An agent-based framework for smart grid balancing exploiting thermal flexibility of residential buildings

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***Abstract*—The Smart Grid is a complex system that encompasses many different fields of expertise. As a consequence, co-simulation tools are emerging as a possible solution to test future scenarios and strategies thanks to their ability to reuse domain-specific simulators in a broader context. Therefore, we propose an agent-based co-simulation framework able to act as a test-bed for multiple Smart Grid strategies. In particular, we tested demand response programmes that exploit the thermal behaviour of residential buildings at the district level. The proposed framework is modular, thus it eases further integration of new modules. Moreover, it is highly flexible thanks to the numerous configuration parameters that allow creating a realistic scenario. The system has been tested over 1000 buildings in a district and an analysis of the effects on the balancing at primary substation, due to micro-deviation from scheduled temperature set-points in the building's premises, is proposed. Results demonstrate that power imbalances can be mitigated already with minor set-points deviations.**

***Index Terms*—Demand Response, Co-simulation, Aggregator, Power Imbalances, RC network**

I. Introduction

The power grid is going towards a radical change that will integrate many small scale producers at the distribution level, shifting from a centralised system to a decentralised one. Unfortunately, the production of distributed renewable energy sources (RES), as well as small-scale residential consumption, are difficult to predict with high accuracy. Therefore, this inaccurate prevision might translate into scheduled demand and generation different from the measured ones, causing power imbalances [1]. Consequently, Demand Response (DR) strategies - i.e. programmes which produce changes in the consumption due to different prices of electricity over time or incentives [2] - might be put into action to address power imbalance issues with the derived flexibility.

In the residential sector, thermal loads account for the largest share of the building consumption and due to their typical nature have a great potential for the flexibility generation [3]. However, several factors such as the comfort of the user and the physical characteristics of the building affect the available flexibility. Therefore, we believe that as a first step an agent-based co-simulation tool represents the proper and cost-effective solution to quantify with good approximation the amount of flexibility, its effects on the grid and, subsequently, to test new algorithms. Indeed, the capability to try out artificial intelligence algorithms in a virtual environment allows to verify more advanced strategies before testing them in the real-world.

In the literature review by Sola et al. [4], it emerges that few studies included the power grid in their co-simulation tools. Furthermore, to the best of our knowledge, an agent-based framework that tests DR strategies exploiting the thermal behaviour of residential buildings at the district level and the relative effects on the distribution network has not been developed yet.

In literature, two major categories of building simulation environments exist [5]: i) those very realistic that focus on a stand-alone building, e.g. EnergyPlus, and ii) those where the building is simplified and represented as an electrical circuit, i.e. RC network. However, the high computational time of the former category sets limits on the scalability of the simulation scenario, especially when the goal is modelling a large district or an entire city.

Therefore, in order to understand the potential for DR in a city, the most viable option is to simplify the model of the buildings as an RC network. However, a myriad of RC schemes exist. In our view, the ISO 13790 compliant 6R-1C thermal model of City Energy Analyst (CEA) [6] has the proper trade-off between computation performance and model accuracy. Moreover, CEA has the advantage of using geo-referenced data and building archetypes, which make the scenario configurable and realistic. Unfortunately, it makes one-shot calculations for the entire year. Thus, we extended CEA offering functionalities to be integrated with time-stepped simulations allowing also further integration with other models. In other words, we have made it possible to use CEA in a co-simulation environment together with the rest of our framework, resulting in a platform for testing DR strategies.

Specifically, in this paper we tested a rule based strategy that exploits the thermal behaviour of buildings in a district. Three main types of agents have been modelled: i) the DSO, which controls the electrical grid; ii) the Aggregator, which is responsible for the DR implementation, gathering thermal flexibility volumes from the residential users; and iii) the Building Agent, which models the building dynamics embedding CEA.

