Chapter 144
Collective Intelligence Function in Extreme Weather Conditions: High-Resolution Impact Assessment of Energy Flexibility on Building Energy Performance

Mohammad Hosseini, Amin Moazami, and Vahid M. Nik

Abstract Collective intelligence (CI) in demand-side management (DSM) can enhance the flexibility of urban energy systems. Extreme climates cause intensively high loads on the urban energy systems resulting in power outages. To avoid this, quick responses are needed from buildings to adjust their operation in favor of the grid. Most of the available approaches are computationally expensive. CI-DSM offers a simpler approach that relies on distributed intelligence paradigm. It allows fast and (semi-) autonomous reactions to the continuously changing environment. This research investigates the application of CI-DSM in a residential building in the south of Sweden. The focus of the study is managing the building's heating demand in an extremely cold winter. Heating setpoint and ventilation rate are defined as the adaptation measures. To activate the system and take an action by the agents, signals of 0/1 with 15-min intervals are sent, when heating demand exceeds the baseline. Managing the performance of buildings using CI-DSM could reduce the heating demand and peak power by 25% and 20%, respectively, over an extreme cold February compared to typical conditions.

Keywords Collective intelligence · Energy flexibility · Extreme weather · Building energy performance

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144.1 Introduction

Smart buildings and smart cities concept are becoming dominant due to the advances in information and communication technologies (ICT) and the prevalence of the internet of things (IoT) (Chourabi et al. 2012), leading toward higher levels of the energy performance of the built environment (Fokaides et al. 2014). The building sector is responsible for around 40% of the total energy use in Europe (Domínguez-Torres et al. 2022). Extreme climate events have been experiencing with stronger magnitudes and higher frequencies in the past two decades (Hosseini et al. 2022), increasing the risk of energy systems malfunction (Jessel et al. 2019) and emphasizing the need for higher flexibility (Perera et al. 2019). The Energy Performance of Buildings Directive (EPBD) promoted a Common Union scheme for rating the smart readiness of buildings, encouraging the use of ICT and other smart technologies to ensure the efficient operation of buildings (Smart' buildings – smart readiness indicator (definition and calculation) 2022). ICT solutions have been introduced to provide interaction between buildings and buildings with grid/microgrid (MG), applying a range of centralized to distributed approaches (Nik et al. 2021)–(Vázquez-Canteli and Nagy 2019). Thereafter, it is crucial to define an optimum algorithm to manage the interaction between agents (i.e., smart control device in thermal zones) in an energy system.

Considering the variety of agents and decisions in an energy system, as well as costly computation processes, this research, among all proposed methods, investigates a nature-inspired solution known as Collective intelligence (CI). Deploying CI on the demand-side management (CI-DSM) can improve the performance of the energy systems by enhancing demand flexibility, increasing the adaptability of the building in environment variations (Nik and Moazami 2021). CI is "a form of universally distributed intelligence, constantly enhanced, coordinated in real-time, and resulting in the effective mobilization of skills" (Suran et al. 2020) which refers to any large, distributed collection of interacting agents with the least or no centralized control (Wolpert and Tumer 1999). Within a CI-based energy system, agents perform reinforcement learning (RL) algorithms, improving the individual performance of agents to maximize the performance of the entire system (Qin et al. 1549). Moreover, distributed intelligence without a main central processor magnifies the suitability of CI to be applied on the demand side; due to the distributed computation that reduces the computation cost (Krafft et al. 2021), and less data sharing leading to higher security and privacy (Arulprakash and Jebakumar 2021).

The performance of CI-DSM is investigated in this research using two adaptation measures on a residential apartment within a multifamily building block in the south of Sweden, exploiting a calibrated building performance simulation (BPS) model. A set of synthesized weather data, representing extreme conditions, developed by Nik (Nik 2016) is used for BPS. To evaluate the realistic extreme cold conditions, the results and analysis are concentrated on short periods in February as the coldest month. The methodology of these process is explained in detail in the next chapter, following by the results and discussion. Finally, the conclusion of the work is presented.

144.2 Methods

The research progress consists of BPS model using a set of representative weather data, in addition to a Python code based on a CI algorithm, simulating the CI-DSM.

144.2.1 Energy Performance Simulation

The BPS modelling, developed in the previous work of the authors (Hosseini et al. 2022), is carried out in Rhino/Grasshopper using EnergyPlus as the simulation engine. The model, consists of a six-room apartment, is calibrated against measured energy use for heating and indoor temperature, based on the in-place measured weather data. Each room is defined as an agent, separated entirely by adiabatic walls, presented in Fig. 144.1. Thereafter, the calibrated BPS model is used to run simulation with representative weather data for the typical and extreme conditions. The model considers the building operated in a conditioned mode for the full year. An ideal active system provides all the energy needs required to meet the winter and summer setpoint temperatures. Heating setpoint is adjusted on 21 °C and air flow rate is set to 0.3 l/s/m^2. (Check Hosseini et al. 2022 (Hosseini et al. 2022) for more information about CV(RMSE), NMBE, BPS settings, schedules, and geometry).

