Comfort-constrained Demand Flexibility Management for Building Aggregations using a Decentralized Approach

L. A. Hurtado, E. Mocanu, P. H. Nguyen, M. Gibescu and W. L. Kling
Department of Electrical Engineering, Eindhoven University of Technology,
5600MB, Eindhoven, The Netherlands

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Abstract: In the smart grid and smart city context, the energy end-user plays an active role in the operation of the power system. The rapid penetration of Renewable Energy Sources (RES) and Distributed Energy Resources (DER) requires a higher degree of flexibility on the demand side. As commercial and Industrial buildings (C&I) buildings represent a substantial aggregation of loads, the intertwined operation of the electric distribution network and the built environment is to large extent responsible for achieving energy efficiency and sustainability targets. However, the primary purpose of buildings is not grid support but rather ensuring the comfort and safety of its occupants. Therefore, the comfort level needs to be included as a constraint when assessing the flexibility potential of the built environment. This paper proposes a decentralized method for flexibility allocation among a set of buildings. The method uses concepts from non-cooperative game theory. Finally, two case of study are used to evaluate the performance of the decentralized algorithm, and compare it against a centralized option. It is shown that flexibility requests from the grid operator can be met without deteriorating the comfort levels.

1 INTRODUCTION

Traditionally, electricity demand is considered uncontrollable, however, relatively well predictable in a certain aggregation level. Thus, power generation needs simply to follow the load at all times. Imbalances between supply and demand might come from unforeseen demand fluctuations and generation units failures. To deal with possible system imbalances, transmission system operators (TSOs) make use of automated, i.e. primary and secondary control, or manual, i.e. tertiary control, power reserves (Entso-e, 2004; Ulbig and Andersson, 2012). This capacity of the system to react and adapt in a tolerable time to these unforeseen events is known as flexibility.

With the introduction of renewable energy sources (RES), distributed energy resources (DER) like storage, and the new type of loads like electric vehicles (EVs), new forms of uncertainty are introduced to the power system operation. These lead to more frequent system problems, e.g. generation-demand mismatch, and network problems, e.g. voltage stability, network congestion, blinding of protecting devices, etc. To deal with these challenges the active and smart control of the demand domain is required (Kefayati and Baldick, 2012). Recently, a considerable amount of attention has been given to the concept of "demand flexibility". Conventionally, flexibility was harnessed from power generation units. However, the flexibility offered by the end-users has the potential to help not only resolve network problems, but also accommodate a higher amount of RES, increase asset utilization and reduce peak demand (Morales-Valdés et al., 2014; Kirschen et al., 2012; Ulbig and Andersson, 2012).

Generally, the use of flexible demand for system and network support activities can be grouped under Demand Side Management (DSM) and Demand Response (DR) activities. Roughly, DSM refers to the long-term and short-term measures designed to influence the consumption pattern in such a way that it will influence the load shape of the utility, i.e. distribution system operator (DSO). Whereas, DR refers to the mechanisms designed to directly influence the demand of consumers in response to supply conditions, for instance through the use of market prices (Lampropoulos et al., 2013; Gellings, 2009). Literature shows that the smart management of flexible loads can indeed support grid operation and offer ancillary system services, without compromising the primary

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Nomenclature:

i	Index for $wall, window, roof$
k	Index for H_2O, CO_2
A_i	Area of i, $[m^2]$
$c_{p,a}$	Heat capacity of air, $[kJ/KgK]$
$c_{p,i}$	Heat capacity of i, $[kJ/KgK]$
$c_{p,w}$	Heat capacity of water, $[kJ/KgK]$
η_{fan}	Rated fan efficiency
$Flex_d$	Requested flexibility, [%]
$Flex_s$	Offered flexibility, [%]
$Flex_a$	flexibility of the aggregator, [%]
γ_{air}	Specific weight of air, $[N/m^3]$
M_i	Mass of i, $[Kg]$
M_{air}	Mass of the building air volume, $[Kg]$
M_{CO_2}	CO_2 molecular weight, $[gr/gr_{mol}]$
N	Occupancy
Q_{gen}	Metabolic heat rate, $[J/hr]$
P_z	Building pressure, $[atm]$
Φ^k_{env}	concentration of k in outdoor air, [gr/hr]
$\Phi_{gen,k}$	Metabolic generation rate of k, $\left[gr_k/m^3\right]$
Φ^k_{humid}	Humidifier mass removal rate of k, [gr/hr]
V_Z	Space volume, $[m^3]$
H_{lat}	Latent heat of condensation, $[kJ/gr_{H_2O}]$
H_{rated}	Rated head of the fan, $[m]$
R	Universal gas constant, $[atm\,m^3/gr_{mol}K]$
ρ_i	Density of i, $\left[Kg/m^3\right]$
ρ_w	Density of water, $\left[Kg/m^3\right]$
T_{env}	Temperature of return water, $[K]$
$T_{r,w}$	Temperature of supplied water, $[K]$
$T_{s,w}$	Temperature of supplied water, $[K]$
$T_{s,a}$	Temperature of supplied air, $[K]$
U_i	Heat transfer coefficient of i, $\left[kJ/hr\,m^2K\right]$
$\dot{v}_{s,w}$	water supply flow rate, $[m^3/s]$
$\dot{v}_s$	Air supply flow rate, $[m^3/s]$
$\dot{v}_r$	Air removal flow rate, $[m^3/s]$
$\dot{v}_{in}$	Outdoor air supply flow rate, $[m^3/s]$
$\dot{v}_{out}$	Exhaust air flow rate, $[m^3/s]$
$\dot{v}_{rated}$	Rated fan speed, $[m^3/s]$

