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Empowering energy flexibility and climate resilience using collective intelligence based demand side management (CI-DSM)

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Abstract. This work investigates the effectiveness of Collective intelligence (CI) in demand side management (DSM) in urban areas to cope with extreme climate events. CI is a form of distributed intelligence that emerges in collaborative problem solving and decision making. It is used in a simulation platform to control the energy performance of buildings in an urban area in Stockholm, through developing CI-DSM and setting certain adaptation measures, including phase shifting in HVAC systems and building appliances. 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 measures. The performance of CI-DSM is simulated for three climate scenarios representing typical, extreme cold and extreme warm years in Stockholm. According to the results, CI-DSM increases the autonomy and agility of the system in responding to climate shocks without the need for computationally extensive central decision making systems. CI-DSM helps to gradually and effectively decrease the energy demand and absorb the shock during extreme climate events.

1. Introduction

Activating Smart Buildings, including their heating, cooling and ventilation systems and appliances, as flexible and responsive actors in electrical and thermal grids is vital to integrate intermittent renewable energy sources and make our energy systems more climate resilient and interoperable. However, in many buildings there is a large number of different technical systems and appliances that are in many cases already some years old, and expensive and complex to replace, also known as 'legacy equipment'. This is a major reason that most buildings at present are not 'smart' buildings.

The available solutions to smart up the buildings are slow and not very practical to integrate the legacy equipment in the flexibility market. Considering consumer-centric solutions, e.g. Google Nest, the provided solutions are dependent on 'data aggregators', e.g. Google. There is however a lot of mistrust towards these systems (hacking, spying, …), since someone 'owns' the data in the end. Considering industry-centric solutions and building management systems, e.g. provided by Siemens,

Bosch, or Honeywell, not all components can be integrated while the energy-saving cost does not necessarily overtake the installation/maintenance cost. Moreover, large-scale mapping of buildings' smartness to increase the energy flexibility in urban areas needs a seamless 'cross-talk' between grid and buildings, but none of the available approaches provide persistent and easy-to-implement solutions for this issue.

Economic and technical feasibility of using buildings as flexible loads requires a larger number of buildings per grid segment whose energy consumption can be modulated, thus avoiding curtailment, but up to date no cost-effective, easy-to-install, secure and user-friendly solutions are available on the market. Energy flexibility also needs to take into account the occupants of a building and their needs and preferences in order to be socially accepted and hence result-effective.

Flexibility can be defined as the adaptability of a system to a range of environmental variations [1]. Defining the relevant characteristics and key performance indicators (KPIs) highly depends on the scope and aspect of the study [2]. 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 [3,4]. Higher climate flexibility helps the system to withstand the climate variations with a minimum degradation of its performance indicators [3]. The demand flexibility of buildings can become a major source of flexibility since buildings account for a large proportion of energy consumption [5,6]. According to Finck et al. [7], the identification, quantification, and control of demand flexibility is the major challenge for future grid operations and requires innovative methods and control strategies.

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 [8], such as climate variations, microclimate, urban morphology, user behavior, energy policies, pricing, and advanced technical solutions (e.g., V2G and IoT) [9,10]. Reaching higher renewable energy penetration levels in such complex systems becomes challenging [3], mainly due to the intermittent characteristics of renewable energy and the complexity with multi-spatial/temporal scales [11]. However, it is still possible to take advantage of the characteristics of complex systems towards reaching a higher flexibility and resilience [12].

In a recently funded European project, called COLLECTiEF, we aim to implement, test and qualify an interoperability and communication platform based on Collective Intelligence (CI) that allows easy and seamless integration of legacy equipment into a collaborative network to manage energy in a scalable manner within existing buildings and neighborhoods in larger urban systems with low cost of installation and computational power [13]. This collaborative network interacts with the grid providing energy efficiency and flexibility, based on user preferences and requests, and uses self-learning to maximize user comfort. The developed CI-based demand side management is called CI-DSM. This work presents the basics of CI-DSM and shares some results of the developed preliminary CI-DSM algorithm, which has been tested based on numerical simulation of the energy performance of an urban area in Stockholm.

2. Methodology

2.1. Demand Side Management using Collective intelligence
CI is a form of universally distributed intelligence that works based on collaborative problem solving and decision making [14]. The collaborative and socially inspired computation systems are identified by their robustness, flexibility, and scalability [15]. CI systems, which are complex by nature, can adapt to uncertain and unknown environments, organize themselves autonomously, and exhibit emergent behavior [16]. This makes CI systems flexible and consequently more resilient against environmental variations or external shocks. The key to developing a CI-based control system is to define simple models of local interactions that give rise to self-organized patterns.

