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Implementing collective intelligence in demand side management

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ABSTRACT

Collective intelligence (CI) is a form of distributed intelligence emerging from collaborative problem solving and decision making. It has the advantages of simple communication and less need of data transfer and computationally extensive central decision making systems. This work implements CI in demand side management (DSM) of a hypothetical urban area in Stockholm, created based on the representative residential buildings in the city. A simple platform and algorithm are developed for modelling CI-DSM, considering the timescales of 15min for communication and applying or disapplying adaptation measures. According to the results, CI increases the autonomy of the system and decreases the heating demand of buildings effectively, consequently increasing the demand flexibility based on climate conditions. CI results in decreasing the energy demand considerably, decreasing the total heating demand over a year by around 50%.

Keywords: collective intelligence, demand flexibility, climate flexibility, climate resilience, demand side management, urban energy system

NONMENCLATURE

Abbreviations	
CI	Collective Intelligence
CI-DSM	CI-based DSM
DSM	Demand Side Management
ECY	Extreme Cold year
GCM	Global Climate Model
RCM	Regional Climate Model
TDY	Typical Downscaled Year
VRE	Variable Renewable Energy

1. INTRODUCTION

The projected scenarios for climate change [1][2], population growth [3] and economic growth [4] in urban areas requires larger implementation of sustainable approaches to cover the energy demand in urban areas [5]. It is vital to 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 [6] [7]. Extreme weather events can induce energy disturbances and retard the renewable energy integration levels [7] [8]. Enhancing energy flexibility on the supply and demand sides can boost the movement towards reliable and robust energy networks based on renewable generation [9]. Higher climate flexibility helps the system to withstand the climate variations with a

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minimum degradation of its performance indicators [9]. The demand flexibility of buildings can become a major source of flexibility since buildings account for a large proportion of energy consumption [10][11]. Buildings can provide higher flexibility in different ways, e.g., utilization of thermal mass, adjustability of HVAC system use, and shifting of plug-loads [10]. The control of demand flexibility is the major challenge for future grid operations and requires innovative methods and control strategies [12][13]. There is a need to improve demand side management (DSM) methods to better account for and implement demand flexibility. DSM refers to the set of means that alter the pattern/magnitude of energy use by reducing, increasing, or rescheduling the demand [14]. 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 [15]. However, DSM increases the complexity of the system operation which limits its market and application [15]. There is a need for less complicated techniques with greater potentials to promote the user's participation [16]. In this work, a novel DSM approach is applied which is based on integrating Collective intelligence (CI) into DSM, called CI-DSM. The method has potential to limit the need for data transfer and storage and to simplify the communication logic, meanwhile increase the collaboration between components in the demand side. Application of CI-DSM is investigated for managing the heating demand of a hypothetical urban area in Stockholm, created based on the representative residential buildings in the city.

2. METHODOLOGY

CI-DSM works based on setting certain adaptation measures to buildings through simple communications between buildings and energy systems using collective intelligence. The application of CI-DSM is simulated for controlling the energy performance of an urban area in Stockholm for a typical weather year.

2.1 Case study

A hypothetical residential urban area in Stockholm with 153 residential buildings is considered, statistically representing the whole range of residential buildings in the city [17]. The energy performance of buildings is modeled in Simulink/Matlab, simulating the energy demand with an hourly temporal resolution [17]. Simulations were performed for the typical weather conditions over the period of 2010-2039. In this regard, the weather data for a typical downscaled year (TDY) 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) [18].

2.2 Simulating CI-DSM

Collective intelligence (CI) is a form of universally distributed intelligence that works based on collaborative problem solving and decision making [19]. The key to developing a CI-based control system is to define simple models of local interactions that give rise to self-organized patterns. CI-DSM is interpreted as an approach to enhance demand flexibility and adaptation during extreme climate conditions to decrease the need for extra energy supply. CI enables the buildings' responses at the local level to give rise to self-organized patterns at an urban scale, helping to pass the extreme events safely. Fig. 1 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 and communicate using forward/backward signals [20]. The backbone of CI is simple communication between components of the system (without a central brain). In this work, the communication rules are set with a simple logic and for a simple network:

- Each building group can communicate only to the next or previous group.
- 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).

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. The only adaptation measure which is defined in this work is extending the span of indoor temperature from 21^{o}C-24^{o}C to 19^{o}C-26^{o}C. Fig. 2 exemplifies the communication for seven time steps. The adopted timescale for communication, and consequently setting the adaptation measures, is 15min.