Thanks to the framework, RES might be added in future, as well as new sources of flexibility. Therefore, a first contribution of this paper is represented by our "plug and play" framework which acts as a test-bed for different DR strategies that exploit thermal inertia of buildings in the distribution sector. Furthermore, the effects of exploiting building thermal management to create flexible demand have been analysed thanks to two ad-hoc modules : i) the DSO operative module ii) the building operative module. The former models the power grid and solves the resource allocation problem, while the latter models the buildings thermal behaviour and implements control strategies quantifying the flexibility reserve.

The rest of this paper is structured as follows. Section II provides insight into already existing tools and works. Then, Section III presents a general overview of the framework and introduces the agents. Section IV describes the simulation settings, while Section V discusses results for the case study analysed. Finally, Section VI summarises the conclusions.

II. Related Works

In the literature, several solutions are proposed to quantify the flexibility of residential buildings. Most authors focus on the development of the model to assess demand calculation, i.e. the thermal behaviour of the buildings, and analyse control strategies used to generate flexibility, which can be rule-based or predictive base, i.e. Model Predictive Control (MPC). Instead, others reuse existing building models in a co-simulation framework for different purpose.

Authors in [7] propose two control strategies relying upon a TRNSYS calibrated building model. They consider both upward and downward flexibility while proposing MPC strategies for optimising set-point scheduling. In [8], the authors study the flexibility reserve of a building by coupling thermal demand modelling with thermal storage solutions. Instead, [3] performed an in-depth study on the effects of set-point changes to quantify flexibility; different building models and different strategies to assess DR events have been tested. Other interesting models are presented in [9] and [10]. The majority of studies that couple the grid perspective and the buildings loads focuses on distributed generation, RES, storage and shiftable appliances such as [11]. Instead, [12] and [13] mainly concentrate on flexibility generation from thermal control for district balancing, but the grid is included only from an economical perspective since all the physical constraints are neglected.

Besides specific building models and control strategies, the co-simulation approach has emerged thanks to its ability to couple different domain-specific models developed with different tools. As an example, [14] outlines an urban energy co-simulation framework on the basis of a co-simulation standard Functional Mock-up Interface and CityGML-based semantic 3D city model. In the two scenarios presented, EnergyPlus and Nottingham Multi Agent Stochastic Simulation are coupled to simulate one and six buildings, respectively. Instead, the authors in [15] proposed a co-simulation framework that uses PandaPower [16] to simulate the electric grid and TRNSYS for the building domain. The building model represents a Spanish single-family house building typology. It analyses four scenarios with 50 consumers, a 3 minutes time-step and an increasing penetration rates of heat pumps to determine the impact on the grid. The MultiEnergy System COSimulator for City District Energy Systems [17] is a simulation platform that allows performing simulations of district scale energy systems. The electrical network has been simulated thanks to Neplan, while the control algorithm decides the operation schedule of heating systems at fixed time intervals. One single family building model has been developed. Based on this model, four energy system models have been realised with different heating systems. The execution of the simulations has been parallelized to reduce the computation time. Different scenarios with 1 minute time step have been tested, the largest one comprises 795 building energy systems.

In conclusion, by creating the proposed agent-based co-simulation framework, we want to couple the quantification of flexibility from building thermal regulation with an Optimal Power Flow (OPF)-based solution for the resource allocation inside a completely modelled electrical grid. This allows a wider analysis w.r.t. [7], [8], [3], [9], [10], [11], [12], [13] that do not address the problem on the broader perspective of a fine modelled grid. The whole framework is designed to be scalable in the number of buildings and aggregators. Moreover, it is completely configurable to adapt to different case studies, e.g different Heating, Ventilation, and Air Conditioning (HVAC) technologies, scheduling, time-steps, envelope standards and typology of use. Furthermore, it uses GIS-based information of the buildings, which makes more realistic the simulation. Thus, w.r.t. other co-simulation frameworks, i.e. [15], [17], we did not generalise a single model, but we characterise each building thanks to different parameters settable in our framework. Furthermore, the framework follows the principle of modularity, thus allowing the testing of different control strategies and the integration of new models in a Plug & Play fashion. Therefore, the proposed rule-based strategy might be replaced by an MPC one to compare the results or a reinforcement learning algorithm might be used to learn the preference over the thermal set-points of the users.