mission of the controlled loads (Schlösser et al., 2014; Baccino et al., 2014; Cheng et al., 2014). In (Morales-Valdés et al., 2014) the effect of comfort relaxation on the energy demands of buildings is presented. In (Hurtado et al., 2014) the effect of different building operation scenarios on a low voltage distribution network is assessed. In (Klaassen et al., 2013) the potential of DSM in the perspective of the DSOs is discussed. In (Kobus et al., 2015) the role of smart appliances in the real electricity demand shift is presented, in the Dutch context. In (Sajjad et al., 2014) the effective use of demand flexibility for peak reduction is discussed, in a residential customers context. However, throughout literature the correlation between comfort and demand flexibility, in the context of grid support is still lacking. Furthermore, flexible resources can be allocated and managed in a similar way as generation resources using market-based approaches, e.g. constrained economic dispatch, or heuristic approaches, e.g. genetic algorithms, to meet a flexibility demand (Berardino et al., 2012; Gupta et al., 2012).

As demand flexibility is a scarce resource that needs to be assigned to various uses, it requires aggregation to have a noticeably positive impact on the grid operation. Buildings differ in size, functions, energy demand and are under constant change. They consist of different systems that differ in dynamics and life time. However, their main function is to provide occupants with a comfortable and healthy indoor environment, i.e. about 50% of the total electrical energy consumed by the building, is used for comfort management (Zhao et al., 2013). Therefore, to guarantee the correct operation of both systems, i.e. electricity grid and building, not only network constraints but also comfort constraints should be included in the allocation of flexibility obligations.

In this paper, comfort is proposed as a necessary metric for demand flexibility in the built environment. As the building objective is different from grid support, comfort needs to be monitored and constrained when offering flexibility. A straightforward building energy and comfort model is developed in this paper to represent the dynamics of building operation, while establishing a relationship between comfort and energy management. Here, only flexibility from the comfort systems is considered, not only because it represents a great part of the total energy consumed by the building, but also because there is a time lapse between comfort variation perception and the comfort system operation, which allows for such systems to be operated in non traditional ways. Furthermore, we propose the use of a n-player non-cooperative game to allocate a flexibility request over a finite number of buildings, without violating the comfort limits for each of the buildings. This is a decentralized approach that reduces the need for the aggregation of information to achieve an optimal solution. Finally, using the building model proposed, two case studies are used to evaluate the performance of the proposed decentralized algorithm.

The remainder of this paper is divided into 5 sections. In the next section the flexibility inherent to the built environment is discussed in terms of power and comfort demand. Furthermore, in this section the envelope model of a building is presented. This model is used to represent the comfort and energy dynamics of each player in the game. In the following section the aggregator's role is introduced. In section 4 the case study consisting of 5 buildings is presented, with the numerical results. Finally, section 5 summarizes and presents conclusions from this work.

2 FLEXIBILITY IN THE BUILT ENVIRONMENT

Being responsible for about one-third of the energy consumed in cities (Park et al., 2011), commercial and industrial (C&I) buildings have the potential to significantly contribute to the efficient operation of the power system, accommodate a higher amount of RES, increase asset utilization and reduce peak demand (Hurtado et al., 2014; Morales-Valdés et al., 2014; Kirschen et al., 2012; Ulbig and Andersson, 2012). However, the main objective of building is far from being either system or network support. In general, building operation involves comfort and energy management tasks. Roughly, comfort management represents more than half of the total building energy demand (Zhao et al., 2013). This means that flexibility, if defined as the demands's capability to react and adapt in a tolerable time to unforeseen system or network events, will potentially have a negative impact on the building comfort.

As mentioned, the first main task of a building management system is comfort management. However, comfort is a complex and subjective human perception. In previous work, the authors conceptualized comfort as a function of both thermal and air quality while CO_2 concentration levels were kept as a system constraint (Hurtado et al., 2014). Traditionally, temperature and relative humidity are used as the metrics to represent thermal and air quality comfort. In (1) comfort is described as a combination of two Gaussian functions representing thermal and air quality comfort.

$$comf = \underbrace{\omega\, e^{\left[\frac{-(T-\mu_T)^2}{2\sigma_T^2}\right]}}_{\text{Thermal comfort}} + \underbrace{(1-\omega)e^{\left[\frac{-(Rh-\mu_{RH})^2}{2\sigma_{Rh}^2}\right]}}_{\text{Air quality comfort}} \quad (1)$$

where, ω is a weight factor; T is the building's temperature; μ_T is the mean temperature value, or the optimal temperature set point; σ_T is the thermal comfort standard deviation, which represents the discomfort tolerance; Rh is the relative humidity; μ_{RH} is the mean humidity, or air quality optimal set point; and σ_{RH} is the standard deviation for air quality comfort, which represents the discomfort tolerance.

The second main task of a building management system is energy management. This work categorizes the energy systems of a building into comfort and non-comfort systems. Energy demand of a comfort system corresponds to the energy consumed for comfort management. Whereas, the energy demand of a non-comfort systems correspond to specific individual systems in local zones.

