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Using collective intelligence to enhance demand flexibility and climate resilience in urban areas

Vahid M. Nik [a,b,c,*], Amin Moazami [d]

[a] Division of Building Physics, Department of Building and Environmental Technology, Lund University, SE-223 63 Lund, Sweden
[b] Division of Building Technology, Department of Architecture and Civil Engineering, Chalmers University of Technology, SE-412 58 Gothenburg, Sweden
[c] Institute for Future Environments (IFE), Queensland University of Technology (QUT), Garden Point Campus, 2 George Street, Brisbane, QLD 4000, Australia
[d] Department of Ocean Operations and Civil Engineering, Faculty of Engineering, NTNU Norwegian University of Science and Technology, Ålesund, Norway

HIGHLIGHTS

- Collective intelligence is applied to manage the demand response among buildings.
- A simple set of rules of engagement and two response timescales are set.
- A finer timescale helps the system to become more effective and agile in absorbing shocks.
- CI improves the autonomy in absorbing shocks without the need for upgrading the central control.
- CI increases the climate flexibility on the demand side, promoting climate resilience.

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ABSTRACT

Collective intelligence (CI) is a form of distributed intelligence that emerges in collaborative problem solving and decision making. This work investigates the potentials of CI in demand side management (DSM) in urban areas. CI is used to control the energy performance of representative groups of buildings in Stockholm, aiming to increase the demand flexibility and climate resilience in the urban scale. CI-DSM is developed based on a simple communication strategy among buildings, using forward (1) and backward (0) signals, corresponding to applying and disapplying the adaptation measure, which is extending the indoor temperature range. A simple platform and algorithm are developed for modelling CI-DSM, considering two timescales of 15 min and 60 min. Three climate scenarios are used to represent typical, extreme cold and extreme warm years in Stockholm. Several indicators are used to assess the performance of CI-DSM, including Demand Flexibility Factor (*DFF*) and Agility Factor (*AF*), which are defined explicitly for this work. According to the results, CI increases the autonomy and agility of the system in responding to climate shocks without the need for computationally extensive central decision making systems. CI helps to gradually and effectively decrease the energy demand and absorb the shock during extreme climate events. Having a finer control timescale increases the flexibility and agility on the demand side, resulting in a faster adaptation to climate variations, shorter engagement of buildings, faster return to normal conditions and consequently a higher climate resilience.

1. Introduction

The IPCC report "Global Warming of 1.5 °C" [1] issued a dire warning that unless anthropogenic CO_2 emissions are halved by 2030, devastating changes will occur in ocean and on land and may play out sooner than previously expected and irreversibly. The frequency of some extreme events has increased over the last 30 years [2] and more weather-related disasters are expected in the future [3]. Increases are projected for heat waves with shorter return periods, droughts, wildfires, river, and coastal floods and wind storms [4]. Weather-related disasters may affect annually about two-thirds of the population in Europe by 2100 [5]. One example is the 2003 heatwave in Europe, causing 70,000 excess summer deaths as a result of, among other factors, maladapted built environments [6].

The energy sector and urbanization are key contributors to climate

* Corresponding author at: Division of Building Physics, Department of Building and Environmental Technology, Lund University, SE-223 63 Lund, Sweden.
E-mail addresses: vahid.nik@byggtek.lth.se, nik.vahid.m@gmail.com (V.M. Nik), amin.moazami@ntnu.no (A. Moazami).

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Nomenclature

AF	Agility Factor (average value)
af^t	agility factor at time t
CAS	Complex Adaptive System
CI	Collective Intelligence
CI-DSM	CI-based DSM
DAI	Distributed Artificial Intelligence
DFF	Demand Flexibility Factor (average value)
dff^t	demand flexibility factor at time t
DR	Demand Response
DSM	Demand Side Management
E^t_{CI}	Energy demand at time t with CI-DSM
$E^t_{no\text{-}CI}$	Energy demand at time t without CI-DSM
$E^t_{extreme,CI}$	Energy demand at time t during extreme weather conditions with CI-DSM
$E^t_{typical,no\text{-}CI}$	Energy demand at time t during typical weather conditions without CI-DSM
ECY	Extreme Cold Year
EMS	Energy Management System
EMSA	Energy Management Systems Aggregator
EWY	Extreme Warm Year
GCM	Global Climate Model
IBP	Incentive Based Program
ICT	Information and Communications Technology
IoT	Internet of Things
KPI	Key Performance Indicator
MAS	Multi-Agent System
PBP	Price Based Program
RCP	Representative Concentration Pathway
RCM	Regional Climate Model
RES	Renewable Energy Source
RTP	Real Time Pricing
TDY	Typical Downscaled Year
TOU	Time-of-Use
V2G	Vehicle-to-Grid
VRE	Variable Renewable Energy

change, meanwhile being affected by its impacts [7]. Increased urbanization will result in higher energy consumption in urban areas, which currently accounts for 65% of the global primary energy consumption, leading to 71% of energy-related GHG emissions [8]. The increased likelihood of more frequent and stronger extreme events [9] can induce malfunctioning of the designed urban infrastructures, including buildings and energy systems. Climate change uncertainties and extreme events can risk energy security in urban areas, affecting both the demand [10] and supply [11] sides. The projected scenarios for climate change [1,12], population growth [13] and economic growth [14] in urban areas demand to take proper climate change mitigation and adaptation actions. It is vital to cover the increasing energy demand through sustainable approaches [15] and increase the share of renewable energy technologies such as solar and wind, which are classified as variable renewable energy (VRE) technologies. VRE and urban demand are highly affected by climate conditions, causing mismatch in demand and generation profiles [11,16]. Moreover, direct integration of VRE technologies in the energy system is not easy and can induce cascade failures and blackouts [17]. Extreme weather events are one of the main reasons for energy disturbances [18,19] which can significantly retard the renewable energy integration levels in the future [11]. The demand side uncertainties can get intensified in urban areas due to increased complexities [20,21] and intensified extreme conditions [22,23]. This will add up to the uncertainties that exist in building performance, occupant behavior, control strategies etc. [24,25]. Such uncertainties induced by buildings at the urban scale can challenge the energy grid [26]. Therefore, rather than aiming for decarbonizing the energy systems and climate change mitigation only, it is essential to also plan for climate change adaptation [27]. Especially in urban areas that are characterized by high-energy density and heterogeneity in their energy use profiles [28]. Otherwise, transition solutions can induce vicious cycles and worsen the situation in the future [29]. Enhancing flexibility on both supply and demand sides can boost the movement towards reliable and robust energy networks based on renewable generation [30].

Flexibility can be defined as the adaptability of a system to a range of environmental variations [31]. Defining the relevant characteristics and key performance indicators (KPIs) highly depends on the scope and aspect of the study [32]. Recent studies on energy system flexibility can be classified into three groups based on considering the flexibility of (1) generation, (2) distribution, and (3) demand [30,33]. Higher climate flexibility helps the system to withstand the climate variations with a minimum degradation of its performance indicators [30]. The demand flexibility of buildings can become a major source of flexibility since buildings account for a large proportion of energy consumption [34,35]. Demand flexibility has been the focus of several studies [36–38], suggesting different definitions for flexibility (e.g. the capability to change the energy demand over time [39]) and different KPIs (e.g. power shifting capability [40] and available structural storage capacity [41]). Buildings can provide higher flexibility in different ways, e.g., utilization of thermal mass, adjustability of HVAC system use, and shifting of plug-loads [34]. According to Finck et al. [42], the identification, quantification, and control of demand flexibility is the major challenge for future grid operations and requires innovative methods and control strategies [43]. There is a need to improve demand side management (DSM) methods to better account for and implement demand flexibility. This becomes computationally challenging, especially considering the complex interactions that exist in urban environments.

An urban energy system is a complex system with the network of interacting factors, inducing complex patterns from relatively simple interactions [44]. Some of these factors are climate variations, microclimate and urban morphology, user behavior, energy policies, pricing, and advanced technical solutions (e.g., V2G and IoT) [45,46]. A major change in the environment of a complex system can induce a chain reaction of responses between the components of the system at the local level, which lead to a global behavior, a phenomenon referred to as emergence [47]. Emergence can be observed for an urban energy system during extreme events such as heat waves [48], increasing the peak loads at a much higher level both in magnitude and duration [49], reducing the renewable energy generation [50], and degrading the efficiency of conventional energy systems [51,52]. Such chain of events implies high stress on the grid, which can lead to the failure of the grid system and blackouts, with probable fatal consequences such as heatwaves in Chicago (1995) [53], Europe (2003) [52] and New York City (2006) [54]. Reaching higher renewable energy penetration levels in such complex systems becomes challenging [30], mainly due to the intermittent characteristics of renewable energy and the complexity with multi-spatial/temporal scales [55]. However, it is still possible to take advantage of the characteristics of complex systems towards reaching a higher flexibility and resilience [27].

As Ottino [56] explains, the “hallmarks of complex systems are adaptation, self-organization and emergence”. There is a growing interest in the research of complex systems with the three characteristics as they can effectively adapt to uncertain and unknown environments by themselves without the need to run extensive computations to control the system [57]. The so-called complex adaptive systems (CAS) are complex systems with the ability to adapt to changes through self-organization [58]. Self-organization is a dynamic mechanism during which a system automatically transforms itself to adapt to a changing environment [59], without any external control [57]. It is an emergent phenomenon that arises from the interactions of individuals at the local level [60]. In connection to complex systems, there have been considerable developments of methodologies for multi-agent systems (MASs). MASs are composed of multiple interactive components (or agents) that are capable of cooperating and solving problems that are beyond the abilities of any individual member [61]. MASs, as a major area under distributed artificial intelligence (DAI), are compound of relatively autonomous and intelligent parts, called agents. An agent can be characterized by a set of properties, which are; (1) autonomy: operating without the direct intervention of humans or others, and having (some) control over its actions and internal state; (2) social ability: interacting with other agents (and third parties); (3) reactivity: perceiving the surrounding environment and responding to its changes; (4) pro-activeness: showing goal-directed behavior and taking the initiative [62 63]. MASs have been used for power engineering applications [64] and energy and comfort control of buildings [65]. MASs can belong to a wider range of systems (e.g., including distributed problem solving and complex adaptive systems) called collective intelligent systems.

Collective intelligence (CI) is a form of universally distributed intelligence that works based on collaborative problem solving and decision making [66]. The collaborative and socially inspired computation systems are identified by their robustness, flexibility, and scalability [67]. The three characteristics that bind all the relevant CI systems together are adaptation, self-organization, and emergence [68]. The emergence of CI is intrinsically a process of self-organization [69]. CI systems, which are complex by nature, can adapt to uncertain and unknown environments, organize themselves autonomously, and exhibit emergent behavior [68]. This makes CI systems flexible and consequently more resilient against environmental variations or external shocks. Considering the characteristics of CI systems and knowing that empowering the autonomous operation of energy systems can improve their resilience [27,70] and help to bounce back towards equilibrium or stability after an extreme event [71], it would be interesting to investigate the potentials of adopting a CI-based DSM (CI-DSM) to cope with climate variations and extreme weather events.

