MULTI-AGENT BUILDING CONTROL IN SHARED ENVIRONMENT

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Abstract: Multi-agent systems have been adopted to build intelligent environment in recent years. It was claimed that energy efficiency and occupants' comfort were the most important factors for evaluating the performance of modern work environment, and multi-agent systems presented a viable solution to handling the complexity of dynamic building environment. While previous research has made significant advance in some aspects, the proposed systems or models were often not applicable in a "shared environment". This paper introduces an ongoing project on multi-agent for building control, which aims to achieve both energy efficiency and occupants' comfort in a shared environment.

1 INTRODUCTION

Intelligent sustainable healthy buildings improve business value because they respect environmental and social needs and occupants' well-being, which improves work productivity and human performance.

MASBO (Multi-Agent System for Building cOntrol) is an ongoing subproject of CMIPS (Coordinated Management of Intelligent Pervasive Spaces) project. It aims to provide a set of software agents to support both online and offline applications for intelligent work environment.

2 RELATED WORK

Developing software agents for intelligent building control is an interdisciplinary task demanding expertise in such areas as agent technology, intelligent buildings, control network, and artificial intelligence.

This section reviews previous work in this area that could help build the core component of MASBO: multi-agent system (MAS).

2.1 Agent Technology and Building Intelligence

Research work conducted by (Davidsson and Boman) uses a multi-agent system to control an Intelligent Building. It is part of the ISES (Information/Society/Energy/System) project that aims to achieve both energy saving and customer satisfaction via value added services. Energy saving is realized by automatic control of lighting and heating devices according to the presence of occupants, while customer satisfaction is realized by adapting light intensity and room temperature according to occupants' personal preferences.

While the discussed system is capable of adjusting the heating and light level to meet personal preferences, these preferences are predefined and can not be adapted or learned according to the feedback or behaviour of the occupants. It can detect a person's presence and adapt the room environment settings according to his/her preferences via an active badge system. The badge system itself, however, does not provide the means to distinguish between actuations from different occupants, which is necessary for occupants' behaviour learning mechanisms proposed in some other research work (Callaghan et al., 2001, Davidsson and Boman, 2005).

In (Callaghan et al., 2001, Davidsson and Boman, 2005), a soft computing architecture is discussed, based on a combination of DAI

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(distributed artificial intelligence), Fuzzy-Genetic driven embedded-agents and IP internet technology for intelligent buildings.

Besides the learning ability, this research also presents another feature in some cases preferable for intelligent building environment: user interaction and feedback to the MAS. However its use of embedded agents makes it difficult to take advantage of sophisticated agent platforms and as claimed by the researchers, places severe constraints on the possible AI solutions.

Further research following (Callaghan et al., 2001) is the iDorm project (Hagras et al., 2004), where an intelligent dormitory is developed as a test bed for a multiuse ubiquitous computing environment. One of improvements of iDorm over (Callaghan et al., 2001) is the introduction of iDorm gateway server that overcomes many of the practical problems of mixing networks. However, iDorm is still based on embedded agents, which despite demonstrating learning and autonomous behaviours, are running on nodes with very limited capacity.

The requirement of user feedback or interactions in intelligent building environment is controversial. Some researchers claim that ambient intelligence should not be intrusive, i.e., no special devices used and no imposing rules on occupants' behaviour. In (Rutishauser et al., 2005), a multi-agent system is discussed for intelligent building control. In contrast to the approach in (Callaghan et al., 2001, Davidsson and Boman, 2005), the MAS is equipped with an unsupervised online real-time learning algorithm that constructs a fuzzy rule-base, derived from very sparse data in a non-stationary environment. All feedback is acquired by means of observing occupants' behaviours without intruding on them. While avoiding intrusiveness could be preferable in some cases, the MAS loses the ability to distinguish between actuations and preferences from different occupants, and thus the preferences learned are not coupled with the occupants but the room they are in. By this way, it is unable to take into account personal preferences.

2.2 Summary of Related Work

After reviewing previous research on multi-agent systems for building control, a list of issues that may need further studies have been summarized as follows:

- The personal preferences are often predefined and can not be adapted or learned according to the feedback or behaviour of the occupants.
- Most systems do not provide a means to distinguish between actuations from different occupants, thus are not able to learn individual preferences.
- To learn preferences of occupants in a shared environment, a single learning mechanism is not capable of handling complex, dynamic building environment.
- Addressing both preferences learning and multi-occupancy in a shared environment complicates the design of the multi-agent system.
- A combination of environmental parameter values is used as personal preferences. More recent work in building construction indicates that a function of such parameters more accurately represents an occupant's comfort or satisfaction degree.