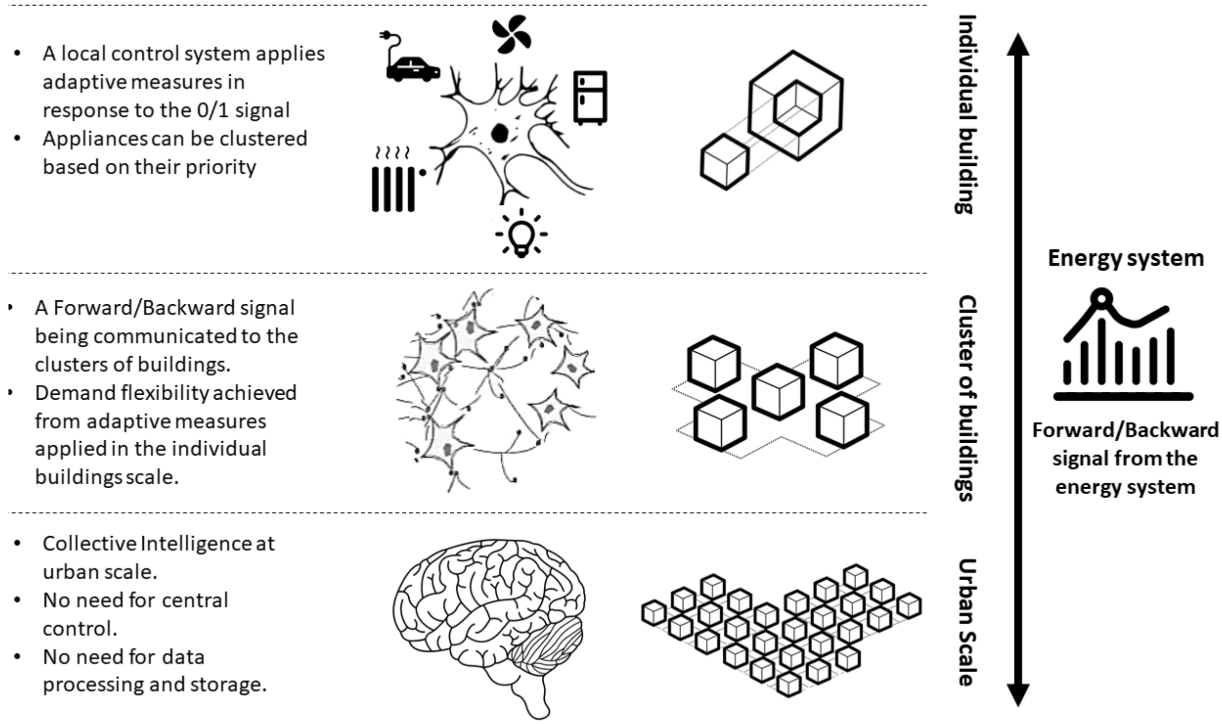

Fig 1 Graphical representation of implementing CI in buildings in an urban area

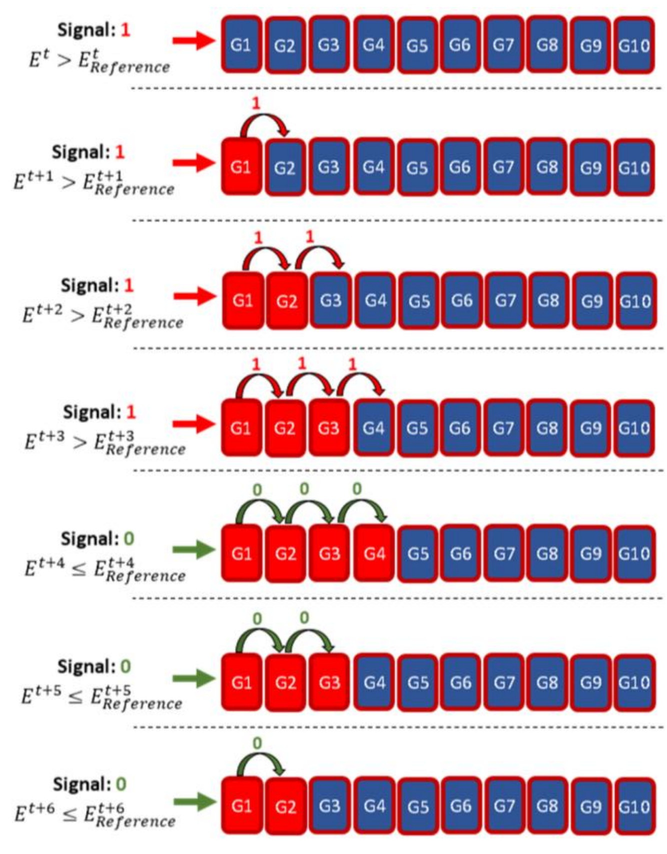

Fig 2 Schematic representation of the CI-DSM logic for applying and disapplying adaptation measures to building groups during seven time steps. Forward signal (1 – red) results in applying the adaptation measure at the next time step while the backward signal (0 – green) disapplies the measure

3. RESULTS

According to the cumulative distributions of the heating demand in Fig. 3, CI results in decreasing the energy demand considerably, decreasing the total heating demand over a year around 50%.

