results to better choose which parameters to vary and in which ranges. This procedure may be further automatized in future actions, but the current potential of PREDYCE to simultaneously test multiple building parameters and automatically edit the model provides a considerable improvement in terms of effort and time with respect to traditional manual procedures, taking few hours to reach results such as the one shown in Fig. 3.

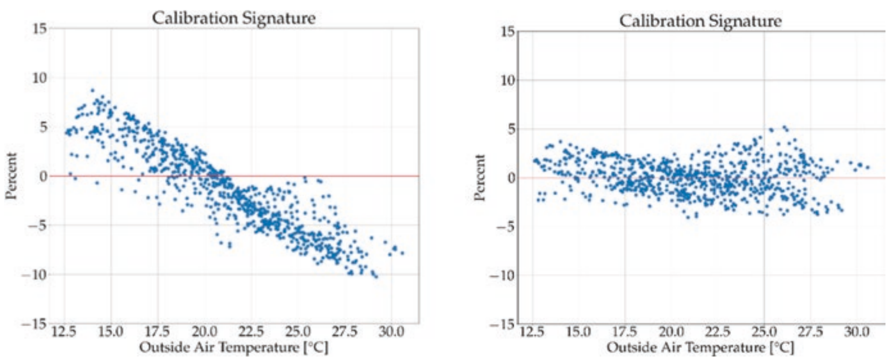

Fig. 3 Example of calibration signatures: (**a**) starting point and (**b**) after model verification on the residential demo building

PREDYCE Performance Gap Scenario

After the model verification phase, updated IDF files are saved as new simulation starting points, and the PREDYCE performance gap scenario is run on the two sample demo cases, considering different building settings. Figure 4 shows the performance gap scenario input/output workflow: among main inputs there is the CSV file containing monitored environmental data; the EPW file that should be also built from monitored data, necessarily an actual weather file; and the input JSON file which allows the user to define schedules, setpoints, and other building activities-related fields as simulation parameters in order to test the parameter impact on the gap against actual behaviour. Moreover, an optional weather input in CSV format is also available, giving the possibility to exploit EPW compiler module functionalities within PREDYCE instead of providing a previously built EPW: in this case, weather station coordinates should be passed through the input JSON file, such that eventually missing weather variables can be computed by the compiler exploiting well-known meteorological formulas. Outputs are instead composed by a zip folder containing the CSV file of aggregated results in which each row represents a considered EnergyPlus run (e.g. the different simulation settings recognizable by keywords *simulated_x*, monitored condition, and finally the delta between monitored KPI and *simulated_x* KPI), the CSV file containing timeseries KPIs with default hourly resolution for both monitored, simulated and delta KPIs (computed as monitored minus simulated results), and finally the optionally required plots.

The input JSON file is used to define both standard and standard modified conditions in which the building model is simulated: particularly, standard modified models were adapted considering a more realistic building usage concerning occupancy, ventilation, and schedules by taking advantage of an inspection-based approach, e.g. see [14]. Moreover, the KPIs to be computed are listed in the input file. In particular, since it focuses on free-running building conditions, distribution of

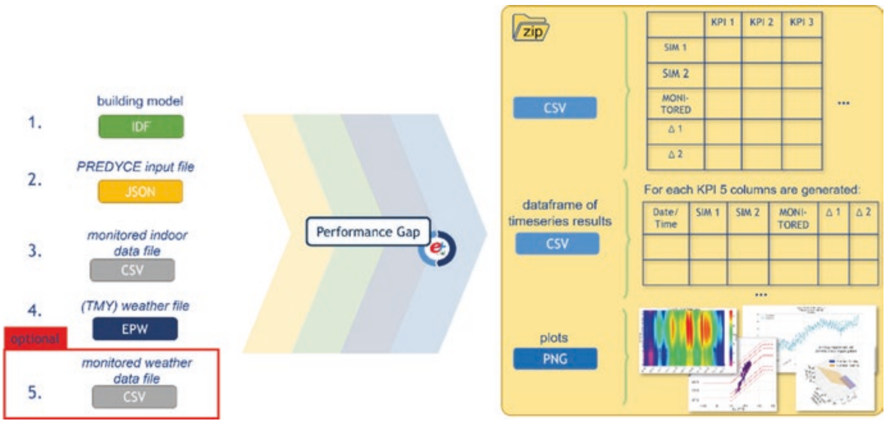

Fig. 4 PREDYCE performance gap scenario input/output workflow

datapoints in adaptive comfort model (ACM) categories is calculated assuming the adaptive thermal comfort model of EN 16798-1:2019 [3]. Additionally, the percentage outside the range (POR) is calculated, returning the percentage of cumulated hours when thermal comfort is not reached, considering them discomfort hours outside cat. II boundaries. Moreover, CO_2 concentration is considered one of the main symptoms of under- and overventilation, returning the number of hours above the threshold of 1000 ppm and under the threshold of 600 ppm, as suggested in Ref. [15]. Besides aggregated KPI results – which are computed on a weekly basis in order to recurringly inform users – when data are not too old to be detached from operational choices while sufficient to describe building phenomena, even time-series results are returned for CO_2 and indoor dry bulb temperature with an hourly timestep, allowing the user to better identify where a potential problem could be located.

Figure 5 shows part of the input file used for the performance gap analysis in the residential unit: the list of KPIs can be seen, together with the spatial aggregations on which each KPI has to be computed (the different activities refer to different rooms in the house, while r01 refers to the entire unit); inside the *preliminary actions* field a list of two JSON structures can be seen, the first referring to building modifications needed to reach standard conditions, the second to reach standard modified usage conditions (e.g. changing ventilation rate or the occupancy). Keywords used within the *preliminary_actions* field refer to methods in the PREDYCE IDF editor module, while KPIs name the methods within the PREDYCE KPI calculator module.