This research work investigates the potential of CI in empowering the climate resilience of urban energy systems by increasing the demand flexibility in urban areas. A CI-DSM system is developed to control and set adaptation measures among buildings, which can be considered as agents in the complex urban energy system. CI enables to increase the level of self-organization in the system without the need for a central brain, through DAI and setting simple communication rules among buildings. Focusing on climate resilience and flexibility, the response of CI-DSM to the variations of the outdoor temperature (which affect the energy demand of buildings) are investigated. For the purpose of this study, a hypothetical neighborhood in Stockholm has been modeled and simulated for three different weather conditions: typical, extreme cold, and extreme warm. The energy demand of buildings during typical conditions is considered as the reference, which is used to set the control and communication strategies among buildings. Extreme weather conditions are considered as extraordinary conditions (or shocks) that CI-DSM should respond to. More than studying the performance of CI-DSM, impacts of timescale in setting the control/response actions are investigated by comparing two temporal scales of 15 min and 60 min. The whole procedure is explained in detail in the following sections. Section 2 provides a concise overview about DSM methods. Section 3 explains the novel CI-based method and the adopted building and climate models. Results are comprehensively explained in Section 4 and finally concluding remarks are discussed in Section 5.

2. Demand side management

DSM refers to the set of means that alter the pattern and/or magnitude of energy use, through reducing, increasing, or rescheduling the demand [72]. DSM has been considered as a tool for load shaping since the early 1980s [72]. It helps to increase the share of distributed generation, decarbonize the energy system, enhance the quality and security of supply, and postpone the need for new network investment [73]. DSM methods are usually a mixture of planning, implementation and monitoring of utility activities that influence the energy use of the customers [74]. Demand response (DR) – which gives the ability to control the energy use based on grid incentives [75] – plays an important role in DSM by improving grid stability through increasing demand flexibility [76] – which enables deviation from the reference load profile [77,78]. DR is a subsequent part of DSM programs, enabling the users to respond to the reliability or price triggers from the utility system operator [79], making the energy use more economic and/or environmentally friendly [74].

The supply from renewable energy sources (RES) can become volatile due to climate variations. DR is an effective and reliable strategy for the successful integration of renewable energy sources through implementing load flexibility whenever the system requires it [80]. It also helps to limit the need for backup generation capacity. Carreiro et al. [80] reviewed the role of energy management systems aggregators (EMSAs) in the Smart Grid context, considering DR technologies and the participation of end-users. Lund et al. [72] have thoroughly discussed DSM and energy flexibility measures, explaining their benefits to increase the share of renewable generation in energy systems. There exist several DSM approaches, such as night-time heating with load switching, direct-load control, load limiting, setting commercial/industrial programmes, frequency regulation, time-of-use (TOU) pricing, demand bidding, and smart metering and managing appliances [73]. DSM and DR methods can be divided into two main groups of incentive based programs (IBPs) and price based programs (PBPs). Incentive based programs are either classical or market based, which the former implies direct load control or load limiter, while the latter enables the user to participate in various incentive based load reduction programs. PBPs operate based on dynamic electricity pricing rates in real time, such as TOU, which is widely implemented since it needs limited enabling technologies. Among PBPs, real time pricing (RTP) is the most promising DR technique, meanwhile the most complex (considering both hardware and ICT). RTP enables the users to choose their load patterns and limits the intervention from the utility side to customers, therefore does not raise huge policy issues [79].

Although the concept of DSM is not new, its implementation has been slow [73]. Network management becomes very challenging when smart appliances are connected to the grid and a cost effective integration of RES is expected [80]. Lund et al. [72] have counted multiple barriers that retard the application of DSM, some related to inadequate ICT infrastructure, the inherent privacy and security risks, timely communication of energy and price information, poor response from non-automated users, weak involvement of stakeholder, inadequate data handling guidelines, and the lack of regulatory processes and policies to promote DSM. Most of the available DSM methods are based on load shifting and price based incentives, needing a two-way communication [74]. They need a significant deployment of sensors and control devices as well as sophisticated energy metering and trading functions. This requires the proper integration of ICT with the energy network and a platform to control and change the pattern and magnitude of the utility's load and communicate with the demand side [73]. The majority of the methods for RTP and DR scheduling require extensive data exchange between the system operator and end-users, which can cause scalability issues in a large-scale deployment [80]. This makes the optimization problem quite challenging, especially considering the large number of end-users with different preferences, conditions and uncertainties [81,82]. Convergence of the Internet and intelligent devices results in having smart energy systems with networks of sensors and smart meters extended till the end-user, changing the patterns of energy production and consumption, meanwhile collecting and sharing data with high frequency (e.g. every 15 min) over long periods. This will result in energy big data which can bring considerable opportunities and at the same time challenges to the field. Some of the energy big data challenges are related to the need for data collection, storage, management and analysis; developing methods for data driven decision making; generating value and useful knowledge; and protecting the user's privacy [83].

All in all, DSM-based solutions increase the complexity of the system operation compared with traditional approaches, which makes them less competitive [73]. Beside implementing techno-centric approaches, there is a need to develop more user-centric and information-based approaches that provide more holistic solutions [84]. There exist multiple mathematically proven DSM techniques, however understanding the everyday user can be very difficult using the available techniques [74]. There is a need for less complicated techniques with greater potentials to promote the user's participation [74]. The future DSMs should be able to integrate human feedback into the control loop and prevent user's discomfort [76]. Moreover, there is a need to further develop methodologies for the quantification of costs and benefits, setting the market structure and incentives [73]. In this regard, data driven solutions, e.g. using machine learning [43] or reinforcement learning [76], can be useful. However, the challenge of dealing with big data still remains.

This work suggests a new method to change the energy use patterns for the benefit of the whole system. The method has potentials to limit the need for data transfer and storage and simplify the communication logic, meanwhile increase the collaboration between components in the demand side. The method is based on implementing CI into DSM, which is called CI-DSM in this work.

3. Methodology

The novel approach which is discussed and presented in this work is based on setting certain adaptation measures to buildings through simple communications between buildings and energy system using collective intelligence. The application of CI is exemplified for controlling the energy performance of an urban area in Stockholm for typical, extreme cold, and extreme warm years, as briefly described in Section 3.1. The procedure of developing CI-DSM and its framework are explained in Section 3.2. Two KPIs are defined for the purpose of this work which are described in Section 3.3.

3.1. Building models and climate data

A hypothetical residential urban area in Stockholm is studied in this work, including 153 buildings. These buildings represent the residential building stock in Stockholm, as presented by the Swedish National Board of Housing, Building, and Planning (Boverket) [85]. The energy performance of buildings is modeled in Simulink/Matlab, simulating the energy demand with an hourly temporal resolution, calculating the energy for heating, cooling, hot water, fans, and heat recovery (if the building is equipped with the heat recovery system). The building energy model is a linear explicit discrete time-variant model based on the lumped system analysis approach [86]. Each building is considered as one zone, governed by the law of conservation of energy at each time step, considering the heat losses due to transmission and ventilation and the heat gains from solar radiation, tenants and appliances. Stockholm is a heating dominated city, where the need for heating is much greater than cooling and many of the existing residential buildings do not having any cooling system installed [87]. To cope with extreme warm conditions and for the purpose of this study, a hybrid cooling strategy (natural and mechanical) has been set which the cooling demand accounts for the latent cooling load. The model has been verified and used for several applications (e.g. [86–88]) and more details about it are available in [86].

Simulations were performed for the typical, extreme cold and extreme warm weather conditions over the period of 2010–2039. In this regard, three weather data sets were used in the energy simulations; typical downscaled year (TDY), extreme cold year (ECY), and extreme warm year (EWY). These weather data sets were synthesized considering five global climate models (GCMs), forced by three representative concentration pathways (RCPs) – RCP 2.6, RCP 4.5, and RCP 8.5 – and downscaled by RCA4, which is the fourth generation of the Rossby Centre regional climate model (RCM) [89] (more information about the preparation and application of RCM weather files in building simulations are available in [88,90,91]). In total, 13 future climate scenarios were used to synthesize TDY, ECY and EWY. TDY is one-year (8760 h) weather data synthesized based on the months with the most typical temperatures; 12 months, each representing the most typical month among the 390 sets of months (13 scenarios, each 30 years of data). Adopting a similar logic, ECY represents the coldest year and EWY the warmest (a detailed description about synthesizing the representative weather files is available in [16]). Fig. 1 compares the moving average of the outdoor temperature for the three weather data sets. It is important to consider that ECY and EWY are the pessimistic scenarios that are used to set the system boundaries. In this work, the energy simulations using TDY are used as the reference (typical conditions) and those with ECY and EWY as extreme conditions to assess the impact of CI-DSM in managing the energy performance of the urban area.

3.2. Implementing collective intelligence into demand side management

The key to developing a CI-based control system is to define simple models of local interactions that give rise to self-organized patterns. Studying self-organization in social insects, Bonabeau et al. [92] identify four basic characteristics for CI: (1) positive feedback, relating to simple rules of thumb promoting the creation of structures; (2) negative feedback, which counterbalances positive feedback and helps to stabilize the collective pattern; (3) amplification of (random) fluctuations, enabling to discover new solutions; and (4) multiple interactions, which can be performed directly or through the environment. Schut [68] distinguishes enabling and defining properties for CI. The enabling ones are on the local/agent level and having them enables CI to emerge. The enabling properties that Schut counts are: (1) adaptivity: changing to deal with the environment; (2) interaction: agents/individuals interact with each other; and (3) rules: describing the behavior of an individual

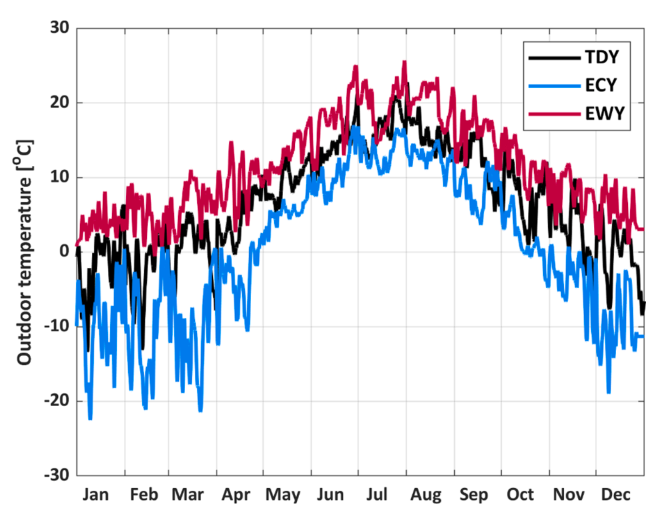

Fig. 1. Moving average of the outdoor temperature in Stockholm for three climate scenarios, representing typical (TDY), extreme cold (ECY) and extreme warm (EWY) years.

or whole system. The defining properties are on the global/system level and having them means the system is a CI one. Schut counts these defining properties: (1) global-local: the aggregation level, concerning the system as a whole and the individuals in the system; (2) randomness: a complex system usually has some randomness to show self-organized critical behavior; (3) emergence: “the whole is more than the sum of the parts” [93]; (4) redundancy: representing the same knowledge (e.g., rules) at different places in a system (e.g., every individual work with the same rule set); and (5) robustness: resistance against malfunctioning.

Several properties of a CI-based system help it to become resilient and pass the environmental shocks and extreme events safely. As thoroughly discussed in [27], being climate resilient implies that the energy system should have certain characteristics, some relevant to its stability, reliability, robustness and flexibility. It is important that the system accounts for plausible extremes and unprecedented factors. A climate resilient energy system should be able to reorganize during extreme events and adopt a transient strategy. In this regard, CI-DSM is interpreted as an approach to improve the climate resilience of urban energy systems through increasing the flexibility on the demand side. This will work as an adaptation mechanism during extreme climatic events to decrease the need for extra energy supply. In other words, CI enables the buildings’ responses at the local level to give rise to self-organized patterns at an urban scale, which helps the energy system to pass the extreme events safely. Fig. 2 graphically represents the idea and demonstrates how the overall CI (the brain of the energy system) emerges from the distributed intelligence of individual buildings (each cell of the brain). At each cell, a central data processing and control system is in charge of applying adaptive measures. It also shows how the buildings are clustered according to their defined priority (check 3.2.2) and communicate using forward/backward signals.