The total power consumption, in watts $[W]$, of a building is expressed in the following equation:

$$P_{total} = \underbrace{P_{AHU} + P_{heater}}_{\text{comfort}} + \underbrace{\sum_{i=1}^{z} P_i}_{\text{non-comfort}} \quad (2)$$

where, P_{AHU} represents the power demand of the Air Handling Unit (AHU) for air quality comfort; P_{heater} is the power consumed by the heating system for thermal comfort purposes; and P_i represents the power consumed by the zone's devices in the Z zones, e.g. lights, computers, etc.

2.1 The Envelope Model

A building is a complex multi-zonal comfort system, governed by the energy and mass conservation principles. In the context of the smart grid and smart cities, for the built environment flexibility to have a noticeable positive impact on the grid operation, aggregation is required. This process requires irrelevant information to be neglected and the simplification of the models used. Thus, in the same context, it is impractical and highly complex to have a detail, zone by zone, model of the building. In this work an envelope model is developed, in which the building is represented as a single zone system. Such model gives a fair approximation to the energy and comfort dynamics of a building. In this model, there are three state variables: the zone temperature (T), the zone relative humidity (Rh) and the zone CO_2 concentration (Φ_{CO_2}) levels. Moreover, the air in the zone is assumed to be fully mixed, i.e. uniform temperature distribution, with constant density, and the pressure losses in the zone and the effect of the building orientation, i.e. solar gains, are neglected. Finally, occupancy (N) and the weather, i.e. temperature (T_{env}), water concentration $(\Phi_{env}^{H_2O})$, and CO_2 concentration $(\Phi_{env}^{CO_2})$, are the uncontrolled inputs.

2.1.1 Thermal Dynamics

With the aforementioned assumptions, the thermal dynamics of the building represented through lumped capacity model described by the energy conservation principle:

$$\frac{dT(t)}{dt} = \frac{1}{M_{air}\, c_{p,a}} \left(Q_{in} + Q_{heater} - Q_{loss}\right) \quad (3)$$

where, Q_{in} represents the internal gains due to the heat generation of occupants; Q_{heater} represents the heat contribution of the heating system used. Finally, Q_{loss} is used to model the heat losses through the envelope of the zone.

The energy transferred to the building is proportional to the energy transferred by the heating system, as expressed in (4), and by heat contribution of the occupants, as expressed in (5).

$$Q_{heater} = \dot{v}_{s,w}\rho_w c_{p,w}(T_{s,w} - T_{r,w}) \quad (4)$$

$$Q_{in} = N\ Q_{gen} \quad (5)$$

The energy removed from the building is the energy lost to the environment through the building envelope. These are represented through the conduction and convective heat transfer mechanisms,

$$Q_{loss} = \sum_{i=1}^{n} U_{i,in}A_i(T_i - T) \quad (6)$$

where, n is number of envelope elements, and their temperature, T_i, is given by:

$$\frac{dT_i(t)}{dt} = \frac{U_{i,in}A_i(T - T_i) + U_{i,out}A_i(T_i - T_{env})}{M_i\ c_{p,i}} \quad (7)$$

where, T_{env} is the outdoor air temperature.

2.1.2 Air Quality Dynamics

Air is a mixture of multiple elements in different concentrations. Indoor air quality is traditionally measured through the water content, i.e. relative humidity, and CO_2 concentration dynamics in the air. These dynamics can be represented through the mass and component balances in the air volume. The concentration change in time of an element k is proportional to the particles of that element added and extracted from the volume, as expressed in the following equation:

$$\frac{d\Phi_k}{dt} = \frac{1}{V_z}\left(\dot{v}_s\Phi_s^k - \dot{v}_r\Phi_k + N\Phi_{gen,k}\right) \quad (8)$$

where, the concentration of element k in the supplied air, Φ_s^k, is given by:

$$\Phi_s^k = \frac{1}{\dot{v}_s}\left(\dot{v}_r\Phi_k + \dot{v}_{in}\Phi_{env}^k - \dot{v}_{out}\Phi_k + \Phi_{humid}^k\right) \quad (9)$$

where, Φ_{env}^k is the concentration of k in the outdoor air, and Φ_{humid}^k is the humidifier mass removal rate of element k, with $\Phi_{humid}^k = 0,\ \forall\ k = CO_2$.

Finally, using the Ideal gas law, relative humidity and the CO_2 concentration can be rewritten as follows:

$$Rh(t) = 100\frac{\Phi_{H_2O}}{\Phi_{H_2O}^{sat}} \quad (10)$$

$$[ppm]\Phi_{CO_2} = 1000\frac{\Phi_{CO_2}R\ T_z}{M_{CO_2}P_z} \quad (11)$$

where, the saturated concentration of water is given by Antoine's equation:

$$Log_{10}(\Phi_{H_2O}^{sat}) = 8.07131 - \frac{1730.63}{T - 39.73} \quad (12)$$

2.1.3 Energy Dynamics

As mentioned, a large part of the building's energy demand comes from the comfort management systems. In this section, and for the rest of the paper, we consider only the AHU and heating system as the flexibility sources of the building. These systems aim to keep the comfort parameters within the designed ranges, according to the dynamics previously described. In a general way, the energy consumed by these systems is used to move and heat up the water (P_{heater}), and the air (P_{AHU}) in the building.