The described methodology can be summarized by the pipeline shown in Fig. 6, including EnergyPlus building model development, model verification adopting monitored data, and the PREDYCE scenario of the same name, followed by the

```
{
    "scenario": "performance_gap",
    "building_name": "r01",
    "start_date": "2021-10-25",
    "end_date": "2021-11-01",
    "kpi": {
        "adaptive_comfort_model": {}, "n_co2_aIII": {},
        "n_co2_bI": {}, "timeseries_t_db_i": {}, "timeseries_co2": {}
    },
    "aggregations": {
        "adaptive_comfort_model": ["act105aa", "act104aa", "act103aa", "r01"],
        "timeseries_co2": ["act104aa"],
        "n_co2_aIII": ["act104aa"],
        "n_co2_bI": ["act104aa"],
        "timeseries_t_db_i": ["act105aa", "act104aa", "act103aa", "r01"]
    },
    "preliminary_actions": [
        {"<to_standard>" :{}},
        {"change_ach": {
            "ach": 3,
            "Schedule_Name": "_residenziale 16798-1",
             "filter_by": "r0",  "relative": false},
        "change_occupancy": {"value": 0.011, "filter_by": "r0", "relative": false},
        "…" : {}
        }]}
```

Fig. 5 Example of input JSON file

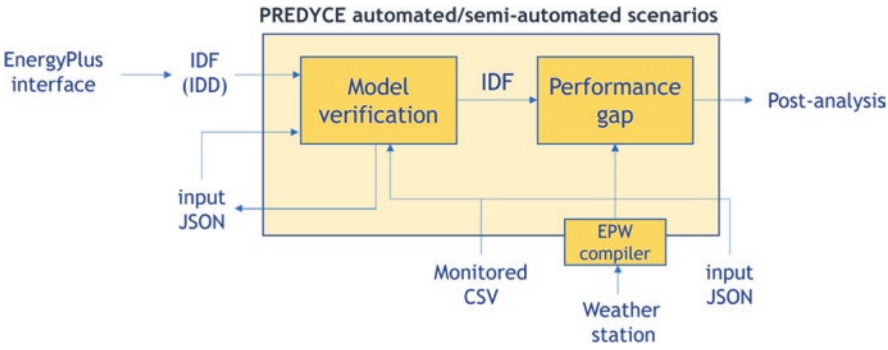

Fig. 6 The methodological pipeline adopted by this chapter

application of the performance gap PREDYCE scenario adopting standard and standard modified IDF input data. Standard scenario is based on given EU input data from standards and norms, e.g. EN 16798-1:2019, while the standard modified scenario refers to adapted input data upon collecting inspection data from the real building including regional and national adaptation, e.g. adapting set points and occupation scheduling.

Demo Building Applications and Results

Demo Buildings General Description

Two demo buildings are adopted in this chapter to support application testing. Both buildings are participating as demonstrations of the EU H2020 project E-DYCE, and they represent two different building typologies: a single-family building and a public school. These buildings are located in Torre Pellice, a small city located in the Turin metropolitan area, in the Pellice Valley, in Northwest Italy. Even if positioned at the bottom of the valley, the climate is cold and influenced by the Alps. It is classified in the Italian climate zone F, reaching 3128 heating degree-days$_{20}$. According to the Italian Presidential Decree n° 412/93 et seq., the climate zone F does not have any specific limitations to the heating activation period, although, for the purposes of this paper, the heating systems were considered active from 5 October through 22 April on the basis of interviews. Torre Pellice is a very representative demo city for small municipalities in Northern Italy and in the Piedmont Region, and it is positioned 5357th in terms of population among the 7978 Italian municipalities (ISTAT 2018). Nevertheless, with 4545 inhabitants Torre Pellice is in line with most small cities, considering that the Italian average is 7980, but the median is 2457. The single-family house typology is also very representative as a demo case considering that, typically, small cities are mainly composed of small houses rather than the multi-block buildings that characterize medium-to-large

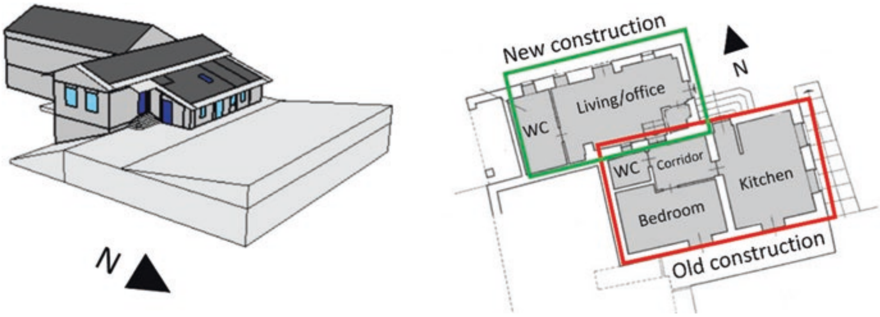

Fig. 7 The considered residential building: (**a**) comprehensive view and (**b**) internal view

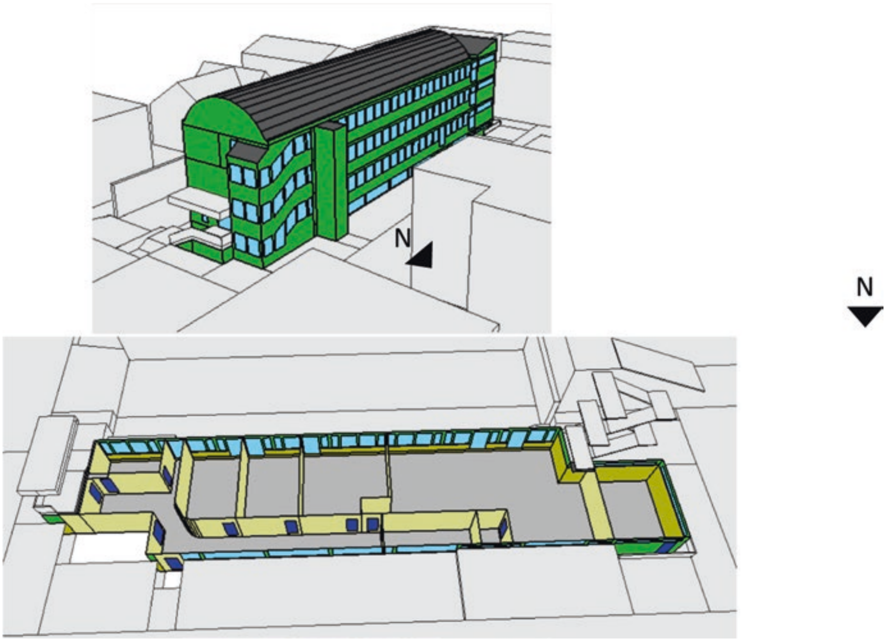

Fig. 8 The considered school building: (**a**) comprehensive view and (**b**) basement floor

cities; see related ISTAT data. Moreover, the considered municipality school is also representative of Italian public school constructions, as it was built in 1975 and features reinforced concrete pillars and external walls with a double layer of bricks and minor infilled insulation due to the cold climate.