3.2.1. *Creating the reference case*

The reference case represents the energy performance of the buildings during typical weather conditions (TDY). For creating the reference case, the energy demand of all the 153 buildings is simulated with the hourly temporal resolution, generating 153 hourly heating and cooling demand profiles over one year. By summing up the hourly profiles we reach the hourly heating and cooling demand profiles of the considered area, which are time series with 8760 data points and representing the heating and cooling demand of the urban area over a typical year.

3.2.2. *Grouping the buildings*

In reality, each building can be considered as a component/agent in the energy network, communicating with the surrounding buildings. However, for the sake of accelerating the calculations in this work, buildings are gathered in ten groups; nine with 15 buildings and one with 18 buildings. The grouping is done randomly; no priority is defined for the buildings but for the groups, according to the group number. For example, 15 buildings are randomly selected and put into Group 1. Then Group 1 has a higher priority for adaptation (or setting new control measures) than Group 2. So, when the energy demand is higher than typical conditions, the adaptation measure is firstly applied to Group 1 and then to Group 2 (in the case of need, at the next time step) and so on. Such priority can also be defined within the appliances and equipment within individual buildings.

3.2.3. *Communication in the network*

The backbone of CI is simple communication between components of the system (without a central brain). In this work, the intention is to define a simple communication routine between building groups and the energy system. The assumption is that the urban energy system supplies

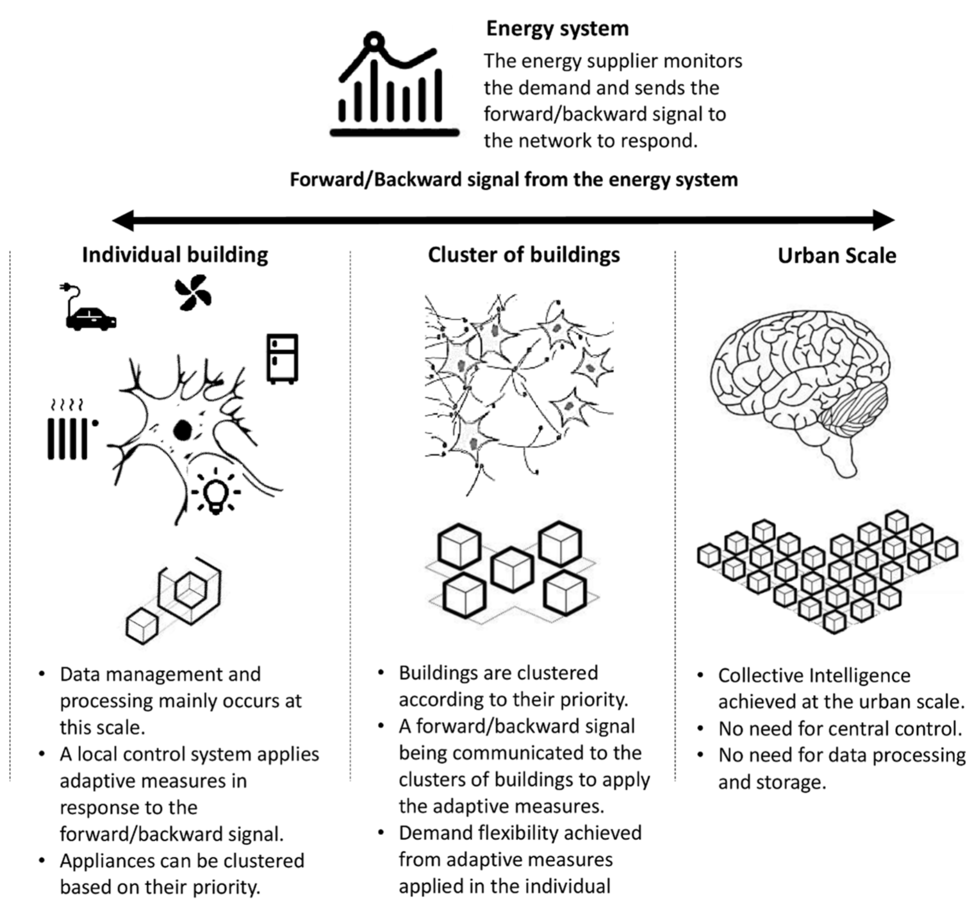

Fig. 2. Graphical representation of implementing CI in buildings in an urban area.

the required energy at each time step while the aim is to decrease the demand to the level of typical weather conditions (as close as possible) during extreme climatic conditions. Therefore, the communication rules are set with a simple logic and for a simple network (check Fig. 3 that represent the rule of engagement schematically):

- Each building group can communicate only to the next or previous group (also referred as the neighboring groups).
- The communication signal is 0 or 1, which 1 is to apply/activate the adaptation measure (forward signal), and 0 is to disapply/deactivate that (backward signal).
- The communication signal is forward (1) if the hourly supply (from the energy system/provider) is above the reference/typical conditions, otherwise it is backward (0).

3.2.4. Setting the adaptation measures

Adaptation measures are those sets of actions to decrease the excess energy demand, compared to the reference conditions, with the purpose of helping the energy system to pass the extreme events safely. In other words, adaptation measures are the planned flexibility measures on the demand side to increase the climate resilience of the energy system.

The only adaptation measure which is defined in this work is extending the span of indoor temperature from 21 °C to 24 °C to 19–26 °C. For example, if there is a cold day, and the energy demand is higher than the typical conditions, the minimum indoor temperature is set to 19 °C. The 2 °C extension results in a smaller heating demand and consequently a lower load on the energy system. As mentioned previously, the priority is with the first group of buildings. For example, if the energy demand at time step t during ECY is higher than TDY, the range of acceptable indoor temperature is set to 19–26 °C for Group 1 at $t + 1$. If the energy demand at $t + 1$ is still higher than TDY for $t + 1$, the adaptation measure is set for Group 2 and so on (forward signal, equal to 1) until reaching the last group. If the energy demand is still higher than the typical conditions after applying the adaptation measure to all the groups, no further action is taken in this work, and apparently higher energy supply, than typical conditions, will be required from the energy system. However, in real cases, we can set a bunch of adaptation measures, for example, decreasing the ventilation rate of buildings, lowering the flow rate of domestic hot water etc. When the total demand is equal or lower than typical conditions, it is checked if any adaptation measure has been applied to the building groups, then disapplying those group by group (per time step) with the reversed order. For example, if the adaptation measure is applied till Group 4 and at time t the energy demand is not higher than typical conditions, then Group 4 gets back to normal conditions at time $t + 1$ and Group 3 at time t + 2 and so on

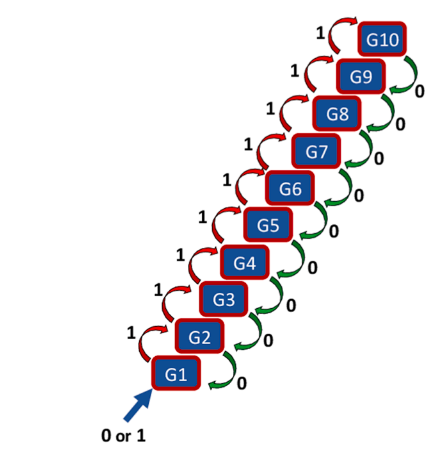

Fig. 3. Schematic representation of the communication signal transfer (rule of engagement) between groups of buildings.

(backward signal, equal to 0) as long as the energy demand condition is fulfilled. An overview of the developed framework to implement CI into energy simulations and control the demand is shown in Fig. 4, while Fig. 5 exemplifies the communication for seven time steps.

There can be several scenarios to set the logic/algorithm for the communication and adaptation measures, varying based on the case, needs, and technicalities, while considering other influencing factors such as price, user response etc. In this work, the intention is to keep that logic very simple, meanwhile general, to make it scalable and increase its applications.

3.2.5. Timescale for communication

The adopted timescale for communication, and consequently setting the adaptation measures, can alter the performance of CI-DSM. To study the impacts of timescale, two timescales of 60 min and 15 min are adopted in this work. The finest timescale is set to 15 min since it is usually the finest timescale to adopt in reality due to the thermal mass of buildings and technical concerns (e.g., unnecessary valve fluctuations) [94].

3.3. Key performance indicators

Several indicators are used in this work to investigate and compare the effectiveness of the designed CI-based adaptation measures, which most of them are standard and widely used. Moreover, two KPIs are defined explicitly for the purpose of this work, namely, *Demand Flexibility Factor (DFF)* and *Agility Factor (AF)*, which are introduced in the following. It is important to remember that these KPIs are defined for the specific purpose of this work and can be modified based on the needs of another work.

3.3.1. Demand flexibility Factor

There is no standard definition or quantification approach for demand flexibility [40]. Considering buildings, a general definition of demand flexibility can be defined as the deviation (or shift) from the reference demand profile [78,95]. Based on the need, any type of energy demand or a combination of them can be used in assessing demand flexibility, while some also include cost in their calculations [78,96]. For example, Le Dreau et al. [96] suggest the flexibility factor as an operational performance indicator, considering variable electricity price and indicating the potential of the system to shift the heating demand from high-price to low-price periods. For the purpose of this work, demand flexibility is defined as the potential of the CI-based system to reduce the energy demand (i.e. space heating and cooling demand) compared to the ordinary system (without CI control). In this regard, *Demand Flexibility Factor (DFF)* is defined according to relations (1) and (2) to have a quantitative reflection on the energy saving achieved using the CI-based system. *DFF* is calculated for each time step for exactly the same weather conditions. Relation (2) is used to calculate the average value, providing the overall view about the demand flexibility over a time span.

$$dff^t = \frac{E^t_{no-CI} - E^t_{CI}}{E^t_{no-CI}} = 1 - \frac{E^t_{CI}}{E^t_{no-CI}} \tag{1}$$

$$DFF = \sum_{t=1}^{t_{end}} \frac{dff^t}{t_{end}} \tag{2}$$

where dff^t [–] is the demand flexibility factor per time unit (hour in this work), E^t_{no-CI} [kWh] is the energy demand at time t [h] when there is no CI-DSM and no adaptation measure is applied, and E^t_{CI} [kWh] is the demand at the same time when CI-DSM is working and applying the adaptation measures in the case of need. Energy demands are calculated for the same weather conditions which is the extreme weather scenario in this case. The maximum of dff^t, and DFF, can be one, which is the case when applying the adaptation measures results in zero energy demand. The minimum should be zero when the adopted measures do not make

