ENERGY EFFICIENCY THROUGH MULTI-AGENTS ADAPTIVE MICROMANAGEMENT

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Finding successful ways to reduce the energy utilization in commercial and residential buildings is of paramount importance in lowering CO_2 emissions and achieving the Kyoto Protocol commitments on climate change. Indoors energy consumption account for roughly 40% in US and EU. Building exploitation are linked to about 36% of the total CO2 footprint. The main approach to ameliorate this situation is to enhanced energy efficiency, decrease the overall consumption and switch to renewable, carbon-free energy sources. In the field of energy efficiency, enhancement of load control and adaptive demand response at every point of consumption are part of the solution. This paper presents the problematic and limits of energy consumption savings while accommodating human comfort propensity. Further we present the simulation results for a grid of independent, autonomous, collaborative agents that continuously monitor human activity in a closed environment and override the user configured comfort preferences towards a default optimum performance/cost whenever the changes do not affect the user experience. In order to better highlight the importance of local micromanagement and to obtain the best approximated average performance, the chosen simulation environment was a 250 rooms hotelier resort and targeted the heating/cooling annual energy cost with human behavior stochastic considerations.

Keywords: multi-agents, energy efficiency, intelligent buildings.

INTRODUCTION

A building's energy consumption depends on numerous factors like structure, insulation, climate, in-terrain positioning, residents, usage patterns, HVAC (heating, ventilation and air conditioning) performance, etc. These factors can be treated as systemic features or exploitation events.

Simulating a building's usage history over a significant period can test usage strategies and indicate improvement options. Real-time monitoring in large buildings is expensive, the case-study timeframe cannot be compressed and the events cannot be exactly rerun. The study results are strongly linked to the observed building and the improvement recommendations cannot be ported elsewhere. Modeling and simulating user activities in virtual environments is cost effective, fast, flexible and permits use-case scenarios testing for better systemic, organizational and procedural design (Fujimoto, 2001).

Multi-agent systems (MAS) architectures avoid the "single point of failure" structural vulnerability encountered in SCADA design, provide support for interconnectivity and interoperability of legacy systems in heterogeneous assemblies and mitigate network service interruption. MAS characteristics determine an inherent better reliability, robustness, extensibility, maintainability, responsiveness and flexibility of the developed solution.

The agents can either be explicitly organized in particular task groups or configured to auto-organize and cooperate towards a preconfigured set of goals (Vasyutynskyy *et al.*, 2007; Rutishauser, 2002). The tasks can be related to Smart Grid operations and optimization, energy consumption with HVAC and lighting, user comfort, security and disaster management, etc.

While from a theoretical point of view the space positioning of some system elements (sensors/actuators) do not deny the conceptual systemic unity and the agent as set of roles distributed across multiple nodes is admissible (Ruairí & Keane, 2007), we consider an agent to be a dynamically configurable, compact unit capable of autonomous and collaborative behavior.

Energy efficiency strategies implemented at building level are impaired by individual originated demands and preferences. While most approaches treat the building's HVAC demand as a whole and propose strategies at building level, the objective of this paper is to demonstrate the importance of micromanagement at user and individual action level. Further, we prove the existence of an important savings margin by overriding a user's preferences whenever his comfort or experiences are not affected.

THEORETICAL BACKGROUND

The overall heat loss aggregates surface losses by conduction and radiation through windows, wall, doors etc., by ventilation and by infiltration. The superficial heat loss varies linear with ΔT and determines a constant cost per time unit to maintain a desired interior temperature for a given outside condition, with **U** = overall heat loss coefficient and ΔT = outside/inside temperature difference:

$$\textbf{Heat loss}\ (W) = \boldsymbol{A}\ (m^2) * \mathbf{U}(W/m^2K) * \Delta \boldsymbol{T}\ (K) \tag{1}$$

In order to estimate the annual energy cost with space heating or cooling we used the degree-days approach (Martinaitis *et al.*, 2010; Bhatia, 2013). This method was first developed in agricultural research and was used to observe the effect of atmospheric temperature dynamics on crops. The concept was imported into building energy consumption analysis as a link between weather changes and energy consumption and it allows to review a building's current energy requirements vs. its past performance.

Heating or cooling degree-days are computed as a daily exterior-interior temperature difference, the interior temperature being considered a reference temperature, usually 65ºF $\cong$ 18 ℃. The method assumes that any outside temperature below the reference temperature will trigger indoor heating in various degrees. An analogue approach anticipates the cooling demand.

$$HDD = \frac{\sum_{i=1}^{24}(T_{H\_base} - T_o)}{24} \text{ for } T_{H\ base} > T_o \tag{2}$$
$$CDD = \frac{\sum_{i=1}^{24}(T_o - T_{C\_base})}{24} \text{ for } T_o > T_{C\ base}$$

Some models considered an hourly basis in sampling, averaging the sum of positive hourly differences, introduced as cooling degree hours (CDH) (Krese *et al.*, 2012). If detailed weather dynamics information is not provided, estimative calculation methods for degree-days have been proposed (Hitchin, 1984; Spano *et al.*, 2002). While the HDH/ CDH method produce better results than HDD/CDD, its predictive usefulness in real human activity scenarios is still reduced because one-hour sampling intervals cannot accurately support human activity modeling.