Focussing on the selected buildings, base geometrical models are shown in Figs. 7 and 8, showing the residential building and the school building, respectively. Considering the single-family house, it has a 93-m^2 surface area subdivided into three main rooms, two bathrooms, a corridor, and a technical space. The house is on a single floor, with a minor change in elevation between the northern – recently adapted to a residential space – and southern part. Considering, instead, the municipality school, it is composed of four floors similarly organized with a long corridor on the north façade and teaching areas facing south. Three of the four floors (ground to second) are used as a middle school, while the basement floor is used as a kindergarten, directly facing an outside recreational area on the north side. Since the school is a complex building, characterized by different usages and consequently schedules and standard requirements, this chapter only focusses on the kindergarten floor. Unlike other floors, the kindergarten is characterized by larger teaching areas: in particular, the area at the end of the corridor is used mainly for lunch and as a sleeping area in the afternoon, while the two rooms at the beginning of the corridor are divided by a movable panel and kept often open as a single, bigger playroom or also used partially as a sleeping area; finally, the central room is used for daily activities.

Sensors have been installed for environmental data acquisition since April 2021 and allow temperature monitoring in all rooms, relative humidity in most rooms, CO_2 in the most representative spaces, and extra parameters in limited rooms, such as TVOC and illuminance, although the latter are not investigated in this chapter. Sensors and monitoring gateways are based on the Capetti WineCap system [16]. The solution allows to access monitored data remotely and in almost real time by developing a SOAP-based API [17] or by using the provided interface. Additionally, a meteorological station has been installed in order to collect weather variables to feed simulation with the same real boundary conditions of monitored data. The station includes a Thies US climate sensor that monitors temperature, relative humidity, wind (direction and velocity), precipitation data, illuminance, atmospheric pressure, and correlated data, plus a delta ohm pyranometer (class 1) for collecting global horizontal irradiation. Among split irradiation models, the well-known Boland-Ridley-Lauret model [18] has been applied to retrieve diffuse and direct components.

Application of the Model Verification PREDYCE Scenario

Regarding the residential house, the month of June 2021 was chosen as model verification time period, without having any information of actual house occupancy but assuming it was occupied.

Figure 9 compares initial and verified model results vs. monitored data (measured) of the single-family house case. The two graphs clearly demonstrate that the model verification scenario may support an improvement in building behaviours with respect to monitored data thanks to the adaptation of boundary modelling conditions. Figure 10 plots monitored and simulated internal temperatures (building average values of both sensors and simulated thermal zones) considering initial and verified models. These graphs help to better understand improvements in the model supported by the PREDYCE tool. Generally speaking, these changes are obtained by manually performing several simulations, i.e. via an EnergyPlus interface, but

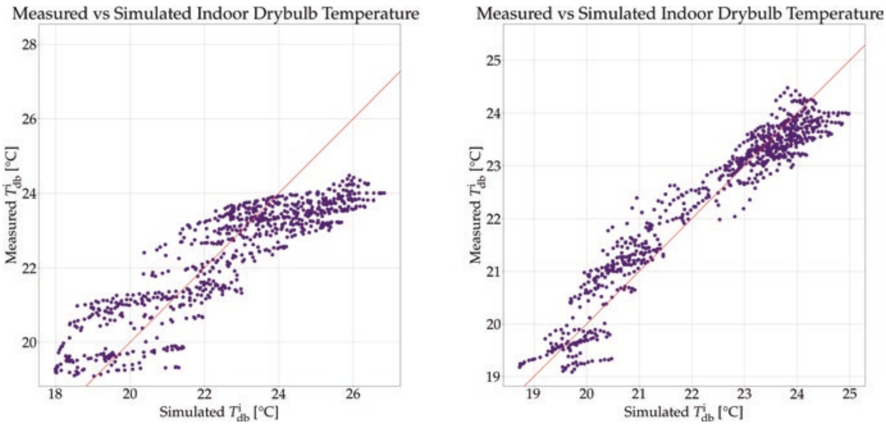

Fig. 9 Indoor temperature measured vs monitored before and after residential house calibration process

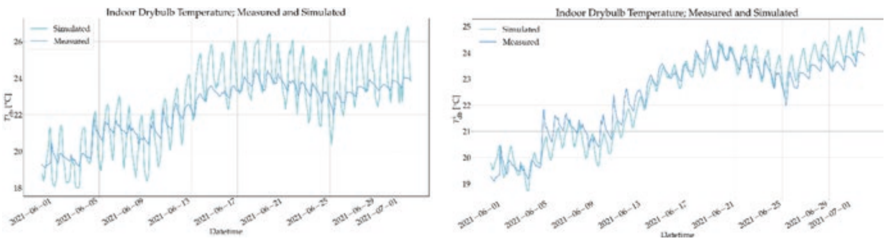

Fig. 10 Indoor temperature trend over time before and after residential house calibration process

the new developed tool allows to automatically compare the two series (without requiring post-production) and to support automatic changes of IDF parameters in given ranges, avoiding to manually perform this task. It is hence possible to verify models in a quicker and more productive way by testing both statistical discrepancies between simulated and monitored data and potentially also analysing the impact of different parameters on these differences. As it is visible from Fig. 10, at the end of the month larger discrepancies occur between verified model and monitored data. Consequently, a drastic change in building usage can be supposed in those days, for example, because of the beginning of a holiday period with consequent occupancy and ventilation going to zero values.

The peculiar construction of the house, made of a newly renovated area and an older uninsulated part, increased the complexity of the process, since both boundary walls and ceiling for the two areas were calibrated as separate parameters, e.g. concerning vertical walls, the best-found values led to a reduction of the model U-value by 90% in the renovated insulated part of the house and an increase of 15% in the old non-renovated area. To reduce the amplitude of differences in temperature between monitored and simulated data, the most effective action was the increase of internal mass, probably because of the massive structure of the mountain house

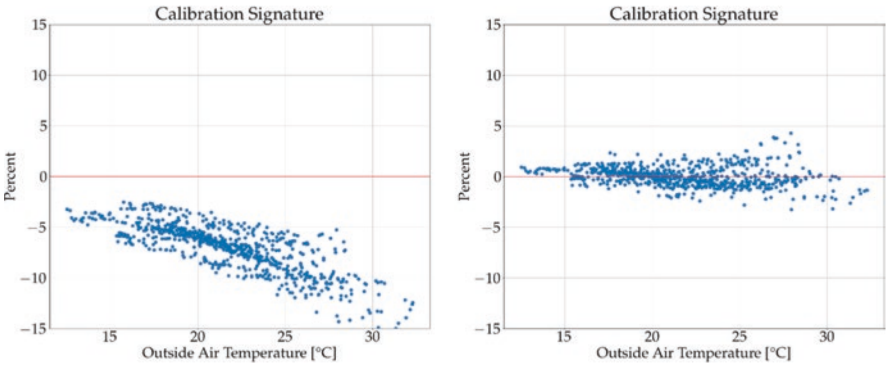

Fig. 11 Kindergarten calibration signatures, before and after the calibration process

considered old. Even internal gains increased, while infiltration through windows drastically dropped. The obtained values are consistent with the building materials and technical elements identified during the inspection phase that followed this analysis.