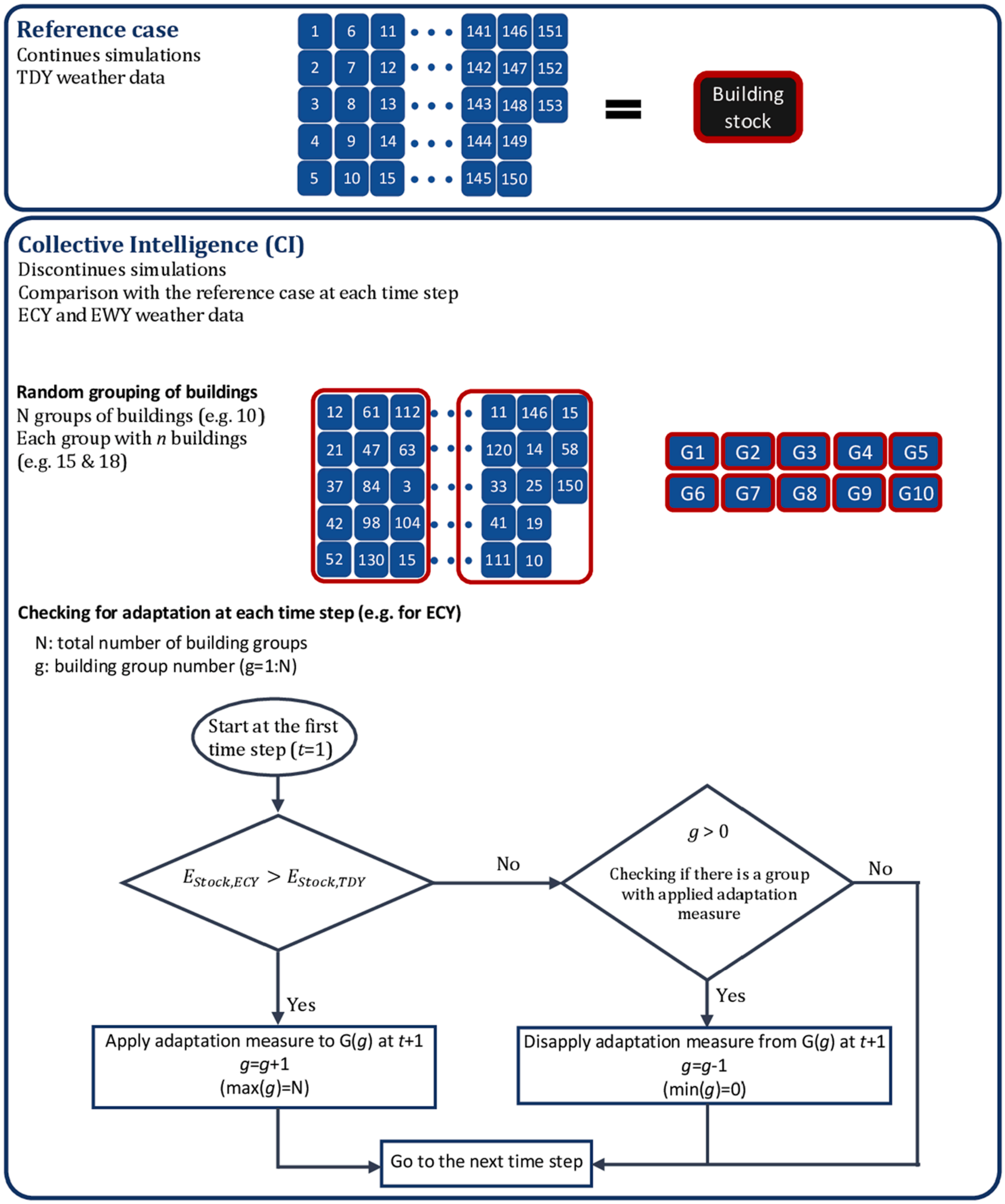

Fig. 4. The developed framework for combining collective intelligence with energy simulations.

any improvements, and the demand is at the same level of extreme conditions without any adaptation. However, if the adaptation measure is bad enough to work worse than the reference case (with no adaptation), dff^t can have negative values.

3.3.2. Agility Factor

A resilient energy system should speedily recover and learn from shocks [97,98]. *Agility Factor (AF)* is defined to assess how fast the adaptation measure helps the system to respond to extreme events and absorb the shock. In other words, how fast the system realizes extraordinary conditions and reacts, trying to decrease the demand to the level of typical conditions. Moreover, *AF* helps to distinguish the differences between the selected temporal scales to set the adaptation measures. *AF* is a reflection on the performance of the CI-based system that absorbs the shock. The agility factor is defined as the following:

$$af^{t+1} = 1 - \frac{abs\left(E^{t+1}_{extreme,CI} - E^{t+1}_{typical,no-CI}\right)}{abs\left(E^{t}_{extreme,CI} - E^{t}_{typical,no-CI}\right)} \quad (3)$$

$$AF = \sum_{t=2}^{t_{end}} \frac{af^t}{t_{end} - 1} \quad (4)$$

where af^{t+1} [–] is the agility factor per time unit, $E^{t+1}_{extreme,CI}$ [kWh] is the energy demand at time $t + 1$ [h] during extreme conditions when adaptation measures are applied using CI (CI-DSM is working), and $E^{t+1}_{typical,no-CI}$ is the demand during typical conditions with no adaptation. The difference between these two energy demands is compared with the previous time step (t). The average of af^{t+1}over time is AF [–], which is calculated according to relation (4). The maximum of af^{t+1}, andAF, can

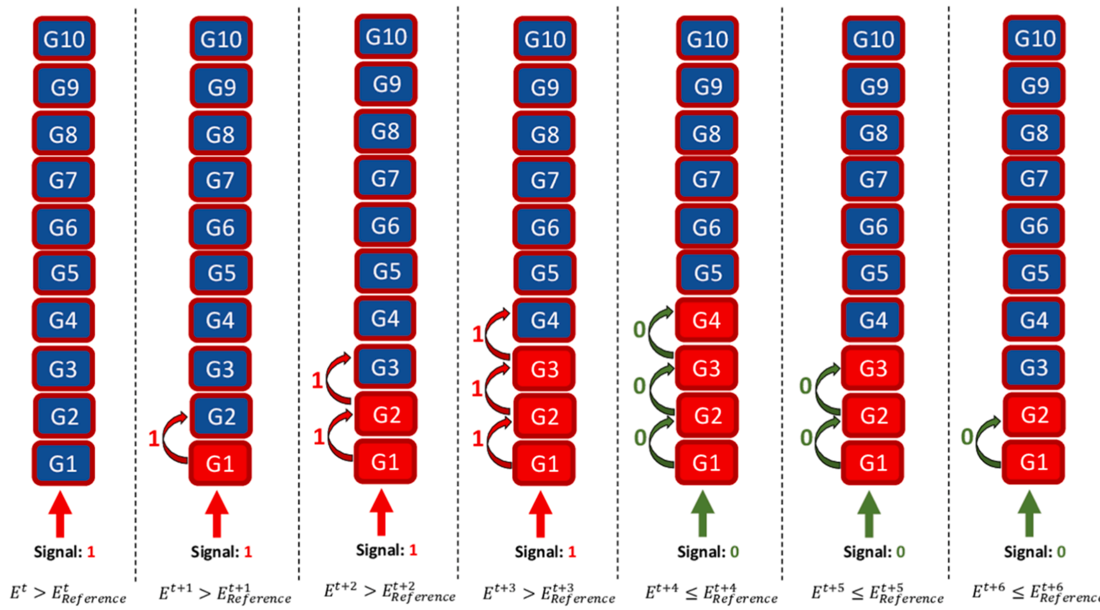

Fig. 5. Schematic representation of the CI-DSM logic for applying and disapplying adaptation measures to building groups during seven time steps. Forward signal (1 – red) results in applying the adaptation measure at the next time step while the backward signal (0 – green) disapplies the measure. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

be one and there is no limit for the minimum value. Having values close to 1 is better since it corresponds to the fact that the energy demand at $t + 1$ is decreased to values close to typical conditions (a smaller difference from the reference values compared to the previous time step). Since the response time is essential when we assess resilience, *AF* is defined in a way to reflect on the extent of the response per time unit. This is specifically useful to compare the effectiveness of different timescales for setting the CI-based control system. In this work, we have selected the typical conditions as the reference for *AF* since extraordinary conditions are those with the energy demand above the typical conditions. Depending on the need, the reference can be selected differently.

4. Results

The combination of buildings, climate conditions and control strategies which are described in Section 3 results in seven sets of energy simulations which are assessed in this section to investigate the impacts of CI and the adopted timescale in controlling the energy demand. In the following, 'ordinary buildings' refers to buildings with no adaptation measure, which means there is no extension in the span of indoor temperature, keeping it as 21–24 °C. The performance of the ordinary buildings during typical weather conditions is considered as the reference in this study (TDY – Reference), while their performance during extreme weather conditions can be considered as the worst case or the maximum demand scenarios (ECY – noCI and EWY – noCI). The other four cases are the solutions to decrease the energy demand during extreme weather conditions through using CI-DSM and applying the adaptation measure, which is extending the span of indoor temperature to 19–26 °C. These four cases are divided based on the weather conditions – extreme cold or extreme warm – and timescale for the CI-based control – 15 min or 60 min (the control logic explained in Section 3.2.4). In brief, the seven cases studied in this section are:

- TDY – Reference: ordinary buildings simulated for typical weather.
- ECY – noCI: ordinary buildings simulated for extreme cold weather.
- EWY – noCI: ordinary buildings simulated for extreme warm weather.
- ECY – CI-60 min: CI-DSM (buildings with adaptation measure using CI) with 60 min timescale and simulated for extreme cold weather.
- ECY – CI-15 min: CI-DSM with 15 min timescale and simulated for extreme cold weather.
- EWY – CI-60 min: CI-DSM with 60 min timescale and simulated for extreme warm weather.
- EWY – CI-15 min: CI-DSM with 15 min timescale and simulated for extreme warm weather.

Since the only adaptation measure is extending the span of indoor temperature, variations in the energy demand are only reflected in heating and cooling demand. Therefore, in the following, the focus is on the indoor temperature (T_{indoor}), heating demand and cooling demand.

The emergent behavior of building groups in response to weather variations is studied by investigating the pattern of applying/disapplying the adaptation measure among buildings, both for CI-60 min and CI-15 min. This is visualized in Fig. 6 for ECY during whole year, while certain cold hours during ECY are visualized in Fig. 7 and certain warm hours during EWY in Fig. 8. The last two figures help to better understand the differences between the two timescales and the penetration level of the emergent behavior. According to the figures, the engagement of the agents (or the application of the adaptation measure on buildings) and the penetration of the emergent behavior depend on the selected timescale. For ECY in Fig. 7 having a finer timescale (CI-15 min) helps the system to absorb the shock faster, with less number of buildings being engaged. The 15 min timescale also makes the system more agile during EWY in Fig. 8 (faster response and recovery, or getting back to normal conditions faster), while it engages a bigger number of buildings (deeper penetration of the emergent behavior) during a shorter period of time. Having the finer timescale of 15 min over a long lasting warm period keeps the emergent behavior moving and pushes the whole system to adapt to new conditions. For the 60 min scale in Fig. 8, the adaptation measure is applied until the sixth group of buildings, and after that, CI-DSM starts to disapply the adaptation measure since the outdoor temperature decreases, and less cooling is needed. In other words, for the less agile system (CI-60 min), the response time takes longer and a smaller number of buildings get affected by the adaptation measure. However, it results in a larger energy demand and consequently a larger load on the energy system.