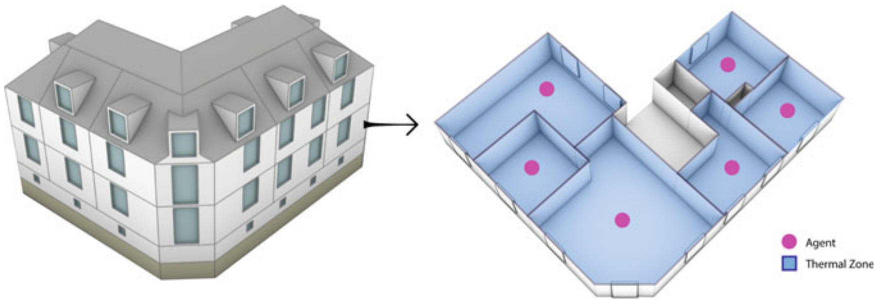

Fig. 144.1 The BPS model: Entire building block (left) and the studied apartment with thermal zones (right)

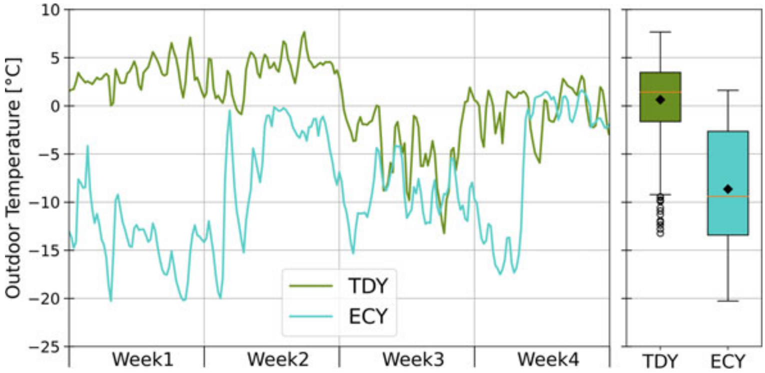

Fig. 144.2 Outdoor drybulb temperature for synthesized weather data over the analysis period: TDY (green) and ECY (blue)

144.2.2 Weather Data

A set of representative typical downscaled year (TDY) and extreme cold year (ECY) over the period of 2020 to 2040 is utilized for BPS. The representative weather data is synthesized from regional climate models (RCMs) dynamically downscaling five global climate models (GCMs) with three different representative concentration pathways (RCPs) (Nik 2016). TDY represents the most typical months in the corresponding period, while ECY shows the coldest projected months. The provided data, include all required data for building energy simulation, shows averages of around 1 °C for TDY and − 8 °C for ECY in February (the analysis period). The outdoor drybulb temperature is depicted in Fig. 144.2. TDY and ECY show a larger difference in the first half of the February than the second half; therefore, the analysis period in this research is divided into two timespans, week 1–2 and week 3–4. (Check Nik, 2016 (Nik 2016) for details of projected future weather data).

144.2.3 Collective Intelligence on the Demand-Side

While complex adaptive systems are commonly used among scientists, the concept of CI is grabbing more and more attention. CI is based on the idea that a group of individuals working together have a higher level of intelligence than each of them (Heylighen 1999). CI is the intelligent behavior that arises in collaborative environment (Lopez et al. 2015), and collective decisions emerges from information exchanges between many agents (Solé et al. Oct. 2016). Currently, due to the highly developed smart technologies and ICT infrastructure, flexible DSM is becoming an essential measure for improving energy flexibility in buildings without much additional investment (Chen et al. 2018). Meaning that buildings are provided a

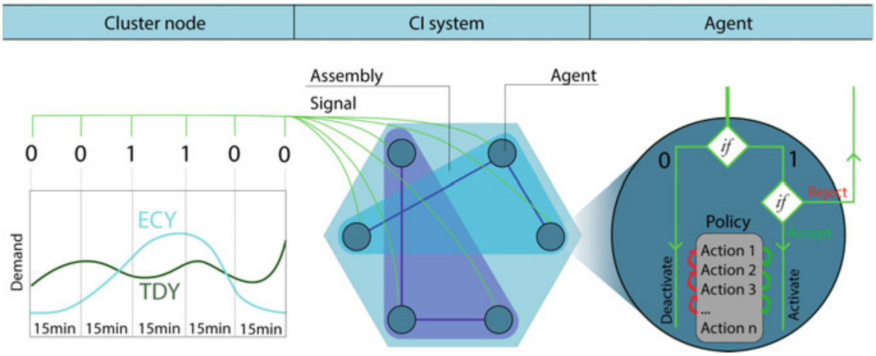

Fig. 144.3 CI system components and workflow

higher level of capability to absorb the shocks, caused by extreme conditions through interaction with other buildings and grid (Luc et al. 2019).