Regarding the kindergarten building model verification, the chosen time period was from 21 June to 21 July 2021, corresponding to the school closure. Consequently, ventilation was considered inactive and was not used as a variable in the calibration process.

Figure 11 compares original and verified model calibration signatures. Even in this case, the original model shows evident discrepancies, while the verified model presents an error perfectly fitting suggested calibration error thresholds; see ASHRAE Guideline 14-2014. Original errors in calibration signatures shifts from a [−2 to −15] range to a [+4, −4] one. The other two following graphs (see Fig. 12) plot internal temperatures over time including in the same graph monitored and simulated results. The latter model (verified) shows a very good correlation and is able to represent real building behaviours under actual weather conditions. The best values found allowed an increase in the U-value of the walls to 1.25 W/(m^2 K), coherently with results found during a subsequent inspection. Roof U-value, instead, fell from 1.79 W/(m^2 K) to 1.2 W/(m^2 K), and infiltration through windows increased. Also, internal mass increased by 20%, while internal equipment gains dropped.

Application of the PREDYCE Performance Gap Scenario

Standard and Standard Modified Scenarios

The verified models retrieved in the previous section "Application of the Model Verification PREDYCE Scenario" are adopted here to run the PREDYCE performance gap scenario. The input JSON file is used to impose to the models (i)

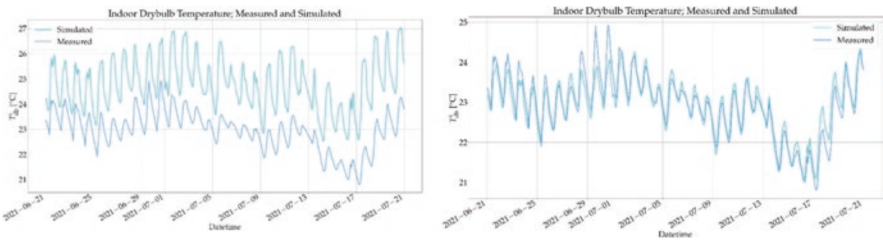

Fig. 12 Indoor temperature trend over time before and after the kindergarten calibration process

standard settings according to Annex C of EN ISO 16798-1:2019, overwriting certain values previously calibrated (e.g. ventilation rate), and (ii) standard modified settings, considering a more realistic building use defined after an inspection. Regarding the residential case, considering its dimension and adjacency (despite through only one wall and floors) to other residential units, the ‘residential apartment standard case’ of the EN 16798 standard was considered. Concerning internal gains, 28.3 m^2/person are used as a standard, while in the standard modified case, the knowledge that the house is inhabited by only one person is used, leading to the total 93 m^2/person. With the units being scheduled for occupancy, appliances and lighting are not modified in the standard modified setting with respect to the standard, since the house is not actually used with a specific home-office pattern, and it was not possible to structure a proper schedule. Ventilation in standard modified conditions was increased from the 0.5 l/(m^2/s) considered as the standard with 3 ACH (air changes per hour), a high value able to perform ventilative cooling, since during the inspection a high usage of natural ventilation during the summertime was underlined.

Concerning, instead, the kindergarten, standard conditions consider a continuous building usage over the year without including any holiday: weekends are considered unoccupied, while a typical weekday is considered occupied from 7 a.m. to 7 p.m., for a total of 12 h per day. Regarding internal gains, 3.8 m^2/person are considered to lead to 4.92 l/(m^2/h) as a CO_2 generation rate. Standard air flow for ventilation is supposed to be 4.5 l/(m^2/s), and the outdoor temperature setpoint for its activation was set to 17.5 °C, corresponding to the standard heating setpoint. Those values were modified considering a more realistic building usage in the considered kindergarten: schedules were changed, since around 16:30 all children leave the school and no after-school service is provided in the rooms; also, holidays were considered assuming the traditional Italian calendar. Moreover, child presence in the main activity areas was reduced with respect to the standard, considering that some of them go home after lunch and that even the outside area is used, reducing the overall indoor presence. Also, ventilation was increased to 2 ACH always active, considering the COVID-19 government advice to keep windows open as much as possible.

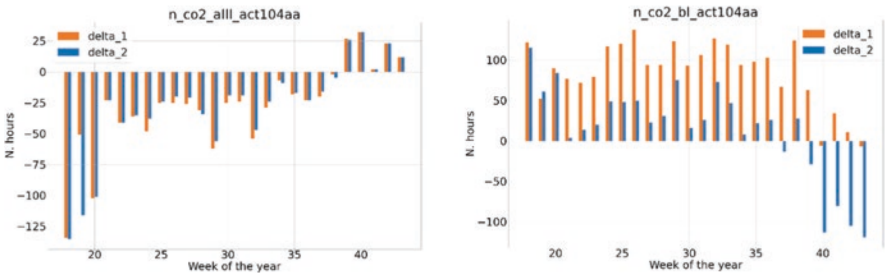

Fig. 13 CO_2 KPIs in residential unit kitchen and living room area representing the difference in number of hours between the simulated (standard = 1; standard modified = 2) and monitored values. The graph on the left shows hours above 1000 ppm, while the graph on the right the number of hours below 600 ppm

Performance Gap Results

Concerning the residential unit, a single CO_2 sensor was installed in a room used both as a kitchen and living room; thus the CO_2 analysis was performed for this specific room, called *act104aa*. Figure 13 shows weekly aggregated results of numbers of hours below the threshold of 600 ppm and above 1000 ppm. Since the performance gap with the standard simulated buildings is negative, it means that there are more hours above 1000 ppm of CO_2 concentration with a standard building behaviour than considering the actual one, except in the beginning of the autumn season. Oppositely, the number of hours below the 600-ppm threshold is greater in the actual monitored behaviour than the standard one. However, it can be seen that, especially from the late spring to the early autumn, the standard modified behaviour results were much more similar to the actual ones than the standard ones, which show a greater gap. This means that the ventilation was probably higher than in colder weeks, with the occupant behaviour causing ventilative cooling, while in later weeks the cold season implied a different usage of window openings to prevent heat dissipation, i.e. the difference between the standard modified and real behaviour become negative for hours below 600 ppm.