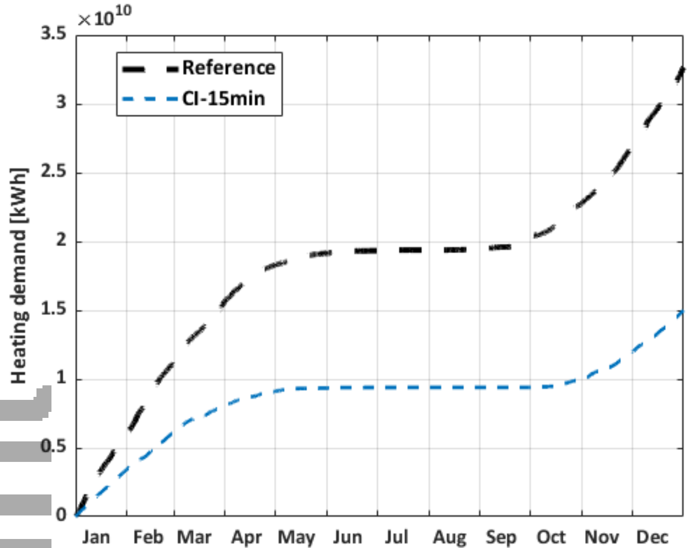

Fig 3 Cumulative profile of heating demand during TDY and ECY.

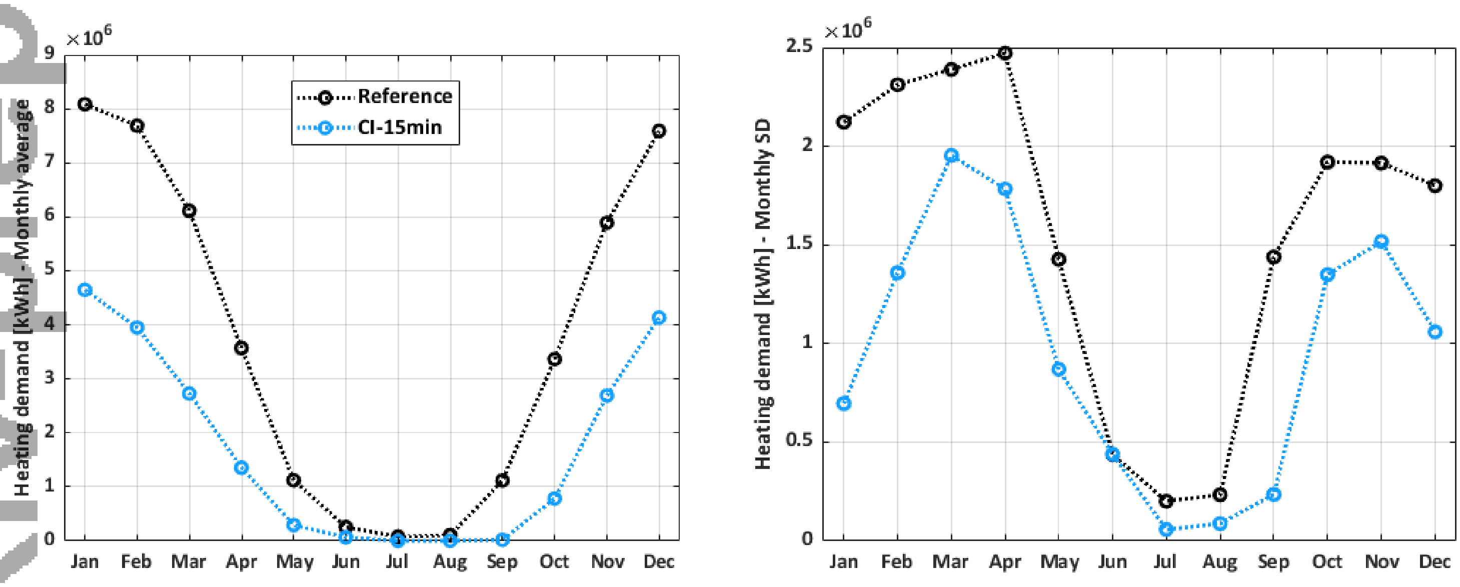

Fig 4 Monthly values for (left) average and (right) standard deviation of the heating.

This is further investigated by looking into the monthly average of the calculated heating demands in Fig. 4. CI-15min has a much smaller heating demand over all the cold months.