3 OVERVIEW OF MASBO

The design of a Multi-Agent System for Building cOntrol (MASBO) emphasizes the dynamic configuration of building facilities to meet the requirements of building energy efficiency and the preferences of occupants. Fig. 1 shows the proposed multi-agent system deployed in two zones. A zone represents the basic unit of building structure under MASBO's control.

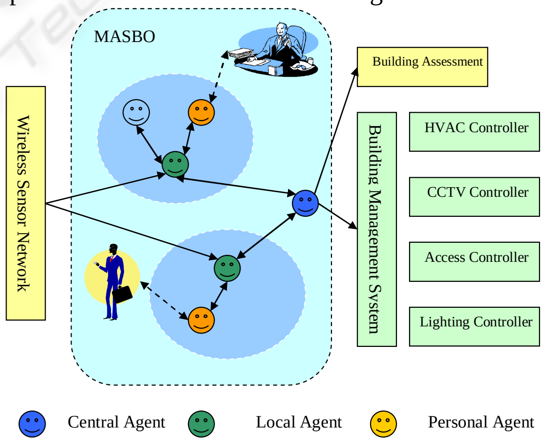

Figure 1: Scenario of MASBO. As the hub of CMIPS, MASBO integrates with the other two components, building assessment and wireless sensor network.

MASBO is designed as a system composed of a number of software agents, capable of reaching goals that are difficult to achieve by an individual system (Wooldridge, 2002).

Personal agents act as assistants that manage user (occupant) specific information, observe the ambient environment, and present feedback from other agents to their users (occupants).

Local agents act as mediator and information provider. They reconcile contending preferences from different occupants, learn occupants' behaviour, and provide structure information of their respective zones...

A central agent provides services that allow operators to start or stop agents, deploy or delete agents, and modify zone information for local agents. It also aggregates decisions received from local agents before converting them to BMS (Building Management System) commands. If a decision did not go through the central agent to reach the BMS (has been abandoned or aggregated), the corresponding local agent will be notified.

For a detailed discussion of agents defined in MASBO, please refer to (Qiao et al., 2006).

4 DECISION MAKING AND LEARNING

The design of decision-making and learning components for MASBO aims to achieve such flexibility that adapting the system to a dynamic, shared building environment will just be a matter of applying different static rules or data analysis methods on dynamic rules.

4.1 Rules

Decision making and learning process in MASBO are built upon rules (fuzzy rules when implemented as a Fuzzy logic controller). A rule in MASBO is defined as:

- Antecedents and actions
- Attributes
  - ID: the ID of the occupant who took the action.
  - Priority: "safety", "security" and "economy" for static rules; "preference" for dynamic rules.
  - Privilege: numbers, e.g. 0 ~ 9, for making decision among conflicting rules.
  - Weight: numbers, execution count, >= 1.
  - Predicted parameters Vector: a vector of parameter values depicting the environment resulted from an occupant's or an agent's action.
  - Predicted TCI: The resulting TCI from an occupant's or an agent's action. A number of ways can be used to calculate this, for instance by using the current parameters just before executing next rule.
  - Effective period: the time span of the rule in effect, e.g., the interval between consecutive rules.

Rules are categorised into two groups: static and dynamic. Static rules are predefined by developers, occupants, or building managers. They are static in comparison to the dynamic rules that are generated at runtime by the learning mechanisms of MASBO.

- Static rules
  - If a zone has no occupants, it must maintain some default environmental settings.
  - If a zone is a corridor or belongs to any other types of common zones, the temperature is set with a default value and the light is turned on only when at least one person is in this zone.
  - If only one occupant is present in a non common zone, such as an office, the local agent must adapt the environmental parameters to his/her preferences.
  - If more than one occupant is present in a non common zone, the local agent needs to reconcile the contending preferences according to the privileges those occupants have in this zone.
  - If occupants' preferences conflict with the rules applied on involved zone, the local agent needs to reconcile the conflicts according to the priorities those rules have in this zone.
  - If actions have been taken by occupants directly on the electrical equipment instead of their personal agents, the decisions made by the local agents in MASBO can be overruled.
- Dynamic rules are generated automatically by the learning process

4.2 Decision Making

The input of decision making process is a parameters Vector and occupant's action. Local agents will only conduct decision making and learning activities when any of those events occur.