Looking at the timeseries of CO_2 in the room (Fig. 14), it can be seen that monitored data follows a random behaviour, which is difficultly represented by simulated trends that follow a fixed schedule in each weekday. Consequently, aggregated results are more useful to highlight potential behavioural gaps in the residential unit. Moreover, looking at the graph on the right in Fig. 14, it can be seen that in late June monitored data flattened, reinforcing the hypothesis of a holiday made upon observing the model verification results in Fig. 10.

Figure 15, instead, shows differences in weekly hour distribution in ACM categories, giving an idea of indoor thermal comfort monitored with respect to standard conditions. Unshown categories resulted to be empty for both simulated and monitored data, meaning that the residential unit is maintained quite cold in the whole period considered. Particularly, monitored data turn out to be, on average, colder

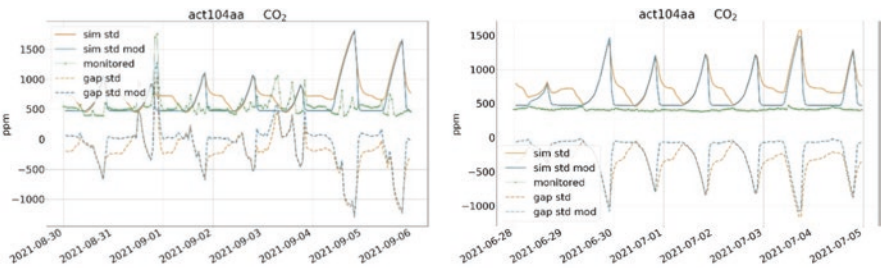

Fig. 14 Timeseries CO_2 values in residential unit kitchen and living room area for different periods

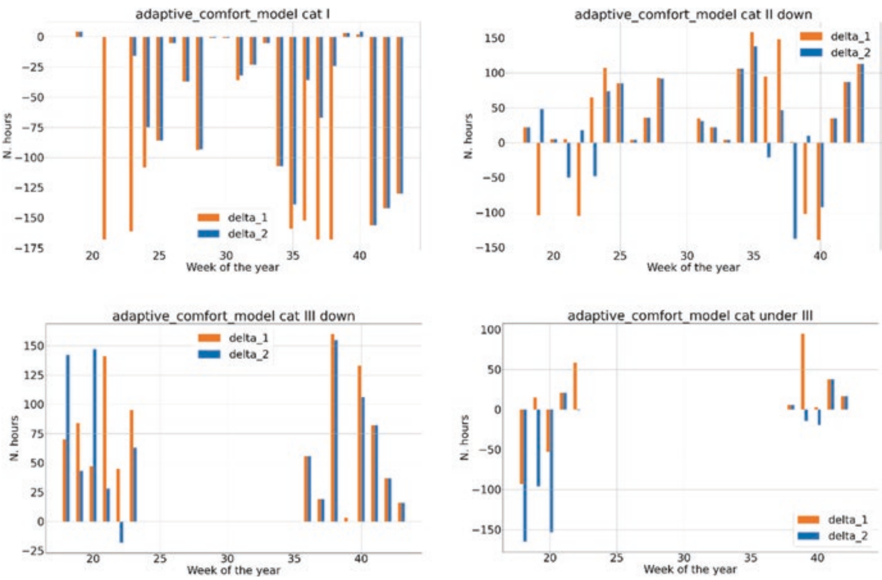

Fig. 15 Distribution of hours in ACM categories, averaged on all residential unit zones

than what is expected in standard conditions, except for the first weeks in May, when there are more simulated hours below comfort cat. III than monitored ones.

Looking at indoor temperature trend over time, the average behaviour shown in Fig. 16 is quite different depending on specific thermal zones, as shown in Fig. 17 (the kitchen) and in Fig. 18 (the second living room located in the newly renovated part of the building). In fact, despite the average monitored behaviour is almost in line with both standard and standard modified simulated conditions, the kitchen area shows several peaks at a higher temperature during the entire month of May and then gradually flattening at the end of the month. The newly renovated area, instead, shows a colder trend with respect to simulated standard conditions, but quite in line with the standard modified in which occupancy is more realistically set. Kitchen peaks are explainable because of a wood stove located in the room, which was used despite the end of the heating season to face the last colder weeks of the

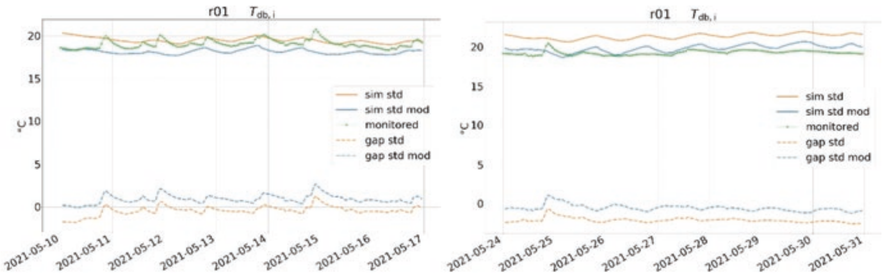

Fig. 16 Timeseries of average air temperature values in all residential unit zones

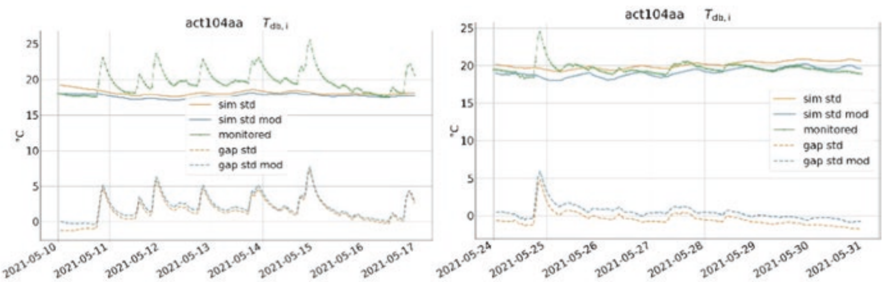

Fig. 17 Timeseries air temperature values in residential unit kitchen (left) and second living room area (right)