The electrical power consumed by the heating system is proportional to the ratio between the system's heat output and its coefficient of performance COP, which is used to describe the ratio between the useful heat produced and the power input.

$$P_{heater} = \frac{Q_{heater}}{COP} \quad (13)$$

where, Q_{heater} is given by (4) as a function of the zone temperature T.

Before new air is added to the building, it goes through several steps. These can be summarized in three general steps: air mixing, air pre-heating or pre-cooling, and air humidification. In the first step, the return air is mixed with new air from the outside, this process helps to control the particles concentration in the air to be supplied back to the zone. In the second step, the mixed air is heated up or cooled down to the desired temperature. This is done by the action of the heating and cooling elements of the AHU. In the last step, water is added to the air to control the humidity of the supply air. The electrical power consumed by the AHU to control the quality of the air in the building is proportional to the power consumed to move the air in and out the zone, to condition the air to the right temperature, and to humidify the air to the desired value. In the envelope model used in this work, this corresponds to the power consumed by the fan, heating and humidifying systems of the AHU, as expressed in the following equation:

$$P_{AHU} = P_{fan,s} + P_{fan,r} + P_{coil} + P_{lat} \quad (14)$$

where, $P_{fan,s}$, $P_{fan,r}$, P_{coil} and P_{lat} depend on the various air flow and mass removal rates used to control, both the water and CO_2 concentrations rates given by

(8), and according to the following equations:

$$P_{fan} = \frac{\gamma_{air}(\dot{v}_{fan})^3 H_{rated}}{\eta_{fan}(\dot{v}_{rated})^2} \quad (15)$$

$$P_{coil} = \frac{\dot{v}_{in} c_{p,a}(T_{s,a} - T_{mix})}{COP_{coil}} \quad (16)$$

$$P_{lat} = \Phi_{humid}^{H_2O} H_{lat} \quad (17)$$

where, $\dot{v}_{fan}$ is the air flow going through the fan, i.e. $\dot{v}_{in}$ for the supply fan, and $\dot{v}_{out}$ for the return fan. Finally, T_{mix} is the temperature of the air in the mixing room, and it is given by:

$$T_{mix} = \frac{((\dot{v}_{in} - \dot{v}_{out})T_{env} + \dot{v}_{out}\, T)}{\dot{v}_{in}} \quad (18)$$

3 FLEXIBILITY AT THE AGGREGATOR LEVEL

Despite C&I buildings being a considerable load to the power system, they are by themselves not big enough to have a noticeable positive impact on the grid operation. This creates the need for an aggregating entity, with the role of accumulating flexibility to meet a request from the grid at the lowest comfort cost (Backers et al., 2014). Here, flexibility [%] is conceptualized as the ratio between flexible power, and the total power demand at a given moment of time. For instance, the building's flexibility, i.e. $(Flex_s)$, is defined as the ratio between the building's flexible power, and the building's peak power. The grid's flexibility request, i.e. $(Flex_d)$, is defined as the ratio between the change in power required, and the total power demanded in the grid. In general, an aggregating entity aims to distribute the grid's flexibility request, $(Flex_d)$, over a portfolio of buildings, each with its own flexibility offer $(Flex_s)$. Such problem is analogue to a constrained resource allocation problem with a hard comfort constraint, as described next:

Minimize

$$\Delta\, Flex = Flex_d - \sum_{j=1}^{B} Flex_{s,j} \quad (19)$$

Subject to

$$comf_j \geq \ comf_{j,min} \quad (20)$$

However, this requires the aggregating unit to have knowledge over the building dynamics and the effect of flexibility on the building comfort. Nonetheless, the aggregator resources are owned and managed by different entities, with different objectives, users and priorities. In the scope of this arguments, let us introduce the concept of a non-cooperative game and develops methods for the mathematical analyse of such game. The game presented is a n-person game defined by means of pure strategies and pay-off functions defined for the combinations of pure strategies.

At the aggregated level a multi-player game is investigated in order to find a optimum flexibility point under a equal comfort condition in a different number of buildings. This full decentralized solution is used to compute one sample Nash Equilibrium point. Nash proved that this equilibrium concept exists for any game with a finite number of players, each of them having a finite number of strategies (Nash, 1951).

In a classical normal form, the optimization formulation of n-person non-cooperative games, $\Gamma(B, Flex_s, R)$, consists of the following:

- A set $B = \{1, ..., j\}$ of buildings (players).
- A finite set $Flex_s^{(j)}$ of strategies for each building $j \in B$, were $Flex_s$ is defined by a set of n-tuples of pure strategies, such as $(Flex^0, Flex^{10}, Flex^{20}, Flex^{30}, Flex^{50})$.
- A reward (pay-off) function, $R_j : Flex_s \to \mathbb{R}$, for each building $j \in B$, which maps the set of all n-tuples of pure strategies into the real numbers.

The payoff function (R_j) has a unique extension to the n-tuples of mixed strategies which is linear in the mixed strategy of each player, $R_j(Flex_s^{(1)}, ..., Flex_s^{(B)})$.