Otherwise, the sampled data will be discarded, as shown in Fig. 2. Three such events are defined as follows:

- "Occupants changed" events (OC)
- "Parameters changed" events (PC)
- "Device operated" events (DO)

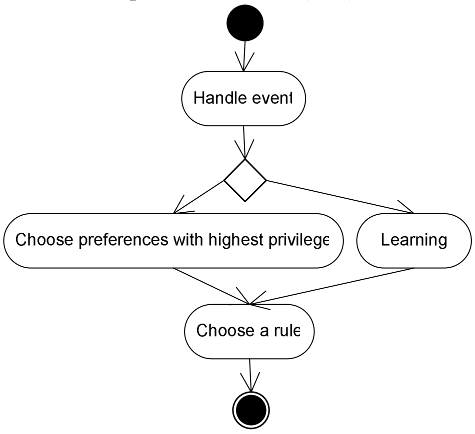

Figure 2: Decision making and learning: handling events, making decisions and learning occupant's behaviour.

Decision making needs to solve conflicts in the following scenarios:

- Preferences conflicting with static rule. Decision will be made according their priorities.
- Occupants with different privilege.
- Dynamic rules with the same antecedents but different actions. Decision will be made according to rule attributes such as weight, predicted Vector, TCI, and effective period.

4.3 Learning

Different learning processes can be categorised into three groups: interactive, supervised, and reinforcement learning. MASBO adopts a combination of those processes, aiming to reduce intrusiveness of the multi-agent system, without losing the capability of learning individual preferences.

By interactive learning, the agent asks for occupant's preference for any given programmable setting and tries to adjust its rule set to achieve this setting. The occupant is then asked to confirm the environment change, the result of which will help the agent to either abandon the new rule or keep the updated rule set. Interactive learning is shown in Fig. 3.

By supervised learning, it assumes that the agents know the action of the user by direct communication between agent and actuator or by building a model to indirectly calculate the user action, as shown in Fig. 4.

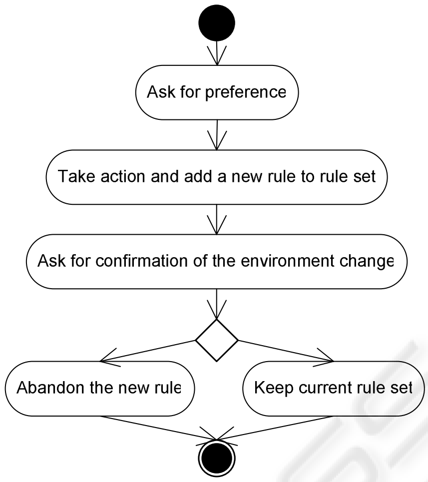

Figure 3: Interactive learning: asking confirmation from the occupant.

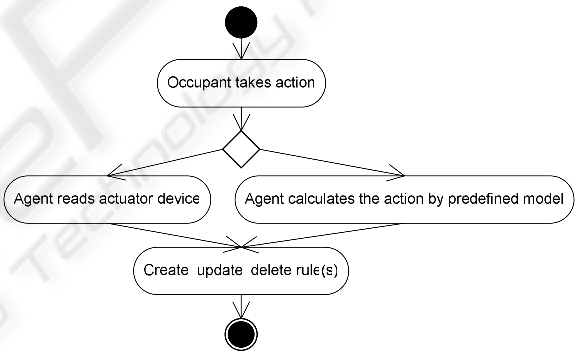

Figure 4: Supervised learning: having direct information of the action taken by an occupant on the actuator.

By reinforcement learning, the agent sets environment parameters according to occupant's preferences, as shown in Fig. 5. The agent will try to guess the value set on the actuator by trying to minimize the difference between the results of user action and agent action using the guessed value.

Even if direct information is known to the agent, reinforcement learning could still be useful by constructing a reward system, as shown in Fig. 6. If an agent turns on a light and the occupant turns it off, the agent would receive a negative reinforcement. If the person does not change anything the agent would receive a positive reinforcement (reward).

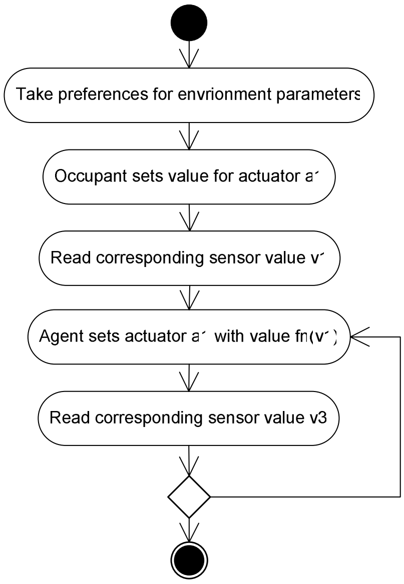

Figure 5: Reinforcement learning: calculating the exact action taken by an occupant.

4.4 Learning in MASBO

An occupant's profile includes an ID and a number of sets of preferences related to different environmental contexts that define such attributes as privilege, location, and time span.

A set of preferences is stored in a parameters Vector. An occupant's preferences are calculated from all the dynamic rules produced for the related occupant.