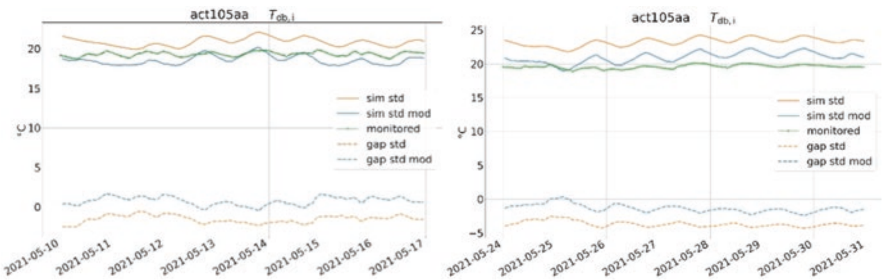

Fig. 18 Timeseries air temperature values in newly renovated residential zone

year. However, the more the other rooms are far from the kitchen, the less they can benefit from the impact of the stove, resulting in colder monitored data even with respect to the standard. The same observations can be made by looking at the POR in Fig. 19, considering both the kitchen and the zone average: during the first simulated weeks in May, simulated behaviour is worse than monitored behaviour, especially in the kitchen, where a higher temperature is maintained, and then during the proper summer season comfort is maintained with almost all hours in cat. II, resulting in POR = 0. Finally, with the beginning of the autumn season, simulated behaviour was recorded to be slightly better than monitored, perhaps because – waiting

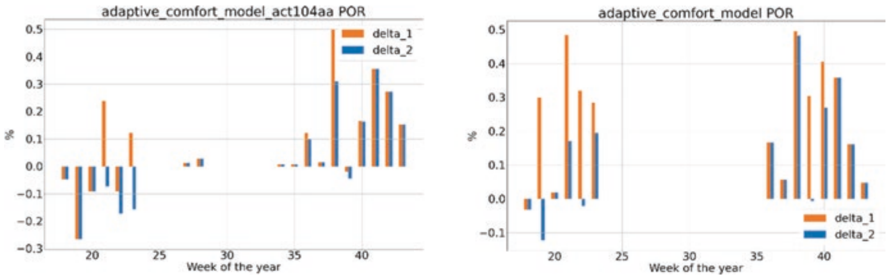

Fig. 19 ACM POR in the kitchen/living room (left) and average in all residential unit zones (right)

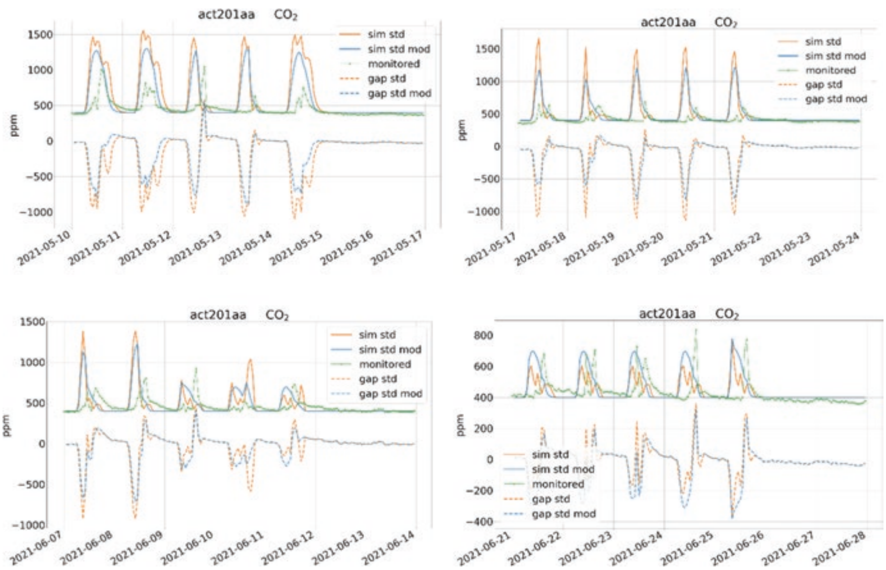

Fig. 20 Timeseries CO_2 values in kindergarten act201aa thermal zone

for the beginning of the heating period – the stove was not used even in the first, colder days.

Concerning the kindergarten results, Figs. 20, 21, and 22 show CO_2 trends over time in the three main activity areas of the floor (*act201aa/ab/ac*) during 4 weeks in May and June 2021. The three rooms show a more regular behaviour with respect to the residential case, because of the cyclic schedule followed by children in the rooms. However, the three areas show quite different trends, underlining the need to analyse different spatial aggregations to investigate the average behaviour that could be affected by room values distribution and to better localize potential problems. Particularly, the three rooms seem to be used in different moments of the day, suggesting the need of even more detailed schedules to better simulate a standard modified behaviour. *Act201aa* is mainly used in the afternoon, which corresponds to lunchtime and the afternoon nap. Differently, *act201ab* is mostly used in the