Theorem 1. *(Nash, 1951) The mixed extension of the finite game $\Omega(B, Flex_s, R)$ has at least one strategic equilibrium.*

Formally, a n-tuple Ω is an equilibrium point if and only if for every j

$$R_j(\Omega) = \max_{\forall \gamma_j, \psi}[R_j(\Omega; \gamma_j)] \quad (21)$$

where $\Omega = (Flex_s^{(1)}, ..., Flex_s^{(B)})$. Thus, an equilibrium point is a n-tuple Ω such that each player's mixed strategy maximizes his payoff if the strategies of the others are held fixed. Thus, each player's strategy is optimal against those of the others. A mixed strategy $Flex_s^{(j)}$ use a pure strategy $\Pi_{j\alpha}$ if $\psi_j = \sum_\alpha c_{j\alpha} \Pi_{j\alpha}$ and $c_{j\alpha} > 0$. From the linearity of $R_j(Flex_s^{(1)}, ..., Flex_s^{(B)})$ in ψ_j

$$\max_{\forall \gamma_j, \psi}[R_j(\Omega; \gamma_j)] = \max_\alpha [R_j(\Omega; \Pi_{j\alpha})] \quad (22)$$

Let $R_{j\alpha}(\Omega)$ be defined as $R_{j\alpha}(\Omega) = R_j(\Omega; \Pi_{j\alpha})$. Then, the following necessary and sufficient condition for Ω to be an equilibrium point is:

$$R_j(\Omega) = \max_\alpha R_{j\alpha}(\Omega) \quad (23)$$

Table 1: Building envelope characteristics.

	Volume $[m^3]$	Area $[m^2]$	Occupancy N_{av}	t_{in}	t_{out}	Peak power $[kW]$	Non-flexible power $[kW]$
Building A	4536	453.6	20	7hr	18hr	8.18	2.45
Building B	18144	1814.4	37	9hr	14hr	12.6	3.78
Building C	10206	1020.6	30	9hr	17hr	10.08	3.02
Building D	1134	113.4	14	12hr	20hr	7.56	2.26
Building E	2268	226.8	10	8hr	17hr	7.57	2.27

An equivalent condition for every j and α is:

$$R_j(\Omega) - R_{j\alpha}(\Omega) \geq 0 \tag{24}$$

More generally, the set of all equilibrium strategies ψ_B are simply the set of *good* strategies of a player which is a convex polyhedral subset of his mixed strategy space. A strong solution exists only when there is a *saddle point* in the pure strategies. In (24) an equivalent form of the non-linear flexibility optimization problem defined in (19) is presented, where $R_{(.)} \simeq Flex_{(.)}$.

This problem has been discussed in the literature in different forms. In the case of cooperative games, the players (agents) exchange information between them, and in the case of non-cooperative games the players do not exchange information, to achieve the same Nash equilibrium point. A more comprehensive discussion can be found in (Khan and Sun, 2002; Rosenthal, 1989), and some examples of different applications for the non-cooperative games can be seen in (Chatterjee, 2009; Fadlullah et al., 2011).

4 CASE STUDY

Using the building model described in section 2, we evaluate the performance of n-person non-cooperative game, and experimentally it is shown that the flexibility request can be met by providing efficient flexibility schedules, while comfort is kept within the required boundaries.

Five different buildings are modelled. The major differences between these five simulated buildings are summarized in Table 1. Each building has three main state variables, the zone temperature (T), the zone relative humidity (Rh) and the zone CO_2 concentration (Φ_{CO_2}) levels. These variables do not only relate to to the comfort, but also to the energy behaviour of the building model, as described in section 2. Different occupancy profiles were used for each building. Each building has an average number of occupants N_{av} with a random variation in time (see Table 1), as expressed in the following equation:

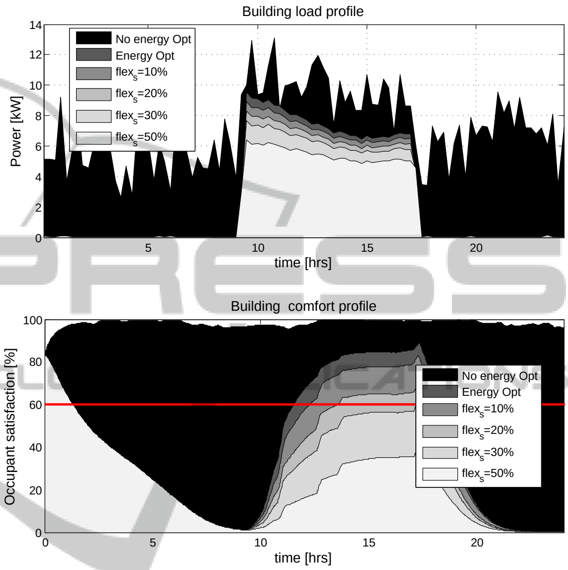

Figure 1: Example building load and comfort profile.

$$N = \begin{cases} \mathcal{N}(N_{av}, 1) & \text{if } t_{in} < t < t_{out} \\ 0 & \text{if } t \leq t_{in} \lor t \geq t_{out} \end{cases} \tag{25}$$

Moreover, the building behaviour is also weather dependant. The model uses simulated weather data for temperature, water and CO_2 concentration in air, representing a typical winter day in The Netherlands. In a first simulation, the peak power for every building is obtained, as summarized in Table 1. Consequently, varying the flexibility offer of each building, $Flex_s$, the building behaviour is obtained for every building. Figure 1 is given as an example to illustrate such behaviour of a building. The upper figure shows the building power demand for different flexibility offers, and the bottom figure shows the occupant satisfaction, i.e. comfort, as depicted in (1). This figure shows that as the flexibility offer is increased, the building comfort profile is deteriorated.