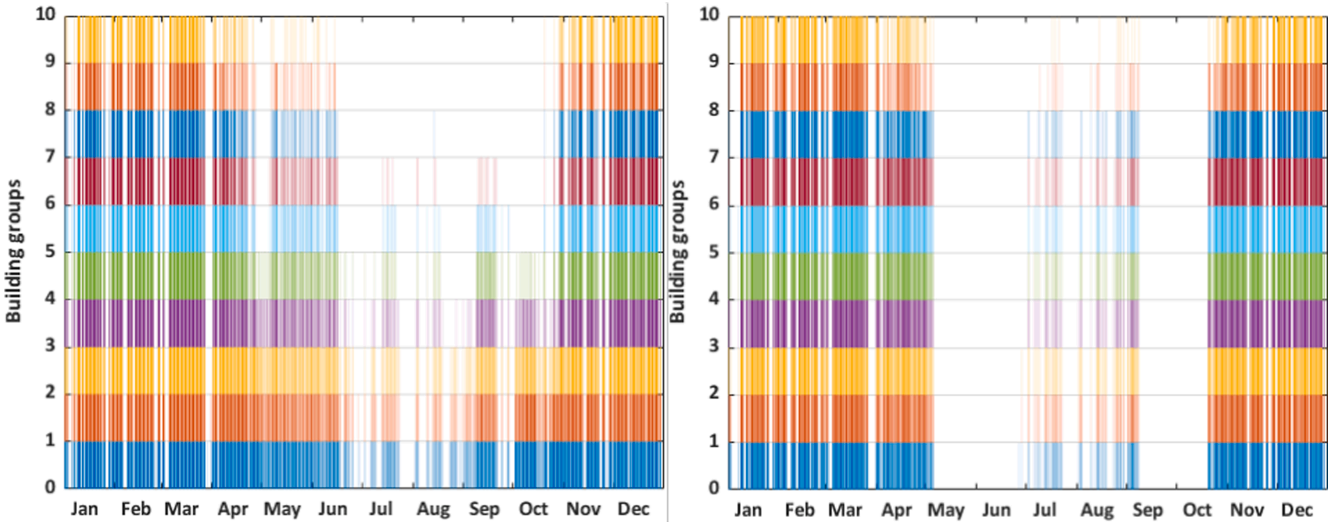

Fig. 6. The pattern of applying/disapplying the adaptation measure (extending T_{indoor} span) during extreme cold year (ECY) when the timescale is (left) 60 min and (right) 15 min.

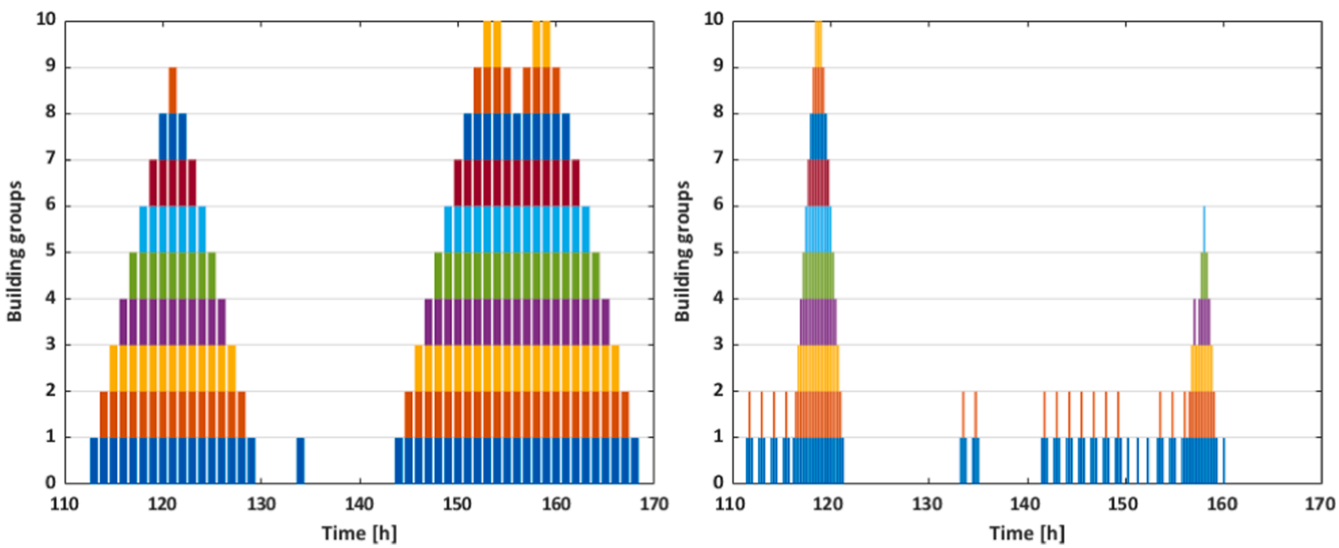

Fig. 7. The pattern of applying/disapplying the adaptation measure (extending T_{indoor} span) during certain hours of extreme cold year (ECY) when the timescale is (left) 60 min and (right) 15 min.

An overall overview of the engagement level of buildings during ECY and EWY with the two timescales is provided in Fig. 9. According to the figure, the 15 min scale results in less/shorter engagement of buildings, i.e., faster return to normal levels, as is visible by a higher percentage of CI-15 min values with zero number of buildings. This difference is more visible during ECY, which makes sense since Stockholm is a heating dominated region and the need for cooling is much less than the need for heating, even during extreme warm years. Therefore, the energy system (both in the urban and building level) is more active to supply the heating demand. The 15 min timescale results in more occasions with all the buildings being engaged compared to 60 min (check building group 10 in Fig. 9); however, the difference is not considerable (around 4%).

The main intention of implementing CI is to support the energy system during extreme climate events by decreasing the demand to values close to typical conditions. The cumulative distributions of the heating and cooling demand in Fig. 10 help to see the impact of CI on decreasing the energy demand. Obviously, not having CI during ECY and EWY results in an enormous increase in the demand. For ECY, the heating demand reaches 64% above the annual demand for typical conditions. For EWY, this increase is enormously high, reaching around 3000% more than the demand for typical conditions. Such a huge relative increase in the cooling demand is because of two facts: (1) the cooling demand during typical conditions in Stockholm is very small (check 'TDY – Reference' in Fig. 10-right), and (2) EWY is a pessimistic scenario with 12 extreme warm months, resulting in enormous increase in cooling demand. It is important to remember that the extreme warm/cold conditions stay for all the 12 months in EWY/ECY, as described in Section 3.1 and Ref. [16]. Implementing CI decreases the energy demand during extreme conditions for both the timescales. During ECY, CI-60 min and CI-15 min reduce the annual heating demand respectively to 38% and 44% less than noCI. Such a decrease is more significant for the cooling demand during EWY, around 1383% for CI-60 min and 2015% for CI-15 min.

Apparently, having the timescale of 15 min to communicate and set the adaptation measure helps to decrease the energy demand more effectively. However, as is visible in Fig. 10, the impacts of having a finer timescale are not very visible during the cold months and its benefits appear from May. Variations in the heating demand profile are

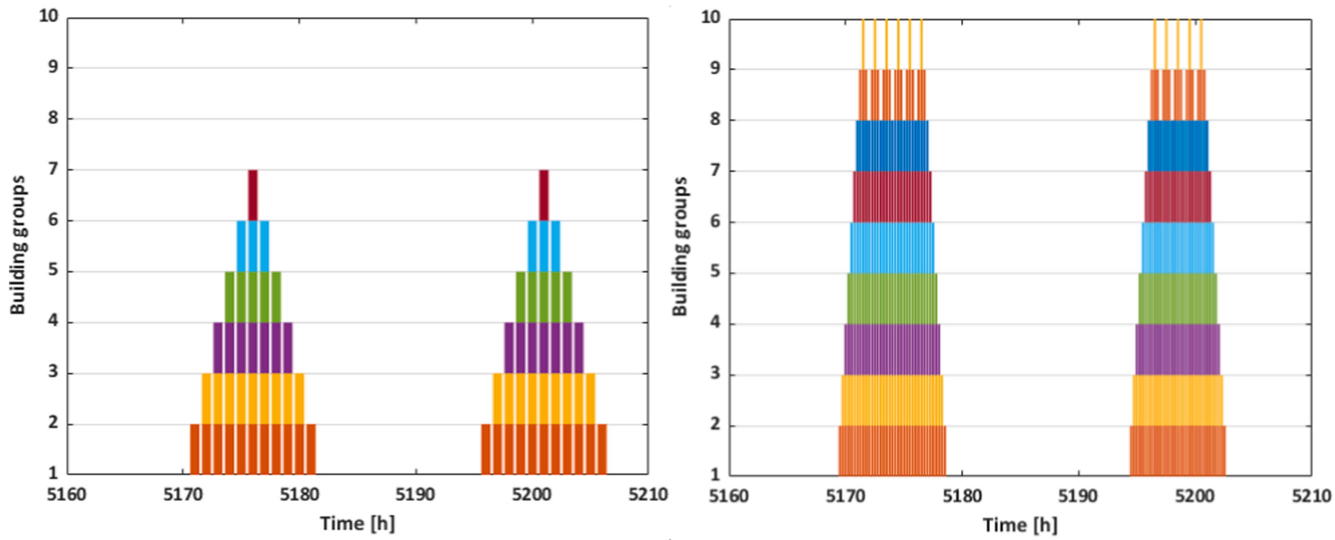

Fig. 8. The pattern of applying/disapplying the adaptation measure (extending T_{indoor} span) during certain hours of extreme warm year (EWY) when the timescale is (left) 60 min and (right) 15 min.

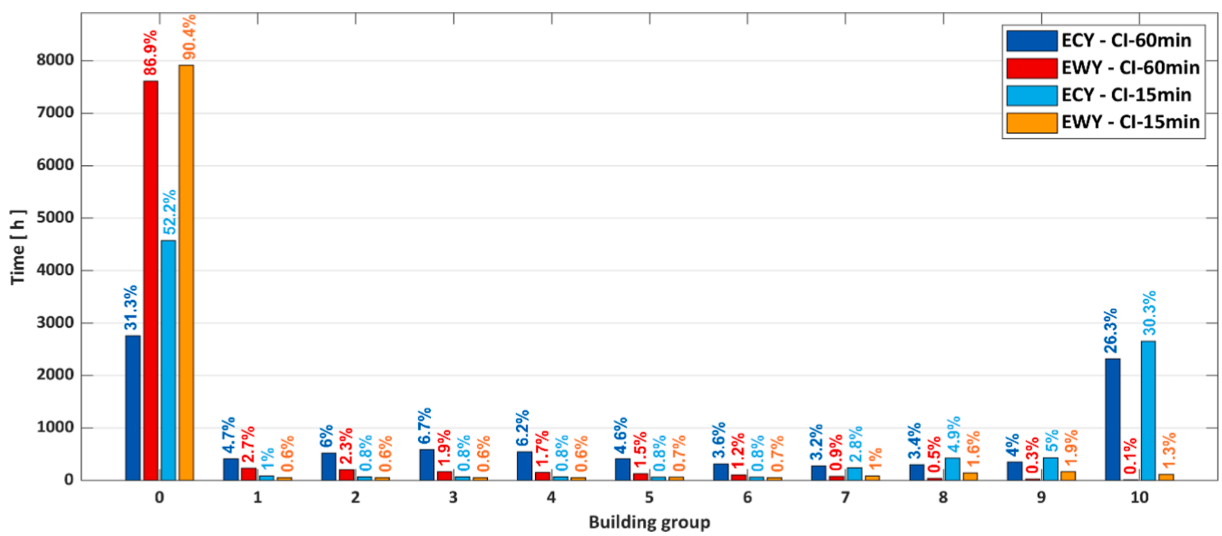

Fig. 9. Annual percentage of the building groups with the adopted measure (extended T_{indoor} span) during extreme cold and warm years when buildings are managed by CI with 15 min and 60 min timescales.

visualized in Fig. 11 by plotting the moving average of heating demand adopting a 24 h window. A closer look is provided in Fig. 12 for three days (with 1 h resolution) in winter and spring. Both CI-60 min and CI-15 min decrease the demand, while their impact is quite similar during winter, compared to spring which CI-15 min keeps the demand lower. This occurs because the difference between the heating demands of 'TDY – Reference' and 'ECY – noCI' during spring is not as large as winter, resulting in more forward-backward jumps between the two profiles when the timescale is 60 min while keeping the 15 min timescale helps to keep the performance closer to the reference case. This is further investigated by looking into the monthly average of the calculated heating and cooling demands in Fig. 13 and Table 1. In Fig. 13, CI-15 min has the lowest heating for an extreme cold year over all the 12 months in a year, with considerable differences from CI-60 min during May, June, and September. These are among the months that the need for heating demand is much lower than the cold season (Nov-Dec & Jan-Mar); however, heating is still needed occasionally. A finer temporal scale for controlling buildings helps to shave the extra demand faster and more efficiently, meanwhile, keeping the buildings more engaged. This is further elaborated by looking into the distribution of the indoor temperature in Fig. 14. During cold months in ECY (the two stacked bar charts on top), most of the buildings are set to the indoor temperature of 19 °C, which is the minimum accepted indoor temperature (and the maximum level of adaptation measure in this case). As is visible, the patterns of indoor temperature during cold months are very similar for ECY – CI-60 min and ECY – CI-15 min in Fig. 14.