Learning occupants' preferences is conducted by observing occupants' behaviour and identifying the person who took the actions. Firstly, the less the occupants need to instruct the building (e.g., adjust the thermostat) to change the environment (in this case, change the temperature), the more they are satisfied. If the occupants are satisfied with the current environment, the MASBO can assume that the environment is preferable to the occupants and thus calculate their preferences accordingly. On the other hand, occupants change the environmental settings via their personal agents and provide feedback on their satisfaction if they would like to. By this way, the environmental change can be traced back to the exact person who made it and the preference learned can be linked to this particular individual instead of all occupants in the shared space. This approach is a combination of the studies in (Rutishauser et al., 2005, Callaghan et al., 2001). It not only reduces intrusiveness of the MAS to occupants, but also allows for the personalized space for individuals.

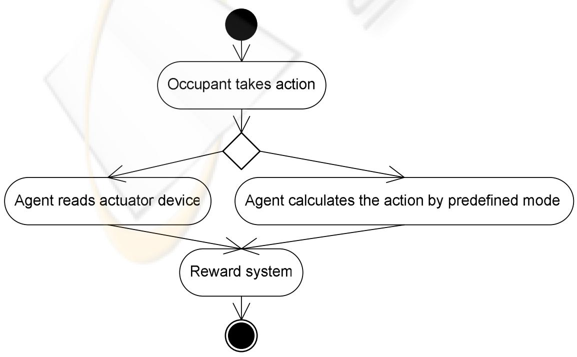

Figure 6: Reinforcement learning: reward system.

The direct outcome of learning is a set of rules that record the related occupant's behaviour under certain environment. The learning process does not produce preferences. The preferences are calculated from the learned rules. As defined in section 6.1, a rule will have the following contents:

- Input: (para1, …, parai, …, param)
- Output: (action1, action2, …, actioni, …, actionn)
- Attributes: ID, priority, privilege, weight, resulting(para1, …, parai, …, param), resulting(TCI), period(start_time, end_time).

An occupant's behaviour, recorded as a large amount of rules, can be analysed using statistics or data mined. Different strategies for analysing the rules can provide different ways to update an occupant's preferences, for instance:

- The predicted Vector of the first rule that has been effective for more than "8" hours since last update of preferences will be used to update current preferences.
- The predicted Vector of all the rules that, grouped by predicted Vector, has the sum of their weights increased "20" within one week since last update of preferences will be used to update current preferences.
- If the preferences of occupant A have not been changed for one week, and the sum of the effective periods of A's all rules during that week is less than "5" hours, update them with another occupant's preferences that have taken effect in most time of that week.
- If the preferences of occupant A have not been changed for "1" week, the preferences of occupant A can be updated according to the predicted Vector of the rule having TCI valued "0" (comfort level in general) and the biggest weight.

- If the preferences of occupant A have not been changed for “1” week, the TCI preference of occupant A can be updated according to the predicted TCI value that occurs most often (personalised TCI value) in all related rules.

An occupant’s personal agent will negotiate with local agents in respect of which learning mechanism to be used for preferences learning. Such design of occupant’s preferences, the rule, and the learning process enables MASBO to search for the best preferences learning mechanisms.

5 EVALUATION

Investigations have been made on previous similar projects (Davidsson and Boman, Rutishauser et al., 2005, Callaghan et al., Hagras et al., 2004) on how to evaluate the model and eventually the implemented system.

- Qualitative simulation.
- Energy consumption quantitative analysis that compares the energy consumption of using or not using MASBO.
- Satisfaction quantitative analysis that checks how well temperature or lighting history records meet specified policies.
- Satisfaction quantitative analysis that compares the learned rules with the occupant’s journal entries.
- The number of rules learned over time that indicates how well the Multi-agent system performs.

6 CONCLUSIONS AND FUTURE WORK

Many efforts have been made on using multi-agent system for intelligent building control. However, while previous work has addressed most of the important features for MAS based intelligent building control, we claim that no research has been done to consider all the following requirements:

- Energy efficiency and occupants' comfort
- Preferences learning in shared environment
- Personalized control and feedback
- Human readable and accurate knowledge representation
- Sophisticated agent platform and techniques

We believe above requirements are essential to a successful intelligent building environment and a complete solution should be able to tackle all of them. The first four requirements have been discussed in this paper. The fifth requirement was presented in (Qiao et al., 2006). The last requirement will be addressed in the next step of this project.

Future work will be carried out in the following steps 1) testing different strategies for preferences learning and decision making in a simulated environment; 2) developing MASBO on advanced agent platform; 3) system integration with wireless sensor network and building automation system, and 4) evaluation by experiments in real world buildings.

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