The grid flexibility request, an hourly reduction request, is set to vary between 0 and 50% of the total flexible power offered by the aggregator. This is the accumulated flexibility from the aggregator's portfolio, $Flex_a = \sum_{j=1}^{B} Flex_{s,j}$. In a similar way, buildings are allowed to provide up to half of their flexible

Algorithm 1: N-player game algorithm.

%Initialization
Buildings → Players
Building flexibilities → Actions
%Get buildings' flexibility response
for all time steps **do**
  for all SmartGrid flexibilities requests **do**
    for all (p,a)∈(Players, Actions) **do**
      initialize rewards R(p,a)
    end for
    PlayGame(Players,Actions,R)
    Nash equilibrium → Buildings' response
  end for
end for

power, i.e. $Flex_s \in \{10\%, 20\%, 30\%, 50\%\}$. For an arbitrary number of buildings, the demand flexibility resource allocation problem can be solved using the pseudo-code from Algorithm 1 and playing a n-player game as described in Section 3.

The proposed solution seeks the right balance between, the request made by the smart grid, and the flexibility available in buildings. In this solution, each building commits discrete parts of their flexible power as a flexibility offer, $Flex_s$, relative to the flexibility request, $Flex_d$.

In the remaining of this paper we present two test cases which involve two and five buildings, respectively. In both cases, we ensure the end-user comfort to be within the limit, i.e. $comf_{min} \geqslant 60\%$, which according to the definition presented earlier in (1), corresponds to the upper and lower comfort limits established by ASHRAE Standard 55-1992.

4.1 Case 1: 2-player Game

In this first case the n-person games is played between two of the five buildings. Buildings D and E are selected for this first case, since they are the smallest buildings, but they also showed the most different occupancy profiles. This means, that these two buildings are able to supply more flexibility with a lower impact on their comfort profiles. The exact results obtained for various smart grid flexibility requests are shown in Table 2 and Figure 2. As mentioned, the building results are presented as percentages of the total flexibility request. For instance, if the Smart Grid flexibility request is 10% of the current electricity demand at midnight, i.e. $time = 24h$, the flexibility offer of buildings D and E is 47.9% and 80.4% respectively. In this case, the buildings can offer higher demand flexibility than that requested by the grid. However, as the flexibility request is increased, the building's offer start to decrease in relation to the request (see: Table 2). Finally, from the Figure 2 it can be seen that the aggregator is able to meet the grid request while ensuring that the comfort of both buildings is kept higher than 60%.

Table 2: Flexibility response under different Smart Grid requests, as percentage of the total flexibility request

	Smart Grid flexibility request at the aggregated level									
	10%		20%		30%		40%		50%	
Time	Buildings flexibility response [%]									
[h]	D	E	D	E	D	E	D	E	D	E
1	0	0	0	0	163.4	163.4	122.5	122.5	98.0	98.0
2	297.7	0	148.8	0	99.2	0	74.4	0.0	59.5	0
3	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0	0
5	0	0	121.6	0	81.1	0	60.8	0	48.6	0
6	180.4	0.0	90.2	0	60.1	0	45.1	0	36.1	0
7	84.7	0	42.3	0	28.2	0	21.2	0	16.9	0
8	93.1	0	46.6	0	31.0	0	23.3	175.7	18.6	140.5
9	0	191.9	0	95.9	0	64.0	151.6	48.0	121.3	38.4
10	0	0	0	150.8	0	100.5	0	75.4	0	60.3
11	0	0	0	0	0	0	0	181.8	0	145.4
12	0	0	0	0	0	0	0	0	0	0
13	0	0	0	0	0	0	0	180.2	0	144.2
14	0	100.3	0.0	50.1	0.0	33.4	0	25.1	0	20.1
15	0	0	0	140.8	0	103.6	0	77.7	56.8	62.2
16	0	0	0	107.9	0	79.7	0	59.8	61.4	47.8
17	0	158.1	0	91.0	0	60.7	0	45.5	0	36.4
18	0	46.0	0	23.0	0	15.3	148.2	11.5	118.6	20.7
19	0	117.9	0	81.4	0	54.3	0	40.7	0	32.6
20	0	0	0	0	0	0	0	0	0	0
21	0	0	0	0	0	0	0	0	0	0
22	127.1	85.5	74.0	42.7	49.3	28.5	37.0	21.4	29.6	17.1
23	0	0	0	0	0	0	0	0	0	0
24	47.9	80.4	24.0	40.2	16.0	26.8	12.0	20.1	9.6	16.1

Additionally, in figure 3, we compared the decentralized Dynamic Game Theory (DGT) approach against a centralized approach using Particle Swarm Optimization (PSO). At the aggregated level PSO is used to allocate the flexibility obligations among the