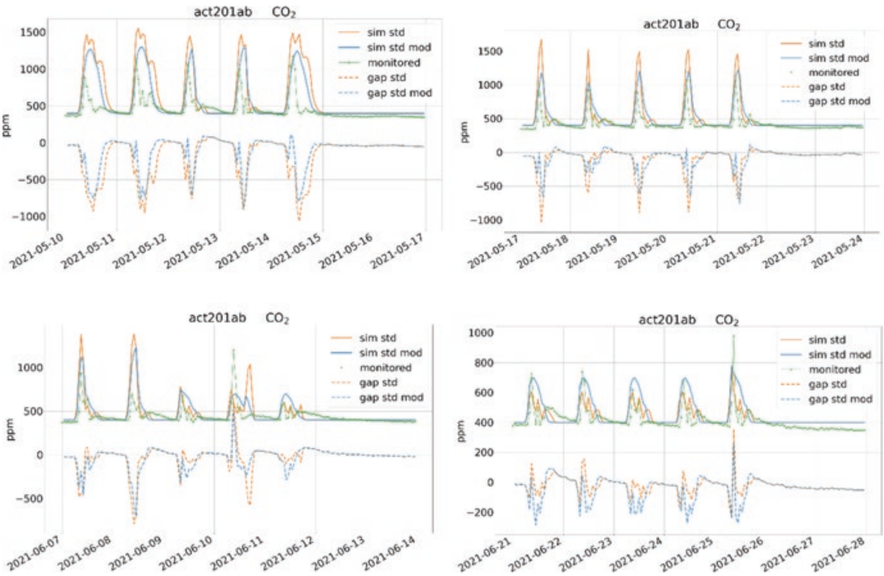

Fig. 21 Timeseries CO_2 values in kindergarten act201ab thermal zone

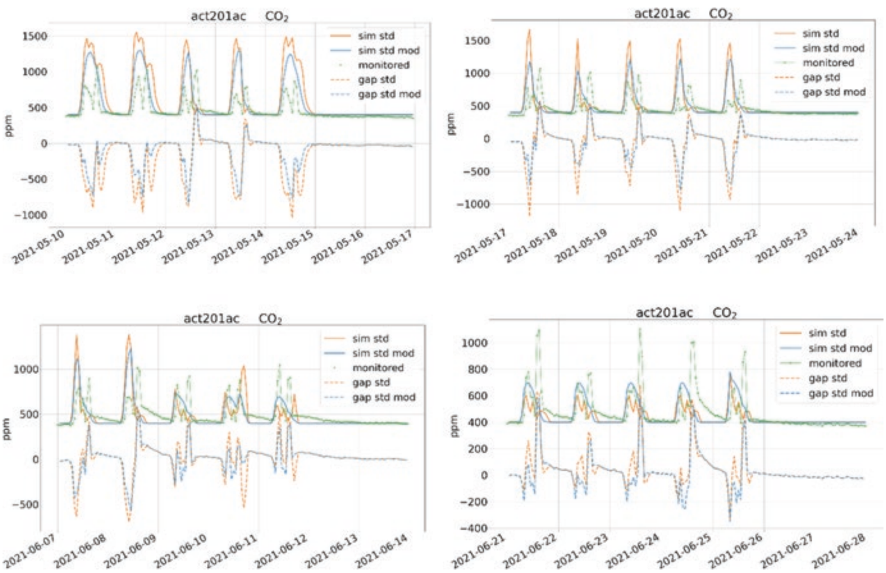

Fig. 22 Timeseries CO_2 values in kindergarten act201ac thermal zone

morning, while *act201ac* usually shows two peaks, one in the morning and the other in the afternoon, corresponding to the double use as playroom in the morning and sleeping area in the afternoon. Peaks of CO_2 concentration seem to increase towards

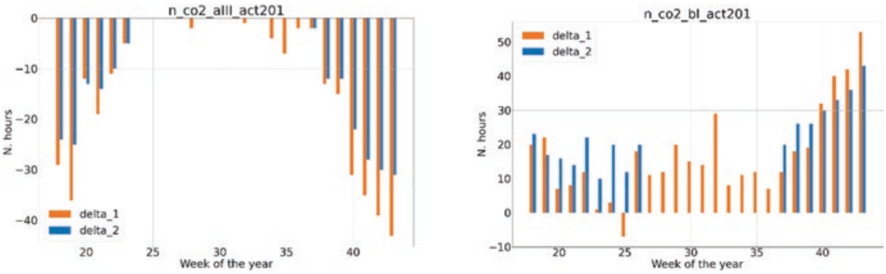

Fig. 23 CO_2 KPIs aggregate results of all kindergarten teaching areas

the warmer summer periods, as if natural ventilation were drastically decreased not to overheat the rooms in the afternoon or reduce airflows or noise during the nap. Moreover, unlike the first weeks of May, when CO_2 trends seem to reach 1000 ppm peaks given the outdoor temperature is still too cold to allow high ventilation rates, in late May all rooms show lower CO_2 peaks, usually below 700 ppm, suggesting an increased natural ventilation usage. In general, CO_2 peaks can be affected by the unnatural ventilation approach forced by covid-19 rules, which can lead to the opposite undesired result of overventilating an area. The latter risk is mainly impacting during the winter months due to higher heating requirements but may also lead to unwanted draft during nap time.

In fact, looking at aggregated weekly results in Fig. 23, both standard and standard modified building simulation settings tend to overestimate the number of weekly hours above the threshold of 1000 ppm despite the performance gap is lower with respect to standard modified behaviour, because of the adapted occupancy schedule which avoids a late-afternoon CO_2 drop and a natural ventilation strategy. For the same reason, the number of hours below the threshold of 600 ppm is greater in the monitored data. Particularly, standard behaviour looks more incongruous with the standard modified than actual monitored behaviour, because of the better balance between occupancy and ventilation and, especially in the summer weeks, the appropriate holiday schedules.

Similar observations can be made also by looking at each room's temperature trend. Particularly, Fig. 24 shows the average teaching area temperature in the same weeks analysed for CO_2 concentration. During the month of May, monitored data show very low temperatures due to the end of the heating season and to the still cold outdoor temperature. Overventilative tendencies could explain the very low peaks in early morning that can reach 15 °C. In June, instead, monitored indoor temperature gets closer to the simulated standard profile, suggesting that the adopted ventilative strategies are also closer to the standard ones. Standard and standard modified behaviours turn out to be very similar in terms of temperature trends, given the input differences are also limited with respect to the residential demo case.

The same results can also be highlighted by the weekly aggregated results for the considered time period. Figure 25 shows the distribution of the identified gaps in ACM categories, together with the POR. Since the POR shows mainly positive

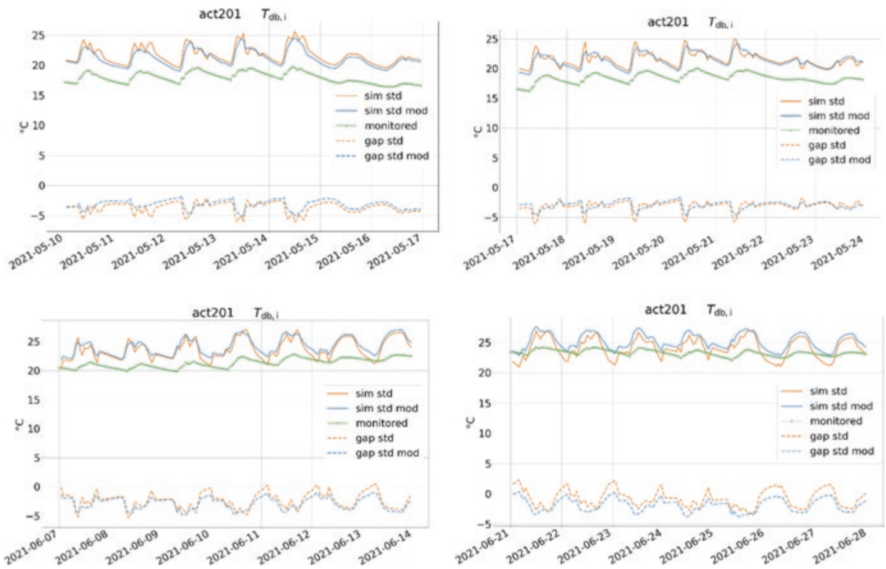

Fig. 24 Timeseries of average air temperature values in all kindergarten teaching areas

results, it means that overall, the kindergarten behaved slightly worse than expected in standard conditions. Particularly, standard behaviours show more hours in adaptive thermal comfort categories I, II up, and III up, while monitored data tend to represent colder temperatures with more data in categories II, III down, and even below cat. III. A similar behaviour can be seen in the central summer weeks, especially in late June and early September, when monitored data are more present in cat. I, while standard behaviours tend to show hotter temperatures than the actual building trend. The central summer weeks, instead, in July and August, are affected by an incorrect standard occupancy, which does not consider holidays.