III. Methodology

This section introduces the framework structure and the interactions composing the simulation process. The main purpose is to have a Plug & Play agent-based co-simulation environment to act as a test-bed for different strategies in the power grid distribution network. Fig. 1 shows the overall architecture of the system, which is divided into three main layers: i) the Data source-layer, which manages the data-structures and the information needed; ii) the Co-simulation layer, which is the core of our framework; iii) the Application layer, which allows end-users to interact with the co-simulation process. This last layer allows to personalise the databases, select the scenario through a GIS-based interface and visualise data and results of the simulations. In the following sections a more in depth description of Data-source and Co-simulation layers is given.

A. *Data-source layer*

In the Data-source layer, data-management and processing are implemented to obtain a complete description of the urban scenario under analysis. The starting point is the gathering of some raw inputs visible in the Data-source layer in Fig. 1: i) *GIS Buildings Information* (e.g. geometries, ages

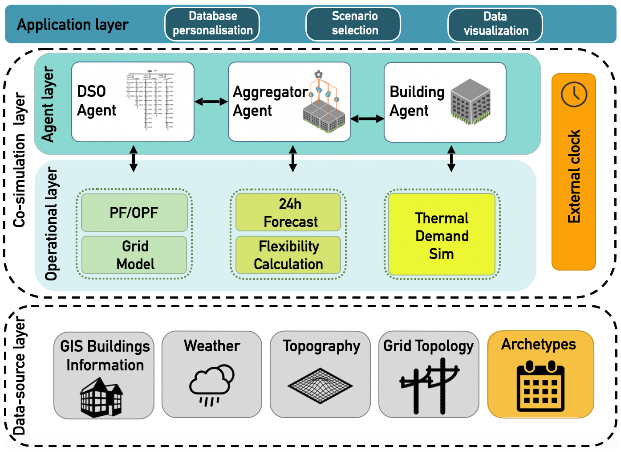


Fig. 1: Schema of the proposed framework.

of construction, height and typology of use); ii) *Weather* information for the chosen simulation period (e.g. outdoor temperature, radiation etc.); iii) *Topography* information about the elevation of the terrain; iv) power *Grid topology*. From these data, we have a preliminary characterisation of the built environment we want to simulate. A further step is done by exploiting the CEA's archetypes [6], which enhance the data description. By correlating the inputs of the buildings with the archetypes new information can be retrieved. Envelope properties, HVAC systems with their related subsystem technologies are associated to each building by means of their age of construction. Scheduling of the occupancy patterns in the buildings are generated based on the typology of use along with the scheduling of temperature set-points and other control parameters. In addition to the information created by exploiting the correlation with the archetypes (which are completely configurable), a solar radiation calculation is performed to have information about the external gains on the buildings.

B. Co-simulation layer

The Co-simulation layer represents the core block of the framework. It is composed of two main sub-layers, i.e. the Agent layer and the Operational layer, and an external clock for synchronisation. The distinction between Operational and Agent layers has been done to gain in modularity. Indeed, modules in the former can be easily replaced, instead the latter offers a predefined backbone for the agents interactions and communications. In particular, as shown in Fig. 1 the operative capabilities of each agent are implemented in the Operational layer in form of plug&play modules. Instead, the communication functionalities, that ensure the message exchanges among all the actors, are implemented in the Agent layer, exploiting the AIOMAS [18] python library. The agents 'live' in different containers that run as separate processes ensuring a distributed architecture. Communication among agents is implemented over the TCP/IP protocol stack thanks to the containers built-in Remote Procedure Calls functionalities. Three typologies of actors have been identified and implemented:

(i) ***DSO Agent*** is in charge of the correct functioning of the power grid and it coordinates the workflow (better addressed in Sec. III-C) by asking for flexibility to the Aggregators. Its main responsibility is to recover the power unbalances at primary substation while maintaining stable its grid portion. To accomplish this task, it exploits the block modules in its operational layer. The *Grid Model* block in Fig. 1 is able to model the power grid. By exploiting the PANDAPOWER [16] python library, it updates possible loads, generators, storage capacities, costs and physical constraints depending on the chosen scenario configurations. The *Grid Model* block prepares the data concerning the gird before solving a Power Flow (PF) or an OPF problem, it does this by using the power information measured or communicated by the aggregators or buildings. Then, the *PF/OPF* block in Fig. 1 is able to compute an OPF-based strategy to solve the balancing problem and reallocating the resources, or a PF for estimating the losses in the system. The OPF strategy is required only for the time-steps of the simulation in which the unbalance is greater than a predefined threshold, this check is performed by the *Grid Model* block.

(ii) ***Aggregator Agents*** allow the implementation of DR strategies. They are the service providers that act as intermediary between the *Building Agents* and the *DSO Agent*. When requested by the DSO, they estimate, from the buildings they aggregate, the amount of flexibility reserve that will be used to balance the grid. Their number, as well as the number of the buildings they are in charge of, is completely configurable to test different aggregation levels. Thanks to the *24h Forecast* module, they estimate the day-ahead power consumption profiles from the buildings and communicate it to the DSO. For the simulations presented the foreseen values are obtained by adding a uniform random noise to the buildings demand values. Moreover, using the *Flexibility Calculation* module, they compute the available flexibility in order to communicate this information to the DSO. The computational load of this task is distributed to the buildings environments, to avoid bottlenecks and parallelise processes.

(iii) ***Buildings Agents*** represent actual buildings in the system and simulate their thermal behaviour. They exploit the *Thermal Demand Sim* block (Fig. 1) to calculate the thermal demand and to act on the building HVAC system. The *Thermal Demand Sim* is one of the main contributions of this work and relies on an extension of the CEA dynamic demand forecasting tool [6]. The original version of this module was conceived to work as a forecasting tool to assess annual energy demand for each building with hourly resolution, exploiting a one-shot calculation. Therefore, it has been modified in order to carry out demand calculations at each time-step separately and for the desired period of time. Thus, *Thermal Demand Sim* is a time-stepped tool that is able to couple the benefits of the previous CEA module (i.e. the deep characterisation of the whole heat chain systems and the fast simplified ISO-13790 compliant RC model for the indoor ambient) with the following new functionalities. By working on a time-step basis, it is possible to integrate new control modules within each portion of the heat-chain, such as the emission system (e.g. the *Flexibility Calculation* proposed by the aggregators of this framework). In addition, the decomposition of calculations allow to reverse them and perform the simulation of power actuation in building premises. These enhancements allow to have a tool for the real-time characterisation of buildings thermal behaviour and control strategies.

C. Co-simulation workflow

Our framework aims at analysing the effects of a DR strategy in which the demand flexibility is taken from the buildings thermal behaviour. This flexibility enables the DSO to optimise the reallocation of resources to fulfil the unbalances between scheduled and measured power profiles.