The outlined CI system in this work is comprised of (1) rule of engagement, (2) signal, (3) agents, (4) assemblies, (5) adaptation measures, (6) actions, and (7) policies. CI-DSM is implemented in the urban scale, divided into divisions equipped with smart device, named cluster nodes. Cluster node is on top of a set of agents and send the periodic signal of 0 and 1 to the agents. The breakdown of the described CI-DSM is illustrated in Fig. 144.3.

The mentioned components need to be defined explicitly. Table 144.1 denoted the definitions for CI-DSM components in this work.

According to the definitions, the workflow of this research starts from making assemblies to provide the connection between agents within the assembly. Each agent can make an assembly with certain points of interest such as similarities in function (e.g., residential or office) or size (e.g., area or energy demand). In this work assemblies are made of three agents including the creator (the agent that make the assembly) and two members (two other agents that are chosen by the creator to make connection with) which are assigned randomly. Due to the small number of agents in this work, each agent can be in several assemblies, which cause eliminating freedom of agents in decision-making, meaning that each choice is dependent on more parameters. In actual case, however, agents would be in only one assembly with more self-customized choices.

In the next step, agents receive the signal from the environment through cluster node. An agent can accept or reject to take action once receives signal 1. Agents tend to rebound to the initial settings; therefore, they do not reject signal 0. In this work they decide based on a random algorithm with 95% probability for accept and 5% for reject. An agent cannot reject a signal 1 if both other agents in the assembly do rejection, and this overrides its choice to accept or reject, saying that at least one agent in each assembly must accept the signal 1.

Adaption measures are (1) heating setpoint [°C] and (2) ventilation rate per floor area [l/s/m^2]. The heating setpoint can be changed in a range from 21 to 17 °C

Table 144.1 Definitions of the CI-DSM components

Components of CI-DSM	Definition
Rule of engagement	The conditions in which an agent needs to take an action; for instance, extreme climate events (universal stimulus) or need for ventilation in a crowded event (local stimulus)
Adaptation measure	The modifiable building characteristic to update the agent's energy performance aiming to achieve the universal energy goals
Signal	The stimulus of the agents which is 0/1 and does not carry any other information. The signal is sent periodically every 15 min to all agents universally
Agents	The smart equipment in thermal zones within the apartment. Agents have a certain level of intelligence and are able to send/receive signals to/from the environment in addition to their assemblies
Action	Action is the response of the agent to the signal which appears in adaptation measures
Policy	A set of actions is called policy, which defines the priority and order of the actions that have to be taken by the agent
Assembly	A group (a subset of cluster node) of agents which each agent creates to provide interconnection. Assemblies are made based on the topological distance which refers to making group with a certain number of agents regardless their physical distance but interest [23]

with 1 °C steps (5 choices). Air flow rate is adjustable from 0.30 to 0.12 l/s/m^2 with 0.06 l/s/m^2 steps (4 choices). Owing to the fact that analysis time step is short (15 min), the effects of air flow between different zones are neglected.

144.3 Results

The heating demand in an extremely cold February adjusted by implementing CI-DSM is presented and discussed in this chapter. To provide a better comparison between heating demand and outdoor temperature, statistical summary of typical and extreme weather conditions is appended to the demand data, denoted in Table 144.2.

The first analysis period (week 1–2) has 13.5 °C lower average temperature in ECY compared to TDY, while the second period has 5.7 °C lower temperature. Applying CI-DSM with 15-min intervals reduces the heating demand by 18% and 25% for week 1–2 and week 3–4, and peak demand by 17% and 20%, respectively. The hourly heating demand under TDY (Baseline), ECY (Without CI-DSM), and ECY (With CI-DSM) for the first period is presented in Fig. 144.4, left diagrams. To neglect the impacts of extreme weather conditions on heating demand over the first period, both adaptation measures (red and orange) are applied to the highest level during nearly all 366 h (14 days). Moreover, all zones (purple) are involved

Table 144.2 Statistical summary of weather conditions and demand in typical and extreme conditions. Relative difference (RD) is calculated from $((x_2 - x_1) \times 100/x_2)$, and difference (Diff.) is $(x_2 - x_1)$