The effectiveness of CI in decreasing the cooling demand during extreme warm summer months is visible in Fig. 13-right, especially for CI-15 min, which decreases the cooling demand around 1.8 times more than CI-60 min in July (check Table 1). The impact of the adopted timescale is further analyzed in Figs. 15 and 16, showing the distribution of the heating and cooling demand, respectively, for 10 days with the highest demand (left) and 10 days with a medium demand and considerable difference between the two timescales (right). For the heating demand in Fig. 15, the two timescales perform quite similarly during the high-demand days while CI-15 min decreases the demand better during medium-demand days. Differences during high-demand cooling days are more visible; CI-15 min decreases the cooling

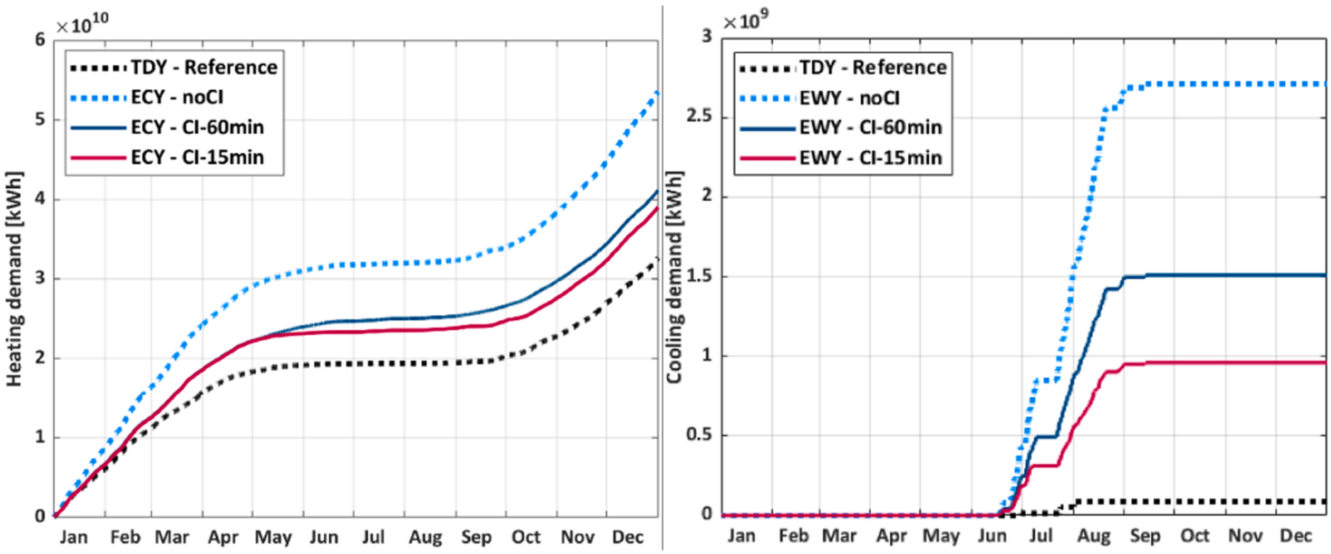

Fig. 10. Cumulative profile of heating demand during TDY and ECY (left) and cooling demand during TDY and EWY (right).

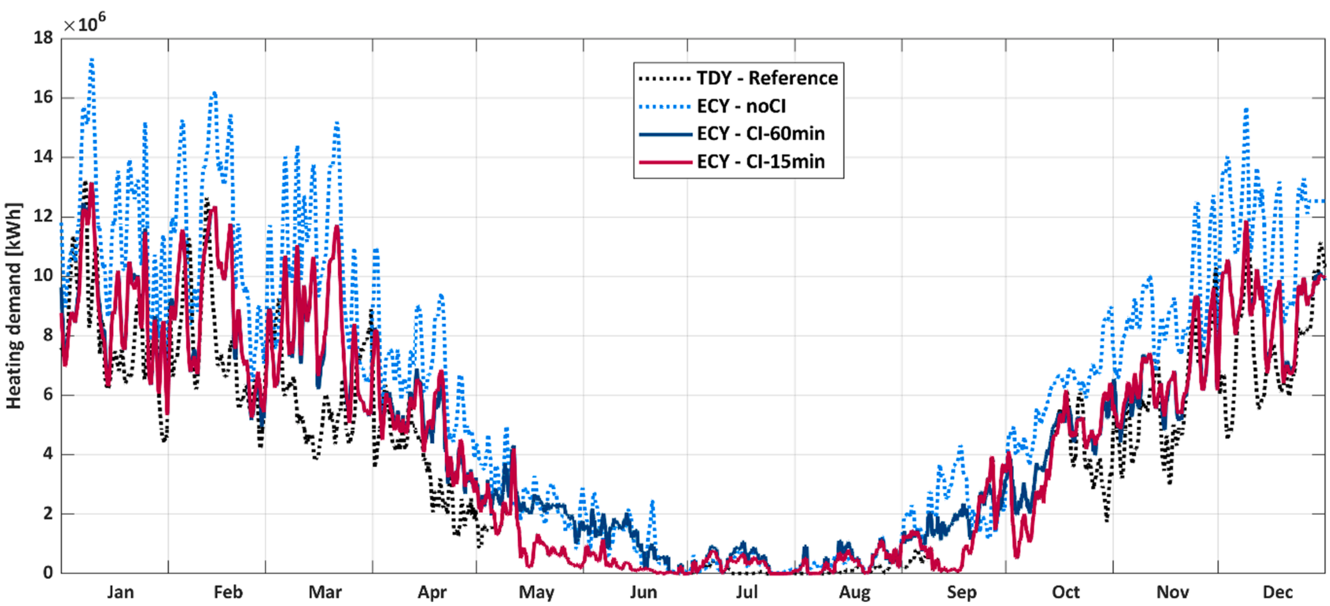

Fig. 11. Moving average of heating demand during TDY and ECY without and with CI with 15 min and 60 min timescales.

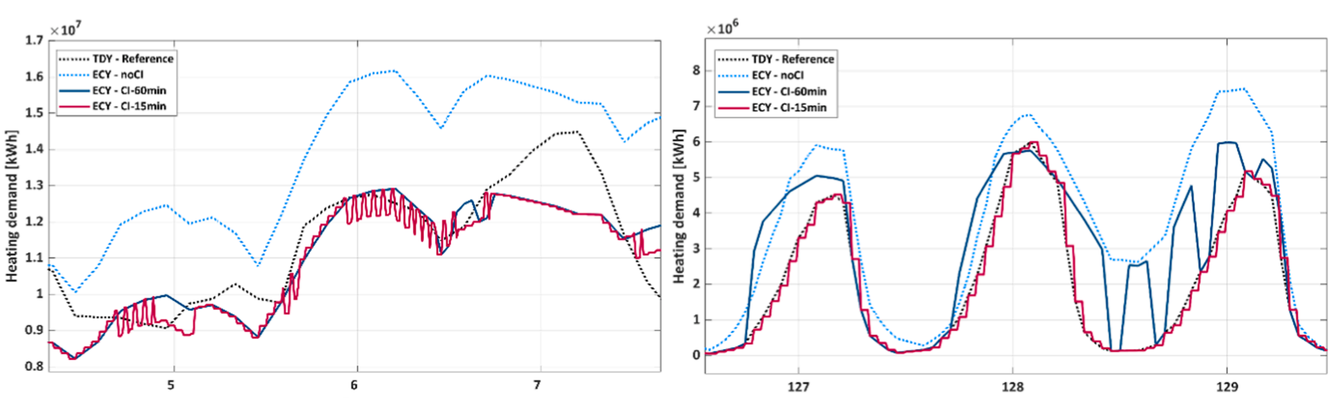

Fig. 12. Hourly variations of heating demand over some arbitrary days in winter (left) and spring (right) for TDY and ECY with different control strategies.

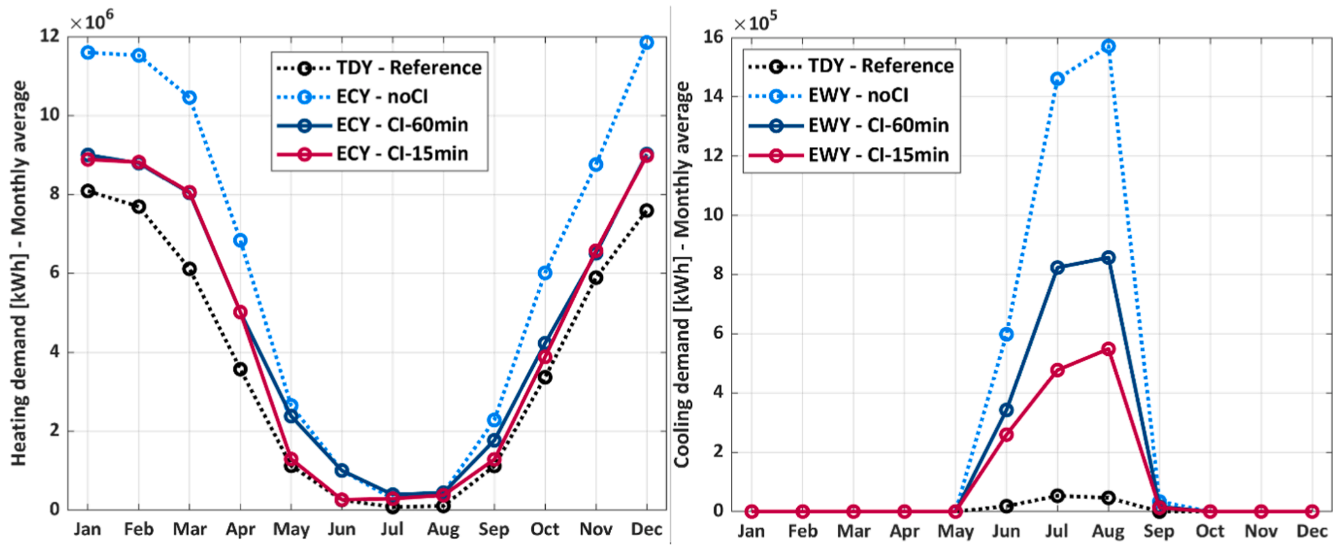

Fig. 13. Monthly values for (left) average and (right) standard deviation of the heating demand during TDY and ECY. The comparison is made for when there is no CI and when buildings are managed by CI with 15 min and 60 min timescales.