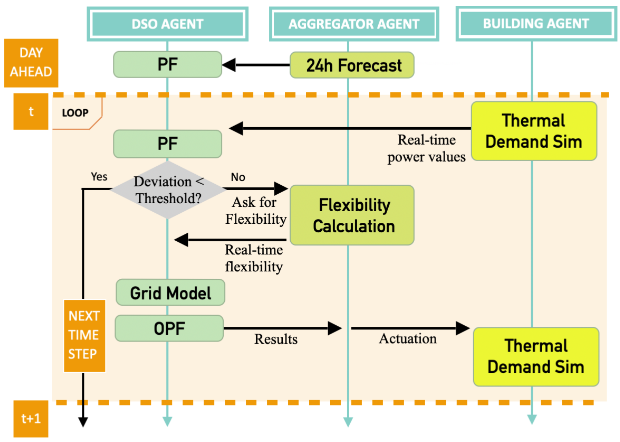


Fig. 2: Interactions taking place during a simulation time step

The process workflow of the simulation can be broken down into day-ahead and intra-day operations as shown in Fig. 2. In day ahead, two main actions are carried out: i) The *DSO Agent* collects the day-ahead forecast from the *Aggregators Agent*. ii) The DSO performs power flow calculations computing the value of the active power at the primary substation for the next 24-hours. Instead, the interactions taking place at each time step during the day are: i) The *Building Agents* compute their real power demand and the *DSO Agent* retrieves them. ii) The *DSO Agent*, exploiting this information, performs power flow calculations and compares the obtained active power value at primary substation with the scheduled one. The *DSO Agent* has a certain power threshold that composes an accepted range for the deviation between those two values. If this deviation falls within the power threshold, the *DSO Agent* is able to cover all the unbalance by itself, meaning that it no longer exploits flexibility from users. Instead if the power threshold is exceeded a message asking for flexibility is sent to the *Aggregator Agents*. iii) *Aggregator Agents* performs the calculation of the flexibility reserve, estimating how much flexibility the *Building Agents* are willing to offer for that time-step. This information is sent to the *DSO Agent*. iv) The *DSO Agent* computes the optimal power flow with the new information, changing the resource allocation to obtain the desired adjustment; v) The iteration is over when the results of the OPF calculation are spread back to the *Aggregator Agents* which modulate the HVAC systems in the *Building Agents* premises, following the indications.

IV. Experimental Set-up

The case study is composed by 1000 buildings in a city district, mostly multi-residential with some exceptions for buildings with a mixed usage typology (e.g. 80% residential, 20% commercial). Each building is supplied by a power to heat system composed by soil/water heat-pump and radiators as emission terminals. These are the technologies taken into consideration for this simulation. However, the framework is flexible in testing different solutions and assigning to each building different HVAC systems. Only the heating season has been taken into consideration, in particular the month of January of a typical meteorological year. We have used a Medium Voltage (MV) power grid consisting of a primary substation with three bus-bars operating at a nominal voltage of 22 kV, which on their turn supply 51 substations equipped with MV/LV transformers. The hierarchy configuration of the agents consists on 1 DSO and 11 aggregators clustering several buildings as shown in Table I.

TABLE I: Case study hierarchy configuration

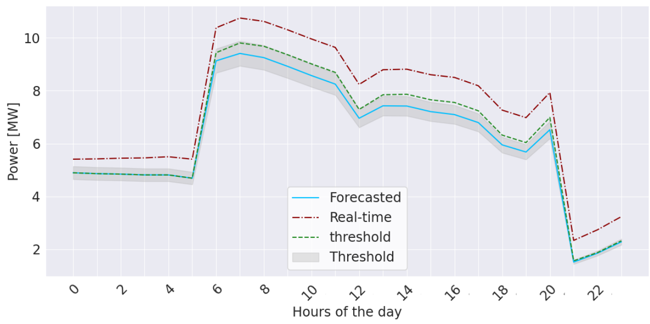
AggregatorID	Buildings	Buses	AggregatorID	Buildings	Buses
AGG_0	71	5	AGG_6	103	5
AGG_1	91	5	AGG_7	89	5
AGG_2	109	5	AGG_8	91	5
AGG_3	100	5	AGG_9	96	5
AGG_4	99	5	AGG_10	55	3
AGG_5	96	5			

By deviating from the scheduled temperature set-points in a range called temperature tolerance, a power flexibility reserve is generated and it can be exploited from the Aggregators or directly from the DSO as needed. In this perspective, we have tested two different scenarios: i) *Fixed deviation scenario*: all the buildings, given a configured tolerance range of temperature deviation, will offer the maximum flexibility in order to stay into the temperature tolerance; ii) *Random* deviation scenario: all the buildings at each time-step will choose the temperature deviation - i.e. the amount of flexibility - randomly, following a normal distribution between no deviation and the maximum amount. Simulations have been performed for each scenario testing three different temperature tolerance ranges, i.e. ± 0.5 °C, ± 1.0 °C, ± 2.0 °C. These temperature values have been chosen to be compliant with the ASHRAE standards [19] on the fluctuations of indoor temperature to avoid user discomfort. Two different time-step resolutions have been addressed, i.e. 1 hour and 15 minutes, to understand the limits of the RC formulation. The framework can be easily ran across different servers thanks to its distributed architecture and the TCP/IP communication.