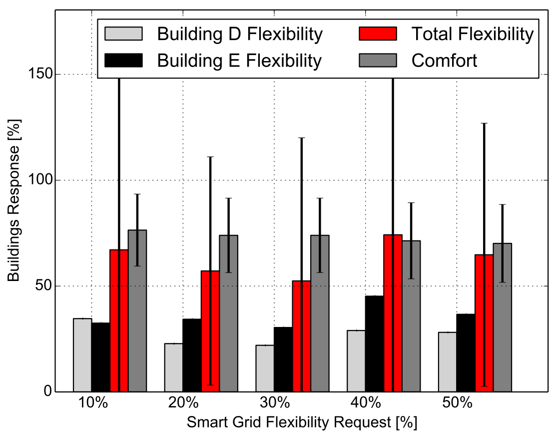

Figure 2: Flexibility responses averaged over a day for 2 buildings under different grid flexibility requests, with mean and standard deviation.

playing buildings. In (Hurtado et al., 2014) more details and the mathematical description of the PSO approach can be found. In the figure the playing buildings' aggregated flexibility is shown as a percentage of the flexibility request. It is observed that the centralized approach offers higher flexibility during the morning hours. However, the decentralized approach offers better results during the afternoon hours, time in which both buildings are occupied.

4.2 Case 2: 5-player Game

In the second case study the n-person non-cooperative game is played between the 5 buildings (i.e. A, B, C, D, and E). In Table 3 the exact results as percentages of the flexibility request at the aggregated level are presented for the various grid requests. As before, every building is allowed to give up to 50% of its own flexible power on an hourly basis, and this is in some cases, is higher than the grid request. In Figure 4 the effect on comfort is also presented. It can be observed how the increase of the flexibility request has a negative effect on the overall comfort level of the building. It can also be seen that the total relative flexibility offer is decreased as the request increases. However, from the table it can be observed that as the request is increased, the number of buildings participating in the flexibility offer increases. From the table it can also been seen that for most of requests buildings B and C do not offer flexibility. Despite being the bigger buildings, i.e. higher peak load, the relation between comfort and flexibility is worst for these two buildings. For instance, Figure 1 shows such relation for the building C.

It is worth highlighting, that in some cases the buildings provide a flexibility response over one hundred percent. This happens due to the fact that the grid requests and buildings response is discretized and we work with fixed flexibility points, i.e. $Flex_s^{(j)} \in \{10\%, 20\%, 30\%, 50\%\}$. This can be used

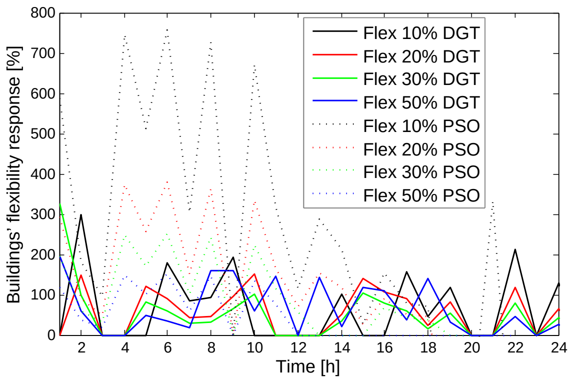

Figure 3: Centralized (PSO) versus decentralized (DGT) buildings' D and E flexibility response.

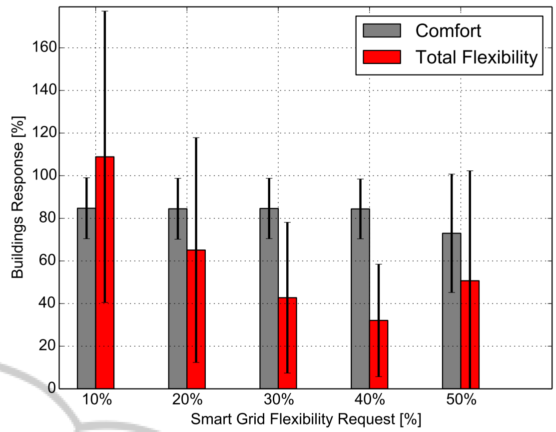

Figure 4: Flexibility and comfort profile responses averaged over a day for all 5 buildings relative to different grid flexibility requests, with mean and standard deviation.

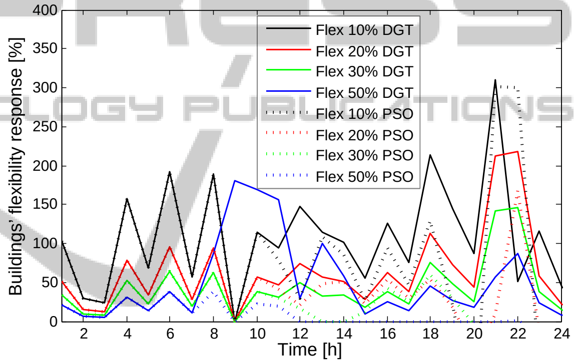

Figure 5: Centralized (PSO) versus decentralized (DGT) buildings' flexibility response.

as an advantage to shift the load to time periods where the Smart Grid flexibility request can not be fulfilled. One solution for this, can be achieved by adjusting dynamically the flexibility games.

In figure 5, we compared again the decentralized DGT approach against the centralized approach PSO. It is observed that in the first 7 hours and in the last hours of the day both methods offer similar solutions. This is mainly due to the fact that during these periods the buildings are mostly unoccupied. Moreover, it is also observed that the decentralized solution has in general better results than the centralized one.

5 CONCLUSIONS

This paper proposed a decentralized algorithm for flexibility request allocation among an aggregated portfolio of buildings. Furthermore, the use of comfort as a metric for flexibility in the built environment

Table 3: Flexibility response under different Smart Grid requests, as percentage of the total flexibility request.