Table 1
Average heating and cooling demand for the reference case (TDY – Reference) and extreme cold and warm years with and without CI (for each month, the relative differences from the reference case are written in parentheses).

		Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Heating demand [MWh]	TDY – Reference	8084	7687	6112	3571	1123	256	79	107	1120	3366	5890	7590
	ECY – noCI	11,600	11,526	10,459	6836	2650	1004	290	437	2285	6010	8762	11,853
		(43%)	(50%)	(71%)	(91%)	(136%)	(292%)	(269%)	(310%)	(104%)	(79%)	(49%)	(56%)
	ECY – CI-60 min	9005	8796	8035	5016	2381	1004	293	443	1770	4227	6509	9027
		(11%)	(14%)	(31%)	(40%)	(112%)	(292%)	(270%)	(316%)	(58%)	(26%)	(11%)	(19%)
	ECY – CI-15 min	8890	8822	8055	5019	1295	264	290	378	1287	3882	6573	8987
		(10%)	(15%)	(32%)	(41%)	(15%)	(3%)	(268%)	(254%)	(15%)	(15%)	(12%)	(18%)
Cooling demand [MWh]	TDY – Reference	0	0	0	0	0	18	53	46	0	0	0	0
	EWY – noCI	0	0	0	0	0	599	1461	1572	34	0	0	0
		(–)	(–)	(–)	(–)	(–)	(3226%)	(2646%)	(3299%)	(–)	(–)	(–)	(–)
	EWY – CI-60 min	0	0	0	0	0	342	823	857	17	0	0	0
		(–)	(–)	(–)	(–)	(–)	(1803%)	(1448%)	(1754%)	(–)	(–)	(–)	(–)
	EWY – CI-15 min	0	0	0	0	0	259	478	549	13	0	0	0
		(–)	(–)	(–)	(–)	(–)	(1341%)	(798%)	(1088%)	(–)	(–)	(–)	(–)

demand more than CI-60 min by faster adaptation of buildings, however there still exist occasions with a large demand (outliers) that increase the average cooling demand. This is also visible for the other ten days in Fig. 16-right.

The level of engagement of the building groups (obeying the adaptation measure) was shown in Fig. 9. It is interesting to know how setting the adaptation measure with different timescales affects the distribution of the indoor temperature. This is visualized in Fig. 17 by comparing the distribution of the indoor temperature among the CI-DSM cases. During ECY, CI-15 min keeps the indoor temperature at the lower bound (19 °C) 9% more than CI-60 min. Even during EWY, CI-15 min keeps the lower bound for around 8%, while it is less than 1% for CI-60 min. Assuming that 21 °C is the ideal indoor temperature in this work, CI-60 min keeps T_{indoor} at the ideal level around 10% more than CI-15 min during both ECY and EWY. However, this comes with a higher energy demand and consequently a higher load on the urban energy system.

The two introduced KPIs, *DFF* and *AF*, are compared in Fig. 18 for CI-60 min and CI-15 min, considering heating demand during cold season (Nov-Dec & Jan-Mar) and cooling demand during warm season (Jun-Aug). Boxplots show the distribution of dff^t and af^t for heating and cooling demands over the considered periods while the black squares show their average values (*DFF* and *AF*). *DFF*s for heating are 0.2360 and 0.2356, and for cooling 0.4901 and 0.6806, while the *AF*s for heating are 0.0324 and 0.0487, and for cooling 0.2432 and 0.3080, respectively for CI-60 min and CI-15 min. The rule of thumb for both the KPIs is ‘the larger the better’, while the maximum amount can be 1 for both. Based on the distribution of dff^t for heating and cooling, the impact of CI in decreasing the energy demand is obvious, especially for cooling demand. CI-15 min shows considerably a better performance for cooling than CI-60 min, while the difference is very small for heating. Based on the values for af^t, CI-15 min helps the system to get back (or get closer) to normal (TDY) conditions faster than CI-60 min, both for cooling and heating. The difference in the agility of the system due to temporal scale is again larger for cooling than heating. In short, a finer temporal scale makes the system more agile and flexible, especially during warmer months when the energy demand is less continuous or is more occasional.

5. Conclusions

A demand side management (DSM) method was developed using collective intelligence (CI), called CI-DSM, as an approach for managing the demand response of groups of buildings in Stockholm during extreme weather conditions, aiming to increase the demand flexibility and consequently climate resilience in the urban area. This was done through setting communication and adaptation strategies among groups of buildings. The intention has been to set the communication strategy as simple as possible without the need for a central brain to decide and

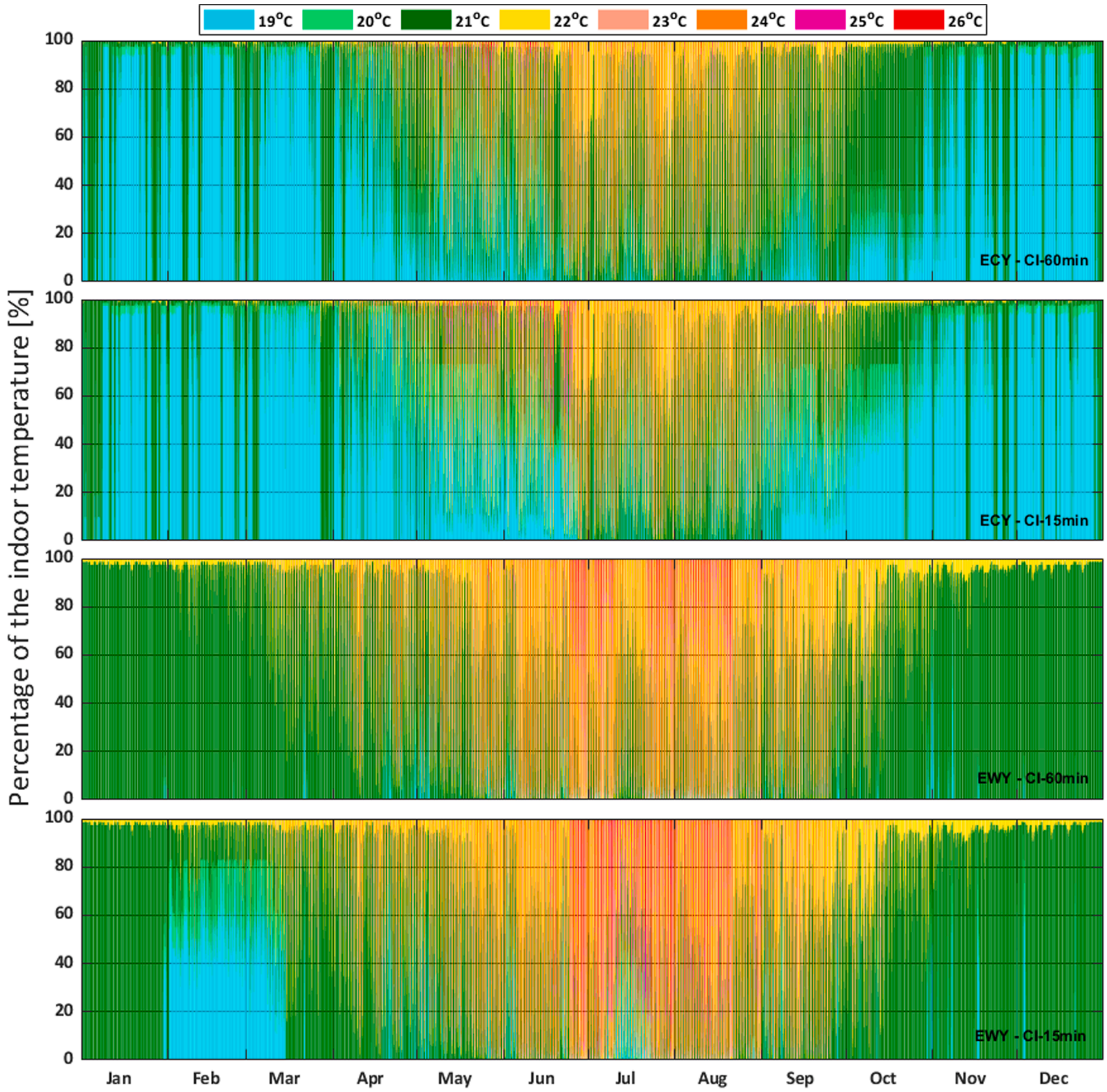

Fig. 14. Distribution of the percentage of the hourly indoor temperature over one year during extreme cold and warm years when the timescale is 60 min and 15 min.

control. The communication was done through forward (1) and backward (0) signals, informing building groups about their adjacent (or neighboring) building groups and the need for applying or disapplying the adaptation strategy, which was extending the range of indoor temperature from 21–24 °C to 19–26 °C. Two timescales of 15 min and 60 min were used to set the CI-based communication and adaptation among buildings. Impacts of the selected timescales on the engagement of buildings (and their emergent behavior), their energy performance and thermal comfort were investigated in this work. A simple platform and algorithm was developed to simulate the energy performance of buildings managed by CI-DSM to investigate the effectiveness of CI in improving the climate flexibility on the demand side. Energy simulations were performed for three climate scenarios, representing typical (TDY), extreme cold (ECY) and extreme warm (EWY) conditions. The performance of CI-DSM was assessed using several KPIs, which *Demand Flexibility Factor (DFF)* and *Agility Factor (AF)* were specifically defined for the purpose of this work.

According to the results, CI can help to gradually and effectively decrease the energy demand during extreme climate events. For the considered cases, CI-60 min and CI-15 min could reduce the annual heating demand respectively for 38% and 44%, compared to the case without CI-DSM. The impact of CI is much greater for cooling demand in Stockholm, reducing the demand for 14 and 20 times, respectively for CI-60 min and CI-15 min. This is due to the fact that Stockholm is a heating dominated city and the need for cooling is limited and occasional during warm summer days, therefore the relative differences are quite large during extreme summer days. The higher flexibility of the 15 min timescale was also confirmed by comparing *DFF* for the two timescales. Moreover, it makes the system more agile, as was confirmed by comparing *AF*s, which results in a faster reaction and adaptation to new conditions as well as a faster return to normal conditions. CI-15 min results in more occasions with all the buildings engaged, however the difference with CI-60 min was small (around 4%). The higher agility of CI-DSM enables the system to respond faster and become more flexible during extreme climate events. This will increase the climate resilience of the system and makes it more stable. However, if extreme climatic conditions continue for longer periods, such as extreme cold winter months in this study, having a finer timescale does not improve the situation. This also depends on the adopted adaptation measures; for example, if more than one adaptation measure is planned (e.g. controlling the hot water usage, window opening, shading etc.), the impact of the selected timescale can be different.