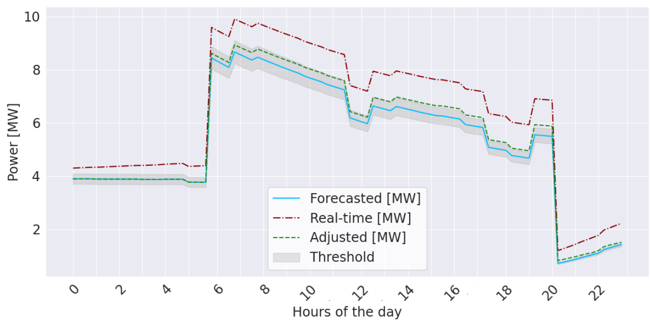
V. Experimental Results

In this section, we present the results of the simulations performed exploiting the proposed framework. The graphs in

Fig. 3 better show the balancing dynamics and the differences between time resolutions. Both Fig. 3a and Fig. 3b report a time snapshot of 24 hours at primary substation, showing the power profile of: i) the day-ahead scheduled trend (light-blue line), ii) the predefined power threshold (light-grey area), iii) the real-time values collected during every time-step (red dashed line) and iv) the adjusted curve (green dashed line) - i.e. the new power profile taking into account flexibility contribution. The scheduled curve is the day-ahead foreseen for the next 24 hours with a tolerance of 0.5°C. Then at each time-step, a new point composing the real-time curve is measured and the unbalance evaluated. The balancing strategy is triggered only when the red curve is out of the power threshold and it results in a new power profile, the modified green trend, which tends to return back to the scheduled values. By comparing Fig. 3a and Fig. 3b, we notice that both balancing behaviours are similar, thus models and strategies work fine with both the time resolutions. However, the scenario with 15 minutes time-step shows a much less smoother power profile. Therefore, as expected, a more frequent regulation on the time basis results in a more scattered behaviour.