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 an earlier work [12], 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 and buildings can help a lot in this regard [17]. 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. Figure 1 illustrates the idea and demonstrates how the CI-based algorithms manage the energy performance of buildings and the energy systems in a saleable manner; buildings are clustered according to their defined priority and communicate using forward/backward (or 1/0) signals.
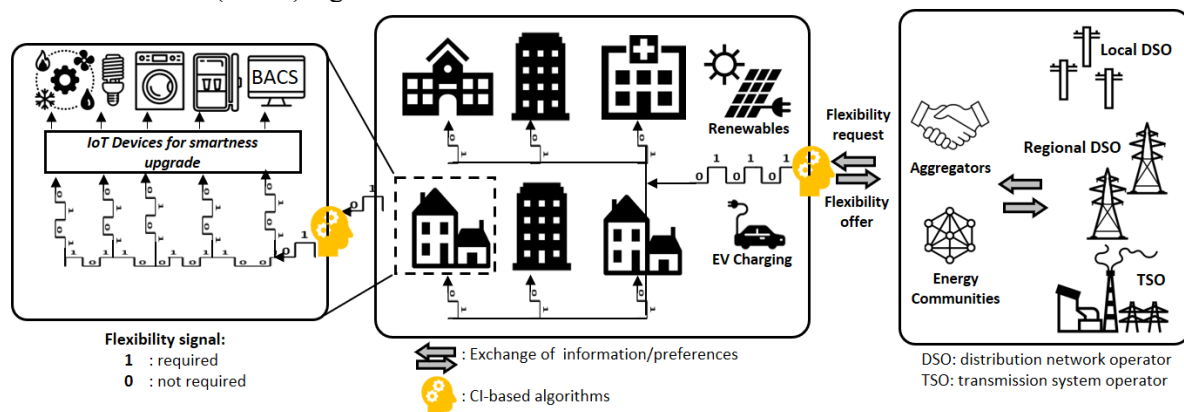

Figure 1. The schematic representation of CI-DSM.

2.2. Case study

A hypothetical residential urban area in Stockholm with 153 residential buildings has been modelled in Matlab for the purpose of this work [18]. 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. 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 and more details about it are available in [18].

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) [19,20].

2.3. Implementing CI-DSM

In reality, each building can be considered as a(n) 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.

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 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. The communication rules are that each building group can communicate only with the neighboring groups, using a 0 or 1 signal, which 1 (forward signal; when the energy supply is above the reference case which is the TDY case in this work) is to apply/activate the adaptation measure, and 0 (backward signal) is to disapply/deactivate that.

The only adaptation measure which is defined in this work is extending the span of indoor temperature from 21°C-24°C to 19°C-26°C, with the purpose of helping the energy system to pass the extreme events safely. 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. 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 of applying the adaptation measures. The adopted timescale for communication, and consequently setting the adaptation measures, can alter the performance of CI-DSM, which has been considered as one hour in this work.
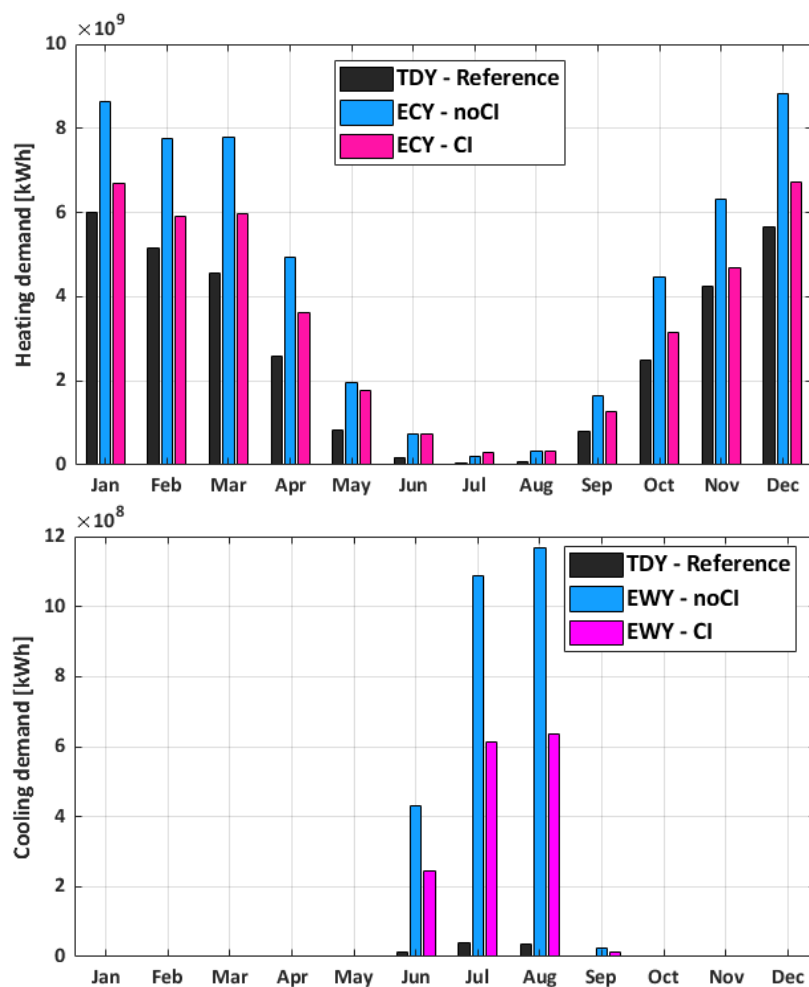
3. Results