Considering that the two considered buildings are located in a mountain region, the main problem to reach the best free-running mode in terms of both thermal comfort and indoor air quality was recorded to be, even in the late spring and late summer, finding a good balance between natural ventilation strategies and consequent natural cooling. Especially in the school, the application of a non-optimized ventilation strategy could result in very cold days and even in increased heating consumption in the corresponding season. Results show that, despite trying to apply the best strategies to maintain indoor thermal comfort and air changes (also considering the pandemic), it is difficult without the aid of visual supports and eventual suggestions to understand when the pollutant concentration is increasing above a certain level and when it is low enough to not require additional ventilation. Also, this suggests that mechanical ventilation machines could be of great aid in maintaining indoor comfort in a school building, especially during colder hours and periods, when overcooling may represent a risk. For this reason, three mechanical ventilation units have been recently installed in another floor of the school building to support further tests and verifications.

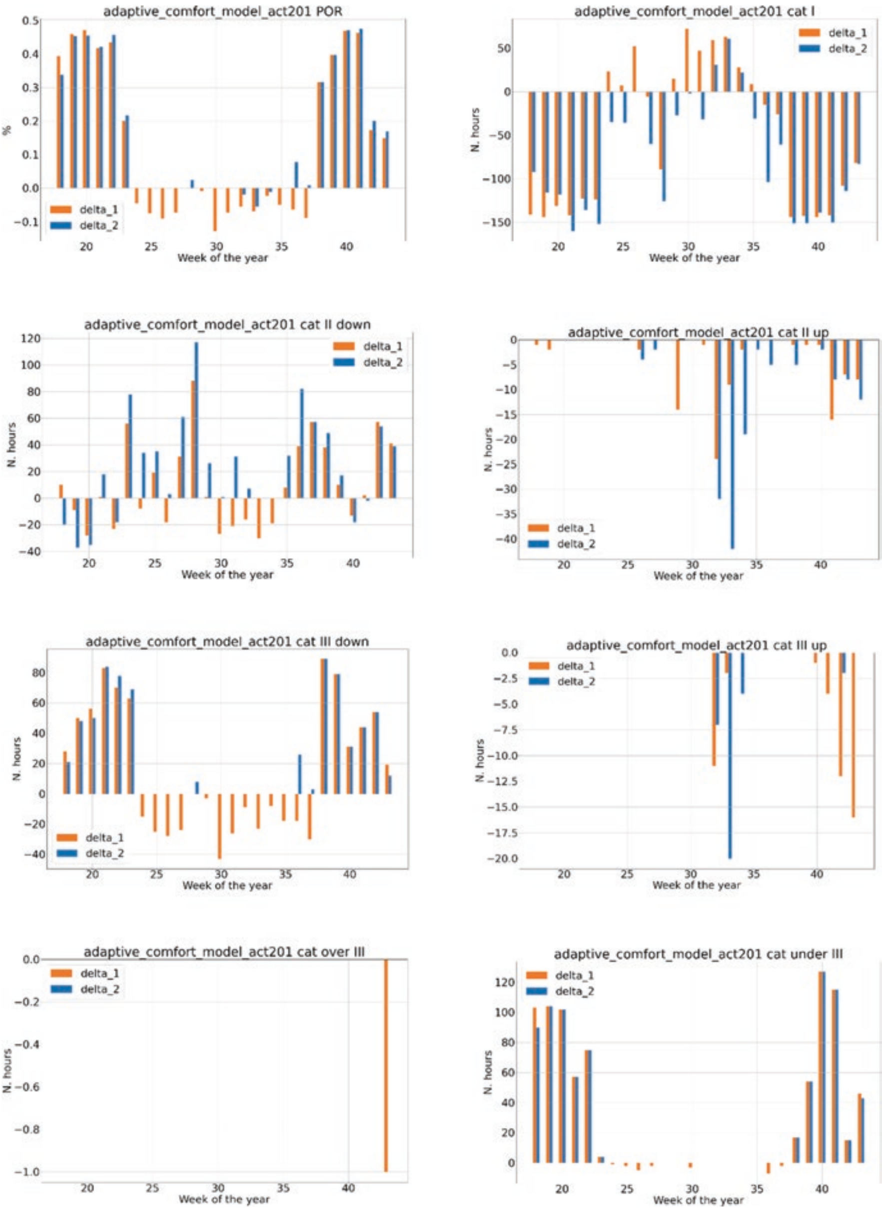

Fig. 25 Average distribution of hours in ACM categories and POR in all kindergarten teaching areas

Results also showed the relevance of both aggregated and timeseries data in understanding potential problems inside the considered space: aggregated results are indispensable in case of random trends, much like the CO_2 concentration in the residential unit, while timeseries data resulted to be of great aid in understanding the more regular school behaviour. Also, considering different levels of spatial aggregation, such as specific rooms or thematic areas (e.g. all the teaching areas together), resulted to be useful in understanding localized problems that could disappear in an average behaviour. Furthermore, the adoption of single zone-specific analyses may help to underline and justify peculiar effects like those given by the wood stove in the residential unit.

Conclusions

The chapter describes initial applications of a new Python library tool able to manage EnergyPlus simulations for different purposes. The current version of the PREDYCE tool is described by detailing the needed inputs and potential outputs of its main scenarios with special regards to the model verification scenario, able to support calibration processes comparing monitored and simulated building data and allowing parametric changes to suggest model error reduction. Furthermore, the performance gap scenario is described to support the identification till real time of discrepancies between monitored and model/simulated building KPIs. The methodology is applied to real demonstration buildings, showing how the proposed pipeline may be used in practice. Results clearly show the potential of the new underdevelopment tool, suggesting several development lines, including the integration on a large building management middleware to support multi-data source integration, taking advantage of the PREDYCE simulation flexibility. This work is part of a larger project that aims to suggest new paths and issues for the next generation of building energy performance certification visions. Currently, PREDYCE faces some limitations: it is developed to work with EnergyPlus version 8.9 (8.x in general), although it may be upgraded to v9.x in future. Additionally, the run of several simulations may benefit from a server facility but may be easily managed through remote REST API services or future middleware solutions. Finally, larger tests on additional demos, considering different building typologies, climates, and national backgrounds, are planned to be performed throughout the coming months.

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