Both degree-days and degree hours formulas use one single indoor temperature reference although the human comfort zone is a variable interval that depends on climate, age, gender, culture, habits etc. We consider more accurate to use two indoor temperature references, a lower "need heating" reference and a higher "need cooling" one. Further, we used weather data for every minute in order to summate and compare temperature differences over an entire year in two different usage scenarios: with and without multi-agents HVAC micromanagement. Given the above considerations of heating/cooling cost being linear with ΔT , the less cumulative temperature differences have to be sustained over a year, the lesser energy will be required, being expected thus a lower exploitation cost.

SCENARIO SETUP

We considered an administrative task group of collaborative agents for each closed space that could have an independent HVAC configuration inside a building. The purpose of each task group was to reduce HVAC energy consumption whenever possible, within a series of constraints. Such HVAC independent spaces can include one or more linked rooms and have the capability to insulate the inside temperature from the rest of the building. We will name in the following such organizational space units “apartments”, regardless of their private, public, commercial or corporate destination.

The considered constraints were:

- Prior to use an apartment, a user must announce in advance with at least one hour and book the apartment for a determined period of time.
- A free (non-booked) apartment will function in “stand-by mode”, maintaining a cold (**Standby-Chill**) or hot (**Standby-Hot**) temperature until booked.
- By default, the apartment is set to function in optimum comfort temperature mode, if the user does not activate personal preferences.
- The agents override the user’s preferences and fallback to the default regime whenever the user’s experience is not affected (user is away or sleeps). The user’s preferences are reinstated immediately after the overriding condition cease to exist.

SIMULATION FRAMEWORK

For commercial buildings, ISO standard 7730 prescribes generic temperatures of 20-24°C in winter and 23-26°C in summer, with exceptions according to room destination. According to World Health Organization (WHO), a temperature of 21°C in the living room and 18°C in other occupied rooms represent “an adequate standard of warmth". In practice, the base temperature is recommendable to be established from case to case (Day *et al.*, 2003).

The presented agent model and scenario constraints were implemented using the SHIELD simulation framework. The framework is oriented to emulate complex collaborative interactions of heterogeneous agents in Intelligent Buildings (Neagoe, 2014).

Our simulation took the standard reference temperature as 18°C, the optimum heating comfort 21°C, optimum cooling comfort 22°C. These values were considered conservatively and prudent, to avoid exaggerating the comfort interval and force better results. The **Standby Chill** and **Standby Hot** temperatures were set at 16°C and respectively 26°C. The simulation considered real weather temperatures recorded in 2013. Processing the injected Max/Min monthly values series, the simulation generates a plausible atmospheric variation (continuous weather scenario) for 525600 minutes (one year) or loads a previous generated pattern.

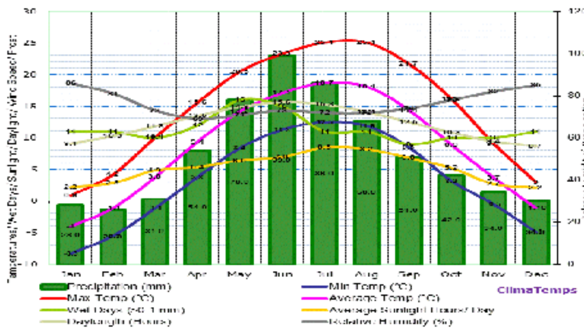

Figure 2. Real weather pattern for Brasov, Romania, 2013

The simulated environment emulated a hotel with 250 apartments with HVAC features managed for each apartment by a group of collaborative agents. The generated weather continuity chart highlights that buildings in Brasov deal mostly with heating demand (reality), cooling being a non-issue:

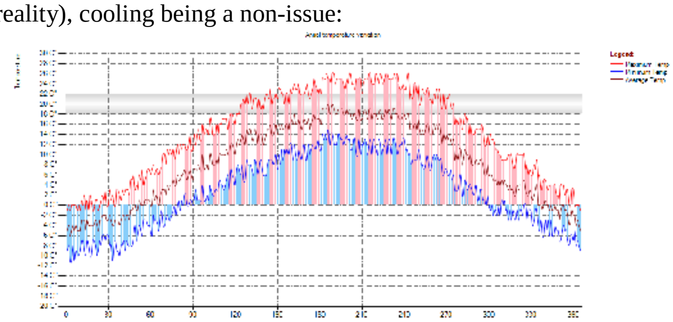

Figure 3. Annual heating and cooling demand, Brasov, Romania, 2013

Since most energy consumption occurs in the cold days with heating, the hotel scenario considered a plausible facility load history, giving a special attention to the possibility that unrealistic usage patterns injected as scenario input could artificially alter the result. The considered occupancy pattern as a (days in month, occupancy percent) series:

Monthly Facility Load = { IAN { 31, **95** }, FEB { 28, **85** }, MAR { 31, **65** }, APR { 30, **40** }, MAI { 31, **45** }, IUN { 30, **55** }, IUL { 31, **65** }, AUG { 31, **75** }, SEP { 30, **70** }, OCT { 31**, 65** }, NOV { 30, **75** }, DEC { 31, **100** } }; // {DAYS IN MONTH, HOTEL LOADING PERCENTAGE}

The occupancy pattern proved to be of major importance in the simulation outcome. The differences in the final result ranged from the lowest energy savings score (6,7%)

for a constant 100% occupancy to the highest (33, 94) for 0% occupancy. The interpretation is straightforward, the 0% occupancy fully "benefiting" from the **Standby-Chill/ Standby-Hot** HVAC regime while at 100% occupancy no standby regime was registered.

Further, for each apartment was generated the daily occupancy history and one of three user types was assigned to use the space. The three user types were: minimalistic user (***R1***), normal user (***R2***) and intensive user (***R3***), randomly generated with 20%-60%-20% probabilities. The ***R1*** type is mostly absent, does not change much or at all the standard HVAC setup and has no extreme preferences(demands 19-22°C in winter and 24-27°C in summer), the ***R2*** normal user is moderately absent and has moderate temperature preferences(21-24°C , 22-25°C) and ***R3*** intensive user that almost never leaves the room and has the costliest "demands" (23-26°C, 20-23°C). All user types "sleep" one single time per 24 hours, at night, for 6 to 10 hours(random).

For each user type, an user event sequence is created for every day he occupies the apartment. He leaves, returns, configures HVAC preferences or not, sleeps. All events have a "cool-down time" while they cannot happen again and do not describe impossible or abnormal user behavior (one cannot be away and asleep at the same time, will not change HVAC preferences 10 times per hour, etc.). The user actions are not altered by exterior influences like price incentives or constraints (Mohsenian-Rad *et al.*, 2010; Ozturk and Kumar, 2013; Ramchurn *et al.*, 2011). To permit an accurate comparison, the simulation stores the user action sequence for each day, for each apartment, in order to run the "unmanaged"/"micromanaged" scenarios in a row.

RESULTS

Using the degree method to compute the heating and cooling effort each minute produces large figures for each day, for the 250 simulated apartments reaching an 10^7 order. The following synthetic chart represents the "**C**lassic **H**eating/**C**ooling **D**egrees Needed" - **CHDN/CCDN** series, computed using two interior comfort reference temperatures Comfort Heat Needed = 21℃ and Comfort Cold Needed = 22℃ and the "**M**icromanaged **H**eating/**C**ooling **D**egrees **C**omfort" **MHDSC/MCDSC** series, where the local agents override user preferences with optimum values while the user is away/sleeps and fallback to **Standby Chill/Hot** mode while free of contract:

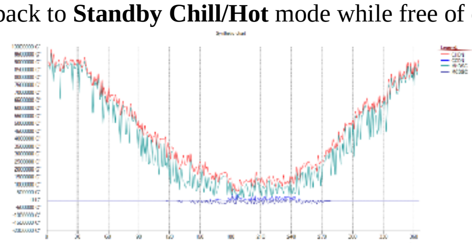

Figure 4. Comparative unmanaged vs. agent micromanagement HVAC effort

The two compared methods used the same annual weather pattern, occupancy series and generated user events series for all simulated apartments. Repeated simulation re-runs with the same input data (monthly min/max temperature series and monthly occupancy series) constantly produced result between roughly 14% and 15%. The above simulation run indicated a 14.421 % gain in energy efficiency.

CONCLUSION

The degree-days (hour/minutes) concept permits the analysis of energy management outcome regardless of a buildings physical characteristics or HVAC installations performance. These factors being the same for each case, the outcome difference comes from usage policy alone. Intelligent agent HVAC real-time micromanagement shows an important savings margin to a building's energy bill. For the simulated case-study presented in this paper the performance gain was equivalent with 35 apartments out of 250 running with no HVAC costs for an entire year. The fact that the simulation used conservative figures indicates a higher performance possible in extreme case scenarios (ex. natural disaster or calamity), when the comfort interval could be automatically adjusted to accommodate the transient conditions. The intelligent micromanagement technique can be applied to any building, residential or commercial, and can be improved with further automatic triggered events like automatic windows and reflective curtains operations, user incentives, humidity control etc.

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