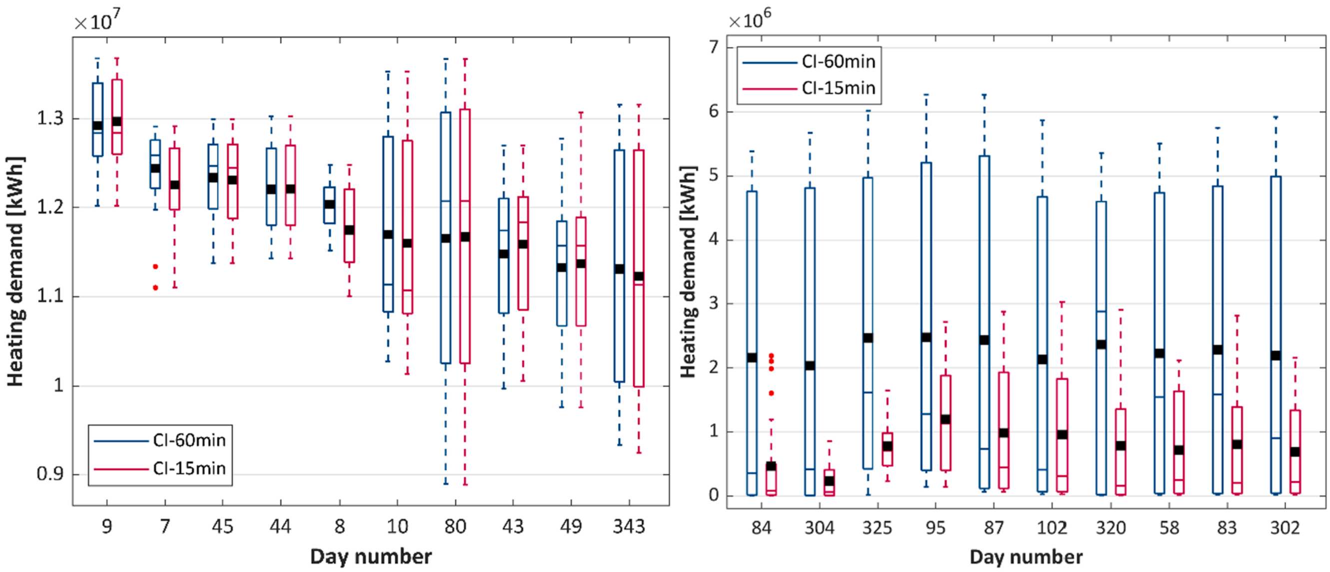

Fig. 15. Boxplots of heating demand during ECY when applying CI with two different timescales for (left) ten days with the highest demand and (right) ten arbitrary days. The black squares mark the average demand.

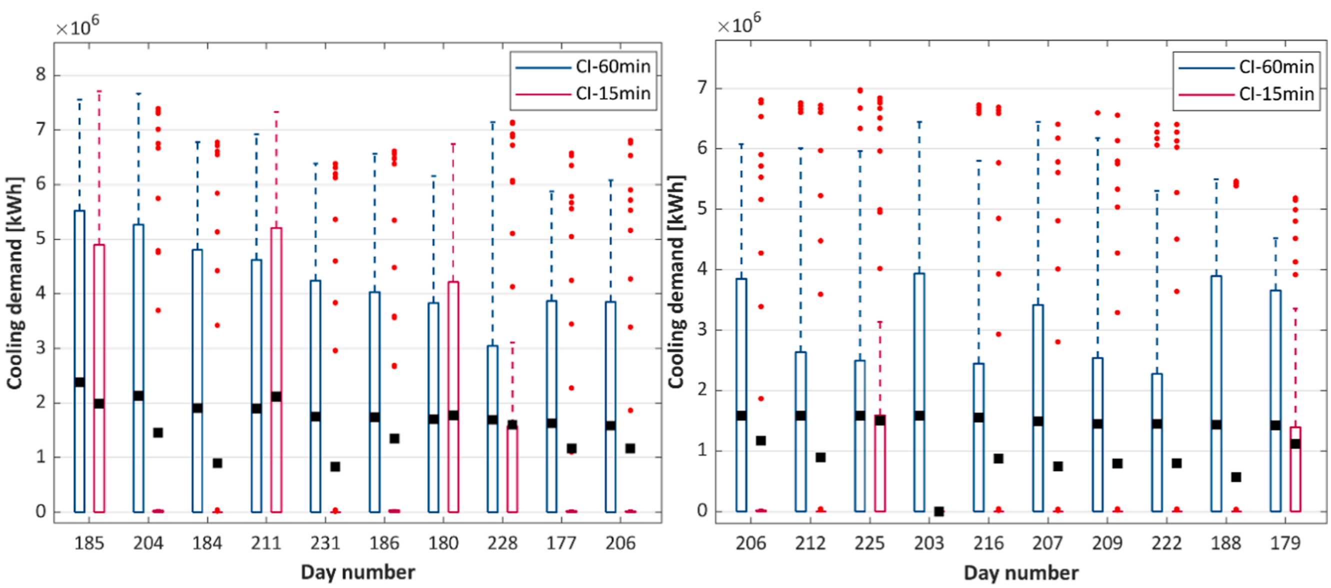

Fig. 16. Boxplots of cooling demand during EWY when applying CI with two different timescales for (left) ten days with the highest demand and (right) ten arbitrary days. The black squares mark the average demand.

This study confirmed the effectiveness of implementing CI in managing the energy performance of urban areas through increasing the climate flexibility of buildings. This can support the energy system during extreme weather events to absorb the shock and increase their climate resilience. The CI concept which is presented here is scalable; e.g. considering a smart building and IoT, the CI concept can start from the scale of building by controlling window openings, shadings, appliances (e.g. fridge, stove, etc.), air conditioning systems and then extend to the block, neighborhood and urban level. Different priorities can be defined for systems/appliances and buildings, depending on the use of the system and building (e.g. if its hospital, office, residential, etc.), including the user preferences. The advantage of CI is that the priorities are taken care of at each unit/building and what is transferred between agents is just a forward/backward signal. This increases the autonomy and agility of the system in responding to the shocks, decreases the calculation load and the need for huge investments in ICT and data storage/management. Application of CI-DSM should be further investigated considering user preferences, price signal and optimization of the energy system performance.

CRediT authorship contribution statement

Vahid M. Nik: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Software, Validation, Visualization, Writing - original draft, Writing - review & editing. **Amin Mozami:** Conceptualization, Investigation, Methodology, Writing - original draft, Writing - review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence

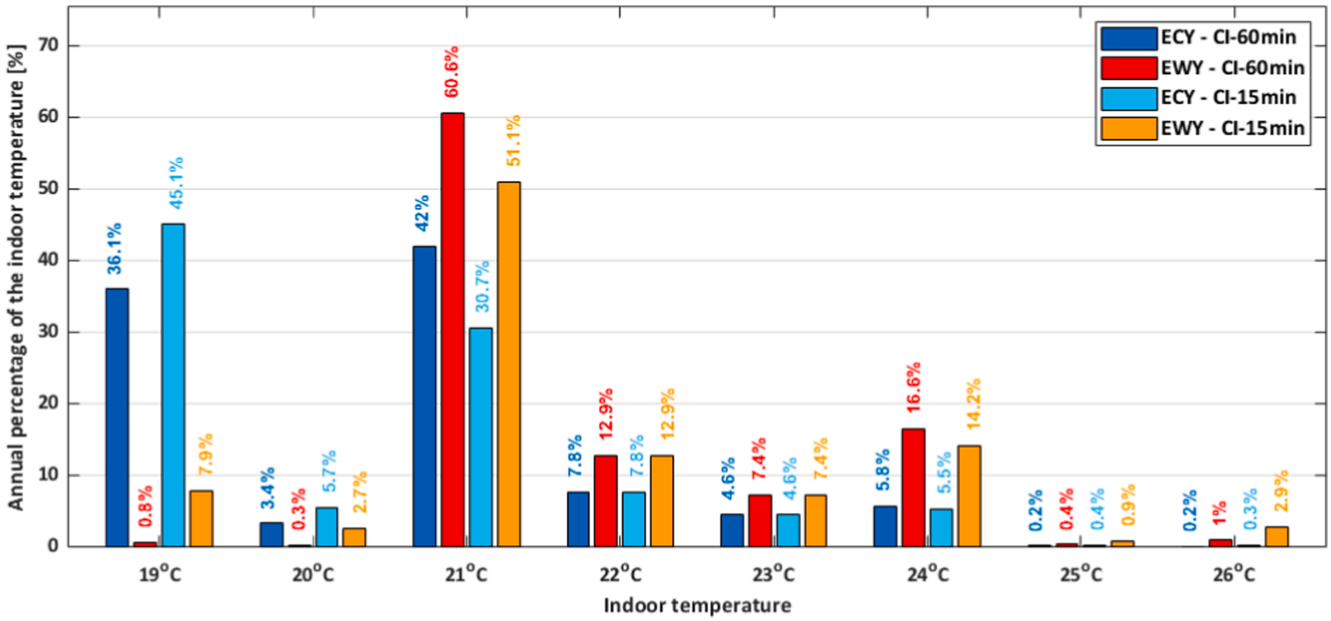

Fig. 17. Annual percentage of the temperature inside buildings during extreme cold and warm years when buildings are managed by CI with 15 min and 60 min timescales.

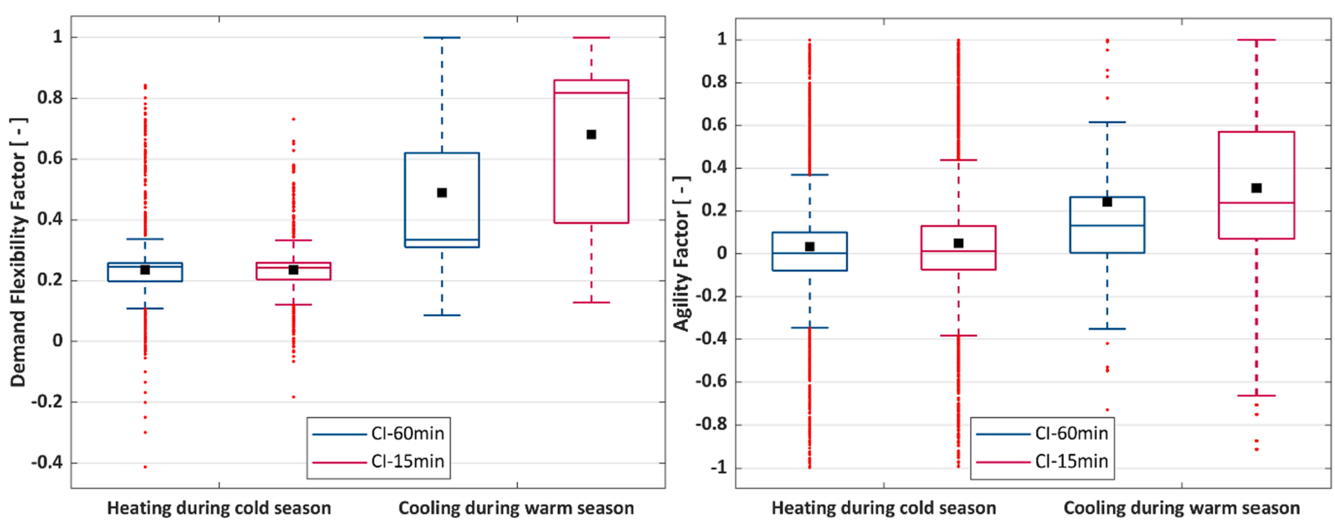

Fig. 18. Distribution of the hourly values of (left) ESF and (right) AF for heating demand during cold season and cooling demand during warm season.

the work reported in this paper.

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