	Smart Grid flexibility request at the aggregated level																								
	Flexibility request [10%]					Flexibility [20%]					Flexibility [30%]					Flexibility [40%]					Flexibility [50%]				
Time	Building flexibility response																								
[h]	A	B	C	D	E	A	B	C	D	E	A	B	C	D	E	A	B	C	D	E	A	B	C	D	E
1	0	0	0	102.4	0	0	0	0	51.2	0	0	0	0	34.1	0	0	0	0	25.6	0	0	0	0	20.4	0
2	0	0	0	29.5	0	0	0	0	14.7	0	0	0	0	9.8	0	0	0	0	7.3	0	0	0	0	5.9	0
3	0	0	0	23.2	0	0	0	0	11.6	0	0	0	0	7.7	0	0	0	0	5.8	0	0	0	0	4.6	0
4	0	0	0	123.5	34.5	0	0	0	61.7	17.2	0	0	0	41.1	11.5	0	0	0	30.8	8.6	0	0	0	24.7	6.9
5	0	0	0	28.8	39.4	0	0	0	14.4	19.7	0	0	0	9.6	13.1	0	0	0	7.2	9.8	0	0	0	5.7	7.8
6	0	0	0	149.24	42.5	0	0	0	74.6	21.2	0	0	0	49.7	14.1	0	0	0	37.3	10.6	0	0	0	29.8	8.5
7	0	0	0	0	57.0	0	0	0	0	28.5	0	0	0	0	19.0	0	0	0	0	14.2	0	0	0	0	11.4
8	0	0	0	0	188.6	0	0	0	0	94.3	0	0	0	0	62.8	0	0	0	0	47.1	0	0	38.0	10.6	37.7
9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	19.5	75.6	60.1	3.0	21.8
10	0	0	0	0	114.6	0	0	0	0	57.3	0	0	0	0	38.2	0	0	0	0	28.6	21.6	65.9	55.7	2.0	22.9
11	0	0	0	0	94.1	0	0	0	0	47.0	0	0	0	0	31.3	0	0	0	0	23.5	8.7	68.2	48.2	12.59	18.8
12	0	0	0	98.8	48.7	0	0	0	49.3	24.3	0	0	0	32.9	16.2	0	0	0	24.7	12.1	0	0	0	19.7	9.7
13	19.3	0	0	0	95.5	9.6	0	0	0	47.7	0	0	0	0	31.8	4.8	0	0	0	23.8	6.8	29.5	26.0	17.8	19.1
14	30.1	0	0	0	71.3	15.0	0	0	0	35.6	10.1	0	0	0	23.7	7.5	0	0	0	17.8	6.0	12.5	6.8	18.2	14.2
15	37.7	0	0	0	16.9	18.8	0	0	0	8.4	12.5	0	0	0	5.6	9.4	0	0	0	2.1	7.5	0	0	0	1.6
16	64.2	0	0	0	61.0	32.1	0	24.4	0	15.8	18.5	0	0	0	20.3	16.0	0	0	0	13.4	12.8	0	0	0	12.2
17	36.9	0	0	0	38.42	18.4	0	0	0	19.2	12.3	0	0	0	10.3	5.5	0	0	0	9.6	7.3	0	0	0	6.1
18	132.5	0	48.8	0	31.6	72.7	0	24.4	0	15.8	48.4	0	16.2	0	10.5	34.8	0	12.2	0	7.9	29.1	0	9.7	0	6.3
19	88.6	43.9	11.8	0	0	44.3	21.9	5.9	0	0	29.5	14.6	3.9	0	0	22.1	10.9	2.9	0	0	17.7	6.6	2.3	0	0
20	0	86.4	0	0	0	0	43.2	0	0	0	3.7	28.8	0	0	0	0	21.6	0	0	0	0	17.2	0	0	0
21	0	136.1	0	173.5	0	0	124.9	0	86.7	0	0	83.3	0	57.8	0	1.1	62.4	0	43.3	0	0	27.2	0	34.7	5.3
22	1.6	0	49.3	0	0	0.8	192.9	24.6	0	0	0.5	128.6	16.4	0	0	9.1	0	19.8	0	0	7.3	0	15.9	0	0
23	36.5	0	79.5	0	0	18.2	0	39.7	0	0	12.1	0	26.5	0	0	9.1	0	19.8	0	0	7.3	0	0	15.9	0
24	0	0	44.6	0	0	0	0	22.3	0	0	0	0	14.8	0	0	0.9	0	11.1	0	0	0.7	0	8.9	0	0

is employed. A building envelope model is developed to describe the building demand and comfort dynamics. Based on this model, a n-player non-cooperative game is set up, with the objective of meeting the flexibility request while ensuring that comfort is not deteriorated below a certain minimum threshold (60%). It is shown that a range of flexibility requests can be met by a portfolio of buildings without violating comfort constraints. However, it is shown that not always the biggest building is the most suitable flexibility source, when taking comfort into consideration.

Furthermore, the decentralized Dynamic Game Theory method was compared against a Particle Swarm Optimization based approach. It is shown that as the number of playing buildings is increased, the decentralized (DGT) approach offers better results. However, deeper research is required in order to generalize this last conclusion. Furthermore, the decentralized approach does not require the aggregating unit to have complete information of the playing buildings, which is a clear advantage as the number of players is increased.

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