Heating demand					Outdoor temperature			
		ECY [kWh]	CI-DSM [kWh]	RD [%]		TDY [°C]	ECY [°C]	Diff [°C]
Week 1–2	Mean	13.1	9.9	−18	Mean	3.4	−10.1	−13.5
	Max	18.2	14.6	−17	Min	−0.9	−20.3	−19.4
	Sum	4416	3333	−18	Max	7.7	−0.2	−7.8
Week 3–4	Mean	11.4	9.3	−25	Mean	−2.0	−7.7	−5.7
	Max	16.2	13.4	−20	Min	−13.2	−17.5	−4.3
	Sum	3827	3120	−25	Max	4.6	1.6	−2.9

in this adjustment progress. The first graph on top shows the performance of CI-DSM to narrow down the deviation between demand for typical (green) and extreme conditions (blue). Nonetheless, due to the extreme difference, heating demand is above typical conditions, except short periods from February 11th over the nights. There are a few hours that some of the agents rejected to take action, even though the demand exceeded the baseline.

The results for the second period, presented in Fig. 144.4, right diagrams, show that CI-DSM could approximately reach the baseline demand (TDY) in the extreme conditions (Dark blue line touches the green line). The heating setpoint is lowered to 17 °C for 140 (38%) hours and air flow rate is cut down to 0.12 l/s/m^2 over 215 (58%) hours out of 366 h. In total, 1882 zone · hour participation happens in this period among all 2016 (366 × 6) zone · hour (93%) and 7% rejection occur.

As explained in the method chapter, to simplify the research progress, most of the parts of the system are created by random algorithms. To further develop the method, it is essential to investigate conditions for agents to accept or reject the incoming signal, optimizing the policy making from possible actions, and to highlight the

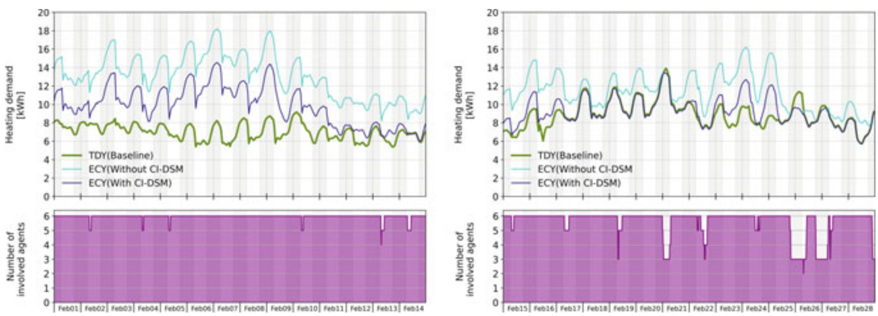

Fig. 144.4 Hourly heating demand, setpoint, air flow rate and involved zone over the first (left) and second (right) period. The gray area represents nighttime (18:00–06:00)

importance of applying user preferences. Applying CI-DSM can provide a higher level of adaptability to climate variations using distributed computation, without essential needs to high computation power through a central brain.

144.4 Conclusions

To deal with the growing frequency of extreme weather events and enhance the energy flexibility with a higher performance and affordability, a demand-side management method based on Collective Intelligence, called CI-DSM, has been developed, taking the opportunity of advances in information and communication technology (ICT) and the common willing for enhancing the level of smart readiness of buildings.

This work investigates an apartment in the south of Sweden with a detailed building performance simulation (BPS) model. CI-DSM is applied to heating system within six thermal zones in the apartment. Each zone is equipped by smart device to enhance the level of intelligence. Thus, each zone is correlated to an agent which can communicate and make decision. Two adaptation measure are defined including heating setpoint temperature and ventilation rate, which can be adjusted as a response to the changes in the environment. Periodic signal of 0/1 is sent to the agents from environment, which activate or deactivate their action. If energy demand exceeds the baseline demand (i.e., energy demand under typical weather conditions), signal 1 is sent and the agent makes a decision to whether take an action based on the defined adaptation measures or reject it. In this work, agents are connected in smaller groups, called assembly. Therefore, agents are able to consider their neighbors' conditions in their decision-making.

The results of the application of CI-DSM show a 25% and 20% reduction in heating demand and peak load, respectively, in extreme cold conditions (ECY) compared to typical weather conditions (TDY). In this research, the provided weather data for ECY shows significantly lower temperature over the first half of the month, where the results show that, even though heating demand is not reduced to the level of TDY, it is curtailed by a considerable fraction. Over the second half, due to a milder difference in temperature, CI-DSM could cut back heating demand to the level of typical conditions, with lower amount of zones participation and more moderate changes in adaption measures.

All in all, applying CI-DSM shows positive effects on energy systems. These effects can be increased by considering more actions and policies through learning algorithms or measurements. Distributed decision-making provides more customized solution based on the agents' conditions and potential. The application of CI-DSM needs to be further explored with a broader range of building conditions and, specially, considering user preferences.

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