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, aiming to increase the demand flexibility. This was done through setting simple communication and adaptation strategies among groups of buildings, using forward (1) and backward (0) signals, and applying or disapplying the adaptation strategy, which was extending the range of indoor temperature from 21°C-24°C to 19°C-26°C. According to the results, CI can help to gradually and effectively decrease the energy demand and increase the demand flexibility. 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.

REFERENCE

[1] Masson-Delmotte V, Zhai P, Pörtner HO, Roberts D, Skea J, Shukla PR, et al. Global Warming of 1.5°C - An IPCC Special Report on the impacts of global warming of 1.5°C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change, sustainable development, and efforts to eradicate poverty. IPCC; 2018.

[2] IPCC. Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA; 2013.
[3] United Nations. World urbanization prospects: The 2011 revision. New York: Department of Economic and Social Affairs Population Division; 2011.
[4] Perrone D, Hornberger GM. Water, food, and energy security: scrambling for resources or solutions? Wiley Interdiscip Rev Water 2014;1:49–68. https://doi.org/10.1002/wat2.1004.
[5] Kammen DM, Sunter DA. City-integrated renewable energy for urban sustainability. Science 2016;352:922–8. https://doi.org/10.1126/science.aad9302.
[6] Nik VM. Making energy simulation easier for future climate – Synthesizing typical and extreme weather data sets out of regional climate models (RCMs). Appl Energy 2016;177:204–26. https://doi.org/10.1016/j.apenergy.2016.05.107.
[7] Perera ATD, Nik VM, Chen D, Scartezzini J-L, Hong T. Quantifying the impacts of climate change and extreme climate events on energy systems | Nature Energy. Nat Energy 2020. https://doi.org/10.1038/s41560-020-0558-0.
[8] Panteli M, Mancarella P. Influence of extreme weather and climate change on the resilience of power systems: Impacts and possible mitigation strategies. Electr Power Syst Res 2015;127:259–70. https://doi.org/10.1016/j.epsr.2015.06.012.
[9] Perera ATD, Nik VM, Wickramasinghe PU, Scartezzini J-L. Redefining energy system flexibility for distributed energy system design. Appl Energy 2019;253:113572. https://doi.org/10.1016/j.apenergy.2019.113572.
[10] Jensen SØ, Marszal-Pomianowska A, Lollini R, Pasut W, Knotzer A, Engelmann P, et al. IEA EBC Annex 67 Energy Flexible Buildings. Energy Build 2017;155:25–34. https://doi.org/10.1016/j.enbuild.2017.08.044.
[11] Nik VM, Mata E, Kalagasidis AS. Assessing the Efficiency and Robustness of the Retrofitted Building Envelope Against Climate change. Energy Procedia 2015;78:955–60. https://doi.org/10.1016/j.egypro.2015.11.031.
[12] Finck C, Li R, Zeiler W. Optimal control of demand flexibility under real-time pricing for heating systems in buildings: A real-life demonstration. Appl Energy 2020;263:114671. https://doi.org/10.1016/j.apenergy.2020.114671.
[13] Perera ATD, Wickramasinghe PU, Nik VM, Scartezzini J-L. Machine learning methods to assist energy system optimization. Appl Energy 2019;243:191–205. https://doi.org/10.1016/j.apenergy.2019.03.202.
[14] Lund PD, Lindgren J, Mikkola J, Salpakari J. Review of energy system flexibility measures to enable high levels of variable renewable electricity. Renew Sustain Energy Rev 2015;45:785–807. https://doi.org/10.1016/j.rser.2015.01.057.
[15] Strbac G. Demand side management: Benefits and challenges. Energy Policy 2008;36:4419–26. https://doi.org/10.1016/j.enpol.2008.09.030.
[16] Gelazanskas L, Gamage KAA. Demand side management in smart grid: A review and proposals for future direction. Sustain Cities Soc 2014;11:22–30. https://doi.org/10.1016/j.scs.2013.11.001.
[17] Nik VM, Sasic Kalagasidis A. Impact study of the climate change on the energy performance of the building stock in Stockholm considering four climate uncertainties. Build Environ 2013;60:291–304. https://doi.org/10.1016/j.buildenv.2012.11.005.
[18] The surface processes of the Rossby Centreregional atmospheric climate model (RCA4) | SMHI n.d. https://www.smhi.se/en/publications/the-surface-processes-of-the-rossby-centreregional-atmospheric-climate-model-rca4-1.89801 (accessed June 11, 2018).
[19] Suran S, Pattanaik V, Draheim D. Frameworks for Collective Intelligence: A Systematic Literature Review. ACM Comput Surv 2020;53:14:1–14:36. https://doi.org/10.1145/3368986.
[20] Nik VM, Moazami A. Using collective intelligence to enhance demand flexibility and climate resilience in urban areas. Appl Energy 2020 (in press).