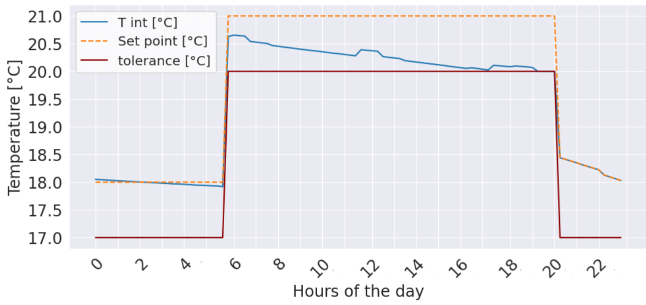
(a) 1 hour resolution



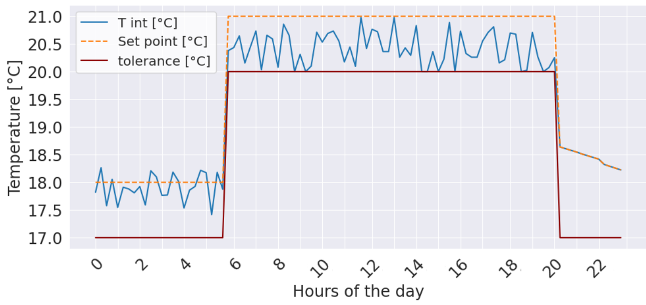
(b) 15 minutes resolution

Fig. 3: Snapshot of the *Fixed* scenario with tolerance of 0.5°C

Table II resumes the results for all the simulations. The metrics proposed to compare results are : i) *% of success*, i.e. the total number of times in which the adjusted curve was brought back inside the predefined power threshold; ii) *% covered by flex*, which represents how much the power unbalance has been fulfilled by the flexibility during the time-steps; iii) *Root Mean Square Error* (RMSE) in MW of the modified trend converging on the scheduled trend (e.g. green and blue lines in Fig. 3, respectively); iv) *T deviation* is the mean deviation in °C from temperature set-points registered during the whole simulation by all buildings. By observing columns *% of success*, *% covered by flex* and *RMSE*, it emerges that the *Random* deviation scenario generally performs worse. This depends on the random choice of temperature deviation in buildings. The only exceptions are the *Fixed* deviation scenario simulations with temperature tolerance of 2°C. In these cases, counter-intuitively, having a larger potential flexibility does not lead to higher performances. Instead, allowing some buildings to deviate from their indoor set-points by larger quantities, at certain time-steps, causes the over-exploiting of the buildings flexibility reserve. When this happens, the over-exploited buildings will run out of flexibility for the subsequent steps in order to recover the high temperature deviations.



(a) *Fixed* scenario tolerance 1.0 °C



(b) *Random* scenario tolerance 1.0 °C

Fig. 4: Snapshot of the inside temperature of a single building in 15 min time-step simulations

Looking at the column *T deviation*, we notice that the temperature deviation generally increases with the tolerance except for the *Fixed* deviation scenario with a temperature tolerance of 2°C. Indeed, in these simulations the temperature deviation is lower than the scenarios with a tolerance of 0.5°C and 1°C. In our opinion this depends on the OPF problem. When solving the OPF with 1°C of temperature deviation, resources are sufficient for the balancing. In the scenario with major deviations (e.g. 2°C), the balancing is performed distributing more evenly the flexibility request among buildings, thus leveraging the indoor temperature deviations. Figure 4 presents the effects of the two scenarios on the indoor temperature in a specific building. As shown in Fig. 4a (i.e. the *Fixed scenario*), the temperature decreases smoothly until

TABLE II: Results of all the simulations

Time-step	Scenario	Tolerance [°C]	% of success	% covered by flex	RMSE [MW]	T deviation [°C]
1 hour	fixed	0.5	68.95	88.67	0.273	0.42
		1	96.64	99.78	0.050	0.46
		2	88.02	99.82	0.273	0.14
	random	0.5	25.54	94.51	0.457	0.25
		1	64.78	88.04	0.275	0.42
		2	91.67	99.68	0.102	0.47
15 min	fixed	0.5	69.90	90.16	0.201	0.39
		1	89.38	99.95	0.079	0.36
		2	85.23	98.40	0.260	0.10
	random	0.5	26.69	97.56	0.374	0.23
		1	69.72	90.17	0.206	0.40
		2	87.82	99.94	0.127	0.35

the tolerance is reached. Instead, the temperature profile in the *Random scenario* (Fig. 4b) highly fluctuates due to the random choice of the flexibility reserve, but always into the temperature tolerance. It is worth noting that these fluctuations does not affect the indoor comfort of the user being within a very short range of temperatures.

VI. Conclusions

Our current studies aim at obtaining a tool for testing different demand-side strategies. As a starting point, we focused on thermal loads, proposing a framework that can estimate the flexibility at the household level exploiting our Thermal Demand Sim and it is able to manage unbalances at the primary substation thanks to the intermediary aggregators. The framework has been tested for 1000 buildings demonstrating the capability of the platform to work within a city district and at different time-step resolutions. Thanks to the modularity of the system different strategies have been tested, showing the effectiveness of the framework to act as a test-bed for further simulations and analysis. With the analysed scenarios, we have demonstrated that even in absence of additional flexibility and generation sources (e.g. storage and RES), good balancing results are obtainable with minor set-points deviations.

In conclusion, the first objectives have been fulfilled, and the framework appears as a promising tool for further integration. The introduction of market perspectives, the analysis of more complex control strategies at the building premises and the expansion of building archetypes for better addressing the diversity of the real world will be the key objectives for future works. All of this will come along with the strong awareness that tools similar to this will lead the way for more efficient and sustainable policies making in a Smart grid context.

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