Figure 2. *Monthly heating and cooling demand for the reference case and extreme climate cases with and without CI-DSM.*

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 monthly bar-plots of the heating

and cooling demand in Figure 2 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, since the cooling demand during typical conditions in Stockholm is very small and 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 Ref. [20]. Implementing CI decreases the energy demand during extreme conditions. During cold months in ECY, CI-DSM reduces the heating demand at least for 22%, with the maximum of around 30% in October, in comparison with noCI cases. Such a decrease is more significant for the cooling demand during EWY, decreasing the monthly cooling demand for 42-45% during warm months.

The level of engagement of the building groups (obeying the adaptation measure) is shown in Figure 3 as well as the annual percentage of the indoor temperature. During ECY, CI-DSM keeps the indoor temperature at the lower bound (19°C) 36.1% of time (Figure 3-bottom), engaging all the building groups for 26.3% (Figure 3-top).
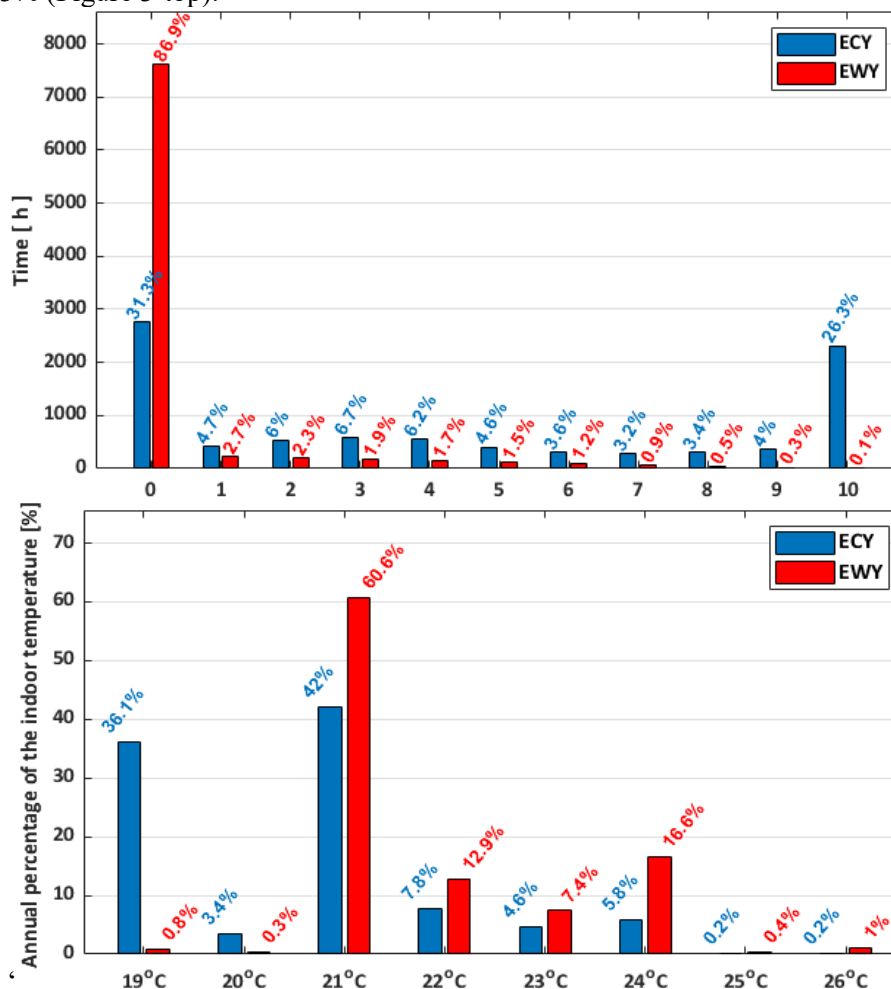

Figure 3. *Annual percentage of the (top) building groups with the adopted measure (extended T_{indoor} span) and (bottom) indoor temperature during extreme cold and warm years with CI-DSM.*

4. 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 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 21ºC-24ºC to 19ºC-26ºC. 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.

According to the results, CI-DSM can help to gradually and effectively decrease the energy demand during extreme climate events. The annual and monthly heating demand reduces considerably (at least 22% for cold months), compared to the case without CI-DSM. The impact of CI is much greater for cooling demand in Stockholm, reducing the monthly cooling demand for around 45%. CI-DSM engages buildings in adapting to climate variations, enabling the urban area to respond fast and become flexible during extreme climate events. This will increase the climate resilience of the system and makes it more stable.

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 will be further investigated in COLLECTiEF considering user preferences, price signal, optimization of the energy system performance etc.

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